S2S4E

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Economic gains from using S2S forecasts in energy producers' decision-making by analysing relevant case studies

Deliverable D2.2

Final Version

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Disclaimer

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Summary

This report aims at studying the economic gains for renewable energy (RE) companies of using S2S forecasts in the context of extreme weather events. The analysis uses the 8 case studies identified in D2.1 and builds on the results of the analysis of user's needs and the identification of decision-making processes that could benefit from S2S forecasts.

Chapter 1 of this report presents the impacts of 8 weather anomalies on the energy markets and the role of S2S in supporting RE companies to mitigate the impacts on their economic activities. Chapter 2 presents a decision analysis is performed on 3 case studies covering those risk management areas highlighted by users as relevant in each context. Particular attention is given to financial decisions. Finally, Chapter 3 identifies the information needed from decision-maker's perspectives through the construction of stylised ensembles.

The analysis in Chapter 1 shows that extreme weather events generate volatility in the energy markets. This volatility, e.g. sudden changes in demand and RE supply with consequences on wholesale prices, is a driver for RE companies to consider S2S forecasts as a mean of managing the risks involved. A relevant result in Chapter 2 is that the role of sub-seasonal forecasts in financial decisions could be valuable both for wind producers and for energy traders. Interestingly, making a decisional error due to a change in expectations (that finally do not match the observations) led by a forecast concerns decision-makers more than gaining from the use of an informative forecast. This suggests the importance for the climate service to provide information about the reliability and uncertainties entailed in the forecasts. Additionally, the analysis of usefulness of sub-seasonal forecasts on operation and maintenance (O&M) activities of a wind farm shows positive results. Thus, seasonal forecasts are found to be relevant for budget planning, although it is not possible to quantify the benefits due to confidentiality reasons. While this study focuses on extreme events, the next steps in the evaluation of S2S4E forecasts will consist of an economic assessment in the operational phase (D.3).

List of acronyms

DSO	Distribution System Operator
DST	Decision Support Tool
ENTSO-E	European Network of Transmission System Operators
O&M	Operation and maintenance
RE	Renewable Energy
S2S Forecasts	Sub-seasonal and seasonal forecasts
S2S4E Forecasts	Sub-seasonal and Seasonal forecast provided by the DST
TSO	Transmission System Operator

Introduction

Sub-seasonal to seasonal (S2S) forecasts range from 10d to 1 month (sub-seasonal) and from 1 to 7 months (seasonal). Research on S2S forecasting is quite a recent field that is raising interest about their applications in different sectors such as energy, agriculture or insurance among many. Decision-makers in these sectors are exploring opportunities to integrate the probabilistic information provided by S2S forecasts into their decisional strategies. Consequently, raising efforts are undertaken to evaluate climate services providing sub-seasonal or seasonal forecasts for decision-making (Bruno Soares, Daly, & Dessai, 2018). However, there is a need for more research and to our best knowledge, the value of sub-seasonal forecasts in the energy sector has not been sufficiently investigated.

The S2S4E project is developing a climate service - named Decision Support Tool (DST) - addressing the needs of the energy sector. The service is being developed in close collaboration with energy companies and with the support of transmission system operators (TSOs) and distribution system operators (DSOs) as well. At the time of writing the report, this is the first tool offering an integrated S2S forecast for solar, wind, hydro generation and electricity demand.

The value of S2S forecasts for decision-making is strictly dependent on the usability and reliability of the information provided by a particular climate service and on the context of the decision. This report offers an assessment of the economic gains of using the DST for RE companies' decision-making processes related to extreme weather events. Extreme events are increasing in frequency and intensity due to climate change (Tippett, 2018). They affect the energy markets and RE sources availability. S2S forecasts, allowing to predict such anomalies, have the potential to improve risk management. S2S4E forecasts also generate value by supporting decision-makers in their usual business activities under normal climatic conditions. The impact of operational real-time forecasts for decision-making processes will be assessed in the following stages of the project (D2.3) when companies will be testing the operational DST. This report focuses uniquely on weather extremes cases.

During previous stages of the project 8 case studies were identified by industrial partners and other stakeholders (D2.1). Different extreme weather events were analysed in each case and forecasts for the period of interest were produced (D4.1). This report analyses the impacts of these 8 anomalies on the energy markets and investigates how S2S forecasts could improve decision-making under uncertainty. For 3 case studies, an in-depth decision analysis of economic gains of using S2S forecasts was conducted in active collaboration with users. The report is structured to address different audiences offering basic analysis in the first chapter for those less familiar with economic concepts and then increasing in complexity. Chapter 1 describes overall energy market effects associated to the extreme weather events in 8 case studies and discusses when companies would benefit from using sub-seasonal or seasonal forecasts. Chapter 2 provides an assessment of decision-specific economic gains when using sub-seasonal forecasts for 3 case studies (an example of seasonal application is also discussed).

In particular, for the first case study, we calculate deviations costs that occurred during the icing event in Romania in 2014 and elaborate on potential gains of using S2S forecasts for budget planning, O&M activities, and financial decisions. The two other case studies focus primarily on financial decisions (i.e., hedging strategies) to mitigate financial risks of uncertain whether events. Using the cold waves that affected Germany and France in 2017 and 2018 as an example, we show in stylised experiments the potential economic benefits of using sub-seasonal forecasts for portfolio-optimization decisions. Chapter 3 presents a theoretical concept of decision-making under uncertainty and identifies information needed from users' perspectives.

Chapter 1

The impact of Extreme Weather Events on the Energy Markets and Companies’ performance

1 The impact of Extreme Weather Events on the Energy Markets and Companies' performance

This chapter offers a general overview of the impacts of extreme weather events on the energy markets in eight case studies, which were identified during previous stages of the project in close collaboration with energy industrial partners and external stakeholders. For each case study, renewable energy producers recognised the potential of achieving economic gains by using seasonal and/or sub-seasonal forecasts in different decision-making processes. The list of case studies follows:

1. Cold spell in France and Germany in 2017
2. Heat wave and solar generation in Germany in 2013
3. Heat wave and wind droughts in Spain in 2016
4. Floods in Sweden 2015
5. Freezing event in Romania 2014
6. Wind droughts in USA in 2015
7. Cold spell in France in 2018
8. Record wind generation in Spain in 2018

These case studies describe the periods with an unusual climate behaviour, which affected the energy markets and therefore, these events were identified by stakeholders as the most relevant and interesting to investigate. For each case study, we provide a brief description of the events. To illustrate potential impacts of weather events on the energy markets, we use data publicly available at the portal of the European Network of Transmission System Operators (ENTSO-E), which provides *inter alia* hourly data on load[1], generation, and prices of electricity for European countries from 2015 onwards. For case studies related to earlier periods, we use other data sources if available. For most of the case studies, we show the development of daily average demand and generation of electricity as well as day-ahead prices for the periods of weather events. We also show average values of those market variables in years before and after the events to highlight abnormal fluctuations in the energy markets. This chapter provides only a general overview over extreme weather events and their potential impacts on demand, generation, and prices of electricity without any in-depth quantitative analysis of causal effects between weather and market variables. Changes in demand, generation and prices of electricity could also depend on many other non-weather-related factors, whose analysis is outside the scope of this projects.

[1] Load corresponds to electricity demand.

1.1 Cold spell France/Germany 2017

Cold spell over Europe created a combination of large increase in electricity demand and lower than normal wind power generation.			
Region:	France, Germany	Period:	17-23 Jan 2017
Forecast type[2]:	Sub-seasonal	Main interest:	Demand and wind
Forecast available[3]:	Wind speed, temperature and demand		

Table 1: Region, period, forecast type and main interest for case study 1.

1.1.1 France

From 17th until 23rd January 2017, there was a cold spell over Europe, which resulted in a substantial increase in electricity demand in France. Cold winter in January 2017 increased the peak demand to more than 20% above the level of January 2016, but noticeably the previous winter (2015/2016) was relatively warm. France was exporting electricity in January 2016, while in January 2017, domestic demand for electricity was satisfied by imports from Germany, Spain, and the UK (ENTSO-E, 2017))[4]. Furthermore, this period was characterised by a relatively low wind speed, which led to a reduction in wind power generation. It should also be noted that several nuclear reactors were under maintenance during this period in France. Moreover, most of Europe suffered from an unusual drought in autumn and winter, which caused an additional pressure on the electricity market. For instance, France experienced one of the driest Decembers in 2016 for decades, which resulted in a reduction in the supply of hydropower generation. Both a higher demand and shortage of power supply caused a strong increase in in day-ahead electricity prices[5]. For example, on 25th January, the day-ahead electricity price in France was approximately 121 Euro/MWh. However, in February, demand and prices for electricity stabilised to their normal levels and by the end of February, demand for electricity was even lower than the average level of 2015, 2016, and 2018 (Figures 1 and 4).

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[2] *Forecast type* indicates whether industrial partners and/or external stakeholders are interested in sub-seasonal or seasonal forecast within the scope of the case study. According to this, forecasts have been produced for the time (week or month) of the case study.
[3] Industrial partners and/or external stakeholders requested specific *forecasts variables* depending of the nature of the anomaly and their decision-making. Forecasts have been produced accordingly for back-testing purposes. Forecasts are available in D4.1.
[4] ENTSO-E (2017): Market analysis – annex to the ENTSO-E May 2017 report on managing critical grid situations: success and challenges. Available at: https://www.entsoe.eu/outlooks/seasonal/
[5] In the report we refer to day-ahead prices for the wholesale market.

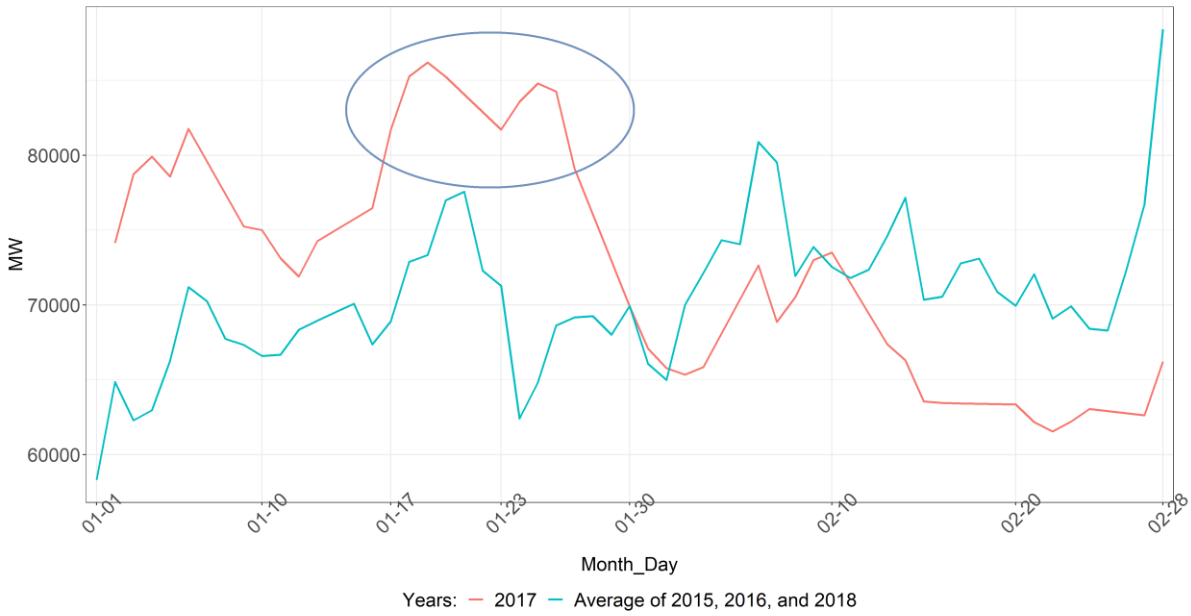

Figure 1: Daily average of hourly power load in France in January-February 2017. Only weekdays are shown. Source: ENTSO-E

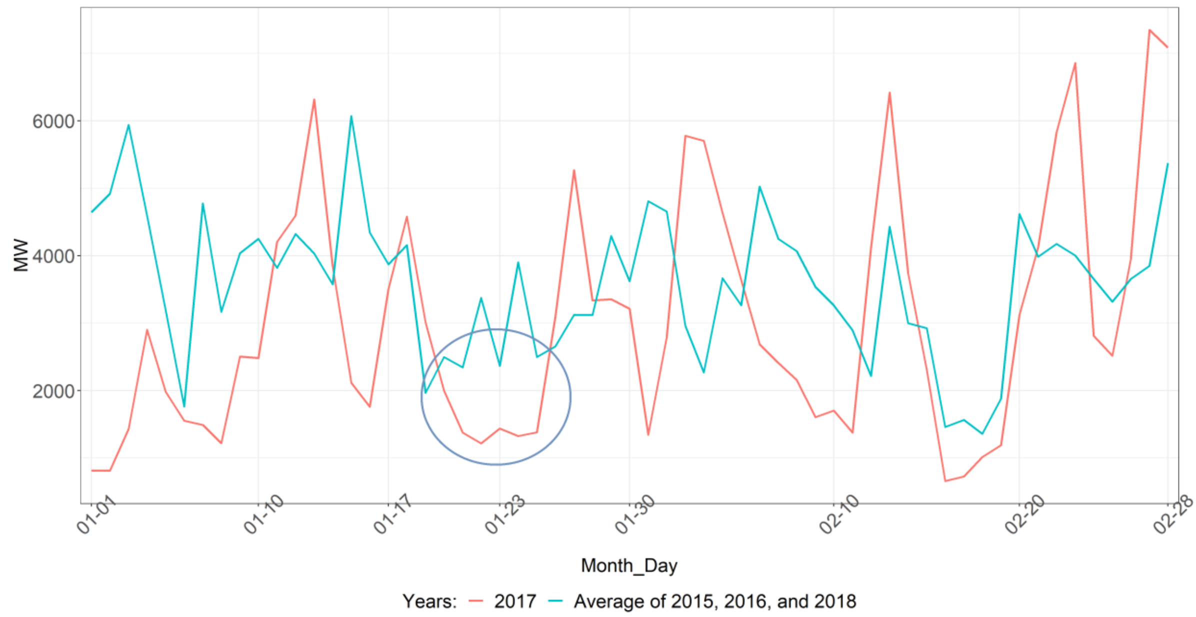

Figure 2: Daily average of hourly wind power generation in France in January-February 2017. Source: ENTSO-E

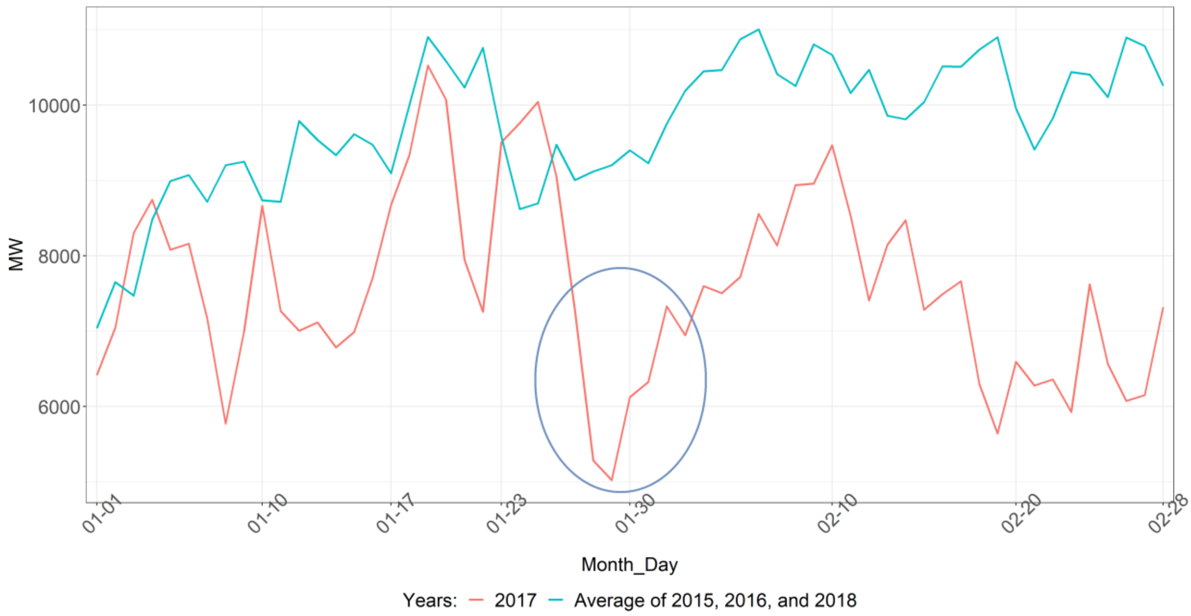

Figure 3: Daily average of hourly hydro power generation in France in January-February 2017. Source: ENTSO-E

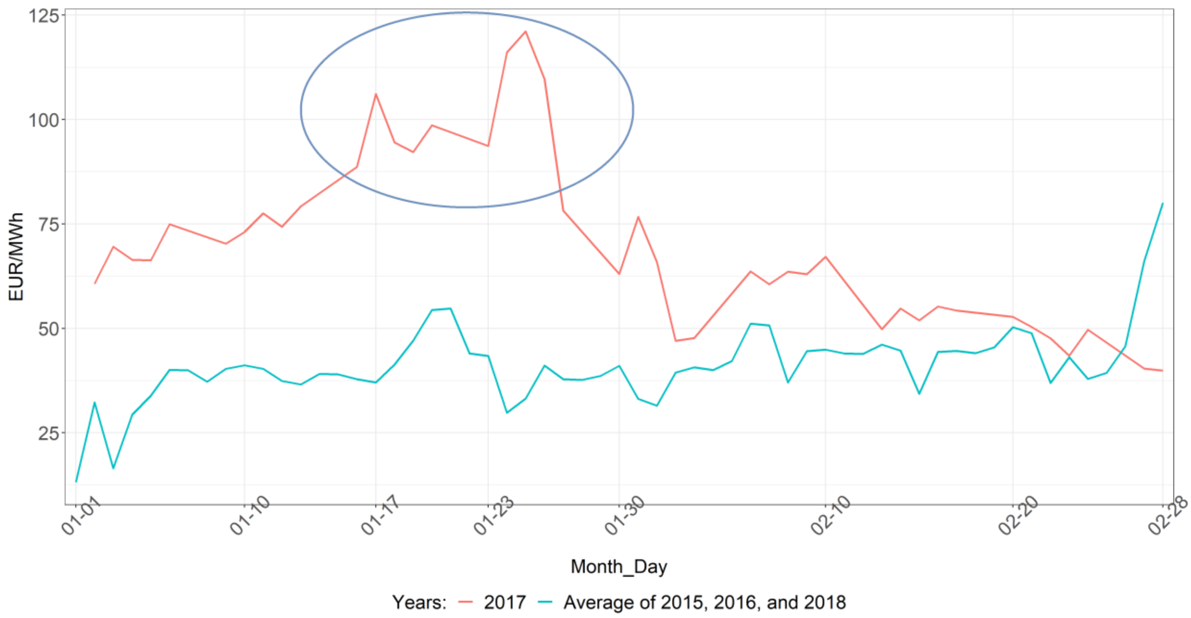

Figure 4: Day-ahead electricity prices in France in January-February 2017. Only weekdays are shown. Source: ENTSO-E

Interviewees revealed that sub-seasonal forecasts of temperature, wind and demand are useful in situations as this one and the one created by the same anomaly in Germany - presented in the following section. In chapter 2 the use of sub-seasonal forecasts in hedging decisions during this anomaly is analysed.

1.1.2 Germany

Germany also experienced a cold spell and low wind speed by the end of January 2017. The German electricity market is less sensitive to changes in temperature compared to the French market. Therefore, the demand was less affected by low temperatures. On the other hand, the Germany electricity market was more affected by losses in wind power generation due to its large amount of installed wind capacity. Low wind and solar generation were compensated by increased fossil fuel generation, so that the demand was satisfied without imports (ENTSO-E, 2017). In 17th and 24th January, there were two price spikes, with the maximal increase in electricity price of 102 Euro/MWh, which has been the highest level since the cold spell in February 2012. This also holds for the monthly average German power price, i.e., January 2017 was the most expensive month in five years since February 2012. Yet, in February 2017, electricity prices stabilised to their average level of 2015, 2016, and 2018.

For both French and German electricity markets, an analysis of sub-seasonal impacts on traders' financial decisions is performed in chapter 2, user cases 1 and 7.

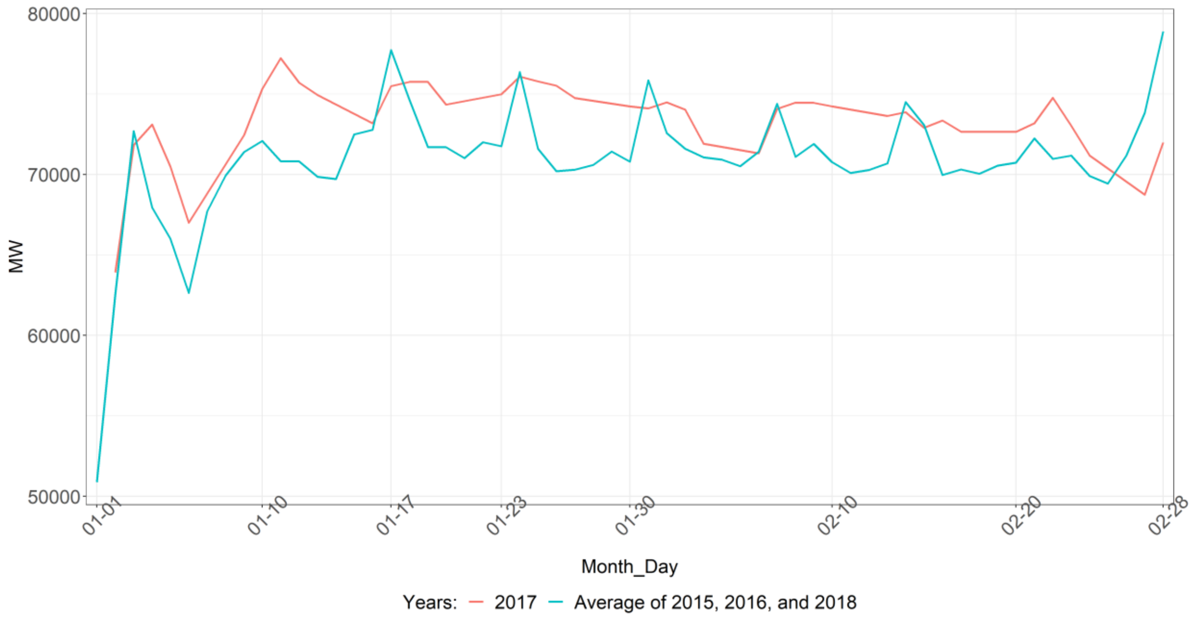

Figure 5: Daily average of hourly power load in Germany in January-February 2017. Only weekdays are shown. Source: ENTSO-E

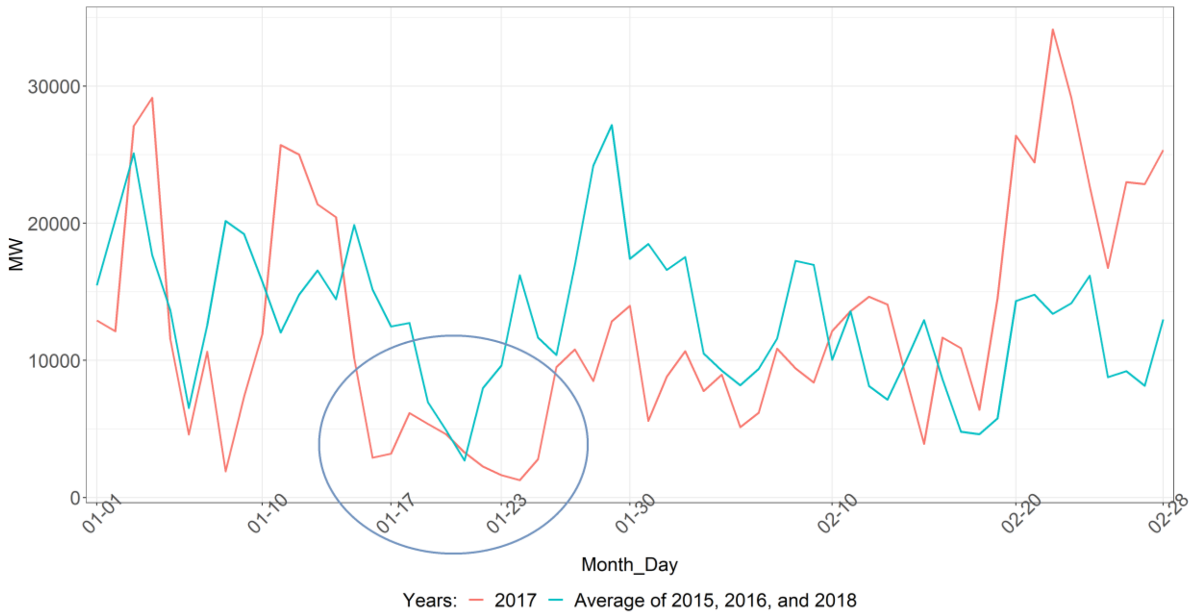

Figure 6: Daily average of hourly wind power generation in Germany in January-February 2017. Source: ENTSO-E

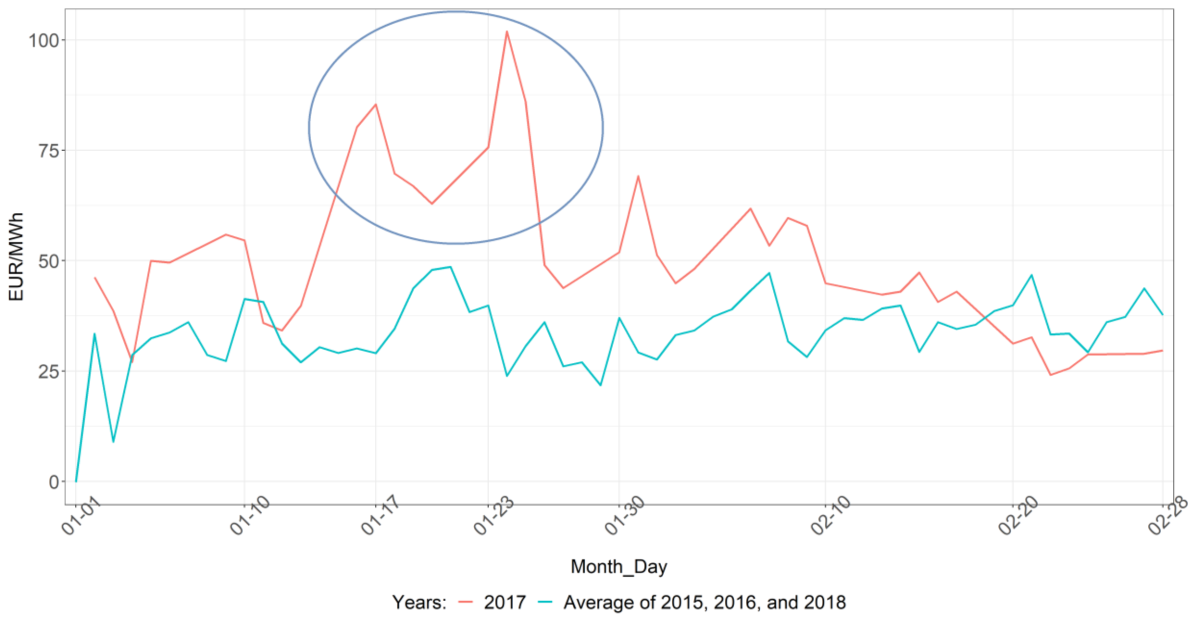

Figure 7: Day-ahead electricity prices in Germany in January-February 2017. Only weekdays are shown. Source: ENTSO-E

1.2 Heat wave and solar generation in Germany 2013

A high-pressure system over central Europe resulted in large electricity demand, higher than normal solar generation and low precipitation rates.			
Region:	Germany	Period:	July 2013
Forecast type:	Seasonal	Main interest:	Demand, solar, wind and hydro
Forecast available:	Precipitation, inflows, solar radiation, solar capacity factor, wind speed, temperature and demand		

Table 2: Region, period, forecast type and main interest for case study 2.

July-August 2013 in Germany experienced abnormally high solar radiation and low precipitation. Temperature anomalies were also higher than the climatological average, while wind anomalies were below the climatological average. It was estimated that excess mortality in Frankfurt am Main due to an abnormally high temperature was 113% among the population aged more than 80 years. Overall, the heat wave caused over 70,000 fatalities in Western Europe (Heudorf & Schade, 2014). Moreover, a high temperature resulted in increases in wholesale electricity prices due to electrical cooling needs, whereas low precipitation and wind speed implied a lower supply of domestic power generation.[6]

High solar radiation led to a moderate increase in solar power production. However, low wind speeds reduced wind power substantially and caused an imbalance in the energy system. With nearly 39 GW of installed photovoltaic capacity, periods of high solar radiation during summer in Germany may affect the relative contribution of energy from different sources considerably. During these periods of elevated solar generation, expensive and polluting conventional power plants may be shut down, with a downturn in the energy trading market as a consequence. In this context, coal power plants are typically used as a backup to ensure security of supply. In Germany, coal supply is largely based on river transport which is dependent on river navigability associated with precipitation levels. In this specific case, the very low precipitation levels restricted transportation capacity on major waterways like the Rhine. Having an accurate seasonal forecast would allow to better schedule the transportation of coal to power plants and thereby alleviate to some extent the shortage of domestic power supply (i.e., imbalances in the energy system).

[6] Data on load was not available for that period.

Figure 8: Daily average of hourly solar power generation in Germany in July-August 2013. Source: Open Power System Data (OPSD)

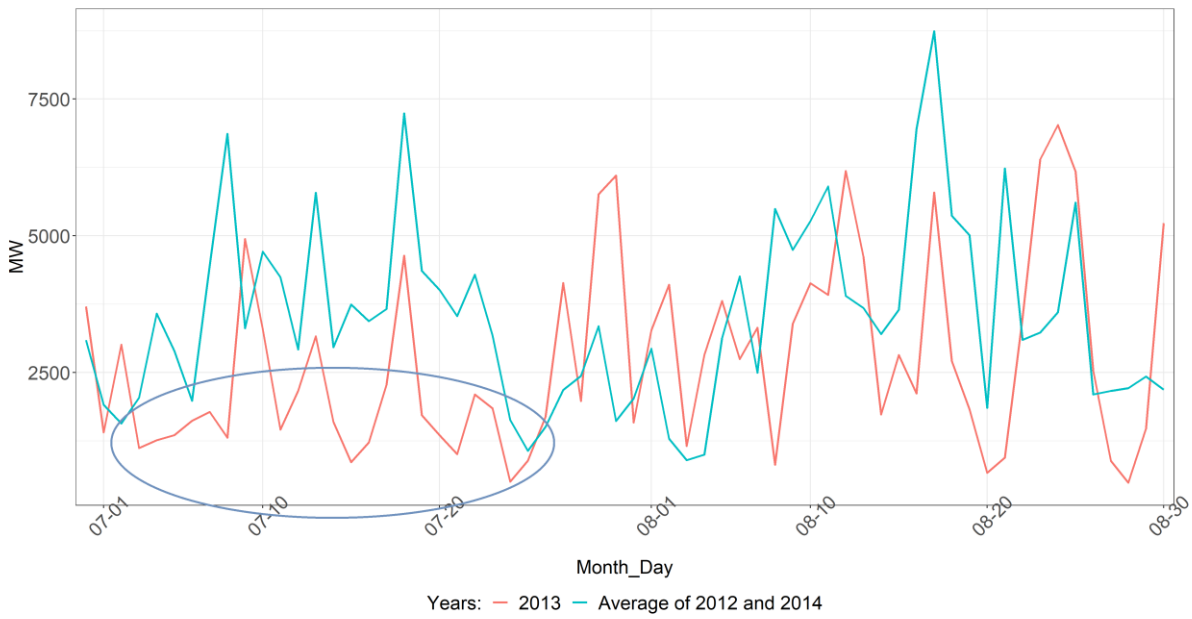

Figure 9: Daily average of hourly wind power generation in Germany in July-August 2013. Source: Open Power System Data (OPSD)

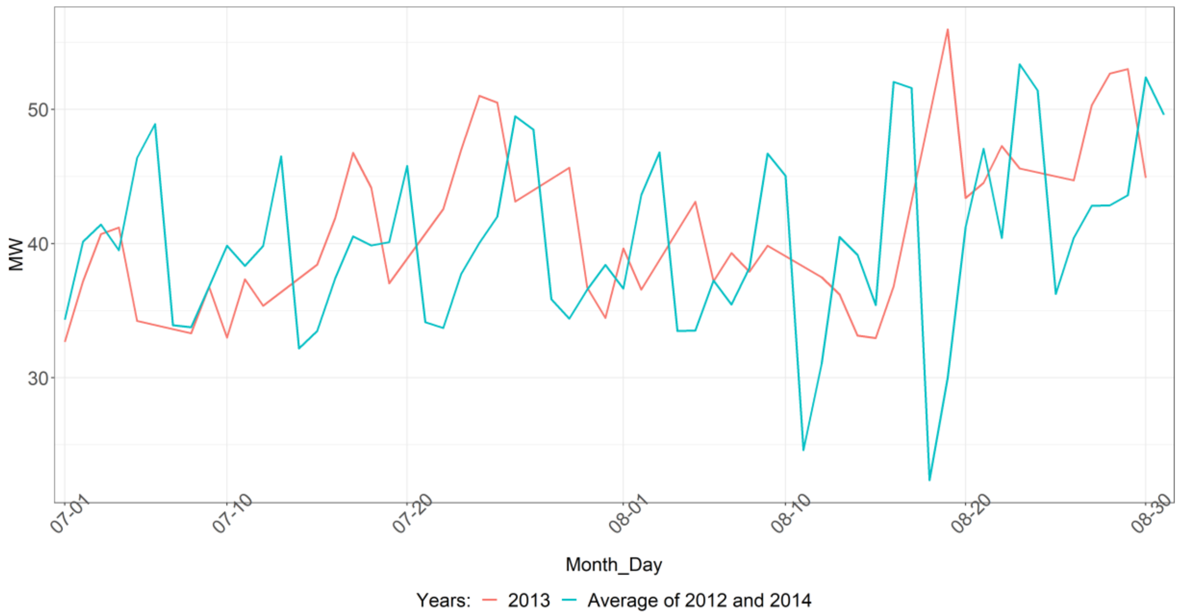

Figure 10: Day-ahead electricity prices in Germany in July-August 2013. Only weekdays are shown. Source: EPEXSPOT

1.3 Heat wave and wind drought Spain 2016

Heat wave and wind drought			
Region:	Spain	Period:	30 Aug-5 Sep 2016
Forecast type:	Sub-seasonal	Main interest:	Demand and wind
Forecast available:	Wind speed, temperature, demand and demand net wind		

Table 3: Region, period, forecast type and main interest for case study 3.

From 30th August until 5th September 2016, Spain was affected by a strong heat wave combined with a notable decrease in wind speed. These conditions led to increases in demand and prices for electricity. For example, in the first week of September, demand for electricity was substantially higher compared to an average load of 2015, 2017, and 2018, whereas wind power generation was lower. Especially on 6th September, there was a strong increase in the demand for electricity.

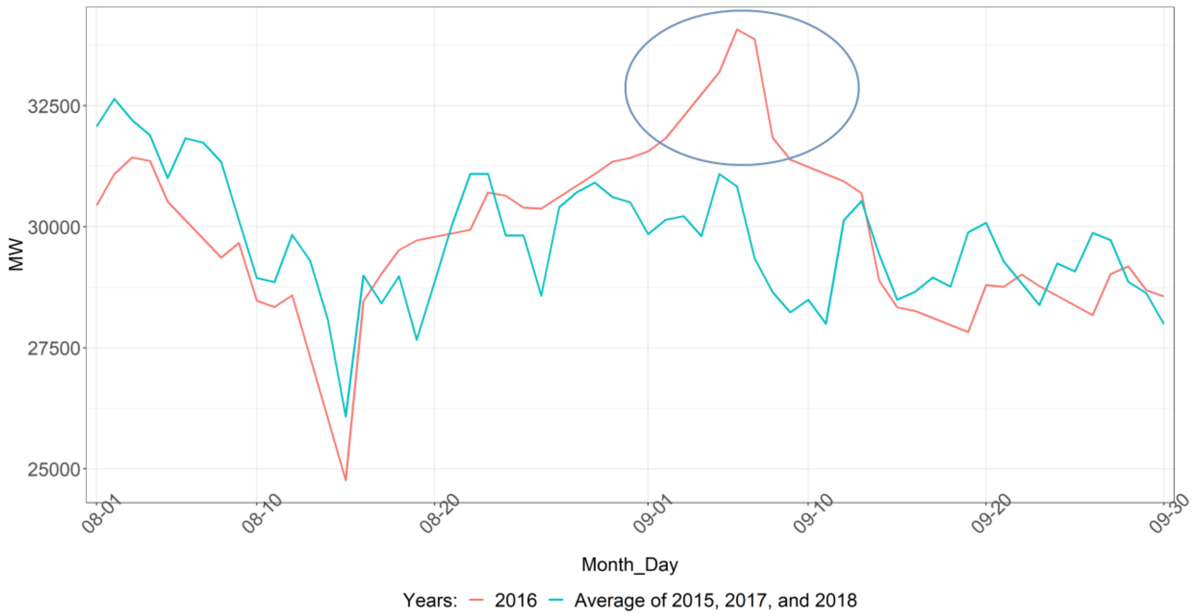

Figure 11: Daily average of hourly load in Spain in August-September 2016. Only weekdays are shown. Source: ENTSO-E

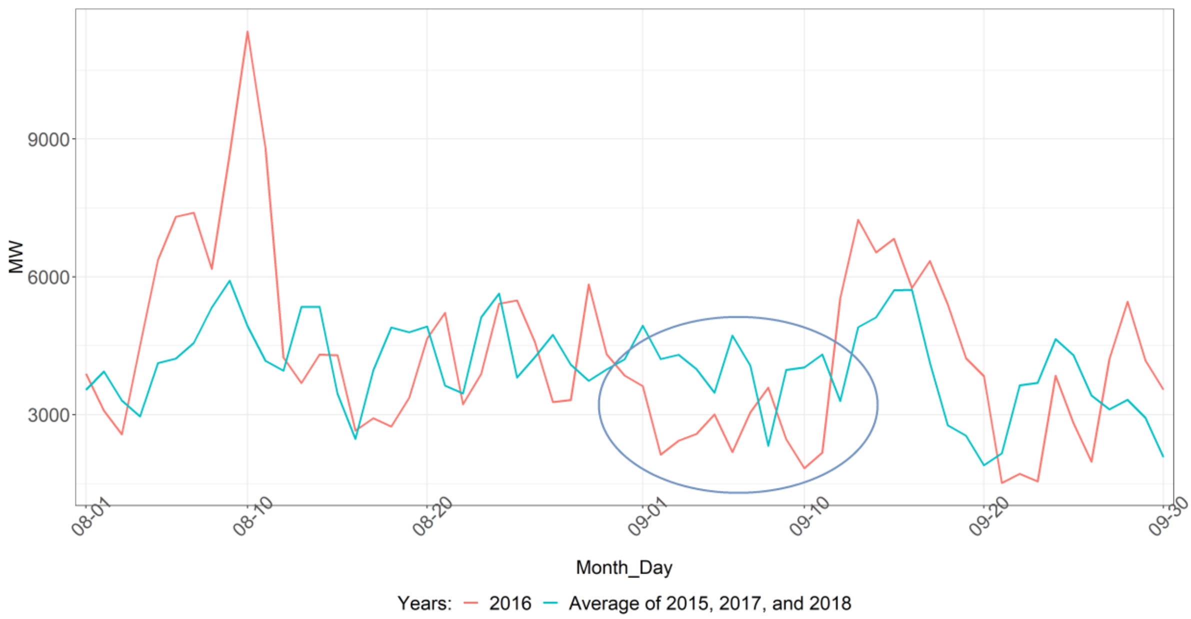

Figure 12: Daily average of hourly wind power generation in Spain August-September 2016. Source: ENTSO-E

According to the Spanish TSO, in 2016 the installed wind power capacity represented 22.8% of the total capacity of electricity generation in Spain, and wind energy supplied 19.2% of the demand. This high level of wind power penetration could have a significant impact on the energy market in periods with lower than normal wind power production. Although the level of electricity prices in Spain in 2016 was lower compared to the average value of electricity prices in 2015, 2017, and 2018, Figure 13 reveals a trend of increasing electricity prices by the end of August and beginning of September. If the risk is not adequately and timely managed in advance, a wind drought could cause economic losses in wind production businesses.

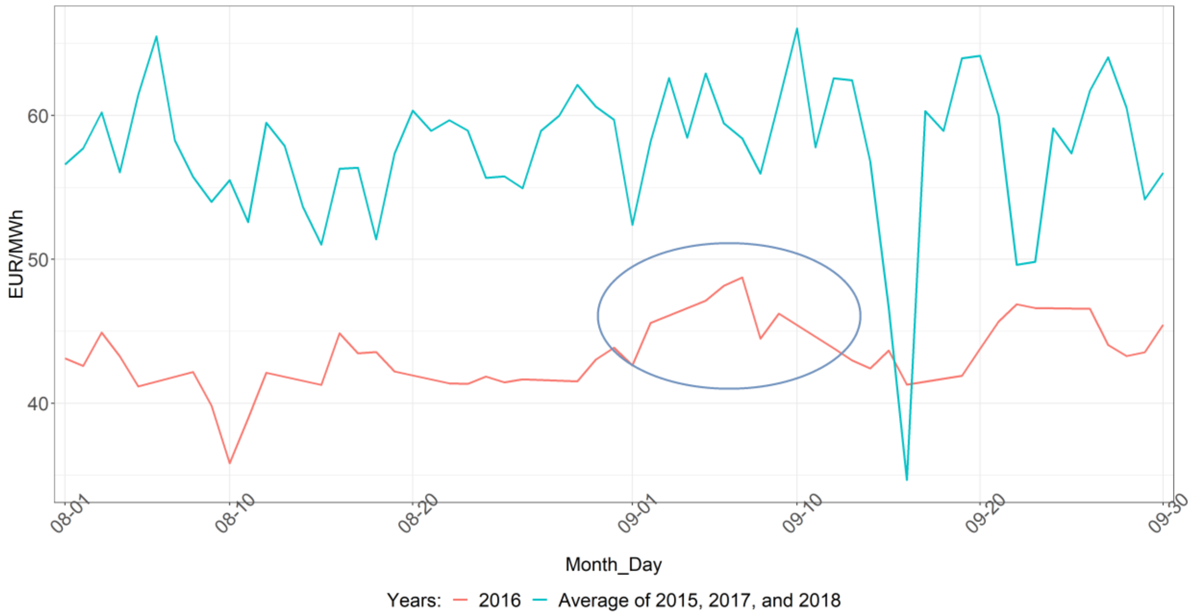

Figure 13: Day-ahead electricity prices in Spain in August-December 2016. Only weekdays are shown. Source: ENTSO-E

1.4 Floods in Sweden 2015

Spring flood in Sweden			
Region:	Sweden	Period:	May – Jul, 2015
Forecast type:	Seasonal	Main interest:	Hydro
Forecast available:	Precipitation, snow water equivalent, and inflows		

Table 4: Region, period, forecast type and main interest for case study 4.

During the period of May-July 2015, surface temperature was below normal, while precipitation was above normal all over Sweden. A combined snowmelt and rain caused a lot of unproductive release of reservoir water in the Umeålven river basin in Sweden. During this period, the amount of hydro power generation was higher than in an average level of power generation in 2016, 2017, and 2018. Average day-ahead prices in May-July 2017 were considerably lower compared to those in the upcoming years. The lack of accurate information about snow availability resulted in a significant economic loss for hydropower generators. Accurate seasonal forecasts could have reduced the water loss during the spill event. For instance, more hydropower generation could have been exploited during the previous months. Better management of reservoir water also allows to boost production when prices are high, contrarily to what was happening as average day-ahead figure shows. If the main cause of the drop in electricity prices is the elevated hydropower production, regulating the production according to prices brings benefits to a company if and only if a small enough share of the market has access to the same seasonal forecast – otherwise prices would be affected by changes in quantities produced.

Moreover, it is worth noticing that currently renewable energy producers in many European countries often benefit from feed-in tariffs, which makes them less dependent on prices fluctuations. However, policies are expected to change over time – as technology matures feed-in tariffs schemes may be gradually removed (Commission, n.d.), making companies seek for new instruments to manage risk.

Figure 14: Daily average of hourly hydro power generation in Sweden in May-July 2015. Source: ENTSO-E

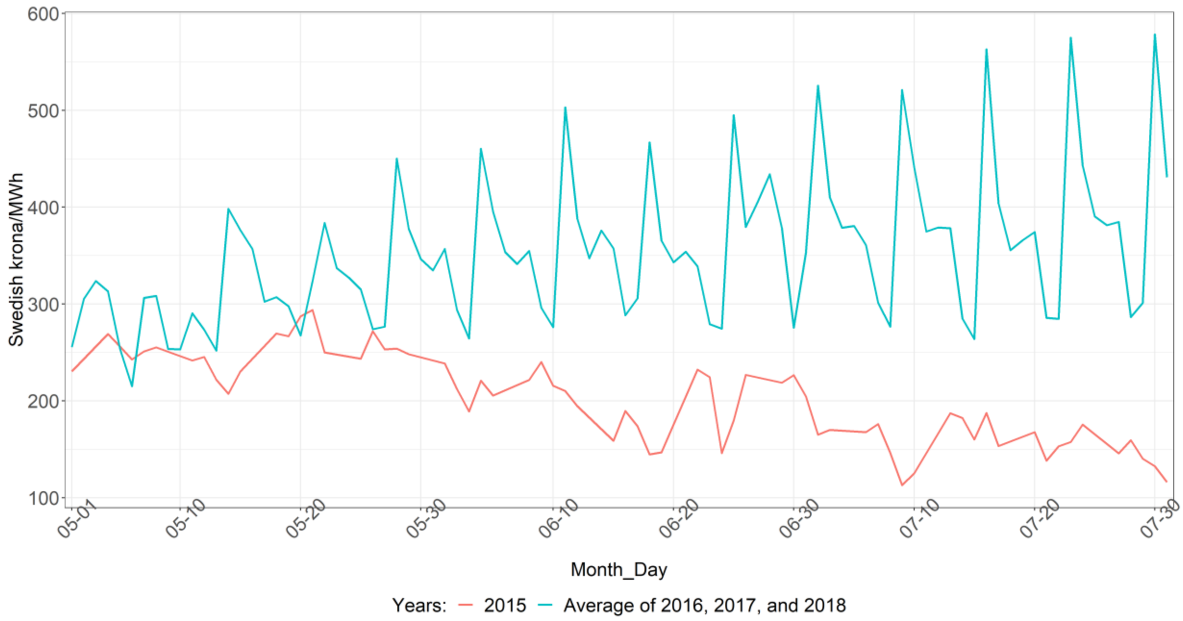

Figure 15: Day-ahead electricity prices in Sweden in May-July 2015. Only weekdays are shown. Source: Nord Pool (2015)

1.5 Icing event in Romania 2014

Icing event in Romania			
Region:	Romania	Period:	28 Jan- 3 Feb 2014
Forecast type:	Sub-seasonal	Main interest:	Wind energy
Forecast available:	Temperature and minimum temperature		

Table 5: Region, period, forecast type and main interest for case study 5.

On the 31st of January 2014, the European Commission's Directorate-General for European Civil Protection and Humanitarian Aid Operations, reported that severe weather conditions (heavy snowfalls, low temperatures and rainfall) in central and eastern Europe, particularly Romania, caused power outages, and transportation problems. In Prahova (centre-east of Romania), 8,500 families suffered from power failures (Reliefweb, 2014).

A very strong icing event occurred in January and February 2014 in Romania. In some of the wind farms in the country both the rotors and the road accesses were frozen for several days. The wind farms, mostly in the east and north east of the country, stopped and, in some cases, they lost communication. Whenever the wind farm manager could not access the site, the day ahead market offers had to be corrected manually. The impact of this event, in addition to the losses inherent to the energy sales, came from the cost of deviations of the manual correction, based on what had happened the previous day. The worst situations were due to the installations' transitions between start and stop. In Romania, the legislation is quite restrictive in this sense, and these deviation costs per MWh are usually very high. The stakeholders of this case study indicated that having information about the event one or two weeks ahead would have been useful, at least to inform the control centre and take action. Data on load, power generation, and prices (except for prices in 2014) in Romania were not available. Case study 5, of chapter 2, presents an analysis of the impact of using sub-seasonal forecasts in two different decision-making processes of a wind farm affected by the Icing.

1.6 Wind droughts in USA 2015

Wind drought in Western USA			
Region:	Western USA	Period:	Jan-Mar 2015
Forecast window:	Seasonal	Main interest:	Wind
Forecast available:	Wind speed, wind power capacity factors		

Table 6: Region, period, forecast type and main interest for case study 6.

During the period of January-March of 2015, surface wind speeds were substantially below normal levels almost all over USA (Figure 16). This episode had a strong impact on wind power generation. Some wind farms did not generate enough cash for their steady payments, and the value of some assets decreased. Informing with some anticipation of probabilities of low wind speed conditions can help stakeholders to trigger some resilience mechanisms. Also, showing practical examples of how much climate oscillations can impact wind power generation will increase awareness of the need of a climate-informed wind resource assessment (Lledó, Bellprat, Doblas-Reyes, & Soret, 2018). Data on prices and load are missing. Nevertheless, reduced wind power generation in January-March of 2015 is unlikely to have a substantial impact on overall supply and wholesale electricity prices in the country. This is because the share of wind power generation accounted only for 5% of total U.S. electricity generation (EIA, 2017).[7]

[7] https://www.eia.gov/todayinenergy/detail.php?id=31032

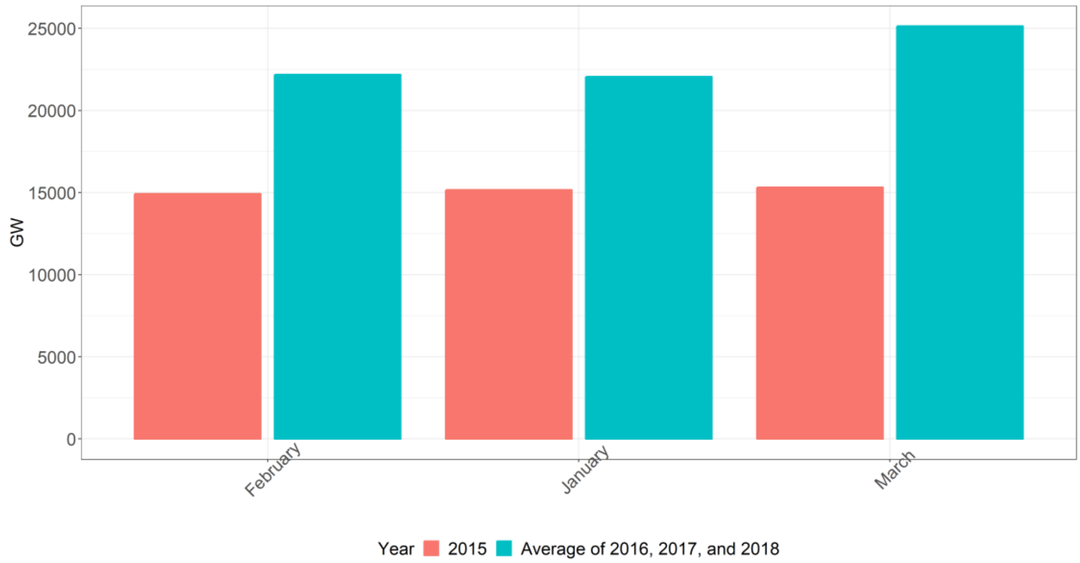

Figure 16: Monthly wind power generation in the USA in January-March 2015. Source: U.S. Energy Information Administration (EIA)

1.7 Cold spell France/Europe 2018

Cold spell over central Europe			
Region:	Europe/France	Period:	27 Feb–5 Mar, 2018
Forecast type:	Sub-seasonal	Main interest:	Energy demand
Forecast available:	Temperature and demand		

Table 7: Region, period, forecast type and main interest for case study 7.

In the period from 27th February until 5th March 2018, most of Europe, but in particular in eastern Europe, was affected by extreme cold temperatures. These temperatures resulted in increases in demand and prices for electricity. In France, during this period, demand and prices for electricity were substantially higher compared to the mean value of prices in 2015, 2016, and 2017. For example, on 1st of March, the French day-ahead price was 84.3 Euro/MWh, which is approximately two times higher compared to the mean value of prices in previous years. Case study 7, of chapter 2, applies the same methodology used for case study 1 to assess the benefits of using sub-seasonal forecasts in hedging practices.

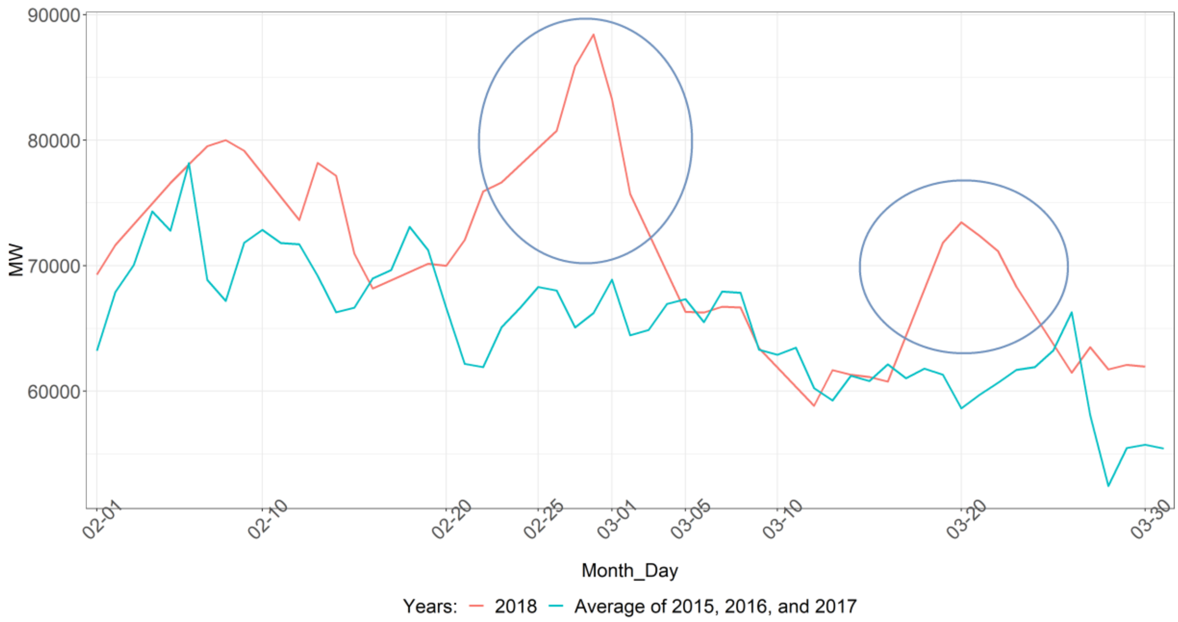

Figure 17: Daily average of hourly load in France in February-March 2018. Only weekdays are shown. Source: ENTSO-E

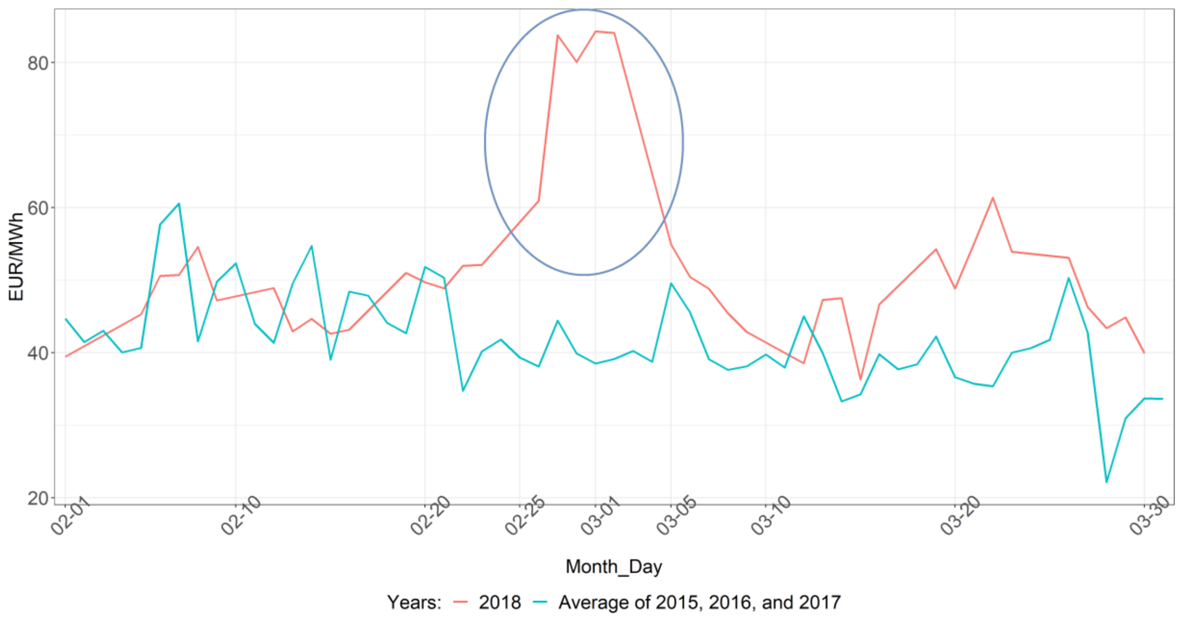

Figure 18: Day-ahead electricity prices in France in February-March 2018. Only weekdays are shown. Source: ENTSO-E

1.8 Record wind generation Spain 2018

In March 2018, the Spanish wind energy system broke his monthly records			
Region:	Spain	Period:	March 2018
Forecast type:	Seasonal	Main interest:	Wind energy, hydro and solar. Supply vs demand
Forecast available:	Wind speed, wind capacity factor, Spanish wind power, precipitation, temperature, solar irradiation and solar capacity factor.		

Table 8: Region, period, forecast type and main interest for case study 8.

In March 2018, low pressure in the eastern North Atlantic and western Mediterranean caused strong storm activities. As a result, Spain experienced a substantial increase in power generation during this month compared to an average value of 2015, 2016, and 2017.

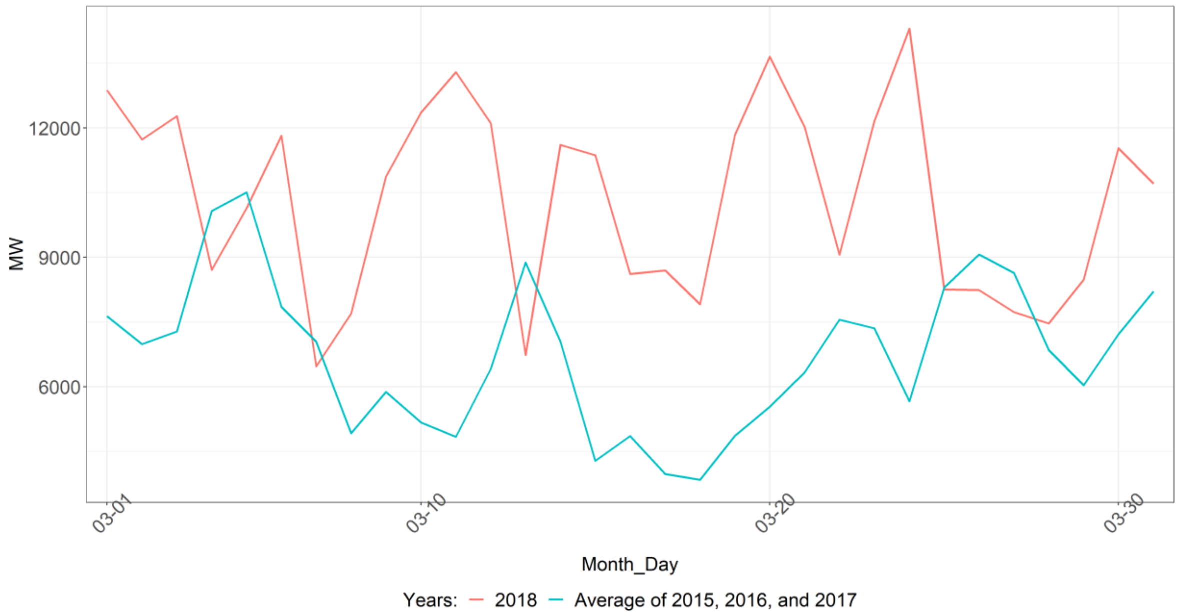

Figure 19: Daily average of hourly wind power generation in Spain in March 2018. Source: ENTSO-E

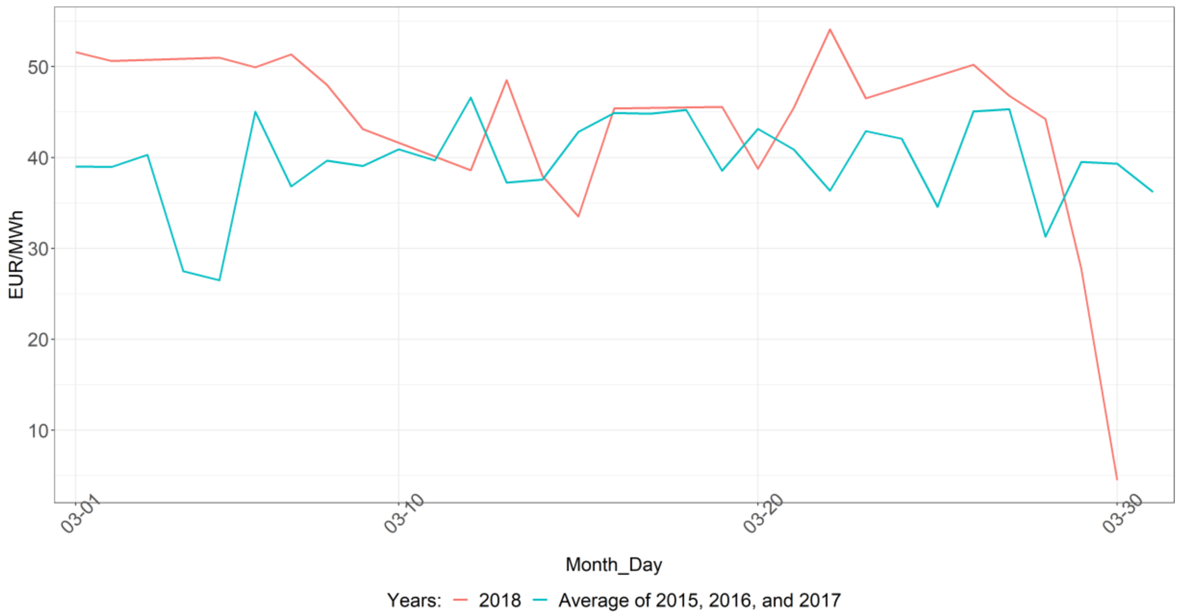

Figure 20: Day-ahead electricity prices in Spain in March 2018. Only weekdays are shown. Source: ENTSO-E

Most of Europe experienced temperatures slightly below normal, so there were no abnormal changes in demand and prices for electricity during this period.

Wind producers would use seasonal (and eventually sub-seasonal) forecasts for different purposes in a situation like the one presented in this case study. For instance, non-critical maintenance should not be planned during this period to keep extra generation capacity available. Knowing about elevated wind production – if no other major factors are affecting the market in the same period – suggests that prices will drop. Hence, the optimal decision would be to sell energy in advance when the price has not declined yet. This selling strategy works under the condition that (most) competitors do not have access to the same forecasts.

1.9 Discussion and conclusions

The above presented extreme events are the result of anomalies of one or more climate variables (e.g. temperature, wind or precipitation). The extreme events caused fluctuations in demand and supply, and thereby affected prices, at different extents according to the characteristics of each country and energy market. These anomalies, depending on their nature, intensity, and duration, had a broad impact. An impact that affected both the energy markets (energy producers, TSOs, DSO) and civil society, i.e., heat-induced mortality (Heudorf & Schade, 2014).

The increasing integration of renewable energy sources in the energy mix leads to more instability in the energy systems becoming more vulnerable to climate variability. For instance, RE producers, whose businesses rely on renewable energy sources availability, are dependent on weather fluctuations. This also poses challenges to the grid system planning to ensure stability and high reliability (Khalaf Alsaif, 2017). For instance, to ensure efficient level of generation capacity available, seasonal forecasts are used to estimate future demand (Duke, Godel, Koch, Suter, & Ladher, 2016).

On the other hand, the transition to a RE system is needed for climate change mitigation. Increasing the use of a number of renewable energy technologies, as well as undertaking efforts to make actual technologies more resilient, should be a priority in order to secure ongoing global prosperity.

Therefore, in line with this urgent matter, the goal of S2S4E project is to make the European energy sector more resilient to climate variability and high impact events. Within the energy sector, the focus of the economic assessment is on RE producers, 3 of them being industrial partners and closely collaborating in the study. Stakeholders contribution has been essential for the present study. The extreme events identified in the 8 case studies and the effects generated on the energy markets – some shown in this chapter - had a huge impact on RE producers' business under different angles. Even if weather anomalies are not under human control and they cannot be avoided, knowing in advance about the risks allows for implementation of better informed risk management practices. This translates in better economic outcomes including avoiding/diminishing losses and – in the best scenarios - incrementing revenues. S2S forecasts are the instrument that decision-makers within RE companies pointed out as potential game changer in the 8 case studies analysed.

Improved performance of RE producers' businesses will likely attract more investments in the sector and ultimately translate in a smoother transition to a low carbon economy. S2S forecasts are an instrument that, together with many other technology advances, has the potential to support this transition.

The next chapter investigates selected examples of decision-making processes of RE companies affected by weather anomalies. The objective is to create a deeper understanding of the potential economic value of S2S in dealing with extreme events.

Chapter 2

Economic gains of using S2S in decision-making

2 Economic gains of using S2S in decision-making

Starting from selected case studies, this section aims at estimating the economic value created by using S2S forecasts in specific examples of *decision-making* of renewable energy companies affected by weather anomalies. While the previous chapter explores the impacts of the extreme events on the energy markets and consequently on the companies operating in those markets, chapter 2 analyses in detail some decision-making processes.

To assess the economic value of climate services for a single economic agent (e.g., a company), a *decision analysis* is often used. In essence, the decision analysis is a type of microeconomic analysis. A single economic agent is assumed to make weather/climate dependent decisions with the objective of maximizing its payoffs (WMO, 2015). The value of the climate service is considered to be equal to the difference between the economic outcome when the information is used compared to that when prior knowledge or no forecasts are used (Rubas, Hill, & Mjelde, 2006).

As S2S forecasts are probabilistic, decisions are taken under uncertainty. However, using the climate service, if skilful, should allow for better informed risk management and, *on average*, to achieve higher payoffs. Notice that the value of S2S forecasts is not intended as the general value of the climate information provided by the service. This is the value that this information adds to a specific decision-maker in the decision context under evaluation. Decision analysis can be applied solely in those cases where the choice of a decision-maker cannot affect an outcome for another decision-maker (WMO, 2015).

During in-depth interviews, conducted at previous stages of the project, relevant decision-making processes affected by weather and climate conditions were identified. Decision maps of weather and climate-dependent decisions, which summarise all relevant information, can be found in section 2.3 of deliverable 2.1[8] of this project. For this report, researchers and energy companies worked together on the in-depth analysis of decision-making on three selected cases. Once analysed the context of the case study, energy companies raised the main issues posed by the extreme weather events and the team analysed further those issues that could be addressed with the support of S2S forecasts. The analysis was performed on stylised decisions. Different approaches to decision analysis are applied given the specificities of each case.

The selection of the three case studies for in-depth analysis was based on the following criteria which emerged from the dialogue between all the parties involved.

- Relevance of the economic analysis for energy companies: the cases selected were pointed out to be the most interesting to perform a detailed analysis by one or more companies.
- Decision-making area: during the interviews a strong interest in evaluating the use of sub-seasonal forecasts in financial decisions emerged. Since, according to our knowledge, the field has not been deeply explored yet, the selected cases allow

[8] Link to the report: https://www.s2s4e.eu/sites/default/files/2018-09/s2s4e_d21.pdf

studying the role played by sub-seasonal forecasts in three different contexts. At the same time, these cases also allow to analyse a few other decision areas and provide an example of application of seasonal forecasts.

- Forecast type: to the best of our knowledge, seasonal forecasts have been subject of more economic evaluations compared to sub-seasonal. Hence, learning about the potential implications of sub-seasonal is a new and interesting exercise helping decision-makers to appropriately use them. Users are more familiar with seasonal e.g. in C3S Climate Data Store only seasonal and projections time scales are covered.
- Degree of confidentiality of information: information on decision-making processes and data about the business are often confidential and cannot be used for the analysis. Although all the 8 cases involve confidential information, the nature of the selected cases allows for simulations and/or discussion with non-confidential or anonymised information.
- Data availability: open data availability varies from case to case and depends on the decisions to be analysed as well. Data and accessibility were evaluated for the selection.

The case studies selected and presented in this section are:

- Icing event in Romania 2014 (Case study #5)
- Cold wave in France and Germany 2017 (Case study #1)
- Cold wave in France and Europe 2018 (Case study #7)

It is important to notice that the findings are valid only for the relative case study. Results are not applicable to similar decision-making processes because extreme events and the market situations are unique. However, the results show that S2S forecasts have the potential to support decision making and to create value for energy companies.

2.1 O&M and wind derivatives: Icing in Romania, 2014 (Case study # 5)

2.1.1 Introduction to the case study

Icing event in Romania			
Region:	Romania	Period:	28 Jan- 3 Feb 2014
Forecast type:	Sub-seasonal	Main interest:	Wind energy
Forecast available:	Temperature and minimum temperature		

Table 9: Region, period, forecast type and main interest for case study "Romania '14"

A very strong icing event occurred in January and February 2014 in Romania. The period as a whole contained three weeks of below seasonal normal temperature (21st January- 10th February), in which the 28th January – 3rd February was the most significant one. Wind-speeds, by contrast, were generally near-normal or above-normal throughout most of the period (Figure 21). However, due to the severe low temperatures, in some of the wind farms in the country both the rotors and the road accesses were frozen for several days. The parks, mostly in the north east of the country, stopped.

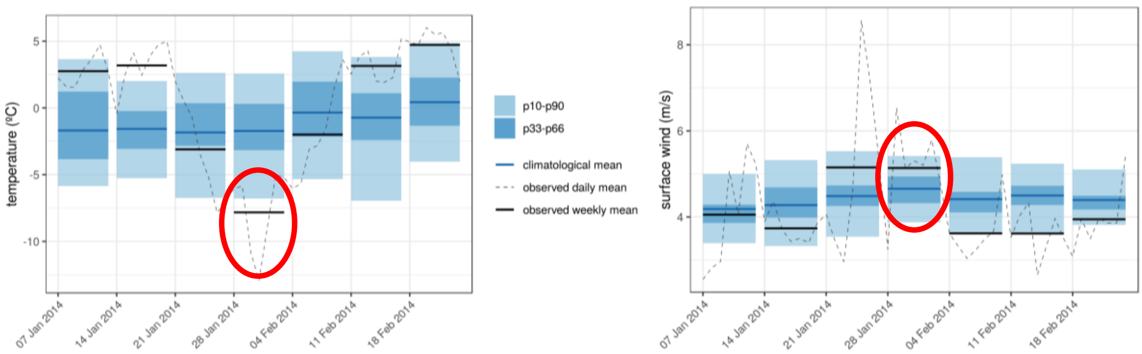

Figure 21: Observed and climatological surface air temperature (left) and 10m wind speed (right) in the region 24–29.5°E and 43.5–47°N during January and February 2014.

An imbalance between electricity demand and supply occurred as a consequence of the wind farms' sudden shut down, causing power outages. Together with transportation problems due to icy roads, preventing due repairs in the wind towers, the cold spell was responsible for 8,500 families suffering from power failures in Prahova, Romania, as reported by the European Commission (European Commission, 2014; Reliefweb, 2014)

In this case study, the impacts of the extreme event on one of the wind energy producers operating in the affected area are analysed. The focus is on those impacts that could have been (partially) avoided if the icing would have been predicted in advance.

Two main impacts of the icing on the company's balance sheet have been identified by the users interviewed. The first and most important one is the impact of missed revenues associated to the inability to sell energy (sold energy). The second impact identified is the one produced by the penalties paid on the difference between the power production offered to the market one day ahead and the real power delivered (deviation costs). Even if icing in the rotors was unavoidable, prior knowledge of a prolonged stop in production is a valuable information for the company as it could enable companies to timely estimate the impact of the shock on the budget and could improve risk management practices. Furthermore, deviation costs could have been diminished by having access to the park and closely monitoring the icing conditions.

Hence, this case study focuses on two decision-making categories (an overview of weather and climate dependent decision areas of energy stakeholders is available in D2.1 of the project[9]): Operations & Maintenance decisions (O&M) and Financial decisions. These two categories are reflected in the study of (Gatzert & Kosub, 2016) on the risk associated to wind park management, in which they analysed various risk categories and among them two weather-depended were found: O&M and variability of revenues.

In the first part of the case study, "Diminishing deviation costs by improving O&M", daily deviations in production and associated cost are calculated with the purpose of demonstrating the possible avoided losses with 10 days ahead planning of **Operations & Maintenance interventions (O&M).** A cost/effective intervention is identified. The difference between deviation costs and O&M intervention costs is an estimate of the benefit of using sub-seasonal forecasts in this specific decision-making context.

The second part of the case study, "Financial risk management through **budget planning** and **hedging practices**", focuses on how these financial decisions can mitigate the impacts of power production variances. The icing caused an unexpected shock on revenues due to the stop of production. To reduce revenue's variability, interviewees expressed the interest to uptake sub-seasonal forecasts to support to their risk mitigation measures. Seasonal forecasts can potentially support budget planning.

The analysis focuses on the wind producers' perspective. It does not take into account damages on different companies and stakeholders (such as the 8.500 families suffering the power

[9] Link to the report: https://www.s2s4e.eu/sites/default/files/2018-09/s2s4e_d21.pdf

outages). Assessing potential impacts of the forecasts on these stakeholders is out of the scope of the analysis.

2.1.2 Methodology and Data

Two in-depth interviews were conducted with two experts from an energy company affected by the icing. These experts are the potential "users" of the climate service in the context of this case study. The users provided detailed information and data about the impact of the anomaly on their wind farm. The questions that were out of their expertise were forwarded to other colleagues that could address them more precisely. The interviews served to collect qualitative and quantitative information and to define an economic assessment methodology that best suites the case given the data availability and the confidential nature of part of them. After the interviews, continuous interaction with users took place for the development and verification of the analysis.

Users' knowledge about the extreme event and the impacts on the company as well as on the energy market was essential to identify the main challenges encountered and potential avoidable damages in case the anomaly was predicted. In the next sections these points are developed.

With respect to data used, some are open data while others are confidential data shared by users to allow researchers to perform the analysis. The results shown are normalised. The table below summarizes the datasets used.

Data	Variables	Period	Frequency	Source	Confidential
Power Generation (hourly)	Initial forecasts, Manual forecasts, Real Power	16.01.2014 / 10.02.2014	Hourly	Anonymous wind farms	Yes
Market Penalties (hourly)	Deficit costs, Excess costs	01.01.2014 / 28.02.2014	Hourly	Transelectrica (transelectrica.ro)	No
Energy Price	Spot Prices	01.01.2014 / 31.12.2014	Hourly	Opcom (www.opcom.ro)	No
Outages	Wind farms stopped	19.01.2014 / 07.02.2014	Daily	Anonymous wind farm	No

Table 10: Data

The analysis is performed using data of a wind farm owned by the same company. The icing days when the turbines were stopped are reported in the table below.

Start	End
20th January	5th February
7th February	8th February

Table 11: Icing days

2.1.3 Decision making analysis and results

2.1.3.1 Diminishing deviation costs by improving O&M

Every day, energy producers have to communicate to the market the amount of energy they will deliver to the grid on the following day. This allows the TSO to balance demand and supply. Every day the wind energy producer follows three steps to define the offer:

1. One day ahead the company receives production forecasts from an external provider. These are called **Initial Forecasts.**
2. Initial forecasts are reviewed and corrected internally. The corrected forecasts are called **Manual Forecasts.** Based on these forecasts, the managers give a final offer to the market for the next day.
3. If the offer is different from the **Real Power** produced, a penalty has to be paid.

At the end of each month the energy producer has to pay a penalty based on the deviation between real power and manual forecasts. In some countries penalties can be more penalising than others (e.g. Romania, Italy and Poland are critical markets). Romania is an **asymmetric market** meaning that there are different costs depending on whether the power production is underestimated (deficit costs) or overestimated (excess costs). Penalties imposed vary also on hourly basis.

The energy producer has a margin of error, which is agreed with an “off taker company”. These are private companies paying for the difference between the offer and the real production up to a certain gap agreed.

Hourly **power deviations** are calculated as the difference between real power and manual forecast (corresponding to the offer made to the market).

Power deviation (MWh)= Real power (MWh) – Manual forecast (MWh)

If power deviation > 0, Production Excess

If power deviation < 0, Production Deficit

Figure 22 (below) compares initial production forecasts, power finally offered and real power during the icing period for the overall production of the wind farms object of the analysis. The values are presented as percentage of the installed capacity of the wind farm. As the figure shows, before the icing (from the 16th to the 18th of January) there was little difference between the three curves, and importantly there is no big gap between manual forecasts and real power. This means that there was a relatively small error in the offer. On the 20th the rotors froze and the wind production stopped completely. However, since the accesses to the parks were blocked by the ice, managers could not access and the day ahead market offers had to be corrected manually. Nobody could realise that the production stopped until the following day, so on the 20th and 21st a noticeable production deficit occurred. The average daily production was expected to be at 47,3% of the installed capacity on the 20th while the actual capacity factor decreased sharply arriving to 0% (with peak deficit of about 75%-points at 7a.m.). On the 21st there was no production with a deviation of 16,15%-points (indicated by the circle A of Figure 23). On the 22nd the offer was pushed down to 0 MWh due to the signal received on the 21st. During the following days of icing almost no penalties were charged (only an 2,74%-points in deficit on average on the 23rd and 1,44%-points on the 24th and 25th, B) being both offer and real production equal to 0 MWh. Conversely, when the rotors defrosted, having no access to the park, managers continued to assume that the rotors were frozen. Hence, the market's offer on the 5th of February for the 6th was again 0 MWh. However, some wind turbines re-started at 5 p.m. of the 5th causing daily average excess of about 4,5%-points (the capacity factor increased from 6% at 5 p.m. to 23% midnight). On the 6th of February, almost 12%-points of production excess were recorded on average (C in figure 23). Managers corrected the offer accordingly for the 7th of February, but the low temperature hit again blocking the turbines and they incurred in another production deficit similarly to the one suffered at the beginning of the icing although smaller in the magnitude. The average daily deviation was around 15,5%-points (D in figure 23).

It is difficult to assess how much the area C – delineated by manual forecast and real power curves - could have been diminished with more accurate forecasts and by having access to the park. Normally, there is an error in market offers, diverging more or less from real power production depending on different factors. Moreover, for the day of defrost (that happened on the afternoon of the 5th) probably the day ahead market offer was 0. Hence, the savings may affect the 6th only. However, it is straightforward that if managers were aware of the icing, they also would expect no production. In these situations, represented by the areas A, B and D of figure 23, the access to the park would have guaranteed to completely eliminate the error. For this reason, from now onward these three areas are considered. The final result will slightly underestimate the benefit.

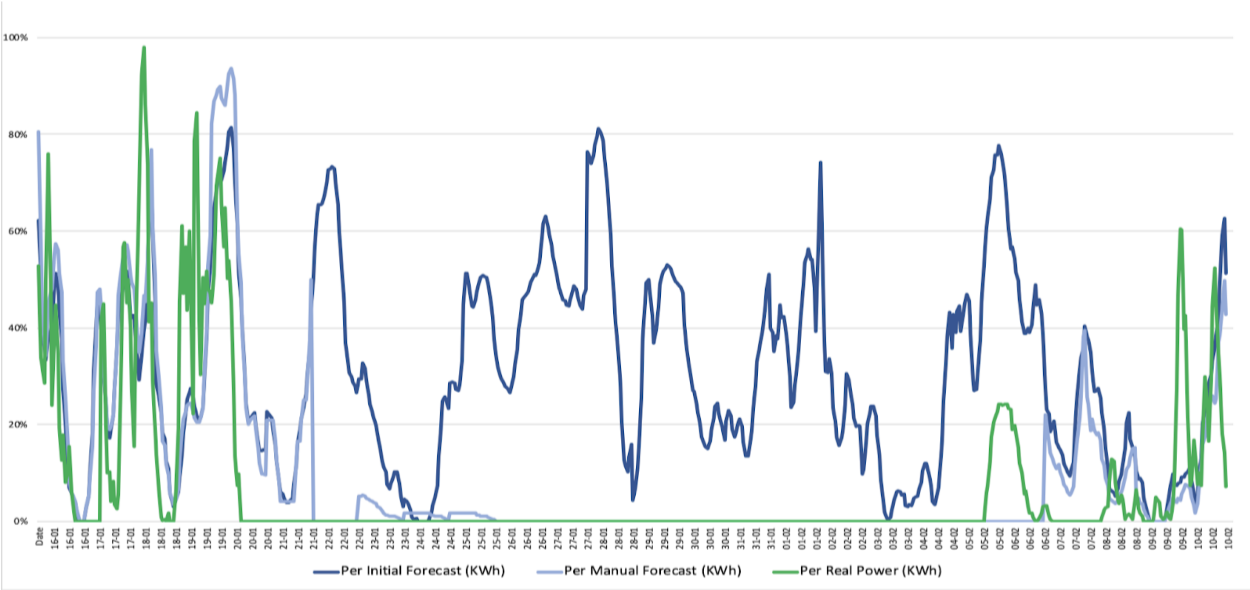

Figure 22: Power Deviation (Jan-Feb 2014), % of installed capacity

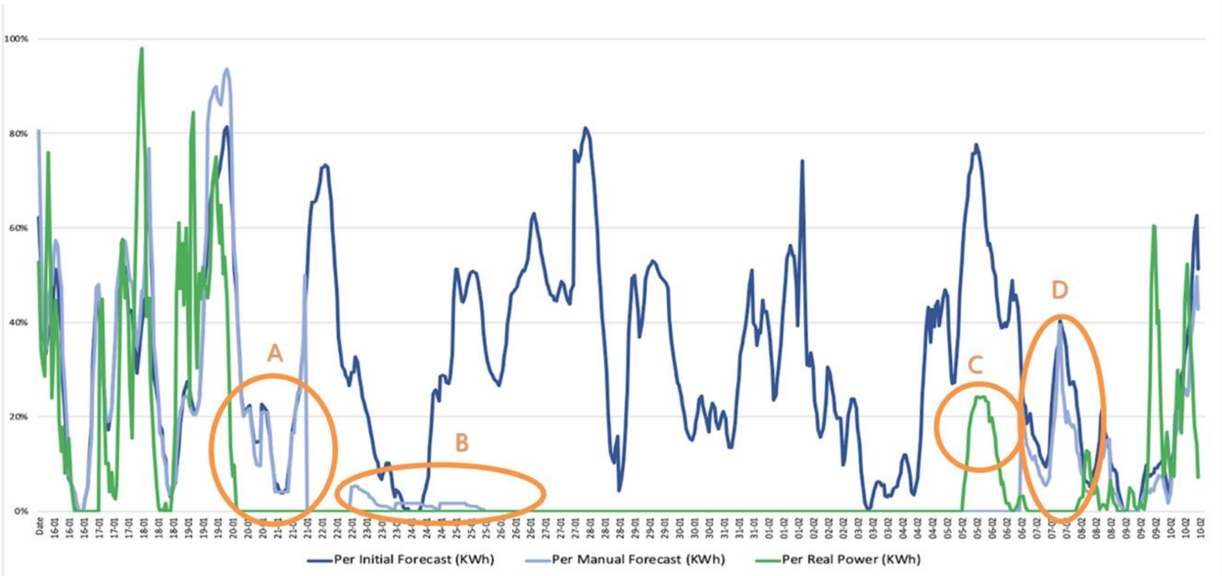

Figure 23: Unexpected starts/stops (Jan-Feb 2014), % of installed capacity

The following step is to calculate what the errors A, B and D meant in monetary terms. As previously mentioned, penalties imposed by the TSO for power deviations vary hourly. Sometimes it happens that the TSO does not charge any penalty or, in few cases, it may happen that the deviation is rewarded meaning that companies are paid back for each MWh of deviation. Moreover, Romania is an asymmetrical market meaning that at a given hour the price to pay for each MWh of excess in production is different from the price charged for deficit. Initially **deviation costs** are calculated hourly.

Deviation cost (RON[10]) = $\begin{cases} Production\ Excess\ (MWh) * Excess\ Cost\ (RON\ /MWh) \\ Production\ Deficit(MWh) * Deficit\ Cost\ (RON\ /MWh) \end{cases}$

Results

The total excess deviation costs (A, B and D) during the period is **thousand RON 50**. According to the average exchange rate of January and February 2014, the amount corresponds to **EUR 11.078**.[11] For comparison, the average monthly earnings of worker employed in the electricity and gas sector in Romania in 2014 accounted for EUR 844.[12]

Once detected the upcoming icing, prevention mechanisms have to be put in place to avoid suffering these deviation costs. The final step consists in identifying a cost/effective solution that would have allowed for real time check of the status of the rotors. According to an interviewee from the O&M department, knowing 10 days ahead about the event would have allowed them to organize snowploughs and work force to ensure the access to the park and guarantee that park managers had control of the rotors' status. To do so O&M would have relied on snowploughs. The cost of snowploughs' transport and labour cost for 4 hours – which is the time needed for the intervention in the park under analysis – are estimated to be **EUR 500**.

The benefit of using the sub-seasonal forecast in this decision-making process amount to the difference between the avoided deviation costs (EUR 11.078) and the intervention costs to timely react to the icing and avoid damages (EUR 500). The estimated benefits amount to **EUR 10.578.** This result underestimates the benefits by not accounting for the excess of production C. Benefits could be maximum about 15% higher than the estimated result in the best scenario.

2.1.3.2 Financial risk management through budget planning and hedging practices

The icing caused a total stop of energy production in the wind farm for **20 consecutive days** (from the 20th of January until the morning of the 8th of February), with exception of a re-start between the 5th evening and the 7th early morning. 20 days with almost no energy sales from a wind farm represent a huge burden on the budget and call for attention to weather-related risk mitigation measures. Even if the stop of production would have been unavoidable also by having previous knowledge of the icing, forecast would have improved risk management practices.

Firstly, one interviewee highlighted that anticipating such extreme is relevant for **budget planning**. Given that the budget is signed off once per year, with some updates during the course of the year, seasonal forecast would be needed for this purpose. However, due to the

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[10] Romanian Leu.

[11] January and February 2014 average exchange rate RON to EUR was 0,2219. Source: https://www.exchangerates.org.uk/RON-EUR-spot-exchange-rates-history-2014.html (last access: 12.04.2019).

[12] Eurostat, 20114. Labour Market – Earnings. Available at https://ec.europa.eu/eurostat/web/labour-market/earnings/database

confidential nature of the information, no data can be used for quantitative analysis. Moreover, the forecasts produced for this case study are sub-seasonal.

To mitigate the impacts of production's volatility, the challenge for the wind farm managers is to optimize the risk management strategy taking into account weather risk. Weather risk can be successfully hedged using a financial instrument called weather derivatives (see Box 1). At the time of the icing no hedging practices were in place. A lesson learned from this extreme event is the possibility of starting **hedging practices**. In particular using wind derivatives (Alexandridis & Zapranis, 2013).

Box 1: Wind Derivatives

A derivative is a contract, between two or more parties, with a value determined by the fluctuations in the underlying asset during a certain length of time (Investopedia, 2019a). Derivatives are financial instruments used to bring security into risk management of speculation. Certain type of derivatives, weather derivatives (Figure 24.), are financial instruments used by companies to hedge against the risk of weather-related losses. Weather derivatives typically have basis to an index which measures a particular aspect of weather (Campbell & Diebold, 2005). In particular wind derivatives – wind speed and wind power derivatives -, are standardised products that depend on the daily average wind speed index (as measured at the met mast or in a meteorological station) or on the delivered wind power index at a certain location (hedging the actual production of the wind farm), respectively (Alexandridis & Zapranis, 2013; Hoyer, 2013).

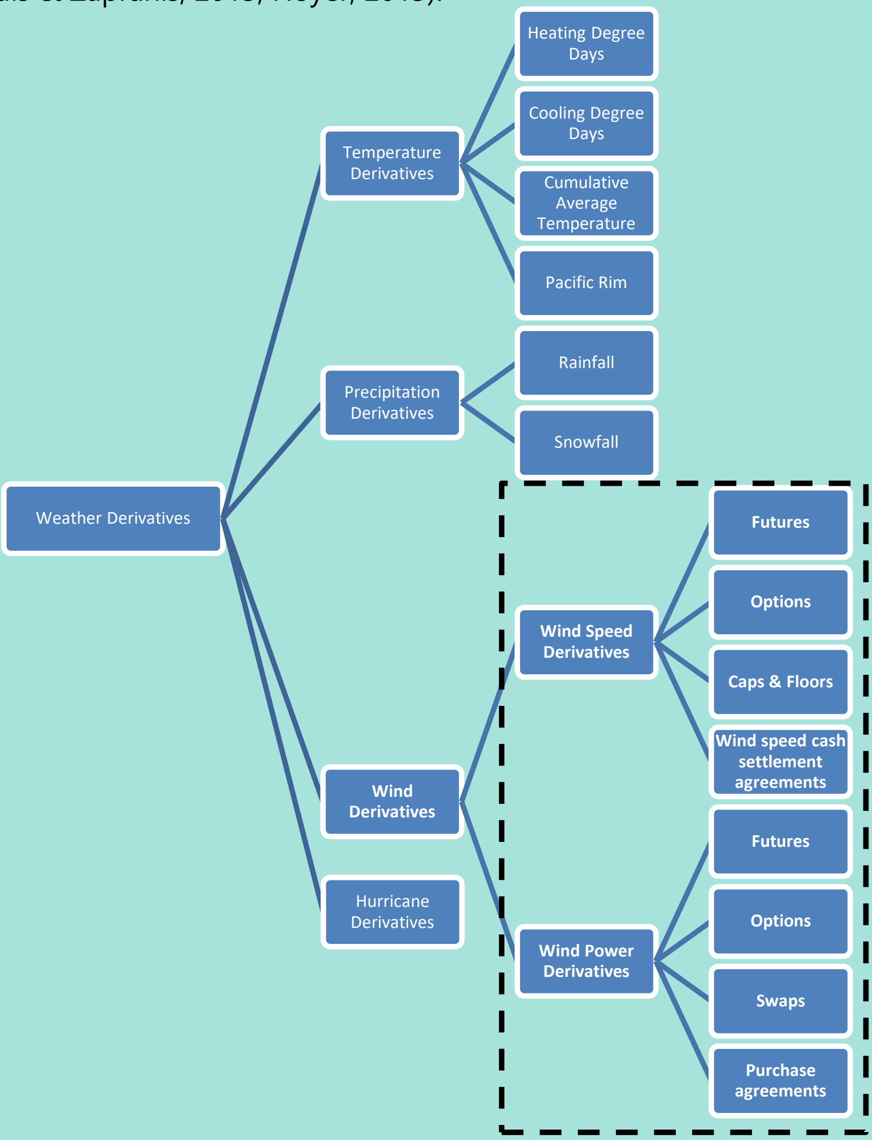


Figure 24. Weather Derivatives – Wind Derivatives types. Source: Own elaboration, based on (Choudhary & Nair, 2017)

Within the wind speed derivatives, there are four main contracts or derivatives:

1. Futures contract – Contract between two parties whereby the seller has the obligation to sell the underlying at a fixed time for a fixed price, just as the buyer has the obligation to buy at the same conditions.
2. Options contract - Call or Put options, giving the buyer the right to buy (or sell) an underlying for a certain price at a possibly fixed point in time, meanwhile the seller of this call (or put) option, has the obligation to sell (or buy) this asset for the price agreed upon, at the time that the buyer executes his option, or at maturity.
3. Caps & floors – In a wind speed cap derivative the buyer receives payments at the end of each period in which the wind speed exceeded the agreed strike price. A wind speed floor is similar, except that payment will be done if the average wind speed over a certain period is below the reference wind speed.
4. Wind speed cash settlement agreements – this contract gives the seller the obligation to pay a certain amount of cash per day in which the wind speed on average was above (or below) a certain fixed wind speed within a certain fixed period.

Wind power derivatives also includes 4 types of derivatives:

1. Futures – analogous definition to contracts for wind speed derivatives.
2. Options – analogous definition to contracts for wind speed derivatives.
3. Wind power swaps – In a swap contract an uncertain amount of electricity is traded for a fixed amount of electricity and an amount of money. A swap can have different maturities, from one day to several months or years.
4. Wind power purchase agreements – Is a contract between two companies in which one company will buy the other a possibly (but not necessarily fixed) amount of wind generated electricity for a possibly (but not necessarily fixed) price per MWh.

In the electricity sector, wind derivatives are extensively traded. Wind producers are dependent on the wind conditions, since their production depend on the wind speed, the wind direction and in some cases on the duration of the wind speed at certain level. In this context, wind derivatives can reduce the risk for wind energy producing companies, allowing them being less dependent of wind, or the lack of wind. Furthermore, prices for certain contracts can be seen as a measure of the risk. Wind derivatives thus can be used as an indication of the price of wind risk, and can be used to financially hedge potential wind risk.

Therefore, as weather derivatives are a good solution for weather dependent companies to manage their risk; it has been an increasing importance for these contracts negotiations to assess the possible weather fluctuations that could have an influence on derivatives pricing. In this sense, climate forecasts – sub-seasonal forecasts – can improve the performance of the methods in which derivatives are traded, since some of them are negotiated several days before the starting day of the contract.

Results

For successful hedging practices in cases like the one under analysis, sub-seasonal forecasts are required. Interviewees pointed out the relevance of having accurate sub-seasonal forecasts of temperature and minimum temperature to allow for hedging in such circumstances. Forecasting the icing few weeks in advanced would have allowed for reducing the losses. An analysis using real data of the wind farm is not possible because these analyses are confidential. However, simulations with generic portfolio sizes created by market analysist were carried out and are shown in the two following case studies (France/Germany 2017 and France/Europe 2018). The analysis performed in the following case studies focuses on one type of derivative: futures. Traders working on the project identified this financial instrument as the most relevant for the analysis as explained in the next case studies.

Clearly, introducing hedging in the risk management strategy requires an investment and time. It is up to the company to perform a cost benefit analysis. Apparently, given the intermittent nature of wind and the increasing climate variability, the risk surpasses the costs of taking action, this is why the use of wind derivatives was considered after the icing in 2014. Climate predictions are needed to hedge successfully.

2.1.4 S2S4E forecasts: Temperature and minimum temperature

So far, sub-seasonal forecasts were mentioned in the case study assuming that the drop temperature is successfully predicted. In this context, this means that by observing the sub-seasonal forecast the decision-maker relies on the information and adapts her/his expectations accordingly. However, in reality this is not always the case since the forecast may be unable to offer usable information for decision-making purposes taking into account user's perspective. Thus, a decision tree should be applied (Figure 25). First, to confirm that there is skill for the variable, region and period of study. Regarding case studies, the skill is a relative measure of how well past forecast reproduced the observations. FairRPSS is a measure of the predictive skill for the probabilistic forecasts for categorical events (below normal, normal and above normal). However, even if there is skill, it may happen that the forecast does not predict the most likely tercile for a specific event. In other words, the forecast's probability distribution function (PDF) may not shift in a way consistent with what happened to occur. This can lead to two different issues for the decision-maker. Either the PDF induces the decision-maker to expect a different situation from what actually occurs (eventually causing errors) or the PDF does not provide any signal to the decision-maker (Decision makers rely on the forecasts only when a certain probability threshold is met. This threshold varies according to the nature of the business, the type of action, the damages associated to an error, the individual risk aversion etc.).

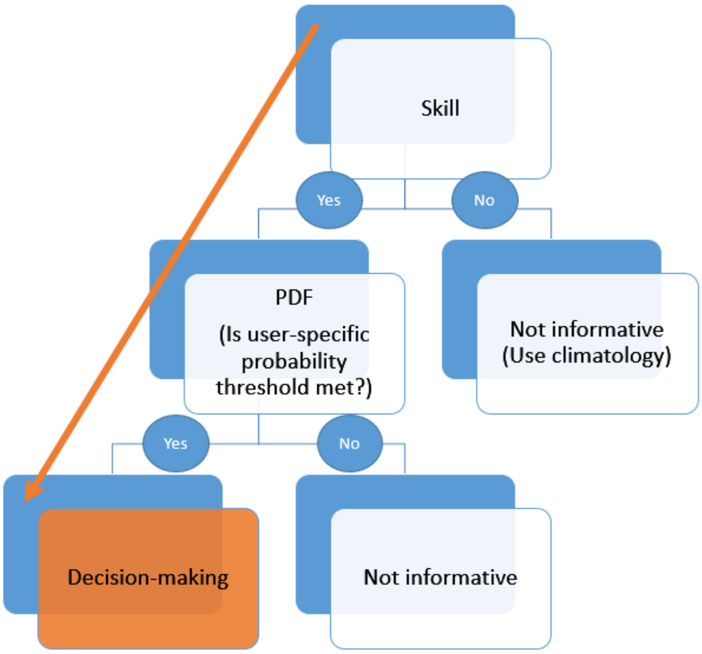


Figure 25: User decision making tree.

In this case S2S4E forecasts of temperature and minimum temperature are now available for the week starting on the 28th of January 2014 (see Annex). However, these forecasts would have been unable to provide useful information for the wind park managers. Only temperature's forecast 2 weeks ahead suggests that an extreme event could occur (26% of the ensemble members indicate that the temperature will be below p10) but the skill is very low. A more detailed explanation and interpretation of the forecast is available in Annex. With this information no savings associated to O&M intervention would have been achieved, keeping the economic situation unchanged with respect to not using forecasts. Penalties would be charged due to unexpected transitions between start and stop in the same way it happened in reality. These forecasts, in a different situation, may perform better. The two following case studies bring examples of successful S2S4E forecasts that potentially allow decision-makers to achieve economic gains.

2.1.5 Final remarks

This case study analyses the gains of using sub-seasonal forecasts in two different decision-making areas related to wind production that were affected by the icing event in Romania. In the first place a quantitative assessment based of decision analysis focused on O&M strategies is conducted. A qualitative analysis of the impact on financial decisions follows.

Since the stop in production caused by the icing was unavoidable, advanced knowledge of the cold spell could have improved the financial strategy to diminish losses associated to the shock. In particular, seasonal forecasts could support budget planning while sub-seasonal forecasts could support the use of financial instruments to manage the risk. Thus, hedging decisions – using future contracts – are the core of the following case studies.

With respect to O&M decisions, the gains of using sub-seasonal forecasts are estimated by measuring the deviation costs and the costs of intervention to avoid the deviation costs. If no action to guarantee the access to the park is implemented, there is a lag between the actual stop in production and the moment park managers realize it (as it was the case in 2014). This implies that the wind producer has to bear deviation costs that would have been avoided otherwise. However, ensuring the access to the park implies costs of using snowploughs and labour costs and requires ideally 10 days of advance notice. The value of the forecast in this decision-making process is represented by the difference between the deviation costs that would be avoided - by knowing in advance about the cold spell and subsequently planning the intervention – and the cost of intervention (snowploughs and man force).

The value of the forecast in decision-making discussed above refers to a hypothetical sub-seasonal forecasts that provide users with sufficient information to update their expectations about the anomaly. Unfortunately, the currently available S2S4E forecasts of temperature and minimum temperature for the cold spell cover only one week of the spell and, for that week, they do not provide usable information for decision-makers. In this case S2S4E forecasts would deliver no value to decision-making.

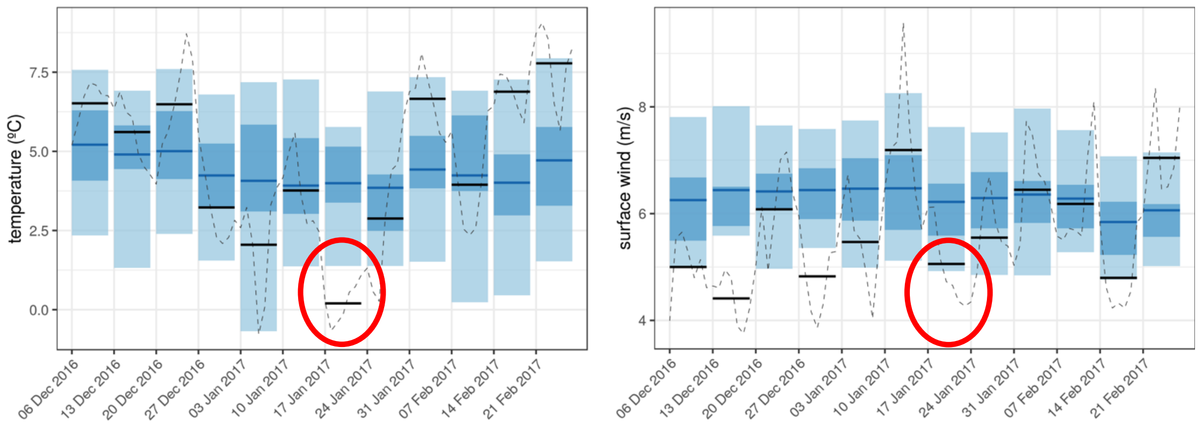
2.2 Hedging: Cold spell and low wind in France and Germany, 2017 (Case study #1)

2.2.1 Introduction to the case study

Cold spell over Europe created a combination of large increase in electricity demand and lower than normal wind power generation.			
Region:	France, Germany	Period:	16-22 Jan 2017
Forecast type:	Sub-seasonal	Main interest:	Demand and wind
Forecast available:	Wind speed, temperature and demand		

Table 12: Region, period, forecast type and main interest for case study "France/Germany '17"

A cold spell over Europe led to extremely low temperatures (below the 10th percentile of climatology), which increased energy demand for heating. Lower than usual wind speeds (~10th percentile) also resulted in a decrease in wind power generation and caused a high risk of energy imbalance in the grid. The anomaly was observed during winter 2016-17, and was particularly significant during the third week of January 2017 (17th – 23rd). The cold spell affected the entire European domain.



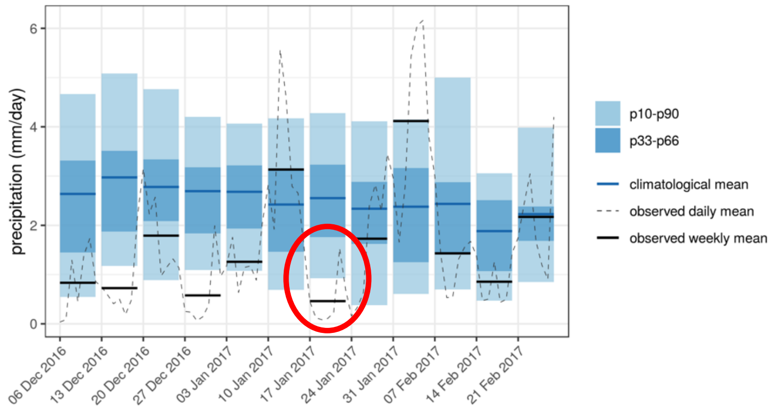


Figure 26: Observed and climatological surface air temperature (top left), 10m wind speed (top right) and precipitation (bottom) averaged over 5o W–12o E, 47–54o N during December 2016 to February 2017.

Particularly in France the cold spell caused a peak of demand reaching 94,2 GW on the 20/01/2017, highest peak since 2012 for France (RTE, n.d.). Hydropower accounts for almost 20% (approx. 25.4GW) of France installed capacity (World Energy Council, 2016), second only to its nuclear capacity of 63.1GW (World Nuclear Association, 2018), followed by wind capacity of 15.1GW (Thomson Reuters, 2019). Moreover, in the fall of 2016, 10 of 58 of France's nuclear reactors were offline due to inspection or maintenance. Even if most of these reactors were back online when the first cold spell of the season occurred, some of them (7 reactors) were still offline. Hence, due the temperature and wind anomaly observed by the week of January 2017, plus the reduced nuclear capacity, France faced a shortage in energy supply and was net importer of electricity over the month of January. A similar situation occurred in Germany, since it suffered from unusual drought in autumn and winter which added more market sensitivity to an expensive "low supply situation".

Box 2: Basic financial concepts definitions

This box offers an introduction to the main financial concepts that are used in this and the following case study. These two case studies analyse the impact of sub-seasonal forecasts on stylised hedging decisions. Hence, if the reader is not familiar with the related concepts, the following definitions are important to understand the analysis.

1. Hedging

A hedge is an investment that aims to reduce the risk of adverse price movements in an asset (Investopedia, 2019b). A hedging instrument is a financial instrument whose fair value or related cash flow should offset the changes in the fair value or cash flow of a designated hedged item (asset, liability, commitment, highly probable transaction, or investment). For investors (e.g. portfolio managers, individual investors and corporations), hedging can be seen as a common practice to protect themselves, and their assets, against negative events and the risk that these events involve. A particular hedging strategy, as well as the pricing of the hedging instruments, depends upon the grade of the risk, and the underlying security, against which the investor would like to hedge.

2. Derivatives

The most common instruments for hedging are the derivatives (Investopedia, 2019a). As described in Box 1; a derivative is a contract, between two or more parties, with a value determined by the fluctuations in the underlying asset (e.g. stocks, bonds, commodities, currencies, indices or interest rates), during a certain length of time. Derivatives instruments include forward contracts, futures contracts, options contracts and swap contracts (Management Study Guide, n.d.).

- Forward contracts: Is a contract between two counterparties, which agreed to sell something at a future date, and the price of the transaction is decided in the present. In these contracts, terms can be reversed before their expiration, but all negotiations are only between the two counterparties. Therefore, commodity exchange (definition below) is not an intermediary to these transactions.
- Futures contracts: Similar to forward contracts, the futures contracts also mandate the sale of commodity at a future, but at a price decided in the present. However, futures are listed on the commodity exchange, so pre-decided sizes, prices and expirations cannot be modified in any way. Therefore, in this type of contracts, the buyer and seller do not enter into an agreement with one another. Rather, both of them enter into an agreement with the exchange.
- Option contracts: These contracts are asymmetrical, since it binds one party whereas it lets the other party decide at later date. So, one party has the obligation

to buy/sell at a later date, whereas the other can make a choice. The last party has to pay a premium for the option privilege.

- Swaps contracts: These contracts enable the participants, two parties, to exchange their streams of cash flows, allowing them to avoid foreign exchange risk amongst other risks. Swap contracts are usually not traded on the commodity exchange.

3. Energy derivatives

Energy derivatives are financial instruments in which the underlying asset is based on energy products (e.g. oil, electricity, natural gas). Energy derivatives can be options, futures, swap or forward agreements, and traded either on commodities exchange or over-the-counter exchange (Clewlow, Strickland, Kaminiski, Masson, & Chahal, 2000).

Companies that use and produce energy will often trade with energy derivatives to help reduce price risk uncertainty. Energy derivatives are vital for those energy players who require price certainty to plan their business operations (Investopedia, 2018).

It is important to note that, for the development of the case studies 1 and 7, we decided to use the energy futures instrument, to evaluate the functionality of the DST in the energy market trading world. This was based on the suggestion of the users, which overseen the necessity of having good skilled sub-seasonal forecasts into their energy futures operations. Moreover, energy futures prices are public information, which can be taken from the European Energy Exchange AG, whereas forwards prices are private information among the two counter-parties.

4. Commodities and over-the-counter (OTC) exchanges

Energy derivatives are traded both over-the-counter and on commodities exchanges.

- Over-the-counter exchanges (OTC): These exchanges occur directly between two counter-parties outside the framework of an established commodity exchange (Investopedia, 2019c).

- Commodities exchange: are legal entities that determine and enforce rules and procedures for the trading standardized commodity contracts and related investment products (Investopedia, 2017). The European Energy Exchange AG, is the leading energy exchange in Central Europe. Located in Germany, EEX is aimed to develop, operate and connect secure, liquid and transparent markets for energy and related products (e.g. power derivative contracts, emission allowances, agricultural and freight products). In the United States, two of the best-known commodity exchanges are the Chicago Mercantile Exchange Group (CME), and the New York mercantile Exchange (NYMEX).

5. Settlement Price

The European Energy Exchange AG (EEX) defines the settlement price as the price that "is determined for each individual contract which can be traded continuously on EEX Power Derivatives and on the EEX derivatives and Spot Markets every day" (The European Energy Exchange AG, 2017) .

6. Day-ahead auctions

A day-ahead auction is where trading takes place on one day for the delivery of the electricity on the next day. In the day-ahead auctions, traders submit their orders electronically, after which supply and demand are compared and the market price is calculated for each hour of the following day. The day-ahead auction power price is often referred to as a kind of reference for power prices (EPEX SPOT, 2017).

2.2.2 Methodology

Given a certain situation, any company and even any trader within the same company is likely to apply a different strategy. For this reason, it is not possible to retrace a common strategy that applies for a meaningful amount of companies. Moreover, it is not the scope of this project to apply any elaborate hedging theory. The goal is to better understand how S2S information can be used in the decision-making process. We thus make some very simplified assumptions to highlight the value of information in the context of this case study.

Simplified hedging scenarios are simulated by changing the initial hypothesis on forecasts availability. The financial instrument used is always *futures*. Each scenario is repeated both for Germany and France.

The baseline assumption for all scenarios is that a company aims to buy a fixed volume (100MW baseload power for one week is chosen as example. This is equivalent to 100MW*24h*7d that makes a total of 16800 MWh,) for the 3rd week of January 2017 (16th to 22nd of January that will be indicated as "week 3 2017" hereafter). This week corresponds to the period when the anomaly hit Germany and France.

In these simulations we do not pay attention to the actual reason for this deal and its volume size. The deal size is fixed and it does not change with time of price fluctuations. This assumption is not realistic. However, we need to isolate the decision to assess the impact of the forecast on a single action keeping everything else constant. The portfolio optimisation depends on many different variables beyond the weather (such as fuel prices, policies, etc.) but the focus of this case is on climate variables only. With appropriate data it would be interesting and relevant for decision-makers to model the interaction of climate and non-climate variables assessing the impact of the climate predictions on real hedging strategies.

An additional assumption applied to each scenario is *perfect information* of non-weather related variables. This means that traders have all the information needed to make the optimal choice except for the uncertainty about weather. This serves to isolate the impact of the forecasts on trader's decisions from other variables that affect the same decisions.

Three scenarios are simulated both in France and Germany, which makes a total of six scenarios simulated. The market where the described operations take place is the European Energy Exchange[13]. In these scenarios, for the sake of readability, we generally refer to a trader that carries out the operations for a company. It is important to notice that there is an assumption behind this terminology which is necessary for a decision analysis to hold: only one or a limited share of the trading companies in the market have the information provided by the forecast. This share should be small enough to not influence market prices. This assumption is realistic for the S2S4E's forecasts exploitation. In fact, in the energy markets there are hundred/s of trading participants and most of them hire many traders that rely on various information and approaches. Nevertheless, competitive scenarios are briefly discussed in the results of this case study.

The scenarios labelled as S1, S2 and S3 assume that a company is interested in buying a given volume of 16800 MWh (equivalent to 100MW baseload power for one week) for week 3 2017. To do so, one option is to not use any financial instrument and instead buying in the day ahead auctions (No Hedging, S1). In this case, the trader buys, for example, 100MW each day within week 3. Contrarily, in the following scenarios (S2 and S3) the trader contracts futures to avoid the risk of facing high prices in the day-ahead market. The difference between S2 and S3 is about the weather/climate information at disposal of the trader. In S2 (Hedging without DST) no sub-seasonal forecasts of DST are used to plan the hedging strategy (Traders have some level of prior climate knowledge that they may use without any update or they rely on the information that was available at the time when the anomaly took place). For instance, the trader could decide to build up a 100 MW long-position for a week (100MW*24h*7d = 16800MWh) in the course of 11 days before delivery (from the 30th of December until the 13th of January). The 30th of December is the first trading day possible because there was no liquidity in the market and almost no energy volumes were traded before that day. The 13th is the last day possible to contract futures since it was the Friday before the delivery week, week 3 2017, and the market is closed on the weekends. In the last scenario, S3 (Hedging with DST), forecasts produced by the DST are used to optimize the hedging strategy.

[13] The European Energy Exchange AG (EEX) is the leading energy exchange in central Europe: eex.com

Title	Abbreviation	Description (Germany & France)
No Hedging	S1	The trader buys energy on the day-ahead auctions
Hedging without DST	S2	Hedging without forecast or with forecast available at the time of the case study
Hedging with DST	S3	Hedging strategy optimized by using DST's sub-seasonal forecasts

Table 13: Summary of scenarios analysed

2.2.3 Data

As a starting point of the analysis, scenarios are elaborated from the perspective of a company active in the EEX market. Assumptions on volumes and dates of energy exchanges were made together with the interviewees.

Depending on the scenario, the trader buys energy on the day-ahead market or using futures. The data used and their sources are reported in the table below.

Data	Source	Link
Germany, Day-ahead auctions, Price [EUR/MWh]	EPEX	https://www.epexspot.com/en/market-data/dayaheadauction/auction-table/2017-01-22/DE/AT
France, Day-ahead auctions, Price [EUR/MWh]	EPEX	https://www.epexspot.com/en/market-data/dayaheadauction/auction-table/2017-01-22/FR
Germany, Phelix DE/AT Base Future, Settlement Price [EUR/MWh]	EEX	https://www.eex.com/en/market-data/power/futures/phelix-deat-futures#!/2017/01/23
France, French Futures, Settlement Price [EUR/MWh]	EEX	https://www.eex.com/en/market-data/power/futures/french-futures#!/2017/01/23

Table 14: Data and sources

Figure 27 shows power future settlement prices in respectively in Germany and in France for week 3 2017.

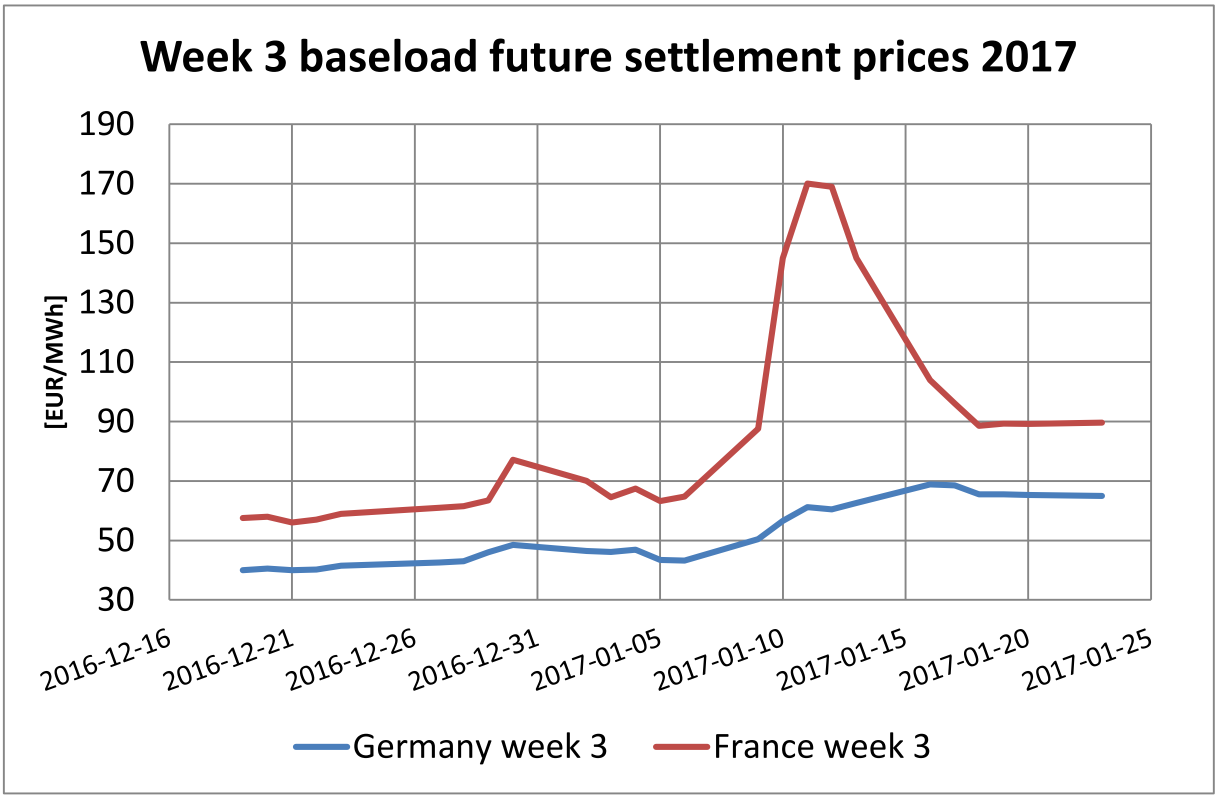


Figure 27: German Phelix DE/AT Baseload Future settlement price (EUR/MWh) and French Financial Baseload Future settlement price (EUR/MWh) for week 3 in 2017. Source: EEX

In Germany final settlement power prices turned out to be the highest compared to the previous five years, reaching 65 EUR/MWh. In France final settlement power prices were even higher, almost 90 EUR/MWh. In Germany the increase in demand was smaller compared to France where the cold wave caused a sharp increase in demand having higher sensitivity to temperature changes (see Figures 1 and 5 in the introduction). This discrepancy is due to differences in the energy mix and household heating systems. Noticeably, the wind speed was below average in both countries. Moreover, in France several nuclear reactors were stopped. Even if from the autumn there were plants blocked, the reparation was expected to be faster. The news that some nuclear plants continued to be on stop most likely increased furtherly the price.

2.2.4 Results

Observing the trend of settlement prices for Germany, it can be noticed that there was no clear signal of the anomaly until one week before delivery (week 3 2017). This suggest that the extreme event was not predicted and the increase in prices was unexpected. On the other hand, in France a cold wave (and eventually low wind) was expected but the forecasts, and consequently the market, over-estimated the magnitude of the anomaly. This is clearly shown in the peak one week ahead which presents prices up to 170 EUR/MWh against the final settlement price of 89,61 EUR/MWh.

Interviewees stated that the value added of the DST, according to their expectations, is that it improves the quality of the forecasts compared to those currently available. In these two particular cases traders would have benefitted from better sub-seasonal forecasts in terms of:

- In Germany, spotting earlier the anomaly and the raise in price.
- In France, spotting the fail (the settlement price peak due to the over-estimation) and adjust the expectations accordingly.

Interestingly, **traders interviewed attribute more importance to avoid the mistake as in the French case than anticipating the anomaly as in the German case**. This finding is in line with a general finding that emerged during interviews with users of various profiles in the initial phase of the project: the damages from a forecast that does not align users' expectations with observations may be higher than the benefits of a successful one in doing so (Vigo et al., 2018).

Simulations of hedging in an idealized case were performed as a first attempt to assess the economic value of the sub-seasonal forecasts in the cases of Germany and France. Table 15 summarizes the results.

Scenario	Relative Benefit [%]	
	Germany	France
No Hedging (S1)	Reference	Reference
Hedging without S2S4E forecasts (S2)	21%	-14%
Hedging with S2S4E forecasts (S3)	33%	29%

Table 15: Summary of results

Comparing S1 and S2, it is possible to observe that there are opposite effects in Germany and France of hedging with weather information available at the time. In Germany, in this particular case, using futures to buy energy in advance allows for savings of 21% compared to not using any financial instrument. [According to the example of a total volume of 16800 MW, the prices to purchase the total volume in Germany are: S1 = thousand EUR 1.091; S2 = thousand EUR 865] On the other hand, in France it would have led to a loss by paying 14% more for the same volume of energy [France: Scen S1 = thousand EUR 1.505; Scen S2 = thousand EUR 1.717]. Interestingly, this happens because of a significant overestimation of future prices - from the 9th to the 13th of January - compared to the final settlement price in France (Figure 26). Interviewees explained that the peak was due to the fact that temperature forecasts over-predicted the magnitude of the cold-wave for some time, influencing market's expectations and inflating settlement prices. Settlement prices in this period were much higher than the final day-ahead prices payed in S1. In this context, having sub-seasonal forecast would have allowed to detect this over-estimation of the cold spell and react accordingly. A trader would decide to buy in advance (starting from the 30th of December, first trading day). To understand whether and when the forecasts provided by the DST could become informative, traders' opinion was asked. Forecasts and relative discussion are reported in Annex. Under perfect information hypothesis and once the forecast is considered informative the trader would choose to buy the whole volume in the day the settlement price is the lowest. In the French case the lowest settlement price is on the 5th of January (63 EUR/MWh) and the S2S4E forecasts are released on the same day (these are 2 weeks ahead of week 3 and according to users these are the first informative release for the purpose. Buying all the volume of energy needed on that day allows to save 29% compared to S1 [France: S3 = thousand EUR 1.06]. Similar situation applied for the German case. Here the lowest settlement price is on the 6th of January (43 EUR/MWh). On this date it was possible to purchase the whole volume for 33% lower price compared to the day-ahead auctions (S1). [Germany: S3 = thousand EUR 72]. Notice that it is not always the case that the settlement price goes down compared to the first trading days. When this is not the case, having exact sub-seasonal forecasts already four weeks ahead brings a clear advantage. It is also quite obvious that the earlier the correct and reliable forecast is provided, the more helpful it is for strategic planning.

All the above mentioned scenarios assume that only a limited share of market players, unable to influence prices, is using S2S4E forecasts or forecasts offering similar information. This is a reasonable assumption. In the energy markets there are hundred/s of trading participants and most of them hire many traders that rely on various information and approaches. If we imagine a future with numerous sub-seasonal (and/or seasonal) forecasts providers and high forecasts' reliability, the benefits each trader could achieve in scenarios such those just analysed would most likely decrease. In fact, a big share of market players would be able to adapt their expectations in advance and, keeping others factors constant, the futures settlement prices would converge faster to the final one.

2.2.5 Final remarks

DST's sub-seasonal forecasts of temperature and demand for week 3 2017 would have improved the hedging strategies of traders both in France and Germany according to the results of the simulations performed. The results obtained are contingent on the specificities of the anomaly and on the way the scenarios are built. While the findings cannot be applied to other situations, they demonstrate that, in this case, forecasts generate economic gains by improving hedging decisions. The magnitude of the savings achieved by the traders depends on the strategy applied, an example was taken to allow for comparison among scenarios and across the 2 countries. But the reader should keep in mind this is an idealised approach, for the purpose of illustration.

Three scenarios were analysed for each country: no hedging, hedging without S2S4E forecasts and hedging with S2S4E forecasts. In Germany traders' main expectation from S2S4E forecasts is to anticipate the anomaly, hence the raise in energy prices, in order to save money by anticipating the purchase. The results show that the payoffs of no hedging are the lowest while hedging with S2S4E forecasts allows for the best performance. On the other hand, in France the challenge was not only to increase savings but, more importantly, to avoid the losses caused by a failing hedging strategy. In fact, due to an over-estimation of the cold spell, hedging without S2S4E forecasts led to worst outcome than no hedging. This error could have been corrected using S2S4E forecasts and increasing the savings.

Interestingly, traders attributed more importance to avoid the losses caused by a strategic mistake associated to wrong expectations (French case) than to the increase in savings due to an improvement in the strategy.

In both cases, temperature and demand forecasts from the DST, are considered to provide useful information for decision-making starting from 2 weeks ahead of week 3 2017, according to interviewees. Given this, action to improve hedging strategies could be taken starting from 2 weeks ahead. By chance, in both cases, the lowest power future settlement price recorded was after the release of the 2 weeks ahead forecast. This led to the optimal hedging strategy. However, it has to be noticed that, in general, the lower power future settlement price could be realised more weeks in advance. This implies that, even if with the S2S4E forecasts available the best result possible is achieved in these particular cases, these forecasts have a margin for improvement. In fact, they were not relevant for decision making before 2 weeks ahead because of the uninformative probability density function (PDF) and low skill score. The wind speed forecast available would have not allowed decision-makers to predict the wind drought.

To conclude, in the context of this case study, the use of S2S4E forecasts would have improved decision-making through hedging, leading to higher payoffs in terms of savings as well as avoided losses in the French scenario, under the assumption chosen for the analysis.

2.3 Hedging: Cold spell in France and Europe, 2018 (Case study #7)

2.3.1 Introduction to the case study

Cold spell over central Europe			
Region:	Europe/France	Period:	27 Feb–5 Mar, 2018
Forecast type:	Sub-seasonal	Main interest:	Energy demand
Forecast available:	Temperature and demand		

Table 16. Region, period, forecast type and main interest for the case study "France/Europe '18"

One of the most recent extreme cold spells in Europe, the winter season 2017 – 2018, is still remembered by the users, due to the repercussions it had for energy demand and transmission. At the end of February and beginning of March 2018, a sudden stratospheric warming[14] occurred over the northern polar region and led to several weeks of extreme cold temperatures over most of Europe. Temperature observations showed to be below normal since the 20th February and, in particular, for the period of 27th February – 5th March, temperature was significantly lower than normal conditions (Figure 28). The daily variation was quite strong with observed temperature differing from climatological mean by about 8ºC.

[14] Sudden stratospheric warming refers to a rapid warming (up to about 50ºC in just a couple of days) observed in the stratosphere (between 10 km and 50 km above the earth's surface). Few weeks later of this temperature increase, a knock-on effect on the jet stream can be seen, which in turn affect the weather to lower down in the troposphere. https://www.metoffice.gov.uk/weather/learn-about/weather/types-of-weather/wind/sudden-stratospheric-warming

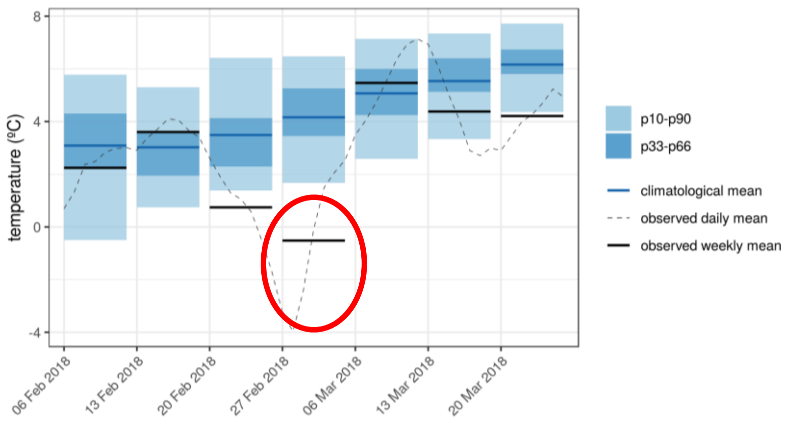


Figure 28: Weekly evolution of the observed temperature in the region 10ºW-30ºE and 36ºN-65ºN during February and March 2018 compared to the climatological distribution. Values obtained from ERA-Interim reanalysis.

Due to cold temperatures, electricity consumption for heating increased in the areas affected. In France, at the time of the event, the seasonal outlook by Météo France announced a rather mild winter, leading the users to consider the possibility of the cold spell as short and temporary anomaly. Indeed, this cold spell - happening comparatively late in the winter period – occurred after a very warm January all over central Europe. This might have caught some market participants off guard. European day-ahead gas prices increased up to 100% and were a major driver also for the power markets.

2.3.2 Methodology

Same methodology as for the previous case study is used for this case study 7. This time the scenarios are calculated for the 9th week of the year 2018 (February 27 – March 5, 2018), which corresponds to the period when the strongest cold spell of the year hit Europe.

2.3.3 Data

Same data sources from previous case study 1, are used for the development of the present case study 7.

Figure 29 below shows power future settlement prices in France and Germany for week 9, 2018.

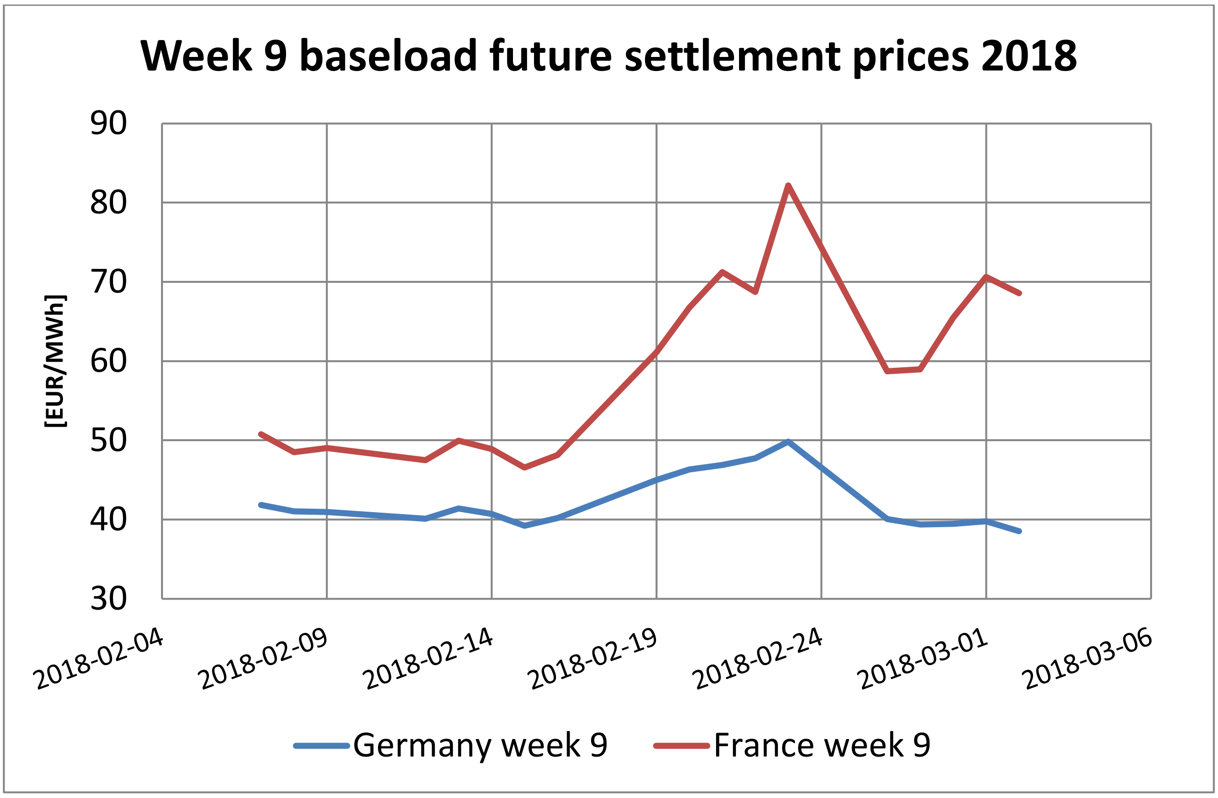


Figure 29: German Phelix DE/AT Baseload Future settlement price (EUR/MWh) and French Financial Baseload Future settlement price (EUR/MWh) for week 9 in 2018. Source: EEX

In France, the cold spell caused a sudden increase in demand because of below average temperatures. Observing the trend of settlement prices, it can be noticed that both countries predicted the upcoming cold spell, even 10 days ahead before week 9. Consequently, starting in February 15th, the market reacted, with rapid increase in future energy prices in both countries, to finally reach the maximum peak (France 82 EUR/MWh and Germany 50 EUR/MWh) on Friday, February 23th, which was the last day for trading the week 9 power futures. However, in both markets there was clearly an over-estimation of final settlement prices. In general, pricing and price modelling is difficult in "extreme" situations due to a low number of data for cross-validation. The French case recalls the over-estimation mistake which happened in week 3 of 2017 (previous case study) even if with lower magnitude. This is observable in the peak of settlement prices in the last trading days. In Germany prices expectations were always higher than the observed day-ahead prices. This can be attributed to the expectations of the strong cold spell. However, prices were finally settled down by the above normal wind speed that characterized this period. Since German energy prices are highly dependent on renewable energy, the high wind power production pushed down the prices (final settlement price – equal to day ahead auction price – was 38,47 EUR/MWh).

2.3.4 Results

Scenario	Relative benefit [%]	
	France	Germany
No Hedging (S1)	Reference	Reference
Hedging without S2S4E forecasts (S2)	19%	-11%
Hedging with S2S4E forecasts (S3)	33%	0%

Table 17: Summary of results

For France, hedging always allows for savings, instead of buying energy on the day ahead market, 19% in S2 compared to the reference scenario. The result of S3 shows that using sub-seasonal forecasts decrease expenses by 14%-points compared to hedging without the S2S4E forecasts (S2) and allows to purchase at 33% lower price compared to the reference scenario. [France: S1 = thousand EUR 1.161; S2 = thousand EUR 936; S3 = thousand EUR 782].

The results show that in Germany it would have been wise to buy energy on the day ahead market (no hedging scenario) instead of hedging. In fact, the average day ahead price of 38 EUR/MWh in week 9, 2018 is lower than the minimum future settlement price recorded from the 5th to the 23rd of February (39 EUR/MWh) due to above normal wind speed. This implies that hedging would cause a loss of 11%, under S2, compared to buying on day ahead auctions [Germany: S1 = thousand EUR 646 =S3; S2 = thousand EUR 719]. Having S2S4E forecasts the rational decision would have been not to hedge. There are no economic gains from S1, but the strategy of buying on day-ahead auctions is supported by the confirmation from the forecasts.

2.3.5 Final remarks

In both countries the cold spell occurred at week 9 of 2018 and it was predicted around 10 days ahead. However, like the previous year, speculations over-estimated the final energy settlement prices. For France, forecasts of temperature and demand would have improved trader's hedging strategies, by allowing savings during the purchase of energy, according to the results of both hedging simulations (with and without S2S4E forecasts). Moreover, S2S4E sub-seasonal forecasts would have improved the hedging results by increasing the savings in a very significant way. For Germany, buying on the day ahead market turned out to be more convenient than hedging (with prices kept low by the above normal wind speed). Hence, S2S4 forecasts do not provide additional benefits compared to not hedging in this specific buying scenario. However, having the S2S4E sub-seasonal forecasts – of different climate variables including wind - would most likely allow traders to make an informed decision of not to hedge. It is important to note that this case study is illustrative to show how sub-seasonal forecasts can support financial decision-making during extreme events. However, it is well known that in real world operations, traders base their decisions on many other factors in addition to weather.

2.4 Comparing the cold spells of 2017 and 2018 (case studies 1 and 7)

Finally, it is interesting to compare case study 7 with previously discussed case study 1, since both cases are characterised by a significant cold spells over central Europe, but also show some major differences. From an energy market perspective, every situation differs as it is mostly related to different setups regarding fuel prices, prices of EU Emission Allowances or power plant availabilities. This results in differences regarding the merit order of power plants and thus different sensitivities of power prices to weather-related changes in power demand or renewable power supply.

In particular, the French power market suffered from a strong wind drought, and lower than normal availability of nuclear power plants in the beginning of winter 2016/2017 (case 1), which has not been the case in winter 2017/2018 (case7). This is relevant since, based on the RTE Electricity Report, the French energy installed capacity mix in 2017 was mainly sustained by its nuclear capacity in first place (48%), followed by hydropower (19.5%), fossil-fired thermal (14.5%), wind (10.4%), solar (6%) and bioenergy (1.5%) (RTE, 2017). In this sense, energy generation observed during both cold spells (Jan 2017 vs Feb/Mar 2018) showed significant differences, mainly regarding the renewable energy share of net public electricity generation (hydro and wind). While in week 3 2017 of case study 1 wind and hydropower generated 1.5TWh (approx. 2%) and 4.4TWh (approx. 6%) respectively - due to below average wind and precipitation - in week 9 2018 of case study 2 RE share, wind 6.6TWh (approx. 9%) and hydro 10.8TWh (approx. 14%), was closer to the installed capacity rates (Figure 30). Therefore, electricity prices in both cases showed similar trends (increasing prices) behind pricing speculations. Nevertheless, the maximum price per MWh was very different in both scenarios, week 3 2017 - 150 EUR/MWh (case study 1) versus week 9 2018 - 80 EUR/MWh (case study 7).

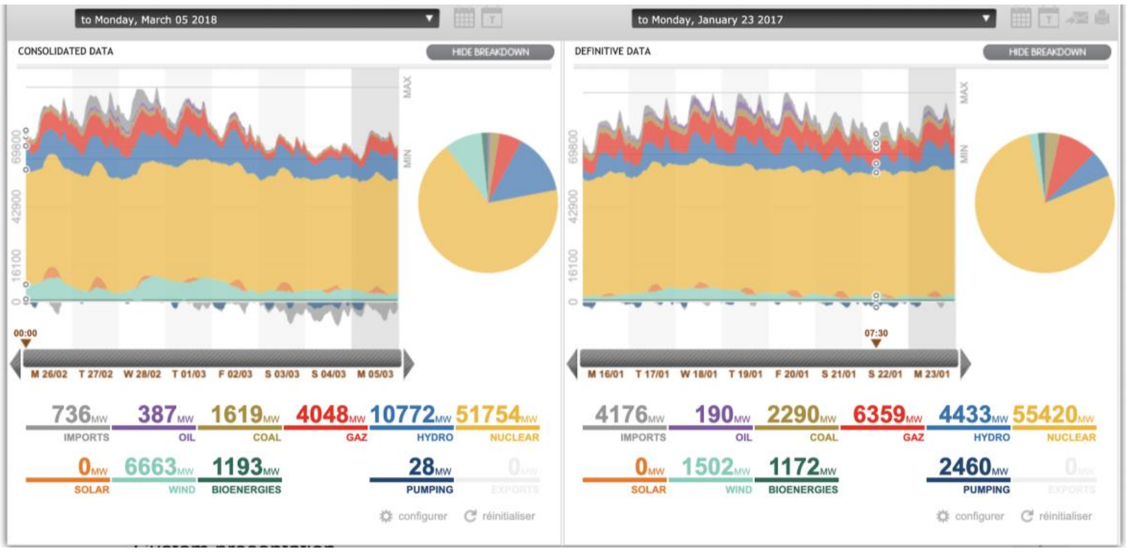


Figure 30: Electricity generation in France - Week 9, 2018 (left) vs. Week 3, 2017 (right). Source: RTE-France (eco2mix mix énergétique en | RTE France)

In this sense, a hedging scenario for a case where a trader is buying energy based on longer-term weather forecasts brings a benefit of approximately 30% reduction in expenses in both cases. While these two case studies (although under a different market setting) are definitely not enough to derive some general conclusions, this finding nevertheless highlights (i) the importance of temperature-dependent demand for the French power market and (ii) the value of respective temperature/load forecasts as e.g. provided by the DST.

Regarding the German power market, differences between both case studies might be much stronger. While both case studies cover the coldest observed weekly average temperatures out of several winter seasons, renewable energy production in Germany differs significantly. Week 9 2018 in case study 7 shows 3.5TWh of German wind power, compared to 0.7TWh in week 3 2017 (case study 1). Indeed, wind power had the largest share of net public electricity generation in Germany in case study 7 (27%, exceeding 15% hard coal and 22% brown coal) (Figure 31), but contributed only to a minor extent (6%) in case study 1 (Figure 32). It is thus not surprising that German electricity prices showed a very different evolution in both cases. Given the amount of German wind power in case study 7, one could indeed also think about a market seller hedging scenario with regard to expectations of a wind-related price drop. The combination with the cold spell makes however for a difficult setting and shows that combination of all weather-related energy market parameters is an indispensable feature of a DST.

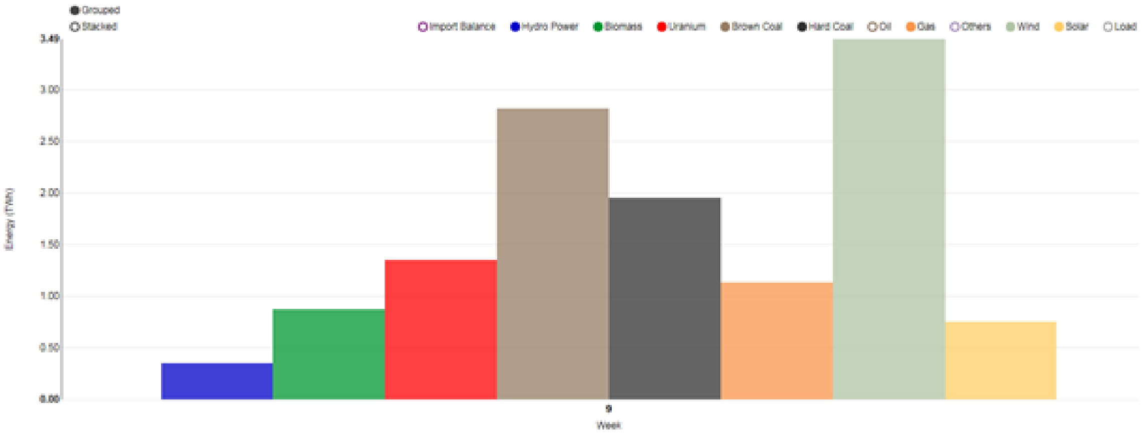


Figure 31. Electricity generation in Germany – Week 9, 2018. Source: www.energy-charts.de

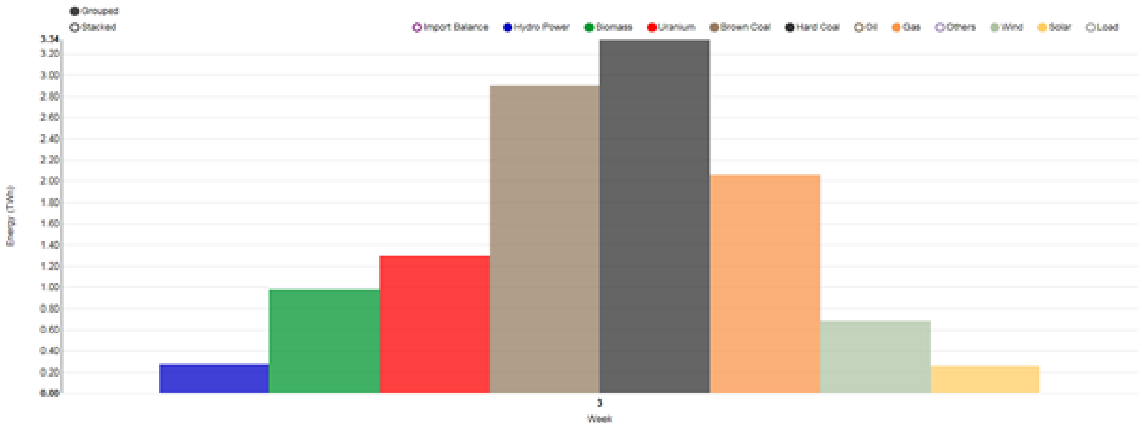


Figure 32. Electricity generation in Germany – Week 3, 2017. Source: www.energy-charts.de

2.5 Impacts beyond RE production

Having an accurate S2S forecast could help producers and traders of electricity to mitigate their financial risks by hedging (e.g., using futures). However, in this section we open a parenthesis to talk about the implications on end-user prices, which are more uncertain and also case specific. End-user prices are determined by interactions between demand and supply as well as by policies (i.e., European Emissions Allowances prices). For example, in Germany, according to interviewees, actual production costs account only for 20% of end-user electricity prices, while the remaining is formed by grid fees and taxes. Hence, the correlation of end-user prices and wholesale prices is not so straightforward. When the domestic supply of renewable energy is insufficient, there are mainly two options to meet the demand for energy.

First, an excessive domestic demand could be satisfied through imports of electricity from other countries. Therefore, cross-border electricity interconnections are so important to ensure a high degree of liquidity and flexibility in the power market. Indeed, the European power market is interconnected, although there might be needs and some possibilities to improve existing interconnections.[15] Due to existing interconnections, it might take just a few hours to trade electricity and transmit it across borders. Thus, S2S forecasts are unlikely to provide any substantial benefit to end-users. Again, if necessary, electricity could be quickly imported, given the assumption that it is available.

Second, temporal shortages in supplies of renewable energy could be offset by using fossil-fuel-based power generation, which however becomes more difficult and expensive in the course of a transition to low-emission pathways. Yet, knowing in advance about an upcoming extreme weather event is unlikely to have any significant impact on end-user electricity prices. For example, coal- and gas-fired power turbines could be activated within a few hours, so knowing about the event few weeks ahead is not that necessary, unless transportation of fossil fuels to power generation requires a long time. Transportation and its duration are rather case specific.

Last but not least, many electricity markets in Europe operate under fixed-price contracts for end-users, which imply the so-called static pricing (i.e., end-user prices are for a certain period). While long-standing weather trends would be taken into account in fixed-price contracts, short-term weather-driven events cannot be passed on to end-users.

Overall, knowing about an upcoming extreme weather event itself will not necessarily make electricity cheaper for end-users. This is because, in many cases, having accurate forecasts does not have any real impact on demand and supply. Under dynamic pricing contracts, a real value of forecasts occurs when adaptation measures require a long time to be implemented; however, this is not always the case because, as mentioned above, electricity could be imported

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[15] Report of the Commission Expert Group on electricity interconnection targets, 2017 available at: https://ec.europa.eu/energy/en/topics/infrastructure/projects-common-interest/electricity-interconnection-targets

or produced using fossil-fuels within a few hours. While having accurate forecasts could allow energy producing companies to optimise their O&M activities and budget planning and thereby potentially increasing their profits, it is not obvious if that would have any significant impact on end-user prices. Hedging itself is just a financial instrument to re-allocate financial risks among energy producers and traders, which is unlikely to have any real impact on end-user prices.

Nevertheless, there are some specific cases, when having accurate S2S forecasts could have implications on end-user prices, given the assumption that the end-user electricity market operates under dynamic pricing contracts. For example, in January of 2017 in France, several nuclear reactors were under maintenance during a cold spell, which to some extent resulted in a shortage of domestic supply of energy. An abnormal increase in wholesale electricity prices could have been avoided by postponing the maintenance of nuclear reactors (if possible at all) if one knew about the upcoming cold spell in advance. Another example is hydro power generation; seasonal forecasts could help to regulate reservoirs. Release of water from the reservoirs, which is not used for energy production, is considered as a loss of production.

While impacts of S2S forecasts on end-user prices could be negligible, environmental impacts could be considerable. S2S forecasts could help producers of RE to become more resilient to climate change and weather variability. Using S2S forecasts, RE companies can better manage their risks and being more profitable, which would encourage the transition towards clean energy. From that perspective, S2S forecasts could induce a non-negligible environmental impact that would benefit the whole society. More research is needed to further explore and estimate the magnitude of socio-economic benefits of S2S forecasts as well as to identify potential challenges.

2.6 Conclusions

Three case studies - selected accordingly to the criteria previously listed - became object of in-depth analysis to investigate potential economic gains of using climate predictions provided by DST on specific decision-making under extreme events. The analysis was based on in-depth interviews and continuous collaboration with experts from energy companies. Both confidential and publicly available data are used. When the necessary data was available, we used a quantitative method, otherwise a qualitative approach was employed. Overall, we found that sub-seasonal forecasts delivered by DST could be useful to support financial decisions and O&M decisions while seasonal forecasts serve budget planning. The first selected case study deals with a strong icing event occurred in Romania in Jan-Feb of 2014, which caused power outages due to a shutdown of several wind farms. Although S2S4E forecasts could not predict the anomaly in this specific case, we found that an accurate sub-seasonal forecast would have allowed to significantly reduce economic losses by taking action around 10 days in advance. In the second and third selected case studies, we assessed economic gains of using DST's sub-seasonal forecasts to mitigate financial risk during the cold waves in France and Germany in 2017 and 2018. The cold waves led to strong increases in demand and prices for electricity. Interviewers confirmed that DST's forecasts feature a better accuracy compared to those available at that time. Sub-seasonal forecasts provided by DST would have estimated better the magnitude of the events, so traders could have reduced companies' losses by using a proper hedging strategy. Hypothetical gains from using *futures* guided by DST's forecasts were analysed in three simplified and illustrative portfolio-optimisation scenarios. Notice that decisions are stylised, hence the findings should be carefully interpreted: the magnitude of the impacts depends strictly on the hypothesis set in the models and the results cannot be applied to other cases even if apparently similar. However, this approach allows different audiences to grasp the fundamentals of the decision processes under analysis and prove that there exist benefits from using S2S forecasts.

Another interesting finding is that traders interviewed weight more the decision-making errors driven by a forecast that "fails" than the benefits achieved due to a correct one. This concern was already raised by users of various profiles during previous stages of the project. This suggests the importance for the climate service to provide information about the reliability and uncertainties entailed in the forecasts. The DST tries to address this issue. A useful forecast has to be reliable. This means that the forecasted probability of an event has to match the observed frequency of the event. To produce reliable probability forecasts from raw data, a calibration with respect to observations (reanalysis) is performed. Moreover, to provide users with information about the uncertainty of a forecast the full probability distribution function is presented by the DST. A forecast quality assessment is performed over a hindcast period (simulation run over a past period for which observations are available to compare). The quality of the forecast is measured with the skill scores (Fair Ranked Probability Skill Scored, for tercile categories and Brier Skill Score for p10 and p90). Last but not least, presenting in the same tool both sub-seasonal and seasonal forecasts of all relevant climate variables provide an overall perspective. These features offered by the DST make this climate service outstand from the available ones.

It is worthwhile to emphasise main challenges and limitations to our analysis and to reveal perspectives for future research. Financial decision-making in the energy market is complex and depends on many other factors rather than weather. We focused solely on weather related factors affecting operational and financial decisions, while other relevant factors were beyond the scope of this project. The conducted quantitative analysis on financial decisions is stylised and case specific. Due to confidentiality of financial data, we were not able to assess real costs that occurred during the analysed weather events. Despite all the limitations, we showed that forecasts provided by the DST could have added value to decision-making. More collaborative studies involving decision-makers in the economic assessments are needed in order to increase the level of detail of the analysis.

Chapter 3

Information needed to assess the demand for S2S forecasts

3 Information needed to assess the demand for S2S forecasts

The objective of this chapter is to show how information from S2S forecasts can be facilitated to meet the needs of potential users by quantifying data needed to explain decision-making under uncertainty, and to derive the demand for this information. The value of S2S forecasts is, in principle, the point where the marginal cost of providing information from the forecasts equals the willingness to pay among those who are willing to pay the least. Potential users of these forecasts are very diverse and it is difficult to have a broad picture of their needs. However, collaboration with industrial partners in S2S4E and stakeholders in this and previous projects, where the needs for seasonal forecasts have been addressed, revealed that presenting the information in a useful manner is not trivial. The way the information is presented may challenge users' interpretation of the forecasts.

The point of departure in this chapter is that there are two different perspectives that can be taken by researchers to identify the user needs about future weather information. One perspective is that taken by scientists who focus on the data they can deliver from climate models to reflect the insights that modellers get from their research on climate systems. We call this a **modelling perspective** or supply perspective. The alternative is a **decision-making perspective**, or demand perspective, which is taken by scientists with knowledge about decision-making. This second type of scientists reflect on which information is needed to explain decisions and to further derive consequences of decisions taken, for example to maximize the economic outcome. From the decision-making perspective, the usefulness of information depends on how it contributes to the decision-makers' understanding of the implications of future weather conditions. An understanding that becomes more important the larger the uncertainties are.

The modelling perspective has been dominating the communication of information from weather forecasts, as well as the communication of seasonal forecasts and climate projections. To some extent, it has been considered as an attempt to establish a clear and honest division between knowledge and interpretations. Researchers provide the knowledge from their insights of the weather and climate systems, while the interpretations are left to the users. As a result, forecasts and projections are presented with a big amount of data from scientifically based models to show what the scientific knowledge has to offer. With this approach, users face difficulties to point out the knowledge they need for their purposes.

This chapter identifies user needs from a decision-making perspective by expanding the interpretation of knowledge to include decisions taken under uncertainty, which involves taking a risk. Explaining decision-making requires a theoretical platform on which these decisions can be understood and analysed. A quick look at how weather forecasts or climate projections are presented (left side of Figure 33) and how this platform is explained (right side of Figure 33) reveals a potential and substantial knowledge gap. This is illustrated in Figure 33, which shows a typical presentation of climate projections on the left-hand side, and the "required reading"-slide from an introductory course on decision-making under uncertainty for economists. While the information presented to show insights from climate sciences is based entirely on numerical calculations, the platform needed to explain decision-making under uncertainty is based entirely on formalized descriptions of preferences.

Without communication between the climate scientists and researchers with insights to decision-making under uncertainty, there is no guarantee that scientific insights from the modelling can be explained. If it cannot, it is possible that users also will have difficulties in finding the scientific insights useful.

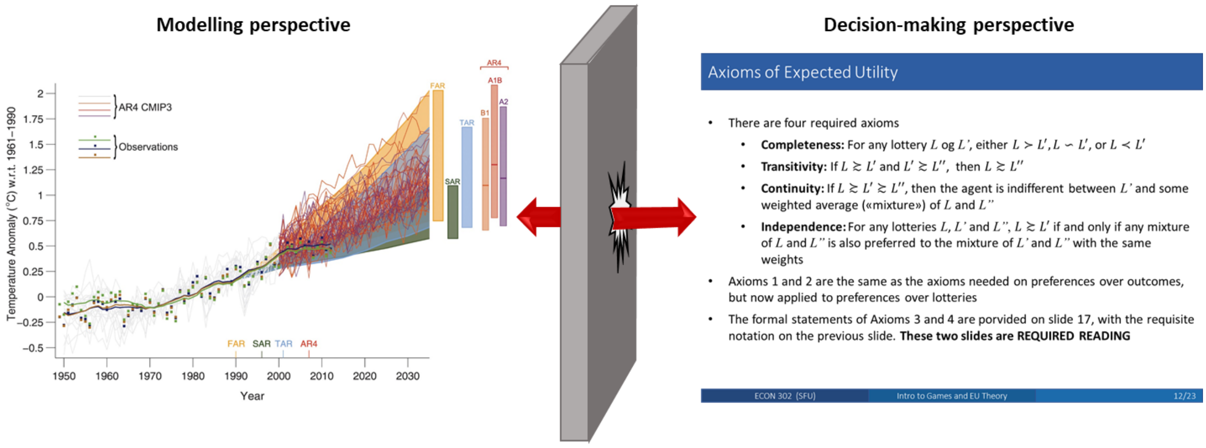

Figure 33: Presentation of useful information about future weather defined from a modelling perspective and a decision-making perspective

Responses among users to the usefulness of the S2S forecasts presented from the modelling perspective strengthens the concerns that the lack of communication between scientists from different disciplines and with different perspectives is considerable. While forecasts are communicated to show data that can be produced by the forecasters, decision-making is usually analysed under an assumption that the information needed to explain decisions is available, which it seldom is.

This chapter points at possible ways to improve the communication between the disciplines, illustrated by the grey wall in Figure 33. We do so by evaluating, in general, S2S forecasts usefulness from the perspective of users. Understanding usefulness as defined in theories of decision-making under uncertainty. The implications of this approach are presented in Section 3.1. In Section 3.2, we create and artificially constructed probabilistic forecast of weekly average precipitation for the coming year. By means of creating an artificial and simplified model we show how the presentation of the results are likely to be interpreted by the users, with suggestions to how information underlying the forecasts may improve the usefulness of the forecasts. The second part of Section 3.2 shows how Monte-Carlo simulations from the simplified model may provide information of relevance for the users, in particular in helping them understand and assess probabilities. The simplified model is based on a likely interpretation of ensembles from the perspective of a user. It thereby provides suggestions to how modellers providing sub-seasonal and seasonal forecasts can support users whose focus is set on how the outcome of their decisions depends on the weather.

Please notice that the assessment of user needs and resulting estimates on the value of the artificial forecast in this section refer to what can be explained, which differs from the true user needs and their assessment of a value before they decide what to do. The two academic perspectives taken here, climate modelling and theories of decision-making, should be tested among users, starting with the user partners within the project. The platform needed to explain decision-making under uncertainty reveals considerable weaknesses in understanding decisions, particularly when the uncertainties are large and future weather is subject to what the users consider as random events. This means that there is no guarantee that use of the theory will help decision-makers find the new information very useful either. One reason may be that the examples presented could be improved, both to better reflect the objectives of the users and to better reflect the scientific knowledge inherent in the sub-seasonal and seasonal forecasts. Another possible reason is the poor understanding of decision-making under uncertainty.

3.1 The platform for explaining decisions that involve risk

The value of S2S forecasts depends on how useful they are to those who make use of it. Thinking about all those who align their lives and doings to ordinary weather forecasts, the potential value is considerable. This has been shown by the attention to the weather in 2018 in our country, Norway, which was rather extreme, with a long-lasting winter, and then a sudden shift to summer temperatures followed by a very dry summer. It caused big problems to some farmers, while other farmers had a better year than normal. Some people enjoyed a great summer at home, and others regretted their early order of a ticket to a safely warm summer in a foreign country. Now, many people think about what weather to expect this year, and they ask for seasonal forecasts. The potential value is probably considerable, but the Norwegian Meteorological Office regrets that they cannot provide sufficiently reliable forecasts. They consider the value of providing seasonal forecasts in its current form close to zero.

Both the demand and the evaluations of reliability depends on the needs among potential users. Most people can live with seasonal variations from year to year without large consequences if the weather turns out different from what they expected, but they might have planned for different activities if they knew. To farmers and to agents in many other economic activities, it is a question of income. How important it is for them to be informed about deviations from the expected weather in coming days, weeks and months differ a lot depending on who they are, meaning that the value to each of them also varies.

The economic value of the forecasts is defined as the value to the one or to the group of people with the lowest needs, or "willingness to pay", which is high enough to cover the costs of delivering them to the new users. The added value to those with higher needs is the welfare surplus. To assess the value of S2S forecasts one must, firstly, map the needs of all potential users, and secondly, attach a value to each of them. Then, the value is equal to the value to the one or to the group whose willingness to pay is large enough to cover the cost of the last improvement made to produce and deliver the information from the forecasts.

It is, of course, rather useless to do such an assessment. Provision of new products and services, in general, and seasonal forecasts, in particular, is in most cases a process of trial and error. If succeeding with potential users expected to have urgent needs for the service, one may try it out to users with lower needs, and in the end see how far one gets before further improvements or adjustments become too expensive to cover the potential needs of new groups of users who may find them useful.[16]

Provision of S2S forecasts is in its initial state. They have been available for many years, but those who produce them assume that they not used as much as they could. They believe that closer communication with potential users will help them extract and process data that better fit the needs of the users, and then make them see how useful the forecasts are. Feedbacks from the user-partners in S2S4E show, however, that there is considerable reluctance about the usefulness of these forecasts among potential users. S2S4E is the 24th project funded by the EU to make users see the benefits. Starting with users with rather different needs, new projects have concentrated more and more on users with particular needs, such as the user partners from the renewable energy sector in this project. A few of them show great interest, however, and the value of the seasonal forecasts provided in S2S4E to them will be assessed further in the case studies. To other users, the value is more or less unknown, but seems to be low at the moment. The modellers expect that there is an unexplored potential, however, which these users are unaware of.

The challenge in convincing them about the usefulness of S2S seems to be related to the communication between the modellers who produce the forecasts and the users. Modellers have a good understanding of what the forecasts tell, and they are well informed about their strengths and weaknesses. The users know very well what evaluations they have to do before they take a decision, but the weather in relatively near future is in most cases one of many factors that matter. It is difficult to single out how much, or to be as exact as the modellers want them to be on what data from the forecasts that might help them improve their decisions. They need to see what they get before they can consider the usefulness. Their main message is that seasonal forecasts produced so far are too unreliable to be very useful.

The attention to the reliability among the users shows that their main concern relates to the evaluation of uncertainties about the weather in coming days, weeks and months. The modellers pay a lot of attention to the uncertainties, so the question is why the users cannot make use of the information that the modellers provide about the uncertainties. A possible answer may be found by an examination of information needed to *explain* decisions similar to those taken by the users. As it turns out, data needed to explain decision-making under uncertainty are not provided from S2S forecasts today, although it might be processed, and perhaps rather easily. If the data cannot be provided today, improvements might be provided over time, both to estimate probabilities and to identify changes in trends. This could enable a separation between short- and long-term changes, which users have asked for.

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[16] The costs of adjusting the forecasts to reach out to new users may be lower than the cost of establishing services to those with the highest needs. This may defend both intermediate and permanent policy support.

Below we explain in detail how decision-making under uncertainty is understood, with the aim of identifying information from seasonal forecasts that can help users increase the value of the decisions they take. The intention is *not* to argue that the modellers have to understand the theory, but to provide suggestions to alternative sets of information than those tried out before. Instead of producing data that reflect the modellers' concerns about the uncertainties in the modelling, we identify data that reflect the decision-makers' concerns about the uncertainties in their income. These data will be identified on a very general and seemingly theoretical basis, however. To enable users to evaluate the usefulness of the suggested information, we use constructed examples of projections to illustrate what information can be provided (Section 3.2). A final assessment of the value of this information depends, however, on what the users think about the potential usefulness.

3.1.1 Evaluation of uncertain outcomes

The usual way to communicate relevant, scientific knowledge to non-experts is to choose metrics that include information that users are expected to care about. Weather forecasts report average temperature, mm precipitation, and wind speed over given periods. The main information to many users is, however, if the weather will be cloudy or sunny. Therefore, forecasts usually include information about expected cloudiness by drawings of standardized categories of combinations of sun and clouds.

Communication about uncertainties is less developed, but when it is done, it is again based on metrics derived from the scientific knowledge, which the scientists believe users are interested to know about. The uncertainties are in some cases amended with intervals, but the intervals are not always clearly defined. An example of a metric defined to communicate uncertainty to users is the definition of risk in IPCCs Special Report on extreme events, probability times outcome, where the outcome depends on many factors, such as damages, the vulnerability of those affected, and their adaptive capacity (IPCC, 2012). As the quantifications are based on scientific knowledge, this definition provides a clearly defined measure for communicating knowledge about risks related to possible extreme events that may happen.

From the perspective of users, who wish to use this information in their decision-making, it is not clear how useful the metric is, however. The information used to provide IPCCs risk estimate is, of course, useful, but the metric itself turns out to be problematic, because it does not provide enough information about the uncertainties that users have to relate to. The only information they get is an assessment of a probability. When multiplied with the outcome, IPCCs suggestion to how to inform about risks does not distinguish between an increase in the outcome and an increase in the probability. If concerned about the usefulness of this information, one must ask if the distinction between the probability and the outcome is irrelevant to decision-makers who evaluate the risks of decision they take. If not, one needs to figure out what other information is needed.

A problem in defining risk as done by the IPCC is that it is easily operationalized as a metric of risk, which does not distinguish between an increase in probability and an increase in outcome. The inappropriateness of such a measure for understanding decision-making was pointed out already by Bernoulli (1738) in his presentation of the St. Petersburg paradox. He considered a lottery with infinitely many possible outcomes, each with a probability $(½)^n$ with return 2^n, (n = 1,2,3,…∞). Then, expected return of each outcome is 1, and the expected return of the whole lottery is

$$Ey = \sum_{n=1}^{\infty} \left(\frac{1}{2}\right)^n 2^n \to \infty \tag{3.1}$$

There is a 50 percent chance of winning 2, and the chance of winning less that than 10 is 90 percent. The chance of winning more than 100 is 1 percent, and there is a 0.1 percent chance of winning more than 1000. However, one cannot exclude the possibility of an enormous return with an extremely low probability. Despite the infinitely high expected return of this game, there are clearly limitations to how much anyone one would pay to take part in this lottery. Turning to extreme events, there are also limits to how much can be expended to avoid the impacts of extreme events with such a distribution.

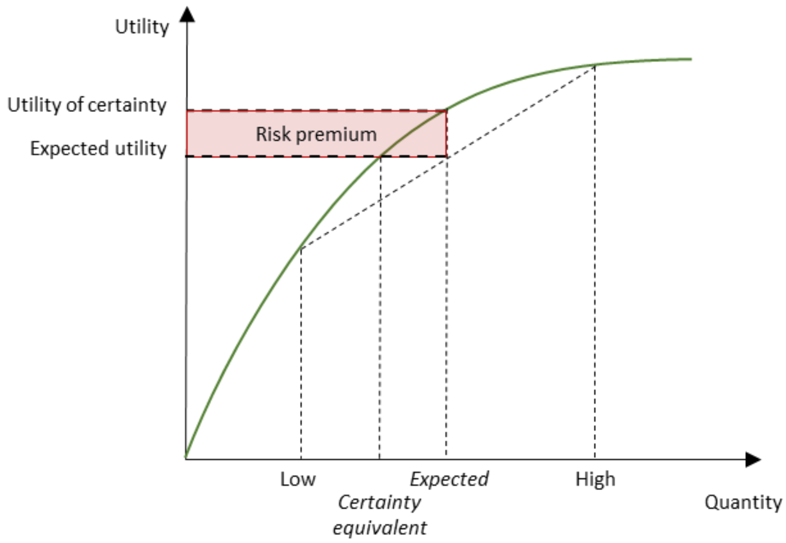

Figure 34: The expected utility of an uncertain quantity

The standard way to deal with this is to replace the expected return with the expected utility of possible returns. By doing so, alternatives with the same expected outcome may be distinguished by characteristics related to the uncertainty. The simple case is illustrated in Figure 34, where the quantities are measured along the horizontal axis, the utility of these quantities are measured along the vertical axis. The green curve shows the utility of the different quantities. It is characterized by decreasing marginal utility, meaning that the higher the quantity, the less utility is gained from one more unit. Uncertainty is illustrated by the "Low" and the "High" quantities, which represent the two outcomes.

If the probability of each of them is 50 percent, the expected outcome is at the middle of the high and low outcomes. Then, the utility of the expected quantity corresponds to that of the utility of a certain quantity, while the expected utility of the two possibilities is a linear combination of the utilities at the respective points, which is lower. The difference is a measure on the decision-maker's attitude to risk, or the risk premium. The difference can, alternatively, be measured along the horizontal axis to show the certainty equivalent, or the quantity that yields the same utility as the uncertain quantity.

The introduction of expected utility provides some guidelines to what information is needed to explain decisions. First, one needs an assessment of probabilities of relevance for decision-making, which reflects the likelihood of having a given outcome observed when we get to know for sure. Second, one needs to have an idea about the distribution of possible outcomes to derive expectations. To illustrate the importance of information about probability distributions, Figure 35 shows the expected utility of three different distributions with the same expected outcome, which is 50. The two symmetric (normal) distributions have different standard deviations. The skewed distribution is characterized by no chance for outcomes lower than 20, but higher chances of very high outcomes. The symmetric distribution with the highest uncertainty yields the lowest expected utility, indicated by the red, dotted line. The symmetric distribution with the lowest uncertainty yields a slightly higher expected utility than the skewed distribution, despite the chance of outcomes lower than possible with the skewed distribution, and lower probabilities of outcomes higher than 75.

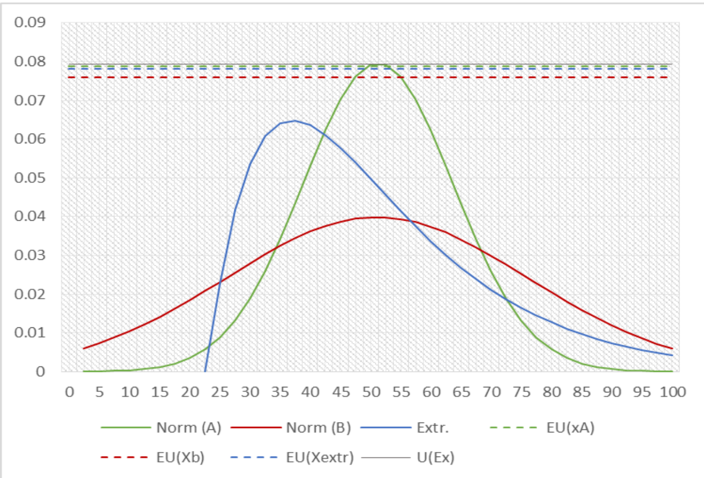

Figure 35: Alternative probability distributions and expected utilities

3.1.2 Priorities over games

Expected utility is a metric that captures some of the concerns that matter to decision makers when they compare a certain quantity of a good, or outcome, with an uncertain quantity of the same good. The next question is if expected utility also can be used to explain choices between different goods with uncertain outcomes. Figure 36 shows the standard approach to explain the choice of different commodities (here two) under certainty. It is based on an ordering of preferences between the two commodities. The blue lines represent combinations of quantities of the two goods that give the same level of total utility, or indifference curves. Under certainty, this description of preferences helps explain the choice of two economic goods by introducing the available budget (grey wall), which shows what combinations are possible. The chosen combination is where maximum total utility (the green area) is achieved under the budget constraint, that is, the tangent between the budget line and the indifference curve.

Think of alternative investments with uncertain outcomes. Expected utility implies that the range of possible outcomes from an investment with given probabilities is replaced by a metric where the utility of all possible outcomes is weighted with the probability of each outcome for all investments with uncertain outcomes. To examine the applicability of this metric for understanding decisions taken under uncertainty, one needs to check if the probability distribution related to one investment differs from the probability distribution related to alternative investments with different probability distributions.

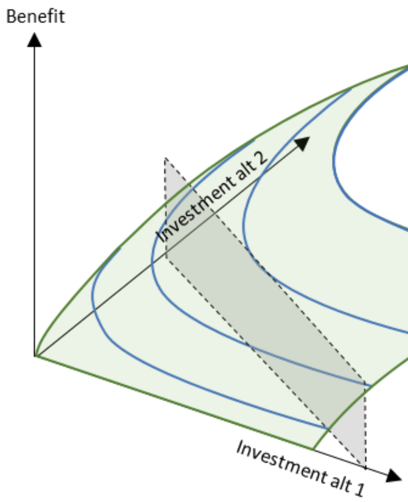

Figure 36: The choice between investments with a given budget and certain returns

The requirements for accepting to use the expected utility metric across alternatives, *the expected utility hypothesis* is expressed by four axioms (Neumann and Morgenstern, 1944). They can be illustrated by comparing preferences over three alternative situations, referred to as games *A*, *B*, and *C*, each with three choices, or lotteries. These are described in Table 18. One may think of the lotteries in each game as investment alternatives illustrated in Figure 36, with one "most likely" outcome and one outcome "if lucky". The probabilities of each outcome are the same in all games, but the outcomes differ. The "most likely" outcomes are higher in *A* than in *B* and higher in *B* than in *C*, but the outcomes "if lucky" is higher in *B* than in *A* and higher in *C* than in *B*. Moreover, the range of the "most likely" outcomes (uncertainty) are the same in all games, but "if lucky", the range are higher in *B* than in *A* and higher in *C* than in *B*.

To check preferences, decision-makers are asked to give their preferences over the composites of lotteries (games), or what investments alternatives would they prefer to choose among. Then, certain criteria, considered as axioms, are required to accept the expected utility hypothesis. We denote the ordering "Game *A* is preferred to, or equally attractive as Game *B*" by $A \gtrsim B$. The four axioms are:

<u>Axiom 1</u> (completeness): For any games *A* and *B*, either $A \gtrsim B$ or $B \gtrsim A$. Decision makers are always able to rank all games, meaning that they can always tell what their priorities are.

	Game A	Game B	Game C

Lotteries	Most likely		If lucky		Most likely		If lucky		Most likely		If lucky	
	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.
1	0.9	95	0.1	165	0.9	90	0.1	230	0.9	85	0.1	295
2	0.8	90	0.2	160	0.8	85	0.2	200	0.8	80	0.2	240
3	0.7	85	0.3	155	0.7	80	0.3	187	0.7	75	0.3	218

Table 18: Games

Lotteries	**π*A* + (1-π)*C***				***B***			
	Most likely		If lucky		Most likely		If lucky	
	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.	Prob.	Outc.
1	0.9	95	0.1	165	0.9	90	0.1	230
2	0.8	90	0.2	160	0.8	85	0.2	200
3	0.7	85	0.3	155	0.7	80	0.3	187

Table 19: Comparison of a linear combination of games A and C with game B with π = 0.5

Axiom 2 (continuity): Let $A \gtrsim B \gtrsim C$. Then, there is a probability π, such that $B = \pi A + (1 - \pi)C$. In words, it is always possible to find a linear combination of the games *A* and *C* that the decision makers find equally attractive as Game *B*. For example, if an equal weighing of *A* and *C* is 318. This is lower than the expected outcome of all possibilities 324 in *B* and reflects the relative risk aversion to a decision maker with π = 0.5. It measures the value of accepting a game where the outcomes can be predicted with higher certainty. The axiom says that it is always possible to find a value for π, meaning that the preferences over games can be assessed for continuous variables for both probabilities and outcomes.

Axiom 3 (transitivity): For every lottery, *A*, *B*, and *C* with $A \gtrsim B \text{ and } B \gtrsim C$, we must have $A \gtrsim C$. The implication of this axiom is that the priorities over alternative games relate consistently to the evaluation of the uncertainties in pairwise comparisons of games. By consequence, the priorities of alternative games are unaffected by different combinations of lotteries within each game at the same level of utility, meaning that the indifference curves in Figure 36 do not cross each other.

Axiom 4 (independence): Assume that $A \geq B$ and let π be the probability that a third choice *C* is present, $\pi \in [0, 1]$. If $\pi A + (1 - \pi)C \geq \pi B + (1 - \pi)C$, then the third choice, *C*, is irrelevant, and the order of preference for *A* before *B* holds, independently of the presence of *C*.

Independence implies that the preferences over two games are unaffected if mixed with a third game that does not change the preferences between the two first two games. Consequently, mixing these two games with the third one does not change the priorities between the first two games. If this holds, we may concentrate explanations to decision-making on uncertainties of investments that we expect are related to each other, without bringing in the uncertainties related to decisions taken to choose among all other goods and services.

The axioms on completeness and continuity can be considered equally acceptable as when applied to preferences under certainty. The transitivity and the independence axioms have been questioned by many, however, and may turn out quite controversial. Different combinations of two games may imply different external contexts under which the uncertainty is evaluated, and thereby lead to a violation of the transitivity axiom. One such "external context" is a combination with a third game, which addresses the independence axiom.

The most well-known criticism of the expected utility-hypothesis is the Allais paradox (Allais, 1953), who questions the independence axiom. The axiom states that if one lottery is preferred to another in a game with two lotteries (Game A), and an irrelevant alternative is added to this game, such that the relative probabilities and outcomes between the lotteries in Game A do not change, the preferences between lotteries do no change. Allais constructed an example, shown in Table 20, which shows that this is not necessarily the case. According to the independence axiom, if the certain outcome, Lottery A1, is preferred to Lottery A2, Lottery B1 also preferred to Lottery B2. Several studies show, however, that most people prefer A1 and B2. Typical comparisons that lead to a violation of the independence axiom is a small probability of a big loss in some lotteries. In Table 20, the small probability of losing everything in A2 instead of accepting a certain payoff is considered more harmful than the small reduction in probability by choosing B2 instead of B1.

Later examples show violations of the independence axiom occur easily when there is uncertainty about probabilities (Ellsberg, 1961), and the message is that application of the expected utility hypothesis has its limitations and may be insufficient to explain all decisions taken under uncertainty. If the information about uncertainty provided to users is based exclusively on information needed if taken under the expected utility hypothesis, one therefore runs the risk of providing biased or insufficient information. However, there is no alternative to the expected hypothesis that explains decision-making under uncertainty in general. The paradoxes apply in most cases to given characteristics of the uncertainties, such as distributions with "heavy tails", or to some categories of decisions. For example, if $x_1 > x_0$, the negative utility of the loss from x_1 to x_0 may be considered worse than the positive utility of the benefit from x_0 to x_1 (Kahnemann and Tversky, 1979).

Game A				**Game B**			
Lottery A1		Lottery A2		Lottery B1		Lottery B2	
Prob	Outcome	Prob	Outcome	Prob	Outcome	Prob	Outcome
1,00	100	0,89	100	0,89	0	0,90	0
		0,01	0	0,11	100		
		0,10	500			0,10	500
1,00	100	1,00	139	1,00	11	1,00	50

Table 20. The Allais paradox

A suggestion for a pragmatic approach to identify relevant information to potential users is to derive information based on the explanations to decision-making under the expected utility hypothesis, but to pay attention to distributions with heavy tails and to decisions where the evaluation of uncertainty is not well reflected by the decisions underlying the axioms behind the expected utility hypothesis. An assessment of the value of S2S has to refer to assumptions about the probability distributions, however.

It is, therefore, essential to provide information about the probabilities, which capture main characteristics about the distributions. Insights to these characteristics are probably useful also for potential users of S2S forecasts, but they can never fully reflect evaluations and experiences done by the users, which in the end are done on a subjective basis (Savage, 1954). Assessments of the value will therefore differ, perhaps a lot, from the actual value.

3.1.3 The timing of a decision

So far, decisions have been described as if based on one set of information about probabilities and outcomes in alternative games when the outcome is unknown, and that nothing can be done from when the decision is taken to the outcome is known. This is a poor description of most decisions taken by those expected to be the most active users of seasonal forecasts. They seldom have a predefined point in time when they must make a final decision on what to do, and then wait to see what the outcome will be. In most cases, their main question is to decide on "what to do when", having in mind what more will be known at a later point in time, when the outcome can be predicted with better information about the uncertainties.

If it is expected that any information relevant to the outcome at a given, future date will become available as this date is coming closer, the question is if the expected benefits of waiting to see exceed the cost of taking a decision later instead of early. The obvious case is a comparison between an investment, which fixes the cost over a long period, with an alternative that allows the investor to adjust the costs according to what will happen. If the expected costs of these alternatives are equal, risk aversion implies that the flexible adjustment alternative will be chosen. Expectations about variations in future prices may also raise the question of when to do what. The price of an air ticket to a tourist destination, for example, tends to increase as the date of departure approaches, but suddenly, the price drops significantly if there is free space left on the airplane. If you are determined to go to this place at a given date, the best is probably to buy a ticket as early as possible. If you are flexible to when, you may take the chance and wait to decide when the time comes, and then buy a ticket for a date when there are seats available. This may involve a risk, however, if there are constraints to how flexible you are to when you can travel. Besides, you do not know what the price will be, and how much money you will save. If you are flexible to where you can spend your holiday, there are many other factors that may be relevant, such as the weather. The dates may be fixed, but you would like to be reasonably sure to avoid a destination where the weather turned out to be "bad".

Then, a seasonal forecast would be useful, if reliable. It might also be useful if "unreliable", for example if there is information on how the reliability improves from a forecast given two months before the forecasted date appears to the forecast given one month before the forecasted date. More recent theories of decision-making under uncertainty emphasizes that insights to possible patterns in how the reliability of forecasts changes over time, or learning, may have a big influence on the economic outcome of decision-making processes that address "what to do when" (Dixit and Pindyck, 1994). Consequently, the potential value of seasonal forecasts is not only, and perhaps not mainly, related to the reliability of a given forecast for a future date or period, but to how the reliability of the forecasts changes as the projected date or period comes closer.

The general theory that addresses these decisions refer to investors, who decide when to fix future costs by an investment, while the income depends on future prices that will fluctuate (McDonald and Siegel, 1984). The theory addresses any decision subject to evaluations of the state of knowledge at different, future dates. It is based on a description of how the expected outcome changes over time, expressed as a stochastic process, with the following, general properties:

$$dx_t = f(x_t, t)dt + g(x_t, t)dz \tag{3.2}$$

dx_t is the change in the expected outcome over time, dt is an indicator of the change in time (continuous), and dz is a stochastic variable with known distribution with $E(dz) = 0$. $f(x_t, t)$ is the expected change in output over time, and $g(x_t, t)$ is the influence of the uncertainty on the change in outcome.

To explain these decisions, one needs an assessment of

$f(x_t, t)$: what is the expected change in x as time goes by, and to what extent does it depend on the observed level of x at a given point in time;

$g(x_t, t)$: how does the influence of the uncertainty depend on the time of observation and the observed x_t;

dz: is a stochastic variable that characterizes the uncertainty.

For example, expected seasonal variations will be reflected by $f(., t)$, which can refer to the decision maker's own experience. This is clearly reflected by the decisions that users in the renewable energy sector take today. A possible influence of x_t on $f(x_t, t)$, meaning that $f'_x \neq 0$, is more difficult to evaluate, but information from seasonal forecasts can be useful if they reflect how an observation in the level of x_t is expected to affect the change in x_t from one forecast to the next. Note that x_t may change from forecast to forecast to reflect expected seasonal variations, for example.

$g(x_t, t)$ reflects similar lessons related to how uncertainty affects changes in the forecasts as the forecasted date or period comes closer. $g(., t)$ expresses a possible trend in updates of the uncertainties, for example if there is a general tendency in providing more certain forecasts as the forecasted date comes closer. $g(x_t, .)$ expresses possible dependencies to the observation in the previous forecast, for example if a hot summer implies that the uncertainty in the forecast for the autumn changes. Again, these are typical lessons that potential users of forecasts do, and they will always base their evaluation on their own experience. However, there are good reasons to expect that insights from those who provide seasonal forecasts may be useful to them, even though the reliability of a given forecast can be questioned. Again, there is a difference between providing relevant information to potential users and making an estimate of the value of seasonal forecasts.

An estimate requires a specification of the stochastic process, but information about $f(x_t, t)$, $g(x_t, t)$ and dz is seldom available. This seems to be a general problem in explaining decisions subject to learning. The reason may be that the theory is relatively new, and most of the attention within economic research has been on the theoretical implications. For example, an assessment of decision criteria puts rather strong limitations both to the description of the learning process and to the representation of the uncertainty, expressed by dz. Learning from history must be expressed entirely by the observation of x at t, without any influence from how x has developed in previous periods. For numerical assessments, dz must be either a normal distribution, a jump process, or a combination of the two. If $g(x_t,.) \neq 0$, a normal distribution implies that the distribution of x_t is a geometrical, normal distribution, however. Implications of the different distributions for assessment of the value of the forecasts will be discussed further in section 3.2.3.

3.1.4 Summary

The tradition within analyses of decision-making under uncertainty has been focusing mainly on conceptual aspects of decision-making in order to understand what makes agents decide what to do when the outcome of the decision is uncertain. There are unknown, but probably important factors not yet understood, but theories also provide vital insights to information needed to explain decision-making under uncertainty. The explanations refer to information that agents base their decisions on, which in the end is a result of subjective evaluations. To explain decisions, we must refer to information that can be identified, however. The main message in the context of assessing the value of seasonal forecasts is that this information is not available. To assess the value of S2S forecasts, and to consider the usefulness of the forecasts in this context, users have to evaluate the probability that the weather will turn out as projected, but information that enables them to do so is not yet available.

The focus on economic decisions helps to limit the representation of uncertainty to uncertainty about the costs and/or the benefits. Then, decisions are explained by comparing combinations of alternatives that yield the same level of utility, as illustrated by the red curve in Figure 37. The first lesson is that one needs to replace the range of uncertain outcomes of alternative choices, illustrated by the blue areas along the two axes, with a metric that reflects the user's evaluation of the uncertainty of each choice. The standard metric is the expected utility of each alternative.

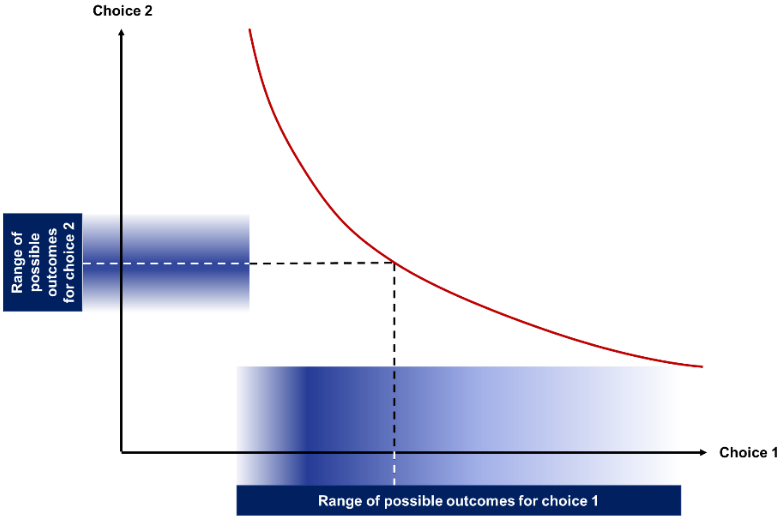

Figure 37: Information needed to explain decision taken with evaluations of uncertainties about alternative options

Then, information about the expected value of the final outcome with range of possible outcomes within a given confidence interval is needed. This is a useful metric for several choices, but there may be alternative metrics that better reflects the decision-maker's attitude to uncertainty for some choices, in particular when there is a possibility of extreme outcomes with low probability.

The second lesson is that the characteristics of the probability distributions themselves may affect the comparison of alternatives. In figure 37, for example, the evaluation of choice 1, with a skewed distribution within a relatively broad range, may change if compared with a similar alternative along the horizontal axis. In that case, the metric that represents choice 1, indicated by the dotted line, may be inadequate. It is, therefore, impossible to provide users with exact information they need, because they have to make a subjective evaluation of the uncertainties of all alternatives they have in any case. To do so, modellers and experts can probably help decision makers better understand the underlying sources of the uncertainty.

The third lesson relates to the decision-making process, as some choices implies a limitation of future options by fixing the costs over a long period of time. In these cases, it may be beneficial to postpone a final decision until more is known. The question, then, is how the uncertainty related to the forecast of a future period is expected to change when the next forecast for this period is provided.

3.2 Identification of information to support decision-makers

Based on the lessons above, this section suggests how information from seasonal forecasts can be derived to explain decision-making under uncertainty. The point of departure is an economist whose aim is to assess the value of the seasonal forecasts, but with strictly limited insights, if any, about the knowledge underlying the S2S forecasts. The only information that is available from the outset is the ensemble of forecasts.

The first question is, therefore, how the ensembles can be interpreted by a non-expert. To do so, we construct alternative forecasting models that link the S2S forecasts to a set of possible explanatory factors that helps to explain decision-making. The alternative models are much simpler than the forecasting models, of course, because they concentrate on relationships between forecasts of the weather and explanatory factors that we, as users, find useful to know about. The simplified models thereby specify information needed to link the S2S forecasts to knowledge about relationships that help users understand the uncertainties underlying the ensembles.

The second question is how the simplified ensembles can be used to provide information of direct relevance for explaining decision-making under uncertainty. Because of the simplicity, we can use the simplified models to run Monte-Carlo simulations, and show how these simulations give a better picture of probabilities than ensembles do. The simplified models help to identify information needed to transform the results from ensembles to estimates of probability distributions, which any user will have to consider in any case to be able to use ensembles for decision-making purposes. They thereby suggest how experts who run the S2S forecasts can contribute to improve the assessments of probability distributions, which non-experts most likely have to consider as pure randomness, unless they get support from the experts. This implies that the main contributions from the experts is not to run more ensembles, or to publish their results in alternative ways, but to provide evaluations that replace evaluations that users have to do anyway.

Finally, we provide some examples to how the concerns of the user may be met by alternative sets of information from the simplified models. This relates mainly to the information of relevance for evaluating the dependency between a weather indicator and the costs and benefits, such as evaluations of threshold values.

3.2.1 Construction of simplified projections

The simplified projections aim at capturing how users are likely to interpret the S2S forecasts. We refer to users with no specific insights to how weather conditions vary over time, except their own experience that it changes significantly over time and for the same period from year to year. We assume, therefore, that they are familiar with the climatology, which they may quantify from the averages provided by the meteorologists. To have a concrete and simple example, we will look at a forecast of weekly average precipitation over a year, which follows a sinus curve.

Then, they are provided with ensembles of seasonal forecasts, which vary around the climatology. With no specific insights to reasons why these differences occur, nor to why the different models project weather differently, they must consider the variations across models as random. On the other hand, if the variations are truly random, they acknowledge that it would be no need for seasonal forecasts for anyone. In that case, the best guess of the expected value equals the climatology, and the variations across models would clearly not provide any information about the uncertainty.

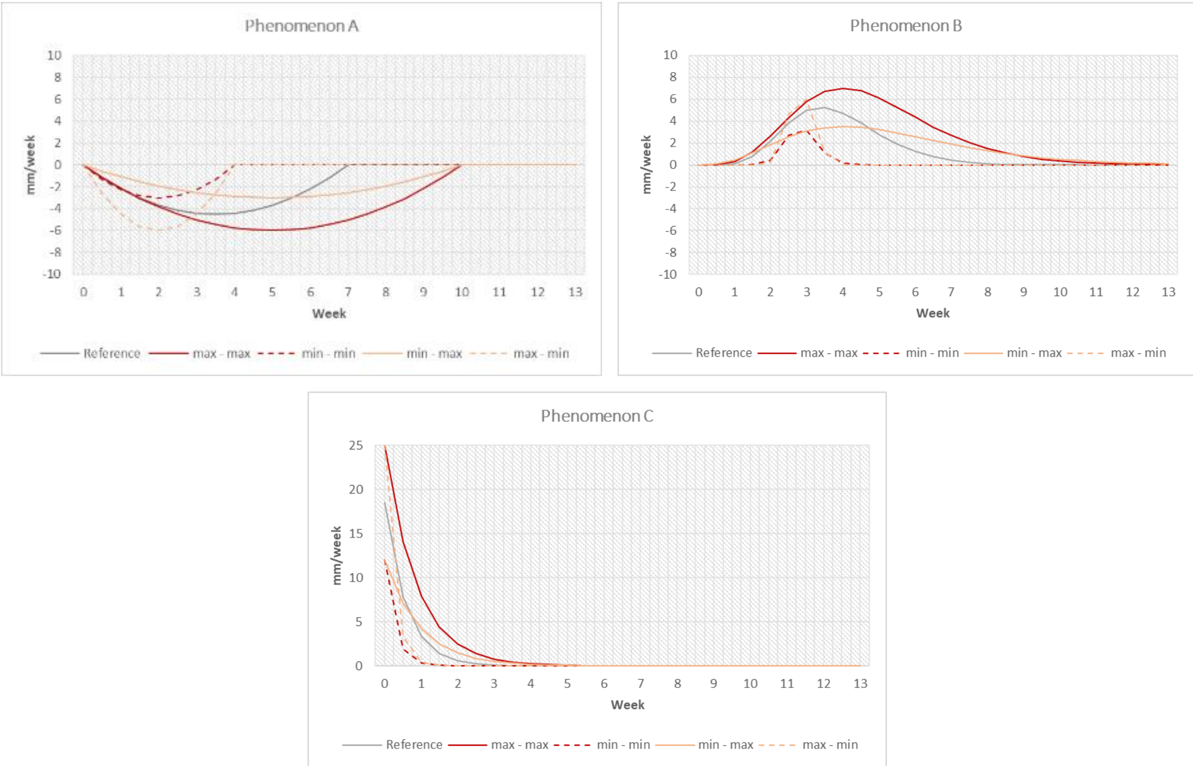

Figure 38: Ranges of "peak" and "duration" of each phenomenon

Assuming that the modellers know more than this, the user will ask for reasons why weekly precipitation differs from the climatology. Here, we assume that the modellers can provide some explanations, which we refer to as phenomena. By a phenomenon, we think of an explanation to why the forecasted weather is expected to deviate from the climatology in coming days, weeks or months It may be due to a given state of the North Atlantic Oscillation (NAO-index), the appearance of El Niño, or to the likely consequences of climate change on the intensity of precipitation. From the outset, higher average temperatures imply higher humidity, meaning that higher temperature leads to more precipitation. Recent findings suggest, however, that the intensity of precipitation periods will increase even in places where annual averages are expected to remain unchanged or even decrease (Hodneborg, et al. 2019). To those responsible for management of water basins and production of hydropower, for example, information about such a phenomenon is important, because it is combined with an expected change in flood episodes due to higher average temperatures. This implies less flooding related to snow-melting and more to the intensity of precipitation during winter.

Because of our ignorant point of departure, we do not refer to specific phenomena below, but confine ourselves to how we think they can be represented in a simplified model, in order to identify information needed to improve the usefulness of projections for decision-making purposes. Here, we introduce three possible phenomena to describe one possibility for a dry period and two possibilities for higher weekly precipitation than expected, shown in Figure 38.

In choosing functional forms, the parameters should reflect information that modellers can provide and that are easily interpreted by the users. The three functions in Figure 38 are all based on two parameters. One reflects the expected week when precipitation peaks, and one reflects how many weeks the phenomena are expected to last. The functional forms used in the examples are simple, but combinations of these three functional forms implies many possibilities, which all can be parameterized by assumptions on expected peak precipitation and duration.

There is uncertainty about peak precipitation and duration, however. From the perspective of a user with no knowledge about the weather systems, this uncertainty appears as random, and assessments of ranges will have to be based on guesses. The different curves in the each of Figures in 38 show the ranges of deviations from the climatology for minimum and maximum choices of each parameter used in the examples below. In addition, we add a random variable attached to the weekly precipitation for each phenomenon, and one random parameter for the whole projection.

The forecast of weekly precipitation in period t, W_t, can thereby be expressed as:

$$W_t = \Phi[f^1(x_{1t}, \mu_{1t}), f^2(x_{2t}, \mu_{2t}), \ldots, f^n(x_{nt}, \mu_{nt})] + \mu_W \qquad (3.3)$$

where $f^i(x_{it}, \mu_{it})$ measures the contributions from phenomenon i,. x_{it} is a vector of explanatory factors, and μ_{it} is a vector of probability distributions related to phenomenon i. μ_W is the additional randomness that links the forecast from the simplified model to the forecast from the S2S forecast from an ensemble member.

Our point of departure is that it is possible to quantify phenomena that explain why the forecasted weekly precipitation deviates from the climatology, and that there are uncertainties to how strong these phenomena are and how long they will last. In addition, there are

	Average	Min	Max	Distribution
Phenomenon A: $Y = (a + bx)x$. Prob = 0.1				
Peak	-10.0	-12.5	-6.5	Random
Duration	12.0	9.0	15.0	Random
Non-predicted	0	-0.5	0.5	Random
Phenomenon B: $Y = x^a/b^x$ Prob = 0.1				
Peak	15.0	11.5	18.5	Random
Duration	13.0	10.5	15.5	Random
Non-predicted	0	-0.5	0.5	Random
Phenomenon C: $Y = ax^{-b}$ Prob = 0.025				
Peak	8.0	6.5	9.5	Random

Duration	5.0	3.0	7.0	Random
Non-predicted	0	-0.5	0.5	Random

Table 21: Summary of information and random choices used in the examples

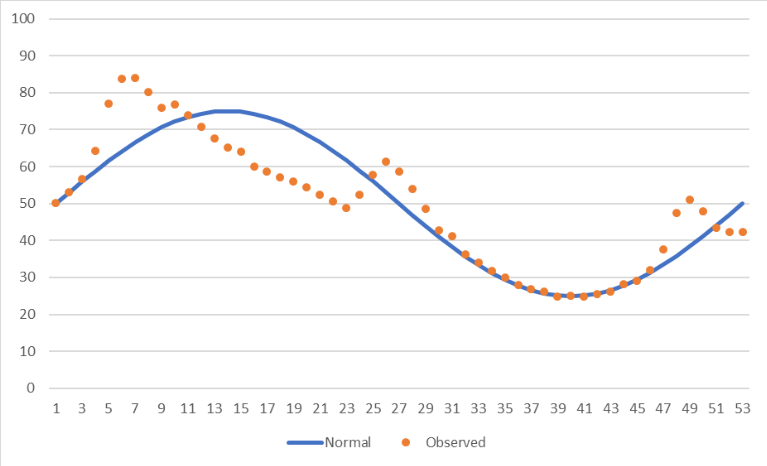

Figure 39: Climatology and observations of weekly precipitation in the example. mm/week

uncertainties related to how often and when they will occur. Again, the ignorant user does not know what the meteorologists can quantify from the outset, and consider them as random, based on their own guesses on probabilities of occurrence and with random appearance. Any information from experts that could help users to choose ranges and probabilities would be helpful. Table 21 summarizes the potential input from the modellers. In the examples, the parameters are constants, whereas modellers would most likely consider them dependent on season. Hence, a and b are probably time dependent functions, $a(t)$ and $b(t)$, in most cases.

To illustrate the observations, we run the simplified model once. The resulting weekly observations are shown in Figure 39, where there is a humid period in the beginning of the year, followed by a dry period until the middle of the year. The second half of the year is more or less normal, except a short humid period towards the end.

3.2.2 Construction of ensembles

The question from a user's perspective is, then, how information from ensembles can be of help to take decisions where the outcome depends on the precipitation in the coming year, which the user think is adequately measured by weekly precipitation. Based on the user's ability to interpret seasonal forecasts reflected by the simplified model, we construct an ensemble by running the simplified model 20 times. The aim is to reflect how a user with strictly limited insights to meteorology and climate is likely to interpret a 20-member ensemble.

According to Equation 3.3, the climatology and the different phenomena are implemented independently. There may be dependencies between the occurrence of the different phenomena or between the probability distributions in a model, but the users are unable to specify them. This means that projected weekly precipitation in a given future week, t, is understood as the change from projected precipitation for the previous week, *t-1*. For projections provided on different weeks, the projected precipitation for week *t-1* can be replaced by the observation. This may help the user evaluate possible benefits in postponing a final decision if it turns out that the uncertainty about the projection will be lower.

There may also be interdependencies across the different models within an ensemble. For example, the modellers may have a common understanding related to the occurrence of the different phenomena, which implies that the probability of a phenomenon in a given week in one model increases if the phenomenon is present this week in the projections from other

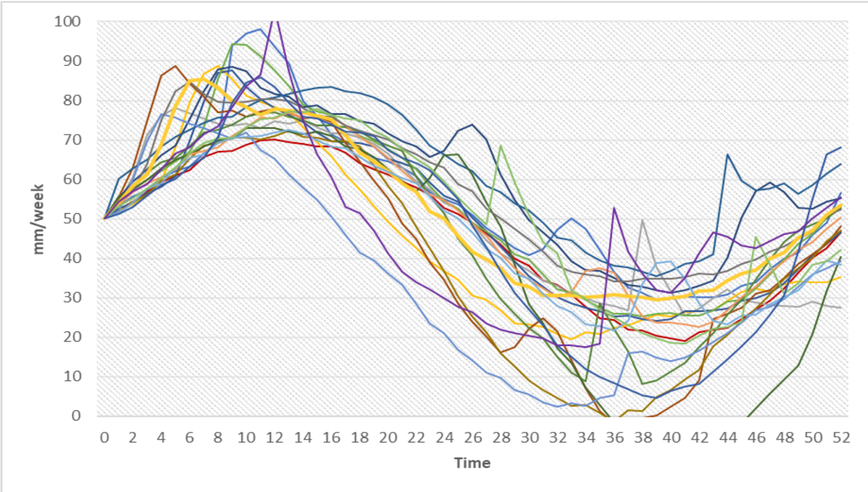

Figure 40: 20 member constructed ensemble of weekly precipitation

models. From the outset, users do not know about these dependencies, however, meaning that the occurrence of phenomena is considered independent across models, and related only to a fixed probability. We assume, however, that the same phenomenon cannot occur within the same model if it is “active” already.

The link between a constructed ensemble and real ensemble from models for S2S forecasts is reflected by the description of the climatology, which replaces the sinus curve used in the examples, and the random factor μ_W in Equation 3.3, which is the difference between the projected forecast from the simplified model and the real projection. The examples to not refer to real projections, however, and μ_W is therefore assumed random. If referring to real ensemble members, this term thereby indicates to what extent the variations published in the real ensembles provide information that can explain the demand for S2S forecasts.

Figure 40 shows the constructed ensemble for weekly precipitation over the coming year. This is, in other words, a possible example of information presented to users from a real ensemble. From a user’s perspective, the question is what insights they can draw from these curves that help them better deal with the uncertainties they have to consider.

We know that the forecasts provided today are considered too unreliable to be useful for most of the users who have been asked. This may be because the variability across models is too large to provide very useful information. In the example shown here, the projections differ by 8 mm/week already the first week and by 12 mm/week the second. The projected weekly precipitation 10 weeks ahead varies from 76 to 96 mm/week depending on model. Without further explanation, this is difficult to interpret for users, whose main concern is not primarily weekly precipitation. For an assessment of the value of the forecasts, the main question is the economic consequences of precipitation, which may be related to accumulated precipitation over several weeks or other indicators that can be derived from information on weekly precipitation, depending on who the user is. As mentioned before, the ensembles also lack information about the likelihood of observing the projected level of precipitation.

On the other hand, the ensembles also provide information that may be used in this context. First, it is possible to check if the ensemble indicates that projections from different models tend to deviate significantly from the climatology over the coming year. Second, we may check whether the distribution of forecasts across models tend to deviate from the average and

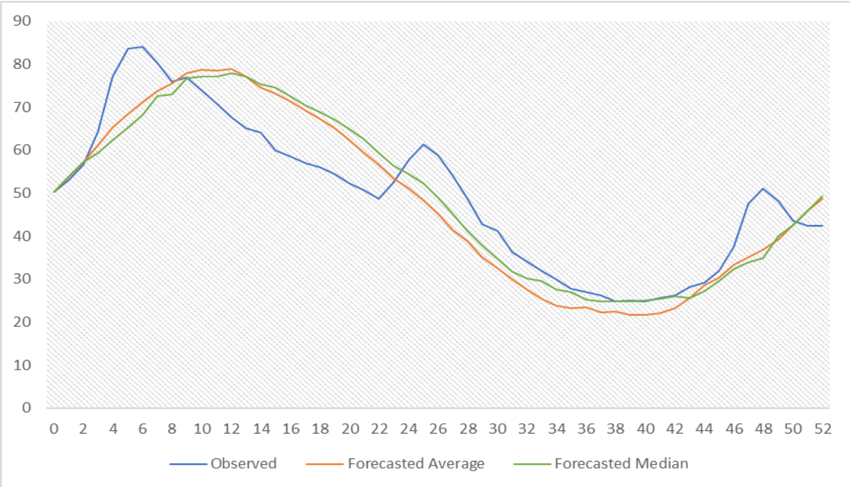

Figure 41: Observations, averages and medians for projected weekly precipitation across models

thereby indicate a skewed distribution. To do so, Figure 41 shows the average and the median across models, including the observations.

The simplified projections, which are based on the random choices in Table 21, do not provide clear patterns, however. The averages across models follow the climatology more or less as described by the sinus curve, and the there is a small difference between the average and the median, meaning that the projected precipitation from different models deviate equally much above and below the climatology. Because of the randomness and all the ignorance underlying the simplified projections, this is as expected. The point here is rather that one may check projections by comparing results across models in the same way to identify possible patterns, which users may find informative.

A comparison of the averages and the medians with observations in this example moreover illustrates the problems that users have in finding ensembles very useful. If they use the standard metrics to represent uncertain outcomes, they may just as well use the known climatology. On the other hand, they have good reasons to expect that the outcome will differ. perhaps significantly from the forecast, but it is difficult for them to reinterpret the ranges that can be read from the ensemble to probabilities that they relate to.

In this context, the apparent widening of the range of forecasts from different models the further into the future the forecasts apply may be relevant to users. It shows how the variability across models changes from one period to the next, which is likely to indicate how the uncertainty about projected precipitation changes from one forecast to the next. This is important information to those who can postpone a final decision until the uncertainty is sufficiently low.

In support of these decisions, Figure 42 shows the standard deviation from the 20-member ensemble of the simplified models. The pattern is clear, although it may be interpreted in different ways. The general trend is that the variability across models decline as the week that the forecast applies for comes closer, but it is difficult to tell how beneficial a postponement of a final decision will be if the outcome depends on weekly precipitation over many weeks in the coming year. The ranges of outcomes from forecasts the next four to six weeks will probably become much lower, while it is difficult to say how beneficial a postponement of a decision

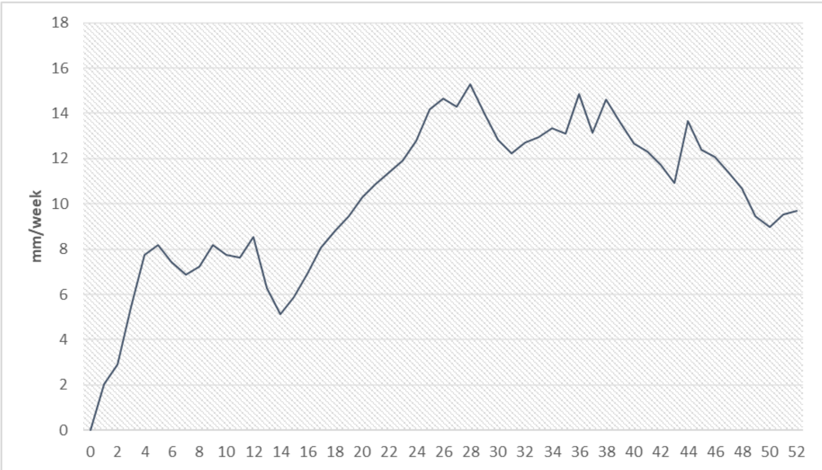

Figure 42: Standard deviation of forecasted precipitation at different future dates across models

that depends on outcomes beyond six weeks will be. From the ensemble, a postponement may be beneficial for outcomes up to half a year ahead, but this is based on an evaluation of this specific ensemble, and the picture may change in the next forecast.

If supported with information from the modellers about the choices in Table 21, the simplified projections will provide better and more realistic information underlying S2S forecasts. This will help users find the forecasts more useful, for example by indications of skewedness in the distributions of projected precipitation or deviations from the climatology that better fits the observations in Figure 41. They will also provide better and more reliable information on how the ranges change over time, shown in Figure 42.

3.2.3 Monte-Carlo simulations

So far, the discussion in this chapter has focused on how the experts who provide of S2S forecasts may contribute to improve the evaluation of future weather among potential users who have no special insights to weather and climate systems. In this section, we show how contributions to the simplified model from experts may be used to improve the information that the users are expected to care about, keeping in mind that this is still based on a theoretical approach to assess the demand for S2S forecasts, in general.

The main concern of the users is to evaluate the probability that a given level of weekly precipitation will be observed. The observations in the example in the previous section are safely within the range of the ensemble shown in Figure 40, but the ensemble refers to an understanding among experts, which is not shared with the users. The users can only make assumptions on how and why the different models project different weekly precipitation in the coming year, as the assumptions shown in Table 21, and then proceed in order to get an idea about the probabilities.

Then, the question is how the few observations reflected by the ensembles can be generalized to provide probability distributions on a general basis. The standard answer is to run Monte-Carlo simulations. The main reason why ensembles have been accepted to visualize uncertainties instead of running Monte-Carlo simulations is that the models used to project weather and climate are too large and complicated to allow for these simulations, which require thousands of runs. If replaced by simplified models to better communicate the knowledge behind the seasonal forecasts to users, however, we also have a model small enough to allow for Monte-Carlo simulations.

To show how such simulations can improve the usefulness of S2S forecasts, we run the same model as in the previous section, which is based on an ignorant user's interpretation of the forecasts, 2 500 times. In this context, it must be emphasized that the users' ignorance about how weather is forecasted by the modellers is assumed to include unawareness about possible differences between ensemble members. Hence, the different projections discussed in the previous section are due only to the assumed randomness in one model. This means that the ensemble shows the results of 20 runs in a Monte-Carlo simulation.

If using the simplified model to reflect the members of an ensemble of S2S forecasts, the parameters, the ranges and the distributions in Table 21 would differ across models. Then, it would be necessary to run more than 2 500 simulations. The benefit in doing so is that information about the explanatory power of the simplified projections, expressed by μ_W in Equation 3.3, is generated. This is useful both for potential users of the results and for modellers who contribute to the descriptions of phenomena and to the choice of parameters. In the projections discussed below, this factor is random, by definition. We therefore have to limit the discussion below to further benefits of having information needed to assess the demand for seasonal forecasts available, when taking the evaluation of users with strictly limited insights to what is known about the weather in coming days, weeks and months as the point of departure.

As a first checkpoint, Figure 43 shows average projected precipitation per week, the median and the standard deviation from all the 2 500 runs. The average is close to an exact description of the climatology, and there is no significant difference between the average and median, except, perhaps a slightly higher median in the dry season in the second half of the year. This means just that the simplified model does not include systematic biases, and that the random choices, which were chosen from the perspective of a non-expert, most likely implies symmetric distributions of the projected, weekly precipitation. The differences between the averages and the medians from the ensembles in Figure 41, which are larger, can therefore be considered as random.

The standard deviations from the Monte-Carlo simulation provides a far more stable picture than the standard deviation from the ensemble, which give reasons to reconsider possible conclusions drawn from the ensemble. First, the variability across models is larger in the short term than the ensemble shows. The ensembles indicate an increase from 1 to 8 mm/week over the first four weeks and further to 14 mm/week after half a year. From then on, the variability is steady or declining. The Monte-Carlo simulations indicate a standard deviation from 13 mm/week already in week one, and then a steady increase to approximately 20 mm/week after half a year. From then on, the standard deviations more or less stabilize.

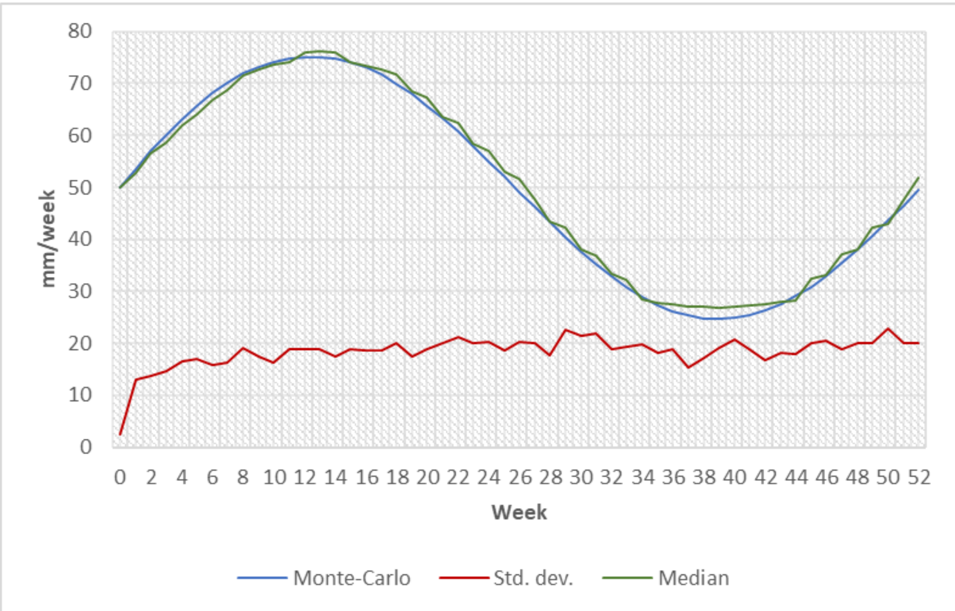

Figure 43: Averages, medians and standard deviations from a Monte-Carlo simulation of seasonal forecasts from the simplified model.

From the perspective users, the two projections thereby provide widely different messages. The ensembles indicate that forecasts provided in coming weeks will be much less uncertain, and that the uncertainty will most likely continue to decline in the coming six months. For forecasts beyond half a year the time they will have to wait to get less uncertain forecasts will be longer. In this "long term", the standard deviation is 10 to 16 mm/week. The Monte-Carlo simulations indicate, on the other hand, that the reductions in the uncertainty will be far less that indicated by the ensemble, but they will be reduced, from around 20 mm/week to around 12 mm/week.

The Monte-Carlo simulations also confirm the impression from the ensemble, that the standard deviation stabilizes for projection beyond half a year. They will not be reduced for projected precipitation the later in the year the projection applies, which might be read from the ensembles. However, intuition suggests that few would consider the clear tendency of lowered standard deviations in Figure 42 in projections from week 36 to week 52 as reliable. The Monte-Carlo simulation provides instead a more reliable picture, which can be used estimate probability distributions that the users care about, and which are needed to assess the demand for seasonal forecasts.

Figure 44 shows the distribution of estimated forecasts for precipitation in weeks 1, 6, 10, 26 and 52 from the 2 500 simulations. The first thing to note is that the assumptions underlying the simplified models, which are based entirely on random choices with equal probabilities for all possible outcomes, gives probability distributions with clear properties when implemented in the simplified model. In this case, the distributions are symmetric, which was also indicated by the comparison between averages and medians, and they give more relevant information about the uncertainty than what can be read from the evaluation of the standard deviations. The changes in distributions from forecasts of precipitation for week 1 to week 10 give a direct

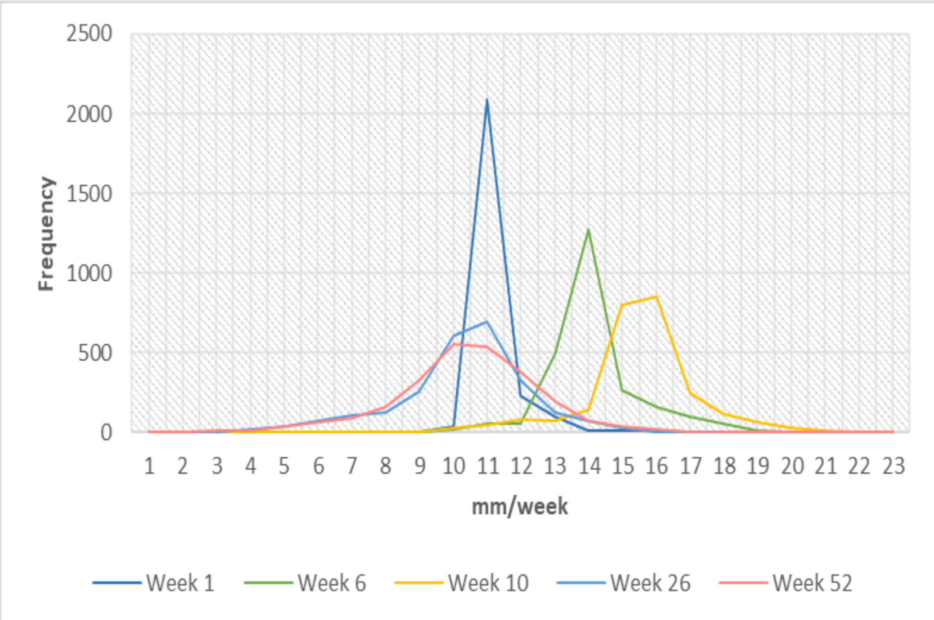

Figure 44: Distributions of forecasted precipitation for different weeks ahead

input to estimation of how this information may affect the demand for the forecasts. In this example, this relates to the evaluation of the uncertainties, as the shift in expected precipitation for the different forecasts can be explained by the climatology.

For the projections in the second half of the year, the improvements are less clear, although the distribution of projections for week 52 is slightly wider than the distribution of projections for week 26. For users whose decisions is primarily about *when* to take a final decision, this information may nevertheless be important. To assess the demand for seasonal forecasts from these users, the changes in expectations and probability distributions then have to be formalized. Recall the representation of stochastic processes in Equation 3.2:

$$dx_t = f(x_t, t)dt + g(x_t, t)dz$$

x_t is the uncertain variable observed at time t, and dx_t and dt represent the changes from one point in time to the next, meaning that dt = 1 when applied in numerical assessments. $f(.)$ is the expected change in the uncertain variable at t, which is read from the climatology. dz is the probability distribution for the change in the uncertain variable, and Edz = 0. Hence, and $g(.)$ represents how the choice of a probability distribution relates to the uncertain variable. As indicated, this may depend both on the level of the uncertain variable and the week for which the forecast is given.

To do numerical assessments of the demand for this information based on how it affects the decisions implies further, and rather strong limitations on the processes. We will not go further into this in this chapter, but instead focus on what information can be provided from the simplified projections that apply in Equation 3.2.

Figure 45 shows the changes in projected precipitation from the previous forecast, provided at t- 1, from the Monte-Carlo simulations. The figures correspond to the information about

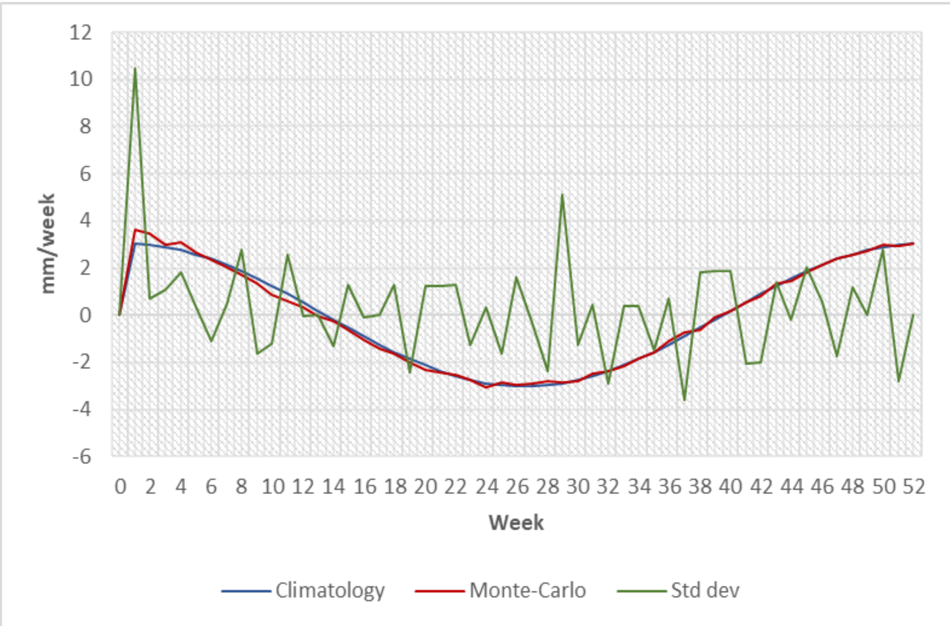

Figure 45. Expectations and standard deviations in the changes in forecasts of weekly precipitation for different future dates

levels in Figure 43. The expected change from the simulations, represented by $f(x_t, t)$ in Equation (3.2), gives more or less the same outcome as the changes in the climatology. This confirms again that the simplified model does not include assumptions that lead to systematic biases. The pattern of the standard deviations is more difficult to interpret. There is no clear pattern in the changes of the standard deviation over time. A tendency might be that the updates lead to higher uncertainty, but with lower corrections for projected changes in near future than for projected changes for weeks later in the year, when the deviations are more often downgraded. From week 10 and beyond, the deviations seem to change from positive to negative corrections following a rather random pattern.

The standard deviations reflect properties of the probability distributions that may help to quantify $g(x_t, t)$ and dz in Equation (3.2), however. The alternative is, therefore, to do Monte-Carlo simulations of the deviations from the climatology. Figure 46 shows the frequencies for the deviations in weekly precipitation for weeks 1, 6 ,12, 26 and 52, similar to the distributions of levels in Figure 44, but here based on 2 500 simulations of the stochastic process in Equation 3.2. Then, a rather clear pattern appears, which is similar to the lessons from the distribution of levels. First, that the random choices in the model do not lead to systematic biases in the uncertainty, meaning that the expected outcome corresponds to the climatology with Edz = 0. Second, there is clear increase in the uncertainty over time, but this increase is low over the second half of the year. Third, there is no apparent dependency between the level of expected weekly precipitation and the uncertainty, meaning that $g'_x \approx 0$.

The advantage of addressing the stochastic process, besides being directly applicable for deciding when to take a final decision, is that possible dependencies between level and uncertainties can be identified. The apparent reason why such a dependency is not found in this example is that all random elements are equally large for all weeks from the outset. It

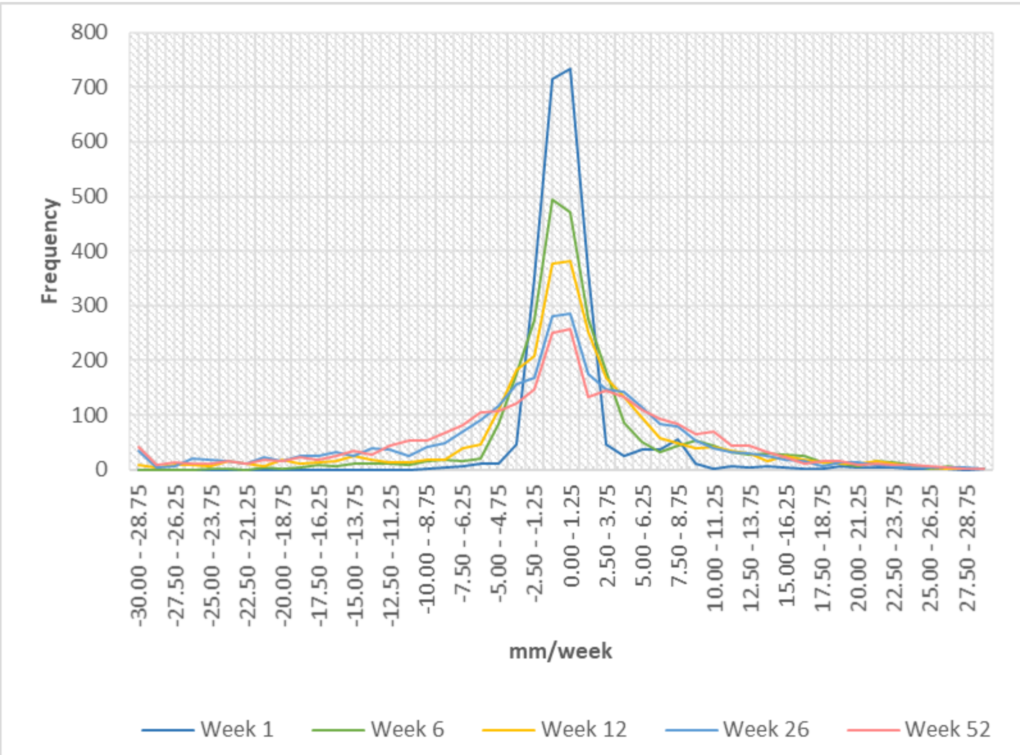

Figure 46. Probability distributions for the random element of the stochastic process g(xt,t)dz in future weeks.

thereby illustrates the need for, and the usefulness of letting experts go select phenomena and suggest functional relationships, to further to help quantify the parameters and characterize uncertain elements in the simplified model.

3.2.4 Examples of information to assess the value of S2S-forecasts

So far, we have concentrated on how S2S forecasts can be interpreted by an ignorant user to makes the information from forecasts of weekly precipitation in the coming year applicable to assess the demand for the forecasts. From the theoretical discussion in the previous section, the aim of the simplified modelling is to provide an explanation to why weekly precipitation deviates from the climatology and the related uncertainties, because this is needed to enable users to evaluate the importance of the uncertainties about weekly precipitation from their perspective. The concerns of users are seldom related only to weekly precipitation. When they evaluate the usefulness of S2S forecasts, the question is rather how the weather indicators affect the costs or income of a good or a service that they sell or buy. Then, the uncertainties they relate to is how costs and income opportunities vary with the weather indicator.

If there is a linear relationship between weekly precipitation and costs and incomes, the information explored above may suffice for the users, but this is seldom the case. Assessments of probabilities from simplified projections may then help users to further appraise the risks involved in alternative decisions. In some cases, this may be done by replacing the weather indicator, such as mm/week, with a function, $h(x_{mm/week})$, which expresses how weekly precipitation affects the income and costs, for example to capture a marginal increase in costs or thresholds.

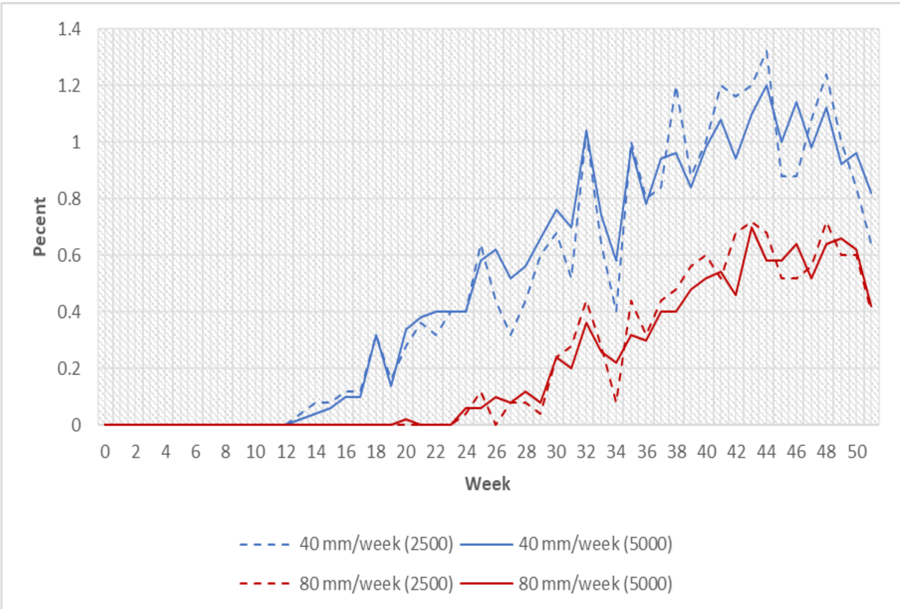

Figure 47. Cases with accumulate precipitation above 40 and 80 mm with 2 500 and 5 000 runs in a Monte-Carlo simulation. Percent

Other, and perhaps more important, is information that can be derived from the probabilities for weather indicators. Evaluations of the likelihood extreme events, for example, are probably based mainly on accumulated precipitation over several weeks. Figure 47 illustrates information drawn from the Monte-Carlo simulations, which may be useful in this context. The figure shows the percent of simulations that give accumulated precipitation above 40 and 80 over subsequent weeks with precipitation above normal. All the “events” are evaluated on the basis of information from forecasts provided in week 0, and the state in week 0 is assumed to be a “normal week”.

The figure shows that decisions where the outcome is known within 12 weeks can be taken without worrying about any of the two the thresholds. For outcomes beyond 12 weeks, there is a chance that a 40 mm threshold will be met, and this chance increases the longer time it takes before the outcome is known. If the threshold is 80 mm, those taking decisions where the outcome will be known within the coming 22 to 24 weeks need not worry about the thresholds, but for outcomes later than this, it may be worth to consider. The value of such information depends critically on the case, but it can be assessed by examining how alternative jump processes affect the expected benefit of decisions taken at different points in time (Dixit and Pindyck, 1994). Note also that the indication of declining probabilities towards the end of the year is due the choice of period of 52 weeks, and do not reflect a change in the trends that can be read from the weeks before.

The figure also shows the difference between running 2 500 and 5 000 simulations. The variability declines with the more simulations, and the explanatory power increases. This does not make much of a different in this simple case, but it may be important in other, more complex cases.

Finally, we emphasize that this is just an example of how the simulations can be used to derive further information of relevance for assessments of the demand for S2S forecasts. To assess the demand, or to evaluate the usefulness for potential users, one needs to relate to specific cases, because the information will differ depending on the problem, or more specifically, what is defined as “output”.

3.2.5 Summary

Efforts made to assess a value of S2S forecasts have been focusing mainly on making users understand what they can get out of the forecasts by a close collaboration with the modellers, hoping that they will be able to point out data that can be produced. This section suggests an alternative approach, which refers to information needed to assess the demand for goods and services when the outcome of a decision is uncertain. The point of departure is potential users of S2S forecasts, who take decisions where the outcome depends on how the weather will be in coming days, weeks or months. Here, we use weekly precipitation as an indicator of the dependency of the weather. The users have no particular knowledge about weather systems from the outset, beyond their own experience, but have access to S2S forecasts.

To illustrate the usefulness of information provided by S2S forecasts and the users’ need for information about the weather in relatively near future, we construct a 20-member ensemble for the coming year, which includes what we call phenomena and a number of random parameters. The phenomena and randomness are constructed to illustrate potential factors that users may understand and relate to in order to bring the information from the ensembles into the broader context of decision-making, but we do not refer to what the modellers know or use in their modelling. The simplified model can instead be understood as a suggestion from users, or from one whose aim is to assess a value for the S2S forecasts, to what kind of information would be of help to evaluate the uncertainties related to the weather in coming days, weeks and months. The aim of specifying phenomena and choices of randomness is, therefore, to provide concrete suggestions to where the modellers may help to improve the simplified projections.

Evaluations of the uncertainties depend critically on the probability distributions and how the uncertainties develop over time. The lack of reliable information about uncertainties is one of the main problems in making users see the usefulness of S2S forecasts. This problem is confirmed when trying to assess the demand for the forecasts. The advantage in transforming the knowledge that modellers have to a simplified model that users can relate to, is that the results from ensembles can be transformed to estimates of probabilities by means of Monte Carlo simulations.

The Monte-Carlo simulations of the simplified mode shows by examples how information from ensembles can be generalised and made useful for estimation of probability distributions and stochastic processes. In general, rather unclear impressions from the ensembles, which give rise to question that may not be relevant, are transformed to a relatively clear picture about probabilities and properties of the uncertainties. Linking the simplified model to real ensembles could further enable a quality check of the simplified model. The main message from this section is, however, that it identifies information that the modellers may provide to improve the usefulness of their work. This is not primarily to run more projections or to sophisticate their own models, but to communicate their insights in a way that helps users understand why the weather deviates from what is expected and support them in making assessments of how much it will deviate.

Conclusion, Bibliography and Annexes

4 Conclusion

This report investigates the economic value of S2S forecasts for decision-making processes of RE companies under extreme weather events. Starting from observing energy markets behaviours during periods of anomalies, RE producer companies have been actively involved during all the study to support and guide the analysis of the potential impacts of S2S forecasts on some specific decisional processes.

The evaluation exercise allowed for a deeper understanding of decision-making processes in the energy sector and the usefulness and applications of S2S forecasts. When analysing the case studies, important roles of the forecasts in decision-making and their valuable features to address the needs of decision makers were highlighted. Specifically, an in-depth analysis was conducted for three cases studies. The most relevant decisional steps were collected in stylised scenarios to conduct the impact analysis of the forecasts. For the first case study on an icing event in Romania in 2014, we found that, although S2S4E forecasts available for temperature would have not been able to correctly shift decision-makers' expectations, sub-seasonal forecasts could have mitigated non-negligible deviations costs by improving O&M and support financial decisions, such as hedging. Moreover, users emphasized the relevance of seasonal forecasts for budget planning. For the second case study on cold spell and low wind in Germany and France in January 2017, the forecasts from the DST provided useful information for decision-making, which could have been used to optimise hedging strategies, thereby alleviating economic losses resulting from incorrectly estimated electricity prices. In the third case study on a cold spell in France in 2017, we also found that the S2S forecast could have improved the financial results from hedge for some energy trading companies. However, the reality is complex and there are many other risk factors besides weather. The scenarios represent a simplification of the reality and the results strictly depend on the assumptions made. Complexity of decision-making processes combined with data confidentiality represented a challenge for the evaluation process. More collaborative studies involving decision-makers in economic assessments are needed to increase the sophistication and enhance applicability of the analysis for real decision-making.

Overall, when S2S4E forecasts are reliable and their PDFs are consistent with the relative observations, they are found to be valuable for risk management of extreme events. An important finding from this study is that users tend to be risk averse with respect to using S2S forecasts. Mistaking a decision due to a forecast that does not align users' expectations with observations concerns decision-makers more than benefits from using an informative forecast. S2S4E tackles this issue by providing forecasts that are calibrated to be more reliable and by presenting information about the forecast uncertainty. Effective risk management practices are important for financial stability. Given that RE production is highly dependent on weather fluctuations, S2S forecasts are an instrument to increase resilience of RE businesses, thereby stimulating the transition to a low-carbon society Finally, this report presents a theoretical concept on identifying information needed from users' perspective.

In conclusion, this study has focused on the evaluation of key periods in the past affected by extreme events. The operational climate service (DST) will be provided from June 2019 to November 2020. During this operational period the DST may have the potential to inform energy companies not only in eventual extreme events but more importantly in their daily decision making. To evaluate the economic value in this operational context, decision-makers will be testing the operational climate service during 18 months. The results will be reported in D2.3 "*The impact of operational real time forecasts for decision-making processes and best practice examples*".

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Annex

In this annex S2S4E forecasts used for the in-depth analysis of case studies number 1, 5 and 7 –conducted in chapter 2 – are reported together with their interpretation.

Case study #1: Cold spell France/Germany 2017

The sub-seasonal forecasts produced for this case study cover wind speed, temperature and demand. While for wind speed and temperature the forecast covers both the area of France and Germany, demand is predicted at national level. For each country a forecast is available.

For wind-speed, Figure a.1 demonstrates the behaviour of a forecast with limited skill. At lead times in excess of one week, the most dominant tercile is above- or near- normal – i.e., the weaker than normal winds are not well forecasted (consistent with the low fRPSS skill scores shown in the figure). At shorter lead times (1 week ahead) the forecast does, however, tend to suggest likely lower-than-normal wind speeds, though there all members underestimate the severity of the event and the near-normal tercile is estimated to be more probable than below-normal. Interestingly, the forecast at lead week 2 (start date 5th Jan) is much spread – more so than weeks 3 and 4 – suggestive of a high uncertainty in the circulation conditions.

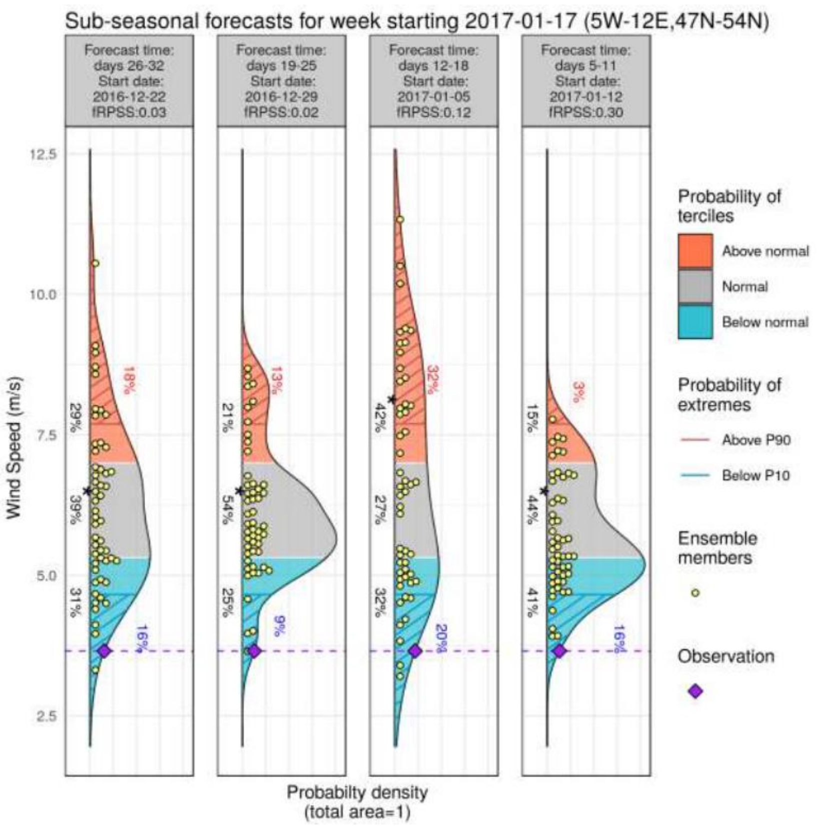

Figure a.1: Sub-seasonal forecast for 10m wind speed averaged over 5oW–12oE, 47–54oN for the week 17th–23rd January 2017. From right to left corresponds to forecasts launched from lead times week 1 to 4 (forecasts times 5-11 days, 12-18 days, 19-25

days, 26-32 days). Methodology: variance inflation calibration to ERA-Interim, based on a 20-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

The temperature during the week 17/01/2017-23/01/2017 in the area of study was close to 0 ºC. The forecasts available 25 days in advance showed the lower tercile as the most likely (44%). The prediction on 29/12/2016 showed more spread in the members and less skill but was consistent in indicating the lower tercile for temperature as the most likely. The forecast on the 05/01/2017 gave a 51% probability to the lower tercile with greater skill (fairRPSS=0.12). Finally the forecast issued on 12/01/2017 with lead time of 4 days, shows better agreement amongst members indicating temperatures close to 0 ºC. The likelihood of the lower tercile was 87% and of the chances of the temperature falling below the 10th percentile were 54%.

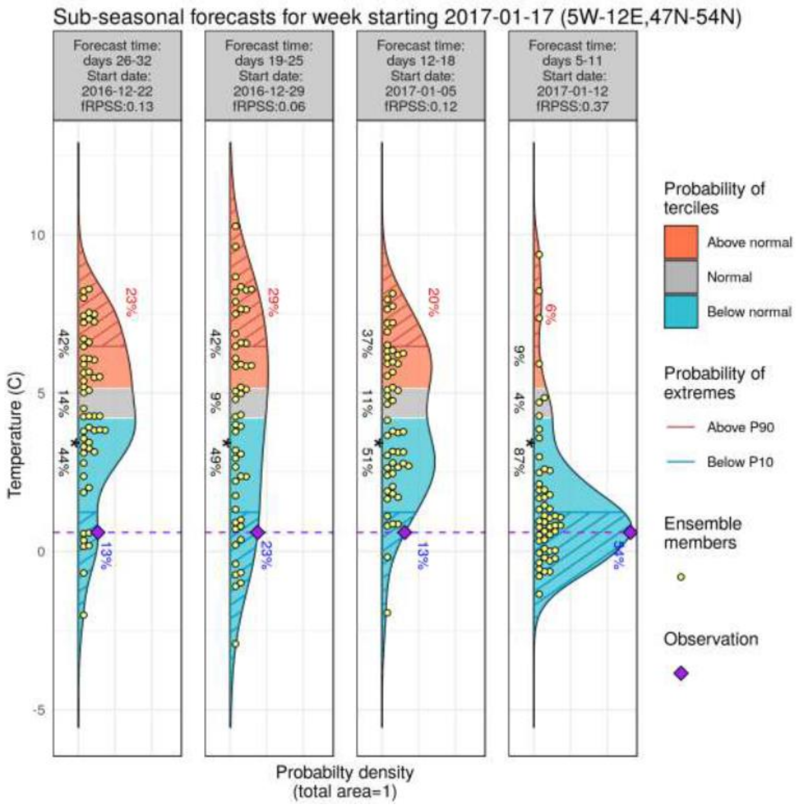

Figure a.2: Sub-seasonal forecast for temperature averaged over 5ºW–12ºE, 47–54ºN for the week 17th–23rd January 2017. From left to right corresponds to forecasts launched from lead times week 4 to 1. Methodology: variance inflation calibration to ERAInterim, based on a 20-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

For demand (which is strongly connected to cold temperatures in winter), Figure a.3 shows that for France the forecasts indicate a preference to above normal demand conditions beginning in week 3. This preference increases slightly in week 2, but becomes particularly pronounced in week 1. The generally positive fRPSS scores (indicated at the top of each forecast PDF) indicate that the forecasts have predictive skill at these time ranges.

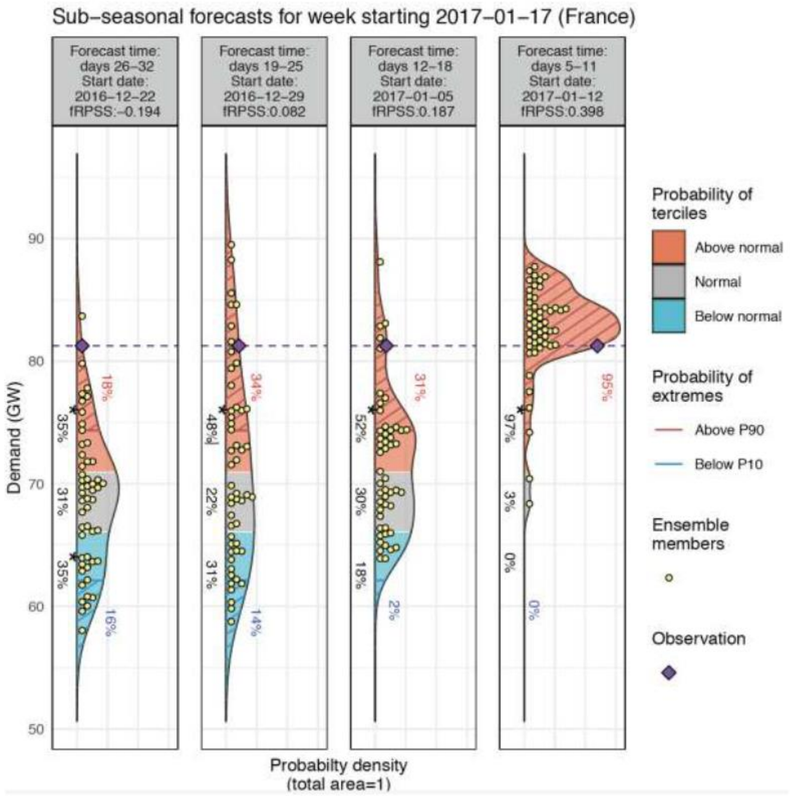

Figure a.3: Sub-seasonal forecast for demand in France for the week 17th–23rd January 2017. From left to right corresponds to forecasts launched from lead times week 4 to 1. Methodology: lead time dependent mean bias correction, applied to both temperature and demand (once converted), calibrated to ERA5, based on a 17-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

For demand in Germany Figure a.4 shows that the forecasts indicate a preference to above normal demand conditions beginning in week 3 as for French forecasts. This preference decreases slightly in week 2 (with negative fRPSS score), but becomes particularly pronounced in week 1, with positive fRPSS scores as for week 3.

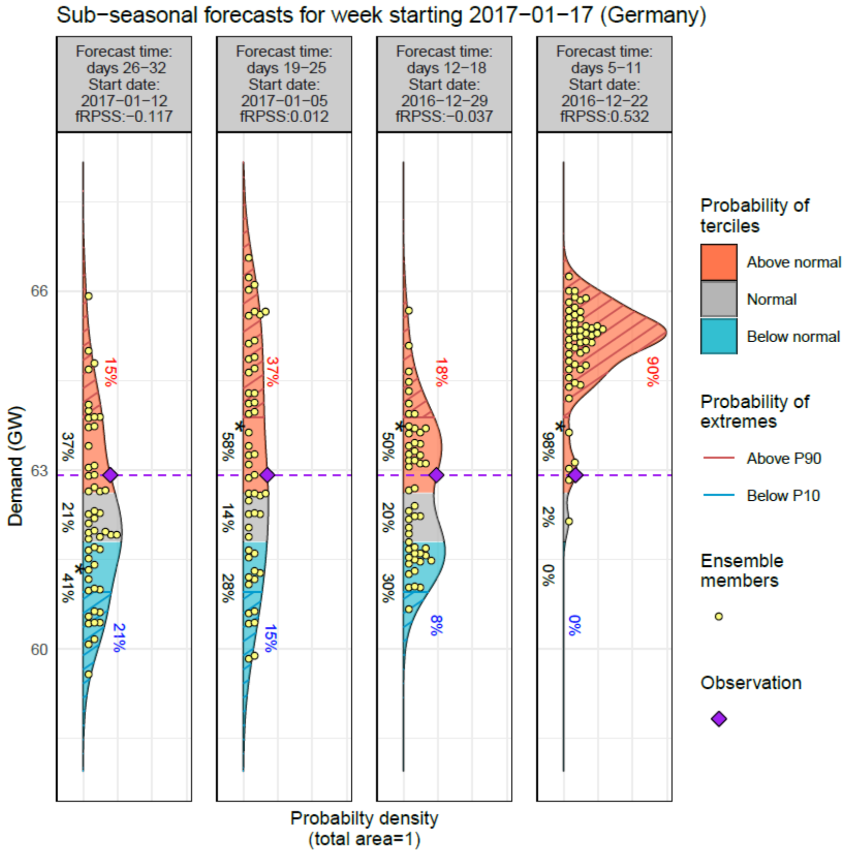

Figure a.4: Sub-seasonal forecast for demand in Germany for the week 17th–23rd January 2017. From left to right corresponds to forecasts launched from lead times week 4 to 1. Methodology: lead time dependent mean bias correction, applied to both temperature and demand (once converted), calibrated to ERA5, based on a 17-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

Case study #5: Icing event in Romania 2014

Figure a.5 presents temperature (A) and minimum temperature (B) sub-seasonal forecasts for the first week of February 2014 over a point within the region of study. Lead times range from 4 to 1 week in advance.

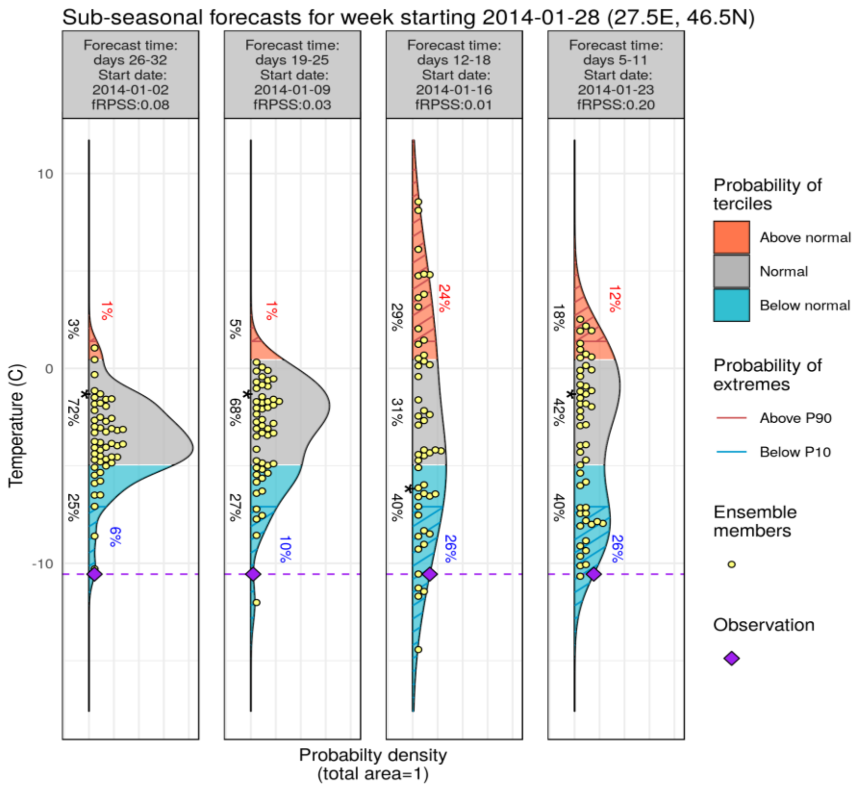

Figure a.5: Sub-seasonal forecast for temperature for a specific grid point (27.5 E, 46.6 N) for the week 28/01/2014-03/02/2014. From left to right corresponds to forecasts launched from lead times week 4 to 1. Methodology: variance inflation calibration to ERA-Interim, based on a 20-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

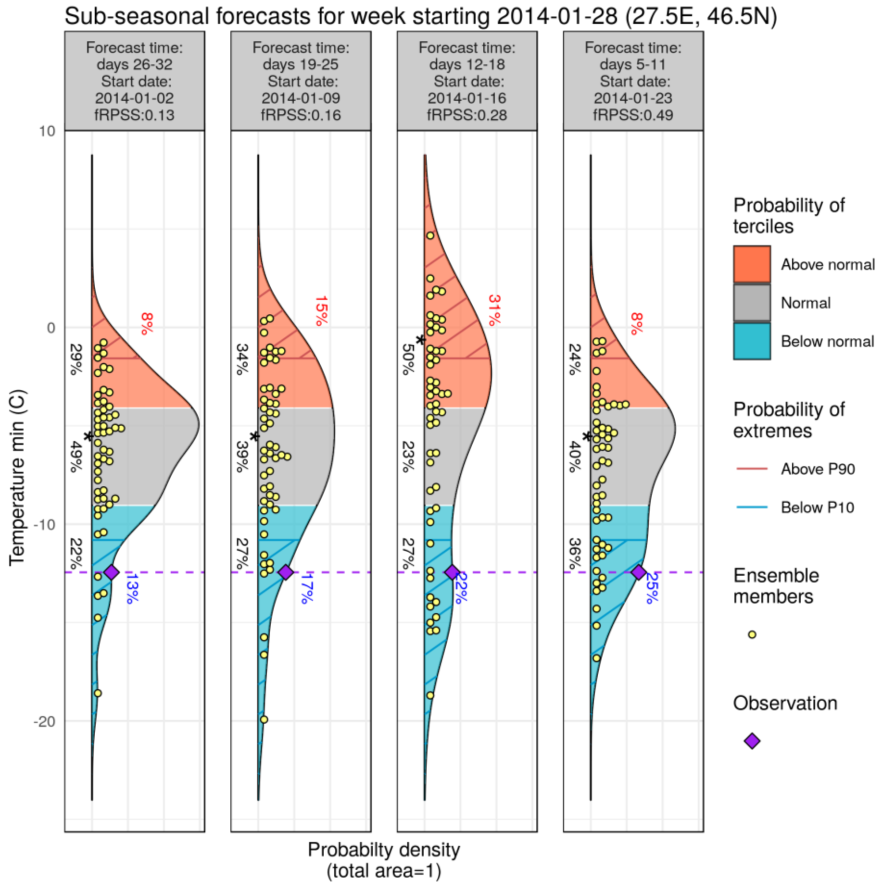

Figure 1: Sub-seasonal forecast for minimum temperature for a specific grid point (27.5 E, 46.6 N) for the week 28/01/2014-03/02/2014. From left to right corresponds to forecasts launched from lead times week 4 to 1. Methodology: variance inflation calibration to ERA-Interim, based on a 20-year hindcast. An assessment of the skill associated with the forecast is indicated in each header (fRPSS = fair RPSS).

The weekly average temperature for that point for the target week from the ERAInterim reanalysis was around -11C. The forecasts were indicating high probabilities of the temperature being in the middle tercile 3 and 4 weeks in advance. In the forecasts issued 2 and 1 weeks in advance, the probabilities of the lower tercile increased, and the forecasts showed similar probabilities for the middle and lower terciles. A broad spread in the ensemble members is seen even for the last forecast. However, some individual members were close to the observation and thus, the probability attributed to the 10th percentile was 26% in both forecasts issued on the 16/01/2014 and the 23/01/2014.
It also must be noted that the model version of ECMWF monthly system employed in these forecasts is CY40R1, since this case study occurs in 2014. ECMWF monthly versions before CY41R1 (implemented in May 2015) have associated hindcast runs of five ensemble members (as opposed to eleven members thereafter). This lower number may affect the quality of the calibration process, as the calibration parameters are less robust.

The behaviour of the forecast for minimum temperature (Figure a.6) is similar to the forecast for temperature (Figure a.5). Forecast issued 4, 3 and 1 weeks in advance was indicating probability of minimum temperature near normal (49, 39 and 40%, respectively). The confidence in predicting minimum temperature for this location and period is high, especially 2 and 1 weeks before the event, however, in this case, forecast didn't predicted the observations.

Case study #7: Cold spell France/Europe 2018

For this case study forecasts of temperature and French demand are available only.

For each forecast, along with the figures, skill scores have been estimated using the hindcasts. Figure a.7 and Figure a.8 show the temperature and electricity French demand forecasts for the four lead times. The temperature forecasts only show potential of capturing the observation two weeks prior to the event; however, results for forecast week 1 were accurate in terms of being below normal conditions but underestimated the temperature value. In terms of electricity demand, and similarly with temperature, the forecasts could not predict the event, only until two weeks prior to it. The signal (described here as probability) was strong that the electricity demand would be above normal conditions.

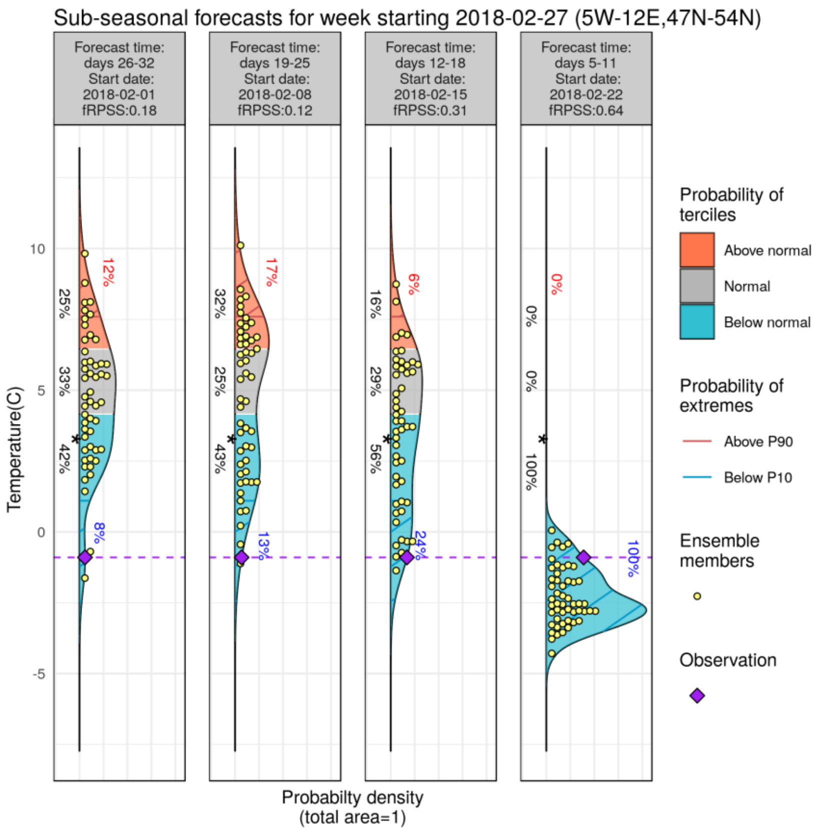

Figure a.7: Temperature forecasts for 27 Feb 2018 issued four, three, two and one weeks in advance for the domain (5W-12E, 47N-54N).

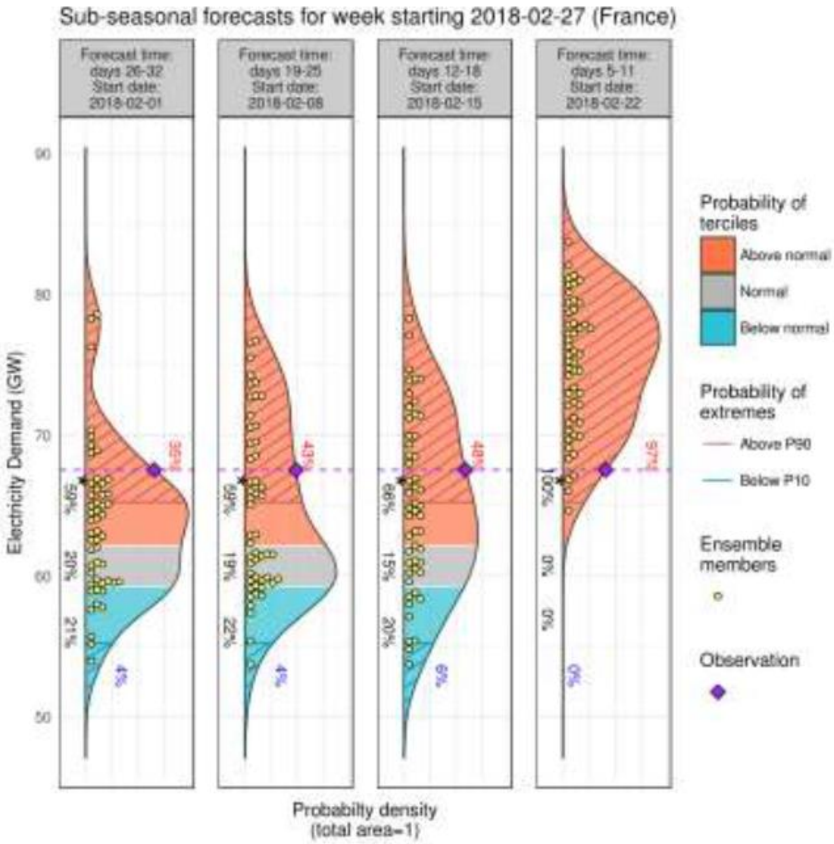

Figure a.8: Electricity demand forecasts for 27 Feb 2018 issued four, three, two and one weeks in advance for France.