

Verification score card

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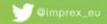
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PREDICTIONS AND MANAGEMENT OF HYDROLOGICAL EXTREMES

Verification score card (Deliverable 4.1)







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Abstract	This report presents the prototype of a verification score card (hereafter called, scoreboard) for hydrological reforecasts developed for IMPREX. Based on a review of verification scores for hydrological forecasts and scoreboard displays, we propose a utility that combines a score database and a web-based display to facilitate the visualization and interpretation of the quality of the forecasts produced during the project. An initial testing on reforecast data is also presented to illustrate the way scores are displayed by the utility developed.	



Dissemination level of this document

Х	PU	Public
	PP	Restricted to other programme participants (including the Commission Services)
	RE	Restricted to a group specified by the consortium (including the European Commission Services)
	СО	Confidential, only for members of the consortium (including the European Commission Services)

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v.2	26/06/2017	MH Ramos	Final version after remarks from EU Project Officer and reviewers, and considering update of the scoreboard display





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Glossary

Forecast verification: the process of comparing forecasts to relevant observations, or assessing the quality of a forecast product or a forecast system.

Forecast quality: how well a forecast compares against a corresponding observation of what actually occurred, or some good estimate of the true outcome.

Forecast value: how a forecast helps the user to make a better decision.

Forecast skill: the relative accuracy of the forecast over some reference forecast.

Score: a quantitative measure of forecast quality.

Skill score: a relative measure (or scaled representation) of forecast quality that relates the forecast accuracy of a particular forecast to some reference forecast. Skill scores range from negative infinity to positive one. A perfect categorical forecast yields skill values of 1. A forecast with similar skill to the reference forecast will have a skill score of zero, and a forecast that is less skilful than the reference forecast will have negative skill score values.

Scoreboard utility: a graphical interface, connected to a score database, to support comparisons between numerical scores of different forecasts or forecast systems.

Score data provider: a partner of the IMPREX project who contributes data to the scoreboard.

Scoreboard user: any person (partner of the IMPREX project or not) who wishes to visualize the quality of a forecast or a forecast system investigated in one of the case-studies of the IMPREX project (under the condition that the score of this forecast or a forecast system is made available by a score data provider).



1 Introduction

One of the main aims of the IMPREX project is to enhance the forecast quality of extreme hydro-meteorological conditions and, as a result, their impacts. Impacts are measured for six targeted types of users involved in the following socio-economic sectors: Floods, Hydropower, Agriculture and droughts, Navigation, Water supply, and Water economy. This wide range of users also represents a wide range of needs concerning the performance of a forecast system. For instance, while a user in the flood protection sector may be more interested in the moment the level of a river or stream will exceed a critical flood alert level, a user in the hydropower sector may search to improve the quality of the weekly or monthly averages of river inflows to a water reservoir to plan its operation.

It was considered useful to the IMPREX project to have a common framework to evaluate and inter-compare the performance of different forecast systems over the case study applications of the project. This report presents **a prototype of a verification scoreboard for hydrological reforecasts**, developed to be used during the IMPREX project. Our focus is placed on the main technical aspects of the implementation of the scoreboard utility and its capabilities. The aim is to introduce the technical concepts behind the tool in order to better satisfy the needs of its potential score data providers (namely, the project's partners implementing the case studies).

This report is organized as follows: In **Section 2**, we present an overview of the main aspects involved in the verification of hydrological forecasts. The aim is to highlight the main issues one has to have in mind when developing a scoreboard. **Section 3** focuses on the utility that was developed, which combines a score database and a web-based display to facilitate the visualization and the interpretation of the quality of the forecasts produced during the project. An initial testing on reforecast data is presented to exemplify the approach adopted. **Section 4** provides a brief conclusion and proposes ways forward for the use and maintenance of the utility during the lifetime of the project and beyond.





2 Verification of hydrological forecasts

2.1 A brief overview of forecast verification

A large part of the performance of a forecast system is measured by the quality of the forecasts delivered by the system. The quality of a forecast measures how well a forecast is compared against a corresponding observation of what actually occurred, or some good estimate of the true outcome. Forecast verification is the process of assessing the quality of a forecast. In hydrology, forecast verification is also called "forecast evaluation". In meteorology, the "value of a prediction" specifically refers to how a forecast helps the user make better decisions.

The quality of a forecast can be assessed through a wide range of metrics (or verification scores)¹ (see details in Wilks, 2011; Jolliffe and Stephenson, 2012). Many forecasters and practitioners recommend the use of several scores to better assess the attributes of a forecast (such as reliability, resolution, discrimination and sharpness): "any set of forecasts can then be ranked as best, second best,..., worst, according to a chosen score, though the ranking need not be the same for different choices of score."²

What scores to choose depends on the user's objectives as well as on the characteristics of the forecasts being evaluated. In several situations, it may be interesting to evaluate the relative quality of a forecast with regard to a reference system or a baseline (e.g., to decide which is better between system A and system B). Here, again, there exist several baselines that can be considered, varying from simple approaches such as climatology (always forecasting an average value) or persistence (the last observation is forecast to persist into the future) to more sophisticated benchmarks that take into account analogue-based features (see, for instance, the twenty-three benchmarks that were designed and used for the assessment of hydrological forecasts in the study proposed by Pappenberger *et al.*, 2015).

² from: Jolliffe, I. T., and D. B. Stephenson (2012), 2nd Edition, Chapter 1 Introduction, page 5.



¹ See, for instance, http://www.cawcr.gov.au/projects/verification/

Relative measures of quality are known as *skill scores*. They measure the improvement of a given forecast relative to a reference forecast, or how much better one forecasting system is in comparison to another forecasting system given the same variables and location.

There are several reasons for assessing the quality of a forecast dataset. Measures of forecast quality can be used, for instance, to guide decisions on the additional human and/or financial resources needed to further develop a forecasting system; to judge how changes in modelling approaches affect the quality of the forecasts; to improve our understanding of uncertainties and biases involved in the forecast processes; and to understand the drivers of forecast performance in a modelling system as well as the strengths and weakness of different forecasting approaches.

Forecast quality may depend on the forecast situation or conditions (e.g., setup of the forecast verification framework). It also varies with human and modelling factors, forecast lead time, forecast location, as well as temporal and spatial scales considered³. Providing information on these factors and on the calculations of the verification scores is therefore important in the communication of forecast quality assessments.

2.2 Main aspects of the verification of hydrological forecasts

Verification of hydrological model outputs (river flows or water levels) is a continuing and necessary effort for modellers and operational forecasters to provide guidance on model development, implementation and on the operational use of hydrological forecasts. Many of the metrics used in the verification of hydrological forecasts come from the meteorological community or have been adapted to answer to the specific needs encountered in hydrological analyses (Casati *et al.*, 2008; Pappenberger *et al.*, 2008).

³ http://hepex.irstea.fr/hepex-science-and-challenges-verification-of-ensemble-forecasts/



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Most often, typical constraints of the modelling of hydrological processes require metrics that target a given variable or focus on a specific aspect of quality searched by an advanced forecast user (Demargne *et al.*, 2009; Brown *et al.*, 2010): for instance, metrics have been developed to evaluate how accurate predictions of flood peaks are in magnitude and timing (e.g., Liu *et al.*, 2011; Zappa *et al.*, 2013) or to evaluate highly temporally correlated seasonal low flows (e.g., Wood *et al.*, 2005; Nicolle *et al.*, 2014; Trambauer *et al.*, 2015).

Hydrological forecast verification focuses more and more on quantifying the quality of probabilistic or ensemble-based predictions (Cloke and Pappenberger, 2009), although metrics for deterministic forecasts are also commonly used (e.g., correlation coefficient, Nash–Sutcliffe model efficiency coefficient or Persistence Index), as well as traditional metrics for categorical events associated to contingency tables (e.g. probability of detection, false alarm rate or Critical success index). A variety of metrics exist for a variety of forecast goals, variables to be evaluated, associated space and time steps, etc. Examples of this diversity of applications of verification metrics to evaluate forecasts in hydrological studies are presented in Table A1.1 in **Annex 1**.

2.3 **Particularities within the IMPREX project**

The IMPREX project focuses on enhancing forecast quality of extreme hydro-meteorological conditions and their impacts. Its partners work to develop methods and tools to improve the forecasting of meteorological and hydrological extremes. It is then important to quantitatively measure if (and how) improved forecasts perform better than the reference forecasts or the benchmark system that is being improved. Additionally, it is also of interest to measure how meteorological forecast improvements impact hydrological forecasts, as well as how hydrological forecast improvements impact risk assessment and management variables, following the flow of information and models that is typically seen in an end-to-end hydro-meteorological forecasting chain. In IMPREX, the value of the improved forecast information is demonstrated in a set of case studies, which evaluate hydrological risks and impacts that are relevant to stakeholders at the regional and European scales. These case studies cover six water sectors, as shown below.

1. Central European Rivers: floods, transport, agriculture and droughts



- 2. Bisagno river basin in Italy: floods
- 3. Thames River Basin in UK: floods
- 4. South-East French Catchments: hydropower
- 5. Júcar River Basin in eastern Spain: hydropower, agriculture and droughts
- 6. Lake Como basin in the Italian Alpine region: hydropower, agriculture and droughts
- 7. Upper River Umeälven in Sweden: hydropower
- 8. Segura River Basin in the Iberian Peninsula: urban water, agriculture and droughts
- 9. The Llobregat River Basin in north-eastern Spain: urban water
- 10. The Messara valley in Crete: agriculture and droughts

Many evaluations of forecast quality will be carried out along the different case studies and sectors during the lifetime of the IMPREX project. Side by side evaluations would help partners and stakeholders to better understand the impacts of the forecasts on the sectors investigated. To facilitate inter-comparisons, a verification scoreboard for the hydrological reforecasts is proposed.

The scoreboard should allow partners to easily store their score data, computed for the many configurations of improved forecasts they may want to test, and visualize the evolution of scores with lead time, across locations within a case study, and using different metrics of forecast quality. In IMPREX, a verification scoreboard should include short, medium, and long ranges. It should also be flexible enough to accept metrics that are traditionally used in forecast verification as well as new metrics, specifically developed to focus on hydrological variables of special interest (e.g., hydrologic threshold exceedances, hydrological extremes of high and low flows) and to quantify the added value of improved forecasts for specific applications (e.g., gain in lead time from anticipating drought conditions, gain in energy production from the use of better forecasts in models of hydropower reservoir optimization, evaluation of transport costs by using probabilistic forecasts in a simulation model for river navigation, etc.).





3 Design of a verification scoreboard utility for IMPREX

In order to contribute to the forecast verification goals of the IMPREX project, a prototype of a verification scoreboard was designed. A standard data format, database and graphical interface composing this utility are presented in the next sections, after a brief overview of examples of existing scoreboards.

3.1 Examples of existing verification scoreboards

Communicating forecast verification data or scores is an important aspect of an operational forecasting centre. It allows forecast developers to be transparent on the quality of their forecasts and users to gain confidence on the forecasts they are using when making decisions. There are several ways to communicate verification statistics. Usually, forecast centres show on their websites, from their operational or the research activities, charts, graphs, numerical tables or summarized information on the quality of past forecasts or on the verification results of studies carried out for specific important events. In general, forecast verification displays are accompanied by instructions on how scores are computed and should be interpreted.

Some examples of scoreboards can be found from the websites of operational forecasting centres. They are shown in **Annex 2**. For instance, Figure A2.1 shows a screenshot of the webpage on verification statistics from the Weather Prediction Centre of the National Weather Service of NOAA in USA. The example shows the evolution of the Bias and the Threat scores over the period 1970-2015 for different lead times. From the same source, Figure A2.2 shows the verification of Quantitative Precipitation Forecasts (QPF) provided for a single event: the Hurricane Sandy, which affected most of the eastern United States (especially the coastal Mid-Atlantic States), in the autumn 2012. Verification is provided through the comparison of the maps of the accumulated precipitation forecasts and the accumulated observed precipitation over the affected areas.

Another example can be found in the website of the UK MetOffice for global long-range predictions. Probabilistic skill maps and plots are available and updated monthly for temperature and rainfall predictions up to six months ahead. Figure A2.3 illustrates how the user can change the "skill score type" to display a ROC score map or a Reliability diagram.



Other options on the visual display include the variable to display, the geographic area, and the period used for the computation of the scores.

The World Meteorological Organization (WMO) has also proposed a verification board for its long-range forecast verification system, jointly managed by the Australian Bureau of Meteorology and the Meteorological Service of Canada. Figure A2.4 shows the display choices available from this board, which include the model to be verified, the type of score, lead time, period, etc. The chart catalogue for forecast verification proposed by ECMWF is illustrated in Figure A2.5. The large variety of options for display and visualizing a given score as a function of several parameters (lead time, variable, threshold, period of computation, etc.) is highlighted.

It is out of scope of this deliverable to achieve the same level of display and generality of the scoreboards examples presented here. Our goal is to propose a utility that can be used during the lifetime of the project to centralize forecast verification scores on hydrological reforecasts for the water sectors studied in the IMPREX project. Scoreboards for hydrological forecasts are rare and this prototype is an attempt to face the challenge of adapting graphic and display options for forecast verification focusing on hydrological variables. The design of the score database and the setup of the display interface are presented in details in the next sections.

3.2 Overview of the concept behind the IMPREX scoreboard utility

Sharing a scoreboard – a tool which allows comparison and collaboration – is an excellent opportunity for a web page, specifically if it is a combination of a back-end data repository with a graphical, shared, interface. This allows analyses and updates to be performed by several users, potentially at the same time. For the IMPREX project, we developed a database (which can reside on a centralized server) as the repository, and an HTML5 graphical user interface (GUI) front-end to query and display score data. **Figure 1** illustrates the verification scoreboard concept set up for the IMPREX project.





A user can connect to the scoreboard utility (App) and start a query for a given case (pertaining to a case study of IMPREX), selecting the choices related to the score the user wants to visualize. This will make the interface display R plots and tables, which the user can export as a PDF file. The interface is connected to the IMPREX score database, which will be fed with scores computed by the IMPREX partners involved in the evaluation of the forecasts for the IMPREX case studies.

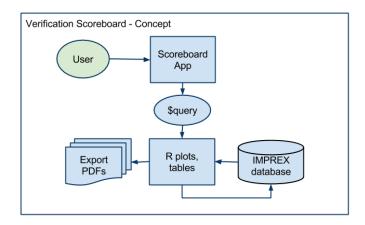


Figure 1: Workflow diagram of the verification scoreboard

3.3 **Design of the score database**

The scoreboard was developed on open-source tools R and PostgreSQL. R is a programming environment and language popularly used for statistical programming. PostgreSQL is a robust database system based on SQL, structured query language. We have incorporated an R package developed by RStudio called "Shiny" to produce the web-based interactive GUI.

In the future, it can be envisaged that the scoreboard may be accessed two ways:

- 1. By navigating to the IMPREX website and clicking on the link to the server URL;
- 2. By downloading or cloning the source repository to run the application through a local R installation (additional libraries may be needed).

While the first option is more anticipated, and the best way to connect to the shared IMPREX score database, a local installation allows users to experiment with file upload formats, visualizing their score input files locally, and creating local databases as needed.



The user may also use the local scoreboard without an internet connection, for example during a presentation.

3.3.1 **SQL database: PostgreSQL**

During the development phase, we used a combination of local database instances⁴ at partner IRSTEA (France) and an instance running on Amazon's free AWS service and local database instances.

Local installers for the PostgreSQL database are available for Linux, Mac and Windows platforms (see **Table 1** for software specifications). A GUI interface (e.g. "pgAdmin") is typically installed along with the instance of the database to help manipulate the database, set password information, and backup data. To clone the schema of the IMPREX database, a DDL (Data Definition Language) script is available, along with more detailed instructions for first-time users.

Adding or connecting to multiple databases is facilitated by an environment text- or ini-file, ".Renviron". User information (username, password) is pulled from this file for local database instances. A template for this file is included in **Annex 3**.

Table 1: Software specification for postgreSQL

Installation source:	https://www.postgresql.org/download/
Version:	Tested on 9.4 and 9.5

⁴ A database is a collection of files that reside on a server. A database instance is a set of memory structures that manage database files. The instance can also refer to the allocated memory and collection of processes running on a server.





3.3.2 Format of data files

In the schema proposed in Figure 1, the "IMPREX database" has score data that need to be provided by the project partners in a pre-defined way. In order to match project requirements, we have identified the RDS R data file format⁵ as the optimal data file format supported.

Compared to the more commonly-used RData file format, RDS prevents from possibly erasing internal variables of the application if a variable name is identical to an object name in an imported file. From a user perspective, producing an RDS file is very similar to producing an RData file. The scoreboard utility also supports text file imports, although it is important to note that file size limitations may play a role on uncompressed files.

Data files support the following common data elements on any user-imported score file: 1. Metadata; 2. Data. The metadata contains contact information for the individual most responsible for the data submittal (an IMPREX partner), as well as details such as model verification start and end dates, score type, case study and forecast system details (see **Figure 2** for an illustration). Scores are included last, and take the biggest part of the file space. **Annex 4** presents a file specification and further explanations.

```
List of 9
BFG data
   Provider : chr "Bastian Klein (Federal Institute of Hydrology BfG)"
   CaseStudy : chr "Central European Rivers"
   ForecastSystem : chr "LARSIMME"
   ForecastType : chr "Perfect Forecast InitMonth01"
   Modelvariable : chr "Discharge"
    ScoreType : chr "MAE"
   ScoreLeadTimeUnit : chr "Month"
    VerificationPeriod: chr "1990/01/01 2010/12/01"
   data :'data.frame': 120 obs. of 7 variables:
   .$ LocationID : chr [1:120] "GRDC6935051" "GRDC6935051" "GRDC6935051" "GRDC6935051" ...
.$ River_names : chr [1:120] "RHINE RIVER" "RHINE RIVER" "RHINE RIVER" "RHINE RIVER" "RHINE RIVER" ...
.$ Station_names: chr [1:120] "BASEL, RHEINHALLE" "BASEL, RHEINHALLE"...
    ..$ Latitude : num [1:120] 47.6 47.6 47.6 47.6 47.6 ...
    ..$ Longitude : num [1:120] 7.62 7.62 7.62 7.62 7.62 .
    ..$ Score_Value : num [1:120] 73.1 84.3 184.9 233.7 142.7 ...
    ..$ LeadTime : int [1:120] 1 2 3 4 5 6 1 2 3 4 ...
```

Figure 2: Example of the header of a score data file (metadata)

⁵ R has its own data file format and usually uses the .rds extension. The .rds file format is usually smaller than its text file counterpart and will therefore take up less storage space. The .rds file will also preserve data types such as factors and dates, eliminating the need to redefine data types after loading the file.



3.4 **Design of the scoreboard interface**

The layout of the scoreboard features typical web page navigation tools; though R software is used to create the webpages, they are standard HTML5 with JavaScript and readable by any platform and browser.

3.4.1 **HTML display**

The web page was developed using R, and specifically RStudio's Shiny package (see **Table 2** for software specifications). **Figure 3** illustrates the main components of the HTML display. We have added the IMPREX logo on the top left corner. In the space below, the left column is dedicated to allow the user to select the IMPREX case study and the system for which scores are to be visualized. A number of filter choices are available, so that the user can choose the location to display (e.g. sub-basins of a catchment included in a case study or location of point stations included in the European-wide case studies), the variable (e.g. streamflow or precipitation), the forecast system (e.g., the benchmark system, a system where bias correction was applied), and the score to plot.

The graphical plot is displayed in real-time, once all the choices have been made. The tabs in the upper part of the plot area allow the user to visualize panel plots (i.e., several score plots for inter-comparison purposes), compare skill scores, and access a summary table of the database, the scores definition and an upload tool. Plots and table can be saved in a PDF file and downloaded.





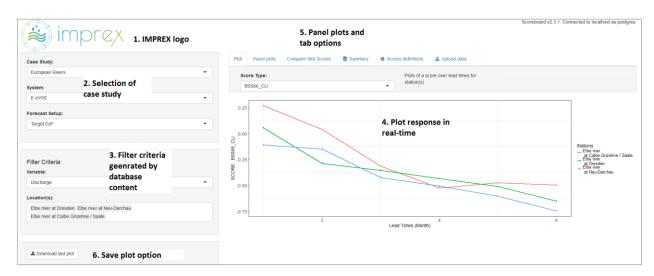


Figure 3: Example of the HTML display of the scoreboard utility

Table 2: Software specification for R and RStudio

Browser compatibility	Tested on Ubuntu Chrome, Firefox; Windows Chrome, Explorer, Edge, Firefox	
Installation source, R:	https://cran.r-project.org/	
Version:	Tested on 3.3.1 and 3.4.0	
Installation source, RStudio:	https://www.rstudio.com/products/rstudio/download/	
Version:	Tested on 0.99.879 and 1.0.143	

3.4.2 Workflow

As shown in Figure 3, once on the scoreboard webpage, the user finds a screen containing selection boxes on the left column, plots on the right column and navigation tabs above the plot. The two approaches to reduce the dataset shown (and work with dynamic plots) are to: 1. Select a listed Case Study, 2. Select a System.



This selection updates the remaining navigation filters, and presents the user with a narrower set of choices. The list of items available in the filter criteria is thus adapted according to the available items in the Score database, which are automatically detected by the interface once the selection of Case Study and System has been done. The user can:

- 1. select one (or more) location(s), a list of locations appear and update the plots,
- 2. select one score to view the associated plot (in the main plot area).

At any point during the use of the Scoreboard the user may view a panel plot with all scores available for the selected locations, download a PDF of the last plot drawn, as well as view a summary table of the database.

An alternative workflow may suit more experienced R users, or those testing their data import format. If the user has installed RStudio (and necessary libraries) locally, they may clone the Scoreboard project to their disk and run it with the following command: shiny::runApp. While this Scoreboard cannot connect to the IMPREX database nor make submissions to it, it can accept and verify a user's RDS or txt file uploads, as well as working with and visualizing the data locally.

3.5 **Example with a test data from IMPREX partner**

The Scoreboard utility was tested based on a test dataset provided by partner SMHI. Data comes from streamflow simulations based on the E-HYPE seasonal forecasting system in Europe, which were verified by SMHI with a variety of scores. These E-HYPE score data were provided in RData file format. It contained scores and skill scores for several stations in Europe. The file contained scores for each month of the year, 6 lead months and each station.

Figure 4 and **Figure 5** show examples of the visualization obtained from the scoreboard utility for score plots, panel plots and summary table, and for selected locations and scores in the E-HYPE test score dataset.





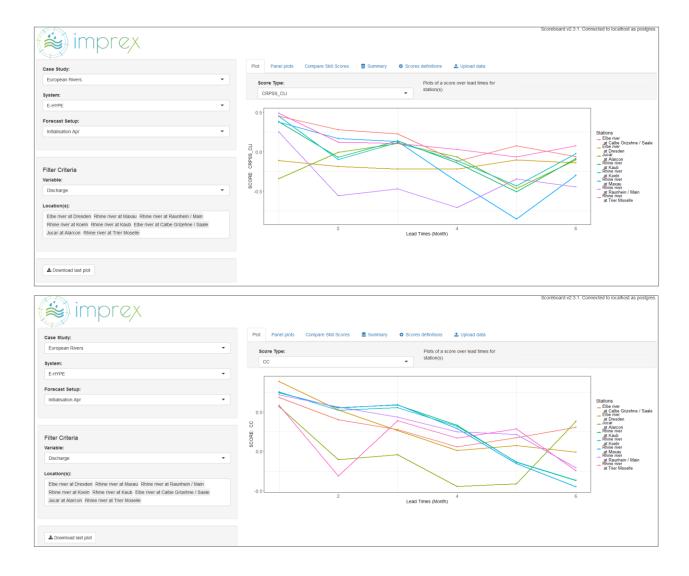


Figure 4: Screenshots of the HTML display interface of the scoreboard utility for 8 locations in the E-HYPE test score dataset, the CRPSS score (top) and Correlation coefficient (bottom)



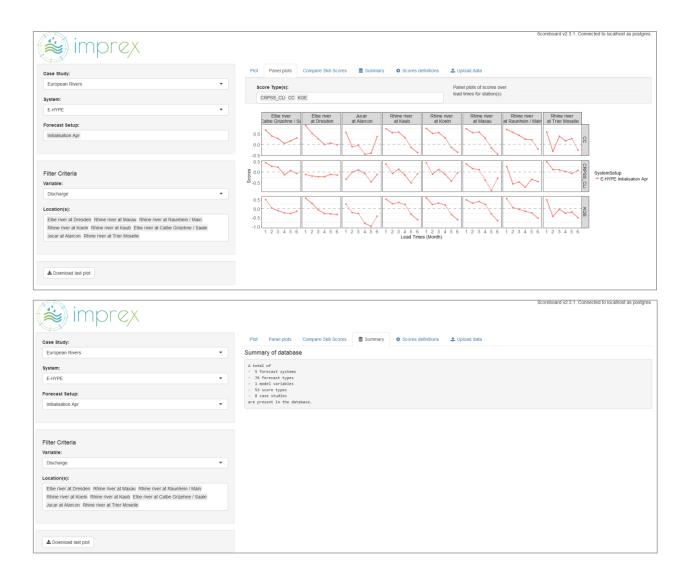


Figure 5: Screenshots of the tab options of the HTML display interface of the scoreboard utility: panel plots (top) with 3 scores (CRPS Skill score, Correlation coefficient and KGE) and 8 locations, and summary table of the E-HYPE test score dataset (bottom)





4 Conclusions and way forward

We have developed and tested a prototype of verification scoreboard utility for the IMPREX project. It is based on a database as the repository for score data collected during the lifetime of the project and an HTML5 graphical user interface (GUI) front-end to query the database and display plots of the scores that were uploaded to it. Following the development and first test phase, priorities and needs were discussed with IMPREX partners, allowing to enhance the utility.

We proposed a RDS format file for the score data, with possibility to a txt file format, after data import process had been agreed among partners. We have written the specifications for the data format and a loader utility was included to facilitate IMPREX partners to upload their score data files.

Some issues remaining include:

- A variety of types of plots can be found in the literature. We have included some of the more common plots. IMPREX partners may have other suggestions and these could eventually be implemented, if technically feasible, including some more integrated and easy-to-understand plots for a general public of users of the scoreboard.
- We have left the possibility in the format file to collect location data (geographic coordinates). The display can thus be enhanced with maps of locations and/or scores.
- We have worked with typical statistical scores, but other types of scores (including those measuring economic gains in the water sectors investigated in IMPREX) could also be included.
- An important step is to identify the host for the database and the web application (Shiny server). This issue was discussed during the 2nd Imprex General Assembly and a decision was taken together with IMPREX partners, the website administrator and coordinator to explore a URL link between partners ECMWF and ARCTIK.
- User manuals with detailed descriptions of the scoreboard utility can be provided to introduce the score data providers and the users to the tool.



5 **References**

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6 Annexes

6.1 Annex 1 – Examples of applications of forecast verification metrics in hydrology

Geographic context, spatial	Metrics used	Verification	Verification		
domain, variable		period	against		
To evaluate the assimilation of satellite soil moisture retrievals into a rainfall-runoff model for flood					
prediction in a large, sparsely mo	onitored catchment (Alvarez-Ga	rreton et al., 2015):			
1 semi-arid river basin in	Nash–Sutcliffe efficiency, RMSE,	1 June 2003 –	Streamflow		
Queensland, Australia. Daily	Peak volume error, Rank	2 March 2014	records		
streamflow, lead time 0 (simulation)	histogram, POD, FAR, CRPS				
To investigate the potential of ra	dar-based ensemble flash-flood	d forecasts, including	evaluation against		
deterministic discharge forecasts	(Liechti et al., 2013):				
3 catchments in the southern Swiss	Brier skill score, FAR and POD,	1389 hourly time	Observed		
Alps. Hourly runoff, lead time up to	ROC area	steps (June 2007–Dec.	discharge		
eight hours		2010)			
To diagnose how rainfall input a	nd parametric uncertainty influe	ence flow simulation (uncertainty in a		
distributed hydrologic model (Ca	rpenter and Georgakakos, 2004	!):			
5 watersheds and sub-catchments in	Ensemble dispersion through a	25 to 30 flow events	Observed		
	normalized inter-quantile range	for each watershed	streamflow		
the southern Central Plains of the	normanzed inter-quantile range	ioi cacii materarica			
the southern Central Plains of the United States. Hourly flow	(90th and 10th percentile)	between June 1993			
	•				
United States. Hourly flow	(90th and 10th percentile)	between June 1993 and May 1999	ower plants, in		
United States. Hourly flow simulations, lead time 0 (simulation)	(90th and 10th percentile) ensemble predictions for reserved.	between June 1993 and May 1999 voir inflow to hydrop	•		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using	(90th and 10th percentile) y ensemble predictions for reservalues given by the control me	between June 1993 and May 1999 voir inflow to hydrop	•		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic	(90th and 10th percentile) y ensemble predictions for reservalues given by the control me	between June 1993 and May 1999 voir inflow to hydrop	•		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014)	(90th and 10th percentile) g ensemble predictions for reservalues given by the control mention:):	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble	e and by the		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014) São Francisco river basin and sub-	(90th and 10th percentile) y ensemble predictions for reservalues given by the control mention. MAE, CRPS, Rank histogram, ROC	between June 1993 and May 1999 rvoir inflow to hydrop mber of the ensemble Three wet seasons in	Observed hydrographs and		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014) São Francisco river basin and subcatchments, in Minas Gerais,	(90th and 10th percentile) y ensemble predictions for reservalues given by the control mental management of the control	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three	e and by the Observed		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days	(90th and 10th percentile) g ensemble predictions for reservalues given by the control ments: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events	Observed hydrographs and inflows estimated by water balance.		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi	(90th and 10th percentile) y ensemble predictions for reservalues given by the control ments): MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events	between June 1993 and May 1999 rvoir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al.,	Observed hydrographs and inflows estimated by water balance.		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assistants.	(90th and 10th percentile) y ensemble predictions for reservalues given by the control ments): MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi North Fork of the American River Basin (NFARB) in northern California,	(90th and 10th percentile) y ensemble predictions for reservalues given by the control methol: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing	between June 1993 and May 1999 rvoir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for	Observed hydrographs and inflows estimated by water balance.		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014) São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi North Fork of the American River Basin (NFARB) in northern California, USA. Water supply values (total	(90th and 10th percentile) y ensemble predictions for reservalues given by the control ment): MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing ratio, Discrimination diagram,	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi North Fork of the American River Basin (NFARB) in northern California,	(90th and 10th percentile) y ensemble predictions for reservalues given by the control methol: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing	between June 1993 and May 1999 rvoir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014) São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assist North Fork of the American River Basin (NFARB) in northern California, USA. Water supply values (total discharge, m³)	(90th and 10th percentile) y ensemble predictions for reservalues given by the control methol: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing ratio, Discrimination diagram, Reliability diagram	between June 1993 and May 1999 rooir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for January to April,	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE observations		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014) São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assist North Fork of the American River Basin (NFARB) in northern California, USA. Water supply values (total discharge, m³)	(90th and 10th percentile) y ensemble predictions for reservalues given by the control methol: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing ratio, Discrimination diagram, Reliability diagram	between June 1993 and May 1999 rooir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for January to April,	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE observations		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi North Fork of the American River Basin (NFARB) in northern California, USA. Water supply values (total discharge, m³)	(90th and 10th percentile) y ensemble predictions for reservalues given by the control menolicity. MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing ratio, Discrimination diagram, Reliability diagram	between June 1993 and May 1999 voir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for January to April,	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE observations		
United States. Hourly flow simulations, lead time 0 (simulation) To evaluate the benefits of using comparison to the deterministic ensemble mean. (Fan et al., 2014 São Francisco river basin and subcatchments, in Minas Gerais, Southeast Brazil. Hourly streamflow, lead time up to 16 days To assess the impact of data assi North Fork of the American River Basin (NFARB) in northern California, USA. Water supply values (total discharge, m³) To evaluate bias correction meth Des Moines River basin, in Iowa,	(90th and 10th percentile) y ensemble predictions for reservalues given by the control methol: MAE, CRPS, Rank histogram, ROC Curve, Brier Skill Score, visual inspection, threshold exceedance diagrams for flood events imilation for ESP seasonal water RMSE, Percent bias, Correlation coefficient, CRPSS, Containing ratio, Discrimination diagram, Reliability diagram ods for ensemble streamflow vertices and the product of t	and May 1999 rooir inflow to hydrop mber of the ensemble Three wet seasons in 2010-2013 and three selected major flood events r supply (Franz et al., 26 to 58 years of historic data for January to April, olume forecasts (Hash 1949 to 1996 historic	Observed hydrographs and inflows estimated by water balance. 2014): Discharges and SWE observations		



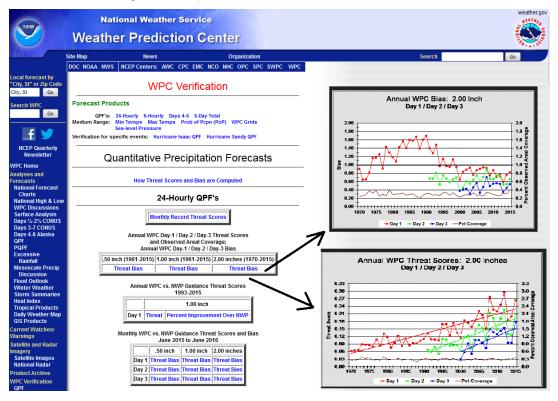
To establish a baseline for future enhancements, and to guide the operational use of the ensemble				
forecasting system studied (Brown et al., 2014):				
8 catchments in USA. Daily averages of streamflows, lead times 1 to 14 days, and time aggregated discharges.	Relative mean error (RME) of the ensemble mean, correlation coefficient, CRPS, BSS, and decompositions, Reliability diagram, ROC	Hindcasts for a 20- year period between 1979 -1999.	Simulated and observed streamflows	
To evaluate the EFAS (European	Flood Awareness System) opera	ational suite (Alfieri e	t al., 2014):	
38452 grid points of the EFAS European river network. Daily streamflows, lead times up to 10 days	Nash–Sutcliffe efficiency, Forecast bias, Coefficient of variation of the RMSE, CRPSS	Operational forecasts and hindcasts from 2009 -2012	A reference discharge simulation using observed meteorological data	
To test a global approach to pro	oducing hydrological ensemble	forecasts in river bas	ins where in situ	
data are sparse (Voisin et al., 20	11):			
4 outlets at the Ohio River basin, USA. Daily gridded runoff forecasts, lead times up to 15 days.	Bias, RMSE, Pearson correlation, Rank histograms, CRPSS	2002-2007	A reference discharge simulation using observed meteorological data	
To investigate the impact of erro	ors in the forcing, in the model	structure and parame	eters, and in the	
initial conditions on hydrologica	I forecasts; to test the post-pro	cessing of hydrologic	al ensembles	
(Roulin and Vannitsem, 2015):				
The Ourthe Orientale at Mabompré in the Ardennes region in Belgium. Daily discharges, lead time up to 10 days	Bias or mean error (ME), RMSE, Spread, CRPS and decomposition	March 2008 to December 2012	Observed discharges and reference discharge simulation using observed meteorological data	
To investigate how data assimila	ation and post-processing contr	ibute to the skill of h	ydrological	
ensemble forecasts (Bourgin et al., 2014):				
202 catchments in France. Hourly streamflows, lead times up to 48 hours	Bias, RMSE, PIT, Normalized mean interquartile range (NMIQR), CRPSS	2005–2009	Observed discharges	





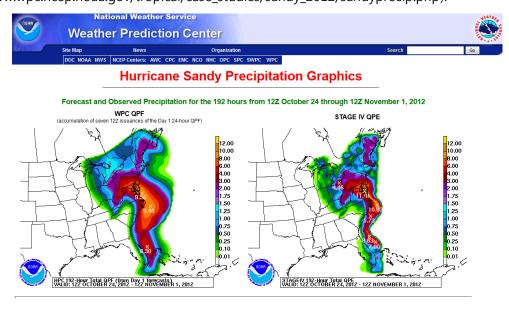
6.2 Annex 2 – Examples of existing verification scoreboards

Screenshot of the Weather Prediction Centre verification webpage (National Weather Service, NOAA: http://www.wpc.ncep.noaa.gov/html/hpcverif.shtml):



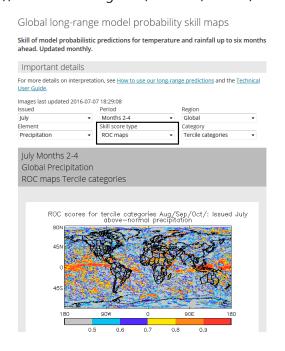
Screenshot of the QPF forecast verification for the Hurricane Sandy of the Weather Prediction Centre verification webpage (National Weather Service, NOAA:

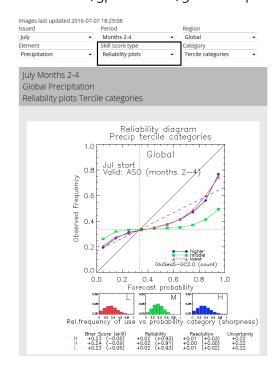
http://www.wpc.ncep.noaa.gov/tropical/case_studies/sandy_2012/sandyprecip.php):



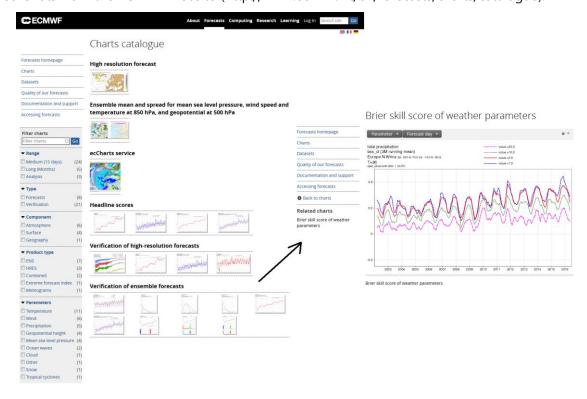


Screenshots from the MetOffice webpage on Global long-range model probability skill (http://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/glob-seas-prob-skill):





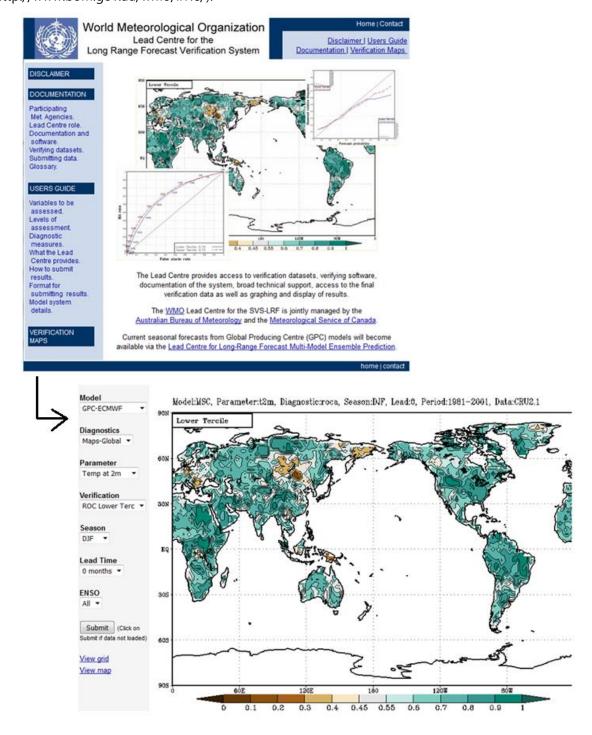
Screenshots from the ECMWF website (http://www.ecmwf.int/en/forecasts/charts/catalogue):







Screenshots from the WMO website on its Long-range forecast verification system jointly managed by the Australian Bureau of Meteorology and the Meteorological Service of Canada (http://www.bom.gov.au/wmo/lrfvs/):





6.3 Annex 3 – Example of .Renviron file

This file should be located in the ~/R home directory of RStudio, or the file location must be updated in server.R and ui.R.

```
# example setup file for your local postgres database
pgserver="localhost"
pgport=5432
pgdb="imprex_real_scores"
api_user="postgres"
api_language=1
pgpassword="irstea"
pgschema="scoreboard"
sb_version="2.3.1"
uploadpassword="BML"
```

6.4 Annex 4 – Format specifications for input files to the IMPREX score database

Below is the file specification with individual descriptions (available in a Read_Me directory).

Files formats and needed data and metadata

The scoreboard works with RDS and text files.

One single data file can only contain data from one experiment evaluated on one score, with one initialisation, but it can include several stations.

NA values must be entered as either:

- NA
- -9999.

I invite you to open these files to better know what to put in. I provide here some important elements of explanation:

- The RDS files are R data files. They contain a list of elements containing the metadata and data you want to upload.
- The text file contains several lines with semi-column separated metadata (8 fields needed) and semi-column separated data.
- In both formats, the metadata are read as characters.
 - Provider : your name
 - CaseStudy: your case study ("Jucar River Basin" for instance)





- ForecastSystem: your forecast system
- ForecastType: the name you want to give to your experiment, e.g. the name of your model, with its time step if you can have several time steps. It is important to give a different name if you want to compare the new configuration with an older one. The score name should not appear here.
- ModelVariable: the name of the variable on which the score is evaluated.
- ScoreType: the name of the score
- ScoreLeadTimeUnit: "Day", "Week", "Month", etc. are examples. If every 15 days you make a seasonal forecast at a monthly time step for the next 6 months, you must put "Month".
- VerificationPeriod: on which period you computed your score
- Data:
 - LocationID: whatever code you use to design your station / grid point
 / area on which the score is computed. This is read as character
 - River_names: read as characters
 - Station_names: read as characters
 - Latitude: read as numeric
 - Longitude: read as numeric
 - Score_Value: your actual score values! Read as numeric
 - LeadTime: the leadtime that is evaluated. If every 15 days you make a seasonal forecast at a monthly time step for the next 6 months, you must put here values from 1 to 6.
- Important notice: some fields must be very carefully filled. Indeed, the database uses some of them to link the different tables of the database. The fields are all the metadata fields (except VerificationPeriod for now) and the LocationID. To illustrate what I am saying, if provider 1 gives CRPSS and provider 2 provides CRPSkillScore, which are basically the same scores, they will not be comparable in the 3rd panel of the scoreboard.









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