



(GRANT AGREEMENT 689029)

European Climate Observations, Monitoring and Services initiative (2)

Deliverable D3.1

***Case study investigation of the CStools toolbox for skill assessment
of climate forecasts***

Deliverable Title	<i>Case study investigation of the CTools toolbox for skill assessment of climate forecasts</i>	
Brief Description	<i>Presentation of three high-level use cases showing the added value of the CTools toolbox to post-processes climate forecasts.</i>	
WP number	3	
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Creation Date	08/06/2021	
Version Number	v1	
Version Date	14/06/2021	
Deliverable Due Date	15/09/2020	
Actual Delivery Date	15/06/2021	
Nature of the Deliverable		<i>R – Report</i>
		<i>P - Prototype</i>
	x	<i>D - Demonstrator</i>

		<i>O - Other</i>	
Dissemination Level/ Audience		<i>PU - Public</i>	
	x	<i>PP - Restricted to other programme participants, including the Commission services</i>	
		<i>RE - Restricted to a group specified by the consortium, including the Commission services</i>	
		<i>CO - Confidential, only for members of the consortium, including the Commission services</i>	
Version	Date	Modified by	Comments
1	14/06/2021	All Co-authors	Adapted from manuscript in preparation to be submitted to GMD.

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1. Executive Summary

Despite the wealth of existing climate forecast data, only a small part is effectively exploited for sectoral applications. A major cause of this is the lack of integrated tools that allow the translation of data into useful and skilled climate information. This barrier is addressed through the development of an R package. CStools is an easy-to-use toolbox designed and built to assess and improve the quality of climate forecasts for seasonal to multi-annual scales. The package contains process-based state-of-the-art methods for forecast calibration, bias correction, statistical and stochastic downscaling, optimal forecast combination and multivariate verification, as well as basic and advanced tools to obtain tailored products. Thanks to the toolbox design in individual functions, the users can develop their own post-processing chain as shown in the use cases presented in this deliverable: the analysis of the extreme wind speed event occurred in March 2018, the SNOWPACK model and the SCHEME hydrological model.

2. CStools toolbox

Within MEDSCOPE Work Package 3, the [R toolbox CStools](#) was developed and served as Deliverable D3.1. This toolbox exploits dynamical seasonal forecasts in order to provide information relevant to stakeholders at the seasonal timescale. The package contains process-based methods for forecast calibration, bias correction, statistical and stochastic downscaling, optimal forecast combination and multivariate verification, as well as basic and advanced tools to obtain tailored products

In order to enhance the stakeholder accessibility of the toolbox, [video tutorials](#), [extensive documentation](#) and [practical examples](#) have been made available online. After an overview of the methods in section 3, we show in detail how the tools provided in CStools can be used for scientifically-advanced impact modeling in section 4. More specifically CStools is used to prepare optimized forecast data to be used to analyse an extreme-wind event, as input for a snow model (SNOWPACK; Lehning et al., 2002a,b) and for a hydrological model (SCHEME; Baguis et al., 2010). In order to enhance reproducibility for different use cases, the structural methodology of data handling is emphasized and explained in detail.

3. Introduction: from climate data to climate information

There are different forecast post-processing steps essential to arrive at climate information. These are provided within CSTools and visualized in Figure 1.

- *Data retrieval and formatting:* Optimal methods for spatial and temporal data manipulation, such as interpolation methods, are needed given the existing wide range of climate data formats. This can be a critical step when trying to combine multiple datasets such as observations and forecasts.
- *Forecast calibration and multi-model forecast combination or scenario selection.* Calibration is necessary to correct systematic errors of the Earth system models (ESM) and to uncover any predictive signal. These biases mostly originate from the crude representation of the climate dynamics within ESMs (Marcos, 2016; Van Schaeybroeck and Vannitsem, 2018; Manzananas et al., 2019). In addition, combining multiple forecasting systems allows to substantially enlarge the diversity of potential weather situations (Hemri et al., 2020). As a consequence, errors are partially compensated and there is an increase in consistency and reliability (Hagedorn et al., 2005). Scenario selection, on the other hand, may often be useful for communication and information synthesis for specific applications (Ferranti & Corti, 2011).
- *Downscaling:* Climate forecast systems, due to computational limitations, provide global seasonal-to-decadal forecasts at a horizontal resolution of typically 100 km. Users, however, require local information and (statistical) downscaling is commonly used to perform realistic transformations from large to small scales (Maraun & Widmann, 2018, Ramon et al. 2021).
- *Skill assessment:* Estimating the quality of the predictions is essential for both improving the current forecast systems and providing useful forecast products tailored to several sectors (Merryfield et al., 2020). The skill estimates should be provided together with the forecast products to allow a correct interpretation of the forecasts. Also, the skill can be measured with respect to a classical forecast (such as the observed climatology or the persistence) to assess the added value of the predictions.
- *Visualization:* Users prefer to have a wide range of tools for easily-adaptable visualization, mostly using geographical maps.

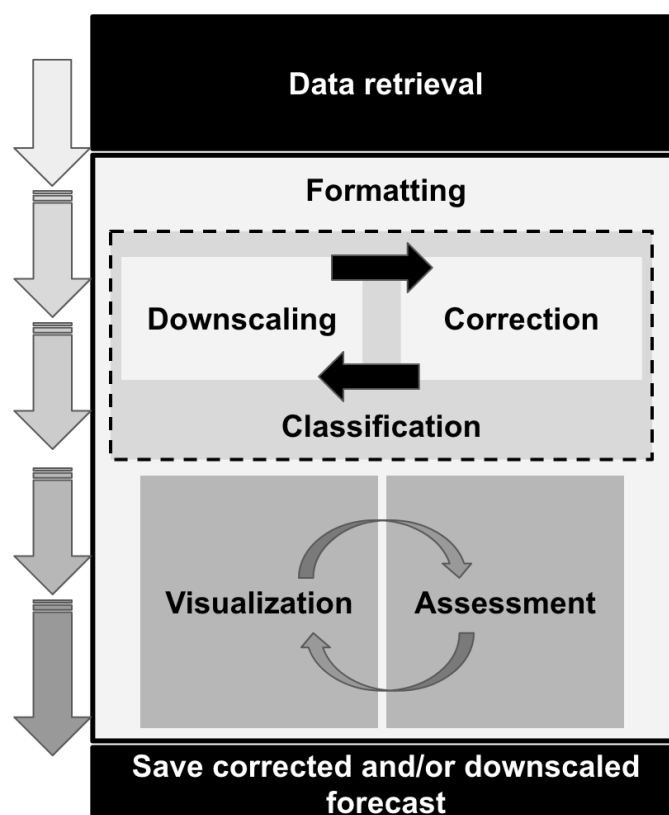


Figure 1. Scheme of the flexible CSTools workflow (from top to bottom). Each box represents a category of functions that are part of CSTools.

Software packages have already been created to analyze different types of climate data. For instance, the Earth System Model Validation Tool (ESMValTool; Eyring et al., 2016a; Righi et al. 2020) was designed to handle climate projections to facilitate the analysis in the Coupled Model Intercomparison Project (CMIP; Eyring et al., 2016b). The R packages s2dverification (Manubens et al., 2018), specsVerification (Sieger, 2017) and easyVerification (MeteoSwiss, 2017) focus on skill assessment of ensemble forecast. The main purpose of these packages is the facilitation of research. CSTools, on the other hand, could be used by both expert climate scientists and end users but its aim is to provide an end result to the final user. Notwithstanding, CSTools profits from and is made compatible with already existing tools.

CSTools also differs from other existing Climate-Services tools concerning target users and objectives. That is the case of the U.S. Climate Resilience Toolkit (<https://toolkit.climate.gov/tools>) which gathers online visualization of specific climate impact indicators. Their target users are different, since CSTools users need may be able to run a create code by themselves. There is the possibility to create a use case for the U.S. Climate Resilience Toolkit using CSTools methods. The Senses Toolkit (<https://climatescenarios.org/>) is a collection of user-centered scenario visualization

tools whose users are climate policymakers, regional climate scenario users and businesses, particularly those with long-term planning horizons. APEC Climate Center (APCC) developed several tools for climate information provision, production and processing. The Climate Information Toolkit ([CLIK](#)), to produce customized multi-model ensemble forecast and station-based downscaling forecast information through various climate model ensemble combinations, is an online tool that allows choosing different settings and visualization options but with rather low flexibility and transparency for the user.

4. Use cases

The reasons for post-processing seasonal forecasts are: adjust systematic model errors which are part of the simulation uncertainty and increase the spatial resolution depending on the user needs. The methods to be applied depend on the final application of the post-processed data and the target region. The following subsections show the full procedure to post-process three datasets using CStools. The first case post-processes and assesses wind speed seasonal forecast in March 2018, when high-speed winds were observed in the Iberian Peninsula, by using only CStools functions. In the second case, the precipitation seasonal forecast for a hindcast period is post-processed following the SNOWPACK model requirements. Finally, post-processing of rainfall and temperature seasonal forecasts is outlined prior to its input for the SCHEME hydrological model.

4.1 Bias adjustment of wind speed forecasts for assessing an extreme event

This section exemplifies the computations required to analyze a target event using seasonal forecasts initialized 3, 2 or 1 month(s) in advance. The code could be adapted to other regions, time periods and variables. The user will need, apart from the data, to correctly modify the parameters. To do so, a detailed description of the code is included below after the impact of the event.

In the case shown here, high wind speed values were recorded in the Iberian Peninsula during March 2018. This analysis can be of interest to the energy sector, given the impacts it had on wind power generation, energy demand and electricity prices. The renewable energy production in 2018 in the Spanish peninsular system grew by 18.5% compared to the previous year, mainly due to the contributions of wind and hydro power in the month of March 2018, when the renewable generation was 51.1% higher than that of the same month of the previous year. A historical maximum of monthly renewable generation was hit with 13,204 GWh (33.1% of share), of which wind energy contributed 7,676 GWh, setting also a new record of monthly wind generation (Red Eléctrica España, 2018). These high amounts of renewable generation in March 2018 resulted in an important drop of the electricity prices: the cost for final consumers was € 0.0418 / kWh compared to € 0.05488 / kWh in February 2018

(<https://www.sernoven.com/blog/2018/04/11/precio-de-la-electricidad-2/>). Given its relevance to the Spanish economy, this information appeared in the press (e.g. <https://www.elperiodico.com/es/economia/20180311/precio-electricidad-luz-borrasca-felix-6681807>). Furthermore, the Spanish Meteorological Agency activated its protocol of early warning system on 47 regions of Spain due to the high-speed winds forecasted and its coastal impact (<https://www.elperiodico.com/es/tiempo/20180311/felix-pone-en-riesgo-a-47-provincias-por-vientos-que-podran-alcanzar-los-140-km-h-668171>). In sum, the procedure outlined in this section may be relevant for climate services that are based on seasonal forecasting of high-wind events.

Here, the seasonal forecasts initialized in December 2017, January 2018 and February 2018 are bias adjusted and assessed. Two functions from CSTools are used to post-process the wind speed seasonal forecasts: *CST_Load* and *CST_BiasCorrection*. The key decisions are the parameters to retrieve the data from files to achieve a coherent analysis of the March 2018 event (Figure 1). The analysis is repeated for three different start dates (i.e. December, January and February). For each start date, three different data types are loaded: the hindcast, i.e. retrospective forecasts initialized in the past for start dates since 1993; the observational reference, covering the same period as the hindcast; and the operational forecast, i.e. the latest simulations initialized just before the event (i.e. December 2017, January 2018 and February 2018). In all the data loading calls, the same region must be requested through the parameters *lonmin*, *lonmax*, *latmin* and *latmax* of the function *CST_Load*, in which the output type required is gridded data rather than area average by setting output parameter as 'lonlat'.

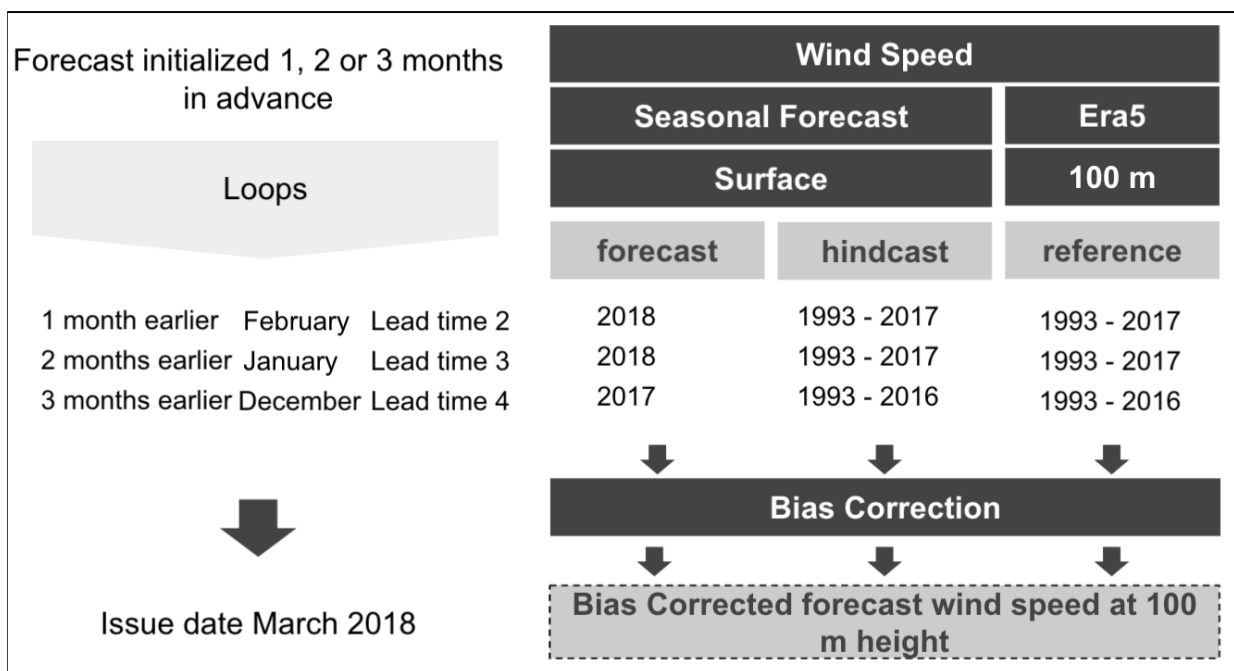


Figure 2: Scheme of the methodology applied. Grey boxes indicate the data, methods and results. The required parameters to analyze the March 2018 event are specified for the simulations initialized one, two and three month(s) in advance on white background.

For the hindcasts and the forecasts we use monthly means of 10 m wind speed from the ECMWF SEAS5 system, obtained from C3S (SEAS5) at 1 degree spatial resolution. For the observational reference, on the other hand, we use monthly-mean 100 m wind speeds from the ERA5 reanalysis (Hersbach et al., 2020) at 0.25° (around 30 km) spatial resolution. Winds at 100 m height are of relevance for energy applications and, although this variable is not available for the seasonal prediction system, the bias adjustment procedure will convert 10 m to 100 m winds similar to the standard conversion assuming a logarithmic wind profile (Drechsel et al., 2012). The different variable names must be specified in the *CST_Load* call through the parameter *var*, since the function needs to read the correct variable written on the NetCDF files in the data storage. Therefore, the *var* parameter is set to 'sfcWind' when retrieving hindcasts and forecasts, while for the reference dataset it is set to 'windagl100'. Given the difference in spatial resolution, a regridding of the reference dataset is also requested by the parameter *grid*. The path pointing to the simulations and the reference are also passed to the *CST_Load* function through parameters 'exp' and 'obs', respectively. Notice that the labels \$STORE_FREQ\$, \$VAR_NAME\$, \$START_DATE\$, \$YEAR\$ and \$MONTH\$ are used when defining the paths. These labels will be interpreted and substituted by the function following the information provided in the other parameters of *CST_Load*.

An index 'mm' indicating the number of preceding months (*mm*) is introduced to loop over the three start dates in order to simplify the code. When *mm* is 1, the bias adjustment for one month in advance, i.e. the February start date, is computed. The target year is set in the 'year' variable as 2018 and the start dates of the simulations to be loaded are created and stored in the 'hcst_sdates' and 'fcst_sdates' variables, which correspond to a vector of dates for the 1st of February from 1993 to 2017 and the 1st of February 2018, respectively. For the February start date, the lead time two (i.e. *mm* + 1) corresponds to the forecast for March which is selected through the *leadtimemin* and *leadtimemax* parameters.

Finally, a simple bias-correction method is used to compute the biases between the hindcast and the reference datasets and then apply a correction to the forecast dataset by *CST_BiasCorrection*. The results of each loop are stored in a list.

```
library(CSTools)
exp_path <- list(name = "ECMWF5",
  path =
"/esarchive/exp/ecmwf/system5c3s/$STORE_FREQ$_mean/$VAR_NAME$_f6h/$VAR_NAME$_$
START_DATE$.nc")
obs_path <- list(name = "ERA5",
  path =
"/esarchive/recon/ecmwf/era5/$STORE_FREQ$_mean/$VAR_NAME$_f1h/$VAR_NAME$_$YEAR
$$MONTH$.nc")
# Target months March (3)
# Assess forecast from 1 to 3 months in advance
months_in_advance <- c('02', '01', '12')
for (mm in 1:3) {
  # Generate the start dates of hindcast period
  year <- ifelse(mm == 3, 2017, 2018)
  hcst_sdates <- paste0(1993:(year - 1), months_in_advance[mm], '01')
  # Load hincast data
  wind_hcst <- CST_Load(var = 'sfcWind', exp = list(exp_path),
    sdates = hcst_sdates, nmember = 25,
    leadtimemin = mm + 1, leadtimemax = mm + 1,
    storefreq = "monthly", sampleperiod = 1,
    latmin = 36, latmax = 44, lonmin = -10, lonmax = 4,
    output = 'lonlat')
  # Generate the start dates of forecast period
  fcst_sdates <- paste0(year, months_in_advance[mm], '01')
  # Load forecast data
  wind_fcst <- CST_Load(var = 'sfcWind', exp = list(exp_path),
    sdates = fcst_sdates, nmember = 25,
    leadtimemin = mm + 1, leadtimemax = mm + 1,
    storefreq = "monthly", sampleperiod = 1,
    latmin = 36, latmax = 44, lonmin = -10, lonmax = 4,
    output = 'lonlat')
  # Load reference data
  wind_ref <- CST_Load(var = 'windagl100', obs = list(obs_path),
    sdates = hcst_sdates, nmember = 1,
    leadtimemin = mm + 1, leadtimemax = mm + 1,
    storefreq = "monthly", sampleperiod = 1,
```

```
latmin = 36, latmax = 44, lonmin = -10, lonmax = 4,  
output = 'lonlat',  
grid = 'r360x181')
```

Bias Adjustment

```
wind_fsct <- CST_BiasCorrection(exp = wind_hcst,  
                                obs = wind_ref,  
                                exp_cor = wind_fcst)  
wind_fsct_BC[[mm]] <- wind_fsct  
}
```

Once the wind forecasts are post-processed, additional CSTools functions can be used to visualize the forecast distributions. The *PlotForecastPDF* function, for instance, compares the probability distribution function of the March 2018 100 m wind speed forecasts issued 1, 2 and 3 month(s) in advance (Figure 3). Three months in advance, only one member exceeds the P90. The simulations initialized one and two month(s) in advance suggest a weak shift towards above-normal conditions (~40% probability of the above normal tercile) and towards extreme high values (12% and 17% exceeding P90). Moreover, the forecast's tercile probabilities do not indicate a shift towards above-normal winds as lead time decreases (the January start date suggests a slightly larger probability of above-normal winds than the February start date). Even though for start dates in both January and February three members exceed P90, the corresponding probabilities are different due to the ensemble dressing applied. In February, the probability of observing extreme wind conditions was almost twice the one in January. Individual ensemble members typically also suggest much weaker wind speed anomalies than observed, except for one member in the February initialization, indicating that in this case the prediction system anticipated this situation as a potential outcome.

Bias Corrected forecasts at IP

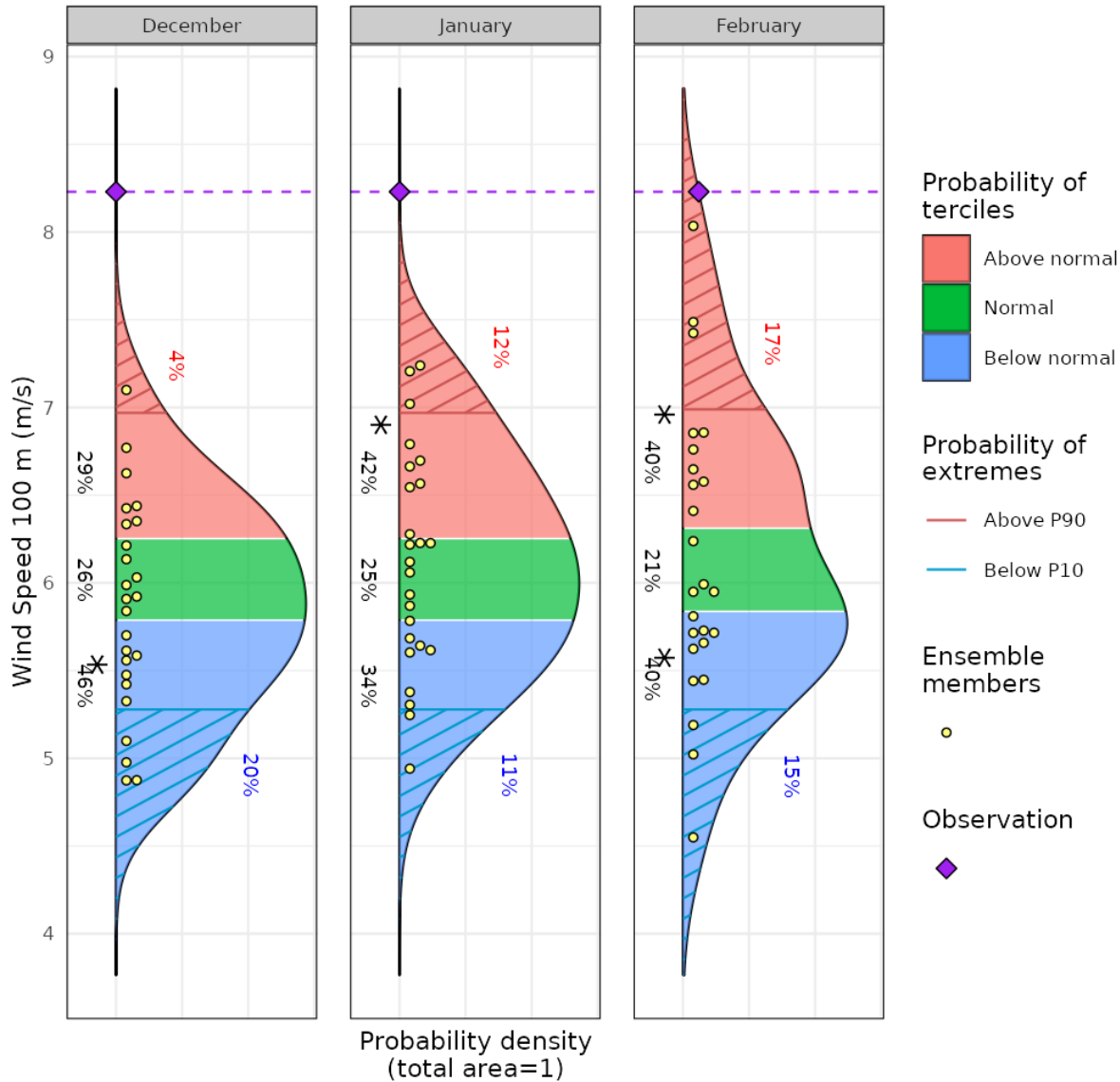


Figure 3: Seasonal forecasts of wind speed at 100 m height, averaged over 10°W-4°E and 36-44°N for March 2018. Each panel corresponds to forecasts launched 3 to 1 month(s) ahead (from left to right). Methodology: simple bias correction with ERA5 observations, based on previous hindcasts since 1993.

The spatial distribution of the tercile probabilities can be displayed with the *PlotMostLikelyQuantileMap* function (Figure 4). An extra layer has been included to mark with crosses the grid points where observations agree on the most likely tercile indicated by the forecast. Three months in advance, most of the region shows that the tercile of highest probability is the below-normal category. One and two month(s) in advance, the colors shift towards the normal and above-normal categories. In the January simulation, the eastern region presents more

above-normal probability of high wind speed values than the western region. In the February simulation, the above-normal probability class is widespread on the whole Iberian Peninsula.

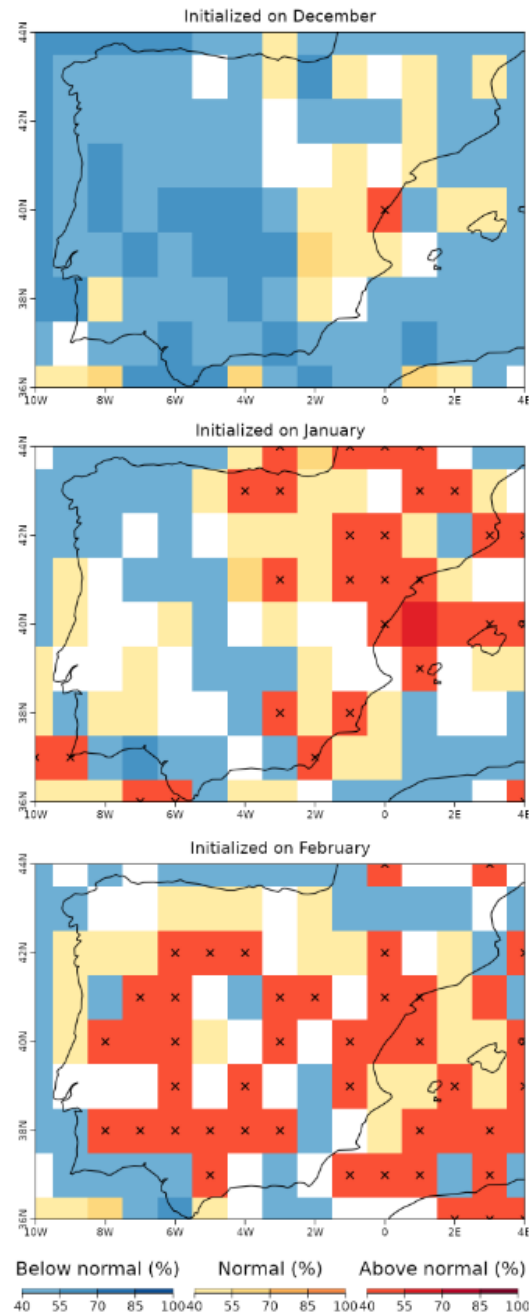


Figure 4: Probabilities of the most likely tercile for the March 2018 100 m wind speeds, as indicated by the forecasts issued 3 to 1 month(s) ahead (top to bottom). The crosses indicate that the observations fell into the most likely tercile displayed by the forecast. White grid points indicate that no tercile category has more than 40% of probability.

Users that can benefit from climate information, such as stakeholders (e.g. energy system planners), are usually not familiar with the probabilistic forecast and the added value that it can bring in their planning. In order to become more autonomous in their decision making, a learning process could be started based on relevant show-case climate events as provided here. Therefore, this use case could be very interesting for climate services developers that need to post-process a seasonal forecast variable and present the results in a concise yet user-friendly manner with a reduced number of images and tables.

When a unsatisfactory outcome happens because of unfavorable atmospheric conditions, even including a seasonal forecast in the decision strategy, this code could be used to evaluate whether the seasonal forecast included the possibility of a unsatisfactory outcome, whether other variables were better capturing the situation in that case, or if a different bias correction method would improve the skill of the seasonal forecast. Furthermore, it is possible to extend this code to compare the results provided by different models.

4.2 Precipitation downscaling using RainFARM for the SNOWPACK model

A snowpack is an essential water reservoir that is fed by snowfall during the cold season and then released in late spring and summer. Mountain meltwater is essential for several economic activities including hydropower generation, agriculture, industry, and meltwater shortage can induce strong economic losses. Therefore, reliable seasonal forecasts of snow resources that, at the beginning of the snow season (November) estimate the snow accumulation at the end of spring (April-May), are highly pursued. These would allow water management authorities and hydropower companies to implement early water management plans several months ahead of a water-demand peak and mitigate the effects of a possible water shortage. To support this need we developed a modeling chain driven by seasonal forecasts of meteorological variables from the C3S seasonal forecasting systems, employing the physical 1-dimensional snow model SNOWPACK (Bartelt and Lehning, 2002), to estimate snow depth and snow water equivalent at selected high-elevation sites in the North-Western Italian Alps.

The RainFARM downscaling method incorporated within CStools is employed to downscale precipitation and then used as input for the SNOWPACK model. This method allows taking into account the orographic effects on the precipitation distribution and generates stochastic realizations for each member of the original seasonal forecast simulations. We generate 10 stochastic downscaled realizations for each ensemble member of the seasonal forecast model. In the following we present the method applied to the SEAS5 model providing 25 ensemble

members, so at the end of the downscaling procedure we obtain 250 fine-scale precipitation fields in total.

Even though several more technical decisions need to be taken by the user, a general scheme could be followed (Figure 5). Important decisions include the downscaling method, the target region, the simulation and observation datasets as well as the season to explore. In this case, the region of interest is the Alpine mountain range in central Europe (42N - 49N, 4E - 11E), within which high-elevation stations are located used by the SNOWPACK model. Since the RainFARM downscaling relies on the estimation of the spatial power spectrum of precipitation fields, a squared domain is required. Moreover this domain has to be larger than the target study area to avoid artifacts/border effects within the target area. The target season is winter, so the 1st November start date simulations available for the period 1993-2018 are considered. The simulations to downscale are daily precipitation data of SEAS5 at 1-degree spatial resolution. The reference datasets employed are i) ERA5 daily precipitation reanalysis at 0.25° (around 30 km) spatial resolution (Hersbach et al., 2020) for the bias correction and for the estimation of the spectral slopes and ii) the WorldClim2 monthly climatology at 1 km spatial resolution (Fick and Hijmans, 2017) for generating the precipitation weights.

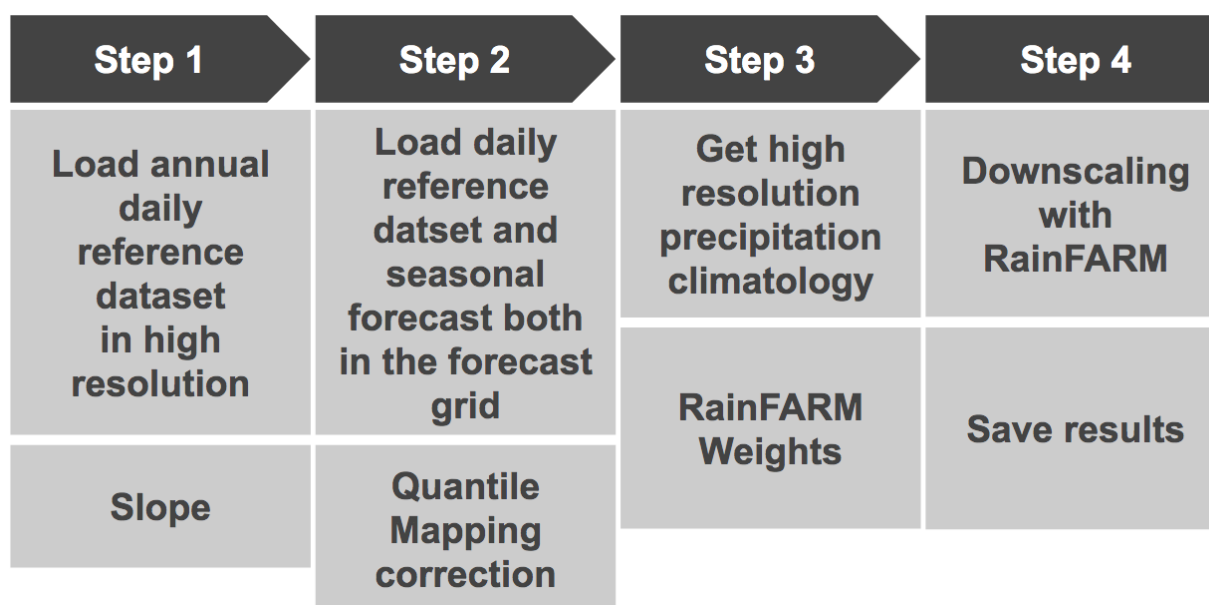


Figure 5: Scheme of the steps that need to be carried out to obtain and save a downscaled precipitation dataset. These steps are explained in detail.

In the scheme (Figure 5), three steps should be carried out before applying the desired downscaling with the RainFARM method. In steps 1 and 3 necessary parameters are computed: the

slopes and the orographic weights; quantile mapping correction is applied to the seasonal forecast in order to correct the bias of the model in step 2, and the downscaling is computed in step 4.

All computations performed in the first step only require the *CSTools* package. As mentioned above, the slope is calculated using ERA5 at its original resolution and over a bigger domain than the target region (37.5N - 53.25N, 2.5E - 18.25E). The path pattern to the data is defined using labels: `$STORE_FREQ$`, `VAR_NAME`, `$YEAR$` and `$MONTH$`. These labels will be interpreted by *CST_Load*. For instance, the `VAR_NAME` will be substituted by the information passed by the parameter *var* which in this case is 'prlr' that stands for precipitation rate and the `$YEAR$` and `$MONTH$` will be interpreted from the *CST_Load sdates* parameter which requires a vector of dates in the format 'YYYYMM01' where YYYY is the year and MM the month. Then, *CST_Load* retrieves the data from files and arranges it with the following dimensions: *dataset* of length 1 since only ERA5 is being requested, *member* = 1 since this reanalysis only provides one simulation, *sdate* dimension is of length 312 which corresponds to the 26 years of 12 months defined in object 'years' with an *ftime* dimension up to 31 corresponding to each day of the month. Notice that for the months shorter than 31 days, the data will be filled with missing values 'NA'. The remaining dimensions, *lat* and *lon* correspond to the squared domain requested in *CST_Load*. Given that *CST_Load* splits the time series among *sdates* and *ftime* dimension when specifying a forecast dataset, our ERA5 path pattern has been requested through this option. On the other hand, specifying the ERA5 path pattern as an observational dataset (in the *obs* parameter), the function will return a continuous time series from 1993 to 2018 which is less convenient for our purposes.

In this example over the Alpine domain, the slope of the spatial power spectrum of ERA5 daily precipitation at 0.25° is not constant throughout the year but it exhibits temporal variability at the seasonal scale. In order to account for this, we calculate the spectral slopes at the monthly scale, fitting wavenumbers 5 and higher in order to better reproduce the slope of the spectrum at the small scales (see Terzago et al., 2020 for details). The result of this code is the spectral slope from January to December.

```
library(CSTools)
era5 <- list(name = 'era5', path =
'/esarchive/recon/ecmwf/era5/$STORE_FREQ$_mean/$VAR_NAME$_f1h-r1440x721cds/$VAR_NAME$_$YEAR$$MONTH$.nc')
years <- unlist(lapply(1993:2018, function(x){paste0(x, sprintf("%02d",1:12), '01'))})
era5 <- CST_Load(var = 'prlr', exp = list(era5), sdates = years, nmember = 1,
storefreq = "daily", sampleperiod = 1,
latmin = 37.5, latmax = 53.25, lonmin = 2.5, lonmax = 18.25,
```

```
output = 'lonlat')
era5 <- CST_SplitDim(era5, split_dim = 'sdate', indices = rep(1:12, 26))
slope <- CST_RFSlope(era5, time_dim = c('sdate', 'ftime'), kmin = 5) # using version from
develop-RFSlopeNAs
```

Code Step 1.

The second step starts loading the data taking advantage of library *zeallot* (Teetor, 2018) that allows us to simplify our code by using an advanced version of the assignment operator (`%<-%`). Again, the paths to the desired data must be defined using labels: for the forecast data the path points to the SEAS5 dataset while for the reference data the path points to the ERA5 reanalysis. Thanks to *CST_Load*, these datasets could be reshaped to a common grid, which, by default, is the grid of the first dataset provided, i.e. the SEAS5 grid. The vector 'StartDates' which defines the period of study for November 1st simulations, is then assigned to the *sdates* parameter.

In order to apply the quantile-mapping correction month by month, the function *CST_SplitDim* is used to divide the forecast time dimension in two: one for identifying the days of the month and another to store each month separately. The result of step 2 is a bias-corrected forecast consistent with the reference dataset: the forecast probability density function matches the one for the references resulting in the same climatology. A simple visual evaluation of the impact of the quantile mapping correction is shown in Figure 6.

```
library(zeallot)
StartDates <- paste0(1993:2018, '1101')
exp <- list(name = 'ecmwfS5', path =
"/esarchive/exp/ecmwf/system5c3s/$STORE_FREQ$_mean/$VAR_NAME$_s0-24h/$VAR_NAME$_$START_DATE$.nc")
obs <- list(name = 'era5', path =
"/esarchive/recon/ecmwf/era5/$STORE_FREQ$_mean/$VAR_NAME$_f1h-r1440x721cds/$VAR_NAME$_$YEAR$$MONTH$.nc")
c(exp, obs) %<-% CST_Load(var = 'prlr', exp = list(exp), obs = list(obs),
                        sdates = StartDates, nmember = 25,
                        storefreq = "daily", sampleperiod = 1,
                        latmin = 42, latmax = 49, lonmin = 4, lonmax = 11,
                        output = 'lonlat', nprocs = 1)
exp <- CST_SplitDim(exp, split_dim = 'ftime')
obs <- CST_SplitDim(obs, split_dim = 'ftime')
exp.qm_months <- CST_QuantileMapping(exp, obs, method = "QUANT", wet.day = FALSE,
```

```
sample_dims = c('member', 'sdate', 'ftime'))
exp.qm <- CST_MergeDims(exp.qm_months, merge_dims = c("ftime", "monthly"),
na.rm = TRUE, ncores = 4)
```

Code Step 2.

Step 3 computes the orographic weights from a fine-scale precipitation climatology. In this case, the WorldClim2 dataset precipitation at 30 seconds resolution is used although other climatologies at high resolution could be used. The WorldClim2 dataset is formatted in tiff files that could be automatically downloaded in the R session thanks to the raster library (Hijmans, 2020). The piece of code for Step 3 shows how to compute the orographic weights for all individual months at once: getting the data from the remote dataset, subsetting for the Alps region with a small increment to correctly compute interpolation (3.5E-11.5E, 41.5N-49.5N), and storing the data in a 's2dv_cube' object to be passed to *CST_RFWeights*.

The target resolution is the one most suitable for each specific application. To run the SNOWPACK model, we are interested in the local scale and we choose a target resolution of 0.01°, corresponding to about 1 km. Therefore, the weights and the RainFARM method (step 4) would be computed with a refinement factor (*nf*) 100. However, such a high refinement factor implies a rather large computational load, and here we show the code using a refinement factor 4. We recommend the users to approximately calculate the expected size of the final output, as follows: the original data input to the downscaling step has 25 members, 26 start dates, 31 daily lead times on 8 months covering a region of 8 by 8 grid points, which 8 times its product is ~ 80 MB; this size will increase by a factor 10 since the realizations and the refinement factor will be applied on both spatial dimensions. For a refinement factor of 100 (4), the expected output is ~80 MB x 10 x 100 x 100 (~ 80 MB x 10 x 4 x 4), so around 8 TB (12.5 GB). The users need to consider that the data size also has implications on the computation time. The result of step 3 is an array with spatial dimensions and an extra dimension for each month containing the weights for which values greater (lower) than 1 will amplify (reduce) the precipitation signal from the seasonal forecast (Figure 4).

```
# WorldClim data to s2dv_cube
library(raster)
worldclim <- getData("worldclim", var = "prec", res = 0.5, lon = 5, lat = 45)
wc_month <- lapply(1:12, FUN = function(x) {
    res <- crop(worldclim[[x]],
    extent(3.5, 11.5, 41.5, 49.5))
    res <- as.array(res)
    names(dim(res)) <- c('lat', 'lon', 'month')
    return(res)
})
xy <- xyFromCell(crop(worldclim[[1]], extent(3.5, 11.5, 41.5, 49.5)),
    1:length(crop(worldclim[[1]], extent(3.5, 11.5, 41.5, 49.5))))
lons <- unique(xy[,1])
lats <- unique(xy[,2])
wc_month <- unlist(wc_month)
dim(wc_month) <- c(lat = length(lats), lon = length(lons), month = 12)
wc_month <- s2dv_cube(data = wc_month, lon = lons, lat = lats,
    Datasets = 'WorldClim')

weight <- CST_RFWeights(wc_month, lon = exp$lon, lat = exp$lat, nf = 4)
```

Code Step 3.

Finally, the downscaling method is run in step 4 using the corrected forecast, the slope and weights computed in the previous steps. Note that this code requires high memory resources, although the computation can be split by start date and realization if necessary. Figure 6 shows the spatial resolution improvement given by RainFARM for a specific date when applying a refinement factor 4(10).

```
weights <- Subset(weight$data, along = 'monthly', indices = c(11,12,1:1:6))
slope <- Subset(slope, along = 'monthly', indices = c(11,12,1:1:6), drop = 'non-selected')
fs <- CST_RainFARM(exp.qm, nf = 4,
    weights = weights, slope = slope,
    kmin = 1, nens = 10, verbose = TRUE,
    time_dim = c("member", "ftime"), nprocs = 4,
    drop_realization = TRUE)

fs <- CST_MergeDims(fs, merge_dims = c("ftime", "monthly"), na.rm = TRUE)
```

```
fs$Dates[[1]] <- exp$Dates[[1]]  
CST_SaveExp(fs, destination = '/esarchive/scratch/nperez/CSTools_manuscript/')  

```

Code Step 4.

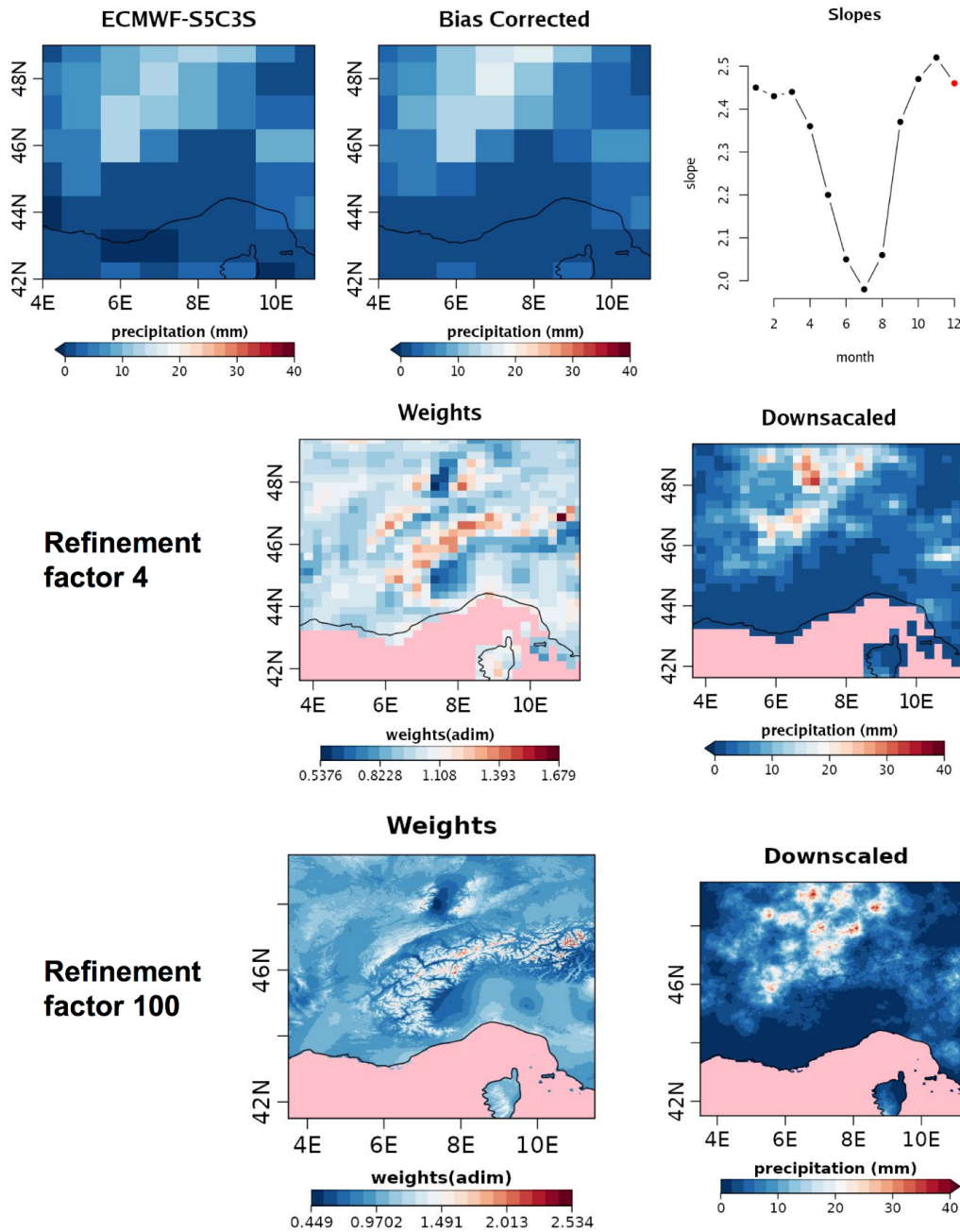


Figure 6: On the top, the comparison of the original (top-left) and bias-corrected (top-middle) precipitation spatial field for SEAS5 for the 11th of December 1993 which are inputs of the downscaling RainFARM method independently of the refinement factor applied, as well as the slope (top-right), which are results of step 1. The slope used for downscaling on the 11th of December 1993 is highlighted in red. In the middle (refinement factor 4) and bottom (refinement factor 100) rows the comparison of the weights and the downscaled precipitation field for SEAS5 for the 11th of December 1993 are shown.

Taking advantage of PlotForecastPDF again, a visualization of the PDF and the individual ensembles spatial average for the original SEAS5, the bias adjusted and the downscaled precipitation is shown in Figure 7. The shape of the PDF is retained in all steps. The 10 realizations requested for each ensemble member to the CST_RainFARM are clearly shown in the top right panel.

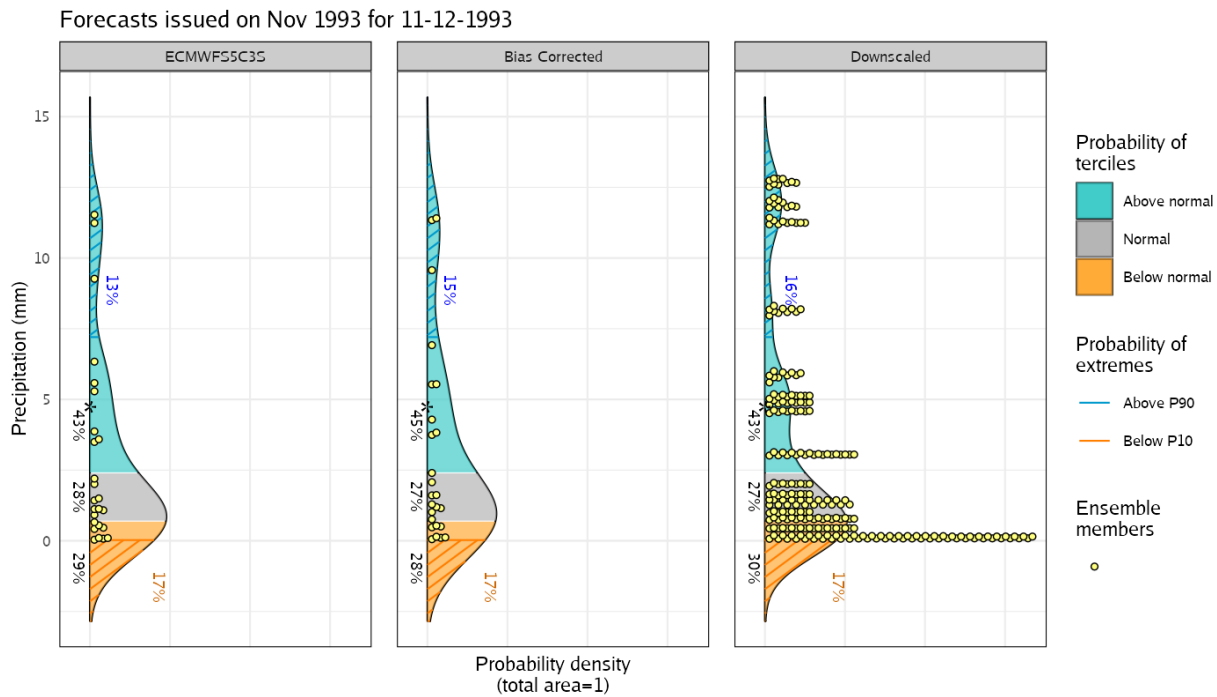


Figure 7: From left to right, PDF for the original, the bias-corrected by quantile mapping and the downscaled spatial field (for refinement factor 4) SEAS5 for the area average on the 11th of December 1993. For each PDF, three categories of equal size are shown: terciles above normal (blue), normal (gray) and below normal (orange), defined according to the area average of ERA5 reanalysis for the period 1993-2018. Percentages represent the forecast probabilities of each tercile, the most likely tercile is highlighted with a star and the blue and orange percentages represent the probabilities for P10 and P90 (hatched areas), respectively.

The SNOWPACK model requires a number of input variables apart from the total precipitation post-processed with CSTools, namely 2 m air-temperature, atmospheric pressure, relative humidity, shortwave and longwave incoming radiation, wind speed and ground temperature, at finer spatial and temporal resolutions (>1 km in space and 1 hour in time) compared to the typical resolutions of the seasonal forecast system outputs (about 100 km in space and 1 day or 6 hours in time). In order to provide the SNOWPACK model with realistic meteorological forcing, we apply bias-adjustment and downscaling techniques depending on the specific variable.

- Temperature seasonal forecasts are bias-adjusted and downscaled to the study sites so that the resulting fine-scale climatology is comparable to the observed climatology obtained from surface station data. The use of CStools functions to obtain this dataset can be found in Terzago et al. (2020).
- All other variables are bilinearly interpolated to the coordinates of the study-sites.

After the spatial downscaling, seasonal forecast data are interpolated in time to one hour temporal resolution with different methods depending on the variable.

Using these variables, the SNOWPACK model is run for each of the 21 seasonal forecasts over the hindcast period 1996-2016, considering those initialized on November 1st and covering the 7 months ahead, in order to reproduce the most relevant period for the snow dynamics, i.e. November-May. Figure 8 shows an example of the SNOWPACK model output, and specifically, the snow depth forecasts obtained from the SEAS5 forecast initialized on the 1st of November 2014 forcing for the area including the station of Bocchetta delle Pisse —2410 m above sea level (a.s.l.). For each forecast, we obtain an ensemble of 250 snow depth /SWE simulations, derived from the 25 ensemble members of the forecast models by 10 stochastic downscaling realizations for precipitation. Except for mid-November, the simulations are able to reproduce the variability of the observed snow depth. Some periods (e.g.: late February) can be considered extreme events since the observed snow depth overcomes the 95 percentile of the simulations.

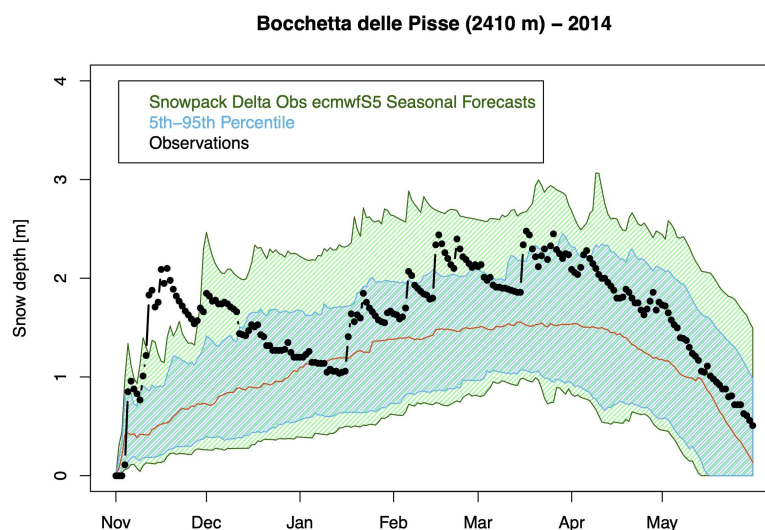


Figure 8: Seasonal forecast of snow depth obtained from the SNOWPACK model driven by the SEAS5 seasonal forecast system data. The forecast, initialized on the 1st of November 2014 and covering the 7 following months, refers to the station of Bocchetta delle Pisse, 2410 m a.s.l. in the North-Western Italian Alps. The green and the cyan shadows show the spread and the

5-95th percentile range of the 250 ensemble-member forecast, while the red line represents the ensemble mean. Observed snow depth is reported as black dots.

4.3 Calibration and Analog downscaling to drive the SCHEME hydrological model.

The aim of this use case is to provide downscaled and calibrated seasonal forecasts as input for the hydrological model SCHEME (Baguis et al. 2010) to simulate extreme river flows of the longest river in Greece, the Aliakmon. This will allow the generation of a seasonal ensemble prediction system that provides the outlooks of water availability for hydro-power and irrigation for the Aliakmon basin.

The SCHEME hydrological model is the semi-distributed version of the daily time-step lumped model developed by Bultot and Dupriez (1976). This model was designed first for the Scheldt and the Meuse River Basins in Belgium and Northern France to estimate the impact of climate changes on the hydrological cycle but it was also used for hydrological predictions in the medium-range (Roulin and Vannitsem, 2005) and in data assimilation of large-scale satellite soil moisture (Baguis and Roulin, 2017). Whereas the model over Belgium relies on parameters collected during a long-standing ground experience, over the Greek catchment, other sources have been sought and the structure of the code has been adapted. At the subgrid scale, the main land covers (CORINE Land Cover) relevant for the Mediterranean region have been grouped according to their properties and -matched with soil map units. In addition to daily rainfall, the SCHEME model requires daily minimum, maximum and average temperature as input to calculate the potential evapotranspiration using a Penman formulation. These will be provided for a domain covering the Aliakmon basin and a large part of Greece.

Post-processing the seasonal forecasts is absolutely necessary as they suffer from biases and much higher spatial resolutions are necessary. Indeed, while the typical seasonal forecasts are provided at a resolution of around 100 km, the spatial resolution required here is 5 km. Our tailored approach focuses on providing high-quality and high-resolution precipitation forecasts. An analog approach is used combining both the synoptic-scale pressure over Europe and the regional-scale rainfall over Greece. For the day of the best analog, the high-resolution fields of both temperature and rainfall over Greece are considered as the end product. This approach ensures the spatio-temporal consistency of both fields. Rather than giving detailed code instructions similar to the previous use cases, an extensive discussion on the data-generation process is provided and the

code is made available online. Note again that all steps are being executed using only CStools functions.

As the reference rainfall dataset the daily data from CHIRPS (Funk et al. 2015) is taken, available at 0.05° resolution. Moreover this dataset incorporates corrections for different mountain elevation and slope, necessary in the orographically-complex Aliakmon basin with elevations above 2000 m. For temperature, we use the ERA5-Land (Muñoz-Sabater et al., 2021) available at around 0.1° and further downscaled to 0.05° resolution using a simple lapse-rate correction.

Figure 9 provides the step-by-step structure of the methodology used while Figure 10 provides a visual representation of an example. As shown in Figure 9, the overall methodology can be separated into a calibration phase (steps 1-2) and a downscaling phase (steps 3-5) that uses an analog approach. The calibration phase starts by loading (using *CST_Load*) the daily forecast and observational rainfall data over Greece at 1° resolution. As forecast data, we take the 25-member of SEAS5 from 1993-2019 initialized in May while the reference is the CHIRPS dataset upscaled to 1° resolution for the same time period. In step 2, these daily rainfall forecasts are calibrated (using *CST_Calibration* with method *bias*) against the CHIRPS dataset. The calibration is done per month of lead time using a leave-one-out or cross-validation approach. Breaking up the data per month was done using the *CST_SplitDim* function.

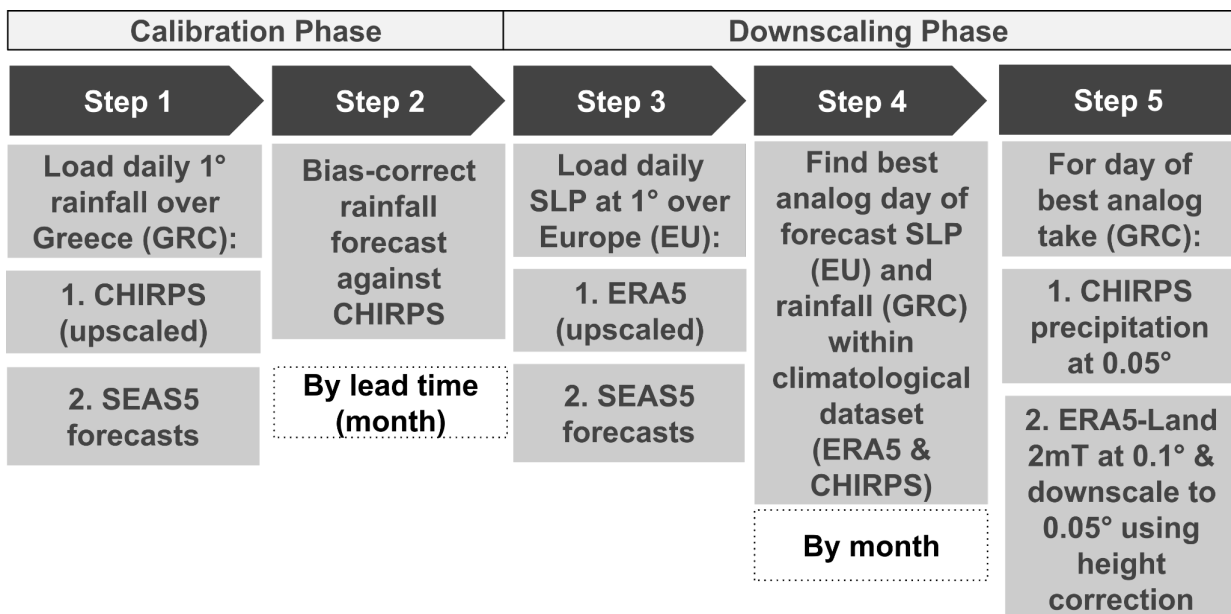


Figure 9: Scheme of the necessary steps to obtain calibrated and downscaled input for the hydrological SCHEME model. The abbreviations used are SLP (sea-level pressure), SEAS5, EU (Europe) and GRC (Greece).

The downscaling phase starts in step 3 (see Figure 9) with loading the sea-level pressure (SLP) of the forecast and reference at 1° resolution over Europe. While again SEAS5 is used for the forecasts, the reference dataset is now ERA5 (Hersbach et al., 2020) and upscaling is applied to obtain the 1° resolution. Subsequently, in step 4, an analog approach is used. Thereby the calibrated precipitation fields over Greece and the SLP fields over Europe of a particular forecast day are selected. These fields are then compared to all fields of a large climatological reference dataset in order to find the best analog (using the *Analogs* function). This dataset covers the period 1993-2019 but includes only days with the same month as the selected day (and excludes the selected day). Separating the data per month was again done using the *CST_SplitDim* function. The criterion to find the best analog is called *Local_dist* and minimizes the Euclidean distances of the large-scale SLP and the local-scale rainfall patterns, both at 1° resolution. Finally, for the day corresponding to the best analog, the CHIRPS precipitation field at 0.05° resolution is then considered as the calibrated and downscaled field of the selected day (See Figure 10c and 10d). In order to obtain the temperature, the ERA5-Land dataset over Greece are considered for the day of the best analog. More specifically the ERA5-Land daily minimum, maximum and average temperature at 0.1° resolution are downscaled to a resolution of 0.05° resolution using lapse-rate height corrections. Finally, the downscaling procedure steps 4-5 are iterated over all days and all ensemble members of the seasonal forecast in order to obtain a fully-calibrated and downscaled seasonal forecast over Greece.

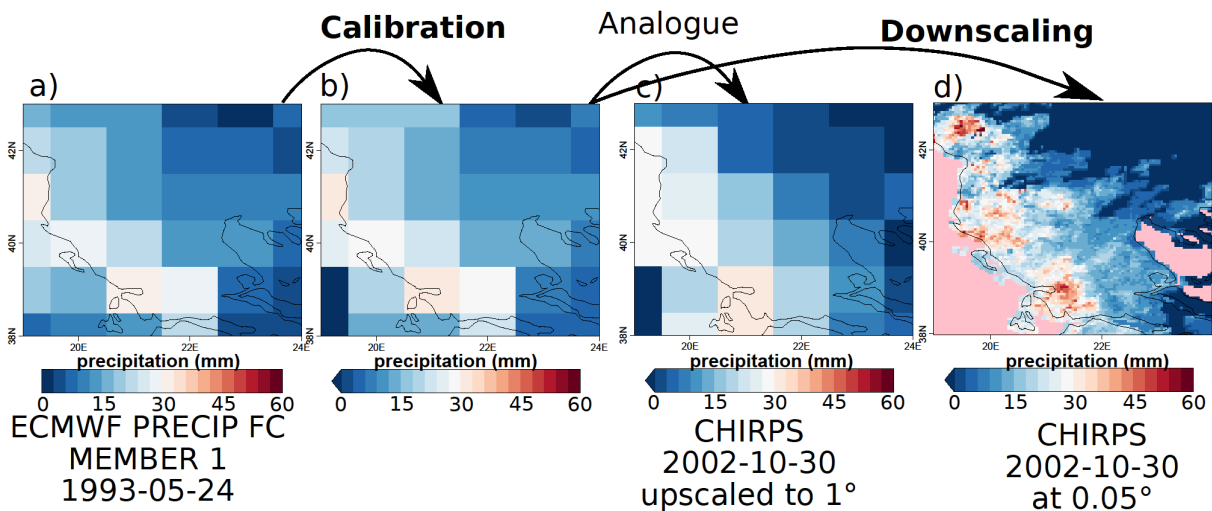


Figure 10: Comparison of the original forecast (a), calibrated forecast (b), the analog (c) and the downscaled (d) forecast over Greece for SEAS5 for the 24th of May 1993.

Code Availability

CSTools 4.0.0 is released under the Apache License version 2.0. CStool is being developed at BSC-CNS GitLab repository <https://earth.bsc.es/gitlab/external/cstools/> and shared in the CRAN repository <https://CRAN.R-project.org/package=CSTools>. The code to reproduce the uses cases and plots shown in this deliverable can be found in the CSTools GitLab repository <https://earth.bsc.es/gitlab/external/cstools/-/tree/master/inst/doc>.

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