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Sub-seasonal and seasonal climate predictions for a sporting goods retailer company: Co-development of a climate service from scratch

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ABSTRACT

Predicting variations in weather conditions beyond a few days is of great interest to decision-makers, as this time horizon aligns with the strategic planning needs of stakeholders in climate-vulnerable sectors affected by seasonality. While the effects of climate variability are well understood in sectors such as energy and agriculture, where the potential applications of climate predictions in decision-making are already being explored, in other sectors, the direct impacts of climate variability on operations or on defining seasonal transitions remain unclear. In this context, our paper describes the knowledge exchange and co-development process carried out during the co-production of an operational climate service for a sports retail company. We developed a climate service that combines sub-seasonal and seasonal forecasts to provide tailored and user-friendly climate information for the upcoming weeks and months. The operational system supported decision-making in selected stores over a year, with regular evaluations helping to build trust in the service and informing new developments for an improved version. This study demonstrates that a co-production approach, where interaction between the user and the scientist is established early in the forecast product development, is fundamental to the creation of a successful climate service. Beyond this specific case, the long-term aim of the work is to compile and synthesise the lessons learned in developing this service at sub-seasonal and seasonal timescales, to encourage its adoption in other comparable retail businesses also affected by climate variability (e.g. the fashion industry and food-snack production).

Practical implications

This research project arose in response to the detection in a sporting goods retailer company of a mismatch between production, logistics and sales processes caused by a variable climate. The supply of logistic warehouses is produced according to the predicted sales (based on the "typical climate", among other factors) and adjusted by the sales that took place in the previous weeks. Thus, the summer of 2018 saw a late arrival of heat in Spain, leading to a low stock of certain seasonal products such as flip-flops (low sales pushed a low supply in Spanish regional warehouses). When the heat arrived, in a significant way, this shortage led to a shallow level of sales due to the lack of stock (which had been sent to other countries at that time). This fact, added to the already low level of sales at the beginning of the summer, resulted in poor results for certain brands during the summer season.

This specific need to anticipate seasonal changes—in the previous example, the Spring-Summer stock transition, which involves shifting from outdoor sports (cycling, trekking, etc.) to water sports (swimming, snorkelling, etc.)—affects the company

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throughout the year. A similar transition occurs between Autumn and Winter, when stock adjustments shift from outdoor sports to winter sports (skiing, winter clothing, etc.). It is important to emphasise that seasonal sports equipment, such as skis, snowboards, diving gear, and paddleboards, typically has higher profit margins. Therefore, optimising the management of these stocks can significantly improve the company's financial performance. In view of this situation, a project was proposed to include climate forecasting in the sales prediction models to try to correct the supply mechanism of logistics warehouses. The expected result was a model not only based on historical "typical climate" (not applicable in the climate change context) and their related sales but also on the sales forecasts based on climate predictions weeks and months ahead (sub-seasonal and seasonal climate predictions, respectively).

However, the expected gain was not only focused on the connection between logistic supply and more accurate sales prediction, but also pointed out a high potential to correct discrepancies between production quantities and final sales. Thus, climate predictions have the potential to help adjust the production quantities and their global distribution between countries. This allows the company to maximise the sales of the products where the climate will be favourable to certain sports (i.e. sell better). An accurate stock in the continental/regional warehouses (related to accurate production quantities and stock regional distribution) maximises the sales, reduces the overstock (and the consequent value loss of the not-sell products) and minimises the logistic movements between warehouses to solve the stock discrepancies.

In addition, during the company's internal discussion of the project, two extra potential benefits were identified:

1. Human resources planning could benefit from climate forecasting by focusing on the working hours in sales peak predicted periods linked to favourable weather. Thus, there is a cost reduction in unexpected extra hours and an increase in workers' well-being by reducing stress through better working hours planning.

2 Secondly, the commercial campaigns could be focused on those products linked with the predicted climate, maximising their impact on sales.

The lessons learned from this project—beyond agriculture, energy, and insurance, which already have companies familiar with the use of climate predictions— sub-seasonal and seasonal climate predictions could be applied to other sectors, including the fashion industry, fresh ready meals retail, and food-snack production, among others, to improve supplier requests, production planning, stock management, and logistics. Below are some examples:

- Fashion industry: Like sporting goods retailers, the fashion industry relies on seasonal clothing collections. More accurate demand forecasting weeks in advance can help optimise supplier orders and production planning, particularly for companies with agile production and distribution systems, such as Inditex. Additionally, the logistics chain across different regions, which is a key aspect for most companies in the sector, could also benefit from improved climate-driven demand predictions.
- Fresh ready meals production: These companies prepare fresh meals, and demand is closely linked to weather conditions. During hot weather, consumers are more likely to prefer refreshing options such as gazpacho or salads, while on cold and rainy weekends, warm meals like cannelloni tend to be more popular. Accurate climate forecasts (in this case, only sub-seasonal predictions due to the target lead time, weeks) could help these businesses anticipate demand fluctuations and optimise production and supply chain management of fresh products such as vegetables, and help to reduce food waste.
- Snack and beverage corporations: The demand for many of these products is strongly influenced by people's ability to enjoy outdoor activities, particularly in countries with pronounced seasonal differences. Warmer weather encourages consumption in open spaces such as terraces, while colder seasons may reduce demand. Improved demand forecasting would primarily help optimise stock levels and logistics, rather than production or supplier management, since these products typically have a longer shelf life.

1. Introduction

In 2024, climate patterns were notably exceptional, following on from the remarkable warmth of 2023. 2024 is the first year with an average temperature exceeding 1.5 °C above pre-industrial levels (C3S, 2025). This increase of temperature in the last years and the internal climate variability of the climate system resulted in widespread extreme weather events worldwide including heatwaves, droughts, wildfires and floods, leading to direct socioeconomic consequences and impacts on human health, ecosystems and infrastructures (e.g. Blunden and Boyer, 2024; C3S-WMO, 2025).

In this context of climate-related challenges, the role of sub-seasonal and seasonal climate predictions gains increasing importance for preparing and mitigating the impacts of anomalous periods and extreme events. Sitting between weather forecasts (targeting from the next few hours to 15 days) and decadal predictions, and climate projections (that estimate the potential evolution of climate over the following years and decades), sub-seasonal and seasonal predictions do not tackle the prediction of exact weather conditions on a specific day several weeks or months in advance but shifts in the climatological probability distribution over large averaging periods. Sub-seasonal forecasts cover periods from 2 to 6 weeks and focus on capturing week-to-week variability (Vitart and Robertson, 2019), whereas seasonal forecasts extend from 1 to 6 months, targeting month-to-month and season-to-season variations (Doblas-Reyes et al., 2013).

That said, the boundaries between weather-climate modelling categories are usually blurred, as some of the physical processes included in the modelling systems are common across different timescales. More specifically, the feasibility of sub-seasonal and seasonal prediction depends on the detailed description of the observed conditions both at the starting point of the simulation (also known as initial conditions), and the more slowly evolving and predictable boundary conditions of the atmosphere such as sea surface temperature, soil moisture, sea-ice and snow cover (Mariotti et al., 2018). At sub-seasonal time scales, the Madden-Julian Oscillation (MJO) is the main process that contributes to forecast quality, having a considerable impact not only in the tropics but also in the middle and high latitudes (Zheng et al., 2018). On the other hand, for seasonal forecasts, the El Niño-Southern Oscillation (ENSO) is considered the main source of predictability, especially in the tropics, but having also far-reaching effects in other regions (Williams et al., 2023).

Historically, although a significant proportion of users have adopted weather forecasts in their decision-making, there has been a clear separation between the use of weather and climate forecasts. This timescale separation has also been accompanied by a divide in the weather and climate research communities, their predictive models and practical applications. Recently, the introduction of sub-seasonal and seasonal climate predictions has come with a new set of challenges. First, providing skilful predictions at sub-seasonal and seasonal time scales is notoriously difficult (especially if we compare them to weather forecasts), although advances in recent years demonstrate that probabilistic sub-seasonal and seasonal predictions can inform better decision-making at some temporal scales and regions (Becker et al., 2022; Kondal et al., 2024; Vitart and Robertson, 2018). However, despite these improvements, users still have reservations about the real applicability of climate predictions. The reasons for such underutilisation are quite diverse (e.g. Bruno Soares and Dessai, 2016): (i) the provision of probabilistic information instead of deterministic, which could create uncertainty in the user's interpretation of these forecasts; (ii) the necessity for a specific conceptual understanding to interpret the skill and reliability of the predictions; (iii) the lack of customization or tailoring of information to specific user needs; and (iv) the reluctance of users to deviate from their established methodologies.

This underuse of climate predictions is not uniform across the various economic sectors affected by weather conditions and their evolution over time. For instance, there is a good understanding of how climate variability affects certain sectors, such as energy, agriculture, health, water management, insurance or wildfires (Hewitt et al., 2012; White et al., 2017, 2022; WMO 2023). In contrast, sectors like retail present a more complicated picture. While it is generally accepted that retail activities show seasonal fluctuations, there is limited clarity on how variations in weather conditions directly impact operations or how to delineate transitions between seasons (Verstraete et al., 2019; Zhang and Robinson, 2022). In general terms, retail companies expect a seasonality in their sales, assuming that future climate conditions will be like past conditions (Thomassey, 2010) and, therefore, an inherent assumption of this approach is that climate variability doesn't have an impact on retail business. However, the evolution of climate variables over time does not need to be extreme to have serious financial consequences on sales and profits (Berlage, 2013).

In recent years, unexpected climate conditions have shown their capacity to critically alter the financial performance of retailers by changing consumers' buying habits or by causing disruptions in the supply chain, which eventually leads firms to end up with poor sales and profits (Islam Molla, 2016). Apparel goods are a prime example of seasonal products, where the sales window can be very small. Careful timing is therefore a crucial factor for retailers in this sector (Tran, 2016). If the products reach the store too early, they risk sitting unsold; conversely, if the products arrive too late, there might be a shortage in demand, which will require companies to reduce prices to stimulate sales (Bahng and Kincade, 2012). Thus, failure to ensure that the precise amount of goods is available at the right time will negatively impact the overall apparel sales and revenue (Bertrand et al., 2015). Consequently, to maximise performance, retailers have to forecast the exact demand for specific products. Hence, understanding and quantifying weather conditions at different time scales holds the potential to significantly improve decision-making in the apparel retail industry.

Addressing the gap between new potential users and climate scientists requires overcoming the traditional linear interaction model that positions scientists and knowledge users on opposing sides. Instead, a co-production approach is essential for crafting robust methodologies and tools to address decision-making needs (Vincent et al., 2018). In 2018, the World Meteorological Organization (WMO) introduced a framework to guide user engagement processes (WMO, 2018). This framework is stepwise, from passive to active user participation. Real-world applications in this field have motivated debates about the methods and results of co-production research (e.g. Norström et al., 2020). Despite its growing adoption, the interpretation of co-production varies depending on the context and those implementing it.

In this paper, we describe the methodology adopted for the co-development of a real-time operational climate service for a sporting goods retailer in Spain. To the best of the authors' knowledge, there are no previous experiences in co-producing a climate service on timescales ranging from weeks to months for the retail sector. Our approach follows the co-production methodology defined by Bojovic et al. (2021), which provides a structured framework for engaging stakeholders throughout the development process. This work aims to provide an example of how the co-development of climate services overcomes the understanding and communication barriers for the uptake of probabilistic sub-seasonal and seasonal predictions and fosters the interaction between users and climate scientists. For the longer term, this collaborative endeavour seeks to set a precedent that can be replicated by the same company in other regions and other retail companies affected by climate variability, such as the fashion industry or food and snack production. This kind of replication would ideally contribute to the formulation of climate adaptation strategies and greenhouse gas mitigation efforts.

The paper is structured as follows: Section 2 describes the data and methods used in the project, with particular emphasis on the co-production process and user engagement. Section 3 focuses on knowledge exchange, which is crucial in collaborative initiatives, detailing the four key aspects that required special attention during the project to facilitate communication and ensure the uptake of the climate service. Section 4 presents the results, and finally, Section 5 discusses the main lessons learned throughout the project.

2. Data and methods

2.1. Data acquisition and postprocessing

In this work, we use climate and sectoral data. The climate data has been directly retrieved from various operational centres and broadcasting organisations. The forecast covers sub-seasonal and seasonal horizons, as explained below. For sub-seasonal forecasts, we retrieve 6-hourly data weekly and aggregate it into daily means. For seasonal forecasts, we download monthly data directly every month. From these forecasts, the different products of the essential climate variables (temperature and precipitation) and derived indicators (maximum and minimum temperature and number of rainy days per week) are computed at weekly (sub-seasonal forecasts) and monthly (seasonal forecasts) time scales. The second type of climate data accessed is the hourly ERA5 reanalysis (C3S, 2017), which is used for forecast evaluation and calibration at weekly and monthly aggregations.

2.1.1. Climate data

ERA5 (C3S, 2017) is the latest climate reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is used during the calibration process to correct the different systematic errors associated with the forecasts. Hence, 1-hourly data for mean temperature and precipitation are retrieved from the Copernicus Climate Data Store (CDS) and subsequently aggregated into weekly and monthly values.

The sub-seasonal forecasts are generated using the NCEP CFSv2 sub-seasonal forecast system. The system is a fully coupled model, which means it considers interactions between the atmosphere, ocean, land surface, and sea ice, allowing it to simulate a wide range of physical processes (Saha et al., 2014). The NCEP CFSv2 sub-seasonal operational predictions have a 45-day forecast period and are initialised every six hours. The hindcast period spans from 1999 to 2011, and each six-hour initialisation generates only one ensemble member (yielding four members per day). In contrast, the forecast period includes four ensemble members for each six-hour initialisation, comprising three perturbed members and one control run (yielding 16 members per day). The method used to create ensemble members is a "lagged" mode, distinct from the more prevalent "burst" mode (in which each initialisation time generates an extensive set of ensemble members (Chen et al. 2013; Weisheimer and Palmer 2014; Vitart 2020). The "lagged" mode, on the other hand, initialises the system with greater frequency, generating fewer ensemble members, but allowing for a more flexible assembly of the final ensemble, because the number of its members is not predetermined (Manrique-Suñén et al., 2023). However, merging ensemble members from various initialisation times requires careful manipulation. In this work, to generate an ensemble of 12 members for the hindcast period, and 48 members for the forecast period, the model runs of three days are combined. The data used were obtained at a spatial resolution of 1° (∼100 km) from the NCEP NOMADS server, which provides access to NCEP CFSv2 data. These data were first aggregated into daily means, and then into weekly averages.

Regarding seasonal predictions, the latest ECMWF seasonal forecasting system (SEAS5; Johnson et al., 2019) has been employed. This system has been operational since November 2017. The operational

SEAS5 seasonal forecasts are produced with 51 ensembles and are initialised on the first day of each month, spanning up to seven months into the future. A set of hindcasts has also been generated for the first day of every month in the 1981–2017 period, consisting of 25 ensembles. The ECMWF SEAS5 seasonal forecast is downloaded on the 6th of every month at a monthly time resolution. The download is executed operationally through the CDS-API (https://cds.climate.copernicus.eu/api-how-to).

2.1.2. Bias-adjustment and forecast quality assessment

Climate forecasts require to be post-processed to remove model drift and properly adjust the ensemble spread. In this study, we rely on the variance inflation calibration method, which is well-supported by existing literature (Doblas-Reyes et al., 2005; Torralba et al., 2017; Manzanas et al., 2019; Manrique-Suñén et al., 2023). This method enhances forecast reliability by correcting interannual variance and inflating the ensemble spread, leading to more dependable probability-based forecasts across various meteorological variables and lead times. Additionally, since forecast error typically increases with lead time, calibration is performed separately for each forecast period. For subseasonal predictions, this process is applied weekly from week 1 to week 4, whereas for monthly to seasonal forecasts, it spans months 1 through 3.

Since the hindcast period of NCEP CFSv2 is rather short (1999–2011,12 years), forecasts beyond 2011 were added to the hindcast to increase its size (by randomly selecting 12 of the 48 members of the forecast ensemble). Additionally, to maximise the use of the hindcast data, three hindcast sets are employed in the calibration of each forecast run. To this aim, a 'running window' along the initialisation dates and centred on the current forecast is employed to define the climate distribution corresponding to each forecast. In this way, a larger sample size is used to characterise the model climatology needed to identify the model drift with respect to the reference climatology (Manrique-Suñén et al., 2020). Then, the real-time forecast data is corrected with the parameters derived from comparing the forecasts and the reanalysis on a grid-point basis.

Regarding seasonal predictions, the hindcast period employed is 1981–2017. The whole hindcast set per each grid-point is also calibrated with leave-one-out cross-validation. The calibrated hindcast provides a long collection of corrected past forecasts employed for a probabilistic forecast quality assessment to compute the skill score metrics.

Two different verification metrics have been selected to inform on the quality of the two forecasts products included in the service: the ranked probability skill scores for tercile events (RPSS; Epstein, 1969; Wilks, 2011) and the brier skill scores (BSS, Brier, 1950; Wilks, 2011) for extreme values represented by the (p10 and p90). These two scores thus address the central requirement identified through the co-production approach: enabling stakeholders to interpret forecast skill for everyday conditions while retaining the ability to assess predictions of high-impact events. To support this objective, their fair versions (Ferro, 2014) correct for ensemble size effects, ensuring that comparisons reflect true forecast quality rather than differences in ensemble configuration.

2.1.3. Sectoral data

The company created a dataset containing daily quality-controlled turnover from 52 different stores in Spain. This dataset includes both online and in-person sales, and further categorises them into 32 sports families, such as winter sports, trekking, etc. The database covers the period from September 2014 to March 2020. The selection of this period represents a compromise: it is long enough to compute stable correlations with climate data but excludes distant years that could introduce socio-economic confounders like shifts in social conduct or company strategies, and specifically excludes the COVID-19 period.

Unfortunately, the sales dataset cannot be included in this paper due to confidentiality constraints. However, this does not affect the interpretation of the results, as shown in Section 4.2, where sales data are used alongside climate data to identify the variables influencing sales across different sports categories. The authors acknowledge the difficulties associated with accessing private data that, in some cases, is essential for both the co-development of a climate service (Ramon et al., 2020) and for assessing its economic value from a user viewpoint (Orlov et al., 2020; Vigo et al., 2023).

2.2. Co-production methodology

The climate service developed in this project followed and adapted the co-production methodology proposed by Bojovic et al., 2021, to foster the dialogue and collaboration between scientists and users throughout the entire process. This iterative engagement allowed for the co-design, co-development, and co-evaluation of the climate service. In this regard, scientists and users worked together to identify the specific climate information needs, co-define indicators and thresholds, and jointly assess the usefulness and effectiveness of the provided services. This interdisciplinary approach enabled a deeper understanding of users' perspectives, values, and decision-making processes related to climate information. By considering these aspects, the project aimed to develop a climate service that was not only scientifically accurate but also relevant and actionable for the intended users in the company. Hence, the project embraces the concept of co-production as a dynamic and participatory process that involves iterative collaboration and interaction. It encompasses various stages: 1) user engagement by raising awareness on the vulnerability of the activities to climate variability; 2) proactive knowledge exchange between scientists and users to understand user needs and scientific assets better; and 3) co-development aiming to increase user empowerment and ensure the usability of the services (Fig. 1). In total, the whole process represented in Fig. 1 and explained in this paper lasted three and a half years.

Engagement with users started with some preliminary discussions (Fig. 1a), taking advantage of specific communication material from previous projects, mainly related to agriculture and energy. In this case, we specifically leveraged materials from MED-GOLD[3] and S2S4E.[4] Like the retail sector, agriculture and energy are affected by temperature variability. These examples showcase the potential value and benefits of using climate services through their own experiences and successful implementation. They serve as real-world examples of how climate information can improve decision-making processes. The conversations started with the Environmental Sustainability Department of Decathlon Spain because they saw it as an opportunity to reduce greenhouse gas emissions due to logistics (further details about user needs included in section 3.1) and as a climate adaptation strategy. User engagement continued throughout the entire co-production process, enabling knowledge exchange and the co-development of new insights, facilitating the creation of tailored tools.

Knowledge exchange with users started with a series of exploratory meetings (Fig. 1b), initially with the initiative's promoters (Environmental Sustainability Department) to identify user needs and explain the potential applications and limitations of climate predictions. These meetings aimed to bridge the gap between scientific knowledge and user requirements, exploring how climate predictions could be translated into valuable services to support decision-making and adaptation strategies within the company.

To validate the initial hypotheses (having a reliable forecast of temperature and precipitation months into the future would be crucial for the business), a series of interviews were conducted with different departments (Fig. 1c). They were formulated based on interactions with the initiative's promoters to ensure the successful adoption of the climate service by targeting several key factors involved in its uptake.

[3] https://www.med-gold.eu.

[4] https://s2s4e.eu/climate-services/case-studies.

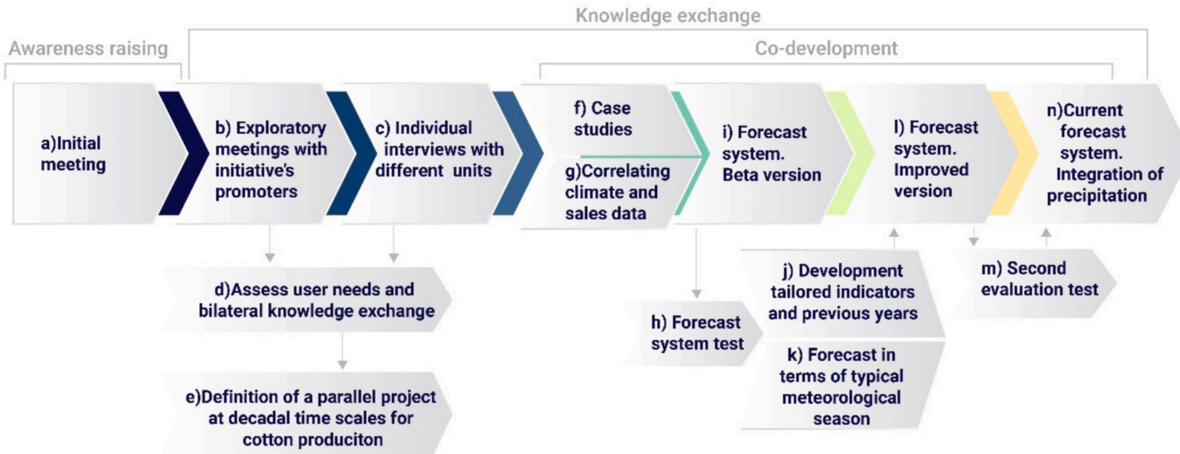

Fig. 1. Co-production process followed in this project involves different tasks (from a to n) organised in three main stages: awareness raising, knowledge exchange and co-development. For clarity, the process is represented as linear; however, in practice, it was a continuous and iterative process that allowed for the transition, for instance, from the development of case studies (f) to an initial operational system (i), which was later improved (l) through co-evaluation processes.

First and foremost, the usefulness and relevance for the user. This is because climate services should address specific user needs, providing actionable and context-specific insights. It is the perceived value of these services when aiding decision-making that substantially influences their rate of adoption (Tarchiani and Bacci, 2024). To this end, the sales and logistics departments of the company and a few specially appointed store managers were identified as a target group because they operate stock distribution between regional warehouses and stores according to the predicted sales. Another important factor influencing uptake is the accessibility and availability of climate services; users need to have easy access to the information and provided tools. In this case, the user was a multinational corporation that already had its established tools and protocols. Coordination with its information technology (IT) department was also essential to ensure the smooth integration of the new climate service information into their existing platforms.

In total, this process—from the initial meeting (a), the exploratory meetings with the initiative promoters (b), and the individual interviews with different departments (c) to assess user needs and explore the potential applications of sub-seasonal and seasonal predictions in their decision-making process (d)—lasted six months. Continuous interaction via email and quick meetings with the Environmental Sustainability Department helped organise the material to be discussed and facilitated interactions between the different departments and the research institution. As explained later in Section 5 (Discussion and Conclusions), the Environmental Sustainability Department became the project sponsor for the remainder of the project, assuming a broader cross-functional responsibility and acting as a nexus between the various departments and the research centre. With all this in place, we were then able to move on to the co-development phase to develop case studies and the forecast system.

2.3. Case studies, an important step to co-develop operational climate services

To support the proof-of-concept phase and illustrate the potential use of climate information, a common approach is to define and analyse case studies (Fig. 1f) that analyse specific past events with unusual climate behaviour affecting a sector. These case studies helped us to co-develop the operational service (Fig. 1i) and its integration into the real-world decision process. From a user perspective, case studies are also useful in two different ways: 1) to get a better understanding of an event and its frequency, envisaging the risk of its future recurrence (e.g. Vautard et al., 2019); and 2) to analyse the forecasts that were available before the event (e.g. Vitart, 2005; Ferranti and Viterbo, 2006) to demonstrate their potential usability under 'real' conditions (e.g. De Felice et al., 2015) and quantify the economic gains of having them (e.g. Orlov et al., 2020).

However, the use of case studies implies some shortcomings that need to be managed during the co-development exchange, like the focus on single episodes that are usually also extreme. Although extraordinary anomalous periods help to understand the characteristics and the potential application of the prediction, users still have to figure out how this can help in their regular decision-making workflows (e.g. is it applicable during the whole year? can I expect similar results in other regions? etc.). From a communication perspective, case studies also have some drawbacks when it comes to bridging the gap between scientists and users in co-producing a climate service. First, it is important to make clear that the performance of the forecasts in a single event should not be seen as a method to estimate the overall skill of the prediction system. The quality of a prediction is always based on past performance over a prolonged period (Jolliffe and Stephenson, 2012), and this must be transmitted to the user from the beginning of case study interactions. Secondly, the typical spatial and temporal resolution of sub-seasonal and seasonal predictions is coarse compared to short-term forecasts. This means that climate predictions often fail to represent local conditions accurately and, as a result, well-established sectoral decision-making thresholds are not directly applicable (MacLeod et al., 2018).

In this project, we selected and analysed four case studies relevant to users, each representing different situations across various seasons of the year. The aim was to compile a small set of examples to examine cases where the skill was either high or low, where the simulations showed no clear signal versus others with sharp probability distributions, cases where the most likely tercile predicted either matched or differed from the observations, and events where sub-seasonal and seasonal predictions could be compared. A notable case study that underscored the influence of climate on the sales of Decathlon was the 'Filomena' event (see Section 4.1). 'Filomena' storm was a significant occurrence of cold and snow that severely impacted a large portion of the Iberian Peninsula in January 2021, leading to substantial shortages in winter equipment materials and mountain footwear (Martínez Botí et al., 2021). The fact that this event emerged during the knowledge exchange phase of the project provided an excellent opportunity to highlight the potential of utilising climate information in our retail context.

3. Co-production of a climate service based on sub-seasonal and seasonal climate predictions for the retail sector

During the co-production of the climate service, it became evident that certain climate concepts and information were interpreted differently among users and climate scientists, leading to potential misunderstandings and discrepancies. To address this, discussing these concepts and simplifying the information provided in the climate service to enhance user interpretation was important. Table 1 summarises the initial questions and comments from users, along with the outcomes and defined tasks. Disparities in terminology and concepts could have hindered effective communication, making it critical to establish and agree upon a shared language from the outset of the project (Norström et al., 2020; Terrado et al., 2022, 2023). This is particularly important when using climate services in decision-making contexts, as it supports a better understanding of their potential benefits and risks. Such knowledge exchange involves both scientific and non-scientific perspectives, and should be regarded as a two-way interaction between users and scientists, ultimately promoting scientific literacy (Bremer et al., 2019; Howarth et al., 2022). The four most relevant knowledge integrations from this project phase are comprehensively analysed in the following subsections (3.1 to 3.4).

3.1. Knowledge exchange from users to scientists: User needs and decision-making processes

Decathlon is the world's largest sporting goods retailer, with over 1,749 stores in 57 countries in 2023 (Decathlon, 2024). The Decathlon Group markets its products under more than 20 brands, each representing a different sport. This project was carried out in collaboration with Decathlon Spain to co-develop a climate service for the country. Table 2 summarises the types of decisions at Decathlon that can be informed by weather forecasts and climate predictions, the relevant time scales for such information, and the potential benefits of making informed choices based on these forecasts. The decision-making framework developed in this project can also be adapted and applied to other retail companies (see the practical implications section).

Starting with short-term lead times, efficient human resource planning is especially critical for sports retailers, where specialised sales staff are needed for specific seasonal sports. In this case, accurate sales predictions for the coming days and weeks can help in allocating the appropriate number of skilled staff to meet the expected demand.

On a slightly longer time scale —spanning weeks to months— retailers must also consider stock distribution and promotional campaigns for seasonal products. For instance, sales forecasts can guide the distribution of water sports products between regional warehouses and stores, ensuring that these items are sold before the end of the summer season to avoid stock being sent back for the following year. Near the far end of the time scale, decadal climate predictions can inform strategic planning years in advance. Like other apparel retailers, sports companies often depend on natural fibres like cotton. Having a better understanding of projected output from typical regional providers can help plan strategies to prevent supply chain bottlenecks and reduce costs associated with natural fibre purchases.

In this study, our focus will be on sub-seasonal and seasonal time scales, forecast windows where climate predictions offer valuable insights for enhancing various aspects of retail operations. Specifically, accurate climate forecasts in this timeframe can contribute to more efficient stock movement, optimised human resource planning, and streamlined production activities. The benefits of such efficiency gains extend beyond cost reduction, also leading to a decrease in the carbon footprint of retail operations.

Table 1
Initial questions and comments from users during the early conversations and project brainstorming meetings (Fig. 1a-c), along with the corresponding outcomes of these discussions.

Initial questions and considerations from users during the initial brainstorming meetings	The outcome of these discussions, along with the defined tasks
We need to understand how climate seasonality affects our business	Recognition that the company is affected by climate variability in multiple ways (Section 3.1).
Can we predict this seasonality? How accurate are these predictions several months in advance?	The concept of forecast skill is key for long-term strategy, and it is important to take this skill into account when analysing forecasts (Sections 3.2 and 4).
Is it possible to predict the change of season? We need information months and weeks ahead.	As seasonal forecasts alone are insufficient, there is a need to combine sub-seasonal and seasonal predictions (Sections 3.3 and 4.1).
Why don't you provide the mean value of these predictions?	The inherently probabilistic nature of forecasts implies a risk when using the mean value (Section 3.4). Instead of providing mean values, the proposed solution was to offer probabilistic forecasts within the context of the observed outcomes from previous years (Section 4.4).
We need to test and validate this new method beyond these statistics (RPSS, BSS, etc.) that we don't understand.	Development of a plan, starting with case studies and testing a forecasting system on a selected group of stores (Sections 2.2 and 4.3).

Table 2
Specific user needs were identified for Decathlon, including the types of decisions that weather forecasts and climate predictions can inform, the relevant time scales for such information, and the potential benefits of using accurate forecasts.

Forecast window and associated decisions and potential benefits			
Weather (<15 days)	Sub-seasonal (1–6 weeks)	Seasonal (1–6 months)	Decadal (1–10 years)
Increase in human resources planning efficiency based on the expected sales. <u>Social benefit</u>: Better working conditions			
	Stock distribution between regional warehouses and stores based on predicted sales linked to the climate. <u>Environmental benefit</u>: GHG emission reduction due to fewer logistic travels. <u>Economic benefit</u>: Margin keeping due to less obsolete inventory.		
	Commercial campaigns based on the expected climate. <u>Economic benefit</u>: Sales increase due to better commercial campaigns adapted to the climate.		
			Natural fibre production projections to develop purchasing strategies. <u>Environmental benefit</u>: Increase climate resiliency in raw materials strategies. <u>Economic benefit</u>: Cost reduction in natural fibres purchasing due to better market decisions. (Not included in this contribution)

3.2. Knowledge exchange from scientists to users: The concept of skill, key for a long-term strategy

Skill is a statistical measure that assesses the performance of a prediction in the past (Wheatcroft, 2019). It allows the quantification of the added value of that forecast relative to other prediction approaches. This evaluation of past forecasts can inform users about the expected performance of future forecasts (Weisheimer and Palmer, 2014). Although it plays a pivotal role in determining whether a specific prediction should be used for decision-making, users have not been trained to utilise it effectively to add value to the decision-making process. Instead, a prevalent method among users to decide the forecast quality is by examining a specific time frame in the past (in our case, several weeks or an entire season) in a qualitative, few-shot comparison manner. To demonstrate the benefits of a long-term strategy that leverages skill assessment, climate scientists can bridge the gap between technical and economic paradigms (more familiar to users) using serious games (Terrado et al., 2019, Crochemore et al., 2021) that can be adapted to different decision-making scenarios. This approach showcases the shift from a traditional perspective of simply gaining or failing in specific events, to the added value of adopting a long-term strategy based on having information about the skill of a certain variable, region and lead time to perform informed decisions and risk assessments.

During the project, to illustrate the benefit of adopting a long-term strategy based on better information, we used the metaphor of playing in a casino with loaded dice: even though one can still lose individual games, over time the advantage ensures overall success.

3.3. Knowledge exchange from users to scientists: The ready-set-go strategy and blending the information from different forecast products

Users have responsibilities at multiple time scales. Thus, providing a combination of forecast products that cover different time scales would be beneficial in such instances. This can be addressed by providing a forecast well in advance (in our case, a seasonal forecast updated once a month) and refining that information with sub-seasonal predictions (updated weekly) as the potential impact draws nearer, to further contextualise the risk at each evaluation step. Previous climate services have already adopted this strategy called the 'Ready-set-go!' approach (Goddard et al., 2014). However, when combining different forecasts (with different initial conditions, timescales or from different systems), it becomes evident that discrepancies within the forecasts may arise as time progresses. These inconsistencies between the predictions are perfectly understandable from the point of view of the climate models (e.g. due to the uncertainty linked to initial conditions). Still, it wasn't easy to harmonise and communicate this information to the user. Thanks to the knowledge exchange, we understood that users (at least, within the framework of this project) don't see this inconsistency between predictions as a problem per se. In an ideal scenario, the preference is for consistently accurate predictions of the highest quality, mirroring the standards achieved in meteorological forecasting. However, once they understand climate prediction's potential applications and limitations, they can deal with these inconsistencies between different forecasts. Some top decision-makers of the company, aware of these limitations, said: "I'd rather make a wrong decision based on data than one based on instinct". In this regard, they see the seasonal forecasts as a tool to monitor mid-range periods, enable an early-warning system and update contingency plans. As the time of a potential impact comes closer, if sub-seasonal predictions at different lead times confirm the signal, users can then mobilise resources and make proper and actionable decisions.

3.4. Knowledge exchange from scientists to users: Probabilistic forecasts vs deterministic decisions

A significant challenge in adopting climate predictions is the probabilistic nature of the forecasts, coupled with the users having a deterministic decision-making mindset (Taylor et al., 2015). This becomes apparent when the users suggest basing their long-term decision workflow on the computation of the mean value of the ensemble members. However, relying solely on the mean value of the ensemble forecast excludes crucial uncertainty information as well as probabilities from different percentiles, significantly diminishing the usefulness of these predictions.

Fig. 2 illustrates this concept and provides the user with an analogy involving a leaf drifting downstream to facilitate the comprehension of the probabilistic nature of climate information. This example used in the interaction with the users illustrates the probabilistic character of climate predictions, considering taking several leaves from the same tree and placing them in the same starting position in a river. Each leaf will then follow a distinct trajectory downstream. If the experiment is statistically robust, we will end up with a potential distribution of trajectories, along with their associated uncertainty. In the realm of climate predictions, uncertainties in the initial conditions are linked to those in the observations or assumptions made during data assimilation (comparable to the variations in leaf shapes and sizes or subtle changes in the river's turbulence). Even though these errors may appear small, they can lead to substantial forecast divergence due to the chaotic nature of the climate system (Lorenz, 1963) and, in our analogy, the river system. Other influences of the river can account for the additional uncertainties that arise from limited resolution, simplified parameterisations, and unresolved nonlinear processes within the forecast system.

Once this concept was assimilated, various options to improve forecast interpretation were discussed. The final solution adopted was the integration of observations from previous years into the forecast (Section 4.4) to enable comparison between the forecast distribution and real situations they could recall.

4. Results. Co-development of the climate service

The co-development of the operational system involved several steps outlined below (Fig. 1, f-n). It began with defining and analysing case studies defined by users that helped to establish the framework of the initial operational system. This initial version underwent a one-year evaluation by a group of company users. Based on their feedback, key improvements were identified, leading to the development of a second version of the operational system that is currently in use.

Fig. 2. The illustration depicts potential paths a leaf follows when falling in a river. It exemplifies how slight variations in initial conditions (leaf size, position, currents, etc.) result in equiprobable trajectories. This example has been used to illustrate why climate predictions are probabilistic.

4.1. Case studies

The Filomena episode was characterised by temperatures well below normal (see section 2.3). Fig. 3a shows the observed tercile for temperature during the week when Filomena took place. With the forecast system ready for testing, it was possible to obtain predictions of what would have been predicted by our service several weeks ahead of the event in terms of the temperature tercile category. The surface temperature conditions brought by the Filomena event were generally well-predicted 3 weeks in advance (Fig. 3b).

Another pertinent case study from the same month, but with conditions contrary to those of Filomena, consisted of an unusually warm period occurring in the last week of January 2021. Fig. 4a illustrates the observed tercile for temperature during that week, while Fig. 4b displays the predicted temperature category for forecasts initialised up to four weeks ahead.

These two case studies proved highly valuable in illustrating the operational system's functionality and aiding the user's comprehension of concepts such as lead time and forecast time. Furthermore, these two case studies were crucial in highlighting how events that might hold significance in the sub-seasonal context can nullify their impact and lead to a flat monthly or seasonal outlook, as demonstrated in Fig. 5a, where it is evident that, within the observed monthly mean temperature tercile, some regions experienced average monthly temperatures. This was important as it helped illustrate the potential application of utilising the synergy between sub-seasonal and seasonal forecasts, rather than relying solely on one, and consequently capturing events of both medium-term and long-term nature.

4.2. Initial variable selection by correlating climate and sales data

Even in sectors where climate undeniably plays a significant role, climate data is rarely the sole factor guiding actions (Goddard, 2016) as it often lacks sufficient weight to support a particular decision within a company's framework. Therefore, assessing the magnitude of the link between climate and user activity (Fig. 1g) is crucial for building and maintaining user confidence. Furthermore, it helps in more accurately selecting or discarding certain climate variables, minimising biases stemming from personal experiences or beliefs.

The first step in this process is to assess the relationship between the sales curve of each sport family and different climate variables. To achieve this, standardised time series of turnover for various sport families (Section 2.1.3), adjusted for seasonality, were created and compared with the corresponding standardised time series of climate variables. These variables, identified by the user during meetings and interviews as the most relevant for influencing sales (Fig. 1a,b,c,d), include weekly and monthly averages of mean, maximum, and minimum temperature and precipitation.

After conducting this analysis for each climate variable, it was found that the correlations obtained for maximum, minimum, and mean

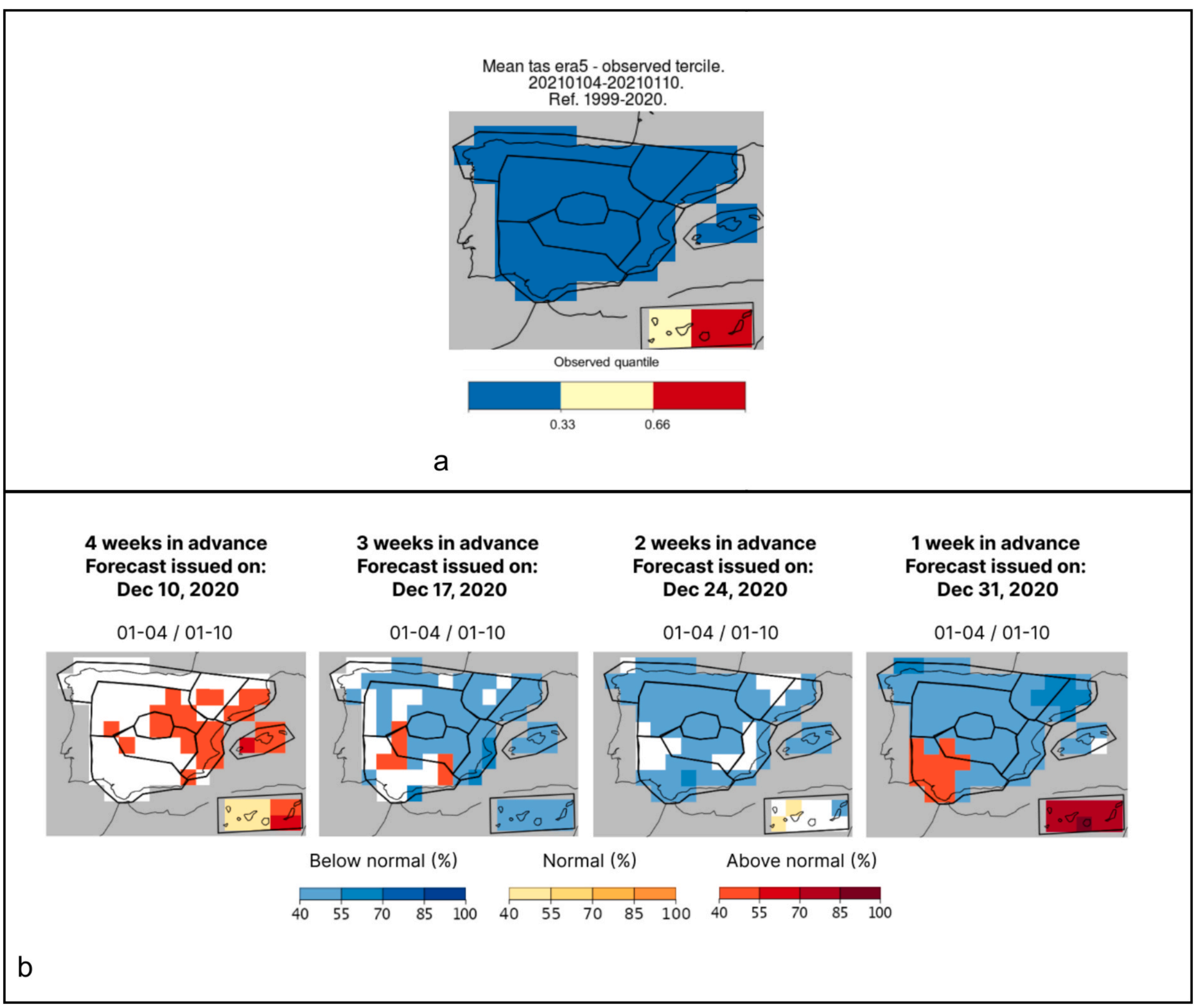

Fig. 3. Illustration of the Filomena event. Fig. 3a shows the observed tercile of the mean temperature for the target period (04–10/01/2021) using ERA5 compared to the reference period (1999–2020). Fig. 3b shows the most likely terciles of the sub-seasonal forecasts weeks in advance. Areas in white represent areas where the prediction had no skill or the most likely tercile had a probability lower than 40%.

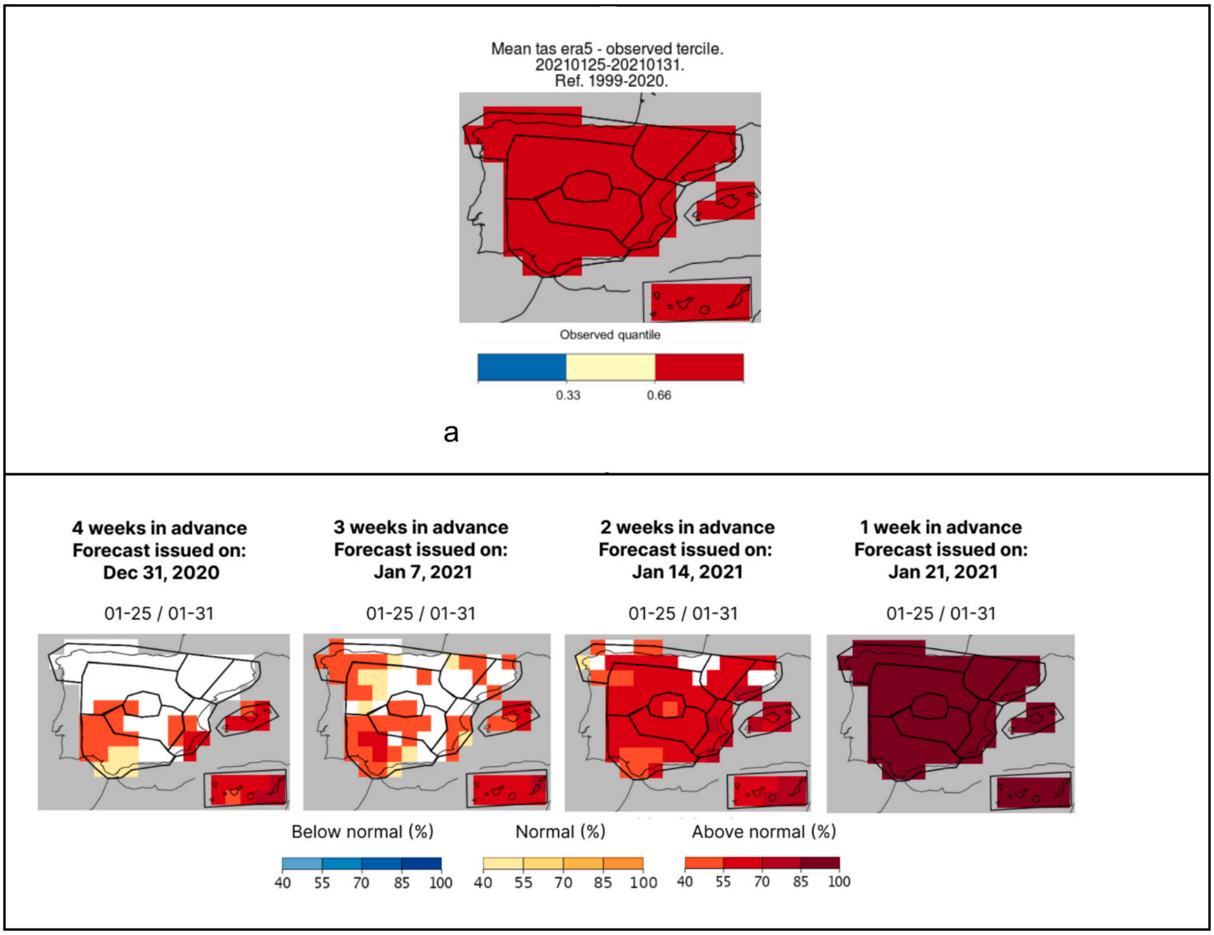

Fig. 4. Illustration of the period 25–31/01/2021. Fig. 4a shows the observed tercile of the mean temperature for the target period using ERA5 compared to the reference period (1999–2020). Fig. 4b shows the most likely terciles of the sub-seasonal forecasts weeks in advance. Areas in white represent areas where the prediction had no skill or the most likely tercile had a probability lower than 40%.

temperatures had the highest values, but the differences between them were not statistically significant. Conversely, precipitation displayed the lowest levels of correlation across nearly every sport family. Given these findings, the decision was made to prioritise temperature as the most suitable variable for the first operational forecast system. An illustrative example, showcasing a time series and the correlation between weekly standardised anomalies of turnover for 'Winter Sports' and weekly standardised anomalies of temperature, is presented in Fig. 6. This figure shows a strong inverse correlation (Pearson correlation coefficient of $r = -0.71$) between weekly standardised anomalies of turnover for 'Winter Sports' and weekly standardised anomalies of temperature, indicating that lower temperatures typically coincide with increased sales of 'Winter Sports' products. While this relationship might appear intuitive, confirming such hypotheses is crucial to substantiate the variable selection process for the forecasting system.

4.3. First forecast system and evaluation test

Following several interactions with the user, the initial forecast product was designed and prepared for testing (Fig. 1i). This initial operational forecast system comprised both weekly and monthly outlooks, encompassing two key components: (1) Sub-seasonal and seasonal maps illustrating the most likely temperature tercile forecast for each grid point (in line with the examples for the Filomena event, Fig. 3), and (2) Probability Density Functions presenting the probabilities of occurrence for each tercile category across the distinct user-defined regions (taking into account specific climate, logistical and purchase information patterns) (first version of Fig. 7b, but without including information about percentile10 and 90, and observations of the last 3 years). These two approaches (maps and probability density functions) were essential for generating a forecasting product that not only covers different time horizons (weekly and monthly) but also offers different degrees of detail, both geographically and at the forecast information level.

Once the operational forecast system was established, the focus shifted towards its implementation. An operational test lasting for one year was devised involving four stores from the Eastern Iberian Peninsula (Fig. 1h). These four stores were selected based on a variety of factors, such as the number of clients or visitors, proximity to urban areas, and whether they are located near the coast or inland. The objective of the test was to enable these stores to incorporate climate information into their decision-making process and subsequently assess whether enhancements could be observed when compared to four similar 'comparable control-stores', i.e., stores sharing the same characteristics as the test stores but without access to climate information. Throughout the test period, monthly meetings were held with the project sponsor, the sales and logistics departments, and the four managers of the test stores to review previous forecasts, discuss upcoming forecasts, and interpret their implications for the stores' decision-making processes. The analysis showed a statistically significant increase in sales across the four test stores compared to the control stores, reinforcing interest in the project and its continuation. For privacy reasons, specific data from this test cannot be disclosed.

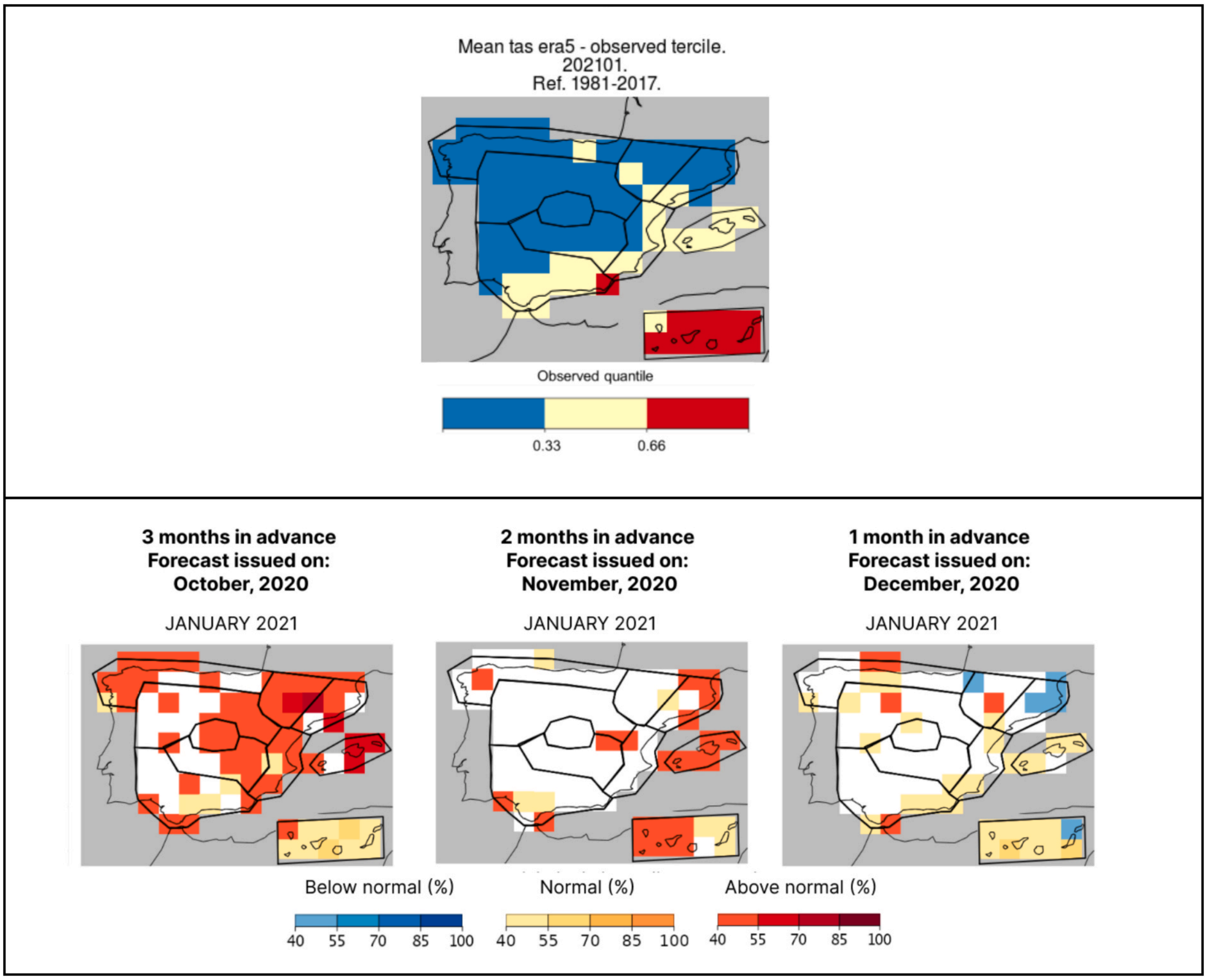

Fig. 5. Illustration of the period January 2021. Fig. 5a shows the observed tercile of the mean temperature for the target period using ERA5 compared to the reference period (1999–2020). Fig. 5b shows the most likely terciles of the seasonal forecasts months in advance. Areas in white represent areas where the prediction had no skill or the most likely tercile had a probability lower than 40%.

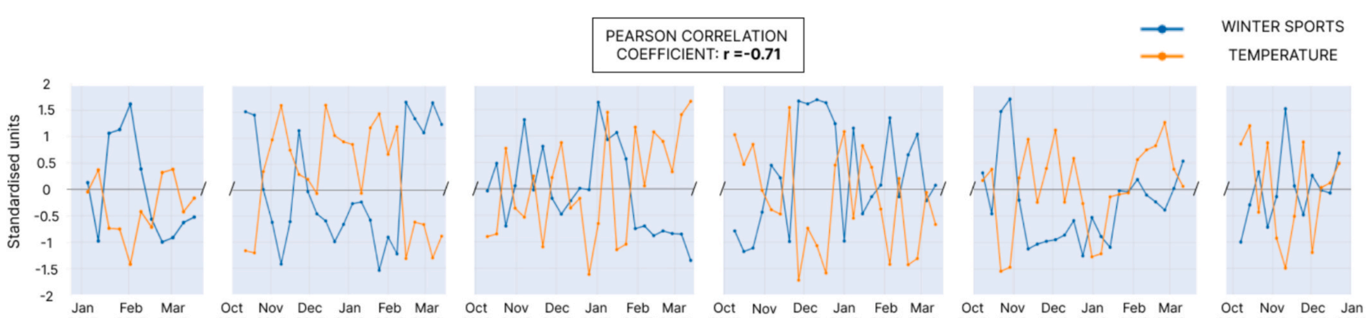

Fig. 6. Weekly mean temperature anomalies compared to weekly mean turnover anomalies of winter sports for North-Western and North-Central Spain (regions defined by the user).

4.4. Development of tailored indicators and previous years

The test involving the provision of climate products from our operational forecast system (Fig. 1h) yielded valuable insights from the user's perspective (Fig. 1j and 1 k). It became evident that extreme events have a greater impact on users than slightly above or below normal conditions. Consequently, information concerning the probabilities of extreme event occurrences was integrated into the probability density functions of regionally aggregated temperature data (probability below or above percentile 10th and 90, respectively) (Fig. 7b). Another key aspect relates to the forecasted variable. Feedback received from the stores participating in the test emphasised the importance of including maximum temperature as a more suitable descriptor of consumer behaviour (Fig. 7a). This adjustment was deemed appropriate because consumers typically engage in shopping or sporting activities during the central hours of the day when the maximum temperature is usually reached. Taking this feedback into consideration, we adapted and provided the same climate-tailored products that were offered for the mean temperature to also account for the maximum temperature (Fig. 1j).

Another valuable insight was the inclusion of observations from the

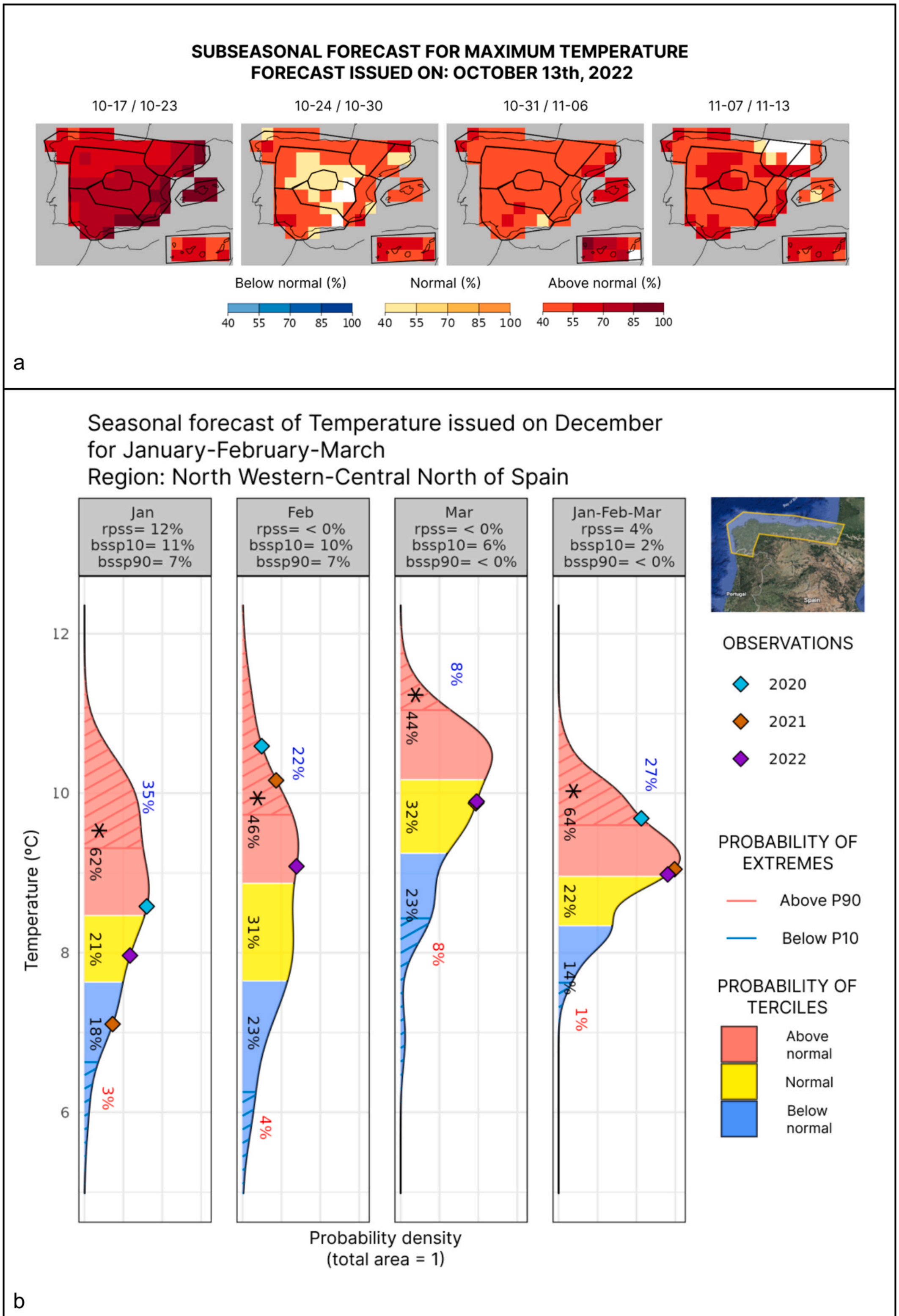

Fig. 7. Examples of the improved forecast outlooks. Fig. 7a, sub-seasonal predictions for maximum temperature, which were not initially included in the first version. Forecast issued on October 13th 2022, for the next four weeks. Fig. 7b, seasonal forecast for temperature, including information about exceeding p10 and p90 and the observations of the previous three years.

same period over the past three years in the probability density function of the forecast (Fig. 1j). The aim was to facilitate the interpretation of the forecasts by comparing them with recent years, as users tend to recall their experiences and actions from recent past events, making the information more relatable and actionable. However, the choice of three years was not arbitrary. Although having a more than three-year past dataset might have been advantageous from a climate standpoint, extending the observation period too far back could have introduced into the analysis consumer behaviours that no longer exist, potentially leading to inaccurate interpretations. Therefore, the determination of the number of years to include struck a balance between maximising the amount of climate data and avoiding the influence of socio-economic factor evolution from distant years. Consequently, from that development onwards, users could compare the concurrent forecast information with past observations for the same week or month and take appropriate actions by analogy to the sales they had already obtained during those periods.

4.5. Adaptation of sub-seasonal predictions to be expressed in terms of meteorological seasons

The store test (Fig. 1h) highlighted challenges in co-developing climate services for the retail sector, mainly due to user perception. Recurrent feedback from the stores indicated that forecasts of sub-seasonal temperature terciles, categorised as above normal, below normal, or normal, could be misleading without a clear understanding of what 'normal' signifies. To enhance the utility of climate information in decision-making, the provision of additional context was essential.

The first step in this regard was to understand the main climate-related 'hotspots' for retailer decision workflows. In our case, retailers must accurately time meteorological season changes to prevent revenue loss. Unexpected shifts in weekly temperatures during these phases, whether occurring earlier or later than expected, could lead to significant imbalances. For instance, in the Spring-Summer seasonal stock change, early summer temperatures might catch retailers unprepared with suitable seasonal products, while a delayed summer could result in excess inventory. Consequently, to provide both temperature prediction context and correlate it with season changes, sub-seasonal temperature predictions were adapted to be expressed in terms of temperatures typical of meteorological seasons (Fig. 1k).

Hence, to express sub-seasonal temperature predictions in terms of meteorological seasons, several retail-centred indicators were defined, namely temperatures typical of winter, early spring, late spring, summer, early fall, and late fall (Fig. 8). They have been defined in this way based on two assumptions: (1) in a climatological year, 25 % of days would be winter (the 25 % coldest days), 25 % summer (the 25 % hottest days), and 50 % would be in-between (spring and fall), and (2) each location has its seasonal characteristics but still a climatological year would have 25 % days of each type per season. The reason for defining the seasons in this way is to customise the start and end dates of each season for each grid point. This is important because different climate zones may have different dominant climate patterns, which means that the timing of seasons can vary between them, as well as the linked social behaviour and consumer patterns.

4.6. Improved forecast system and second evaluation test. Integration of precipitation into the climate service

The initial store test yielded highly positive feedback (Fig. 1l), indicating the added value of climate information for climate-sensitive

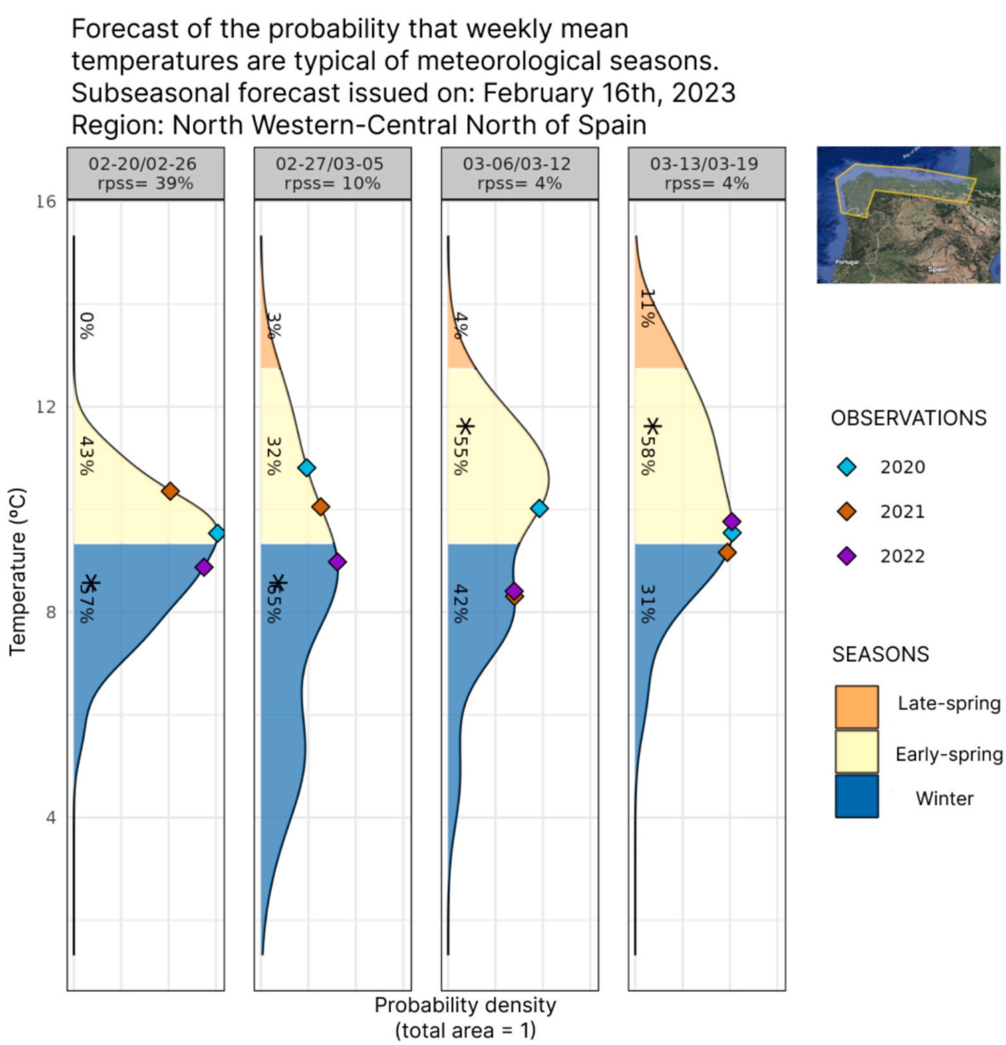

Fig. 8. Sub-seasonal forecast expressed in terms of the typical meteorological season according to the predicted temperature.

decisions. The participating stores outperformed 'comparable stores' (those of the same type as those in the test but lacking access to climate information). Insights from this test were used to further refine the climate product to align with user needs (Fig. 1j and k). With the goal of a nationally applicable climate product, a second test phase was conducted in the North Western – Central North region of the Iberian Peninsula (Fig. 1m). This region features different climatic characteristics and consumer behaviour compared to the initial test area.

During the subsequent knowledge exchange phase, several key insights emerged. The first one was related to the climatic differences between the new and the initial regions (the northwestern and eastern Iberian Peninsula, respectively). For instance, in the first area studied, summers were consistently characterised by hot and dry conditions, whereas in this new region, there was a higher degree of climate variability linked to rainfall patterns, which directly influenced consumer behaviour.

In light of these distinctions, a new knowledge exchange process was initiated to adapt to the changing climatic context. Thus, to align the climate service with the new baseline, the forecast system was adjusted to incorporate information regarding the predicted number of rainy days per week. After this initial knowledge exchange, there were very positive (albeit cautious) expectations about the potential of the proposed climate products.

However, after the different improvements and the inclusion of more information (extremes, new variables, forecast expressed in terms of meteorological seasons), it was pointed out that the information was overwhelming and challenging for the end users to interpret (store managers participating in the test). Considering these factors, it was

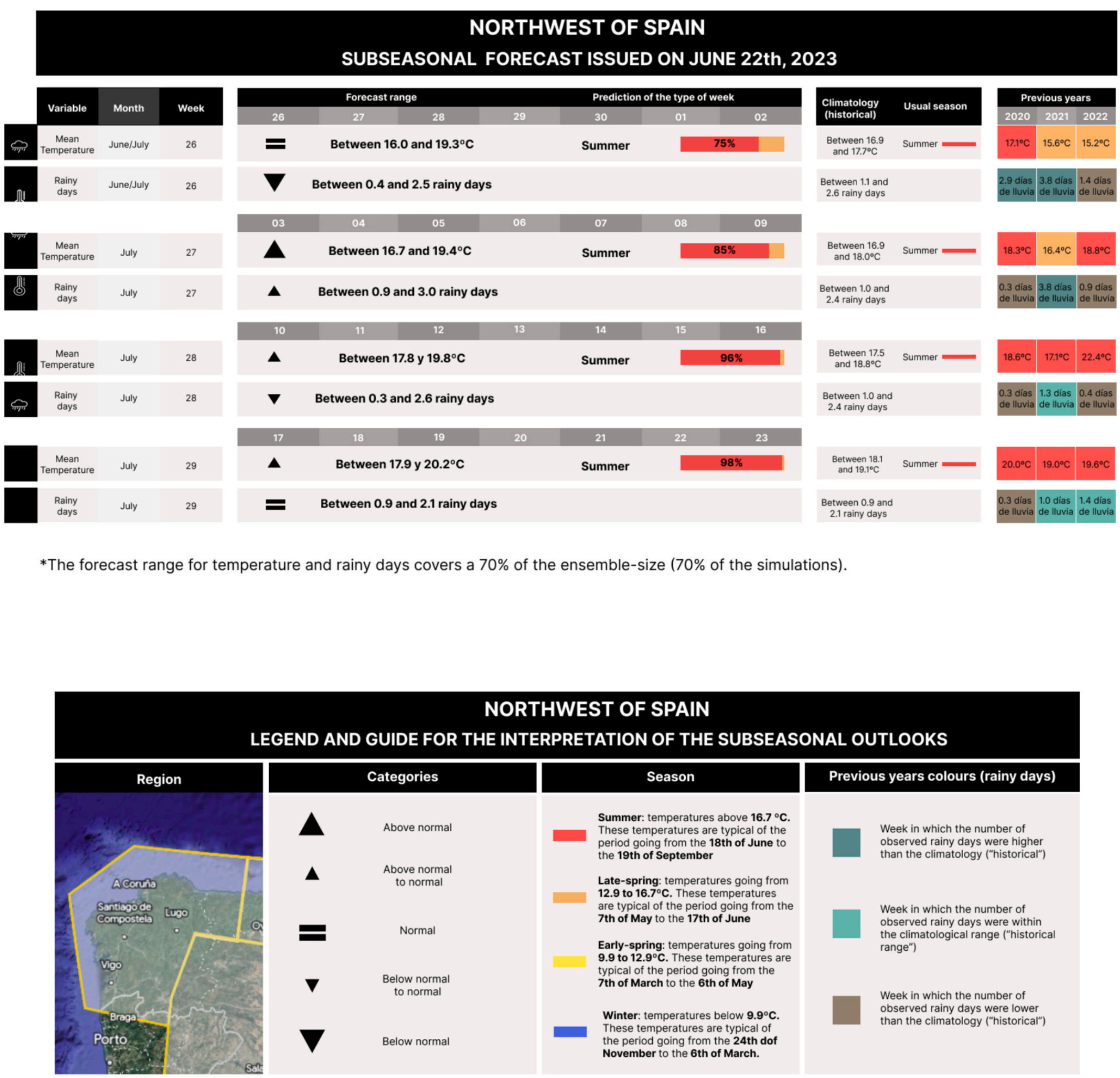

Fig. 9. Final version of the forecast outlooks. After the different revisions and the inclusion of new indicators and information, there was a need to rethink the final product and create a novel design that was easier for users to interpret. An example of sub-seasonal includes information about temperature, number of rainy days, percentage of the meteorological season and the observations of the previous years in a single table.

decided to further adapt and synthesise the information provided (Fig. 1n). This involved changes in visualisation and the introduction of temperature ranges to provide better context to the user. An example of this tailored climate product for the initialisation date of 22nd June 2023 for the Northwest of the Iberian Peninsula can be found in Fig. 9a, while Fig. 9b shows the legend and tips for the interpretation.

5. Discussion and conclusions

This work describes the knowledge exchange and co-development followed during the co-production process of an operational climate service for the Spanish division of a sporting goods retail company. It aims to compile and summarise the lessons learned when developing this climate service to promote their uptake in other comparable retail companies affected by climate variability (e.g. the fashion industry, food and snack production). Similarly, as is the case in other sectors, such as energy and agriculture, champion users who have successfully adopted the climate service within their company can act as ambassadors in their field, encouraging a broader adoption of these services.

The main achievements attained during the co-development process are outlined below. Firstly, the process led to a deeper understanding of how variable weather conditions impact business performance, particularly how weather influences customers' decisions to purchase seasonal products. Access to turnover data from various stores, categorised by day and by sport family, proved essential in this regard. This information enabled us to identify the key variables and define the appropriate forecast windows to be integrated into the climate service.

A central need identified was the optimisation of stock management and logistics between stores and regional or national warehouses. In this context, having information available months in advance was crucial. Equally important, however, was the ability to anticipate seasonal transitions. While it is certain that summer or winter will eventually arrive, the capacity to anticipate these shifts several weeks ahead proved to be a critical advantage. Introducing sub-seasonal and seasonal forecast information into the retail sector—arguably for the first time, as far as the authors are aware—can be considered a major achievement of the project. Demonstrating the usability of combined sub-seasonal and seasonal forecasts, as shown through the case studies selected for January 2021, was a key milestone. Beyond these specific examples, the establishment of a systematic verification process from a decision-making perspective was also significant. The first operational version of the system produced sub-seasonal and seasonal forecasts for one year, and the information was used by selected stores to support activity planning. Regular meetings were held to co-evaluate the impact of decisions based on the forecasts and to guide actions using new information. This systematic co-evaluation, linking specific decisions to their outcomes, including their monetisation, was essential for building trust in the climate service.

Following the deployment of the initial version, new functionalities were identified and integrated. One notable addition, which was especially well received, was the presentation of sub-seasonal forecasts in terms of meteorological seasons. However, while these new features enhanced the comprehensiveness of the system, they also introduced challenges. The additional layers of information made interpretation more complex, particularly for store managers who had not been involved in the project from the outset and thus lacked familiarity with the system. As a result, further efforts were required to improve the user-friendliness of the platform, particularly through user experience (UX) design work, to ensure broader accessibility and understanding.

Beyond these achievements, we introduce below two key managerial and administrative aspects of this collaboration that have been critical to the co-development process.

Manage user expectations and align strategic and operational objectives within the user's workflow: The role of the project sponsor

To achieve effective management of risks and opportunities arising from climate variability, the engagement between the users and providers of climate information needs to establish a clear and direct link between climate information and decision-making (Hewitt et al., 2017). Within this context, considerable effort has been invested to underscore the significance of not only scientists' commitment and willingness to engage with users, but also their ability to attentively listen, comprehend, and address user requirements (e.g. Porter and Dessai, 2017). However, when transitioning to the practical implementation of a service within a company, an added layer of complexity emerges. Companies are not homogeneous structures; they are composed of diverse departments with distinct responsibilities, mandates and needs that collaborate within a framework defined by established protocols and internal methodologies. Thus, the execution of a climate service like the one presented here is transversal to different departments and, consequently, achieving alignment between strategic objectives (defined by individuals in managerial roles) and operational objectives (defined by those in technical roles) becomes paramount to ensure that the service properly meets user expectations.

To achieve this alignment, the company appointed a project sponsor (e.g. Englund and Bucero, 2015) who could effectively harmonise the objectives and needs within the company with the scientific knowledge and climate information provided by the climate scientists. In this context, the role of the project sponsor involved acknowledging the current limitations and realities of the climate service to manage user expectations effectively. The project sponsor took on a broader cross-functional responsibility, leading the company's team and ensuring that the specific needs of various business departments were clearly defined and aligned through regular meetings. During these meetings, specific targets were set and recorded, followed by discussions with the scientists from the climate service. This approach helped to focus scientific efforts on areas of greatest relevance to the company, directing attention to where climate information could have the most actionable impact.

Contracts vs publicly funded projects to produce climate services

Most climate services research in Europe relies on funding from European programs, which ensures alignment with the European research agenda and structural consistency. However, this dependence on predetermined criteria and the availability of funding may constrain research development and innovation potential within the field (Bruno Soares and Buontempo, 2019). This research project has been funded through a private contract with the company. Compared to working within the context of competitively funded projects with public funds, there are both advantages and disadvantages for both researchers and the company. On the positive side for research, it allows for much more direct contact with the end-user, facilitating in-depth discussions about their needs and enabling a more thorough co-evaluation of the climate service, throughout most of the project in this case, but especially during the monthly meetings held during the test periods (Fig. 1h and 1 m). Tailored research for a user who is a leader in their sector enables scalable research that can later be useful for additional users within the same industry and sectors with similar needs. In the medium term, direct collaboration within the framework of a contract can be pivotal in gaining a deeper understanding of societal needs and defining more ambitious research lines that can be further developed within the context of future competitive public funding contexts. However, the downside is that it pushes researchers out of their comfort zones, requiring them to work within shorter timeframes than they are accustomed to in research. Special attention must also be paid to mitigate conflicts of interest, which have been tackled by incorporating a contractual clause permitting the publication of the work. Moreover, the project's advancements have contributed to the enhancement of a publicly available software package (Pérez-Zanón et al., 2022).

From the company's perspective, such collaborations also have pros and cons. On one hand, it gives the company a better understanding of how climate affects them and how to design strategies to adapt.

However, participating in the co-development of a service from scratch requires a significant time investment from the company, and competitors may subsequently benefit from this development. Direct communication between the project sponsor from the company and climate services researchers is crucial to ensure a good relationship that aligns the interests of both parties.

Finally, it is also important to highlight that, based on the outcomes and lessons learned from this project, several future lines of research have been identified. While sub-seasonal and seasonal forecasts offer actionable insights for decision-making, their predictive skill partly depends on large-scale teleconnections and boundary forcing mechanisms that can vary year to year. In other sectors, such as wind energy, bridging atmospheric teleconnection indices to near-surface climate variables have proven valuable for understanding and improving skill (Torralba et al., 2020; Lledó et al., 2022). In the retail context, a deeper exploration of these meteorological drivers—encompassing modes of variability like the North Atlantic Oscillation or oceanic temperature anomalies—could further enhance the resilience of climate services to their interannual fluctuations. Thus, while a comprehensive analysis of these predictability drivers falls beyond the scope of the present study, we aim to explore their influence and potential applications in future research.

Overall, this work has laid the foundation for a fruitful collaborative approach to research and engagement in developing climate services for the retail sector. This initial progress offers valuable insights for streamlining future components of climate services. The objective is to build upon our current progress and focus our efforts on creating a forecasting system that can directly translate climate information into potential changes in sales for different sports categories, as initially suggested by the company. To achieve this, we will develop an impact model that can establish a correlation between climatic variables and sales anomalies.

Beyond this research line, a new opportunity has emerged through discussions with the company's central offices (the global environmental department): developing a complementary climate service based on decadal predictions (Fig. 1e). Retail companies, such as the fashion or sports industries, heavily rely on vegetable raw materials like cotton. These companies typically plan their operations for 1–3 years. Traditionally, the strategy for mitigating crop-related volatility involved diversifying production areas to reduce vulnerability. However, the increasing variability in climate over the coming years poses challenges to the agriculture sector (Solaraju-Murali et al., 2022). This heightened climate variability is making production volatility more susceptible. As a result, in the near to medium term, we also aim to develop a climate service based on decadal predictions tailored to global cotton cultivation.

CRediT authorship contribution statement

Albert Soret: Writing – original draft, Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization, Visualization, Funding acquisition. **Albert Martínez-Boti:** Writing – review & editing, Software, Investigation, Formal analysis, Data curation. **Raul Marcos-Matamoros:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Formal analysis. **Nube Gonzalez-Reviriego:** Writing – review & editing, Supervision, Methodology. **Francesc Roura-Adserias:** Writing – review & editing, Software, Investigation. **Lluís Palma:** Writing – review & editing, Software, Methodology. **Sergio Benito Martín:** Validation, Investigation, Formal analysis. **Sergio González-Ubierna:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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