HUMAN CENTRED CLIMATE SERVICES

Deliverable D3.1

Preliminary report on the skill assessment and comparison of state-of-the-art methods for forecasts and projections of extremes

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I-CISK

Innovating Climate services through Integrating Scientific and local Knowledge

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Author(s):	Lluís Pesquer (CREAF), Ilias Pechlivanidis (SMHI), Yiheng Du (SMHI), Rebecca Emerton (ECMWF), Paolo Mazzoli (GECOsistema), Györgyi Bela (IDEAS), Ilyas Masih (IHE), Sumiran Rastogi (IHE), Marc van den Homberg (RC510), Micha Werner (IHE).
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Executive Summary

Climate Services (CS) have a crucial role in empowering citizens, stakeholders and decision-makers in taking climate-smart decisions that are resilient to climate change and compatible with achieving climate neutrality. The results supported by a scientific evidence base contribute towards a sustainable economy, lifestyle, environmental protection and resource use. CS aim to transform climate-related data and information into customised products, among others projections, forecasts, information, trends, economic analysis etc., in order to further support adaptation, mitigation and disaster risk management. To achieve this advanced scientific knowledge, monitoring and modelling of climate change and the impacts of climate extremes are needed. A key barrier that impedes the current generation of CS achieving the full opportunity of their value-proposition relates to the failure to incorporate the social and behavioural factors and the local knowledge and customs of their users. Additional challenges are in: (i) the understanding of the multi-temporal and multi-scalar dimension of climate-related impacts and actions; (ii) the translation of CS-provided data into actionable information; (iii) the consideration of reinforcing or balancing feedback loops associated to users' decisions based on CS; (iv) the lack of transdisciplinary approaches across the full CS value chain; and (v) need to deliver tailor-made and robust services at the scale relevant to users.

The I-CISK project aims to seize these untaken opportunities by developing next-generation CS that follow a social and behaviourally informed approach for co-producing CS that meet the climate information needs of citizens, decision makers and stakeholders at the spatial and temporal scale relevant to them. In the seven geographically diverse living labs (LL), each with different relevant sectors, I-CISK showcases its human-centred co-design, co-creation, co-implementation, and co-evaluation approach across key sectors vulnerable to climate change in Europe and beyond.

This document focuses mainly on the skill assessment of state-of-the-art predictions of hydro-meteorological variables relevant for the I-CISK LLs, and consequently sets the benchmark for quantifying the added value from other scientific methods explored within I-CISK. The skill assessment is very important for the CS produced during the project; the usefulness of these CS and trustfulness of their users highly depends on the reliability of the predictions on which these CS are based.

The document presents an initial set of different methods being used to generate hydro-meteorological forecasts, predictions and projections, and further lists different methodologies used to assess the skill and robustness of predictions. Driven by inherent limitations in model-based seasonal meteorological predictions, biases in the raw seasonal precipitation and temperature predictions over Europe are highlighted, and the significant reduction of these biases achieved after post-processing (bias-adjustment). Moreover, the document presents an analysis of seasonal hydro-meteorological prediction skill including streamflow extremes (floods and droughts) at the scale of the LLs in the project. Finally, a brief review of the state-of-the-art of the integration of local and scientific knowledge is provided. This review is developed from the rich literature in the field, and explores the integration of knowledges from the perspective of their integration in climate services. Different dimensions of local knowledge that are relevant in this context are explored, and a typology for levels of integration is introduced.

Keywords

Climate Services; User needs; Seasonal predictions; Bias adjustment; Extreme events; Local data; Local knowledge

About I-CISK

I-CISK's ambition is to innovate how climate information is used, interpreted and acted on through a next-generation of Climate Services that follow a human centred, social and behaviourally informed approach; integrating the knowledge, needs and perceptions of citizens, decision makers and stakeholders with climate information at spatial and temporal scale relevant to them.

Climate Services (CS) are crucial to empowering citizens, stakeholders and decision-makers in taking climate-smart decisions that are informed by a solid scientific evidence base, that contribute towards a sustainable European economy, lifestyle, environmental protection and resource use, and that are resilient to climate change and compatible with achieving climate neutrality. European and international collaborative research efforts, including Copernicus and GEOSS have established a solid scientific foundation for an effective CS value chain, including advanced scientific knowledge, monitoring and modelling of climate change and the impacts of climate extremes. However, several barriers challenge the current generation of CS in achieving the full opportunity of their value-proposition. These challenges include the failure to incorporate the social and behavioural factors and the local knowledge and customs of climate services users. Additionally, the effectiveness of climate services is challenged by; the still poorly developed understanding of the multi-temporal and multi-scalar dimension of climate-related impacts and actions; the translation of CS-provided data into actionable information; consideration of reinforcing or balancing feedback loops associated to users' decisions; and the lack of trans-disciplinary approaches across the full CS value chain.

I-CISK aims to seize these untaken opportunities through a human-centred framework for co-production of next generation CS that spans the full CS value chain taking the downstream part of the value chain as a starting point. The I-CISK framework realises the full potential of information provided through CS by empowering actors to take the impacts of extreme climatic events and climate change into account in their decisions.

Disclaimer

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1 Introduction

1.1 Purpose of this document

In the Description of Work of the I-CISK project, it is stated that efforts will be targeted towards innovation and enhancement of existing climate services (CS) and downstream impact-based products, and consequently on the support of decisions and policies in multiple sectors accounting for their local trade-offs. In Work Package (WP) 3, one of the aims is to address the local needs and sectoral gaps of existing CS and therefore various state-of-the-art methods will be used together with tools/methods to integrate local state-of-the-art observations and local knowledge. Both continental/global and local-scale process-based impact models, e.g. for the water and agriculture sectors, will be used to assess sub-seasonal, seasonal and centennial changes and impacts at the Living Lab (LL) scale. Therefore, a continuous dialogue with various WPs, e.g. WP1, WP2, WP3 and WP4, has been established to ensure a continuous exchange and feedback of information required to translate datasets into tailored information and indicators for local use.

The objectives of WP3 are to:

- To advance local impact predictions and projections of climate change and future extremes through developing modelling chains that efficiently integrate existing CS while also combining local data and knowledge for local tailoring.
- To explore different scientific state-of-the-art methods to bridge data and services that are currently separated on temporal and spatial scales (from forecasts to projections) and increase the trust in local predictions.
- To evaluate the usefulness of the integrated impact predictions and assessments for local operations and decision-making from both a scientific and a user perspective.
- To unlock the benefits of transformation of data to information for and within the climate-sensitive LL regions and sectors by improving the confidence information of indicators while enhancing their usability.
- To develop user-driven visualisation tools that assure robust and seamless transfer of produced information from CS, and communicate predictions, explicitly including uncertainty, for guided decision-making.
- To provide recommendations for product adaptations, extensions and CS improvements, and deliver fit for purpose tools, methods and products for user-tailored real-time operational services

To achieve part of the objectives listed above, this document presents the currently ongoing work and reports on the preliminary progress in WP3, while it addresses a series of specific objectives that include:

- Defining the different future time horizons and exemplifying state-of-the-art methods used to generate hydro-meteorological forecasts, predictions and projections.
- Listing the traditional methodologies used to assess the skill and robustness of predictions, including common benchmark methods.
- Quantifying the biases in seasonal meteorological predictions over the European domain and exploring the spatial biases after post-processing (bias-adjustment).
- Benchmarking the seasonal hydro-meteorological predictive skill, including extremes, over the spatial scale of the living labs.
- Reviewing different approaches to the integration of local data and knowledge at the scale of the living lab to address the local user needs.

1.2 Structure of this document

The deliverable is structured in six chapters:

- **Chapter 1** (current) is the introduction to the document presenting the scope.
- **Chapter 2** describes the different temporal scales and reviews the corresponding methods involved.
- **Chapter 3** provides a review of the state of the art in the integration of local and scientific knowledge.
- **Chapter 4** carries on the availability of large-scale (continental and global) climate services and highlights the necessity for integration of local knowledge. In addition, it sets the background for numerically benchmarking the services, and summarises the user requirements from the LLs.
- **Chapter 5** shows the assessment of one of the proposed I-CISK methodology, i.e. post-processing, to remove the biases in the seasonal meteorological predictions.
- **Chapter 6** shows the assessment of other I-CISK proposed methodologies to fit to the local needs in a pan-European scale and selected LLs.
- **Chapter 7** concludes the main body of the document and summarises future work.

2 State-of-the-art methods and systems for forecasts, predictions and projections

2.1 Description of the future time scales

Here we start with the definition of forecasting, prediction and projection, prior to defining the time scales. Forecasting refers to a calculation or an estimation which uses data from previous events, combined with recent trends to establish a future event outcome. Prediction is an actual act of indicating that something will happen in the future with or without prior information. Both forecasting and prediction relate to more or less the same concept, that is future oriented. Hence, the only difference between prediction and forecasting is on the considered temporal dimension, and hence all forecasts are predictions but not all predictions are forecasts. Finally, projections are estimates of how the Earth system might change under different scenarios, i.e. CO2 emissions.

To account for the future, weather and climate models have been introduced. Weather and climate span a continuum of time scales (see Figure 1), while there has been an effort to define and differentiate them so that research and services can better address the corresponding solutions during decision-making. However, the range of the intermediate weather-climate periods can slightly vary following different authors. Initially, we define five main time scales:

- **Medium-range weather forecasts**: up to 14 days ahead (typically cover 10 days ahead)
- **Sub-seasonal forecasts**: up to 6 weeks ahead (also known as extended-range or monthly forecasts)
- **Seasonal predictions**: up to 1 year ahead (typically cover 6-7 months ahead)
- **Decadal predictions**: up to 10 years ahead
- **Centennial projections**: up to the end of the 21st century

Medium-range weather forecasts and centennial projections have been investigated for several decades due to their importance in daily decision-making and policy-making to tackle climate change respectively. However, the necessity to address the user needs for the next weeks and years, led to an increased scientific emphasis towards the other scales.

The sub-seasonal to seasonal (S2S) time range – which corresponds to predictions beyond two weeks but less than a season – fills the gap between weather and climate forecasting and represents a central component for 'seamless' weather/climate prediction (White et al., 2021). In the literature, there is a tendency to combine (at least conceptually) the S2S time scales. This is done because both future horizons address longer term needs and decision-making in comparison to medium-range horizons that commonly address day to day needs. However, despite the different weight in decision-making those future horizons have, we note that the underlying physics to generate sub-seasonal and seasonal predictions differ. The S2S time-scale is sufficiently long so that much of the memory of the atmosphere's initial conditions is lost, and it is probably too short so that the variability of the ocean is not large enough. However, recent research has indicated important potential improvement in the predictability for this time scale which can be realised through better representation of atmospheric phenomena (the Madden Julian Oscillation, MJO), improved initialisation and coupling of the land-ocean cryosphere and stratosphere.

S2S forecasts provide predictions of how the average atmospheric conditions over particular periods of time are likely to be different from the long-term average. Forecasts at such a time-scale are useful to a number of sectors, including energy, agriculture, water resources management, tourism etc., and can allow better decision-making from the users or even improved preparedness in the case of extreme conditions (Bazile et al., 2017; Sene et al., 2018). Moreover, the prediction at the monthly and seasonal timescales is potentially very useful in order to: (i) produce products which extend the medium-range forecast horizon, (ii) benefit from hindcasts for pre- and post-processing to produce output of higher quality (e.g., model-based return periods), and (iii) re-design decision support frameworks complementing them with early information.

Decadal predictions aim at responding to the need for short climate projections by providing interannual climate information. They bridge seasonal predictions and climate change projections as they focus on intermediate time scales, from several years up to a few decades. Decadal predictions combine the complexity from forecasting and projections, they need to consider both initial conditions of the climate system as well as the evolution of long-term climate forcing.

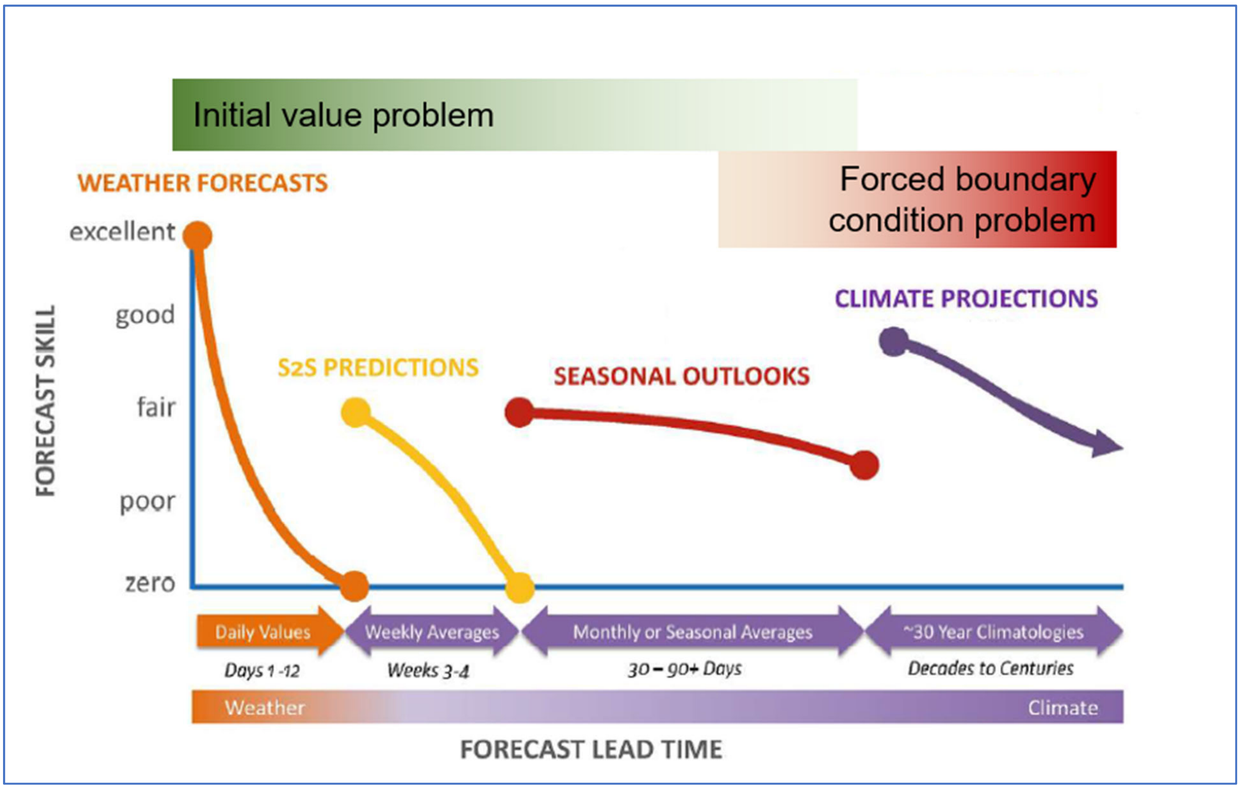

Figure 1 Time scales ranges and the relevance of initial values and forcing

It is shown in Figure 1 that the reduction rate of the skill with lead time is different for different scales. The weather forecasts start from a close to "excellent" skill but quickly decrease. On the other side climate projections start with less quality skills but they are more stable. This pattern is firstly caused by the different weights of the initial conditions and forcing in the suitable models at different time scales, and secondly on the purpose of the forecast horizon which at long horizons does not aim to address daily dynamics but rather trends and changes to the normal conditions

2.2 Exploring medium-range weather forecasting

With different levels of complexity and computing efforts needed, the usual weather forecasting methods are:

- Persistence and trend forecasting: This is the simplest method, which assumes a continuation of the present. It relies upon current conditions to forecast the weather in the next few (up to 12) hours following the past trends.
- Analogue forecasting: the analogue forecaster's task is to locate the date in history when the weather is a perfect match, or analogue, to the date/time target's weather. Then the forecast for next hours/days is whatever happened in the next hours/days of the analogue date matched.

- Numerical Weather Prediction (NWP): In NWP a system of hydrodynamic equations that describe the evolution of the atmosphere and ocean are resolved. Given the current boundary conditions, NWP applies a set of physical laws, including a large number of variables, for modelling the dynamics of the atmosphere and ocean, and their complex interactions. These equations are solved by high performance computing environments.
- Machine-learning (ML) forecasting: This method is based on the training of artificial neural networks (ANN). The training is carried out on historical observations without explicit knowledge of atmospheric physics. There are different subtypes of the ANN families: convolutional neural, generative adversarial neural, variational autoencoder, deep learning (DL), etc.
- Statistical forecasting: This method bases predictions on statistical analysis of historical data, often accounting for large-scale climate variability (such as the El Niño Southern Oscillation, ENSO, and similar climatic patterns). It can be combined with other forecasting methods such as NWP.
- Ensemble forecasting: It entails multiple realisations for a single forecast (NWP or neural-network base), time and location. This is a probabilistic method in which different realisations are generated through applying different perturbations to the control (unperturbed) forecast. The ensemble forecasting is an approach to capture uncertainty due to the chaotic nature of the atmosphere. The uncertainty in the forecast can then be assessed by the range of different forecasts generated. Currently, the research community inclines toward grand ensemble based on multiple models (Sahail et al., 2021).

Finally, some hybrid methods are available with some components mentioned before: hybrid NWP/ML (Frnda et al., 2022) or NWP/ML/DL (Schultz et al., 2021).

2.3 Exploring sub-seasonal forecasting

The main motivation for sub-seasonal forecasting is to provide meteorological information in the time range of 10 to 46 days (about 6 weeks ahead) and hence address related relative user needs. Forecasting services using sub-seasonal information could close the identified gap between forecasts on the medium and seasonal range (White et al., 2017). Although the objective of such forecasting service is not to capture short extreme events, e.g. floods, they are able to detect anomalous conditions on events lasting about weeks, such as droughts (Dutra et al., 2014).

S2S is often considered a complex time scale for weather forecasting, sometimes called the "desert of predictability". It is both too long for much memory of the atmospheric initial conditions and too short for changes in the boundary conditions of the atmosphere. Most methods are based on the corresponding type of weather forecasting adding specific components (atmospheric chemistry, ocean, cryosphere, land surface, hydrology, MJO, ENSO, etc.) of the Earth System modelling and their interactions.

The ongoing (2019-2023 phase II) S2S Prediction Project http://s2sprediction.net/ brings together a specialised research community to improve forecast skill and understanding of the sub-seasonal to seasonal timescale with special emphasis on high-impact weather events. The project also focuses on promoting the initiative's uptake by operational centres and exploitation by the applications community, while also capitalising on the expertise of the weather and climate research communities to address issues of importance to the Global Framework for Climate Services. The S2S database (Vitart el al., 2017) aims to identify common successes and shortcomings in the model simulation and prediction of sources of sub-seasonal to seasonal predictability. For instance, the correction of the usual underestimation of the amplitude of the MJO teleconnections over the Euro-Atlantic region.

2.4 Exploring seasonal predictions

Seasonal predictions describe how the average atmospheric conditions over particular periods of time are likely to be different from the long-term average. Statistical or dynamic or even hybrid models have been used to provide predictions for the coming months, typically 7 months ahead but could reach up to 1 year ahead. Predictions at such a time-scale are useful to a number of sectors, i.e. water resources management, agriculture, energy, and can allow better decision-making from the users or even improved preparedness in the case of extreme conditions (Sene et al., 2018).

Among the different types of models, dynamic (i.e. coupled atmosphere-ocean-land General Circulation Models; GCMs) models are those mostly used. These models share some similar hypotheses, particularly in terms of physical representation, with those used in weather forecasting. However, they also need to include the behaviour of the Earth system components that evolve more slowly than the atmosphere. Seasonal forecasts are launched from an observed state of the climate system, which is then evolved in time over a period of several months. Moreover, model initialisation differs between the available climate prediction systems, i.e. weekly and monthly initialisations.

Seasonal prediction is justified by the long predictability of the atmospheric boundary conditions (ocean/land/ice), which can be of the order of several months and by their impacts on the atmospheric circulation. Predictive errors (driven by uncertainty in the initial conditions or the processes hypotheses which are conceptualised in the model structure) usually grow through the model integration, reaching magnitudes comparable to the predictable responses. Some errors are random (aleatory) and some errors are systematic and are determined and corrected by comparing retrospective forecasts (hindcasts) with observations. The effect of random errors in the model are quantified through the use of different realisations (ensembles). Although the objective of such prediction systems is not to capture short extreme events, e.g. floods, they are able to detect anomalous conditions on events lasting about weeks, such as droughts (Dutra et al., 2014).

Seasonal predictions commonly found in climate services can be generated with different approaches. However, depending on the variable of interest the approaches found can differ. Particularly for hydrological variables, the inherent uncertainty in the initial hydrological conditions and meteorological forcing, contribute (or not) to the seasonal hydrological predictability. Some relevant seasonal hydrological predictions are listed below:

- *Climatology*: This is generated for each initialisation time (every week or month) by randomly selecting years within the available historical time series for the location of interest. Candidate time series start on the same day as the initialisation date in all available historical years, however it has been recommended to exclude the forecast year (or a window of years around it) in order to avoid biases. Climatology is commonly used as a benchmark, when assessing the predictive skill (see Section 3). Specifically, for hydrological variables, e.g. streamflow, this method can be defined as “streamflow climatology”.
- *Dynamical Prediction*: A dynamical approach based on seasonal climate predictions from a Global Circulation Model (GCM) has been extensively explored in climate services. In the case of impact assessment, GCM-based meteorological predictions are used as an input to an impact model. Particularly for an impact hydrological modelling, the initial model states at each simulation are used for predicting a hydrological variable, for instance streamflow, and hence the difference in skill between the GCM-based predictions and the method below is attributed to the improved (or not) dynamic climate forcing.
- *Ensemble Streamflow Prediction (ESP)*: This approach is commonly found in seasonal hydrological services and assumes that during each forecast, the ensemble of historical meteorological data contains adequate information to predict the future. In ESP, meteorological (precipitation,

temperature, humidity etc.) data are resampled to force the initialised hydrological model (Wood and Lettenmaier, 2006). Hydrological variables are simulated for each initialisation using the current catchment conditions as initial model states at each simulation, hence generating an ensemble of hydrological predictions (Crochemore et al., 2020). As for climatology, on the initialisation date, the meteorological forcing from the historical years are used. The initialization of the hydrological model states allows the consideration of the initial conditions as a source of predictive skill and hence makes the ESP methodology advantageous over other approaches, i.e. streamflow climatology (Girons Lopez et al., 2021). Nevertheless, ESP can also lead to prediction overconfidence since the historical meteorological data can limit the ability to capture unprecedented events (Harrigan et al., 2018).

2.5 Exploring decadal predictions

Decadal climate predictions focus on describing the climate variability for the coming years. Decadal predictions can arise from two main sources: the radiative forcing and the internal variability. They originate from the slow components of the internal climate variability and they are mainly associated with the sea surface temperature and ocean heat, including greenhouse gases' emissions and variations in natural climate forcing (i.e. volcanic and solar activity) as well.

In general, many methods and models for decadal predictions are explained in the next section 2.6 because centennial climate projections methods can be also applied into decadal time scales. Indeed, more specific methods or parametrizations of the initial conditions for decadal prediction are:

- *Full-Field Initialization* (FFI): The initial state is the best estimate of the observed climate state. However, as the forecast proceeds the model drifts towards its preferred climate state and a posteriori bias correction needs to be applied. The bias depends on the forecast lead time and its correction and characterization require a set of hindcasts (Pohlmann et al., 2009).
- *Anomaly Initialization* (AI): It attempts to avoid drift by initialising models with observed anomalies (the differences from the observed mean climate) added to the model mean climate obtained from historical simulations (Smith et al., 2007). It introduces dynamical imbalances leading to shocks and biases in the forecasts. A set of retrospective forecasts (hindcasts) is used to correct the bias
- *Quantile Matching* (QM): It consists of the initialization at the prediction with the model state whose percentile in the model distribution is the same as the percentile of the observed state in the observed distribution at the initialization time (Volpi et al., 2021). QM aims to reduce the drift and limit inconsistencies coming from the differences between the model and the observed variability amplitude.

At this time scale, the decadal climate prediction project (DCPP) (Boer et al., 2016) is a very relevant initiative that coordinates different efforts in the scientific community. The DCPP is composed by:

- *Hindcasts*: It comprises the generation and analysis of a large time series of retrospective forecasts. They are used to assess and understand historical decadal prediction skills.
- *Forecasts*: The ongoing production of quasi-operational decadal climate predictions in support of multi-model annual to decadal forecasting and their applications to societal needs
- *Predictability*, mechanisms and case studies: coordination of decadal climate predictability studies, particularly on climate shifts and variations, including the study of the mechanisms that determine these behaviours

Finally, another relevant initiative in this decadal scale is:

- *Decadal Climate Prediction System* (DePreSys): It is the decadal prediction system developed and run by the Met Office, Hadley Centre (UK). The initialisation is achieved by relaxing to full-depth analyses of ocean temperature and salinity, atmosphere analyses of winds, temperature and surface pressure. This initialisation improves the forecast skill of globally-averaged surface temperature in past test cases.

2.6 Exploring centennial projections

Climate projections are dependent on scenarios of future anthropogenic and natural forcing. The main challenge of mid/long term climate predictions compared to weather forecasts is that the prediction of socio-economic development is even more difficult than the prediction of the evolution of the physical system.

The Coupled Model Intercomparison Project (CMIP) is the most relevant worldwide project for the climate projections modelling, not exclusively to mid/long term ones, but mainly, it also covers other time scales (i.e. decadal). Since 1995, CMIP has coordinated climate model experiments involving multiple international modelling teams, currently the CMIP6 is the active phase.

The current CMIP joins 21 research institutions that each develop their own models. A selection of them are:

- CESM (by National Center for Atmospheric Research, USA): It is a fully-coupled, global climate model that provides computer simulations on atmosphere (CAM), land CLM, ocean (POP, MOM6), ice (CSIM) of the Earth's past, present, and future climate states. (Danabasoglu et al. 2020).
- EC-Earth (by Europe-wide consortium, including SMHI): It integrates some European models from different institutions, including ECMWF models: IFS is the Integrated Forecast System, NEMO for the ocean, LIM for sea-ice, TM5 for the atmospheric chemistry and transport and LPJ-Guess for vegetation.
- IPSL-CM (by Institut Pierre-Simon Laplace, France): It comprises of the LMDz model for the atmosphere, INCA and REPROBUS for atmospheric composition, NEMO for the ocean, ocean dynamics (NEMO-OCE), sea-ice (NEMO-LIM) and ocean biogeochemistry (NEMO-PISCES), and the ORCHIDEE model for terrestrial surfaces.
- HadGEM2: (by Met Office, UK): The HadGEM2 family includes a coupled atmosphere-ocean configuration, with or without a vertical extension in the atmosphere to include a well-resolved stratosphere, and an Earth-System configuration which includes dynamic vegetation, ocean biology and atmospheric chemistry.
- Mk3L (by CSIRO, Australia): It is a coupled general circulation model that incorporates a spectral atmospheric general circulation model, a z-coordinate ocean general circulation model, a dynamic-thermodynamic sea ice model and a land surface scheme with static vegetation.
- MPI-ESM (by Max Planck Institute for Meteorology, Germany): It couples the atmosphere (ECHAM6), ocean (MPIOM, JSBACH) and land surface (JSBACH) through the exchange of energy, momentum, water and carbon dioxide.

3 State-of-the-art in integrating local knowledge and local data

3.1 Introduction

Climate services have a well-recognised potential of empowering decision makers in taking climate smart decisions (Goddard and Goddard, 2017); including stakeholders from a wide range of sectors, public agencies and policy bodies, and citizens. This potential is, however, in many cases not fully realised, and the uptake of climate services may be hampered by a number of barriers; including the lack of understanding of user's needs, lay perceptions, local knowledge, and capacity levels (Jacobs and Street, 2020), differences between the spatial and temporal scales at which information is provided and the scales relevant to users (Howard et al., 2020), difficulty of access, as well as lack of sustainability of climate services (Vincent et al., 2020). Research shows, however, that the users climate services may serve, often have well developed knowledge of the climate systems around them based on their observation and experience (Tadesse et al., 2015; Plotz et al., 2017; Orlove et al., 2010), and that recognising and integrating these knowledges through co-creation of climate services can help close the usability gap (Plotz et al., 2017; Vincent et al., 2018; Cash et al., 2003), despite challenges to these knowledges as a result of demographic, climatic and environmental changes (Plotz et al., 2017).

In this section we provide a brief review of the current state of the art in the integration of local knowledge in climate services. We do not aim to provide a full review of the multiple dimensions of local knowledge, rather the aim is to review of the current state of the art from the perspective of how local and scientific knowledge are integrated in climate services. The process of how local knowledge is included in establishing climate services in a co-creation process depends on the organisations involved (Cash et al., 2003), but this process is beyond the scope of this section. A more complete analysis of the integration of local knowledge in the context of the co-creation framework, including the co-identification of local knowledge will be developed in WP2 (Task 2.2) and related deliverables.

We first briefly explore what we consider as local knowledge, both within the scope of this review but also to establish a reference for of the dimensions of local knowledge within the context of integration of local and scientific knowledge in the I-CISK project. We then review how local knowledge is used in climate services, and introduce a basic typology of how local knowledge and scientific knowledge are considered and/or integrated within climate services. Finally, we provide a reflection on the challenges and directions of local and scientific knowledge integration in climate services, and a brief outlook on how these challenges will be addressed in the I-CISK project.

3.2 What constitutes local knowledge and data

To define local knowledge is itself a challenge. What constitutes local knowledge and who the owner of that knowledge is, and in particular the aspects of local knowledge that are relevant within the context of a climate service, is highly dependent on the (local) context of the decision process the climate service intends to serve, as well as the stakeholders and decision makers that are involved. The United Nations Food and Agricultural Organisation (FAO) offers a broad definition of local knowledge; describing it as "a collection of facts related to the entire system of concepts, beliefs, and perceptions that people hold about the world around them. This includes the way people observe and measure their surroundings, solve problems, and validate new information. It includes the processes whereby knowledge is generated, stored, applied and transmitted to others" (Building on Gender, Agrobiodiversity and local knowledge). Within this framework it is important to note that local knowledge is not only held by tribal or indigenous communities, but also by other communities, including those in rural and urban environments, settled and nomadic communities, original inhabitants and migrants (ibid).

Hermans et al. (2022) point out that what discriminates between scientific and local knowledge is that while scientific knowledge is developed through a formal and agreed methodology, local knowledge reflects the accumulated knowledge of the people of the environmental context in which they live and to which they are closely related. This local knowledge may then be intrinsically used in making predictions related to how environmental conditions, including the weather, may develop, or the consequences changing and extreme these environment conditions (such as droughts, heat waves, etc.) may have. In the context of disaster risk reduction (DRR) and early warning systems (EWS), the role local knowledge has is described as the experience of local surroundings, identification and monitoring of indicators, to detect, cope or adapt to disasters as well as communicate disaster risk (Dekens, 2007). Hadlos et al. (2022) characterise local and indigenous knowledge extracted from field-based studies within DRR and EWS to six overarching forms; namely, early warning systems, risk knowledge and perception, structural measures, livelihood-based adaptation, social cohesion and beliefs. Much of the literature on local knowledge considers the knowledge of those closely related to the environment, such as for example farmers living in rural environments. There is not much literature on how local knowledge can be understood in urban areas. In urban areas, there is a much larger mobility of people as well as change in the environment (for example due to rapid urbanisation), which will influence how people can build up (local) knowledge of the risks due to natural hazards surrounding them. Also, Hermans et al. (2022) found that most studies in their literature review on local knowledge for early warning systems are geographically concentrated in the Global South

Scientific knowledge in contrast is knowledge that is established through a formal and agreed methodology, such as local meteorological or hydrological observations and indicators derived from those observations is then referred to as local data. Arguably, this distinction between scientific and local knowledges being based on how formal the process of knowledge generation is, is somewhat grey. Some researchers consider local indicators established through the use of formally locally collected observational data as local knowledge (Reyes-García et al., 2016), while citizen science is a process that generates and consolidates both scientific and local knowledge (Wehn et al., 2021; Tengö et al., 2021).

Local knowledge is referred to in literature using various names, either to help distinguish who the owner of the knowledge is and/or to clarify to what the knowledge may pertain. These include indigenous knowledge (Iloka, 2016), traditional knowledge and local traditional knowledge (Plotz et al., 2017; Chisadza et al., 2015) or traditional ecological knowledge (Berkes et al., 2000)among others. Plotz et al. (2017) as well as other authors underline that most literature on local knowledge related to climate services considers traditional and or indigenous knowledge discussed within the context of development research, where formal data such as from hydro-meteorological observations are scarce. However, we recognise that local knowledge that is relevant in the diverse contexts and different sectors in the Living Labs of the I-CISK project may be knowledge that has developed over many generations, or that has evolved in a shorter time-span, and that belongs both to indigenous and non-indigenous people (ibid).

Within the climate services that are co-created in the I-CISK living labs, we also consider the role of local data collected through a formal data collection process. This may include data such as local meteorological and/or hydrological observations collected by formal institutions within the geographical context of each living lab, such as the national hydrometeorological services (NHMS), or other public and/or private bodies. Also, local data can be collected through more informal processes, such as citizen science or volunteered geographic information. The scientific knowledge these local data provide may be used to complement the knowledge that is obtained from larger scale datasets such as obtained from global and/or regional climate predictions and projections.

Another way to look at local data in relation to local knowledge is as follows. In order to better understand what makes up local knowledge, we can position local knowledge in the commonly used Data Information Knowledge Wisdom (DIKW) pyramid. Mulder et al. (2016) flipped this conventional view, where data are the raw building blocks of knowledge, arguing instead that data is generated from different sources of knowledge. We can dissect local knowledge into information and data for each category or dimension of local knowledge. For example, local knowledge on the ecological (or flora and fauna) dimension can be narrowed down to information about animal behaviour (a specific fish species as a sign of upcoming floods) (Šaki Trogrlic et al., 2019). In some cases, this usually qualitative type of information can be converted into a preferably quantifiable indicator, such as quantifying the increase in number of fishes. We emphasise that by this process of "datafying" the local knowledge, one no longer captures all the contextual knowledge and lived experience, and is reducing or transforming local knowledge to scientific knowledge and to different small building blocks.

3.3 Types of local knowledge and local data

Acknowledgement of the value that local knowledge can bring in improving the design and delivery of climate services has led to credible efforts towards tapping its potential, with a growing body of literature that captures the various dimensions of local knowledge in the context of climate services. Table provides an overview of some of these dimensions across various studies. Most of the approaches within climate services literature tend to focus on capturing local knowledge through indicators within the meteorological category (Bucherie et al., 2022; Streefkerk et al., 2022). This can be attributed to evidence of traditional, local knowledge-based forecasting methods adding significant value in enhancing the spatial and temporal resolution of scientific forecasts (Masinde, 2015) as well as being useful in communicating weather and climate information to local communities (Tadesse et al., 2015). Literature makes limited attempts at placing a specific timeframe for the occurrence of local knowledge indicators. Šaki Trogrlic et al. (2019), based on research in Malawi, found that assigning a timeframe for a specific indicator is a challenging task, as a high degree of disparity is observed, even within the same village. Nevertheless, it is possible to link the observations on different local knowledge dimensions to for example the different phases in disaster risk management. For example, local knowledge on early warning versus local knowledge for early action or response after floods have happened can be mapped (ibid). There seems to be less literature on local knowledge in relation to climate change adaptation, as it is more complicated to capture how local knowledge changes over longer time periods and because, due to climate change, possibly also some of the extreme weather events will be outside the lived experience (Kelman et al., 2012). Similarly, also understanding how "local" local knowledge is, is not straightforward. These ambiguities and differences in spatial and temporal coverage and resolution between local and scientific knowledge directly influence how the integration between local and scientific knowledge and data can take place.

Beyond climate services, scholarship on disaster risk reduction and adaptation has focussed on other, broader dimensions of local knowledge, including; risk perception, early action strategies, livelihood diversification, role of institutions and social capital, and belief systems of communities (Šaki Trogrlic et al., 2019; Hadlos et al., 2022). There is therefore an opportunity for climate services to learn from broader literature and look at local knowledge more holistically as a way to better understand user needs embedded within their local contexts. This also means that nearly all phases in the co-creation framework of I-CISK can leverage local knowledge and local data. For example, in the *co-explore climate information needs and desires* phase, a better understanding of local knowledge can help in identifying gaps in existing climate services. In the *co-identify adaptation and DRR plans to support* phase, the local knowledge on existing livelihood-based adaptation strategies can be identified. In the *co-develop climate data and knowledge* phase, the local knowledge can be actually integrated (which is the focus of this section). Similarly, Tan et al. (2022) showed how citizen science can contribute through knowledge to all parts of the warning value chain.

Table 1 Dimensions of local knowledge relevant to perception of climate relevant information

Dimensions of local knowledge	Description	Reference (Examples)
Meteorological conditions	Anomalies in ambient temperature and/or wind direction and speed prior to wet season related to drought	(Streefkerk et al., 2022)
Meteorological conditions	Wind speed, temperature and cloud formations over Lake Malawi as precursors to flash flood events	(Bucherie et al., 2022)
Flora and Fauna	Density of leaves and fruits and flowering levels as an indication of drought conditions	(Chisadza et al., 2015)
Flora and Fauna	Changes to the biophysical system as an indication of a changing climate at the local level	(Reyes-García et al., 2016)
Climate change perception	Experienced climate knowledge to improve service delivery of climate services	(Clifford et al., 2020)
Local spatial knowledge	Local knowledge of spatial and temporal patterns of floods, droughts and rainfall	(Pauli et al., 2021)
Risk perception	Changes in temperature, inter-seasonal changes in rainfall and recurrence of extreme events	(Singh et al., 2022)
Local impacts	Awareness and judgement of local impacts of heavy rainfall for disaster preparedness	(Sudmeier-rieux et al., 2012)
Livelihood-based adaptation Strategies	Crop selection	(Chen and Cheng, 2020)
	Changing planting schedules	(Šaki Trogrlic et al., 2019)
	Improving irrigation and water management systems	(Lirag and Estrella, 2017)

As discussed in section 1.3, we distinguish local knowledge and local data. While in some cases local data can be seen as directly linked to local knowledge, in this context we refer to local data as data that is locally collected through a (scientifically) formal process. In some cases, more informal processes may also result in useful local data. The recent Citizen Science Guidance Note by the WMO (2021) summarises the influence of citizens (as sensors, interpreters, engagers and collaborators) and scientists (instructing, collaborating, or co-creating) on different types of citizen science projects. When there is no influence at all from the scientists involved, we could argue that this represents the local data that is part of local knowledge. This is also in line with Leach and Fairhead (2002), who consider that citizen science implies a certain engagement with, and usually a more dominant discursive role for, the science of expert institutions than is the case with local knowledge. Understanding and characterising local knowledge (and associated local data) is usually through qualitative techniques, such as focus group discussions and key informant interviews. Citizen science projects typically use more quantitative and formalised techniques, though are not limited to these (Hicks et al., 2019; CitizenscienceDRR, 2022).

In the context of the I-CISK project, citizens can refer to those in communities, such as in rural areas in Lesotho, but also to hotel owners in Greece or olive farmers in Spain. Given I-CISK's co-creation framework, the citizens and scientists in the Living Labs will operate mostly in the collaboration and co-creating side of the spectrum for the to be collected local data. Of course, Living Lab actors may also already have local data. Here one can think of e.g. commercial farms that have rainfall records over a long period of time (Landman et al., 2020), but also communities that have local knowledge on hydro-meteorological indicators.

3.4 Typology of integration of local and scientific knowledge in climate services

The advancing interest in using co-creation processes for delivering usable climate information has consequently also led to growing interest in exploring local knowledge and ways to integrate it with scientific knowledge in climate services. Several authors argue the relevance of local knowledge in the context of environmental decision-making, disaster risk management or to enhance (seasonal) climate forecasts (Jiri et al., 2016; Plotz et al., 2017; Streefkerk et al., 2022). The integration of local knowledge within climate services also presents the opportunity to better tailor the information to match the end-user needs (Kniveton et al., 2014) and to improve communication to local communities (Tadesse et al., 2015).

Dryball et al. (2009) discuss, in the context of environmental management, processes of social learning among actors. They explain that participation and interaction among different actors can range from coercion (the will of one group is imposed on the other), informing, consulting, enticing, co-creation to co-acting (active participation). This spectrum of interaction between communities and external actors can be used, to some extent, to describe the spectrum of how the holders of LK and SK relate to one another, reflecting power relations between the actors. We will shortly give an example of the two extremes. Coercion can be the result when holders of SK consider SK the most valuable knowledge system and where they focus on "extracting" those parts of LK that can be validated scientifically and used to for example localise scientific forecasts. Co-acting reflects a process in which both LK and SK co-exist, each have their respective value and mutual learnings occur based on collaboration and negotiation.

Studies have defined knowledge integration in several ways. Berggren et al. (2011) defines it as a combination of specialised knowledge to reach an end result, while it has also been interpreted as the process of transforming individual knowledge to a collective one (Okhuysen and Eisenhardt 2002). Plotz et al. (2017) looked at methods of integrating local knowledge, coming up with the typology that includes: consensus building approaches and science integration approaches. The former is described as a process wherein the final product (in this case a forecast) is an agreed outcome of negotiation between the local and the scientific knowledge holders. The negotiation process may follow a very structured approach or a less formal one, depending on the context. This approach also relies on the last mile actors and local social networks to build a common understanding (ibid). The science integration process, on the other hand, employs local knowledge for validation. For example, local indicators of weather patterns which are extracted through surveys with stakeholders are processed to validate indicators established using existing scientific datasets (ibid). Other approaches of integration include establishing knowledge timelines and participatory downscaling processes that aim to draw on the similarities between knowledge types, and exploring the limits of current information (Kniveton et al., 2014). We note that most of the approaches for integrating local and scientific knowledge are when producing the climate service, so prior to the service becoming operational, or when evaluating climate services, (Hirons et al., 2021) state that evaluation should be ongoing and combine meteorological verification with decision-makers feedback. However, integration also takes place when a climate service is delivered. For example, when climate service users triangulate themselves between their local knowledge and the knowledge provided in the climate service. In Table we develop an extended typology of integration. This provides an overview of the wide range of levels of integration of LK and SK within climate services as found in relevant literature. Table 3 provides selected examples of integration from literature, showing that in many of these several of the levels of integration may be considered.

Table 2 Typology of approaches to integrating local and scientific knowledge and data in climate services

Level of integration	Description	Reference
Science-dominated	In this approach, the information provided through the climate service derived from scientific knowledge is considered the most valuable (described as coercion). This level of integration is often found in global forecasting systems that are developed using global scientific datasets and models.	(Dryball et al., 2009)
Consensus	In the consensus approach, scientific knowledge (e.g. seasonal forecasts obtained from a climate model) and local knowledge (e.g. seasonal forecast based on traditional knowledge of meteorological signs) are considered equally by scientific experts and traditional knowledge holders. The two knowledges are combined to develop a consensus forecast.	(Plotz et al., 2017)
Validation	Local knowledge is used to evaluate information provided by the climate service, or scientific knowledge is used to evaluate the accuracy of local knowledge-based forecasts. Referred to as science integration in Plotz et al.	(Landman et al., 2020; Gilles et al., 2022)
Triangulation	Scientific knowledge provided through the climate service is triangulated by users with their local knowledge of their environment. This could include comparison of (seasonal) forecasts the climate service provides with environmental cues observed by the user.	(Shah et al., 2012) (Gwenzi et al 2016)
Informing	Local knowledge is used to inform how scientific knowledge can be interpreted. Examples include where (Meteorological) indicators based on local knowledge are used to inform how scientific datasets and models are interpreted.	(Bucherie et al., 2022; Streefkerk et al., 2022)
Conditioning and Bias Correction	Notes: here local knowledge and in particular local data is used to condition model uncertainties and correct biases. This is through formal mathematical approaches such as quantile mapping or bayesian approaches.	

Table 3 Examples of local knowledge integration approaches that have been discussed in literature

Type of integration	Description	Reference
Model input (Forecast threshold model); Informing and validation	Meteorological indicators based on local knowledge on predicting dry conditions during rainy season	(Streefkerk et al., 2022)
Validation (Statistical integration)	Using wind-related indicators for forecasting rain and optimise local and modern forecasts	(Gbangou et al. 2021)

Participatory geographic information system (PGIS) or participatory mapping	Understanding vulnerability and local adaptation actions using spatially explicit mapping of local knowledge	(Cruz-Bello et al., 2018)
Crowdsourcing local data to validate models or Community-based observation networks	Use crowd-sourced flood observations to quantitatively assess model performance of for example flood forecasting models	(Dasgupta et al., 2022) (Le Coz et al., 2016) (Alessa et al., 2016)
System level integration across the early warning value chain	Participatory approach to connect top-down scientific knowledge-based systems with bottom-up community-based systems and local knowledge.	(Tarchiani et al., 2020)
Use site specific records to improve forecast skill of global or regional models	Use site recorded farm rainfall records for the development of skillful forecast systems specific to the farm	(Landman et al., 2020)
Participatory downscaling	The use of knowledge timelines and participatory downscaling to validate meteorological forecasts and build trust in these forecasts among farmers in Senegal and Kenya	(Kniveton et al., 2014)

3.5 Challenges and directions local and scientific knowledge in climate services

Examples from recent literature reviewed in the preceding sections clearly establish the need for exploring local knowledge and its value in producing climate information that is more salient to user needs. However, local knowledge still remains underutilised within design, delivery and communication of climate services, predominantly because there is still a lack of a unified understanding of what constitutes local knowledge (Hadlos et al., 2022). Currently, within climate services literature, local knowledge related to meteorological indicators is more frequently discussed than other dimensions (Streefkerk et al., 2022). Research has, however, revealed that local knowledge and its use can have wider socio-economic, political and environmental dimensions (Šaki Trogrlic et al., 2019). Furthermore, clearer links need to be drawn between climate services and the local knowledge embedded within the livelihood practices, coping and adaptation strategies, and social network of local communities, so that the information or advice provided is more suited to end user needs. The ongoing discussion around local knowledge also does not fully consider knowledge held at different levels of governance (from livelihoods to local government bodies to higher levels of government) as well as along the climate services value chain itself. Calvel et al. (2020) study this in the context of drought warning, exploring local knowledge related with communication structures (dissemination channels) and decision-making. There is also a need to better understand the role of local knowledge within urban environments and commercial sectors (for e.g., tourism). Current representation is skewed towards agriculture, water and natural resource management. A literature review on climate services for adaptation (Boon et al., 2022) found that the majority of interventions either did not identify a clear sectoral focus or mostly discussed the aforementioned categories. The diverse contexts of the living labs that have been established in the I-CISK project, and the range sectors and diversity of local knowledge holders in each of the Living Lab provide the opportunity to reduce this skew.

Additionally, it is also important to look at local knowledge in terms of its ‘relational’ aspect i.e., ‘who’ is being included or excluded in the problem understanding process (Bouwen, 2001). Šaki Trogrlic et al. (2019) discuss the intergenerational and gendered differences in local knowledge of local communities and the need to have a more holistic and representative view of local knowledge. This concern is addressed within the co-creation framework of the ICISK project, and will need to be carefully documented within the context of each of the seven Living Labs.

While these are some of the gaps that have been identified when it comes to local knowledge, there is a clear need to unpack these in a more systematic manner. More specifically, it is important to understand the various dimensions of local knowledge. This can shed further light on the question of what constitutes local knowledge, and can help to start building a common understanding. This will also serve as a stepping stone towards identifying various entry points and pathways through which local knowledge can help build a more salient and human-centred climate services.

In this section, specific pathways are identified as to how local knowledge can be integrated with scientific knowledge. Before being able to integrate local and scientific knowledge, one has to characterise and understand local knowledge. The overview of the dimensions of local knowledge, as well as the typology of levels of information, illustrates that the integration of local knowledge and scientific knowledge extends well beyond the combining of quantitative data, such as in for example bias correction of forecasts using local data. Breaking local knowledge down into local (quantitative) data, has the risk of losing the more contextual qualitative information, though that may be necessary for some integration approaches. However, within the co-creation process of developing climate services, such as in the living labs in I-CISK, these additional dimensions of local knowledge and types of integration should be explicitly considered.

4 Advancing large-scale climate services through integration of local data

4.1 Introduction to Climate Services

The European Commission's Roadmap for Climate Services (2015), set the definition of climate services which accounts for those covering "*the transformation of climate-related data together with other relevant information into customised products such as projections, forecasts, information, trends, economic analysis, assessments (including technology assessment), counselling on best practices development and evaluation of solutions and any other services in relation to climate that may be useful for the society at large. As such, these services include data, information and knowledge that support adaptation, mitigation and disaster risk management (DRM)*." Consequently, a climate service needs to provide science-based and user-specific information relating to past, present and potential future climate, assisting society in adapting to climate variability and change.

Typically, national services have the mandate to provide forecasts and warnings, and many national and local organisations produce their own forecasts and climate services. In addition to these, a range of global and continental scale forecasting systems and climate services exist to support the needs at the large-scale (continental and global scale) and also address inter-dependencies between regions and even occasionally countries. While local services benefit from local knowledge and experience, and often by the existence of high-resolution models over the small domains, large-scale services can provide complementary information to support local CS and existing capabilities. Among others, large-scale services provide data and information at transboundary domains, while these can be found at long lead times and even in a probabilistic approach. Moreover, they can provide information where no other local prediction systems are available (without a massive scale-up of resources for service customization) and for organisations working at international scales (such as humanitarian organisations) (Emerton et al., 2016).

Specifically, for the seasonal time scale (which is the time scale that this report is mainly focusing on), a number of research and operational centres provide predictions of meteorological variables at the global scale and at a time range from 1 to 12 months ahead. The most common prediction systems are: ECMWF SEAS5, CMCC-SPS, MeteoFrance System 7, GloSEA5 from the UK MetOffice, NCEP CFSv2 etc. As mentioned in Section 2, these prediction systems rely on coupled atmosphere-ocean-land GCMs; however, their configuration (i.e. spatial resolution, ensemble members, initialization etc.) differs between them and hence the forecasting skill varies as a function of variable of interest, geographical domain, lead time, and aggregation period. Consequently, multi-model approaches are expected to be beneficial to understand better the uncertainty stemming from differences in the model configuration.

4.2 Description of European and global Climate Services

International organisations have been coordinating efforts to co-create climate services for large-scale applications. Below, we summarise these efforts, since they can act as benchmark climate services to which I-CISK human-centred CS, which focus on a more local scale, will add value.

4.2.1 The Copernicus services

Copernicus is the European Union's Earth Observation Programme (www.copernicus.eu) and provides a range of services covering the atmosphere, oceans, land, climate change, security and emergency services. Many of the services are global, while others cover only the European domain.

The Copernicus Atmosphere Monitoring Service (CAMS) provides data and information on atmospheric composition, for sectors such as health, environmental monitoring, renewable energy, meteorology and climatology. This includes global atmospheric monitoring and forecasting of greenhouse gases, reactive gases, ozone and aerosols, and near-real-time monitoring and 4-day forecasts of European air quality.

The Copernicus Marine Environment Monitoring Service (CMEMS) provides information on ocean and marine ecosystems, including currents, winds, sea ice, temperature, salinity and biogeochemical components.

The Copernicus Land Monitoring Service (CLMS) supports applications such as urban planning, forest management, water management, agriculture, conservation and climate change adaptation and mitigation, through provision of information on land cover and its changes, land use, vegetation and surface energy variables. CLMS undertakes monitoring of biophysical parameters (every 10 days globally) that aid monitoring of vegetation, crops, water cycle and more, and provides maps of land cover and land use, with varying complementary information, at European and global scales. Imagery, reference data, and mapping of hotspots that are prone to specific environmental challenges, are also available through the CLMS.

The Copernicus Emergency Management Service (CEMS) provides monitoring and early warning information for a range of hazards at European and global scales, including floods (the European Flood Awareness System – EFAS (Figure 2), and Global Flood Awareness System - GloFAS, which both provide a range of products for river flow, flood hazard and risk and seasonal forecasting), fires (the European Forest Fire Information System, EFFIS, monitors forest fire activity in near-real-time and supports wildfire management for the EU, Middle East and North Africa), and droughts (the Drought Observatory provides drought-relevant information and early warnings for Europe (EDO) and globally (GDO)).

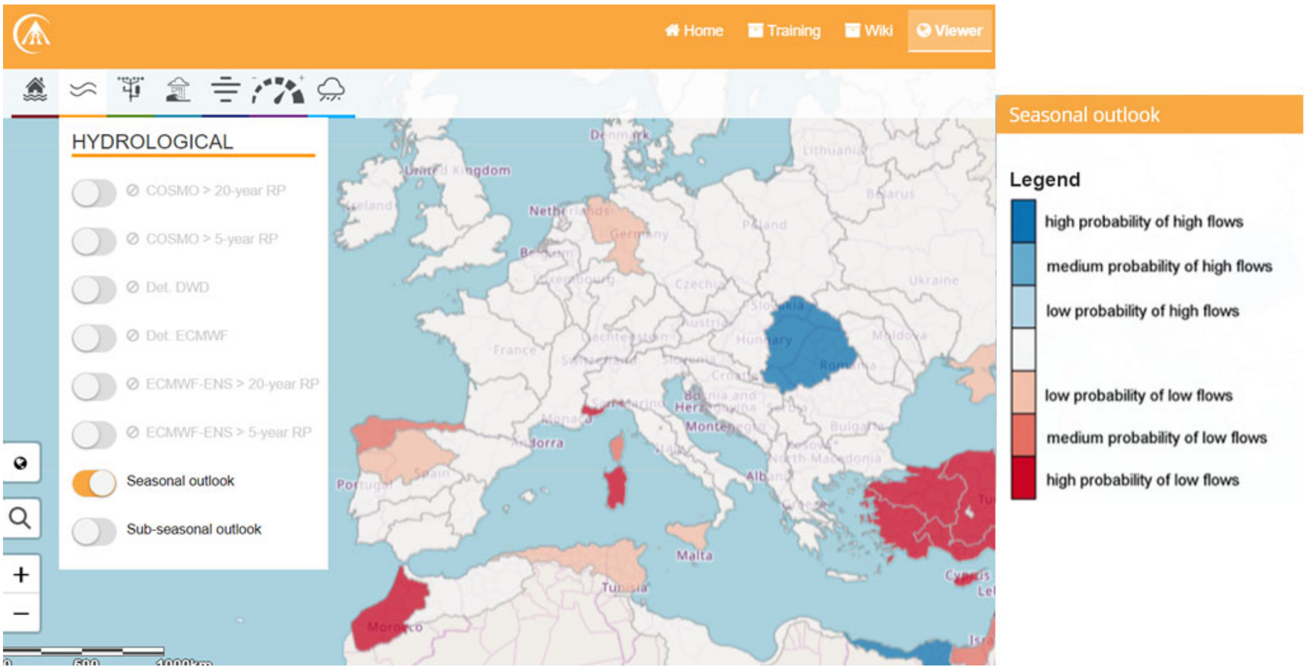

Figure 2 The seasonal outlook available in the EFAS service provided by CEMS.

In relation to the main vulnerabilities of the I-CISK living labs (Deliverable D1.1) EDO and GloFAS are two of the most relevant Copernicus services. The EDO is a collection of drought-relevant information such as maps of indicators derived from different data sources (e.g., precipitation observations, satellite-based measurements, modelled soil moisture content) with different tools and products that display and analyse functionalities, and drought reports that describe past droughts events and predict the situation of imminent droughts. On the other hand, GloFAS supports relevant national and regional authorities and international organizations in decision making and preparatory measures before major flood events (particularly in large trans-national river basins). GloFAS provides probabilistic hydrological predictions and overviews across the world on time scales from days to few months.

Finally, the Copernicus Climate Change Service (C3S) provides a wide range of information on our past, present and future climate alongside tools to enable climate change mitigation and adaptation strategies. This includes climate bulletins, and the provision of data information for a range of sectors, users and topics through the (free and open access) Copernicus Climate Data Store (CDS), global and regional reanalysis datasets (including the atmosphere, ocean, land and carbon), observation-based products, real-time climate monitoring, multi-model seasonal forecasts and climate projects for regional and global scales.

4.2.2 Global Earth Observation System of Systems

The Global Earth Observation System of Systems (GEOSS) is a set of coordinated Earth observation, information and processing systems that interact and provide access to diverse information for a broad range of users in both public and private sectors. The GEOSS Portal (https://www.geoportal.org/) is the single Internet access point for all this information. Relevant GEOSS projects and initiatives in the climate and water resources domains are:

- The Global Water Sustainability (GEOGloWS) is an Initiative under the Group on Earth Observations (GEO). It provides access to actionable water data, information, and knowledge to bridge the digital divide and promote global equity through a service. The GEOGloWS - ECMWF flow forecasting service (https://geoglows.ecmwf.int/) is one example of these provided services.
- The Global Drought Information System (GDIS) (Figure 3) is an information system ingesting global space-based and land-based Earth Observations for the purpose of early detection (through monitoring and prediction) of drought, combined with the data processing capability to identify increases of drought occurrence with increases in global warming. GDIS provides these CS: Evaporative Demand Drought Index (EDDI), Global Precipitation Measurement (GPM), Global Soil Moisture monitoring, Standardized Precipitation Index (SPI) from NOAA Climate Prediction Center.
- The GEO Global Agricultural Monitoring (GEOGLAM) aims to improve food security by producing and disseminating relevant, timely, and actionable information on agricultural conditions at national, regional, and global scales. The Crop Monitor (https://cropmonitor.org/index.php/cmreports/climate-forecasts/) is an example of CS by GEOGLAM and their collaborators.
- AquaWatch is a GEO Initiative that aims to develop and build the global capacity and utility of Earth Observation-derived water quality data, products and information to support water resources management and decision making.

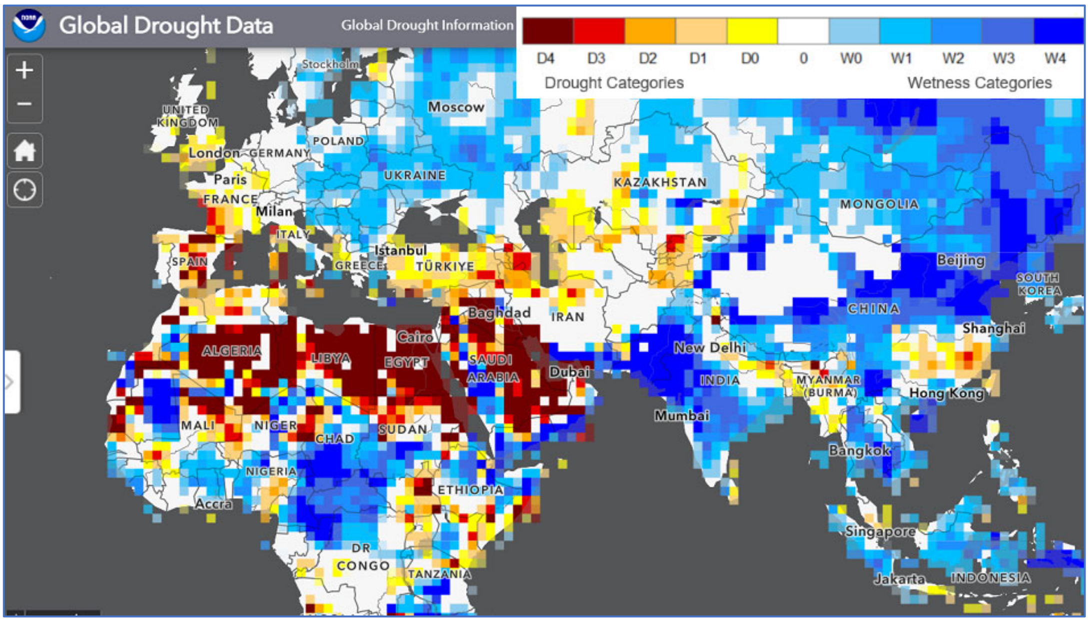

Figure 3 The Global Drought Monitor tool of GDIS.

4.2.3 The WMO services

The World Meteorological Organization (WMO) develops the Climate Services Information System (CSIS) as the core of the Global Framework for Climate Services (GFCS). It produces and delivers authoritative climate information products through operational mechanisms, standards, communication and authentication. Its functions include climate analysis and monitoring, assessment and attribution, prediction and projection (from monthly to centennial scales), climate adaptation and risk management, and the corresponding system operation and infrastructure. Examples of WMO climate services those are relevant for I-CISK:

- Global Data-processing and Forecasting System: The GDPFS is organized as a network of Global, Regional and National Centres. Information about designated GDPFS Centres and their products is available on the GDPFS Web Portal https://wmo.maps.arcgis.com/apps/dashboards/7c3d45e5003a417988bad63e91ad8748. It facilitates the development, operation and enhancement of a network of global, regional and national centres/systems for the generation and dissemination of analyses and forecast products for all time-scales (from minutes to decades), as well as severe weather advisories and warnings, and related operational information.
- Integrated Drought Management HelpDesk: This is a component (https://www.droughtmanagement.info/) of the Integrated Drought Management Programme. The wider scope of the Programme is to build climate resilience, reduce economic and social losses, and alleviate poverty in drought-affected regions of the world through an integrated approach to drought management, which cuts across sectoral, disciplinary and institutional jurisdictions. It especially aims to support regions and countries to develop more proactive drought policies and better predictive mechanisms.
- The Public Weather Services (PWS): This programme aims to enable the delivery of weather and related services for sound decision-making on public safety and cost-efficiency in all social and economic activities affected by weather. It also engages in education and awareness to help citizens make the best use of forecasts and warning information.

4.3 Benchmarking predictions

4.3.1 Evaluation of predictions

Performance evaluation generally measures the ability of the predictions to reproduce the historical intra- and inter-annual variability, and the probability of events (e.g. summer 2022 drought in Europe) matching the observed occurrence of those events. These evaluations are important to be provided together with prediction products in order to communicate the trust that users should put for decision-making; however, it is important to note that in these evaluations the reference dataset ('observations') might vary from one service provider to another, and hence a re-evaluation of predictive performance need to be conducted. The quality of observations used for model initialisation is a key component for the quality of the predictions. Particularly for hydrological applications, initial hydrological conditions have been shown to be a key driver of predictability (Girons-Lopez et al., 2021).

Nevertheless, evaluation of predictions is a key (usually numerical) process leading to the quantification of their usability in adding value to decision-making. This process is usually done consistently through time, so that prediction developers and users can assess whether the predictions are getting better. A number of evaluation metrics has been proposed to numerically quantify the performance of the predictions focusing also on their different characteristics, i.e. reliability, sharpness, accuracy, overall performance, extremes etc. (Crochemore et al., 2016). In particular, reliability is defined as a prediction attribute that refers to the statistical consistency between observed frequencies and prediction probabilities. Moreover, sharpness is a property of the predictions only, it refers to the concentration of the predictive distribution and indicates how spread out the members of an ensemble predictions are. Among the many metrics that can be found in the literature, the most common metrics are: the ranked probability score (RPS) and the continuous ranked probability score (CRPS) addressing the overall performance; the Brier score (BS) commonly used to address the extremes; the interquantile range (IQR) to address sharpness; the anomaly correlation (AC) to address the predictive temporal variability; and the mean absolute error (MAE) to address the accuracy in the predictions.

In the case that two different systems and/or methods are compared, skill metrics are used, which allow quantifying the added value of a system towards a benchmark (reference system). Recently there have been efforts to propose performance and skill metrics that move beyond traditional statistical metrics and instead are more meaningful to the users, i.e. economic benefits (hence being better understood or can relate to) (Giuliani et al., 2020). Hence users can directly assess if they are getting a return on their investments in research and system upgrades.

4.3.2 Benchmarks and reference systems

To conduct an evaluation of predictions, one needs access to past predicted events and/or a historical time series of predictions and observations. Hindcasting (retrospective forecasting) is not strictly a prediction time scale, however the deep understanding of the time trends and spatial patterns of past hydro-meteorological variables distributions is a key information for the predictions. Hindcasts (or re-forecasts) are very useful for calculating the performance and skill (obtained from the predictions and the 'observations', known also as reference), while diagnostics provides valuable insights for the evolution of the prediction systems. The predictions during the hindcast period are named re-forecasts and are provided to assess the performance and skill of the prediction system. Moreover, given that estimates of the future are always uncertain, the hindcasts now provide a range of realisations (ensembles) to help users deal quantitatively with the probable temporal variations in the predictability of the atmosphere and land processes. Consequently, the assessment of these re-forecasts should consider the probabilistic properties of the information provided. Sub-seasonal to seasonal re-forecasts from most state-of-the-art service providers are available over a 10 to 40 years' historical period. The availability (or not) of long historical records limits the number of (sub-) seasons available, and hence can affect the assessment of the prediction service.

A benchmark system is used when one assesses the added value of a ‘new’ prediction system. The consideration of the benchmark system is important because one can quantify the added predictive value in terms of meteorological forcing and initial conditions. Climatology has been commonly used as a benchmark for both meteorological and hydrological investigations, yet this method has been considered ‘easy’ to beat since neither the initial model conditions nor the meteorological forcing drive the predictability. Particularly for hydrology, the ESP method, described in Section 2, has been used, with the predictive skill being driven by the initial hydrological conditions. Conclusively, by comparing the performance of a system against that of the climatology, we can get an estimation of the impact of both initial conditions and meteorological forcing on the predictions. Consequently, by comparing the performance of a system against that of ESP, we in turn get information on the impact of using a different meteorological forcing on the predictions.

Finally, it is important to clarify the role of the reference dataset considered to assess the prediction performance and skill. Predictions are usually evaluated with respect to their performance against the historical "reference simulation" (also known as "pseudo-observations" or "perfect" forecast) per initialization and lead time. Hence in this case model outputs (i.e. predictions) are compared to a model output (i.e. reference simulation), and consequently model limitations are neglected. An assessment of the predictions could also be done against the historical observations (e.g. ‘real’ streamflow observations), and in this case, the prediction performance and skill would be subject to the model limitations (model structure and parameterization)

4.4 User requirements from the I-CISK LLs

In this section we aim to provide a summary of the living labs and an assessment of whether and how the current state-of-the-art CSs address user needs. The information below is based on work conducted in WP2 of this project, which is relevant to WP3 as this investigate various scientific methodologies to address the user requirements at the LL scale.

Through the project scoping process, initial discussion meetings and establishing of the I-CISK Living Labs (LLs), and targeted questionnaires and interviews, a preliminary overview of the current use of CS in the LLs, alongside our knowledge so far of the decision-making processes, barriers to use of existing CS, and needs for improved and tailored CS, has been produced (Deliverable D2.1). The full report is available through the I-CISK website (www.icisk.eu/resources; Moschini, Emerton et al., 2022) and a summary of key information related to this preliminary report of state-of-the-art methods for forecasting and prediction of extremes is provided here. Detailed reports on the characteristics of each LL are also available as part of D1.1 through the I-CISK website (Masih, Van Cauwenbergh et al., 2022).

The seven LLs are located in The Netherlands, Spain, Italy, Greece, Hungary, Georgia and Lesotho. As part of WP2, information on decision-making, use of CS and user requirements has been collected, with varying levels of detail due to differences in the stages of establishing the LLs that are expected at this stage of the project. Co-exploring the needs surrounding the value of CS, climate data and information is key in the design and development of CS. It is important to understand the decision-making context of CS end-users, the barriers to the use of existing CS, and how these issues can be addressed in the development of next-generation CS to provide CS that are useful, usable and effectively address user requirements. These aspects will continue to be co-explored iteratively throughout the project. The project scoping, and interviews with 21 individual participants in four of the seven LLs, indicates the wide range of decision-making contexts and specific decisions that are already, or have the potential to be, made using CS information.

Based on responses to interviews and questionnaires held through WP2 so far, some of the key motivations for improving CS and their use include “the importance of influencing preparedness and adaptation strategies, the increased risk of hazards and extreme events due to climate change, avoidance of conflict due to water demand, impacts of extreme events on many (if not all) sectors, easier exploitation of existing information, policy support, and a drive for actors to see directly how CS can help them move from reactive to proactive decisions and actions.” (Moschini, Emerton et al., 2022). Some of the challenges faced in using the CS currently available include insufficient resolutions (temporal and/or spatial, such as aggregated information), accessibility of the CS (difficulty downloading data, information not reaching intended audience or certain sectors), and insufficient variables for the decisions that need to be made. The needs of the LLs range from improving availability of CS at a range of timescales (such as introducing seasonal forecasts where only medium-range are currently used), providing spatial resolutions that are relevant for the decisions being made, and CS that are tailored to specific sectors and provide impact-based / action-based forecasts or additional variables that are not currently available.

Tables 2 to 7 in D2.1 (Moschini, Emerton et al., 2022) provide information on the CS that are available and/or used by each of the seven LLs, although it is not yet clear whether all the available CS are actively used for decision-making, and other CS may be available and have not yet been integrated into decision-making or used by those who have so far been able to participate in the questionnaires/interviews. The majority of the CS mentioned as being available or used in the LLs are national and regional/local CS, e.g. from hydro-meteorological services or environment agencies. Very few large-scale or international CS were mentioned so far, but those highlighted include seasonal outlooks from regional Outlook Forums, seasonal forecasts from ECMWF, and information from the Copernicus Land Monitoring Service. Given the range of global and large-scale CS that are openly available and have the potential to provide additional or complementary information where local information may not be available, or to address some of the challenges mentioned above, this raises the question of why these large-scale CS may not be being utilised alongside information from local sources. It will be of interest to explore the awareness of these large-scale CS, whether they are being used but have not been mentioned during communications so far in the project, or whether there are barriers to their use, in order to further understand the possibilities and motivations for connecting global and local CS and knowledge, and tailoring CS for local needs.

5 Impact of post-processing on seasonal climate prediction error

5.1 Experimental objectives

Seasonal climate predictions lack the necessary downscaling and tailoring, and hence effort is still ongoing to improve service predictability and usability. As mentioned in section 2, the predictability of S2S predictions is subject to multiple sources of error and uncertainty, which are present in the various components of the production chain going from climate models (their parameterization, initialization, bias-adjustment, etc.) to the service that provides impact indicators (impact model setup, structure and parameterization). In addition, predictability is characterised by strong spatial variation and commonly a temporal degradation of its skill in longer time scales (see Fig.1).

Here, the objective is to explore the biases that are present in the seasonal climate predictions, and also apply a post-processing method (also known as bias-adjustment method) in order to reduce these biases and results towards a climate prediction product that can be applied for impact (i.e. hydrology) assessment at the local scale. In addition, here we aim to explore and better understand the biases in space from different seasonal prediction systems.

5.2 Data availability

We assessed the precipitation and temperature predictions which are driven by two climate prediction systems; the ECMWF SEAS5 (Johnson et al., 2019) and the CMCC Global Seasonal Ensemble Prediction System version 3.5 (CMCC-SPS3.5; Gualdi et al., 2020). Both systems generate time-series of 6 (CMCC-SPS3.5) to 7 (ECMWF SEAS5) months ahead with a monthly initialization. The parallel investigation of the two systems allows detection of spatial-temporal complementarities in the predictions. We note that in order to quantify the impact of climate variability on hydrology at the local scale, both seasonal prediction systems have to be downscaled and bias-adjusted. Only then can these predictions drive the hydrological impact model (Hundecha et al., 2016) to provide local information of the hydrological conditions; see results in Section 5. Particularly for CMCC-SPS3.5, the access to the predictions was due to an internal SMHI-CMCC collaboration. More information about the systems used can be found in Table 1.

Table 4 Properties of the seasonal climate prediction systems

Name	Source	Handled by	Post processing	Ensemble members	Time frame	Resolution
ECMWF SEAS5	C3S-CDS	ECMWF- CDS	DBS method	25 (hindcasts)	1993-2015 (hindcasts)	0.33°
CMCC-SPS3.5	CMCC	SMHI	DBS method	40 (hindcasts)	1993-2016	0.5°

5.3 Post-processing methodology

To adjust the reforecast data for biases and drifting, a modified version of the Distribution Based Scaling (DBS) method was considered and used (Yang et al., 2010). The DBS forecasting method was originally developed to adjust climate projection biases and has been adapted here for seasonal predictions. In essence, the DBS method implements a parametric quantile-quantile mapping in which the temperature is conditioned on precipitation occurrence. Here, not all meteorological variables were bias-adjusted but instead only precipitation and temperature using an available reference dataset that covers the entire European domain. Note that here precipitation and temperature were bias-adjusted separately and not following a method that explicitly considers the interdependence between the two variables. However, given that the DBS bias-adjustment is conducted for both variables towards observations, it is expected that the separate adjustment still respects the variable interdependence which is present in the actual reference dataset (HydroGFD).

The HydroGFD version 2.0 (Berg et al., 2018) data set was used as a reference of bias adjustment for both ECMWF SEAS5 and CMCC-SPS3.5 meteorological forecasts (daily temperature and daily precipitation) for the period of 1993-2015. The product consists of the ERA5 reanalysis product corrected by GPCC for precipitation and the CRU product for temperature, and hence the monthly mean water balance is constrained to observations. The product is available at a 0.5° resolution and hence the seasonal predictions had to be converted to this resolution prior to their bias-adjustment. Using this reanalysis product, we overcome the technical challenge of daily data typically not being available on a large scale (national, continental, global).

5.4 Assessing the impact of post-processing on predictive error

Here we present both the biases in the raw and post-processed seasonal predictions from the two systems (ECMWF SEAS5 and CMCC-SPS3.5), taking winter months (DJF) and summer months (JJA) as examples. As expected, the biases in the raw data do not follow the same pattern in terms of magnitude and spatial variability, while after the DBS-based bias-adjustment (BA), they are significantly reduced both for precipitation and temperature. The seasonal precipitation predictions in Figures 4 (ECMWF SEAS5) and 5 (CMCC-SPS3.5) both display large positive and negative biases, especially in regions with complex topography and coastal areas (e.g., Spain, France and south-eastern Europe). In general, in northern Europe, ECMWF SEAS5 tends to overpredict precipitation in the winter (rain and snowfall season) and underestimate precipitation in the summer. While in southern Europe, ECMWF SEAS5 shows a clear overestimation in the summer precipitation. In most parts of Europe, temperature is underpredicted by ECMWF SEAS5 on average 1 and 2°C in all months and all lead months, except February. CMCC-SPS3.5 shows a similar bias pattern in terms of spatial variability only with slightly larger amplitudes.

While the DBS method is highly effective, some biases still remain in meteorological predictions (especially in precipitation, since the biases for temperature are close to 0), which originate from an assumption of a theoretical distribution of daily data. Hence it is important to note that in a production chain, such remaining biases will be further propagated, potentially affecting the quality of hydrological predictions. Nevertheless, the results here indicate that state-of-the-art seasonal prediction systems are still subject to biases for European impact assessments. Although these systems can be used to extract seasonal information of predicted anomalies, their usability for actual local impact assessments is questionable, and hence a post-processing is necessary. The post-processing applied here shows that the bias corrected dataset has fewer remaining biases and can be considered as an input to impact models for local assessments.

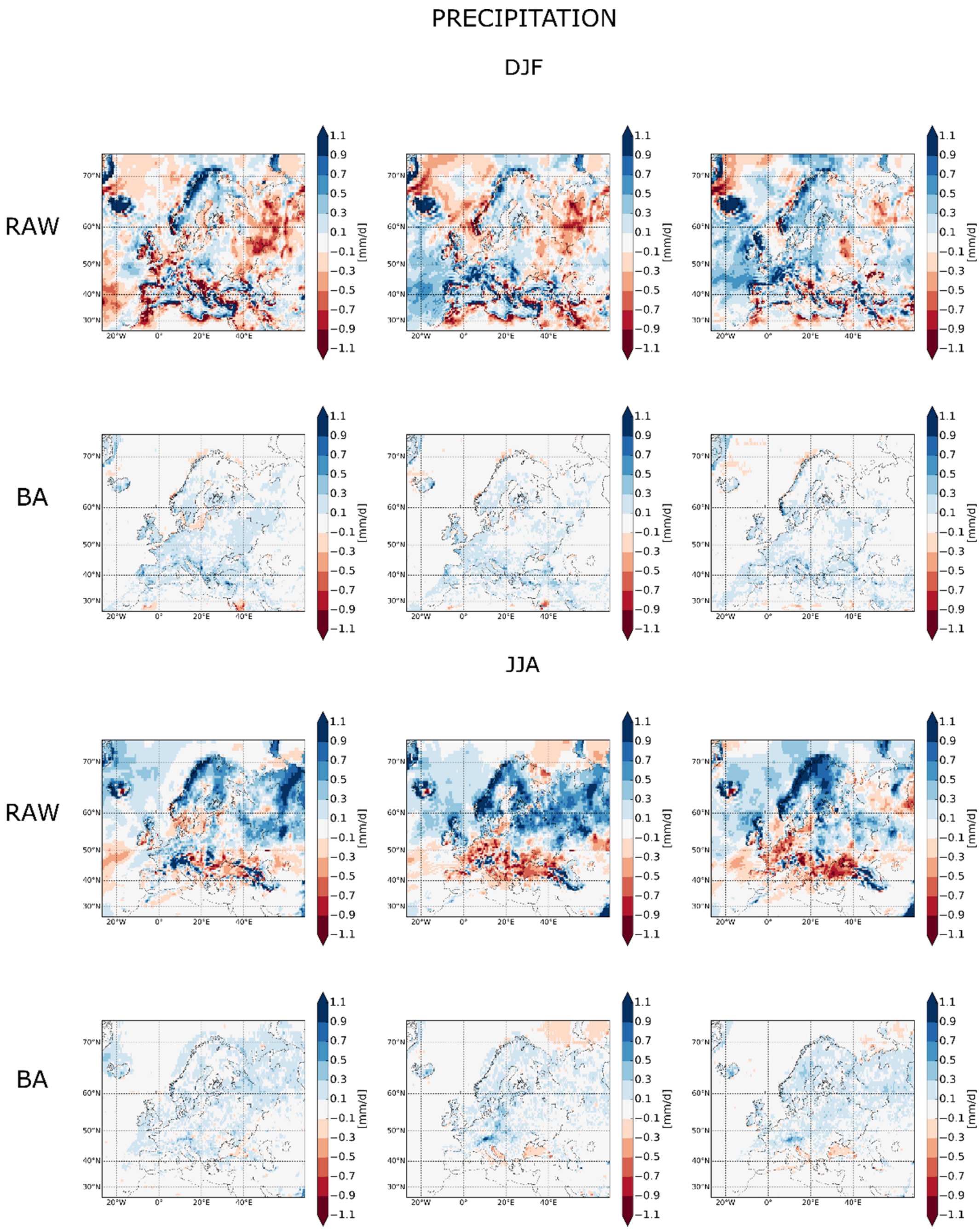

Figure 4 Biases in raw and bias-adjusted precipitation predictions for the winter and summer months and for lead month 0. The predictions are based on the ECMWF SEAS5 prediction system.

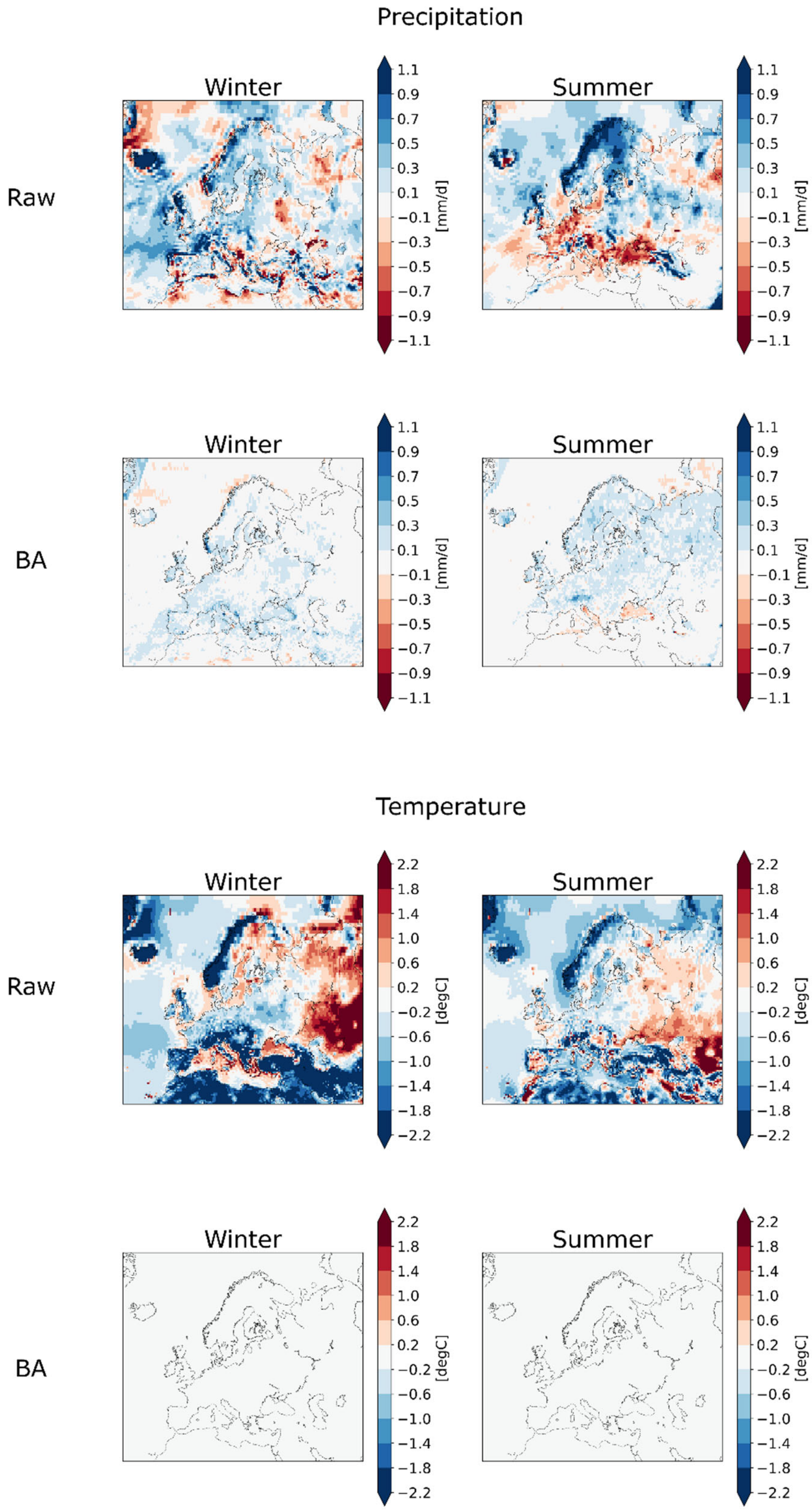

Figure 5 Biases in raw and bias-adjusted precipitation and temperature predictions for the winter and summer months and for lead month 0. The predictions are based on the CMCC-SPS3.5 prediction system.

6 Assessment of fit-for-purpose methodologies at selected Living Labs

6.1 Experimental objectives

The main objective of the I-CISK project is to develop next-generation CS that follow a social and behaviourally informed approach for co-producing CS that meet the climate information needs of citizens, decision makers and stakeholders at the spatial and temporal scale relevant to them. I-CISK showcases its human-centred co-design, co-creation, co-implementation, and co-evaluation approach across key sectors vulnerable to climate change in Europe and beyond. This is done in seven geographically and sectorally diverse living labs (see Figure 6). In this section, we present:

- the performance of seasonal hydro-meteorological predictions conditioned to the scale of each LLs, including the general accuracy and predictability of extremes. These results are also considered as benchmarks during the continuous scientific efforts of tailoring the state-of-the-art climate services to the needs of local users.
- local examples in three LLs located in three different climatic regions and hence subject to different vulnerabilities. These are: the Andalucia (Spain) subject to droughts, the Upper Secchia River (Italy) subject to water availability, and the Bucharest (Hungary) focusing on urban heat.

Figure 6 Locations of the I-CISK Living Labs.

Finally, we note that the examples presented in this section are at a preliminary stage and they will be completed/complemented in Deliverable 3.2 “Skill assessment and comparison of state-of-the-art methods for forecasts and projections of extremes”.

6.2 Assessing the seasonal hydro-meteorological prediction skill

6.2.1 Hydrological modelling

The Hydrological Predictions for the Environment (HYPE) is a semi-distributed process-based model capable of simulating the hydrological processes from a single basin to global scale. The model has conceptual routines for most of the major land surface and subsurface processes. The snow accumulation and melt processes are modelled using the degree-day method with land use dependent parameters. HYPE simulates the water flow paths in soil, which is divided into three layers with a fluctuating groundwater table. A fraction of rainfall or snowmelt infiltrates into the topsoil, which is limited by a soil type dependent maximum rate. If the soil moisture in the upper soil layer exceeds a threshold for macropore flow, part of the remaining water forms macropore flow. Potential evaporation (PET) is estimated using the modified Jensen-Haise model (Oudin et al., 2005), whilst PET is achieved only if either the actual soil moisture exceeds a large portion of the soil field capacity or the sub basin is defined as a waterbody. For soil moisture below this limit in non-waterbody areas, the actual evaporation, computed using the crop coefficient method in Allen et al. (1998), decreases linearly to zero at the wilting point. Runoff from the soil zone is computed when the soil moisture exceeds field capacity and it percolates from upper to lower soil layers when the soil moisture in the upper layers exceeds field capacity. The ground water level is estimated based on the level in the soil zone where the pore space is filled.

Here, we use two setups of the HYPE model; one at the continental scale covering the entire pan European region (Hundecha et al., 2016), and another at the world-wide scale covering the entire globe (Arheimer et al., 2021). The European model has a spatial resolution of about 35400 sub-basins, i.e. in average 215 km^2 and is referred to as E-HYPE v3.0. The global model has a spatial resolution of more than 130,000 sub-basins, i.e. in average about 1000 km^2, and is referred to as WWH. Both models run at a daily time step. In I-CISK, the Living Labs that lie in the European domain were investigated with the E-HYPE model, while those outside the European domain (Georgia and Lesotho) were investigated with the WWH model.

6.2.2 Evaluation framework

The skills of seasonal predictions were assessed by Continuous Rank Probability Score (CRPS; Hersbach, 2000) and Brier Score (BS; Brier, 1950) on both high (90th percentile) and low (10th percentile) streamflow extremes. The skills of these two scores (CRPSS and BSS respectively) were achieved by using simulated climatology as a benchmark. The skills of seasonal predictions on five E-HYPE output variables were conducted and analysed as a function of lead weeks and for each season. The hydro-meteorological variables considered here are: streamflow (COUT), temperature (CTMP), precipitation (CPRC), soil moisture (SRFF) and evapotranspiration (EVAP). Moreover, the seasonal prediction skills on streamflow extremes from both the E-HYPE and WWH hydrological models were further analysed using the BSS10 (low extreme; 10th percentile as a threshold) and BSS90 (high extreme; 90th percentile as a threshold) metrics for different lead weeks within the low and high streamflow periods (defined by the climatological terciles; low streamflow period during <33rd percentile, and high streamflow period during >66th percentile). To further extract the information at the local scale, we focus on each Living Lab and generate the skill scores accordingly.

For the Living Labs in the pan-European region (the Netherlands, Hungary, Italy, Spain and Greece), the E-HYPE model with meteorological forcing from both ECMWF SEAS5 and CMCC-SPS3.5 re-forecasts were analysed. For the Living Labs in Georgia and Lesotho, the WWH model forced with the ECMWF SEAS5 meteorological re-forecasts was used. In all cases the seasonal re-forecasts were bias-adjusted prior to be introduced in the hydrological models.

6.2.3 Assessment of seasonal hydro-meteorological predictability

Here we present the results of predictive skill for a number of hydro-meteorological variables at the living lab scale. The skills of seasonal predictions forced by ECMWF SEAS5 were aggregated for each season and assessed as a function of lead week (see Figure 7). In general, the skill deteriorates with increasing lead time, but the deterioration rate differs depending on the variable, season and Living Lab. In the Spanish LL (ES), the predictions showed high positive skill for streamflow especially in the spring and summer months (MAM and JJA). The skill started from over 0.8 right after model initialization and remained above 0.5 for a rather long lead time; 20 weeks in MAM and 10 weeks in JJA. It is also worthy noticing that in the winter months (DJF), the streamflow predictions actually remained skilful for the entire time horizon, with a CRPSS being over 0.2 at the furthest lead week. The predictions for the other variables also showed positive skill compared to the simulated climatology (benchmark), only with lower skill and faster deterioration speed compared to streamflow. Similar patterns were also revealed for the skill in the Greek LL (GR). In the LLs in Hungary (HU), Italy (IT) and the Netherlands (NL), the predictions for the five hydro-climatic variables had similar skill and deterioration speed. In general, higher skill was achieved in the first 4 lead weeks in these three LLs, ranging from 0.3 to 0.8 depending on the season and variable. In the LL in Georgia (GE) and Lesotho (LS), the predictions derived from the WWH hydrological model forced with the ECMWF SEAS5 seasonal predictions was assessed at a monthly scale. Overall, higher skill was found for the hydrological variables, including streamflow, soil moisture and evapotranspiration, while the skill for precipitation and temperature sometimes reached negative values, indicating no skill compared to climatology. This was also observed for temperature in the LLs in Georgia and Lesotho.

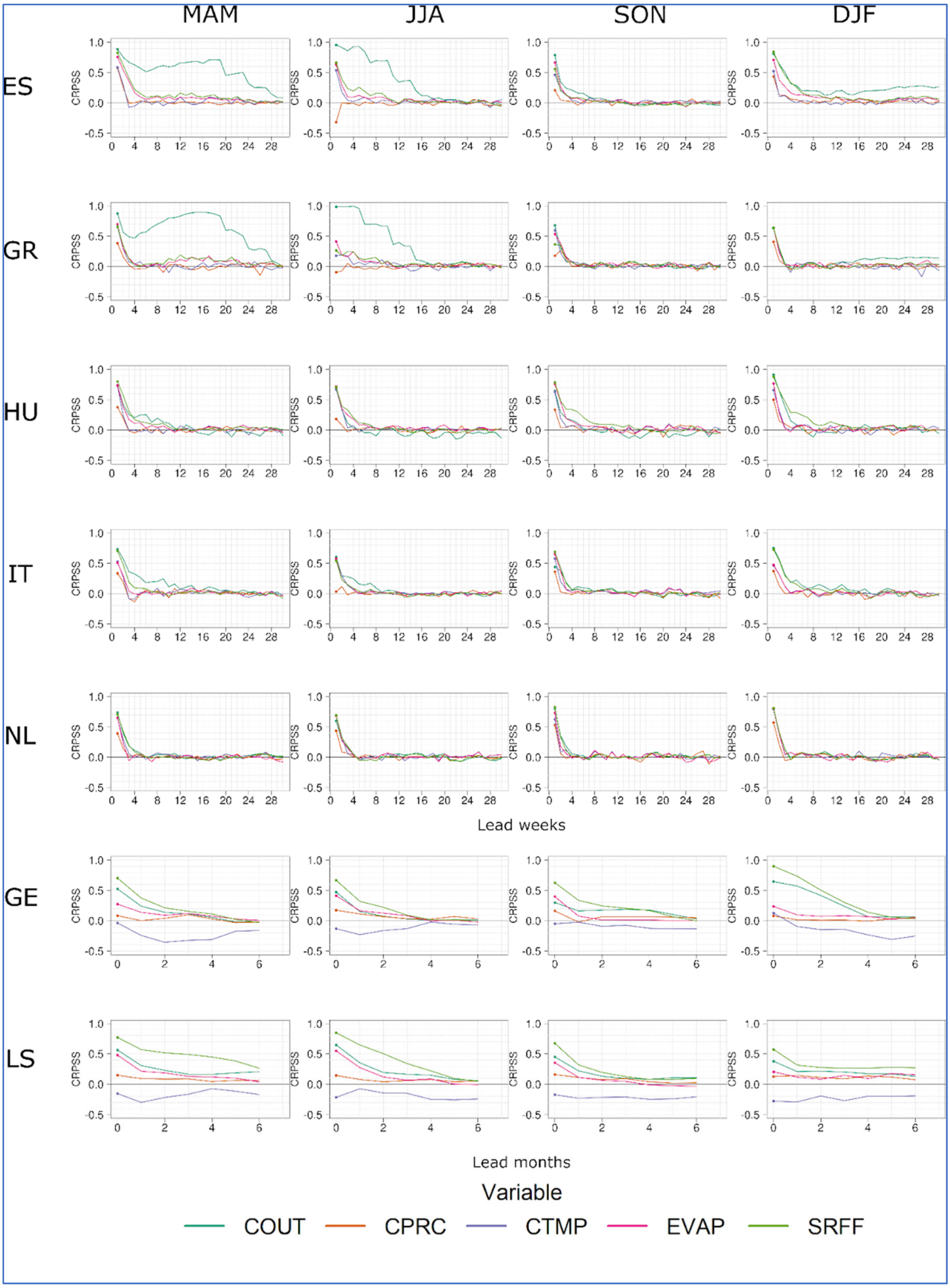

Figure 7 Seasonal prediction skill (in terms of CRPSS) for different hydro-meteorological variables downscaled to the scale of the Living Labs. The hydrological models are driven by the ECMWF SEAS5 predictions

The skills of seasonal hydro-meteorological predictions forced with CMCC-SPS3.5 were also aggregated and assessed similarly to those for ECMWF SEAS5 (see Figure 8). In general, the skill has similar patterns as the one for ECMWF SEAS5, with a deterioration pattern with increased lead weeks. Nevertheless, only small differences between the ECMWF SEAS5 and CMCC-SPS3.5 systems were observed by comparing Figures 5 and

6. For example, in the winter months (DJF) in the Hungary LL, the skill of all the hydro-meteorological variables from CMCC-SPS3.5 were slightly lower than the one for ECMWF SEAS5, especially for precipitation (CPRC), temperature (CTMP) and evapotranspiration (EVAP). Meanwhile in the LL in Italy, the skill from CMCC-SPS3.5 showed a slower deterioration speed during the first 2 lead week(s) than that from ECMWF SEAS5. Those results highlight the possibility of improving the seasonal prediction skill for different lead weeks by optimising (over even averaging/combining) the prediction systems for each LL.

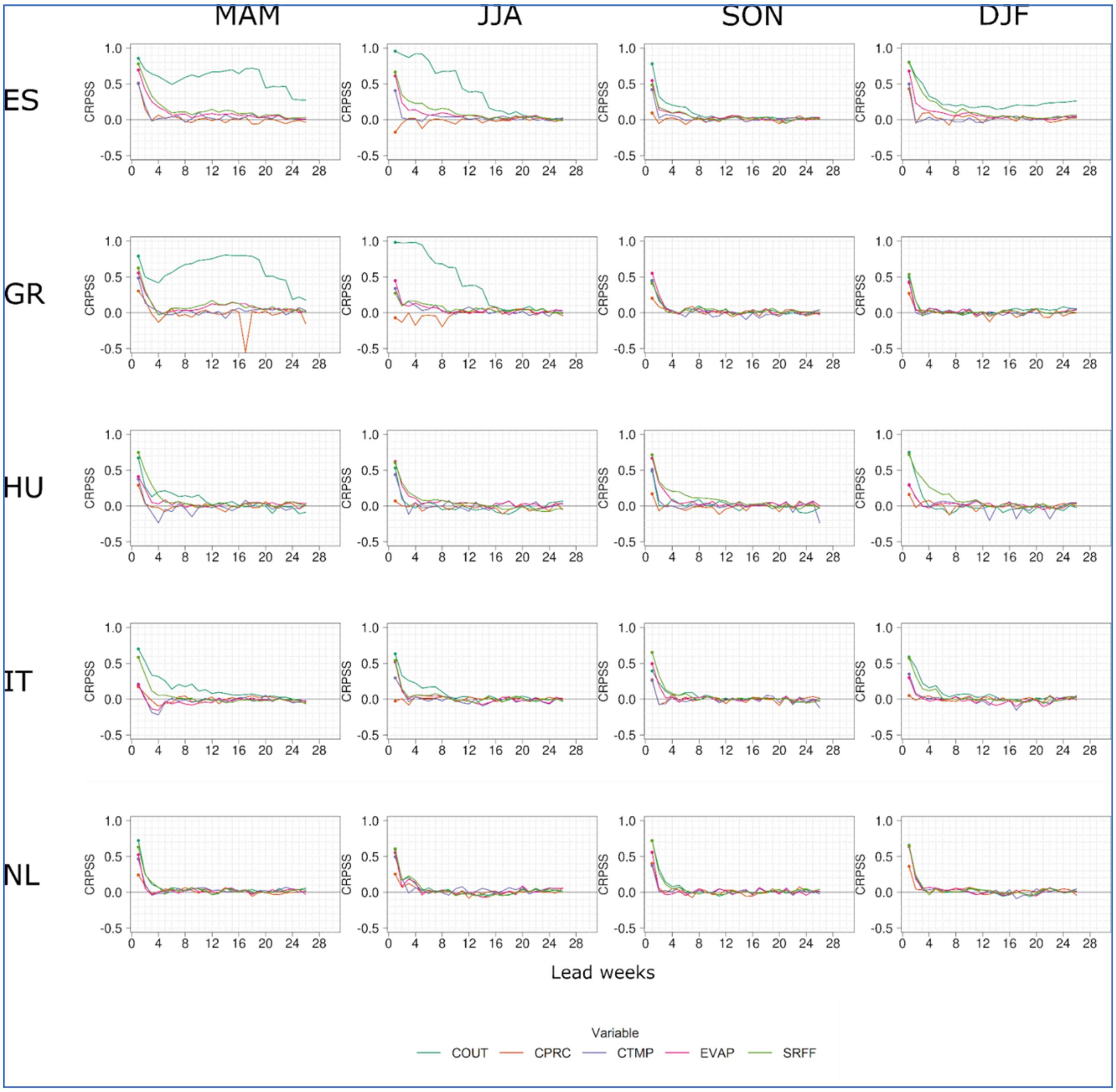

Figure 8 Seasonal prediction skill (in terms of CRPSS) for different hydro-meteorological variables downscaled to the scale of the Living Labs. The hydrological models are driven by the CMCC-SPS3.5 predictions.

6.2.4 Assessment of seasonal predictability of streamflow extremes

The scientific literature has recognised that both droughts and floods have increased in frequency and magnitude over Europe, posing immediate socio-economic threats, which creates a need for high-quality hydrological predictions on extremes. The prediction beyond the medium-range scale aids strategic planning for energy production, agriculture, and other activities that usually happen on a seasonal scale. Hence, assessing the quality of seasonal prediction of streamflow extremes is fundamental to I-CISK since it also sets the benchmark for the future work.

Here, we assess the predictions in terms of their skill for the hydrological extremes and at each LL. The Brier Skill Score (BSS; Brier, 1950) was calculated for each sub-basin in each LL, for each target week and lead time for both low (BSS10) and high (BSS90) streamflow extremes. Target weeks are defined as low-streamflow / high-streamflow weeks for each sub-basin based on the terciles derived from simulated climatology. The BSS for the target weeks is then pooled and analysed for different lead weeks. Results of seasonal predictions for streamflow extremes are shown in Figure 9. The skill of low/high streamflow extremes for the different LLs is overall high (greater than 0.6) for the medium-range future horizons (i.e. 1–2 weeks ahead) for both ECMWF SEAS5 and CMCC-SPS3.5. However, as expected the skill deteriorates as the lead weeks' increase. A faster deterioration rate is observed for the high streamflow extremes compared with the rate for the low streamflow extremes. This is especially obvious in the LL in Spain (ES) and Greece (GR), where the predictions of low streamflow extremes remain skilful (BSS > 0) until the furthest time horizon. Based on this investigation, further interpretations can be made by linking the skill of streamflow extremes to the hydrological regimes (see also Pechlivanidis et al., 2020). For example, in the LLs in Italy and the Netherlands, which are considered as river systems with small memory (streamflow being highly responsive to precipitation), a faster deterioration of prediction skill takes place for both high and low streamflow extremes. However, in the LLs in Spain and Greece, where the areas are with highly variable streamflow regimes and response is sometimes driven by snow melting besides precipitation, the predictions have a higher and longer skill for the low than the high streamflow extremes.

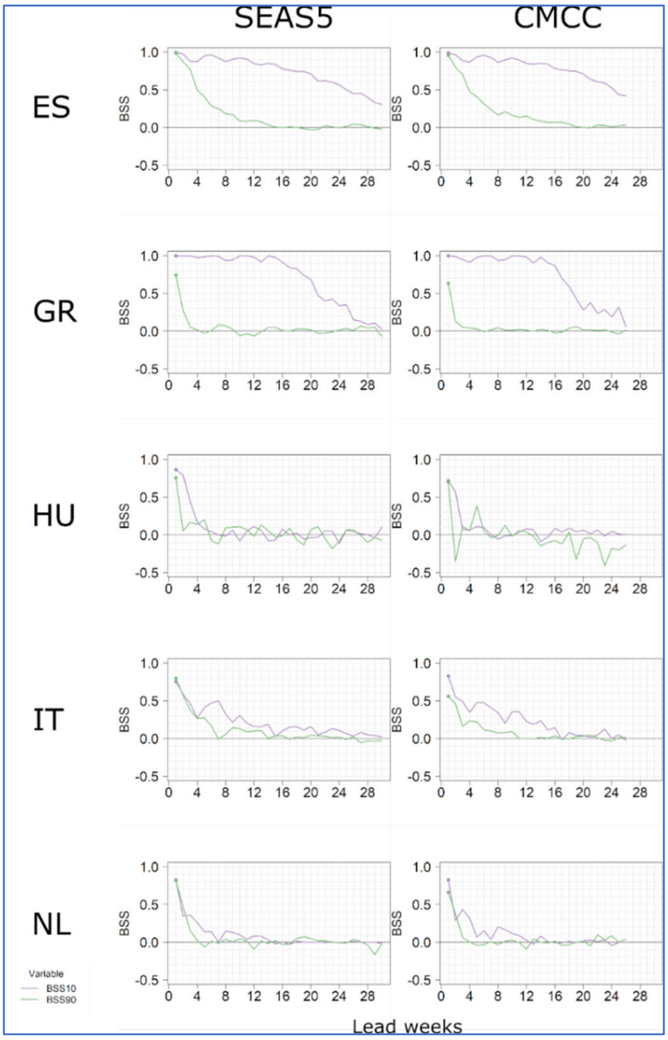

Figure 9 Seasonal prediction skill (in terms of BSS) for streamflow high (BSS90) and low (BSS10) extremes downscaled to the scale of the Living Labs.

6.3 Drought models in the Andalucía (Spain) Living Lab

6.3.1 Background and methodology

The main goal of the present experiment is to show how the integration of local data to the climate models can tackle some of the requirements (see section 3.5) of the users at the Spain LL; in this case the spatial resolution of the mentioned available CS is not with enough detail for their demanded CS. A second goal is the evaluation of the contribution of the remote sensing data to the explanation of the spatial pattern involved meteorological variables.

The core of the Andalucía (Spain) LL is the Los Pedroches region, located between the Guadalquivir and Guadiana River Basin Districts (RBD). A second subregion of interest includes the Sierra de Cazorla, Segura and Las Viñas Natural Park, in the Upper part of the Guadalquivir River basin. For the modelling purposes, the study is an extended region of this core one, the whole Guadalquivir rivers basin plus the Guadiana part of the Los Pedroches region (Figure10). This extended region allows to include enough statistical heterogeneity in the involved independent and dependent variables for explaining the spatial variability pattern of the climate studied variables.

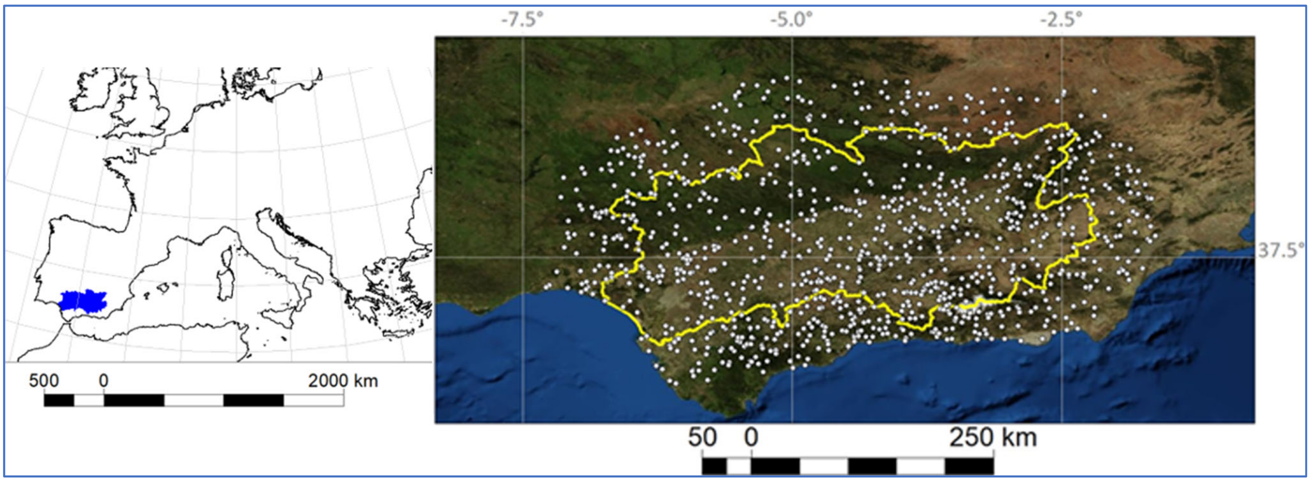

Figure 10 On the right, gauge precipitation stations (white point locations) used for the local models in the Andalucia Living Lab (yellow boundaries), on the left, map situation of this region (blue polygon).

Drought events are considered the main climate vulnerabilities in this region. In the initial part of the local assessment, we generate hindcasts of medium (250 m) spatial resolution of monthly drought indices (SPI and SPEI). The second step we generate downscaled short term climate projections. The downscaling is based on the knowledge of the finer resolution of the spatial patterns of climate variables involved, since the detailed pattern of historical data can be used into projections (Marchi et al. 2020).

In this preliminary report, we focus on the first step, the second step will be addressed in the final version of this deliverable (D3.2 - Skill assessment and comparison of state-of-the-art methods for forecasts and projections of extremes).

These drought indices are generated in an extended region, collecting measurements of monthly average temperature (T) and aggregated precipitation (P) that generate continuous digital models of T and P and the corresponding SPI and SPEI. Currently, the spatial resolution of existing available drought indices like 27 km (Copernicus JRC EDO https://edo.jrc.ec.europa.eu/), and 1.1 km (Drought monitor CSIC https://spei.csic.es/) are at a lower spatial resolution than the I-CISK drought products. The generation of medium resolution models implies the obtaining of the finer spatial variability pattern, this is a key process in order to downscale forecasts and climate projections.

Figure 11 shows the overview of the methodology of this first step: the model characterization of the spatial variability pattern at medium resolution. This methodology is based on Ninyerola et al., 2007; the novelty is the contribution of remote sensing products following Mira et al., 2017. Basically, the method is composed by two parts:

- multiple regression: different variables (elevation, aspect, distance to coast, vegetation indices…) explain the highest possible part of the variability (Peres et al., 2020; Terzago et al., 2018)
- spatial interpolation of the residuals from multiple regression

The output of the model is tested and evaluated with the output quality layers and global uncertainty indicators (Pesquer et al., 2014).

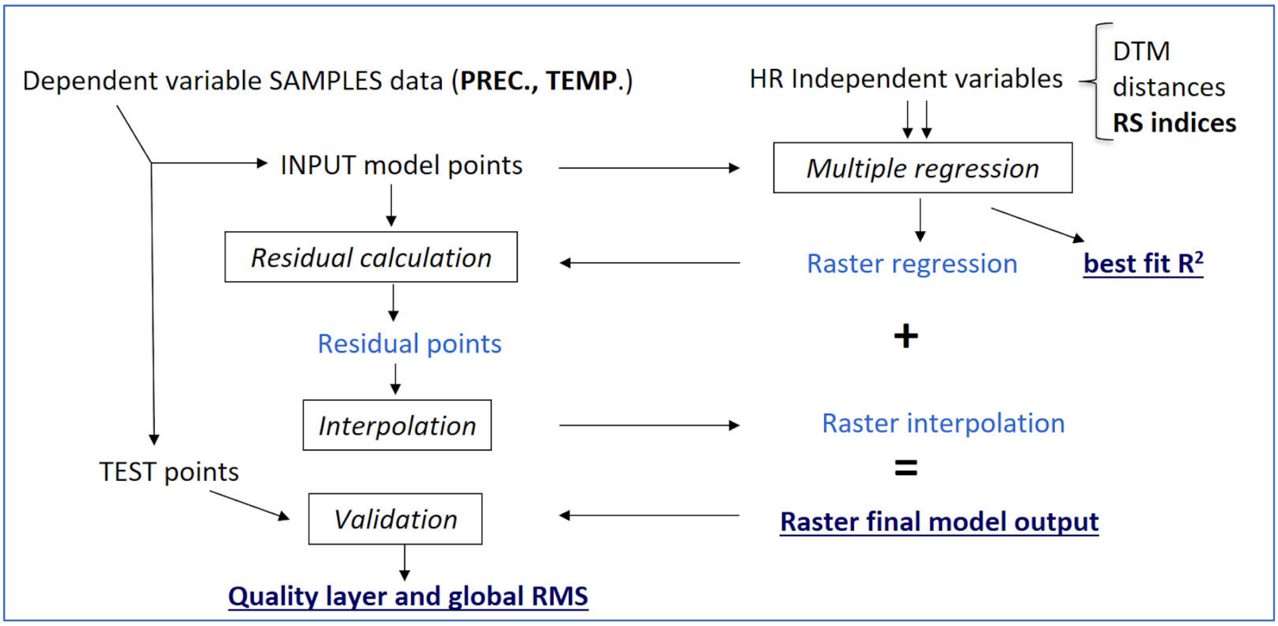

Figure 11 Flowchart for the generation of the finer spatial variability pattern method.

6.3.2 Precipitation

For the model characterization of the spatial variability pattern of the extended region of the LL, two different times series are analysed:

- large: aggregated monthly precipitation (10^{-1} mm) in the 1950-2019 period. Climate averages of remote sensing products are included.
- short-RS: aggregated monthly precipitation (10^{-1} mm) in the 2000-2019 period. The time series of remote sensing data, available in the same period, are included.

The high-resolution variables used in the regression model part are: squared distance to Mediterranean Sea, squared distance to Atlantic Ocean, elevation, cosinus of aspect and two remote sensing indices: Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI). We tested NDVI and NDWI, with the same month of analysis of precipitation or with one, two or three months of offset.

The NDVI used is a synthesised version from MOD13Q1 MODIS 16-day composite product. We generated aggregated monthly products and we replaced the NDVI values in the locations of gauge stations where the land cover (Copernicus Corine Land Cover) is an impervious surface by the neighbouring vegetation NDVI values. Figure 12 shows the improvement of the correlation between NDVI and precipitation with the synthesised product.

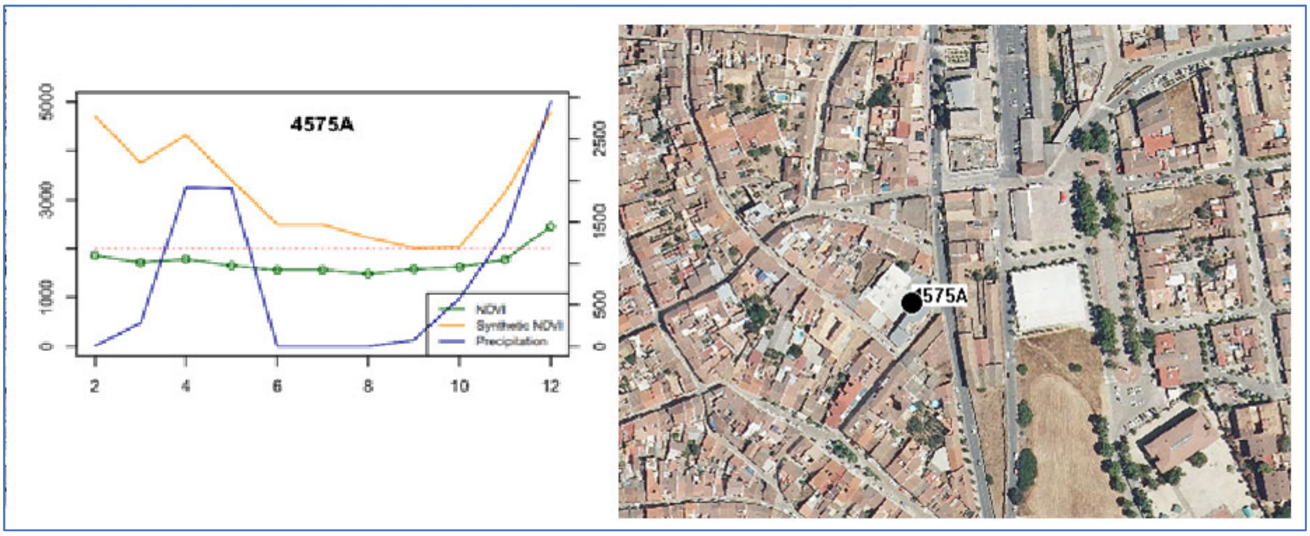

Figure 12 The yellow line of synthetic NDVI shows a more coherent response of vegetation to the annual precipitation pattern (line blue) than the original NDVI (in green). This modified (synthetic) product is needed in meteorological stations located in urban areas.

A similar method for replacing original values in non-vegetated regions is used with NDWI. In this case, the improvement of the modified version is not clear. Table 2 shows compared results for all months of the selected year (2000), with both vegetation indexes, and the correlation with the same month of precipitation and the next one, next two or next three months (indicator of the vegetation response to the precipitation). The best correlation remote sensing product is highlighted with a green cell, light brown in case there are two exactly equal values. These preliminary results show that NDVI is a better predictor than NDWI and the modified version improves some results but not all of them, so we should refine this synthetic product. There is no clear pattern of which is the time offset of the response between precipitation and NDVI, month +1 seems to be the main offset.

Table 5 Compared contributions of vegetation indices in the regression modelling of precipitation. 'out' means that the product is rejected by the model because its contribution is not significant. Green colour is the best one for a month, light brown means that there is not a clear result, tied results.

		NDVI	NDVI mod.	NDWI	NDWI mod.			NDVI	NDVI mod.	NDWI	NDWI mod.
Year 2000		r^2	r^2	r^2	r^2	Year 2000		r^2	r^2	r^2	r^2
January	month +3	0.200	0.194	0.190	0.187	July	month +3	0.096	0.099	0.089	0.088
	month +2	0.190	0.187	0.194	0.193		month +2	0.110	0.109	0.088	out
	month +1	0.206	0.204	0.195	0.195		month +1	0.104	0.103	0.089	0.089
	-	0.169	0.168				-	0.086	0.086		
February	month +3	out	0.474	out	out	August	month +3	0.132	0.125	out	out
	month +2	out	0.474	0.476	0.475		month +2	0.149	0.137	oyt	out
	month +1	0.475	0.474	0.486	0.480		month +1	0.124	0.126	out	out
	-	0.472	0.472				-	0.124	0.124		
March	month +3	0.370	0.368	0.345	0.345	September	month +3	out	0.224	out	out
	month +2	0.342	0.348	out	out		month +2	0.236	0.223	out	out
	month +1	0.353	0.352	out	out		month +1	0.254	0.249	out	out
	-	0.339	0.341				-	0.223	0.222		
April	month +3	0.411	0.443	0.378	0.379	October	month +3	0.430	0.431	out	out
	month +2	0.432	0.459	0.395	0.401		month +2	0.427	0.434	0.431	0.430
	month +1	0.426	0.459	0.412	0.412		month +1	0.436	0.448	out	out
	-	0.362	0.363				-	0.425	0.426		
May	month +3	0.189	0.193	0.180	0.179	November	month +3	0.300	0.305	out	out
	month +2	0.188	0.193	0.175	0.176		month +2	0.300	0.311	0.295	0.293
	month +1	0.206	0.209	0.198	0.203		month +1	0.305	0.323	0.301	0.306
	-	0.163	0.164				-	0.286	0.286		
June	month +3	out	0.157	out	out	December	month +3	0.517	0.520	out	out
	month +2	out	0.157	out	out		month +2	0.510	0.508	0.487	0.486
	month +1	out	0.157	out	out		month +1	0.509	0.520	0.504	0.498
	-	0.157	0.157				-	0.485	0.485		

6.3.3 Temperature

At this preliminary stage, we collect and filter time series of monthly mean temperature from different databases: local and global. The proposed set of input variables in the regression part is similar to the precipitation. The main difference is in the remote sensing contribution: we will introduce in the model regression land surface temperature (LST) from MODIS and/or ASTER instead of NDVI/NDWI that we used in the precipitation model.

6.3.4 Drought indices

We generate SPI and add SPEI drought indices using the previous mentioned variables. The SPI is calculated from the anomalies of precipitation times series, thus, the generation of finer spatial resolution of precipitation models directly implies finer drought indices maps. SPEI is calculated from precipitation and potential evapotranspiration (PET) that uses temperature (still under development in this preliminary DL) as input variable (Vicente-Serrano et al., 2010). Figure 13 shows a comparison example in April 2000. In this example, SPI distribution shows some differences in the levels of drought severity because the source databases are different, but the more relevant difference is the spatial resolution, where the finer spatial resolution of precipitation and temperature times series allows to obtain the finer SPI drought maps by I-CISK (3 months' time scale).

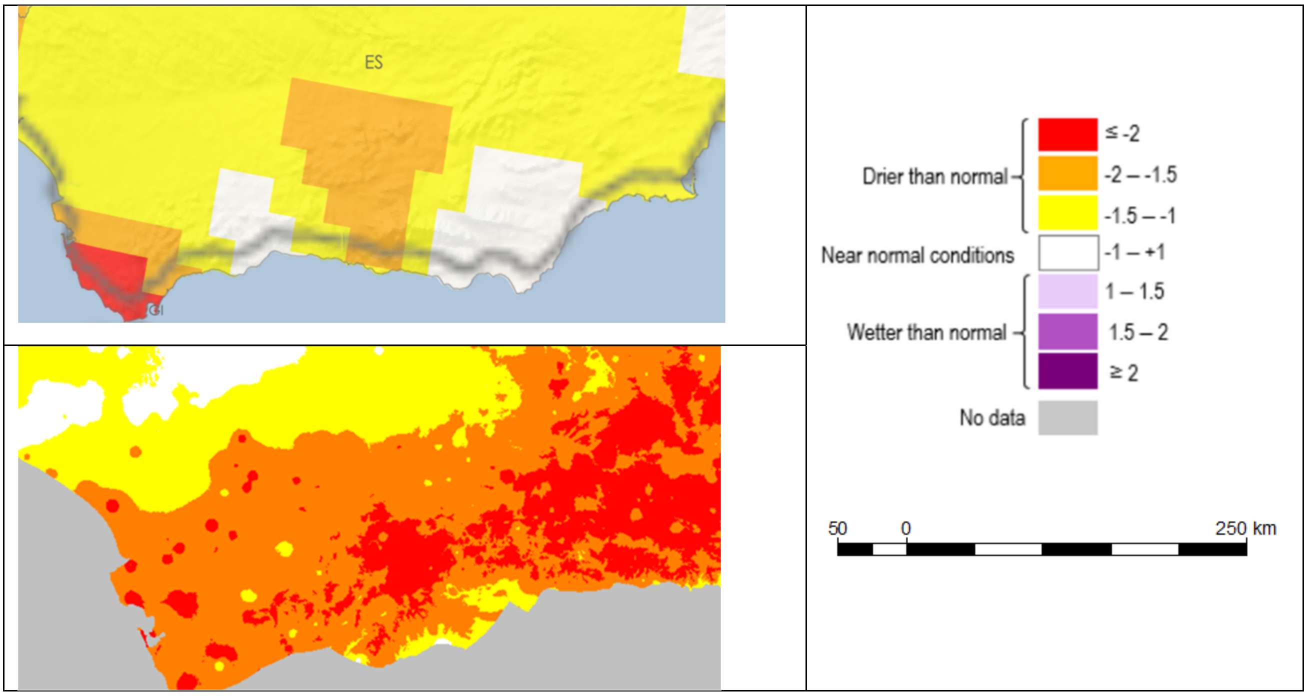

Figure 13 SPI at coarse (0.25 deg.) spatial resolution by EDO (upper figure). On bottom, SPI at finer resolution (250m) by I-CISK (lower figure).

6.4 Upper Secchia River (Italy) Living Lab

The Italian LL explores water availability in the upper catchment of Secchia River, in the provinces of Modena and Reggio Emilia (Emilia Romagna Region, Figure 14).

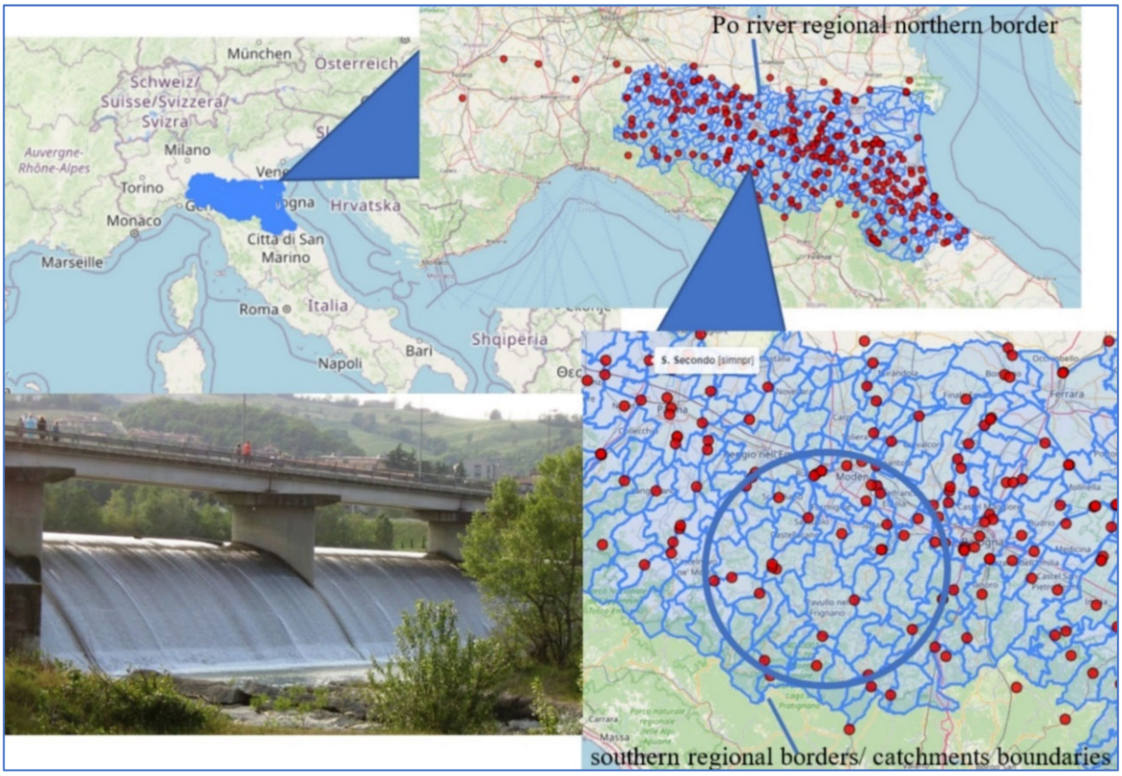

Figure 14 Location of the study area in RER- Italy, south of the Po River, in the upper provinces of Reggio Emilia and Modena (administrative boundaries and dots representing river stage monitoring stations from Regional Env. Agency networks) and the weir at the upper catchment closure of Secchia River.

The catchment outlet is at the *Castellarano* weir, where most of the involved stakeholders have tangible interests and derive water for various usages. Here water scarcity is a serious hazard, as the extremely dry season of 2022 has shown, resulting in one of the most severe droughts ever in this region.

We have co-identified with them the need to design a Climate Service for water resources forecast with focus, at this stage, on medium-range forecasts. The local assessment has initially identified the available sources of information including:

- The ground truth: daily data of river discharge recorded at one-gauging station immediately upstream of the catchment closure, from regional monitoring network (Figure 14)

- The local and upstream data we can use to drive forecast (Hydro-meteorological data, coarse resolution forecasts from upstream climate services as Copernicus CDS, local higher resolution forecasts from regional providers, particularly from the Regional Environmental Agency ARPAE, Figure 15 and 16)

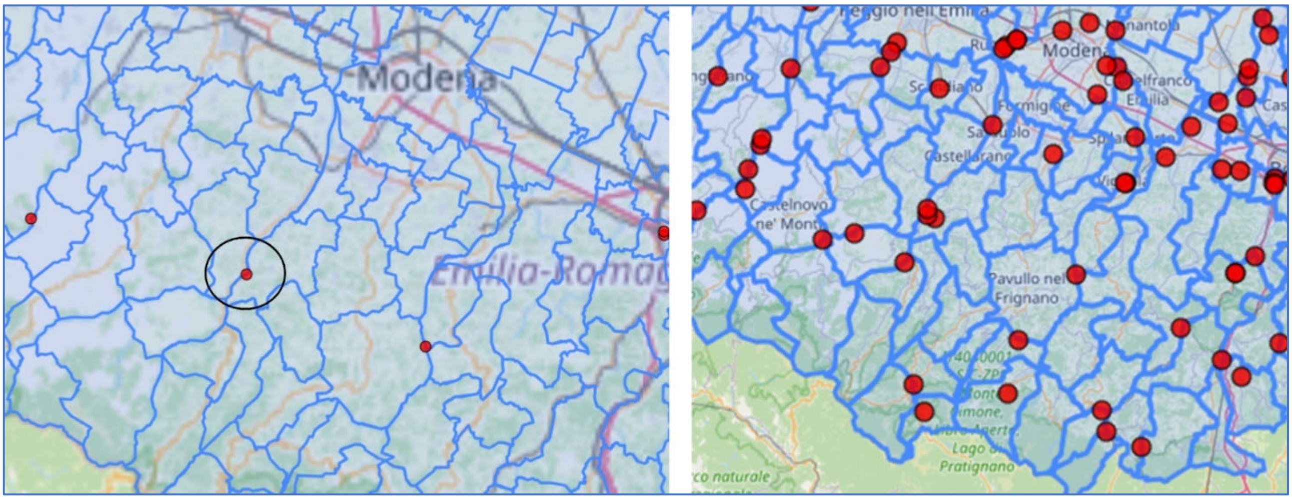

Figure 15 Example of local data collected with the help of the users: discharge station (upper left) and meteorological stations (upper right).

Identifying and collecting these heterogeneous sources of knowledge, and preparing a dataset with values up to the past 10 years (depending on data availability, particularly for forecasts) closes the first part of the analysis done in the Lab.

The following activities, that so far have been preliminary identified, include the extraction of time series of input data over the catchment, identification of data driven forecast algorithms (with preference for ML) to convert data into discharge forecasts, and to tune with collected data. At the end of the workflow is the operationalization of the Climate Service, periodically retrieving data, running forecasts and providing access to the service, likely through a Web based interface that shows results and error metrics as well.

6.4.1 Methodology

The collected input knowledge includes geospatial data in grib/netcdf format from local weather forecast services of upstream climatic services (multitemporal input variables as precipitation and temperature) that describe actual state of the catchment and give forecast of variables (likely) related to discharge generation (Figure 16). In the first phase, as stated previously the collection of available input data from heterogeneous sources sets the ground for subsequent activities that ranges for data management

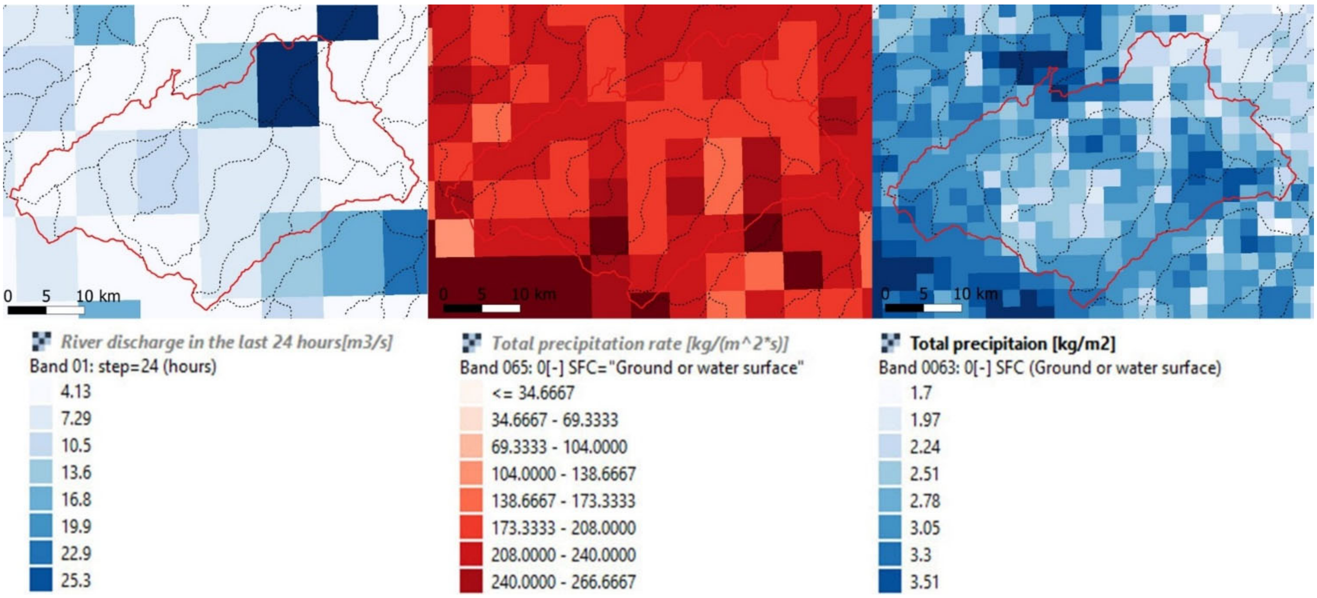

Figure 16 Example of collected forecast and status maps (multiband raster) from left to right, Copernicus CDS daily river discharge forecast @ 10 km spatial resolution, local ARPAE daily precipitation maps @ 5 km resolution and forecasted COSMO 2 precipitation maps @2 km resolution (also provided by ARPAE), with overlay of river catchment upstream of the Castellarano weir and the river network.

By means of devoted tools to be developed this multiband raster shall be averaged over the catchment area to extract a single "input signal" for each variable, stored in a simple database (e.g. .csv format) together with other inputs (e.g. ground station meteorological data) and target output variables (e.g. time series of recorded discharge). This operation includes gap filling to add missing values in the database. For the envisaged workflow dealing with different spatial resolution is not a big issue as the lumped information over the catchment is the variable to seek. This database shall be passed to selected ML algorithms to be tuned to retrieve desired forecast, and results shall be stored in the same database as before.

6.4.2 Results

The first part of the workflow has resulted with identification of local and upstream knowledge and sketch of the workflow for the following activities. Despite being early at the development stage, we have identified target achievements and indicators of performance, basing on user expectations and previous experiences from past H2020 projects and literature publications (Essenfelder et al., 2020; De Gregorio et al., 2018) to be refined along the development of the CS.

Concerning forecast skills practical applications of discharge forecast mainly relies on established error metrics indicators both of forecast accuracy (such a % Root Mean Square Error, with expected target around 30 to 50% in the ranges of discharge of major interest for practical applications) and predictive power (Nash Sutcliffe Index and correlation coefficient of the predicted Vs recorded time series well above 0.5). Skills shall be evaluated separating the dataset in (past) values used for tuning forecast algorithms, and most recently (10 to 20%) just for deriving error metrics.

Further reflections have been done also on ways to display the produced knowledge, with an early mock-up of the possible GUI and its main functions (Figures 17 and 18).

Figure 17 Sketch of a possible service GUI. A: Input features (e.g. rainfall and temperature, ground stations or averaged, recorded discharge, meteorological forecast); B: discharge forecast for lead times of interest; C: Time series of variables of interest; D: Lumped error metrics for the selected period; E: Configuration options; F: error graphs and graphic indicators of forecast performances (see also next figure).

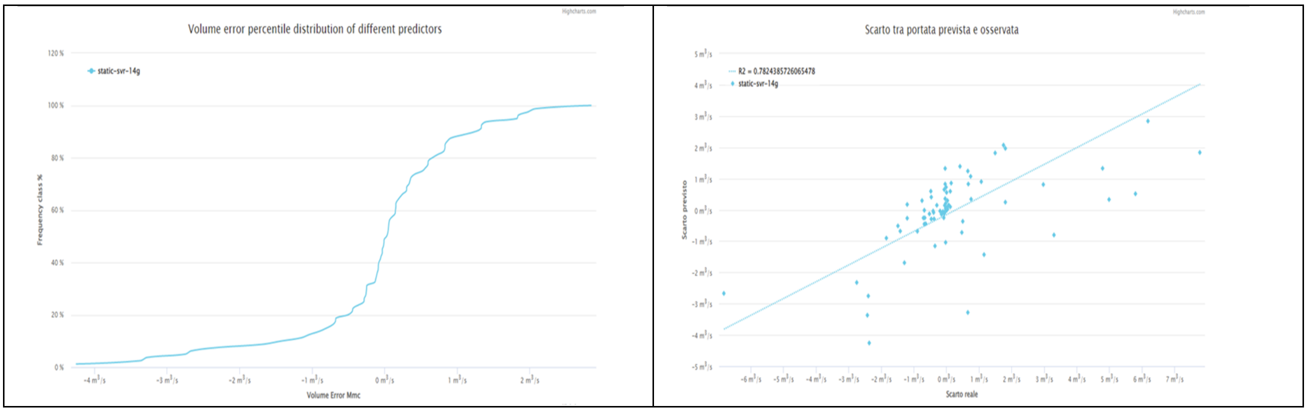

Figure 18 Example of performances graphs (on the left correlation among observed versus predicted residuals, on the right error frequency distribution).

The table below (Table 6) identifies the local data contribution at the end of the first stage of the analysis.

Table 6 Collected local data at the end of first stage of analysis.

Type of data	Format	Location	Time start	Time end	Time step	Source	Resolution
River discharge	csv	station		2021	daily	ARPAE	
Precipitation	grib	catchment	2001		hourly/daily	ARPAE	5 km
Max temperature	grib	catchment	2001		hourly/daily	ARPAE	5 km
Min temperature	grib	catchment	2001		hourly/daily	ARPAE	5 km
Evapotranspiration	grib	catchment	2001		hourly/daily	ARPAE	5 km
Relative humidity	grib	catchment	2001		hourly/daily	ARPAE	5 km
Wind speed	grib	catchment	2001		hourly/daily	ARPAE	5 km
Solar radiation	grib	catchment	2001		hourly/daily	ARPAE	5 km
Soil map	shp	catchment	2001	2001		JRC	1:1000 1 km

Land use class map	shp	catchment	2017	2017		RER	1:10000
Digital elevation model	geotif	catchment	2015	2015		RER	5m
Short term forecast P/T COSMO	grib	catchment	2001		72 hours	RER	5 km

6.5 Budapest Living Lab

The main goal of the Budapest experiment is to show another potential CS in which the spatial resolution of existing CS is far from the user demands. This LL in an urban environment is a complex system where the local data is absolutely needed. In this case, the citizen contribution is very relevant and also the remote sensing products can improve the skill assessment of I-CISK predictions.

6.5.1 Background

In the Living Lab located in Erzsébetváros (Elizabeth district), we initiated a participatory research process to be able to understand the urban heat island phenomenon more fully in the district and to capture the perceptions of citizens on the heat stress they have to endure during heat waves. For this, we've encouraged all citizens to participate in the research process.

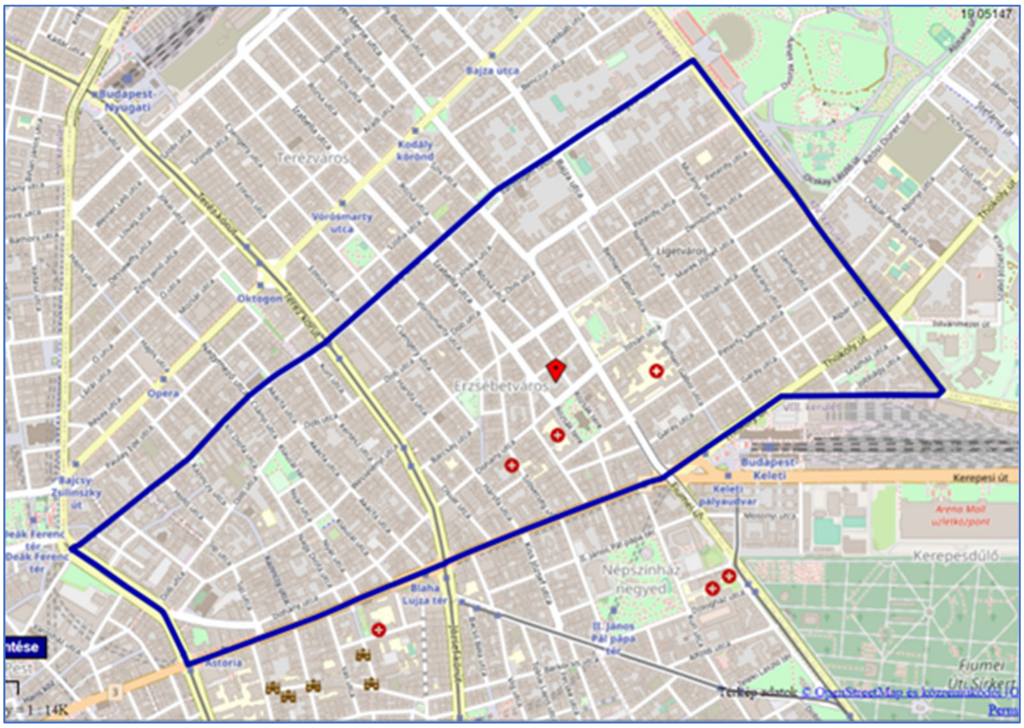

Figure 19 Map of the Elizabeth district.

Urban residents of the Elizabeth district may be exposed to higher heat loads during heat waves than the population of peri-urban districts in general, due to the urban heat island (UHI) phenomenon, which causes higher temperatures over this inner-city area than over the surrounding rural areas. This problem will be exacerbated in the future by global climate change and urban population growth.

Heat domes can relocate and affect nearby locations within a week or two. Because of the weak breezes and increased humidity typically caused by the stationary weather pattern of heat domes, these effects can be extremely harmful to people. The inability of the human body to cool itself heat impacts dome even harsher and more damaging.

In the city, UHI can be interpreted at three levels: meso, local and micro. The present study is primarily concerned with understanding the climatic processes at the local and micro scales, and with identifying hot and cold spots and heat traps. To facilitate the adoption of mitigation plans and to quantify the impacts of urban heat islands, it may be important to project current and future land surface temperatures (LST) and identify distribution patterns.

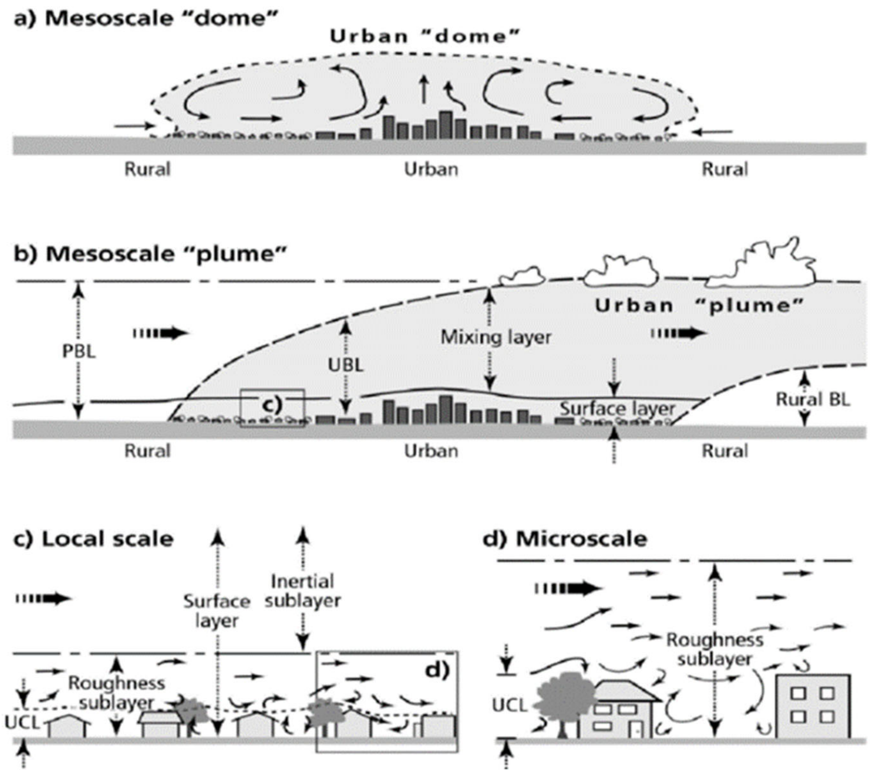

Figure 20 Schematic of the relative horizontal scales and vertical layers typical of urban areas: (a) Meso-scale dome, (b) Meso-scale plume, (c) Local-scale, and (d) Micro-scale.

The results of our study are expected to have implications for heat and climate change planning strategies for the Elizabeth District. Innovative interventions to mitigate urban heat could be developed that are fully adaptive and collaborative. Mitigation strategies will need to be considered in light of these findings.

6.5.2 Calculation of high resolution LST for urban heat island mapping

The Land Surface Temperature is the skin temperature of ground. From a climate perspective, the accurate understanding of LST helps to evaluate land surface–atmosphere exchange processes and surface energy budgets in models. Moreover, when combined with other properties such as albedo, vegetation and soil moisture, LST provides a valuable metric of the surface state. LST is defined by GCOS as an essential climate variable (ECV).

The calculation of land surface temperatures (LST) from satellite images is essential for many fine-scale applications (Zhou et al. 2019). It is also used in a wide variety of applications such as monitoring of global climate change, studies of different kinds of surfaces. However, the accuracy of the calculation is often limited by different environmental and geographical conditions. We perform a computational form of LSTs using data from multiple sources. We use a number of sources to obtain our data, including ground measurements, UAV remote sensing and satellite readings. However, high resolution LST has been a challenging subject for researchers for quite some time because several sources (missing pixels etc.) can cause uncertainties in the calculation. Land surface temperature is a key variable when quantifying the impacts of urban heat islands.

6.5.3 Satellite LST

LST derived from satellite thermal infrared bands. Satellite-based sensors are unable to record ST with both a high spatial and temporal resolution. The LST data is affected by the incoming solar radiation, which affects the surface temperature. The temperature can also change over the course of a day because of the wind and due to an inversion effect. Furthermore, the LST variation is greatly affected by land cover and temperature inversion, two of which can affect the LST data greatly.

6.5.4 Low-altitude thermal infrared remote (TIR) sensing data (UASs)

LST measurements from small UAS will be utilized in combination with thermal imaging technology and parallel image processing algorithms to improve and expand on existing methods for urban heat island studies.

Small Unmanned Aerial Systems (UASs) and the miniaturization of thermal camera technology have enabled higher resolution airborne thermal mapping. More broadly, the concept also explored the potential for recalibrating design strategies to prevent urban heat island effect to maximize impact.

6.5.5 CNN network for producing high resolution LST

We will develop a CNN (convolutional neural network) that will process the satellite and UAS baseline imagery, which will produce a high resolution LST map of the district. If this CNN network is large enough, it can detect different structures, and the AI decides what the absorption may be based on image segments rather than pixels.

This CNN network can be run as a software module and thus can be used later, even in other neighbourhoods, and will be able to predict the LST of a given neighbourhood with a high enough degree of confidence.

- Pre-processing phase: production of the basic satellite and UAS LST images (upgrading of satellite images, production of LST images from thermal camera drone images) for training and validation.
- Training phase: (see Figure 20): use drone measurement LST images, satellite photos and LST images to teach CNN. Drone measurements are only available for a few days; however, satellite image capture is frequent.
- Processing phase: Using newly acquired satellite image, high resolution LST can be determined. Street measurements can be used to check the validity. Furthermore, using image fusion techniques, map visualizations can be produced according to the needs of the local population. Image fusion is a complex process involving images with different resolutions and different radiometric features. However, there are different algorithms that can be used to fuse these images into a single product. Machine learning methods represent a promising solution for image fusion.
- Re-training phase: if new UAS data are available, system re-training is capable to generate corrected high resolution LST

During the street survey (see next section), measurements are taken of heat radiating in different directions. We measure at selected locations how much of the heat radiated in different directions is the same as the heat radiated upwards (thermal radiation anisotropy).

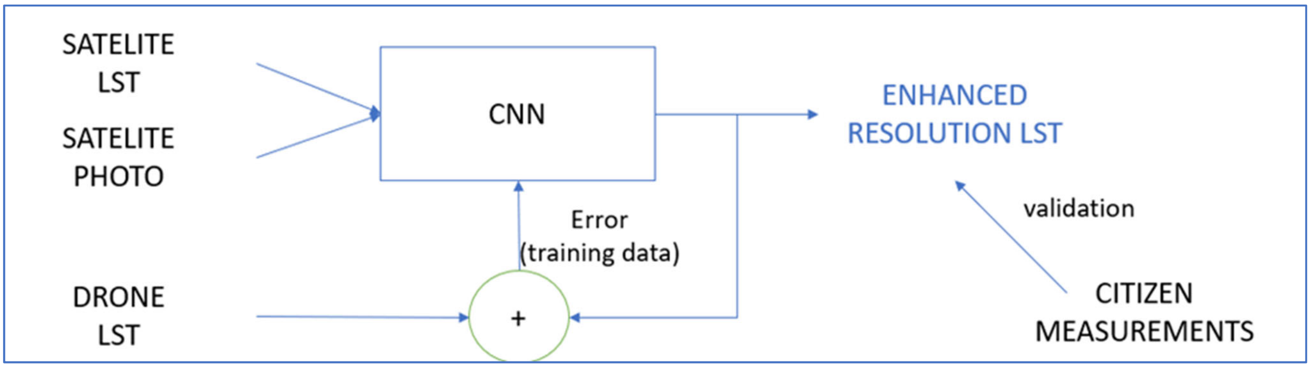

Figure 21 CNN network for high resolution LST.

6.5.6 Citizen Measurement: Urban Heat Island and Thermal Comfort Assessment

We are launching a citizen-sensing campaign that will measure several components of urban heat waves and urban heat islands (air temperature, humidity, dust, and thermal heat pictures) in the district.

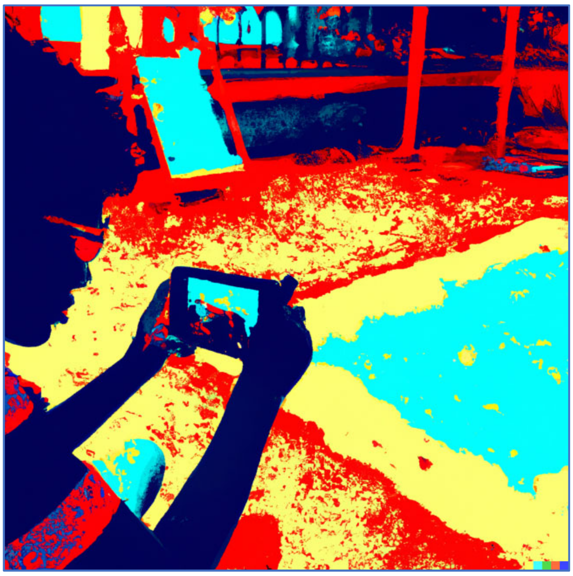

Figure 22 Impression of local resident taking a measurement with a device that was developed to understand urban heat islands and heat waves. Citizens can contribute to well-suited adaptation methods and better policy measures. The project will empower residents to measure their own thermal exposure and understand the thermal conditions in their living environment. Colours in the image indicate heat, with redder colours indicating higher surface temperature.

Specifically, we are looking at how heat is distributed on city streets throughout the whole of Elizabeth District. Our methodology is to conduct visual field surveys using a thermal imaging camera (FLIR). We carry out a series of street-scale surveys with volunteers in the Elizabeth district. They are using thermal imaging cameras to take street-level temperature measurements. They are comparing the thermal characteristics of different physical elements in the city streets and trying to find out how heat is generated in the city. This type of research is useful for understanding the thermal environment in the district, which affects the health and well-being of city dwellers.

Thermal imaging is a technique that allows residents to "see" how hot (or cold) things are by measuring the infrared radiation emitted by objects, different physical elements of urban streets (pavements, walls, grids, manhole covers, etc.). The resulting data can reveal details that are not visible to the naked eye. Thermal mapping can help designers identify areas that need sidewalks, shading or shade trees.

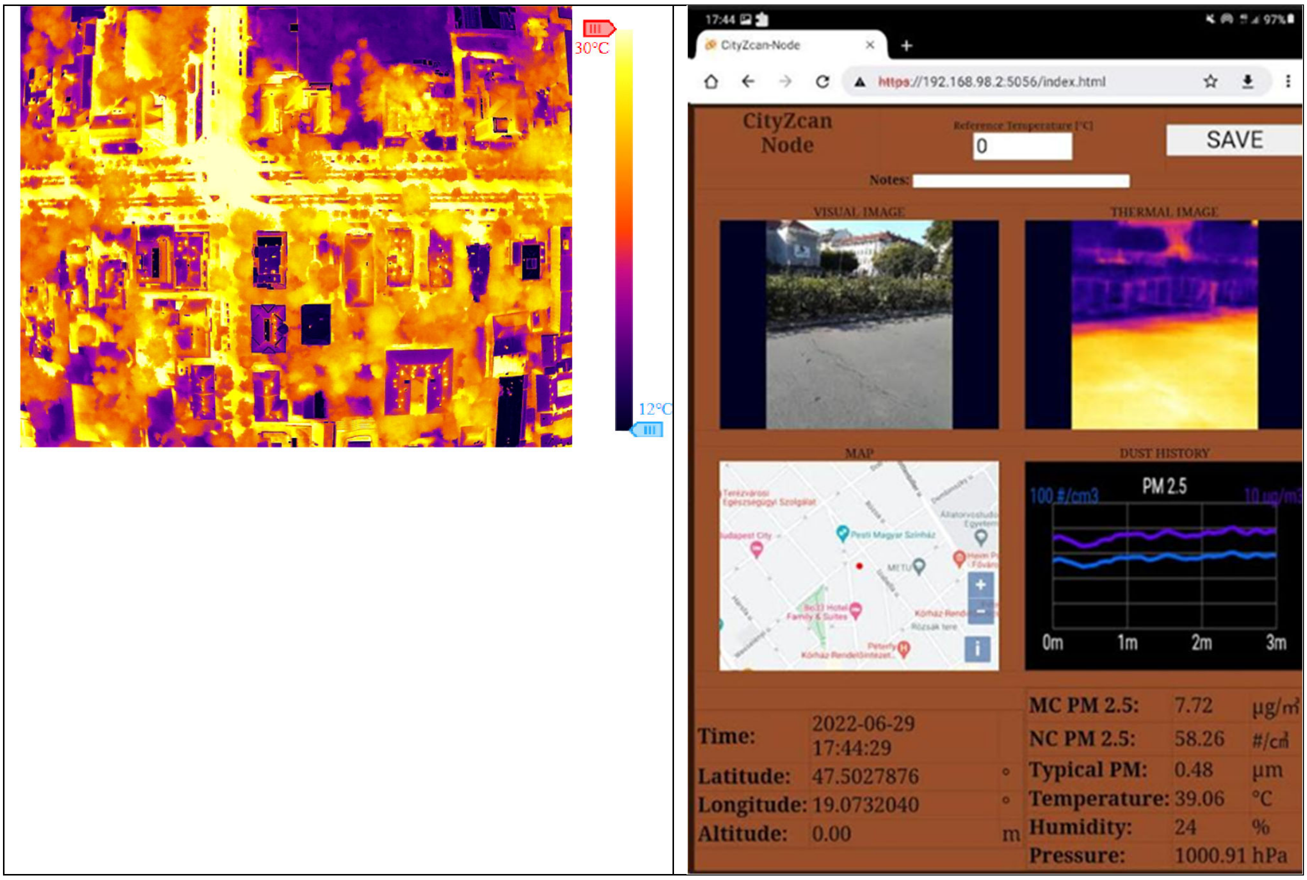

Figure 23 Thermal image of city blocks recorded in Budapest on 7/1/22 (left image). CitiZcan sensor box user interface (citizcan.com) (right image).

7 Conclusions and future work

7.1 Conclusions

In recent years, climate services have (increasingly) received attention by the scientific, development and decision-making communities, since the data and information provided can support adaptation, mitigation and disaster risk management. The (co-)generated products of such services cover different time horizons from historical to present and to future, including observations, forecasts, predictions and projections. Despite recent efforts for co-creating climate services, climate services development procedures have not put users at the centre, which has limited the potential for integrating local data and knowledge that add value to local decision-making and actions. The I-CISK project is putting effort on the co-creation of human-centred climate services, and the scientific work conducted in the project aims to explore fit-for-purpose methodologies, tailored to address local needs. This document is setting the scene to the available state-of-the-art Climate Services and presents those CS that address the needs of the water- and climate-related sectors. This summary of the state-of-the-art Climate Services for the European and global domains is key for the I-CISK project that aims to add value to the products of these services from both a scientific and user perspective.

The analysis presented in this report benchmarks the seasonal predictive skill for each of the seven living labs and explores their local data availability. We note that this report is a preliminary, with more complete results and insights planned to be presented in Deliverable 3.2. The scientific work presented in this report is conducted at two spatial scales: the European-wide scale and the local scale of the living labs. The European analysis is aiming to acknowledge the biases in the raw predictions from two different seasonal climate models (ECMWF SEAS5 and CMCC-SPS3.5) and to further highlight the need for post-processing (bias-adjustment) in order to reduce the biases and generate a product that can be used for local impact assessments.

We conclude that these biases are not similar in terms of magnitude while as expected the spatial variability of biases differs depending on the seasonal climate model used. However, even when a bias-adjustment post-processing method is applied, remaining biases still exist, with their magnitude depending on the variable of interest. In particular, we conclude that remaining biases are more apparent for precipitation than for temperature, where remaining biases almost reach zero.

Despite the remaining biases in the meteorological forcing, analysis of seasonal hydro-meteorological predictability at the living lab scale shows skill for the first lead times (up to 2 months ahead). As expected, different variables show different level of skill, i.e. precipitation is less skilful than soil moisture or streamflow, and this conclusion holds for predictions with both seasonal climate models. Moreover, depending on the hydro-climatic properties of the living lab, the hydro-meteorological variables showed different prediction skill. Additional to the predictive skill across the full distribution of flows, the analysis also focuses on the high and low streamflow extremes. Results show that in general low streamflow extremes (droughts) have higher predictability than high streamflow extremes (floods). This conclusion is well linked to previous findings indicating that the river memory is a key factor controlling the seasonal hydrological predictability.

Three case studies are developed from a selection of representative climate vulnerabilities in three I-CISK LL. The selected vulnerabilities: drought, water availability and heat urban islands are identified as the main demands of the stakeholders in these LL, but the variables, time scales, spatial resolution and other properties are going to fit to the user demands in the I-CISK next stages. The three presented studies show the relevant role of local data and knowledge for understanding the local spatial patterns of the variability of the variables involved (monthly precipitation, land surface temperature, river discharge, etc…). The knowledge of these patterns is going to be used for the improvement the corresponding forecasts, predictions and projections in the next steps of the LL modelling studies and the next-generation of CS.

7.2 Moving forward with the Living Labs

Prior to defining the steps for future work, we communicate some of the conceptual pillars that are driving the scientific steps.

- The currently ongoing I-CISK research is conducted in close collaboration with the LL stakeholders within the co-creation process.
- We strongly argue that I-CISK climate services need the integration of local data and knowledge to improving the both the relevance and the quality of the forecasts, predictions and projections at the requested time horizons (future periods and aggregation windows) and spatial resolution.
- The co-created I-CISK climate services are expected to communicate accurately and effectively the uncertainty (e.g. through maps and/or graphs) in the local impact indicators in order to better inform the decision-makers.

The planned future work will be developed in two main directions:

- To extend the presented preliminary methods and models to all I-CISK Living Labs: In this preliminary report, we show results from two seasonal prediction systems at the pan-European domain and three local studies specifically addressed to their corresponding LL: Andalucía (Spain), Upper Secchia River (Italy) and Budapest (Hungary). Deliverable 3.2 will include examples for the seven living labs, and also some examples of a merged analysis between some of them, for instance those from the same sector and climate vulnerability (see Figure 4).
- To fit the models to the living lab requirements in order to achieve the maximum usability in the involved sectors. In the current stage of the I-CISK project, we collected living lab user needs based on existing knowledge. The ongoing co-design activities in each of the living labs will allow us to refine in more detail these requirements and to continue remaining modelling efforts at the local conditions for generating I-CISK user-tailored climate services.

Finally, methodologically we will continue the efforts to narrow the scaling and predictability gap. To do so, we will test various techniques to increase accuracy and reliability at local conditions and decrease bias and uncertainty in climate projections. This will be done by:

- Post-processing (including downscaling and bias-adjustment) ensemble meteorological predictions to the resolution of impact modelling using local data.
- Implementing dynamic sub-sampling methods based on teleconnection indices in order to improve the seasonal hydrological predictability.
- Assessing the benefit of a multi-model ensemble approach and averaging methods, particularly at the seasonal time horizons, given the spatiotemporal complementarity that was observed between ECMWF SEAS5 and CMCC-SPS3.5.

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Appendix 1 Glossary

Acronym	Definition
AC	Anomaly Correlation
ANN	Artificial Neural Network
BA	Bias-Adjustment
CII	Climate Impact Indicator
CRPS	Continuous Ranked Probability Score
CS	Climate Service
CMIP	Coupled Model Intercomparison Project
C3S	Copernicus Climate Change Service
DCPP	Decadal Climate Prediction Project
DRM	Disaster Risk Management
DST	Decision Support Tool
DL	Deep Learning
ECV	Essential Climate Variable
EDO	European Drought Observatory
EFI	Extreme Forecast Index
ENSO	El Niño Southern Oscillation
ESP	Ensemble Streamflow Prediction
GCM	Global Circulation Model
GEOSS	Global Earth Observation System of Systems
IQR	Interquantile Range
LL	Living Lab
LST	Land Surface Temperature
MAE	Mean Absolute Error
MJO	Madden Julian Oscillation
ML	Machine Learning
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NWP	Numerical Weather Prediction
PET	Potential Evapotranspiration
RPS	Ranked Probability Score
RMS	Root Mean Square
SCF	Seasonal Climate Forecast
SEAS	Seasonal Ensemble Prediction System
SPEI	Standardised Precipitation Evapotranspiration Index
SPI	Standardised Precipitation Index
S2S	Sub-seasonal to Seasonal
UHI	Urban Heat Island
WMO	World Meteorological Organization
WP	Work Package
WWH	World-Wide HYPE

Colophon:

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