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Deliverable D3.3

Recommendations for further improvements of operational seasonal forecasting systems

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1.1	01/06/21	L. Batté	Preliminary version – structure of the document; some sections need to be completed
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1.3	15/06/21	L. Batté	Final edits and executive summary

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Chain based On climate PrEdictions

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1 EXECUTIVE SUMMARY

This deliverable builds on activities from MEDSCOPE Workpackages 2, 3 and 4 to provide a set of recommendations for future development of operational seasonal forecasting systems. In this document we chose to focus not only on the numerical models used for seasonal forecasting, but also on the set of data and tools made available to possible users of information on this time scale. The work presented here provides an update on work reported in previous deliverables from the project. Section 2 gives an overview of knowledge gained from the assessment of state-of-the-art seasonal prediction systems, and how progress in understanding sources of predictability and uncertainties can also be exploited to provide information on the forthcoming season over the Euro-Mediterranean area. Many of the studies cited in this section contribute to the MEDSCOPE Special Issue in Climate Dynamics, which should be completed in the upcoming months once all submitted papers have been reviewed. Section 3 presents how some recommendations highlighted in Section 2 were included into the CSTools toolbox as R functions to handle and exploit seasonal forecast datasets. Future plans for the toolbox are also presented as a recommendation to further develop such fundamental tools for the design of climate services based on seasonal forecasts. Finally, Section 4 summarizes and discusses main points of feedback from scientists working in WP4 on the development of climate services prototypes to producers of seasonal forecasts. One key aspect is the documentation of the most appropriate workflows to have appropriate and high quality data tailored to their use.

2 Recommendations based on the assessment of state-of-the-art Seasonal Prediction Systems

MEDSCOPE deliverable D2.2 (Prodhomme et al., June 2019) provided an overview of the ability of state-of-the-art climate prediction systems to represent mechanisms of predictability in the Mediterranean region, and also gave insight on the actual seasonal prediction skill in current operational seasonal forecast systems as well as with an empirical model developed at **AEMET**. This section enhances the conclusions from D2.2 based on recent publications in (or beyond) the framework of MEDSCOPE. A Special Issue in Climate Dynamics gathers contributions on sources of predictability and variability over the region, and now includes several publications assessing their representation in state-of-the-art seasonal prediction systems. Key findings are summarized in sections 2.1 and 2.2, and section 2.3 summarizes recommendations based on these studies.

2.1 Skill over the Euro-Mediterranean region

Deliverable D2.2 highlighted the large diversity of skill levels over the Euro-Mediterranean region depending on the operational system, the region of interest, forecast initial date and lead time.

Further evaluations of seasonal forecasting skill were led by project partners in the framework of MEDSCOPE and related activities such as the Mediterranean Climate Outlook Forum (MedCOF).

Météo-France introduced a new seasonal forecast system, System 7, in autumn 2019. This system was evaluated alongside the previous System 6 and ECMWF SEAS5. Synthesis tables for probabilistic (area under ROC curve) and deterministic (correlation) scores are available on the website http://seasonal.meteo.fr for parameters such as near-surface temperature and precipitation over a list of geographical areas. Reliability was also computed over the re-forecast period for each initial month and up to month 6. One example of such evaluations is shown in Figure 1.

CMCC computed correlation for near-surface temperature and precipitation over the Mediterranean region for several operational forecast systems and the empirical forecasting system designed at **AEMET**, as part of the Mediterranean Seasonal Climate Update disseminated on the MEDSCOPE website (https://www.medscope-project.eu/products/mediterranean-seasonal-climate-update/). The evaluation will be extended to the Ranked Probability Skill Score in the forthcoming bulletins.

CNR evaluated several aspects of skill for these two parameters in five systems contributing to Copernicus Climate Change Services and concluded that although these systems have limited correlation skill with respect to simple persistence, they do improve resolution and discrimination for most of the Mediterranean region, with better performance for the higher and lower terciles, versus the middle tercile (Calì Quaglia et al. 2021). This study also evaluated performances of multi-model ensembles (MMEs) either by grouping all ensemble members, or subsetting random members from each model so as to build an ensemble size comparable to individual models. As found in previous studies, there is a sensitivity of some skill measures to ensemble size, but model diversity already allows for some improvements with respect to individual systems. Calì Quaglia et al. (2021) argue that the use of subset MMEs can allow for a reduction of computation costs in applications and impact models, while ensuring generally higher performance levels than individual models.

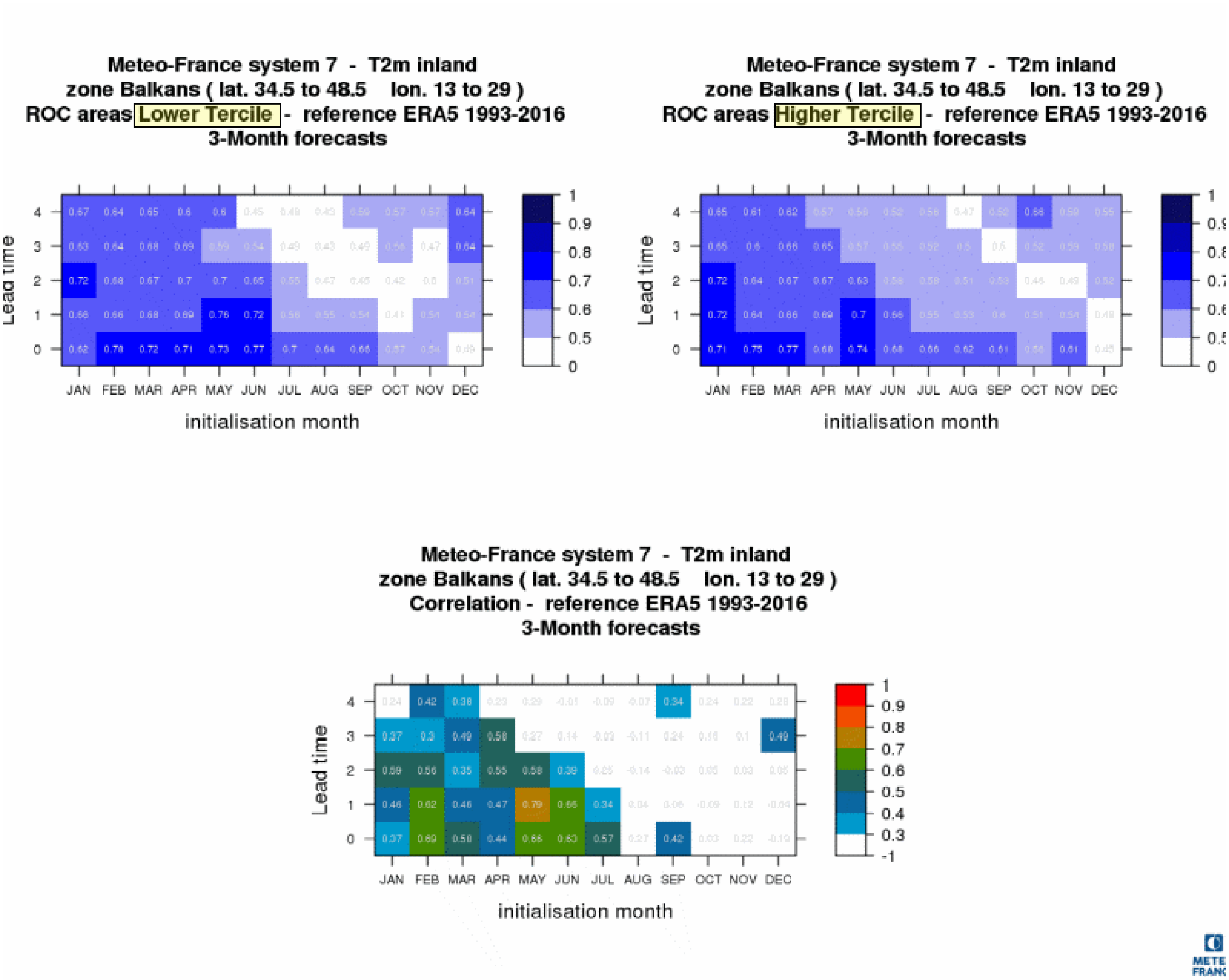

Figure 1: ROC areas for the lower tercile (top left) and upper tercile (top right) and correlation (bottom) of 3-month average 2 meter temperature over land in Météo-France System 7 re-forecasts with ERA5 reanalysis data, computed over an extended Balkans region (34.5-48.5°N; 13-29°E) for each initialization month (x-axis) and each forecast time (y-axis).

In addition to the evaluation of heat wave prediction skill over the Euro-Mediterranean region with C3S systems (see D2.2) focusing on the Heat Wave Magnitude Index (Russo et al. 2014) at the gridpoint level, the skill of the ECMWF SEAS5 system in reproducing the HWMI and another index called Total Heat Wave Magnitude (THWM) index was assessed over several regions in Europe (Prodhomme et al. 2021). The THWM, instead of focusing on the largest heat wave of a time window, sums the heat wave standardized intensities over the time window, accounting for several events in each season. Figure 2 shows the correlation between indices computed in SEAS5 re-forecasts initialized in May and ERA5 reanalysis used as a reference, according to the start date and the length of the time window considered. Significantly higher skill than a linear trend model is found over the Mediterranean region (subfigure f) when focusing on windows starting in July, or when including the first month (May) in the analysis.

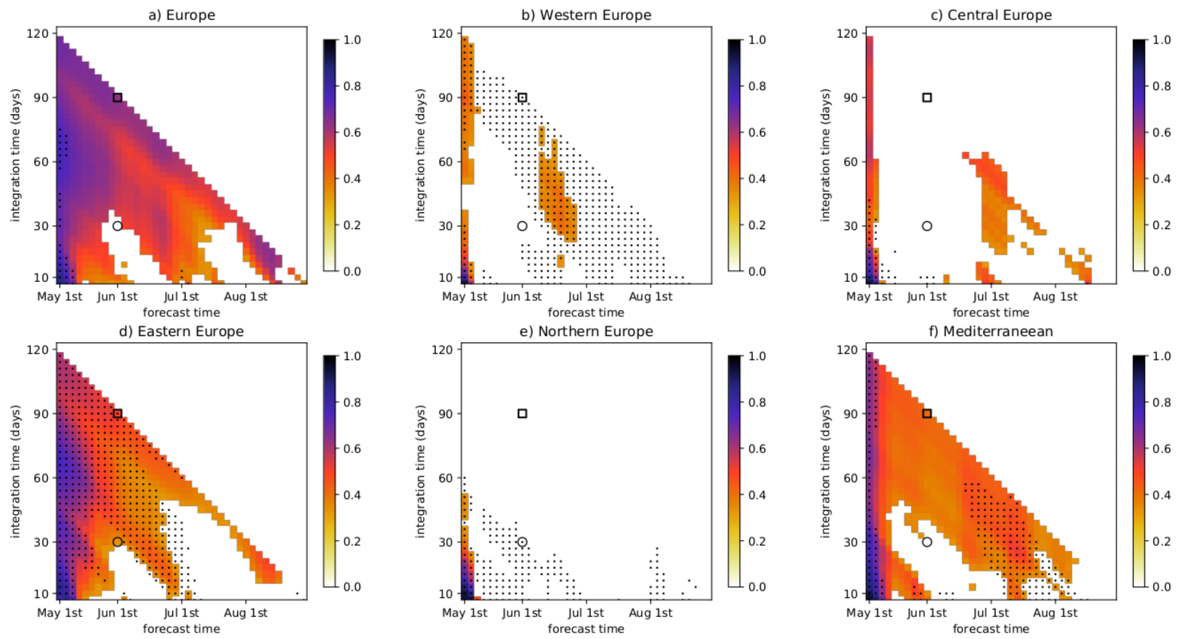

Figure 2: Correlation of SEAS5 THWM heat wave index with corresponding ERA5 index for different regions of Europe, according to the forecast time (first date of the window in the x-axis) and integration period (in the y-axis). The black circle corresponds to the prediction of the month of June, while the black square the JJA season. All re-forecasts are initialized on May 1st. Only correlation values significant at the 95% confidence level and higher than that of a linear trend model are shown (stippling shows where correlations are significantly higher than the linear trend model at a 90% confidence level). Figure from Prodhomme et al. (2021).

2.2 Representing sources of predictability

A preliminary version of the empirical model developed at AEMET was described in Rodriguez Guisado et al. (2019). The version was based on multiple linear regression of variability modes to produce probabilistic forecasts of temperature and precipitation. A second version was then designed using Partial Least Squares regression and is described and evaluated in Rodriguez Guisado and Rodriguez Camino (2021) (see also MEDSCOPE Deliverable D2.3). The model automatically selects predictors for a given initial date and forecast time from a pool of potential predictors so as to maximize the amount of variance explained by these predictors, using a leave-one-out technique over the re-forecast years. It can also be used to diagnose sources of predictability on past re-forecast cases. Figure 3 adapted from Rodriguez Guisado and Rodriguez Camino (2021) shows an evaluation using this empirical model of the influence of soil moisture on the ROCSS. Here soil moisture information is provided to the empirical model as EOFs of volumetric soil water from the first three layers of the ERA5 reanalysis.

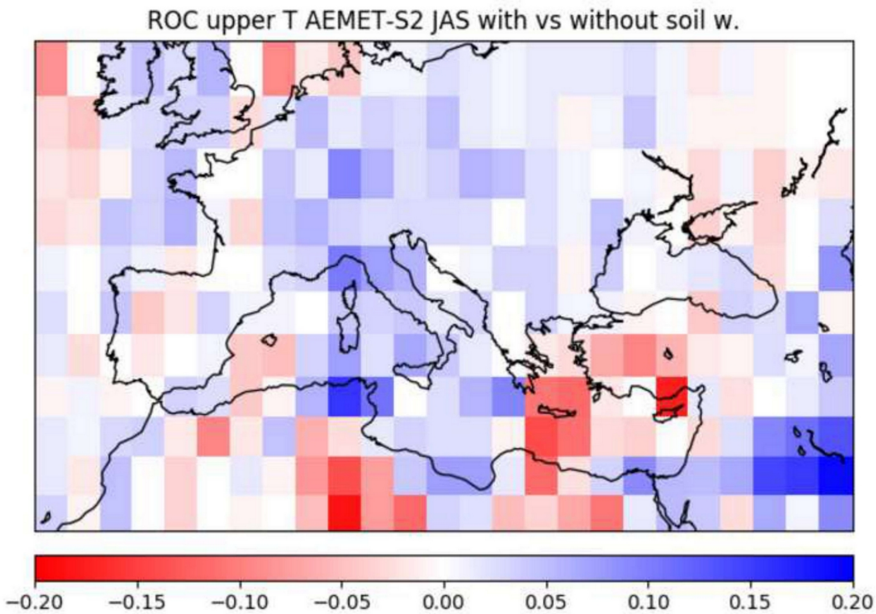

Figure 3: Difference in area under ROC curve for upper tercile JAS temperature empirical forecasts with and without soil wetness as a predictor. Blue areas are where ROC is improved by including soil moisture information. Figure from Rodriguez Guisado and Rodriguez Camino (2021).

Two studies, recently published in the dedicated Climate Dynamics Special Issue, point out the role of soil moisture on the predictability of the Mediterranean region - and are therefore consistent with results from the empirical model study. It is found that dry soils lead to a reduction of precipitation for early summer months, while wet soils tend to favor the persistence of precipitation throughout summer over several areas (Ardilouze et al., 2021). In addition, dry and wet soils at the beginning of the summer strongly impact near-surface temperatures for most part of the season, which turns out to be warmer and colder than normal, respectively. Moreover, if a sustained source of surface water is maintained during the summer, through e.g. crop irrigation, local temperatures would be lower and extreme values strongly moderated. This aspect should be considered in the seasonal forecast outlooks of regions subject to vast irrigation practises (Materia et al., 2021).

Systems contributing to the C3S multi-system seasonal forecasts exhibit different levels of skill in representing the boreal winter stratospheric polar vortex, wave-mean flow interaction and coupling between the stratosphere and troposphere (Portal et al. 2021). This study also pinpointed the importance of predicting the 100-hPa meridional eddy heat flux to correctly forecast the evolution of the stratospheric polar vortex.

Another potential source of predictability for Northern Hemisphere circulation explored in the framework of MEDSCOPE and evaluated in current operational seasonal forecasting systems is the variability of snow cover over Eurasia (Ruggieri et al. 2021). This study identifies an anomalous circulation in response to snow cover anomalies, which projects on the Arctic Oscillation. No evidence of a stratospheric pathway is found.

Focusing on late boreal winter, Mezzina et al. (2020) evidenced the asymmetries in the extra-tropical response to El Niño and La Niña in an idealized setup with three atmospheric models, related to the enhanced or weakened response of tropical convection to anomalous SST forcing. Mezzina et al. (2021) compared the impact of ENSO on the stratosphere in the same set of experiments, and found similar conclusions for the magnitude of the stratospheric response, with a higher amplitude stratospheric temperature and zonal wind signal in El Niño than La Niña conditions.

Giuntoli et al. (2021) studied the predictability of Mediterranean weather regimes in the C3S re-forecasts, and provided evidence that two of these regimes were clearly related to the El Niño Southern Oscillation: a meridional regime in La Niña years, and an anticyclonic regime during El Niño years. Despite small signal-to-noise ratios, most C3S systems reproduce this signal and show some skill in forecasting the anomalies of weather regime frequencies. Selecting three out of the five models studied allows to enhance the multi-model performance, and predictability is lowest during ENSO-neutral years.

Another potential source of predictability, at least for the Western part of the Mediterranean basin, is the North Atlantic Oscillation. Although dynamical models show contrasted levels of skill (with large uncertainties) in representing this mode of variability, weighting of ensemble members according to proximity to a forecast NAO index Gaussian PDF allows to improve precipitation forecasts over the Iberian peninsula with ECMWF SEAS5 (Best Estimation Index, Sanchez-Garcia et al. 2019). Dobrynin et al. (2018) uses empirical NAO forecasts to select ensemble members from a seasonal forecast model, producing a subsample of it, showing improvements on temperature, precipitation and surface pressure winter forecasts skill over Europe and the Mediterranean Basin.

2.3 Summary of recommendations based on evaluation of current systems

From the evaluation of current skill of seasonal prediction systems, given the limited prediction skill, a thorough analysis of skill (both over the re-forecast period, and conditional to identified sources of predictability) is a mandatory first step. However, the limited sample size in terms of hindcast years leads to uncertainties in skill scores calculations and evaluation of model performance (Hemri et al. 2020). In addition to the usual skill scores, mostly computed for temperature and precipitation, attention should be paid to the ability of models to simulate climate drivers, climate variability patterns and teleconnections that are relevant at a seasonal scale over the region of interest (Kumar et al. 2020). For these evaluations, Volpi et al. (2020) showed using a large ensemble and longer re-forecast period that the typical ensemble size and re-forecast length in current systems was sufficient to enable a robust estimate of model performance.

Regarding the representation of key sources of predictability for the seasonal time scale over the Mediterranean region, results emphasize the importance of land surface initialization to tap these sources, both for the autumn/winter and spring/summer seasons. Improved modelling of the troposphere and stratosphere interactions could be a means of progress in some models (such as MF) which fail to correctly reproduce the mechanisms at play in the variability of the boreal winter stratosphere. Despite modulations of the signal in the North Atlantic / Euro-Mediterranean sector (Benassi et al. 2021), ENSO is a key source of predictability at the seasonal time scale.

Irrigation should be contemplated in post-processed evaluations of seasonal forecast outlooks, in regions characterized by a high agricultural density. Dynamical predictions, in fact, do not usually consider the effect of irrigation on near-surface temperatures, as long as farming practices are not resolved or parameterized in the GCMs, possibly resulting in biased forecasts.

Future work on improving the coupled systems and their initialization strategies should contribute to enhancing seasonal prediction skill over the region. However, the restricted signal-to-noise ratio and levels of predictability make multi-model approaches highly relevant for reliable and skilful predictions over the region. Sub-sampling strategies either based on past skill of individual models, on representation of key processes, or clustering approaches to reduce the ensemble size can be a useful way to extract the most relevant information from the available sources; yet these approaches must be used with caution, and most often the full multi-model can still provide additional skill due to an enhanced ensemble size. Besides sub-sampling and clustering strategies, a full multi-model approach with a careful selection of models is also worth exploring. Once the relevant drivers and variability patterns have been identified for all seasons, in addition to assessing the skill of the forecast system based on hindcasts, it is recommended, following Kumar et al. (2020), to analyse candidate models for their ability i) to forecast patterns that contribute to the climate variability for each season and ii) to simulate the proper teleconnections linking remote drivers and climate variability patterns. In this sense, analyses like Giuntoli et al. (2021), assessing ENSO teleconnections, or Ruggieri et al. (2021), investigating how models reproduce observed anomalous fluxes and dynamics related to snow cover anomalies, provide a useful first step.

However, length of available hindcasts still provide limitations on model's performance analysis. Skill scores calculation present relatively high uncertainty, and evaluation of how teleconnection mechanisms are reproduced in operative models is limited by the low number of events (like ENSO) present on the period available. Besides, calibration or statistical techniques, like Best Estimation Index (Sanchez-Garcia et al. 2019) have shown ability to improve skill when applied on a single model with a long enough hindcast. So, in addition to trying to improve coupled systems and initialization strategies, it could be worth considering investing an effort on providing longer hindcasts of current systems, which would allow for a better characterization of model biases and skill, together with the use of additional calibration and postprocessing techniques that could help to extract more information from model ensembles.

3 PLANS FOR FURTHER IMPROVEMENT OF CSTOOLS

The Medscope Toolbox, CSTools, in the current version 4.0.0, gathers essential functions and methods to postprocess climate forecasts. A complete overview of CSTools is available in D3.2 and Pérez-Zanón et al. (2021).

Several functions developed for CSTools address the points discussed in Section 2:
- Assessment of skill for individual systems and the multi-model can be done using the CST_MultiMetric function (see the example presented in the CSTools package vignette on CRAN https://cran.r-project.org/web/packages/CSTools/vignettes/MultiModelSkill_vignette.html as well as the YouTube video tutorial number 4 – How to identify the best system for your region and season – linked on the MEDSCOPE website)

- Weighting according to the NAO index can be applied using the CST_BEI_Weighting function (see https://cran.r-project.org/web/packages/CSTools/vignettes/BestEstimateIndex_vignette.html and the video tutorial number 8 – Improved forecast skill using the NAO on the MEDSCOPE website)

- Computation of weather regimes can be done using the CST_WeatherRegimes function (see https://cran.r-project.org/web/packages/CSTools/vignettes/WeatherRegimes_vignette.html); clustering of ensembles can be done using CST_EnsClustering (see the vignette https://cran.r-project.org/web/packages/CSTools/vignettes/ENSclustering_vignette.html)

One originality of the CSTools software is that it allows the end-users to create a chain of functions covering all the steps from (1) retrieving data from files, (2) manipulating the data and (3) saving it again on a storage system. Indisputably, the relevance of CSTools relies on (2), the functions and methods that allow the postprocessing of climate forecast, but steps (1) and (3) cannot be underestimated given the number of datasets and novelties in storage systems that constantly bloom.

On the side of the methods already integrated into CSTools, new calibration methods are expected to be integrated in the subsequent versions. This is the case, for instance, of the method by Eade et al. (2014) which adjusts the forecast variance ensuring that the ratio of predictable components (RPC) is equal to one. Additionally, because the current version of the Calibration function allows for the calibration of hindcasts only, an enhancement of this function to calibrate an actual forecast given the analysis between hindcast and a reference is strongly considered. For the tailored visualization tools, we are also contemplating a new multipanel option unifying the legend for the functions that allows visualizing the most likely quantiles.

Some applications require simple climate indicators, such as extreme temperature events, while others, like hydrological models, may require a more complex sets of parameters. The saving function included in CSTools is currently designed to save the postprocessed forecast, such that it can later be used as the input of applications coded in a different programming language. However, the computation of climate indicators could be added to CSTools in order to allow end-users to create their applications without breaking the CSTools chain. For instance, functions to compute the consecutive number of days exceeding a threshold could allow users to compute the heatwave duration index and the cold wave duration index. In a similar way, other indicators specific for the agricultural sector, such as the Growing Season Temperature index (GST) which is defined as the average of daily average temperatures between April 1st to October 31st in the Northern Hemisphere, could be of interest to end-users. In the case of the energy sector, wind power density and wind capacity factor, which are based on the essential climate variable of wind speed could also be part of this extension[1].

As a last remark, the step of retrieving data from files in a much flexible manner is a further development crucial for the future of CSTools. This step currently allows to load multiple climate forecasts and a reference dataset for the corresponding dates, allowing regridding onto a common grid specifying several characteristics (e.g.: the method or the output grid), however, testing this function with the latest datasets is vital, as well as updating it such that it can follow the most up-to-date data conventions for the different forecast horizons.

1 Note that such indices have been implemented in another R package, CSIndicators, developed by BSC as part of H2020 projects MEDGOLD (776467) and S2S4E (776787), with functions compatible with CSTools.

4 RECOMMENDATIONS BASED ON FEEDBACK FROM USERS OF SEASONAL FORECAST DATA

In the framework of WP4 activities in MEDSCOPE, users of seasonal forecast data provided feedback on the datasets provided to work on climate service prototypes (summarized in Milestone 4.3). Some key aspects for operational forecast providers are summarized here.

4.1 Variables, temporal and spatial resolution

The main focus of correction methods in MEDSCOPE was set on near-surface temperature and precipitation fields, with corrected data made available to help design prototype climate services in the agriculture, energy and water sectors.

Applications often consist in the development of climate indicators which depend on a range of meteorological and environmental variables as input to modelling chains. Most of the correction and calibration methods in the CSTools package focus on one variable. However some approaches such as those based on analogs or weather regimes can be used to correct several variables, as long as appropriate reference datasets for the variables of use are provided. Overall, the main focus of correction methods was generally set on precipitation, temperature and atmospheric pressure fields. Some users of the data stressed that other fields such as surface radiation or near-surface winds had very limited skill and large errors – despite correction attempts – which made them challenging to use in impact models.

Some methodologies exist to correct forecasts consistently across variables, such as copula-based methods (Li et al. 2020). These weren't specifically addressed in the framework of the MEDSCOPE project. More generally, the ability of correction and calibration methods to enhance the quality of seasonal forecast data for applications will depend on a combination of factors:

- the sample size for correction estimates (e.g., number of re-forecast years to train the correction methodologies on)

- the quality of the reference datasets for the variables of interest

- the baseline skill of the prediction system(s) used

4.2 Benchmarks for seasonal forecast skill

Another recommendation provided by WP4 scientists is the need to benchmark more clearly the seasonal forecast skill of operational systems, so as to clearly show if and where the seasonal forecast quality would meet the user's expectations. Deterministic and probabilistic scores sometimes fall short of providing this information, especially if the reference is a naïve forecast (or climatology).

On the other hand, scores tailored for one application seldom suit another, so operational forecast providers are faced with the need to select from a wide array of possible evaluation criteria. As a result, seasonal forecast data or information are sometimes provided without a set of relevant scores to inform the user on their limitations, or with skill measures and downscaling strategies tailored to the applications directly implemented in the institute providing the forecast. Designing appropriate benchmarks and skill measures requires more interaction between users and data providers. More time should be set aside for these interactions, and to find the balance between evaluation tools and metrics generic enough to be used for several applications and specific enough to provide relevant information for a given user.

Systematically benchmarking seasonal forecast prototypes against empirical or statistical approaches (including climatology) has been shown to enhance the understanding of strengths and weaknesses of dynamical seasonal forecasting, and such methodologies should be common practice.

4.3 Documentation of workflows

More generally, the development of workflows tailored for sectoral applications in WP4 was facilitated when precise documentation was provided. The CSTools vignettes are a key asset for the uptake of the functions included in the package and should be generalized.

Some delays arose from the Covid-19 pandemic and slowed down the co-construction of some applications, but this context makes proper documentation (including examples to build common vocabularies) and regular interaction all the more necessary for the successful uptake of climate prediction data.

5 REFERENCES

Ardilouze, C., Materia, S., Batté, L. et al. (2020) Precipitation response to extreme soil moisture conditions over the Mediterranean. *Clim. Dyn.* https://doi.org/10.1007/s00382-020-05519-5

Benassi, M., Conti, G., Gualdi, S. et al. (2021) El Niño teleconnection to the Euro-Mediterranean late-winter: the role of extratropical Pacific modulation. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05768-y

Cali-Quaglia, F., Terzago, S. and von Hardenberg, J. (2021) Temperature and precipitation seasonal forecasts over the Mediterranean region: added value compared to simple forecasting methods. *In revision for Clim. Dyn.*

Dobrynin, M., Domeisen, D. I. V., Müller, W. A., Bell, L., Brune, S., Bunzel, F., et al. (2018). Improved teleconnection-based dynamical seasonal predictions of boreal winter. *Geophys. Res. Lett.*, 45, 3605– 3614. https://doi.org/10.1002/2018GL077209

Giuntoli, I., Fabiano, F. and Corti, S. (2021). Seasonal predictability of Mediterranean weather regimes in the Copernicus C3S systems. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05681-4

Hemri, S., Bhend, J., Liniger, M.A. et al. (2020). How to create an operational multi-model of seasonal forecasts? *Clim. Dyn.* 55, 1141–1157 https://doi.org/10.1007/s00382-020-05314-2

Kumar, A. et al. (2020). Guidance on operational practices for objective seasonal forecasting. WMO 1246, 106 pp., https://library.wmo.int/doc_num.php?explnum_id=10314

Li, M., Jin, H., & Brown, J. N. (2020). Making the output of seasonal climate models more palatable to agriculture: a copula-based postprocessing method, *J. Appl. Met. Clim.*, 59(3), 497-515. doi:10.1175/JAMC-D-19-0093.1

Materia, S., Ardilouze, C., Prodhomme, C. et al. (2021). Summer temperature response to extreme soil water conditions in the Mediterranean transitional climate regime. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05815-8

Mezzina, B., Garcia-Serrano, J., Bladé, I. et al. (2020). Multi-model assessment of the late-winter extra-tropical response to El Niño and La Niña. *Clim. Dyn.* https://doi.org/10.1007/s00382-020-05415-y

Mezzina, B., Palmeiro, F. M., Garcia-Serrano, J. et al. (2021). Multi-model assessment of the late-winter stratospheric response to El Niño and La Niña. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05836-3

Pérez-Zanón, N., Caron L.-P., Alvarez-Castro C. et al. (2021). CSTools: Assessing skill of climate forecasts on seasonal-to-decadal timescales. R package version 4.0.0. https://CRAN.R-project.org/package=CSTools

Pérez-Zanón, N. et al. The CSTools Toolbox: from climate forecasts to climate forecast information. *In preparation for Geophys. Mod. Dev.*

Portal, A., Ruggieri, P., Palmeiro, F. M. et al. (2021). Seasonal prediction of the boreal winter stratosphere. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05787-9

Prodhomme, C. et al. (2019). Assessment of the ability of state of the art climate prediction systems to represent mechanisms of predictability in the Mediterranean and role of systematic errors. MEDSCOPE Deliverable D2.2.

Prodhomme, C., Materia, S., Ardilouze, C. et al. (2021). Seasonal prediction of European summer heatwaves. *Clim. Dyn.* https://doi.org/10.1007/s00382-021-05828-3

Rodríguez-Guisado, E., Serrano-de la Torre, A. Á., Sánchez-García, E. et al. (2019). Development of an empirical model for seasonal forecasting over the Mediterranean. *Adv. Sci. Res.*, 16, 191–199, https://doi.org/10.5194/asr-16-191-2019

Rodríguez-Guisado, E. and Rodríguez-Camino, E. (2021). Sources of predictability over the Mediterranean at seasonal time-scale: building up an empirical forecasting model. *Submitted to Clim. Dyn.*

Ruggieri, P., Benassi, M., Materia, S. et al. (2021). On the role of Eurasian autumn snow cover in dynamical seasonal predictions. *In revision for Clim. Dyn.*

Russo, S., Dosio, A., Graversen R. G., et al. (2014). Magnitude of extreme heat waves in present climate and their projection in a warming world. *J. Geophys. Res.: Atm.* 119(22): 12,500-12,512 doi:10.1002/2014JD022098

Volpi, D., Batté, L., Guérémy, J.-F., and Déqué, M. (2020). Teleconnection-based evaluation of seasonal forecast quality. Climate Dynamics, 55: 1353–1365. doi: 10.1007/s00382-020-05327-x.