

The logo for iDAAlert, featuring the text 'iDAAlert' in a stylized font. The 'i' is white with a blue dot, 'DA' is white, and 'Alert' is blue. The background of the top section of the page features a crowd of people on the left, a flock of birds in flight in the center, and a microscopic view of cells on the right.

iDAAlert

Infectious Disease decision-support
tools and Alert systems

D3.1 Report describing the process of seamlessly linking S2S forecasts to climate-sensitive disease indicators

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Alba Llabrés-Brustenga
Martín Lotto Batista
Bruno M. Carvalho
Georgina Charnley
Rachel Lowe

Barcelona Supercomputing Center, BSC

D3.1 Report describing the process of seamlessly linking S2S forecasts to climate-sensitive disease indicators	
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Author(s)	Alba Llabrés-Brustenga Martín Lotto Batista Bruno M. Carvalho Georgina Charnley Rachel Lowe
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R=Document, report; **DEM**=Demonstrator, pilot, prototype; **DEC**=website, patent fillings, videos, etc.; **OTHER**=other

PU=Public, **CO**=Confidential, only for members of the consortium (including the Commission Services), **CI**=Classified

Project overview

As our planet heats up due to climate change, outbreaks of zoonotic diseases are increasing and expanding to new parts of the world, in particular, Europe. IDAlert aims to tackle the emergence and transmission of zoonotic pathogens by developing novel indicators, innovative early warning systems, and decision-support tools for policy-makers, as well as evaluating adaptation and mitigation strategies to build a Europe that is more resilient to emerging health threats.

IDAlert is a five-year Research and Innovation Action (RIA) project coordinated by Umeå University (Sweden). The consortium comprises 19 organisations from Sweden, Germany, France, Spain, Greece, The Netherlands, Italy, UK, and Bangladesh, with world leading experts in a wide range of disciplines including zoonoses, infectious disease epidemiology, social sciences, artificial intelligence, environmental economics, and environmental and climate sciences.

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Executive Summary

Europe has warmed at twice the global average rate over the past seventy years, with serious implications for human health through extreme weather events and gradual climatic changes. Europe has seen an increased risk for climate-sensitive infectious diseases (CSID), such as dengue, malaria, Lyme, and leishmaniasis, driven by fluctuations in climatic and environmental patterns. Climatic factors such as temperature, precipitation, and humidity influence vector distribution and pathogen survival rates. Thus, monitoring conditions for disease transmission is key for reducing the burden of CSIDs. Work Package three (WP3) aims to develop an early warning tool to protect Europe from CSID threats by designing a seasonal risk indicator platform. This platform will integrate climate predictions with CSID indicators to facilitate timely decision-making and proactive action.

This report showcases the adaptation of two indicators initially developed in the context of the Lancet Countdown in Europe: the suitability for malaria transmission and *Ixodes ricinus* questing activity indicators. The methodology presented in this report integrated seasonal climate predictions into the CSID indicator models to predict climatic suitability for disease transmission. This involved calibrating climate forecasts before the calculation of the indicators and assessing the skill, using the Continuous Rank Probability Skill Score (CRPSS) for climate variables as well as the Brier Skill Score (BSS) for indicators.

CRPSS values indicated moderate reliability of climate forecasts in southern Europe with decreasing skill over time. Suitability for malaria transmission and *Ixodes ricinus* activity, however, showed significant spatial and temporal variations, with higher predictive skill in certain regions. The developed framework successfully integrated climate predictions with CSID indicators, demonstrating enhanced predictive skill.

This report introduces an operational framework for integrating climate predictions with CSID indicators, showcasing its practical application and predictive skill. Despite challenges in predicting climate at seasonal timescales in parts of Europe, the framework effectively demonstrates the feasibility of monthly CSID predictions at the monthly timescale. Future work will focus on refining models, expanding the suite of indicators from a One Health perspective, and enhancing visualisation tools.

1. Introduction

Europe has warmed at twice the rate of the global average in the past seven decades (van Daalen et al., 2024). Growing evidence shows that climate change has an adverse impact on human health through extreme weather events and gradual climatic changes, affecting physical and mental well-being, healthcare access, and disease transmission.

In this context, climate-sensitive infectious diseases (CSIDs) are an emerging public health threat in Europe owing to their notable upsurge in recent decades to changes in the vector distribution (van Daalen et al., 2024). Climate services for health, using data from in situ observations, satellite-based remote sensing, climate reanalysis datasets, and climate predictions have been successfully implemented worldwide for understanding drivers of disease and foreseeing their dynamics (Di Napoli et al., 2023). Predicting when and where conditions will be suitable for disease transmission is crucial for timely decision-making and proactive action.

Work Package three (WP3) aims to create an early warning tool to protect Europe from current and emerging zoonotic disease threats. This involves designing a seasonal risk indicator platform that integrates reanalysis and sub-seasonal to seasonal (S2S) climate predictions with validated indicators. Specific objectives include adapting CSID indicators for S2S decision-making, evaluating S2S forecasts to identify regions in Europe for early action protocols, implementing a real-time validation platform, and downscaling and calibrating seasonal disease risk indicators for specific countries.

This report showcases the development of two case study indicators of transmission suitability for CSIDs, as a proof of concept of seamlessly linking seasonal forecasts to CSID indicators: suitability for malaria transmission and suitability for *Ixodes ricinus* activity.

1.1. Climate sensitive infectious diseases (CSIDs)

Climatic factors such as temperature, precipitation patterns, and humidity, can directly affect the distribution and abundance of vectors or the survival rate of pathogens (Romanello et al., 2023; van Daalen et al., 2024). Malaria is widely acknowledged as a CSID because both the vector, *Anopheles* mosquitoes, and the *Plasmodium* parasites are influenced by climate (Patz et al., 2000). Before the Global Malaria Eradication Program, Europe witnessed the endemic circulation of malaria, mainly caused by *P. vivax* (Boualam et al., 2021). While Europe has officially been malaria-free since 1974, sporadic cases still occur among travellers and local transmission events have been reported in Germany, the Netherlands, Spain, France, Italy, Greece, and the UK (Fischer et al., 2020). Factors linked to socio-economic development and increased life expectancy have helped prevent malaria reemergence in Europe (Zhao et al., 2016).

Recent analyses revealed that Northern Europe has experienced an increase in the duration of the suitable season for *Plasmodium vivax* transmission by 0.28 months from 1951-1986 to 1987-2022. Similarly, Western Europe saw an increase of 0.17 months during the same

period. Notably, this upward trend in transmission suitability has been particularly pronounced in non-urban areas, especially those with moderate social deprivation. Also, there has been a notable increase in malaria importation events from endemic regions to areas with suitable conditions over the past decade (van Daalen et al, 2024).

Tick-borne diseases (TBDs) are the most prevalent vector-borne illnesses in the Northern Hemisphere (Rochlin et al., 2020). In Europe, Lyme disease (LD) stands out as the most common TBD, with over 200,000 cases reported annually in Western Europe alone (Marques et al., 2021). LD is caused by bacteria belonging to the *Borrelia burgdorferii* sensu lato complex, manifesting clinically from self-limited skin lesions to long-term arthritis (Stanek et al., 2012). Following LD, tick-borne encephalitis (TBE) ranks as the second most widespread TBD, caused by the *Flaviviridae* family virus, known as the TBE-virus (Wondim et al., 2022). Despite the availability of a vaccine, TBE affects approximately 2.19 individuals per 100,000 inhabitants annually in Europe, resulting in meningitis and meningoencephalitis in 33% of cases (Wondim et al., 2022).

In recent decades, there has been a notable rise in the frequency of LD and TBE, along with an expansion in the distribution of their primary vector: *Ixodes ricinus* ticks (Jenkins et al. 2022, Vandekerckhove et al., 2021, Mysterud et al. 2017). Ticks, being ectothermic parasites, rely on environmental conditions for feeding, development, and reproduction (Randolph et al. 2004). Temperature stands out as a key driver of tick questing activity, the process of seeking and attaching to a host. As temperatures dip below a certain threshold, ticks enter a diapause stage until conditions become favourable again. Likewise, humidity plays a crucial role in tick survival, as they are prone to dehydration while awaiting a host (Randolph et al. 2004).

There is evidence of climatic conditions becoming more suitable for malaria transmission and for tick species to migrate toward higher altitudes and latitudes (Mysterud et al. 2017, van Daalen et al. 2024). Despite a widespread consensus regarding the escalating risk that these CSIDs pose to vulnerable populations, there remains a pressing need to monitor changes in the length and the start of the transmission season to timely deploy control measures.

Threshold-based indicators are simplified models that use the vector climatic requirements to consider whether conditions are suitable for acquiring and transmitting the pathogens. The suitability for malaria transmission and *Ixodes ricinus* activity indicators are two examples of this class of indicators, currently included in the Lancet Countdown in Europe reports (van Daalen et al., 2024). While these indicators were initially designed to report the number of months per year with favourable climatic conditions, they are flexible to be adapted into a seasonal forecasting platform as case studies for evaluating the process of seamlessly integrating seasonal climate forecasts in CSID indicator models.

1.2. Climate predictions

Climate predictions encompass subseasonal forecasts, seasonal forecasts, and decadal predictions (Figure 1). Each type provides valuable insights into different temporal ranges in which to understand and anticipate climate variability and change (Merryfield et al., 2020).

Subseasonal forecasts' lead time (or the duration between the issue of the forecast and the forecasted or target period) is up to five weeks while seasonal forecasts issue predictions from two weeks up to eight months and decadal predictions from one to 30 years ahead; however, the reliability of the prediction often decreases with the lead time (Vitart et al., 2017). The three types of climate predictions rely on both the initial conditions of the climate system and the slowly varying climate drivers, such as oceanic circulation patterns, sea surface temperature, and changes in sea-ice extent and snow cover (Merryfield et al., 2020). Subseasonal and seasonal forecasts focus on capturing large-scale climate patterns and teleconnections that influence seasonal climate variability, such as El Niño-Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), and provide information on climate patterns, including average temperature and precipitation anomalies (Merryfield et al., 2020).

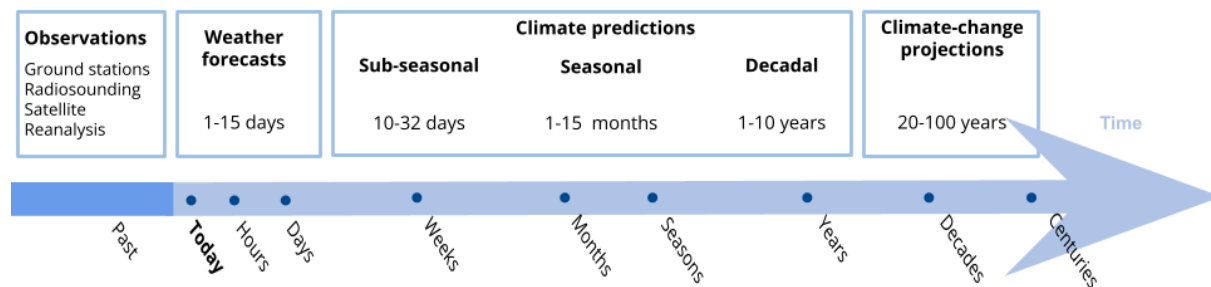


Figure 1. Time scales of different climate datasets.

Over the past few decades, climate predictions have evolved substantially, reaching a level of reliability that makes them advantageous for current operational production by several meteorological forecast services worldwide (Merryfield et al., 2020). These predictions effectively bridge the timescale gap between short-term weather forecasts and long-term climate projections (Robertson et al., 2015). Weather forecasts address questions such as "what will the weather be like in a specific location on a given day?" and are typically accurate only a few days in advance. In contrast, climate projections tackle questions such as "how will the components of the climate system evolve under different boundary conditions?" and are designed to explore conditional futures based on various sets of boundary settings also known as scenarios.

The ability to predict the climatic patterns of the upcoming season is key for decision-making across various sectors, such as agriculture, water resource management, energy production and public health (Merryfield et al., 2020). By anticipating seasonal climate conditions in advance, decision-makers can mitigate risks, optimise operations, and capitalise on opportunities, ultimately enhancing resilience and sustainability in the face of climate variability and change.

Seasonal climate predictions, while essential for understanding and preparing for future weather patterns and climatic extremes, are subject to systematic errors due to various factors. These include simplifications made to reduce computational time and meet output deadlines, such as approximations in fluid dynamics equations, parameterisation of

variables, and using limited spatial and temporal resolution; additionally, imperfect knowledge of the initial conditions of the climate system contributes to these errors (Doblas-Reyes et al., 2013). To address these shortcomings, climate models are issued as an ensemble of several members each of them with a slight perturbation of the initial conditions, thus providing an outcome of a range of possibilities (Johnson et al., 2019). Moreover, a spectrum of methods exists for correcting systematic errors and adjusting forecasts. These encompass bias adjustment methods, which adjust the mean, variance and/or higher order elements of the distribution; ensemble recalibration techniques, which use the temporal correspondence between past predictions and observations; and statistical downscaling techniques that use large-scale predictors to refine the variable of interest (Manzanas et al., 2019). All of these post-processing options are commonly referred to as calibration techniques or methods and will be denoted as such throughout the remainder of this report.

1.3. Towards a seasonal indicator prediction platform

Seasonal climate forecasts and reanalysis products are publicly available as gridded products. However, data products need to undergo processing steps to be adapted to the spatial and temporal resolution that end users require (Fletcher et al., 2021). This report presents the methodology for seamlessly integrating seasonal climate predictions in CSID indicator models, to predict climatic suitability for disease transmission in an operational framework. Two threshold-based models were selected as CSID indicator case studies: the suitability for malaria transmission indicator and the suitability for *Ixodes ricinus* activity indicator. This process is tailored to the CSID indicators, with thresholds derived from the existing literature and refined to align with informative outputs. To showcase the methodology, forecasts issued in May 2022 were selected as a case study with lead times of up to three months. The final product consists of the predicted CSID indicators and their associated quality (which depends on the spatial region and target month), as well as the quality assessment of the prediction of the underlying climate variables.

2. Methods

2.1. Climate data

Six-hour forecasts and hindcasts for temperature, dew point temperature, and accumulated precipitation were obtained from the Copernicus Climate Change Service (Buontempo et al., 2022), covering the period from January 1981 to December 2022, at a resolution of 1.0°x1.0°. We used twenty-five ensemble members from the model SEAS-5.1 (Johnson et al., 2019) released monthly by European Centre for Medium-Range Weather Forecasts (ECMWF) and available at <https://doi.org/10.24381/cds.181d637e>. While forecasts are issued monthly for up to six months, hindcasts were produced once for historic periods. The six-hour data were then averaged into monthly values. Monthly relative humidity was derived using the August-Roche-Magnus equation from the temperature and dew point temperature (Alduchov and Eskridge, 1996).

Hourly reanalysis data were employed for calibrating the predictions. Monthly temperature, dew point temperature, and total precipitation from the ERA5-Land (Muñoz-Sabater et al.,

2021) products were extracted at a 0.1°x 0.1° resolution for the period between January 1981 and December 2022, available at <https://doi.org/10.24381/cds.e2161bac>. Similar to the forecasts, monthly averages were computed for each variable, and relative humidity was derived from temperature and dew point temperature.

Before calibrating the predictions, all variables were averaged to match the target spatial resolution for the indicators, NUTS3. Forecasts and reanalyses were extracted for countries covered by the European Environment Agency (EEA), plus the United Kingdom. Spatial aggregation was done using the R-package *exactextractr*, which computes averages considering the proportion of the grid cells that fall within each polygon. We chose to calibrate the spatially aggregated data to avoid introducing noise from downscaling forecasts and then upscaling to the desired resolution (Heuvelink, 1998).

2.2. Forecast calibration

To recalibrate predictions of temperature-related variables, the Error-in-Variables Model Outputs Statistics (EVMOS) was selected (Vannitsem, 2009). This method is an ensemble recalibration technique that applies a variance inflation to ensure the correction of both the mean and the variance of the forecasts using the distribution of forecasts and observations in the past. This calibration method is available in the *CST_calibration* function from the R-package *CSTools* (Pérez-Zanón et al., 2022) and it was used with leave-one-out evaluation method.

To correct precipitation and humidity predictions, the QUANT method was selected for bias correction. This technique uses a non-parametric transformation through the empirical quantiles of the cumulative distribution function of observed and predicted values; it is ranked as one of the best methods to correct systematic errors in precipitation prediction models, conserving the skill of the correction for extreme precipitation (Gudmundsson et al., 2012). This method is available in the *CST_QuantileMapping* function within the R-package *CSTools* (Pérez-Zanón et al., 2022).

2.3. Skill assessment

The quality assessment of the forecasts was performed on both the calibrated climate variables and the final indicator. This assessment involves evaluating the climate variables using the Continuous Rank Probability Skill Score (CRPSS), with climatology serving as the reference, and the final indicator with the Brier Skill Score (BSS).

The CRPSS is a relative measure of how well the forecasted probability distribution matches the observations from the reanalysis dataset, relative to the reference, in this case the climatology. Thus, positive values of CRPSS indicate an added value of the forecasts over the reference (Wilks, 2011). The CRPSS was selected for assessment of the calibrated climate variables because it evaluates the entire probability distribution of the forecasts, which provides a complete picture of the forecast performance regardless of the threshold used in the calculation of the indicator.

The BSS is a metric used to evaluate the accuracy of probabilistic predictions, especially in the context of binary (yes/no) outcomes and is therefore chosen to evaluate the final climatic suitability indicator (Wilks, 2011). The BSS indicates the added value (positive BSS) of the indicator calculated from the forecasts in comparison to the reference indicator, defined as the average indicator of the past years.

2.4. CSID indicator case studies

The indicator for malaria transmission suitability is based on the optimal survival and proliferation conditions for both the vector and the parasite. Suitable conditions include precipitation accumulation exceeding 80 mm, average temperatures between 14.5°C to 33°C for *P. vivax* and 18°C to 32°C for *P. falciparum*, and relative humidity above 60% (Patz et al., 2000; Grover-Kopec et al., 2006).

The suitability indicator for *Ixodes ricinus* questing activity reflects optimal conditions for tick feeding behaviour. Favourable climatic conditions for nymph activity were identified as temperatures ranging from 10°C to 26°C and relative humidity over 45% (Nolzen et al., 2022). Data from the Global Biodiversity Information Facility (GBIF) reveals that 82.4% of ticks are found in land cover classes such as discontinuous urban areas, moors, heathlands, non-irrigated croplands, and both coniferous and broadleaf forests (GBIF 2023).

These indicators were initially developed to calculate the number of months per year with favourable climatic conditions, incorporating environmental factors of land cover classes (van Daalen et al., 2024). Within WP3, these indicators were further refined to illustrate the probability of suitable conditions occurring in any given month, along with the skill of these predictions. The probability of suitability was defined by the ratio of ensemble members from the forecasting model that met the climatic criteria to the total number of ensemble members, multiplied by 100. Moreover, it is possible to evaluate the onset and duration of the suitability season for a selected year. To extend the analysis over a 12-month period beyond the six-month forecast window, month-specific historical averages can be integrated into the timeline (Figure 2).

To demonstrate the application of these indicators, along with calibration and skill assessment techniques, forecasts made in May 2022 for up to three months were used as a case study. While probabilities were calculated at the NUTS3 level, data on the onset and duration of the suitability season was summarised at the country level. This was done to highlight regions within the country that showed the highest probability of climatic suitability, helping in visualisation.

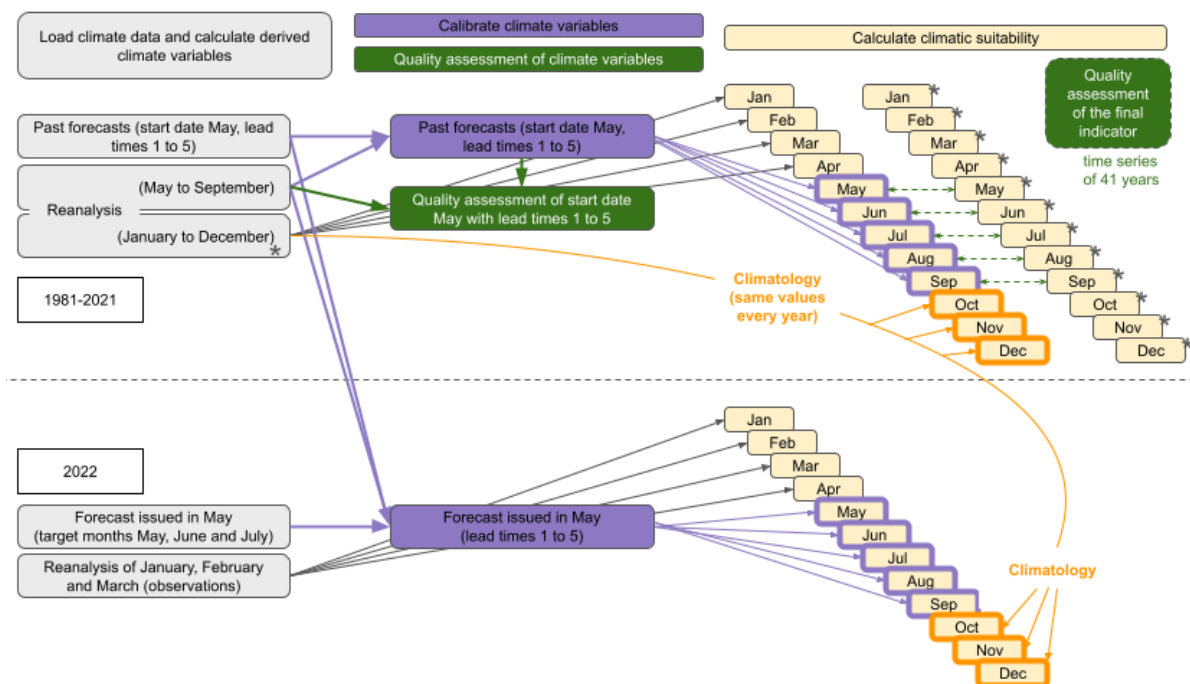


Figure 2. Climate data processing pipeline demonstrating the data used for quality assessment and to produce the forecasts. Note, beyond 5 months, the climatology (historical averages) per month is used to estimate the evolutions of the entire season.

3. Results

3.1. Skill in climate forecasts

CRPSS values showed that significant portions of Europe, especially in central and northern regions, consistently had limited skill in predictions, indicating that forecasts are generally not better than climatology (Figure 3). Nonetheless, there is a great level of spatial heterogeneity in the skills of each variable. Focussing on temperature, regions in southern Europe and parts of Scandinavia exhibited moderate skill, decreasing with longer lead times in June and July. Relative humidity forecasts showed a modest skill in southern Europe and eastern Europe, with little improvement over the months and extensive areas indicating no better performance than the climatology. Total precipitation forecasts also revealed some skill in South and South-East Europe, with decreasing performance in June and July, leaving most of Europe greyed out. Overall, CRPSS outcomes suggested that climate forecasts issued in May 2022 in southern regions of Europe were moderately reliable at a short lead, although skills for the remainder of the continent, as well as for longer lead times, decreased notably.

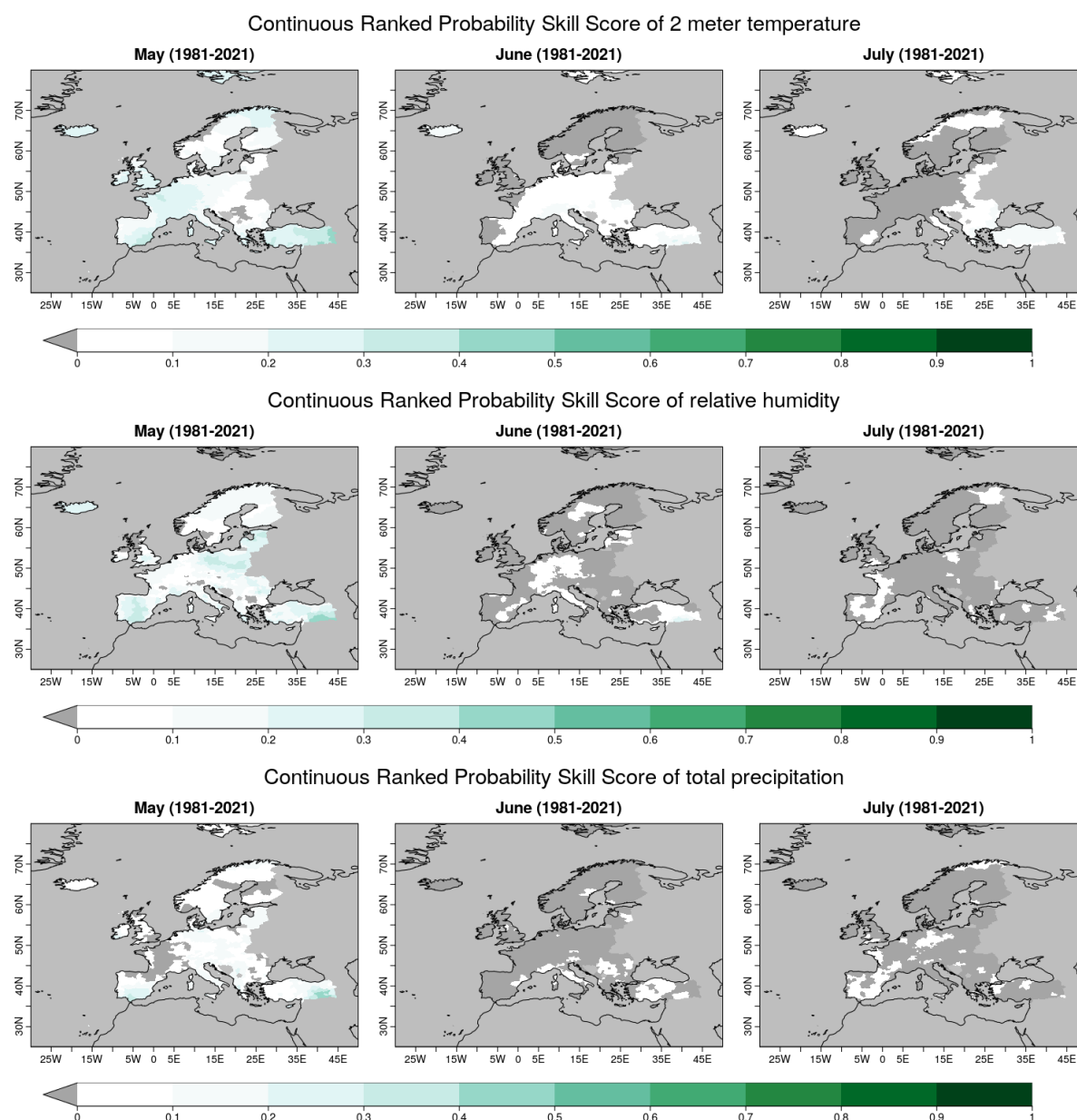


Figure 3. Continuous Ranked Probability Skill Score (CRPSS) for forecasts issued in May 2022. CRPSS for monthly forecasts of temperature, dew point temperature, and total precipitation at a NUTS3 level, covering a three-month forecast window: May, June, and July. The skill score was calculated using reanalysis data as the reference climatology. Positive values indicate superior forecasting skill compared to the reference, while negative values, shown in grey, suggest that the forecast did not enhance skill sufficiently for the specific district and month.

3.2. Suitability for malaria transmission

Suitability for *P. falciparum* transmission was initially low in May with probabilities below 40% across most regions. However, by June, there was a marked increase in Central and Eastern Europe, with probabilities exceeding 50%, and further rising to 60-80% by July. In the case of *P. vivax*, the suitability began at low to moderate levels in May (20-40%) but showed a significant rise in June, particularly in Central Europe where probabilities reached

up to 80%. This trend continued in July, with widespread high suitability (above 60%), particularly in Central and Eastern Europe (Figure 4).

The BSS revealed spatial and temporal variations in the skills of the climatic suitability for malaria transmission indicators across Europe (Figure 5). For *P. falciparum*, the highest skill scores were observed consistently in the Iberian Peninsula and northern Europe. Although some regions from southern Europe exhibited negative or non-significant BSS, the results showed a fairly good predictive skill also in those regions. Likewise, *P. vivax* showed higher forecast skills in Central and Northern Europe at shorter lags, while declining with longer leads in Western Europe.

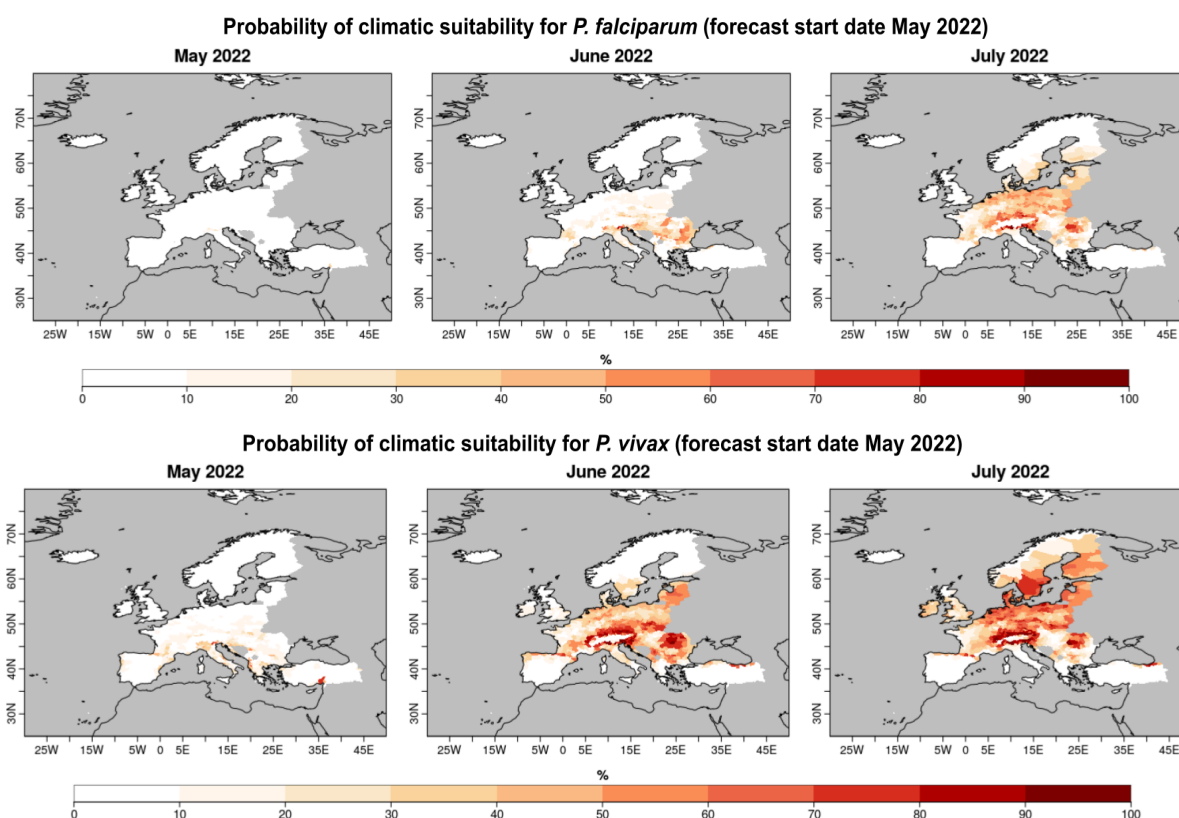


Figure 4. Probability of suitability for malaria transmission (May–July 2022) by NUTS3 district. The probability was determined by the ratio of ECMWF model SEAS-5.1 ensemble members predicting suitable conditions for malaria transmission to the total ensemble members ($n=25$), multiplied by 100 to express the result as a percentage.

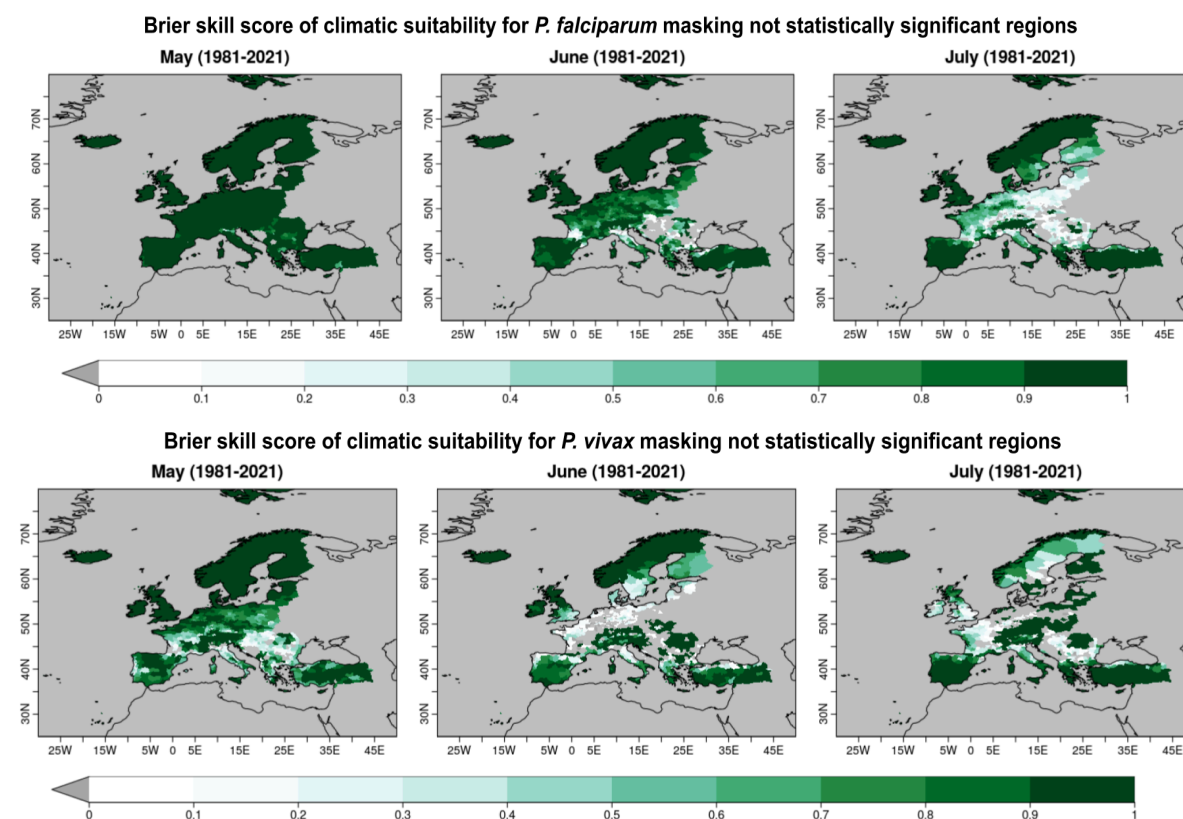


Figure 5. Brier skill score (BSS) for indicator forecasts issued in May 2022. BSS for monthly probability of the suitability for malaria transmission indicator at a NUTS3 level, covering a three-month forecast window: May, June, and July. The skill score was calculated using the indicator computed with historical reanalysis data. Positive values indicate superior forecasting skill compared to the reference, while negative values, shown in grey, suggest that the forecast did not enhance skill sufficiently for the specific district and month.

3.3. Suitability for *Ixodes ricinus* questing activity

The climatic suitability forecasts for *I. ricinus* activity displayed consistently high suitability between May and July 2022, with most regions showing probabilities above 80% in the first month. By June and July, nearly all of Europe experienced probabilities exceeding 90%, indicating uniformly favourable conditions (Figure 6). In contrast, the BSS for *I. ricinus* activity showed a more consistent spatial pattern with general higher skill scores in Central and Northern Europe throughout May, June and July. (Figure 7) These results indicate that forecasts based on climatic suitability for ticks were reliable across all three months, with some exceptions in Southern and Eastern Europe.

Using this indicator to showcase the length of the transmission season predicted for 2022, Figure 8 indicates that the suitability for tick activity started in the peninsula in April and extended towards the rest of the continent, finishing in September 2022. However, the length of the suitable season was not equal across all countries. For example, warmer countries such as Spain, Portugal, and Cyprus exhibited the longest suitable season, while the Alps had suitable conditions for only two months (Figure A1).

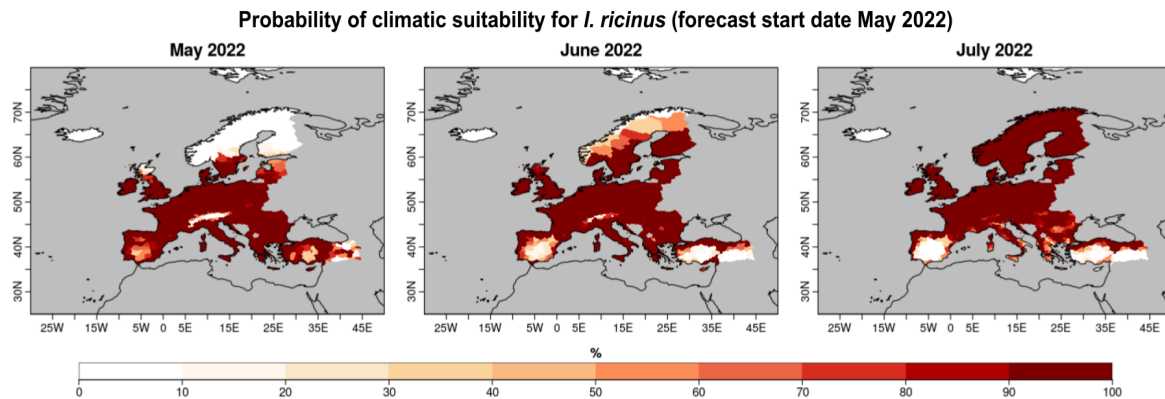


Figure 6. Probability of suitability for *I. ricinus* questing activity (May–July 2022) by NUTS3 district. The probability was determined by the ratio of ECMWF model SEAS-5.1 ensemble members predicting suitable conditions for malaria transmission to the total ensemble members (n=25), multiplied by 100 to express the result as a percentage.

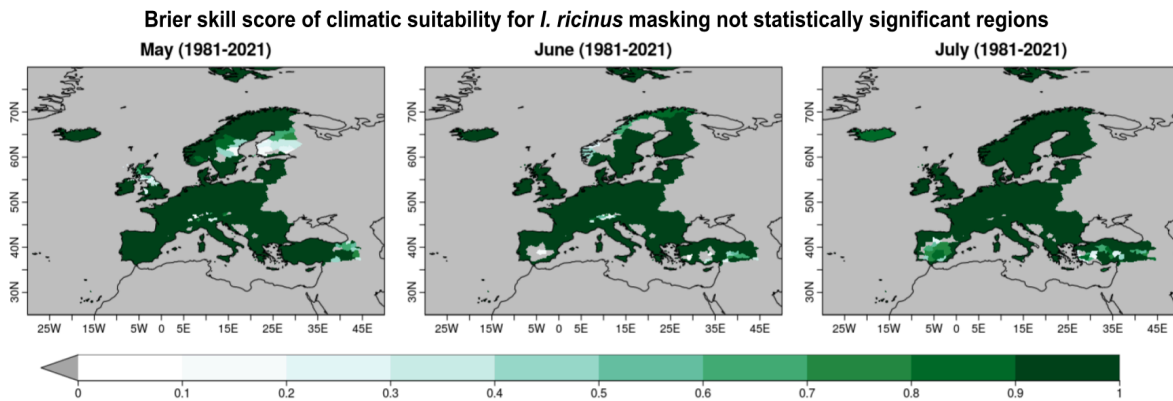


Figure 7. Brier Skill Score (BSS) for Indicator Forecasts (May 2022). BSS for the monthly probability of suitability for *I. ricinus* questing activity, at a NUTS3 level over a three-month forecast period: May, June, and July. The skill score was calculated against the average indicator from the past (1981-2021) as the reference. Positive values indicate that the forecast outperforms in skill the historical data alone, whereas negative values, shown in grey, indicate insufficient forecasting skill for the particular region and month. Additionally, regions where the skill score is not statistically significant are greyed out.

Probability of climatic suitability for *I. ricinus*

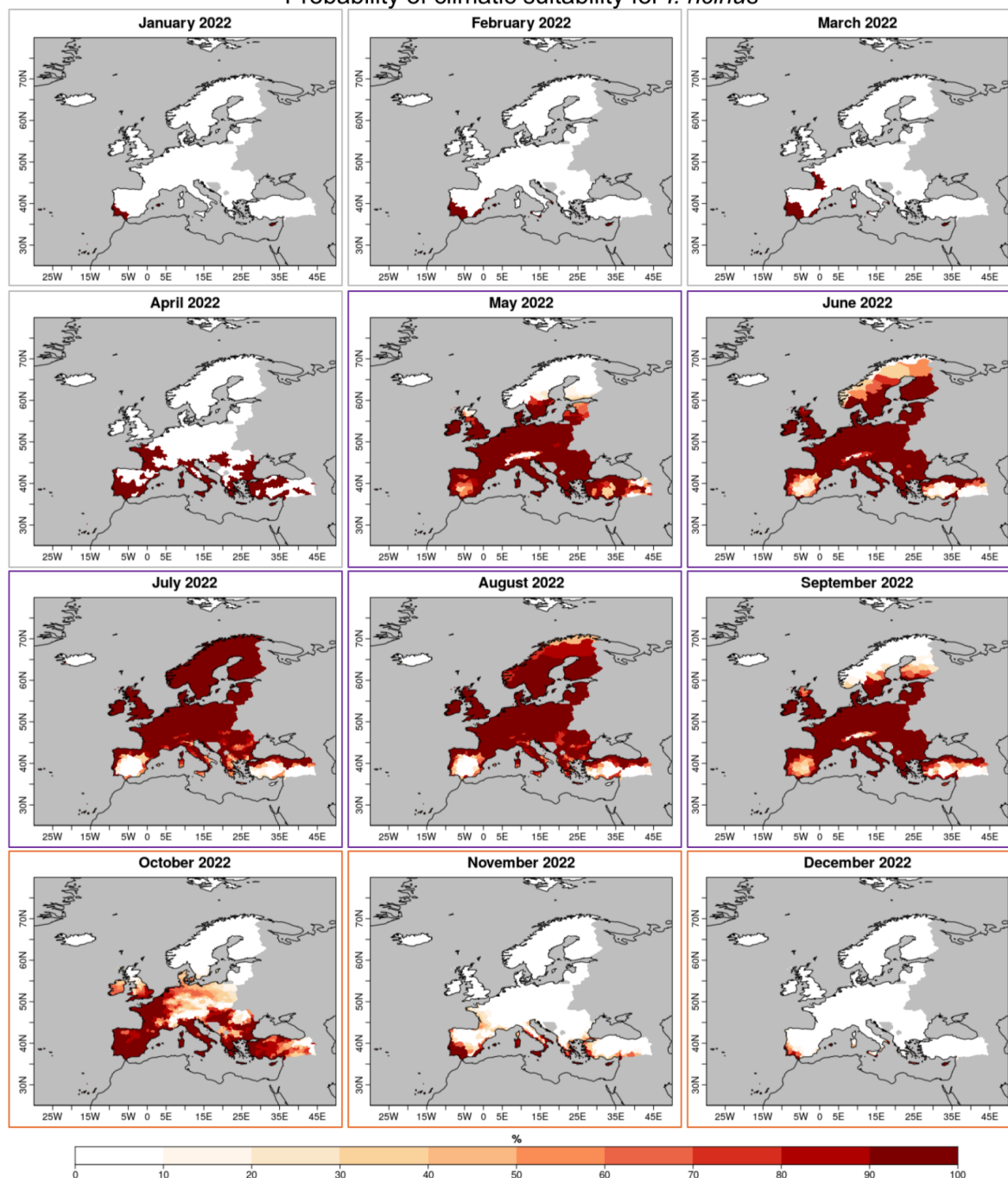


Figure 8. Suitability probability per country for a 12-month period for *I. ricinus* questing activity. To evaluate the onset and duration of the suitability season for a selected year, a combination of observed historical data, and six-month window forecasts were employed. To extend the analysis over a 12-month period beyond the six-month forecast window, month-specific historical averages were integrated into the timeline. Grey squares around the maps indicate data from reanalysis, purple squares indicate data from forecasts and orange squares indicate reanalysis data averaged over 1981-2021.

4. Discussion

This report explores the development of an operational framework to seamlessly integrate climate predictions in models for climate sensitive infectious diseases (CSIDs). By employing the forecast issued in May 2022, we focussed on two specific CSID indicators: the suitability for malaria transmission and the suitability for *Ixodes ricinus* questing activity. We assessed the prediction skills of both the climate inputs and the indicator forecasts. The results not only showcased the practical application of the system but also highlighted the enhanced predictive skill achieved through this integration.

Until recently, the development of climate-based monitoring tools for CSIDs was largely confined to academic research. The implementation of these tools in decision-making processes face numerous obstacles, including a lack of historical and real-time data, and coarse spatial and temporal resolutions. Nonetheless, advancements in computational power and the increasing availability of reanalysis products have enhanced climate services for health. Within the framework of the Lancet Countdown's family of reports, a wide range of indicators has been introduced to monitor the long-term impacts of climate on health. The indicators highlighted in this report are effective for detecting trends and are flexible enough to transition from tracking long-term dynamics to assessing seasonal probabilities. However, effectively communicating this information to end users remains a challenge.

In this context, WP3 aims to develop an early warning tool that effectively communicates forecasts and their reliability to protect Europe against current and emerging CSID threats. The initial steps included developing a forecasting workflow that extracts information from climate models, processes it, and computes the indicators. This report showcases various tools used to calibrate predictions and evaluate their accuracy, providing a foundation for interpreting the results of these forecasts.

The CSID indicators used in this report were initially developed for tracking annual changes and trends, while the S2S timescale requires monthly results. This challenge was surpassed by defining the probability of a suitable month incorporating the inherent variability in the forecasting methods. The computation of this probability provided valuable information about the expected conditions in the near future, while also giving a first insight into the start and length of the suitable season within a 12-month forecast window (Figure 8).

In conclusion, the developed framework effectively addressed the challenges of monthly forecasting on the S2S timescale, although there were significant challenges in the skill of the forecasts. The observed spatial and temporal patterns underline the importance of tailored climate forecasts in anticipating and managing CSID risks. Future work will aim to refine these models further to improve forecasts reliability, as well as expand the suite of indicators covered.

5. Next steps

After developing the methodological framework for extracting and processing forecasts for use in computing CSID indicators, our focus has shifted toward enhancing the efficiency of

the code and broadening the range of indicators. Future developments will include forecasts for diseases such as leishmaniasis, West Nile Virus, and those transmitted by *Aedes* mosquitoes, such as dengue, Zika and Chikungunya, and rodents, such as leptospirosis and hantavirus. Additionally, we plan to expand our research to include more tick species like *Ixodes persulcatus*, a vector for Lyme disease and tick-borne encephalitis (TBE), and *Hyalomma*, which transmits Crimean-Congo Hemorrhagic Fever (CCHF). We are actively exploring new methodologies and consulting with experts in the field.

We are also expanding the range of data sources used to compute the indicators. Adopting a One Health approach, we aim to include factors such as the migration of hosts and vectors, as well as human population movements in and out of areas where diseases are endemic. We are also gathering case registries to validate our indicators through correlation analysis and statistical modelling.

Finally, with the seasonal predictions provided, we intend to enhance our visualisation tools to better illustrate how seasonality has evolved over time. This will involve analysing trends such as changes in the number of continuous months with suitable conditions in grid cells and shifts in the timing of peak seasons throughout the year.

References

- Alduchov OA, Eskridge RE. Improved Magnus form approximation of saturation vapor pressure. *Journal of Applied Meteorology and Climatology*. 1996 Apr;35(4):601-9.
- Benali A, Nunes JP, Freitas FB, Sousa CA, Novo MT, Lourenço PM, et al. Satellite-derived estimation of environmental suitability for malaria vector development in Portugal. *Remote Sensing of Environment*. 2014 Apr;145:116–30.
- Boualam MA, Pradines B, Drancourt M, Barbieri R. Malaria in Europe: A Historical Perspective. *Front Med*. 2021 Jun;8.
- Buontempo C, Burgess SN, Dee D, Pinty B, Thépaut JN, Rixen M, Almond S, Armstrong D, Brookshaw A, Alos AL, Bell B. The Copernicus climate change service: climate science in action. *Bulletin of the American Meteorological Society*. 2022 Dec 7;103(12):E2669-87.
- Doblas-Reyes FJ, García-Serrano J, Lienert F, Biescas AP, Rodrigues LR. Seasonal climate predictability and forecasting: status and prospects. *Wiley Interdisciplinary Reviews: Climate Change*. 2013 Jul;4(4):245-68. doi: 10.1002/wcc.217.
- Doblas-Reyes FJ, Hagedorn R, Palmer TN. The rationale behind the success of multi-model ensembles in seasonal forecasting—II. Calibration and combination. *Tellus A: Dynamic Meteorology and Oceanography*. 2005 Jan 1;57(3):234-52.
- Di Napoli C, Romanello M, Minor K, Chambers J, Dasgupta S, Escobar LE, Hang Y, Hänninen R, Liu Y, Lotto Batista M, Lowe R. The role of global reanalyses in climate services for health: Insights from the Lancet Countdown. *Meteorological applications*. 2023 Mar;30(2):e2122.
- Fischer L, Gültekin N, Kaelin MB, Fehr J, Schlagenhauf P. Rising temperature and its impact on receptivity to malaria transmission in Europe: A systematic review. *Travel Med Infect Dis*. 2020 Jul;36:101815.
- Fletcher IK, Stewart-Ibarra AM, García-Díez M, Shumake-Guillemot J, Lowe R. Climate services for health: from global observations to local interventions. *Med*. 2021 Apr 9;2(4):355-61.
- GBIF.Org User. Occurrence Download [Internet]. The Global Biodiversity Information Facility; 2023. Available from: <https://www.gbif.org/occurrence/download/0035929-230530130749713>
- Grover-Kopec EK, Blumenthal MB, Ceccato P, Dinku T, Omumbo JA, Connor SJ. Web-based climate information resources for malaria control in Africa. *Malaria journal* [Internet]. 2006 May;5. Available from: <https://pubmed.ncbi.nlm.nih.gov/16689992/>
- Gudmundsson L, Bremnes JB, Haugen JE, Engen-Skaugen T. Downscaling RCM precipitation to the station scale using statistical transformations—a comparison of methods. *Hydrology and Earth System Sciences*. 2012 Sep 21;16(9):3383-90.
- Heuvelink GB. Uncertainty analysis in environmental modelling under a change of spatial scale. In *Soil and Water Quality at Different Scales: Proceedings of the Workshop “Soil and Water Quality at Different Scales” held 7–9 August 1996, Wageningen, The Netherlands 1998* (pp. 255-264). Springer Netherlands.

- Jenkins VA, Silbernagl G, Baer LR, Hoet B. The epidemiology of infectious diseases in Europe in 2020 versus 2017–2019 and the rise of tick-borne encephalitis (1995–2020). *Ticks and Tick-borne Diseases*. 2022 Sep 1;13(5):101972.
- Johnson SJ, Stockdale TN, Ferranti L, Balmaseda MA, Molteni F, Magnusson L, Tietsche S, Decremer D, Weisheimer A, Balsamo G, Keeley SP. SEAS5: the new ECMWF seasonal forecast system. *Geoscientific Model Development*. 2019 Mar 22;12(3):1087-117.
- Manzananas R, Gutiérrez JM, Bhend J, Hemri S, Doblas-Reyes FJ, Torralba V, Penabad E, Brookshaw A. Bias adjustment and ensemble recalibration methods for seasonal forecasting: A comprehensive intercomparison using the C3S dataset. *Climate Dynamics*. 2019 Aug 15;53:1287-305. doi: 10.1007/s00382-019-04640-4.
- Marques AR, Strle F, Wormser GP. Comparison of Lyme Disease in the United States and Europe. *Emerg Infect Dis*. 2021 Aug;27(8):2017–24.
- Merryfield WJ, Baehr J, Batté L, Becker EJ, Butler AH, Coelho CA, Danabasoglu G, Dirmeyer PA, Doblas-Reyes FJ, Domeisen DI, Ferranti L. Current and emerging developments in subseasonal to decadal prediction. *Bulletin of the American Meteorological Society*. 2020 Jun 26;101(6):E869-96.
- Muñoz-Sabater J, Dutra E, Agustí-Panareda A, Albergel C, Arduini G, Balsamo G, Boussetta S, Choulga M, Harrigan S, Hersbach H, Martens B. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth system science data*. 2021 Sep 7;13(9):4349-83.
- Mysterud A, Jore S, Østerås O, Viljugrein H. Emergence of tick-borne diseases at northern latitudes in Europe: a comparative approach. *Sci Rep*. 2017 Nov 24;7(1):16316.
- Nolzen H, Brugger K, Reichold A, Brock J, Lange M, Thulke HH. Model-based extrapolation of ecological systems under future climate scenarios: The example of Ixodes ricinus ticks. *PLOS ONE*. 2022 Apr 22;17(4):e0267196.
- Patz JA, Graczyk TK, Geller N, Vittor AY. Effects of environmental change on emerging parasitic diseases. *Int J Parasitol*. 2000 Nov;30(12–13):1395–405.
- Pérez-Zanón N, Caron LP, Terzago S, Van Schaeybroeck B, Lledó L, Manubens N, Roulin E, Alvarez-Castro MC, Batté L, Delgado-Torres C, Domínguez M. The CStools (v4. 0) toolbox: From climate forecasts to climate forecast information. *Geoscientific Model Development Discussions*. 2021 Dec 6;2021:1-32. doi: 10.5194/gmd-15-6115-2022.
- Randolph SE. Tick ecology: processes and patterns behind the epidemiological risk posed by ixodid ticks as vectors. *Parasitology*. 2004 Oct;129(S1):S37–65.
- Robertson AW, Kumar A, Peña M, Vitart F. Improving and promoting subseasonal to seasonal prediction. *Bulletin of the American Meteorological Society*. 2015 Mar 1;96(3):ES49-53.
- Rochlin I, Toledo A. Emerging tick-borne pathogens of public health importance: a mini-review. *J Med Microbiol*. 2020 Jun;69(6):781–91.
- Romanello M, Di Napoli C, Green C, Kennard H, Lampard P, Scamman D, Walawender M, Ali Z, Ameli N, Ayeb-Karlsson S, Beggs PJ. The 2023 report of the Lancet Countdown on health and climate change: the imperative for a health-centred response in a world facing irreversible harms. *The Lancet*. 2023 Dec 16;402(10419):2346-94.

- Stanek G, Wormser GP, Gray J, Strle F. Lyme borreliosis. *The Lancet*. 2012 Feb 4;379(9814):461-73.
- van Daalen KR, Tonne C, Semenza JC, Rocklöv J, Markandya A, Dasandi N, Jankin S, Achebak H, Ballester J, Bechara H, Beck TM. The 2024 Europe report of the Lancet Countdown on health and climate change: unprecedented warming demands unprecedented action. *The Lancet Public Health*. 2024 May 12.
- Vandekerckhove O, De Buck E, Van Wijngaerden E. Lyme disease in Western Europe: an emerging problem? A systematic review. *Acta Clinica Belgica*. 2021 May 4;76(3):244–52.
- Vannitsem S. A unified linear Model Output Statistics scheme for both deterministic and ensemble forecasts. *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography*. 2009 Oct;135(644):1801-15. doi: 10.1002/qj.491
- Vitart F, Ardilouze C, Bonet A, Brookshaw A, Chen M, Codorean C, Déqué M, Ferranti L, Fucile E, Fuentes M, Hendon H. The subseasonal to seasonal (S2S) prediction project database. *Bulletin of the American Meteorological Society*. 2017 Jan;98(1):163-73.
- Wilks DS. *Statistical methods in the atmospheric sciences*. Academic press; 2011 May 20.
- Wondim MA, Czupryna P, Pancewicz S, Kruszevska E, Groth M, Moniuszko-Malinowska A. Epidemiological Trends of Trans-Boundary Tick-Borne Encephalitis in Europe, 2000–2019. *Pathogens*. 2022 Jun;11(6):704.
- Zhao X, Smith DL, Tatem AJ. Exploring the spatiotemporal drivers of malaria elimination in Europe. *Malar J*. 2016 Mar;15(1):1–13.

Appendix

COUNTRY	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
AL	0	0	0	1	1	1	1	1	1	1	0.9	0.02
AT	0	0	0	0	1	1	1	1	1	0.8	0	0
BE	0	0	0	0	1	1	1	1	1	0.95	0.15	0.02
BG	0	0	0	1	1	1	1	1	1	1	0.22	0
CH	0	0	0	0	1	1	1	1	1	0.68	0	0
CY	1	1	1	1	1	0.8	0	0	0.76	1	1	0.98
CZ	0	0	0	0	1	1	1	1	1	0.44	0	0
DE	0	0	0	0	1	1	1	1	1	0.9	0.02	0
DK	0	0	0	0	1	1	1	1	1	0.71	0	0
EE	0	0	0	0	0.64	1	1	1	0.96	0.02	0	0
EL	1	1	1	1	1	1	1	1	1	1	1	1
ES	1	1	1	1	1	1	1	1	1	1	1	1
FI	0	0	0	0	0.4	1	1	1	0.96	0.02	0	0
FR*	0	0	1	1	1	1	1	1	1	1	0.54	0.07
HR	0	0	0	1	1	1	1	1	1	1	0.68	0
HU	0	0	0	1	1	1	1	1	1	0.93	0.05	0
IE	0	0	0	0	1	1	1	1	1	0.78	0.05	0
IS	0	0	0	0	0	0.12	0.76	0.4	0	0	0	0
IT	0	1	1	1	1	1	1	1	1	1	1	0.9
LI	0	0	0	0	0.68	1	1	1	0.88	0.07	0	0
LT	0	0	0	0	1	1	1	1	1	0.15	0	0
LU	0	0	0	0	1	1	1	1	1	0.41	0	0
LV	0	0	0	0	0.96	1	1	1	0.96	0.1	0	0
ME	0	0	0	0	0.96	1	1	1	1	0.46	0	0
MK	0	0	0	1	1	1	0.96	1	1	1	0.05	0
MT	1	1	1	1	1	1	0.56	0.24	0.96	1	1	1
NL	0	0	0	0	1	1	1	1	1	0.95	0.1	0
NO	0	0	0	0	0.76	1	1	1	0.72	0	0	0
PL	0	0	0	0	1	1	1	1	1	0.59	0	0
PT	1	1	1	1	1	1	1	1	1	1	1	1
RO	0	0	0	1	1	1	1	1	1	1	0.12	0
RS	0	0	0	1	1	1	1	1	1	0.98	0.1	0
SE	0	0	0	0	1	1	1	1	1	0.24	0	0
SI	0	0	0	0	1	1	1	1	1	0.98	0.02	0
SK	0	0	0	0	1	1	1	1	1	0.78	0	0
TR	0	0	0	1	1	1	1	1	1	1	0.93	0.12
UK	0	0	0	0	1	1	1	1	1	0.98	0.29	0.02

Figure A1. climatic suitability for *I. ricinus* questing activity in European countries, showing maximum probability of the climatic suitability of any NUTS3 level region within the country and following the approach of merging observations, forecasts and climatology depending on their availability. FR* excluding FRY10 (Guadeloupe), FRY20 (Martinique), FRY30 (Guyane), FRY40 (la Réunion) and FRY50 (Mayotte).