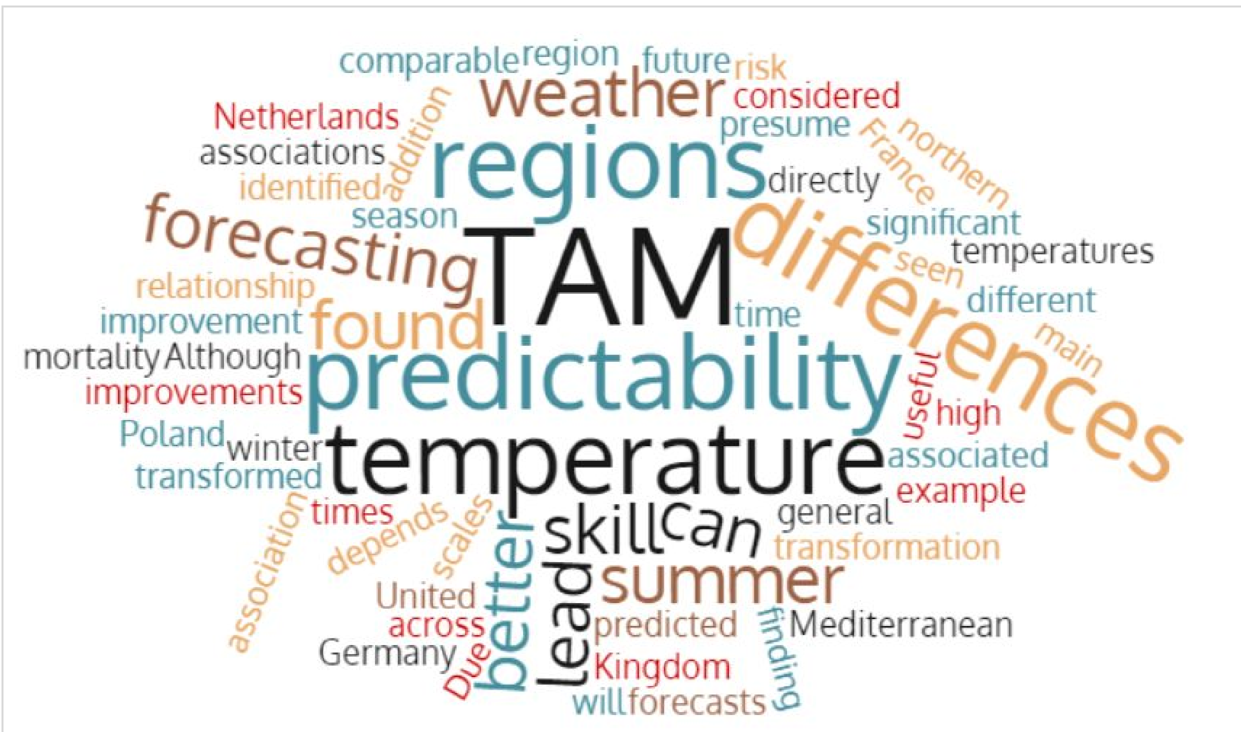
Evaluation of the product
Case Study 2 Temperature-related human mortality in European regions



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Summary for publication

Many European countries have designed weather early warning systems of heat stress indicators. This process was especially evident after the summer 2003 heatwave, which had an unprecedented impact on mortality across the continent, causing more than 70,000 premature deaths in western countries alone. Implementing adequate health preventing measures, which have a positive impact on reducing temperature-attributable mortality (TAM), is essential in public health decision making, particularly in a context of climate change and rising temperatures.

Yet, these systems have room for improvement. We identified some of the key aspects that could be refined after consulting several stakeholders and end-users from a wide-range of professional fields. They emphasised the need of a unified Pan-European service that provides relevant and comparable information. At the same time, the service should be flexible enough to adapt to the different climatic and socio-economic structures of the European societies. Since most of the current systems are solely based on climate data, they also highlighted the need to include mortality data to model the real impact of weather and climate. Lastly, end-users demanded that the system was able to produce warnings for multiple lead times beyond the traditionally used 1 to 2 days. Hence, to design prototypes of European weather early warning systems that address these needs, our objective was to study the predictability of temperature-attributable mortality in Europe at the regional scale using weather forecasts with lead times of up to 15 days.

Here we present the results of our study. Our main finding is that temperature predictability can be transformed into TAM predictability. Due to the differences in the temperature-mortality associations, significant differences in the TAM predictability are found across the regions. These differences would not be identified if only temperature forecasts were considered. We have seen better predictability in summer for regions associated with a high risk of mortality for summer temperatures, such as the Mediterranean and the northern regions of Germany and the Netherlands. While for winter, better skill is found in regions with a different temperature-mortality association; for example in France, Poland and the United Kingdom. Although it depends on the region and season, in general TAM can be predicted on weather time scales, as lead times with useful skill are comparable after the transformation of temperature into TAM. In addition, there is a relationship between temperature predictability and TAM predictability, so we presume that future improvement in the weather forecasting will directly lead to improvements in TAM forecasting.

Work carried out

The first step of our analysis was to homogenise the weather and health data. For health, we used our own database of mortality, which contains information about daily counts of all-cause mortality for the period 1998-2012 in 147 NUTS2 regions in 16 European countries, representing more than 400 million people. These countries, mapped in Figure 1, are Austria (acronym AT, with data for nine regions), Belgium (BE, 11), Croatia (HR, 2), the Czech Republic (CZ, 8), Denmark (DK, 1), France (FR, 22), Germany (DE, 16), Italy (IT, 21), Luxembourg (LU, 1), the Netherlands (NL, 1), Poland (PL, 16), Portugal (PT, 5), Slovenia (SI, 1), Spain (ES, 16), Switzerland (CH, 7) and the United Kingdom (England and Wales only; UK, 10).

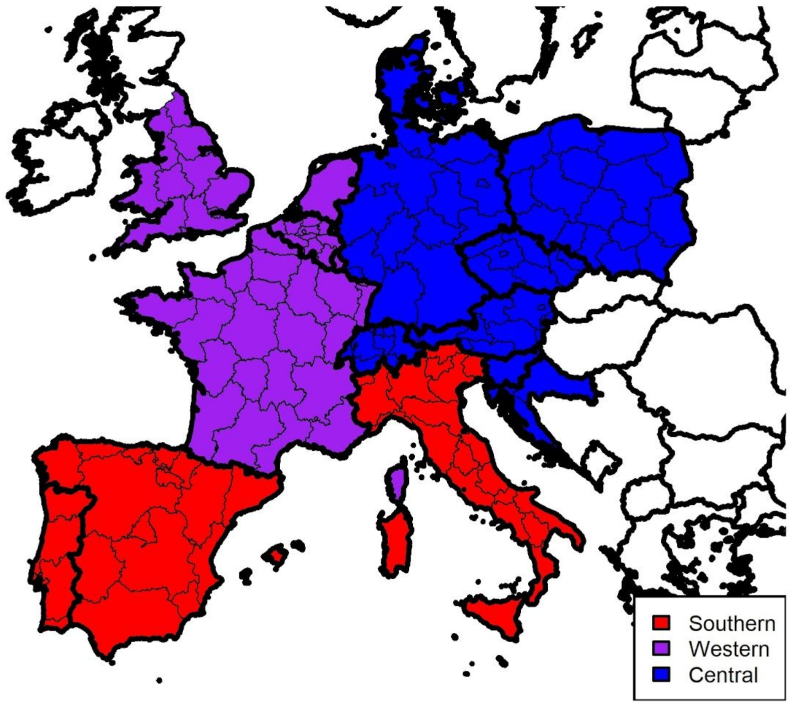

Figure 1: Region classification of the 147 NUTS2 regions considered in the study.

The weather forecasts were accessed through the European Centre for Medium-Range Weather Forecasts (ECMWF) web portal (https://apps.ecmwf.int/datasets/data/tigge/levtype=sfc/type=pf/). Provided are 4 daily runs of ensemble weather forecasts covering lead-times of up to 15 days. We obtained gridded data from ECMWF of 2 metre temperature forecasts at 12 UTC from +0 hours to +360 hours in intervals of 24 hours (i.e., temperature forecasts at 12 UTC for the corresponding day and the following 15 days). These forecasts are available from December 2006 till present, and we processed the data for the period 2007 to 2012 to have 6 full years of daily temperature and mortality data.

Also from ECMWF, we used the ERA5 dataset, which provides hourly estimates of a large number of atmospheric, land and oceanic climate variables. Similarly, we downloaded 2 meter temperature at 12 UTC for the period 1998-2012.

The next step was to homogenise the two datasets by transforming the gridded temperature data into administrative units (the 147 NUTS regions of mortality data and their corresponding countries), thus obtaining a unique dataset with daily time series of counts of death, temperatures from ERA5 and temperature forecasts for the corresponding day (lead time 0) and the 15 previous days (lead time 1 to 15).

The statistical analysis that we performed consisted of two main parts: first, the fitting of the temperature-mortality relationship by means of epidemiological models, and second, the generation of health forecasts. We then compared the skill of the temperature and TAM forecasts.

Fitting the temperature-mortality relationship

For the first part of the statistical analysis, we followed the Distributed Lag-Non Linear (DLNM) framework, used in many studies for modelling the delayed short-term association between temperature and mortality. This first part of the statistical analysis can be divided into two stages. The starting point was to apply in each region a standard time-series quasi-Poisson regression model allowing for overdispersion to derive estimates of region-specific temperature-mortality associations (with the ERA5 daily temperature at 12 UTC), reported as Relative Risks (RR) in the study period (1998-2012, excluding the outlier month of August 2003), as follows:

$$log(E(Y)) = intercept + S(time,\ 8\ df\ per\ year) + dow + cb$$

where *Y* denotes the daily time series of mortality counts; *S* is a natural cubic B-spline of time with 8 degrees of freedom (df) per year to adjust for the seasonal and long-term trends; *dow* corresponds to a categorical variable to control for the day of the week; and *cb* is the cross-basis function that combines the exposure-response and lag-response associations. The former association was modelled with a quadratic B-spline, with three internal knots placed at the 10th, 75th and 90th percentiles of the historical daily temperature distribution. The latter association was modelled with three internal knots placed at equally spaced intervals in the log scale, with a maximum lag of 21 days to account for the long-delayed effects of cold temperatures and short-term harvesting.

In the second part, we performed a multivariate random-effects meta-analysis, controlling for the whole-period temperature average and range, as well as the country of the regions, to estimate the mean RR values associated with the temperature-mortality curve across regions, and to derive the best linear unbiased prediction (BLUP) of the reduced coefficients in each location. Country associations were predicted with the estimated coefficients of the specific values of the controlling variables included in the meta-analysis. A parallel multivariate random-effect meta-analysis was performed without controlling for the country of the regions to obtain the temperature-mortality association for the whole of Europe. We then extracted the minimum mortality temperature (MMT) from the continental, national and regional associations.

Considering that each daily temperature generates different risks of mortality on the corresponding and the following days (for example, summer temperatures have a more immediate effect than winter temperatures), and the cumulative risk is calculated as the sum of the contributions to the risk of the temperature in the lag dimension, the attributable fraction (AF) and the attributable number (AN) of deaths attributable to non-optimal temperatures is calculated as:

$$AF_{x,t} = \frac{RR_{x,t}-1}{RR_{x,t}}, \; AN_{x,t} = AF_{x,t} \cdot \sum_{l=l_0}^{L} \frac{n_{t+l}}{L-l_0+1},$$

where *x* is the exposure, *t* the day when the exposure occurred, $RR_{x,t}$ is the overall cumulative risk for the exposure *x* on day *t*, and the summation in the $AN_{x,t}$ formula represents the mean of the total deaths that occurred between day *t* and the following *L* days (l_0 is the minimum lag, *L* the maximum lag, and n_{t+l} is the total mortality on the day *t+l*).

In this way, we generate the health forecasts applying the following procedure: temperature forecasts at lead times from 0 to 15 are transformed into RR by means of the curves that describe the temperature-mortality relationship in each region; these into AF, and by adding the mortality, they are finally converted into health forecasts. The final outcome is the attributable number of deaths forecasted for the different lead times, expressed in daily deaths per million inhabitants.

Temperature and TAM forecast skill

As the next step, we wanted to evaluate how well temperature and TAM are predicted. To accomplish this, we used the Anomaly Correlation Coefficient (ACC), which is "frequently used to verify the output from numerical weather predictions models" (https://www.cawcr.gov.au/projects/verification/#Methods_for_foreasts_of_continuous_variables). The formula for the ACC is the following:

$$ACC = \frac{\sum(F-C)(O-C)}{\sqrt{\sum(F-C)^2}\sqrt{\sum(O-C)^2}},$$

where *F* is the series of forecast values (in our case, temperature and TAM at lead times from 1 to 15), *O* the series of observed values (temperature and TAM at lead time 0) and *C* is usually defined as the climatological mean of temperature. To adapt the formula for the health forecasts, we use as *C* the smoothed function of the mean annual cycle of temperature and TAM at lead time 0. To do so, we averaged the values by day of the year (leap days were not considered for the calculation of the mean annual cycle) and we smoothed them with a natural spline with 6 df in a Gaussian model for temperature, and 12 df in a quasi-Poisson model for TAM. The result is a measure of the temperature and TAM forecast skill for each region along the 15 lead times. To measure for how long the useful skill lasts and make the comparison between regions more comprehensible, we have defined the concept of "predictability lead time" as the shortest lead time in which ACC < 0.6 (Krishnamurti et al., 2003, Jung and Matsueda, 2016). In addition, we calculated the skill by season to account for the possible seasonal differences; we considered December-February as winter months, March-May as spring, June-August as summer and September-November as autumn.

Commonly, health plans and early-warning systems are targeted at the extreme summer and winter days in terms of temperature. Consequently, we also wanted to quantify how well extreme days can be predicted both for temperature and TAM. We identified the days in the period 2007-2012 with higher

TAM in (i) winter and (ii) summer as those in which the attributable number at lead time 0 was higher than 90th percentile of the distribution of daily attributable numbers in (i) July and August and in (ii) December and January, respectively. Then we calculated the Receiver Operating Characteristic (ROC) curves and the Area Under Curve (AUC) of the ROC curves, to see if temperature and TAM forecasts at lead times between 0 and 15 could classify correctly these extreme days. In this case, the predictability lead time is the shortest lead time with AUC < 0.9.

Main results achieved

The dataset we analysed included nearly 60 million counts of deaths over a population of more than 400 million people (Table 1).

Country	Nº of regions	Total deaths	Population	Temperature (ºC)
Austria	9	1.141.272	8.202.653	10.7 (6.6-14.2)
Belgium	11	1.583.164	10.556.782	12.9 (11.4-13.5)
Switzerland	7	925.582	7.485.455	9.4 (6.2-12.6)
Czech Republic	8	1.608.397	10.313.111	11.7 (11.1-12.6)
Germany	16	12.587.890	81.939.102	12.2 (11.4-12.7)
Denmark	1	845.778	5.435.979	11.0 (11.0-11.0)
Spain	16	5.425.785	41.604.654	17.3 (13.5-21.3)
France	22	7.943.058	61.058.653	14.3 (12.9-17.1)
Croatia	2	767.907	4.297.560	15.6 (15.3-15.9)
Italy	21	8.519.719	58.031.633	15.4 (4.2-20.3)
Luxembourg	1	54.505	469.919	12.1 (12.1-12.1)
Netherlands	1	2.058.694	16.282.222	12.9 (12.9-12.9)
Poland	16	5.576.630	38.203.631	11.9 (10.8-12.7)
Portugal	5	1.495.532	9.948.620	19.1 (16.3-20.9)
Slovenia	1	278.794	2.011.259	13.8 (13.8-13.8)
United Kingdom	10	7.731.538	53.816.908	12.1 (10.7-13.1)
EUROPE	**147**	**58.544.245**	**409.658.141**	**13.6 (4.2-21.3)**

Table 1: Descriptive statistics of the dataset analysed divided by countries. Population is the average of the daily populations in all the period, and the temperature represents the average, minimum and maximum mean temperature of the regions in each country for the ERA5 dataset.

The association between temperature and mortality is usually described as an asymmetric U-, J- or V-shaped curve. These shapes are mainly determined by the existence of a temperature of minimum mortality from which the risk for the colder and hotter temperatures (the cool and hot tails) can be flatter or more pronounced. In Figure 2 it can be observed how temperatures affect differently the European regions and countries. There are countries with higher risk for summer temperatures (e.g. Spain, Portugal, Italy), and others with higher risk for cooler temperatures (e.g. United Kingdom, France, Croatia). The MMT can be found in different percentiles of the temperature distributions generating these different shapes. For example, Spain's association curve is more U-shaped, with a wide range of temperatures close to the MMT. Others have steeper tails as Croatia, the Netherlands or the United Kingdom, where the risk increases more rapidly when temperatures differ from the MMT.

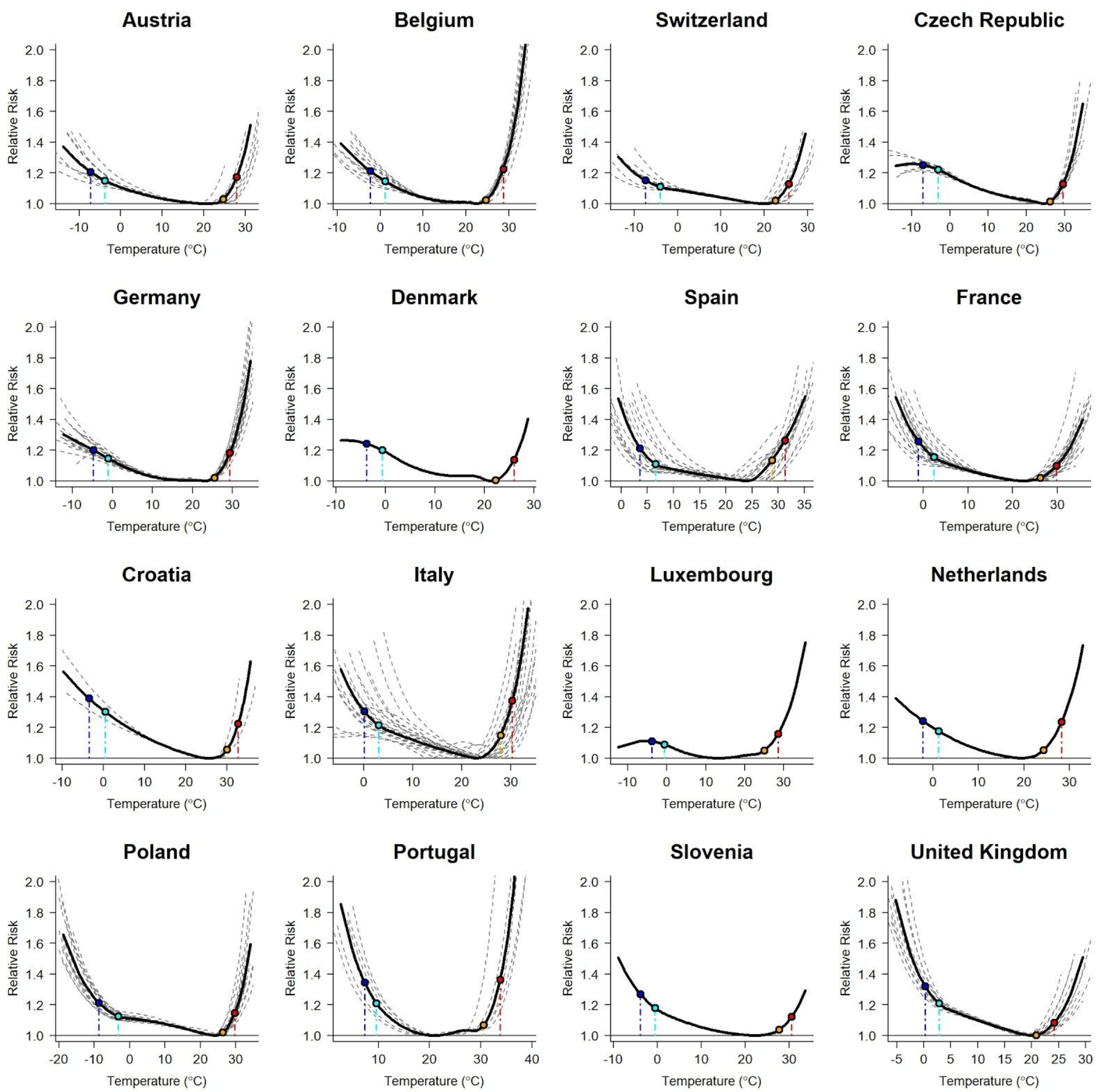

Figure 2. Temperature-mortality relationships for the period 1998-2012. The thick black line represents the relationship for the countries, and the grey dashed lines the relationship for the corresponding regions. Dark blue, cyan, orange and red dots indicate the RR at percentiles 1, 5, 95 and 99 of the distribution of daily temperatures for the countries.

Figure 3 shows the temperature and TAM forecast skills for the early 2012 European cold wave [https://en.wikipedia.org/wiki/Early_2012_European_cold_wave]. Daily temperature and AN anomaly for the period January 27 - February 17, 2012 are calculated from the respective mean annual cycles. For these days, a decrease of the expected temperature can be seen in the observed anomaly for the whole of Europe, especially in eastern and northern Europe as compared to western and southern Europe. However, the spatial distribution of the observed mortality anomaly changes, with higher AN anomalies (measured in deaths per millions inhabitants) in France and north of Italy, and lower AN anomalies for the regions of Germany, the Czech Republic and Poland. Visually studying the maps, it can be detected that the negative temperature anomaly could be predicted one week in advance. Even some hints of the future cold wave could be observed 10 days before. No anomalies are however predicted 15 days in advance. Similar results are observed for TAM, with also good predictions one week ahead of the event, and a decay of the predictability for longer lead times, with no anomaly in mortality predicted 15 days ahead. In conclusion, TAM associated with this cold spell is predictable at the time scale of temperature predictability.

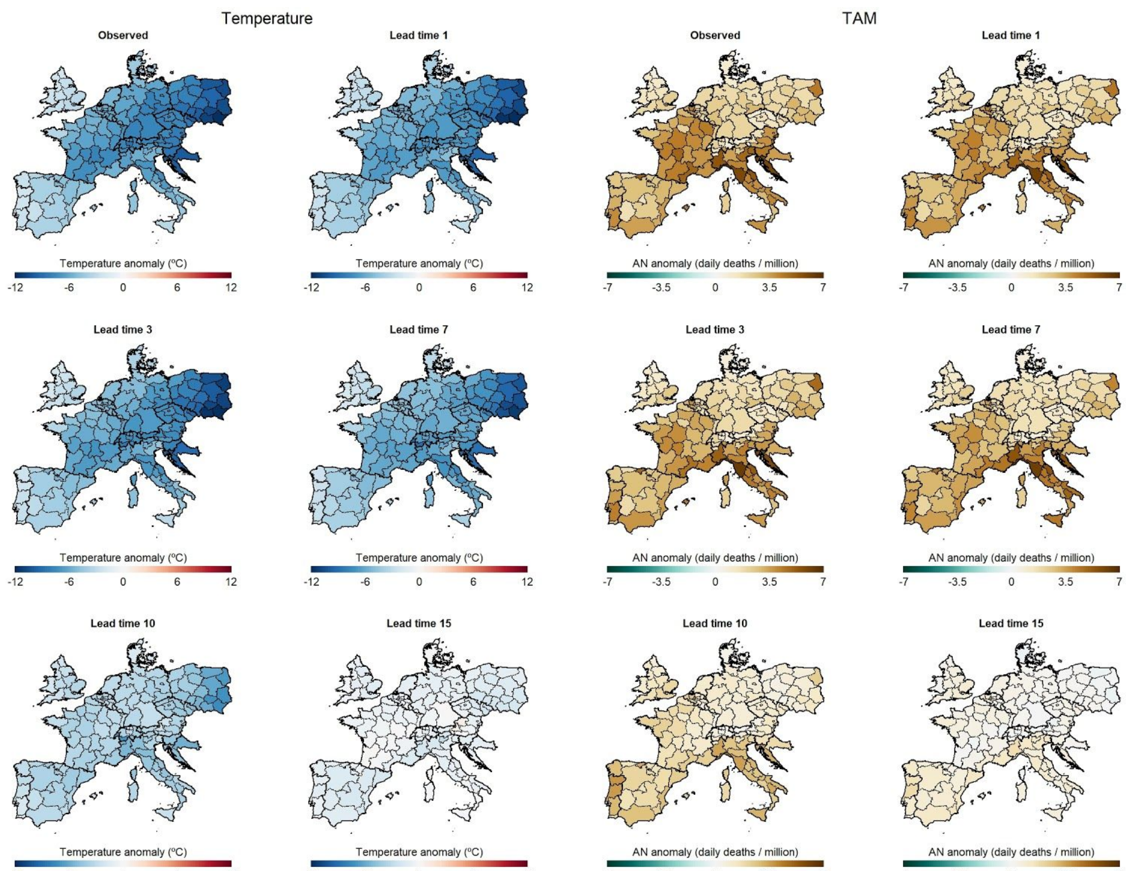

Figure 3: Temperature and TAM forecast skill for the 2012 European cold wave
(from January 27, 2012 to February 17, 2012).

To give an overall view of the predictive skill, Table 2 shows the temperature and TAM skills for Europe considering the pooled temperatures and the overall temperature-mortality association. In general, similar values are observed in every season for the day in which we consider that the predictive skill is lost (i.e. for the lead time at which ACC becomes less than 0.6) and for the decay in ACC over the lead times (other columns). We obtain better predictive skills in the winter months as compared with the summer months. In all cases we observe useful predictability one week in advance, up to almost 11 days in the best case. Values for Europe shown in Table 2 are better than values for any of the individual regions we will see next. The reason may be that generally large-scale circulation weather patterns are easier to predict than smaller scale regional patterns (Ferranti et al., 2018). This behaviour results in the best temperature forecasts for the whole continent and, consequently, the best TAM forecasts. Nonetheless, we focused our analysis on the individual regions for two reasons; in order to address the regional differences that exist in the temperature-mortality associations, and because early warning systems are principally targeted at these (or smaller) scales.

Season	Measure	Lead time ACC < 0.6	ACC lead time 1	ACC lead time 3	ACC lead time 7	ACC lead time 10	ACC lead time 15
Annual (all months)	Temperature	8.8	0.96	0.94	0.76	0.49	0.16
	TAM	9.6	0.97	0.96	0.80	0.57	0.27
Winter (Dec-Feb)	Temperature	10.5	0.99	0.99	0.86	0.64	0.31
	TAM	10.8	0.99	0.99	0.88	0.67	0.37
Spring (Mar-May)	Temperature	8.8	0.95	0.94	0.77	0.46	0.06
	TAM	9.6	0.96	0.94	0.81	0.56	0.18
Summer (Jun-Aug)	Temperature	7.3	0.91	0.87	0.62	0.36	0.10
	TAM	7.6	0.93	0.89	0.62	0.38	0.00
Autumn (Sep-Nov)	Temperature	8.5	0.95	0.94	0.75	0.41	0.08
	TAM	9.5	0.97	0.96	0.79	0.55	0.25

Table 2: Temperature and TAM predictive skill for Europe in the period 2007-2012.

In Figure 4 it can be seen how the predictive skills for temperature and TAM decay over lead times 0 to 15. We consider ACC at lead time 0 in each region as the reference. A slower decay can be seen in the first 4-5 days of both temperature and TAM skills, and from this point on, there occurs a clear change of slope and skills start to decrease faster. Comparing temperature and TAM predictive skills, the curves have similar behaviours, with comparable values across the lead times. One of the principal differences is the major spread in the regional curves for the TAM predictive skill. For the temperature skill, all regions fall in the 6.9-8.2 predictability lead time range, with a similar mean value for central (7.5 days), southern (7.5) and western Europe (7.4). However, for the TAM predictive skill, a wider variability can be observed between regions than for temperature, with a range of 5.7 to 8.8 days the best skill is clearly found for western (7.8 days), compared with central (7.2) and southern Europe (7.0).

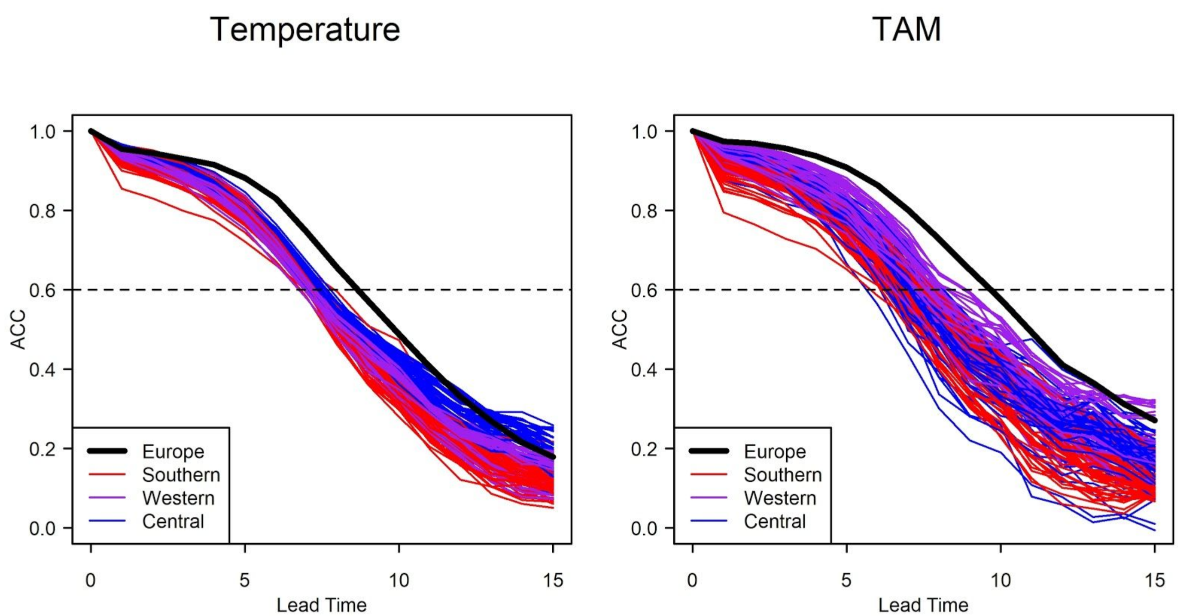

Figure 4: Decay of temperature and TAM forecast skill through lead times 0 to 15 days for the period 2007-2012.

Up to this point we considered the predictive skill for the whole year, but we expect seasonal differences for both temperature and TAM. So, in Figure 5 we map the lead time up to which we can find useful skill in each region by season. Both for temperature and TAM, the best predictive skill is obtained in the cold season. For 95.2% and 93.2% of the regions, the better temperature and TAM predictive skills are found in the winter months, respectively. While the worst skill is found in the summer months; when 83.7% and 85.7% of the regions have the worst temperature and TAM predictive skills.

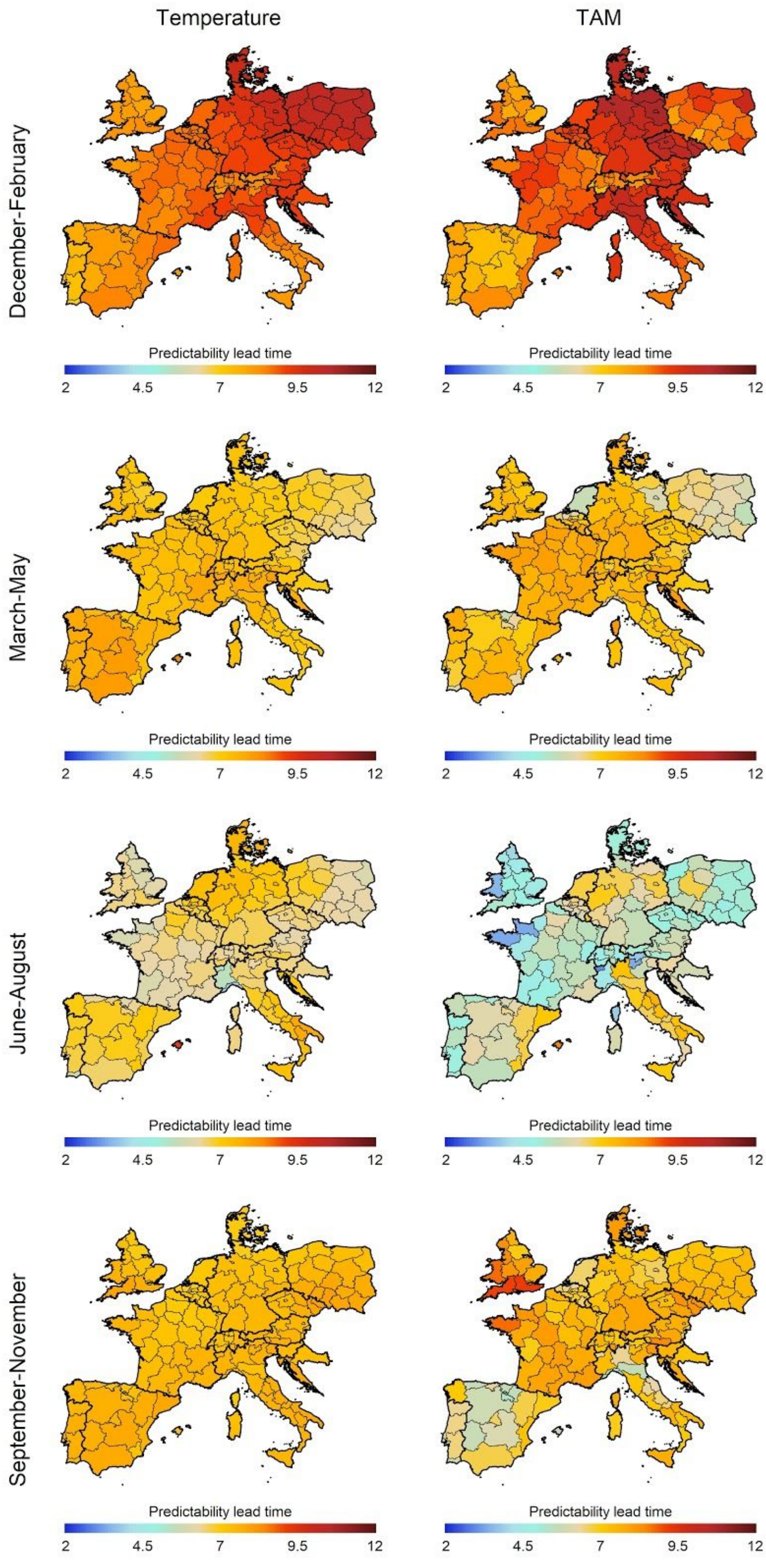

Figure 5: Lead time for which the temperature and TAM predictive skills are lost shown by season in the 147 European regions. We set 0.6 as a threshold value of ACC and we consider that the skill is lost for smaller values.

In summer there is a considerable loss of skill in the TAM forecasts as compared to temperature. In 92.5% of the regions the predictive skill is worse for TAM, with approximately 1 day less of predictability skill. The spatial pattern of the temperature predictive skill is quite homogeneous for all Europe around a mean value of 6.6 days. However more differences are seen in the TAM skill. Countries like France and the United Kingdom lose their skill faster, being the predictability lead time 1.3 and 1.8 days smaller, respectively. Due to particularities in the temperature-mortality associations in these regions, errors in the forecast of summer temperatures implies more substantial variation in the TAM, and therefore worse summer TAM predictability. These particularities can be seen at Figure 2, the regions in these countries are characterized by a MMT that is close to the hotter temperatures, with a short hot tail. Also they do not have a mortality peak in the summer months as some other regions such as the Mediterranean. On the other hand, the best predictability is found in the Mediterranean, Northern Germany and the Netherlands, which are characterized by a high mortality risk in the summer months.

However, winter temperatures tend to be much colder than the MMT in all regions. In addition, the winter tail in the temperature-mortality relationship is not as pronounced as the slope of the summer tail (see Figure 2 again). This makes the transformation of temperature into TAM quite straightforward, therefore the predictive skill for TAM is comparable or even better than for temperature. In the maps, we see a gradual loss of temperature skill that goes from a median loss of 7.2 days in the Portuguese regions to 10.1 days in the Polish regions. As mentioned above, similar values are observed for the TAM predictive skill in the winter months as for temperature, with some differences (e.g. improvement in France and Northern Germany, and worsening in Poland). The worst mean TAM skill is observed in Portugal (7.5 days) and Spain (7.9), where the predictability lead time is smaller than 8 days, while for regions in Croatia (9.8), Germany (9.9), Denmark (10.3) and the Czech Republic (10.3) we find the highest TAM predictability lead time in winter.

Although the highest risk of mortality is found in the most extreme conditions, there exists a risk attributable to non-optimal temperature in the whole range of temperatures. So we should consider TAM in periods with milder temperatures too. In fact, similar predictive skills are found for spring and autumn. To sum up, the predictability lead time for temperature in spring is 7.2 days with a range that goes from a minimum of 6.4 days to a maximum of 8.3 days, while in autumn it is 7.4 days with a 6.9 and 8.0 days range. For TAM, the mean values are similar, only the ranges are wider, i.e. 7.2 days (5.5-8.4 days) in spring and 7.2 days (5.2-9.2 days) in autumn.

In Figure 6 we compare the predictability lead time for temperature and TAM in all regions and seasons. Although we found different behaviors in the mortality forecasts depending on the season, partly due to the peculiar shapes of the temperature-mortality associations, it is also true that better temperature predictive skill is transformed into better mortality predictive skill in all regions and time periods. This means that an improvement of weather forecasts will lead to a similar improvement in the TAM forecasts.

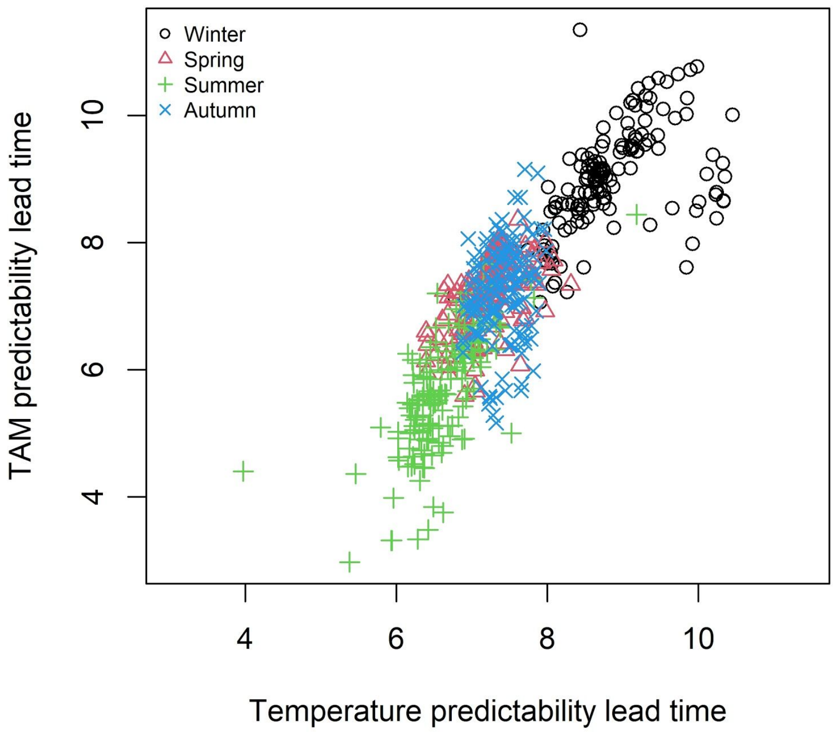

Figure 6: Comparison between temperature and TAM predictive skill by season. Each point represents the day in which the predictive skill is lost (ACC < 0.6) for each of the 147 European regions and seasons.

Finally, we evaluated how well the temperature and TAM forecasts identify extreme days in terms of TAM. We considered extreme days as those with AN higher than the 90th percentile of the daily AN distribution for the summer (July and August) and winter (December and January) months. Then, we calculated the ROC curves and the AUC, considering the skill threshold of 0.9. In Figure 7, we see that the predictability lead time in summer extreme days is lower for TAM than for temperature in 85.0% of the regions, while in winter it is better in 85.6% of the regions. We observe similar temperature predictability skills for summer and winter extreme days. In summer, the predictability lead time is 5.7 days, with a range of 3.7 to 7.5 days, and for winter, 6.0 days with a range of 2.8 to 8.0 days. The spatial distributions are alike as well. But for TAM the situation is different. Summer extreme days can be predicted in the regions of the Mediterranean coast, the Netherlands and Northern Germany, with predictability lead time between 5.5 days to around 7 days. Summer skill is worst in regions where the TAM mortality in summer is not significant, i.e. England & Wales, the rest of France, Poland, the Czech Republic. The highest TAM skill for winter extreme days is found in England & Wales (predictability lead time up to 7.8 days), Poland (7.8) and Croatia (7.8). Moreover, some regions in France, Germany and the north of Italy have values over 7 days. The lowest values are in Portugal (5.5) and Spain (6.2), regions in the south of Italy, and other countries such as Switzerland (6.3) and the Czech Republic (6.3).

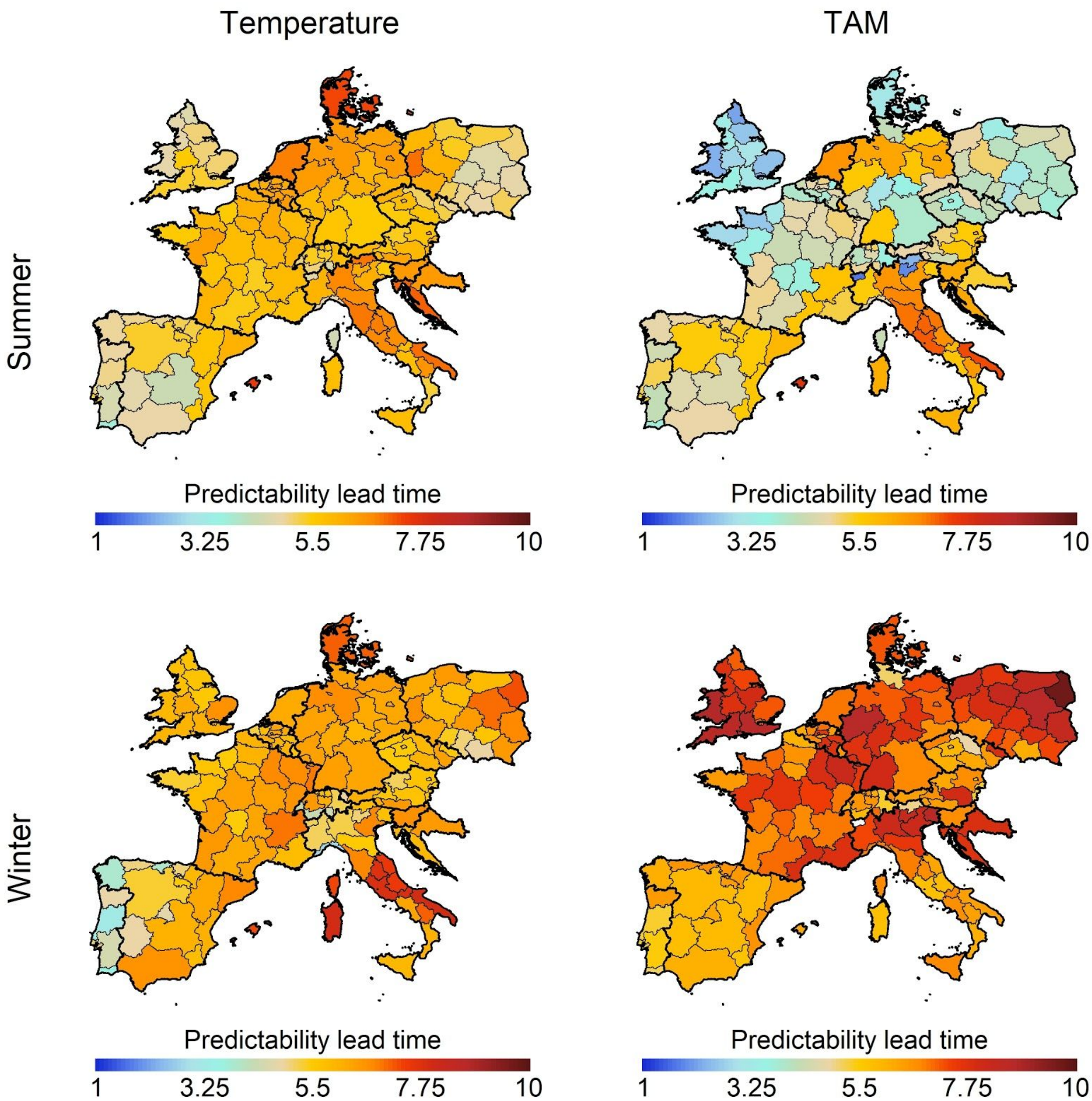

Figure 7: Lead time for which the temperature and TAM predictive skills are lost for extreme days in summer and winter in the 147 European regions. We set the threshold of AUC = 0.9 as the point where skill is lost.

Impact

The results presented in this deliverable assess the predictability of temperature-attributable mortality in a very large ensemble of European regions by using weather forecasts at lead times of up to 15 days. These results could be used to design climate-related health early warning systems, and contribute to the following Blue-Action impacts:

- **To improve stakeholders's capacity to adapt to climate change**. The use of health data in the design of climate-related health early warning systems will lead to more accurate models describing the real impact of climate variability. We interacted with international institutions such as the ECMWF, with the objective to explore potential partners in the private sector to make the heat health early warning system operational. Other stakeholders and possible collaborators could be contacted in order to build future collaborations that can go beyond our prototype to an operational weather health early warning system. Given the theoretical work done here, similar early warning systems can be developed by using other health data, such as occupational accidents or hospital admissions.
- **Improvement of the capacity to respond to the impact of climatic change** on the environment and human activities in Europe. We have been working closely with the City Council of Almada, in Portugal, partner in Blue-Action, and other relevant national and international health agencies. In addition, the system has been built based on the experiences of existing operational schemes.
- **Contribution to better servicing the economic sectors that rely on improved forecasting capacity** through the collaboration between selected stakeholders and scientists. The interaction with business stakeholders in the beginning of the project has outlined the final results of the product. In terms of the private sector, the system can be applied for a wide range of activities, including health insurances and occupational health and safety.
- In the short-term, this system can be adapted to d**evelop risk-based forecasts of extreme weather phenomena at subseasonal-to-seasonal (s2s) time scales** through an innovative, process-oriented description of the weather systems in which extremes are likely to form.

The development of a prototype of European health early warning system is relevant for the **public and private sectors**, as it will have several potential applications. The Societal Readiness Level (SRL[1]) scale is a way of assessing the level of societal adaptation of, for instance, a particular product/service for integrating it society. Within the Blue-Action project, we scaled up the prototype of our product from

- Stages SRL 1-3: reflecting early work in the research project, including suggesting and testing on a preliminary basis a technical and/or social solution to a technical or a societal problem, including identifying relevant stakeholders and how to include them; to
- Stages SRL 4-6 to represent the actual solution(s), the research hypothesis, and testing it/them in the relevant context in co-operation with relevant stakeholders (Almada and other relevant national and international health agencies), while keeping a focus on impact and society's readiness for the product.

In these past months, we have reached the Stages SRL 7-9 with the evaluation of the solution, its refinement, and adequate dissemination.

[1] https://newhorrizon.eu/societal-readiness-level-thinking-tool/ and https://innovationsfonden.dk/sites/default/files/2019-03/societal_readiness_levels_-_srl.pdf

Lessons learned and Links built

The key message is that temperature predictability can be transformed into temperature-attributable mortality (TAM) predictability. TAM can be predicted on weather timescales, for lead time periods beyond 1 or 2 days, which are the lead times nowadays considered in many weather heat stress early warning systems. The different temperature-mortality associations in each region makes TAM predictability more variable than temperature forecasts, generating different spatial patterns and changes depending on the season.

However, a clear, nearly-linear relationship between the predictability of temperature and TAM can be observed. Moreover, depending on the season and region, there is little or virtually no reduction in predictive skill due to the climate-health epidemiological transformation, so future improvements in the predictability of temperature could lead to improvements in the predictability of TAM. We have been using real time forecast data, and these results can be adapted to create operational systems of TAM addressing the real burden of non-optimal temperatures in each region.

Contribution to the top level objectives of Blue-Action

This deliverable contributes to the achievement of the following objectives indicated in the Description of the Action.

- **Objective 6 Reducing and evaluating the uncertainty in prediction systems,** by evaluating temperature and health forecasts for different regions with a unified but yet flexible methodology that provides relevant and comparable information adapting to the different climatic and socio-economic structures.
- **Objective 7 Fostering the capacity of key stakeholders to adapt and respond to climate change and boosting their economic growth,** by giving new inputs that should be considered for the implementation of weather health early warning systems, considering not only temperature data but also mortality to better measure the impact of weather.
- **Objective 8 Transferring knowledge to a wide range of interested key stakeholders**, by considering the weaknesses of the current schemes and the needs of the stakeholders in the design and development of the weather health early warning systems.

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Dissemination and exploitation of Blue-Action results

Targeted dissemination activity for sharing knowledge and transferring it have been described in the deliverable "D5.10 CS2 Dissemination of the temperature-related human mortality product" and will not be repeated in this document.

As indicated in the Description of the Action, the audience for this deliverable is the general public (PU). The deliverable is made available to the world via CORDIS and OpenAIRE.
The results of this case study have been made available in the Horizon Results Platform.