evalhyd v0.1.1: a polyglot tool for the evaluation of deterministic and probabilistic streamflow predictions

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Abstract. The evaluation of streamflow predictions forms an essential part of most hydrological modelling studies published in the literature. The evaluation process typically involves the computation of some evaluation metrics, but it can also involve the pre-processing of the predictions and the post-processing of the computed metrics. In order for published hydrological studies to be reproducible, these steps need to be carefully documented by the authors. The availability of a single tool performing
5 all of these tasks would simplify the documentation by the authors, but also the reproducibility by the readers. However, this requires for such a tool to be polyglot (i.e. usable in a variety of programming languages) and openly accessible, so that it can be used by everyone in the hydrological community. To this end, we developed a new tool named `evalhyd` that offers metrics and functionalities for the evaluation of deterministic and probabilistic streamflow predictions. It is open source and it can be used in Python, in R, in C++, or as a command line tool. This article describes the tool and illustrates its functionalities using
10 Global Flood Awareness System (GloFAS) reforecasts over France as an example data set.

1 Introduction

Whether it is referred to as validation, evaluation, or verification (Beven and Young, 2013, sect. 5), the action of comparing streamflow model outputs against streamflow observations is routinely performed by hydrological modellers. This comparison is typically carried out in view to estimate model parameters or to assess model performance. To these ends, one or more
15 measures of the goodness of fit between streamflow time series is used, sometimes referred to as objective functions, performance metrics, or verification scores depending on the context. While there is a variety of metrics to perform such a task (Crochemore et al., 2015; Anctil and Ramos, 2017; Huang and Zhao, 2022), those that are chosen are often the same, for instance the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) or the Kling-Gupta Efficiency (KGE) (Gupta et al., 2009) for the deterministic evaluation of streamflow predictions, or the Brier Score (BS) (Brier, 1950) or the Continuous Rank
20 Probability Score (CRPS) (Hersbach, 2000) for the probabilistic evaluation of streamflow predictions. Note that we use the term predictions as an umbrella term to include both simulations and forecasts (see definitions in Beven and Young, 2013, sect. 3).

The computation of the metrics described in the literature is sometimes performed directly as part of the workflow analysing the predictions, which is error-prone and hardly traceable, thus limiting its reproducibility. In other cases, specific tools are
25 developed for the computation of the metrics, but they are not always open source and rely on different programming languages

commonly used in the hydrological community (e.g. Python, R, Matlab, Julia). As a result, discrepancies in the computation of the metrics may exist. Moreover, before computing the metrics, streamflow time series are often subject to pre-processing (e.g. handling of missing data, data transformation, selection of events) and, after computing them, the metrics can also be subject to post-processing (e.g. sensitivity analysis, uncertainty estimation). Such pre- and post-processing steps may also differ and,

30   because they are rarely documented in detail, they can lead to further discrepancies. Together, these discrepancies are likely impeding on the reproducibility of published results in hydrological sciences (Hutton et al., 2016; Stagge et al., 2019).

Unlike meteorological predictions, which are typically issued on a spatial grid, hydrological predictions are often issued at discrete locations along the river network typically, but not only, where hydrometric stations are located. In addition, hydrological predictions often focus on specific extreme events (i.e. floods, droughts). In hydrology, evaluation tools have

35   thus to be adapted to these conditions. There exists a variety of evaluation tools with varying degrees of adequacy with the specificities of hydrological predictions. Inventories of tools specific to hydrology can be found in Slater et al. (2019) and at https://cran.r-project.org/view=Hydrology (last access: 23 June 2023) for R, or at https://github.com/raoulcollenteur/Python-Hydrology-Tools (last access: 23 June 2023) for Python. The Ensemble Verification System (EVS) (Brown et al., 2010) is certainly the most advanced example of an evaluation tool dedicated to discrete hydro-meteorological ensemble predictions.

40   But one major drawback of EVS is that it requires for the inputs to be provided as data files of a certain non-standardised format. This requires reformatting model outputs, which can be truly limiting and inefficient when dealing with large sets of model outputs (e.g. large model ensembles, large samples of catchments). In addition, the use of a non-standardised file format limits its integration in reproducible analysis workflows (Knoben et al., 2022). Other evaluation tools have been developed, mostly from the meteorological community, e.g. `verification` (https://cran.r-project.org/web/packages/verification, last

45   access: 10 May 2023) or `scoringRules` (https://cran.r-project.org/web/packages/scoringRules, last access: 10 May 2023) in R, `ensverif` (https://pypi.org/project/ensverif, last access: 10 May 2023) or `properscoring` (https://pypi.org/project/properscoring, last access: 10 May 2023) in Python. However, these are not specific to hydrology, they lack pre- and post-processing aspects, or they feature a limited diversity of metrics.

In this context, an evaluation tool that is tailored to hydrology, both in terms of the richness in the metrics it gives access to

50   and the relevance of the functionalities it features, and that can be used in a variety of programming languages has the potential to offer a community-wide solution to improve on the reproducibility of published hydrological studies. This article presents `evalhyd`, an evaluation tool specifically designed to meet such needs in hydrological evaluation. First, the objectives of the tool are described, before its design principles, its main functionalities, and its available evaluation metrics are unfolded in turn. Then, a case study using the tool is provided as an illustration of its capabilities. Finally, the limitations and the perspectives

55   for further developments of the tool are discussed.

2   Objectives of the tool

The purpose of `evalhyd` is to provide a utility to evaluate streamflow predictions. It aims to feature the most commonly used metrics for deterministic and probabilistic evaluation (see e.g. Huang and Zhao, 2022), as well as all the necessary

functionalities required to pre-process the data analysed and post-process the metrics computed. Typically, these are rarely
documented in the literature and this can limit the reproducibility of research findings (Hutton et al., 2016).

In line with Principle 3 for Open Hydrology advocated for by Hall et al. (2022), the tool must be open access. The tool must
also be polyglot, which means that it must be usable in a variety of open source programming languages, in order to be usable
by as many users as possible. In practice, this means that a separate package must be available for each programming language,
thus forming a software stack.

3   Design principles

3.1   A compiled core with thin satellite bindings

The software stack, named `evalhyd`, features a core library written in C++, named `evalhyd-cpp`, which implements
all the available functionalities and evaluation metrics. The implementation of the core is written in a compiled language
to be computationally efficient. This is important since large-sample studies (see e.g. Gupta et al., 2014) and large hydro-
meteorological ensembles (see e.g. Schaake et al., 2007) have become very common in hydrological model evaluation studies.
The core library is also directly usable in C++ as an evaluation library.

In addition, the stack features satellite bindings which are distinct packages whose only purposes are to interface the core
with high-level programming languages. These are named `evalhyd-python` for Python and `evalhyd-r` for R. They
are intended to be as thin as wrappers can be to avoid duplicated efforts across bindings. A command line interface, named
`evalhyd-cli`, also exists for those not using any of the programming languages mentioned. The only drawback with the
latter is that it is only able to work via intermediate data files, which presents the same limitations as EVS of relying on a specific
data file format. On the contrary, the Python and R bindings work directly with native data structures of those languages, thus
completely eliminating the need to decide on a specific file format, and allowing for any model output to be processed without
requiring for them to be reformatted.

Note that both the core library and the satellite bindings use the libraries from the `xtensor` software stack underneath
(https://github.com/xtensor-stack, last access: 12 May 2023) and, in particular, they leverage the bindings available for multiple
programming languages (i.e. `xtensor-python` and `xtensor-r`). As such, there is scope for the development of a satellite
binding for Julia in the future (i.e. using `xtensor-julia`).

For the remainder of this article, we will keep referring to the software stack as the one tool for convenience, since all the
functionalities and evaluation metrics are available in all packages.

3.2   A two-entry-point interface

Across the software stack, the interfaces are intentionally kept as identical as possible given the syntactic differences across
languages (as illustrated in Figure 1 and Figure A1). Thus, users of different `evalhyd` packages can easily help each other,
and this also minimises inconveniences when users transition from one language to another.

(a) C++ interface

```cpp
1  #include <xtensor/xtensor.hpp>
2  #include <evalhyd/evald.hpp>
3
4  xt::xtensor<double, 2> obs =
5      {{4.7, 4.3, 5.5, 2.7, 4.1}};
6  xt::xtensor<double, 2> prd =
7      {{5.3, 4.2, 5.7, 2.3, 3.1},
8       {4.3, 4.2, 4.7, 4.3, 3.3},
9       {5.3, 5.2, 5.7, 2.3, 3.9}};
10 auto res = evalhyd::evald(obs, prd, {"NSE"});
```

(b) Python interface

```python
1  import numpy
2  import evalhyd
3
4  obs = numpy.array([[4.7, 4.3, 5.5, 2.7, 4.1]])
5  prd = numpy.array([[5.3, 4.2, 5.7, 2.3, 3.1],
6                     [4.3, 4.2, 4.7, 4.3, 3.3],
7                     [5.3, 5.2, 5.7, 2.3, 3.9]])
8  res = evalhyd.evald(obs, prd, ["NSE"])
```

(c) R interface

```r
1  obs ← rbind(c(4.7, 4.3, 5.5, 2.7, 4.1))
2  prd ← rbind(c(5.3, 4.2, 5.7, 2.3, 3.1),
3              c(4.3, 4.2, 4.7, 4.3, 3.3),
4              c(5.3, 5.2, 5.7, 2.3, 3.9))
5  res ← evalhyd::evald(obs, prd, c("NSE"))
```

(d) Command line interface

```
   ./obs.csv
1  4.7,4.3,5.5,2.7,4.1

   ./prd.csv
1  5.3,4.2,5.7,2.3,3.1
2  4.3,4.2,4.7,4.3,3.3
3  5.3,5.2,5.7,2.3,3.9

1  ./evalhyd evald "./obs.csv" "./prd.csv" "NSE"
```

Figure 1. Comparison of the interfaces for the deterministic entry point `evald` across the `evalhyd` software stack through a simple example evaluating deterministic predictions (`prd`, of shape $\{series : 3, time : 5\}$) against observations (`obs`, of shape $\{1, time : 5\}$) using the Nash-Sutcliffe efficiency (NSE): **(a)** C++ interface fed with `xtensor` data structures, **(b)** Python interface fed with `numpy` data structures, **(c)** R interface fed with R data structures, and **(d)** command line interface fed with data in CSV files.

90   Each package has two entry points to its interface, named `evald` and `evalp`, two functions for the evaluation of deterministic predictions (see trivial examples in Figure 1) and probabilistic predictions (see trivial examples in Figure A1), respectively. Note that the names and the order of the parameters of these two entry points are strictly identical across the software stack.

3.3 A multi-dimensional paradigm

Both `evald` and `evalp` entry points take multi-dimensional data sets as inputs in view to accommodate for the specific needs
95   identified for deterministic and probabilistic predictions, as detailed below.

For probabilistic evaluation, streamflow predictions are at the minimum two-dimensional, that is $\{ensemble\ members, time\}$, corresponding to an ensemble forecast for a given site and a given lead time. However, there are also metrics that need computing on multiple sites or on multiple lead times at once. This is why the predictions are expected to be four-dimensional, that is $\{sites, lead\ times, ensemble\ members, time\}$, and the observations to be two-dimensional, that is $\{sites, time\}$. Note
100   that the input ranks are kept fixed, even if the problem does not require all dimensions. For example, even if the problem only features one site and one lead time, the input must remain four-dimensional.

For deterministic evaluation, streamflow predictions are at the minimum one-dimensional, that is $\{time\}$, corresponding to a simulation for a given site. However, it seems opportune to accommodate for multiple simulation time series, as is the case in Monte Carlo simulations or multi-model approaches for example. This is why the predictions are expected to be two-

105   dimensional, that is $\{series, time\}$, and the observations to be two-dimensional, that is $\{1, time\}$. Note that for convenience, the Python and R bindings allow for one-dimensional inputs, which can be useful when used in a model parameter estimation context.

4   Key functionalities

4.1   Memoisation

110   Certain evaluation metrics require the same intermediate computations. For example, the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) and the Kling-Gupta efficiency (Gupta et al., 2009) both require to compute the quadratic error between the observations and their arithmetic mean, so it is computationally more efficient to compute this error once, and reuse it if both metrics are requested by the user.

    In computer science, this refers to the concept of memoisation (or memo functions) first introduced by Michie (1968) in the

115   context of machine learning. `evalhyd` applies this concept by isolating the recurrent intermediate computations across the evaluation metrics, and by storing these for potential later reuse if multiple metrics are requested at once. This is why the user is advised to request all desired metrics in a single call to `evalhyd` rather than in separate calls.

4.2   Handling of missing data

  Streamflow observations are seldom complete and missing data is very common. Various data filling methods exist to overcome

120   this problem (see e.g. Gao et al. (2018) for a review), but this is typically done by the streamflow data providers themselves where possible, so it is not deemed as a task that an evaluation tool should perform. Therefore, if streamflow observations remain lacunar, `evalhyd` disregards the time steps where observations are missing (i.e. where they are set as *not a number*).

    In addition, for the case of probabilistic evaluation, some streamflow prediction values may also need to be flagged as *not a number*. This is illustrated in Figure 2 for a fictitious data set featuring daily predictions for three lead times. By design,

125   `evalhyd` expects only one observation time series for a given site. Therefore, when several lead times are considered at once, a temporal shift of the predictions must be applied, and invalid dates must be identified as *not a number*. That is because the earliest observations are not needed for the longer lead times and the latest observations are not needed for the shorter lead times.

4.3   Masking

130   Depending on the context of the evaluation, it may be desirable to only consider sub-periods of the streamflow records: for example, to focus on specific flood events, or more generally to consider only high or low flows. `evalhyd` offers two avenues to perform such subsets: temporal masking and conditional masking.
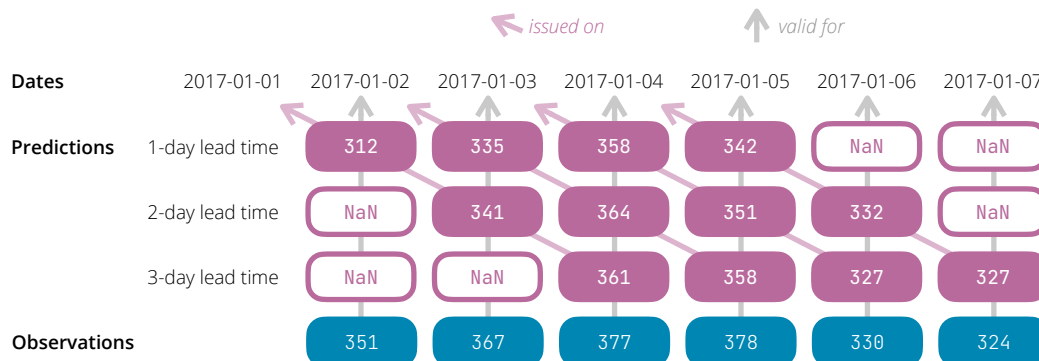
Figure 2. Illustration of the need to insert "not a number" values (symbolised as `NaN`) before and/or after the prediction values to align the prediction dates with their observation dates when several lead times are considered at once. This example features a small fictitious situation where daily forecasts are issued on four consecutive days (2017-01-01, 2017-01-02, 2017-01-03, and 2017-01-04) for three lead times (1-day, 2-day, and 3-day). Each rounded rectangle corresponds to a streamflow value (observed on the first row, predicted on the three following rows).

Temporal masking corresponds to directly providing a mask (i.e. a series of boolean values of the same length as the streamflow time series) whose values are set to *true* for those time steps that should be considered in the evaluation, and to *false* otherwise. This mask is typically expected to be generated by the user in the high-level programming of their choice.

Conditional masking corresponds to a convenient alternative to generate the temporal mask for the user through the specification of conditions. The conditions can be based on streamflow values (either streamflow observations, or mean or median streamflow predictions), or on time indices. Table 1 provides examples of the syntax to use to specify such conditions alongside their plain meaning. The conditions on streamflow values are helpful to focus the evaluation on particular flow ranges (e.g. low flows or high flows) by specifying streamflow thresholds, whereas the conditions on time indices are helpful to focus on specific flow events (e.g. notable floods or droughts) by selecting relevant time steps.

Note that the concept of memoisation is also applied by `evalhyd` if several masks are provided. Since metrics typically compute some form of error between pairs of observation and prediction time steps before applying some form of temporal reduction (e.g. sum or average), it is computationally more efficient to store the error computed for individual pairs before reducing them according to the various masks (i.e. subset periods) provided or generated.

4.4 Data transformation

It is common practice in hydrology to apply transform functions to the streamflow data prior to the computation of the evaluation metrics. This is typically done because hydrological models tend to produce larger errors on flows of higher magnitude, which results in putting more emphasis on high-flow periods when computing the metric. To reduce the emphasis on high flows or to change the emphasis altogether, various transform functions can be applied (see e.g. Krause et al., 2005; Oudin et al., 2006; Pushpalatha et al., 2012; Pechlivanidis et al., 2014; Garcia et al., 2017; Santos et al., 2018).

Table 1. Example of masking conditions possible in `evalhyd`.

Condition	Plain meaning
On streamflow values	
`q_obs{>median}`	consider periods where streamflow observations are greater than their median
`q_prd_median{<=250}`	consider periods where median streamflow predictions[a] are lower than or equal to 250[b]
`q_prd_mean{<qtl0.8}`	consider periods where mean streamflow predictions[a] are lower than their 80th percentile
On time indices	
`t{20:53}`	consider period from 21st[c] time step to 53rd[c] time step[d]
`t{12,13,14}`	consider period including 11th[c], 12th[c], and 13th[c] time steps

[a] conditions on streamflow predictions are only available for probabilistic evaluation

[b] streamflow unit in condition is assumed to be the same as in the input data

[c] indexing starts at zero (i.e. first time step is at index 0)

[d] last index is not included

evalhyd offers several data transformation functions to be applied to both the streamflow observations and predictions prior to the computation of the evaluation metrics. These include the natural logarithm function, the reciprocal function, the square root function, and the power function. For those functions not defined for zero (i.e. the reciprocal function, the natural logarithm, or the power function with a negative exponent), a small value is added to both the streamflow observations and predictions as recommended by Pushpalatha et al. (2012): by default, one hundredth of the mean of the streamflow observations is used, but it can be customised by the user.

This functionality is the only one that is only applicable to deterministic predictions, i.e. via the evald entry point, because it is currently only common practice in a deterministic context. Later versions of the tool could remedy this depending on user feedback.

4.5 Bootstrapping

It is crucial to assess the sampling uncertainty in the evaluation metrics, that is to say their variability from one study period (i.e. one sample) to another. Clark et al. (2021) recommend using a non-overlapping block bootstrapping method, where blocks are taken as distinct hydrological years to preserve seasonal patterns and intra-annual auto-correlation.

evalhyd implements such a bootstrapping functionality to provide an estimation of the sampling uncertainty in the evaluation metrics it computes. The number of evaluation sub-periods considered (i.e. samples) as well as the number of years (i.e. blocks) in each sub-period are specified by the user. Then, the tool randomly samples years within the whole study period accordingly. As many evaluation metric values are computed as there are samples. These values can either be returned directly or as summary statistics (either mean and standard deviation, or distribution of quantiles).

5 Evaluation metrics

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The tool features a variety of metrics for the evaluation of deterministic and probabilistic streamflow predictions. The collection of deterministic metrics is presented in Table 2, while the collection of probabilistic metrics is presented in Table 3. The deterministic metrics are accessible via the `evald` entry point, and the probabilistic metrics are accessible via the `evalp` entry point.

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Skill scores are sometimes used to compare the score of the predictions with the score of a reference, e.g. Kling-Gupta Efficiency Skill Score (KGESS) from KGE (Knoben et al., 2019) or Continuous Rank Probability Skill Score (CRPSS) from CRPS (see e.g. Yuan and Wood, 2012). They are formulated as the difference between the predictions score and the reference score divided by the difference between the perfect score and the reference score (see e.g. Wilks, 2011, eq. 8.4). However, the reference is not always clearly defined. Therefore, `evalhyd` only provides the scores for which this is the case: the Nash-

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Sutcliffe Efficiency (NSE), where the reference is taken as the mean of the observations; the Relative Operating Curve Skill Score (ROCSS), where the reference is taken as random forecasts; and the Brier Skill Score (BSS), where the reference is taken as the sample climatology (i.e. constant forecasts of the sample climatological relative frequency, analytically corresponding to the uncertainty term of the Brier Score, see Wilks (2011), eq. 8.43). For all other metrics, the reference needs to be chosen by the user before `evalhyd` can be used to compute the predictions score and the reference score separately. Then, they

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can be combined following the ratio-based formulation mentioned above to get the skill score. The illustrative example in the following section provides a demonstration of this where the CRPSS is computed using two references provided by the user (the persistence and the climatology).

6 Illustrative example

In order to illustrate the capabilities of `evalhyd`, open access data sets were chosen from the literature and evaluated. The

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prediction data chosen are the ones produced by Zsoter et al. (2020) and correspond to river discharge reforecasts from the Global Flood Awareness System (GloFAS) for the period 1999-2018. The observation data chosen are the ones produced by Harrigan et al. (2021) and correspond to river discharge reanalysis data from the GloFAS hydrological modelling chain forced with ERA5 meteorological reanalysis data for the period 1979-2022. In addition, the study by Harrigan et al. (2023) is used as it provides evaluation results for this data set for the period 1999-2018 using the CRPSS computed against two different

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benchmarks (persistence and climatology). In this example, the focus is put on the 23 GloFAS stations located in France.

The first objective of this example is to show that the results published by Harrigan et al. (2023) can be reproduced using `evalhyd`. The second objective is to show the many possibilities offered by the functionalities and the metrics of `evalhyd`, which could be used to further analyse the reforecasts, for instance.

Table 2. Collection of deterministic metrics available via `evald` entry point in `evalhyd`.

Identifier	Range*	Unit	Details	Related references
MAE	$[\mathbf{0}, +\infty[$	same as q	Mean absolute error	Willmott and Matsuura (2005); Moriasi et al. (2007)
MARE	$[\mathbf{0}, +\infty[$	same as q	Mean absolute relative error	–
MSE	$[\mathbf{0}, +\infty[$	same as q	Mean square error	Moriasi et al. (2007)
RMSE	$[\mathbf{0}, +\infty[$	same as q	Root mean square error	Barnston (1992); Willmott and Matsuura (2005); Moriasi et al. (2007)
NSE	$]-\infty, \mathbf{1}]$	unitless	Nash-Sutcliffe efficiency	Nash and Sutcliffe (1970)
KGE	$]-\infty, \mathbf{1}]$	unitless	Kling-Gupta efficiency	Gupta et al. (2009)
KGE_D	$[0, +\infty[$	unitless	Decomposition of the Kling-Gupta efficiency	Gupta et al. (2009)
KGEPRIME	$]-\infty, \mathbf{1}]$	unitless	Modified Kling-Gupta efficiency	Kling et al. (2012)
KGEPRIME_D	$[0, +\infty[$	unitless	Decomposition of the modified Kling-Gupta efficiency	Kling et al. (2012)
CONT_TBL	$[0, +\infty[$	unitless	Contingency table	–

* optimal value in bold where applicable

6.1 Reproducing published results

200 Figure 3 (Figure A2) provides the GloFAS reforecasts performance against the climatology benchmark (against the persistence benchmark) using the CRPSS. It focuses on four of the 17 lead times available, thus mirroring Figure 6 (Figure 7) in Harrigan et al. (2023). In order to be more precise and exhaustive in the comparison between their published performance and the performance obtained with `evalhyd`, Figure 4 (Figure A3) provides a complete comparison of the performance against the climatology benchmark (against the persistence benchmark) for each station and for each lead time. The data points all lying

205 on the 1:1 line demonstrates that the performance is identical and, therefore, that the published results are indeed successfully reproduced using `evalhyd`.

6.2 Showcasing some useful functionalities

The evaluation tool `evalhyd` features many more metrics and functionalities than those used to reproduce the published results above. This section makes use of the same GloFAS reforecasts as an example data set to showcase some additional

210 functionalities available to further explore the performance of streamflow (re)forecasts, e.g. metric uncertainty estimation or focus on certain flow ranges.

Table 3. Collection of probabilistic metrics available via `evalp` entry point in `evalhyd`.

Identifier	Range[*]	Unit	Details	Related references
BS	$[\mathbf{0}, +\infty[$	unitless	Brier score	Brier (1950); Wilks (2011)
BSS	$]-\infty, \mathbf{1}]$	unitless	Brier skill score	Hamill and Juras (2006); Wilks (2011)
BS_CRD	$[\mathbf{0}, +\infty[$	unitless	Calibration-refinement decomposition of the Brier score (i.e. reliability, resolution, and uncertainty)	Wilks (2011)
BS_LBD	$[\mathbf{0}, +\infty[$	unitless	Likelihood-base rate decomposition of the Brier score (i.e. type-2 bias, discrimination, and sharpness)	Wilks (2011)
REL_DIAG	NA	unitless	Reliability diagram (i.e. forecast probabilities, observed frequencies, and sampling frequencies)	Weisheimer and Palmer (2014)
CRPS_FROM_BS	$[\mathbf{0}, +\infty[$	same as q	Continuous ranked probability score derived from Brier scores	–
POD	$[0, 1]$	unitless	Probability of detection	–
POFD	$[0, 1]$	unitless	Probability of false detection	–
FAR	$[0, 1]$	unitless	False alarm rate	–
CSI	$[0, 1]$	unitless	Critical success index	–
ROCSS	$]-\infty, \mathbf{1}]$	unitless	Relative operating characteristic skill score	–
CRPS_FROM_ECDF	$[\mathbf{0}, +\infty[$	same as q	Continuous ranked probability score derived from empirical cumulative density function	Hersbach (2000)
QS	$[\mathbf{0}, +\infty[$	same as q	Quantile scores	Gneiting and Raftery (2007)
CRPS_FROM_QS	$[\mathbf{0}, +\infty[$	same as q	Continuous ranked probability score derived from quantile scores	Gneiting and Ranjan (2011)
RANK_HIST	NA	unitless	Rank histogram	Talagrand et al. (1997)
DS	$[0, +\infty[$	unitless	Delta score	Candille and Talagrand (2005); Anctil and Ramos (2017)
AS	$[0, \mathbf{1}]$	unitless	Alpha score	Renard et al. (2010)
CR	$[0, 1]$	unitless	Coverage ratio	–
AW	$[\mathbf{0}, +\infty[$	same as q	Average width	–
AWN	$[\mathbf{0}, +\infty[$		Average width normalised	Bourgin et al. (2015)
WS	$[\mathbf{0}, +\infty[$	same as q	Winkler score	Winkler and Murphy (1979); Gneiting and Raftery (2007)
ES	$[\mathbf{0}, +\infty[$	same as q	Energy score	Gneiting et al. (2008)

[*] optimal value in bold where applicable; NA means not applicable
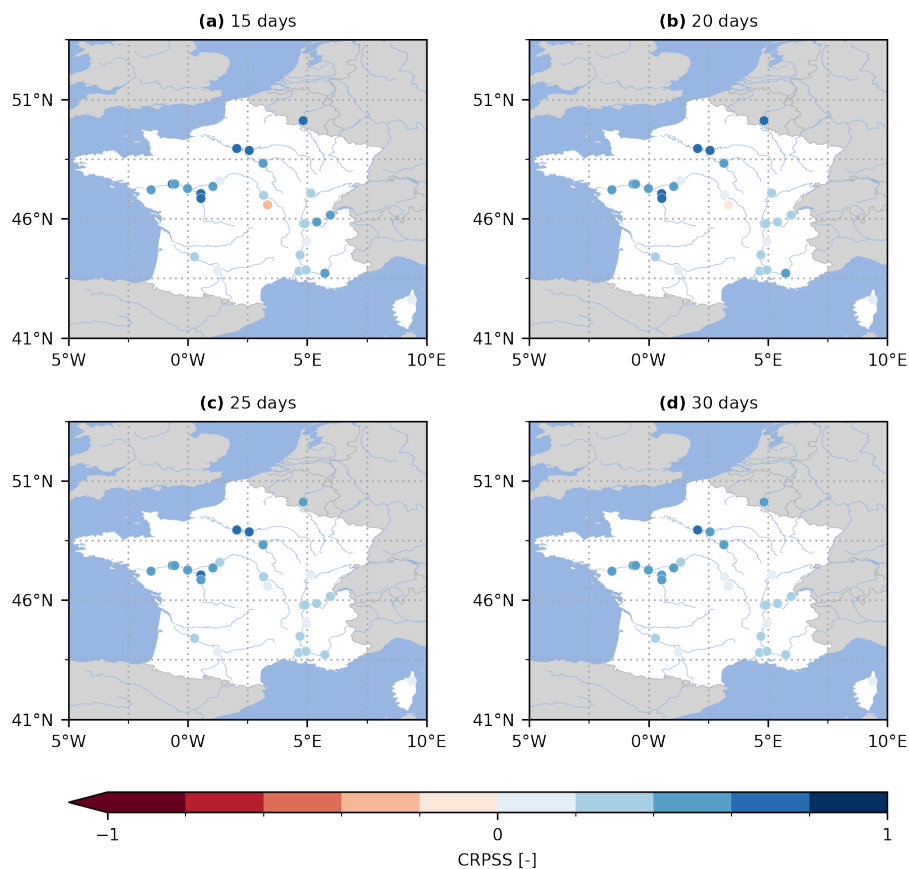
Figure 3. Continuous Rank Probability Skill Score (CRPSS) for the GloFAS reforecasts (v2.2) against the climatology benchmark. The CRPSS is computed with `evalhyd` for all 23 GloFAS stations located in France, and for four lead times (i.e. **(a)** 15 d, **(b)** 20 d, **(c)** 25 d, and **(d)** 30 d), mirroring a zoomed-in version of Figure 7 in Harrigan et al. (2023).

6.2.1 Uncertainty analysis using the bootstrapping functionality

In order to estimate the sampling uncertainty on the metric values, `evalhyd` bootstrapping functionality can be used (see subsection 4.5 for details). Figure 5 showcases the results obtained using this bootstrapping functionality with 1000 samples of 10 years each, summarised using a distribution of quantiles and displayed as box-plots. The evaluation metric used is the Brier Skill Score (BSS) against the climatology benchmark to assess the performance of the reforecasts in predicting the exceedance of a threshold set as the 20th observed percentile, and the 12-day lead time is considered.

These results obtained with `evalhyd` can be used to explore the variability in performance across the GloFAS stations by, for example, comparing the median performance (varying from 0.323 to 0.903 here). In addition, the varying widths of the

CRPSS as reported by Harrigan et al. (2023)
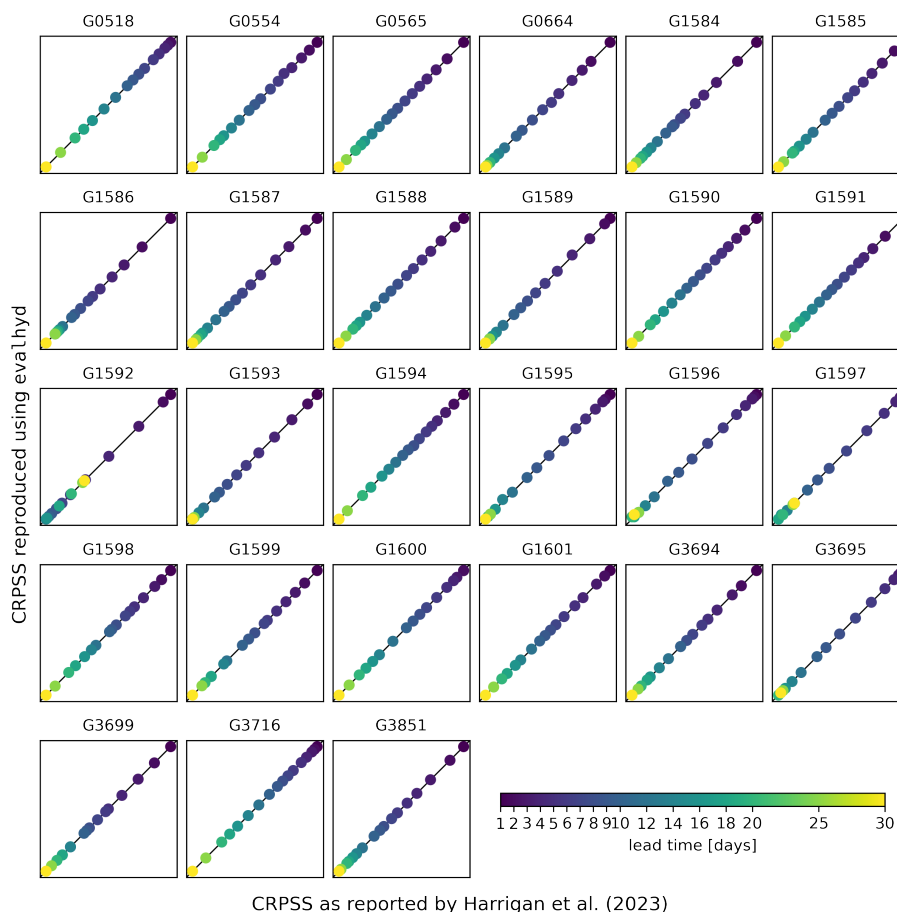
Figure 4. Comparison between the CRPSS reported in the Supplement of Harrigan et al. (2023) (x-axis) and the CRPSS computed using `evalhyd` (y-axis) against the climatology benchmark. Each panel represents one of the 23 GloFAS stations located in France, and in each panel, the diagonal represents the 1:1 line, and each data point represents one of the 17 lead times in the GloFAS reforecasts (v2.2).

220   boxes across the GloFAS stations (from 0.030 to 0.139 here) can be used as a measure of the uncertainty associated with the predictive performance of the flood events from one station to another.

6.2.2   Data stratification using the masking functionality

The predictive performance of streamflow forecasts may vary depending on the flow range considered (e.g. flood forecasting vs. drought forecasting). Bellier et al. (2017) suggest a forecast-based sample stratification for continuous scalar variables in
225   order to consider the merits of streamflow forecasts on different ranges of flows. Such analyses can be easily performed using the conditional masking functionality of `evalhyd`.

     Figure 6 provides an example stratifying the rank histogram into three components, one for low-flow periods (using the masking condition "periods where the predicted median is below the 30th predicted percentile"), one for average-flow periods
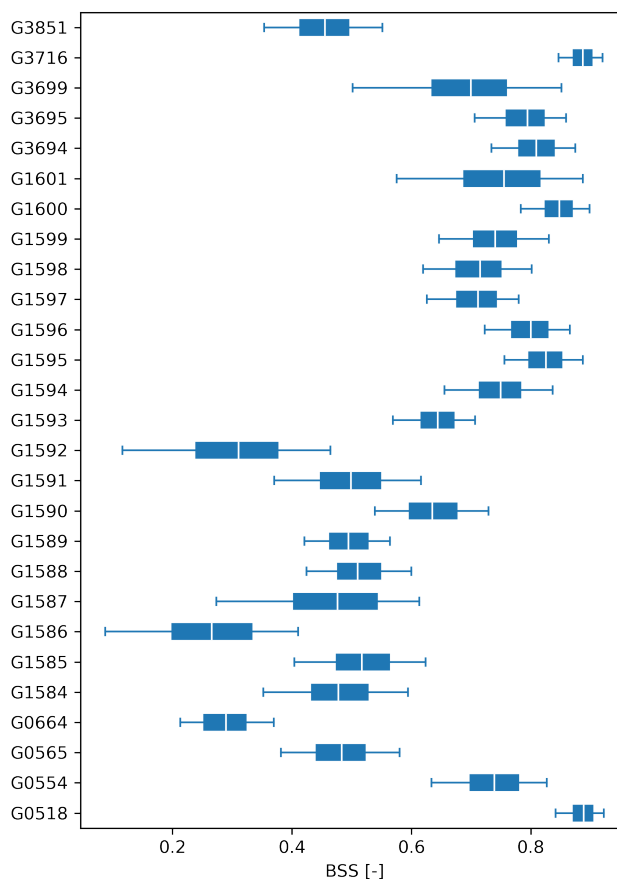
Figure 5. Brier Skill Scores (BSS) on the exceedance of a 20th percentile threshold (x-axis) for the GloFAS reforecasts (v2.2) for all 23 GloFAS stations located in France (y-axis) for a 12-day lead time. Each boxplot represents the sampling distribution obtained using the bootstrapping functionality of `evalhyd` (with 1000 samples of 10 years each), where the box is formed of the inter-quartile range (i.e. 25th-75th percentiles) and is split using the median (i.e. 50th percentile), and the whiskers are stretching from the 5th to the 95th percentiles.

(using the masking condition "periods where the predicted median is between the 30th and the 70th predicted percentiles"), and one for high-flow periods (using the masking condition "periods where the predicted median is above the 70th predicted percentile").

These results obtained with `evalhyd` can be used to explore the dispersion of the GloFAS reforecasts. For example, for a given station (G0664, Le Bevinco at Olmeta-di-Tuda) and a given lead time (6-day lead time), the U-shapes of the histograms for low-flow and average-flow conditions suggest an under-dispersion of the reforecasts, while the upslope-shape for high flow conditions suggests a small negative bias.
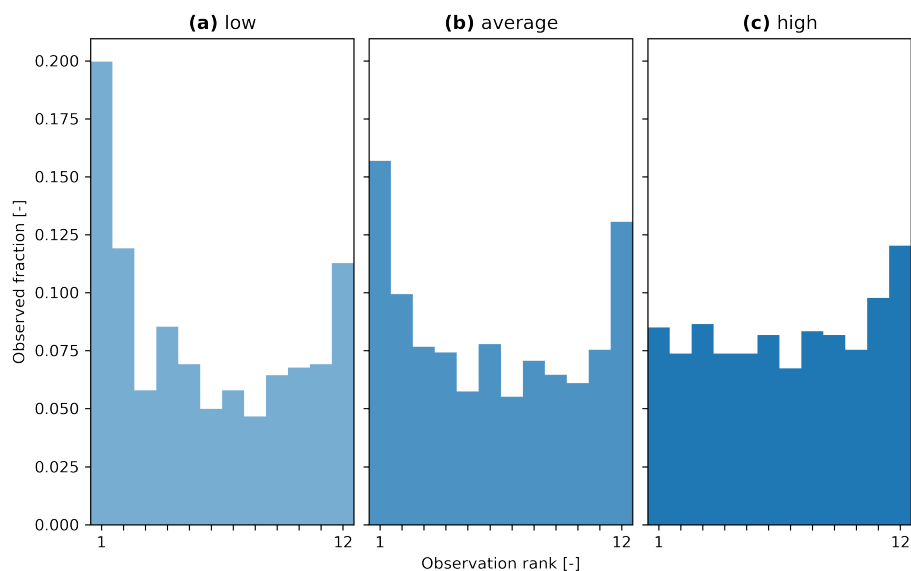
Figure 6. Rank histograms for the GloFAS reforecasts (v2.2) for the GloFAS station G0664 (Le Bevinco at Olmeta-di-Tuda) and for the 6-day lead time, stratified using the conditional masking functionality of `evalhyd`: **(a)** for low-flow conditions (i.e. for periods where the predicted median is below the 30th predicted percentile), **(b)** for average-flow conditions (i.e. for periods where the predicted median is above or equal to the 30th predicted percentile, and below or equal to the 70th predicted percentile), and **(c)** for high-flow conditions (i.e. for periods where the predicted median is above the 70th predicted percentile).

6.2.3 Multivariate analysis using the multi-dimensional paradigm

Gneiting et al. (2008) proposed the Energy Score (ES) as a multivariate generalisation of the CRPS. This metric makes it possible to aggregate the performance of several study sites in order, for example, to explore regional trends in forecasting performance. The inclusion of multi-variate metrics would not have been possible without the multi-dimensional paradigm
240 chosen for `evalhyd`.

Figure 7 provides a multi-site equivalent of Figure 3 by aggregating the GloFAS stations into six main hydrographic basins in France. The performance is measured against the climatology benchmark using the Energy Skill Score (ESS). Given the varying number of stations in each basin, it is preferred over the Energy Score (ES) to allow for a comparison across basins.

These results obtained with `evalhyd` can be used to explore regional trends. For example, the performance for the four
245 lead times considered suggest that the reforecasts for the Meuse, the Seine, and the Loire river basins are the most skilful, regardless of the lead time considered, while the reforecasts for the Garonne and the Corse river basins are the least skilful.
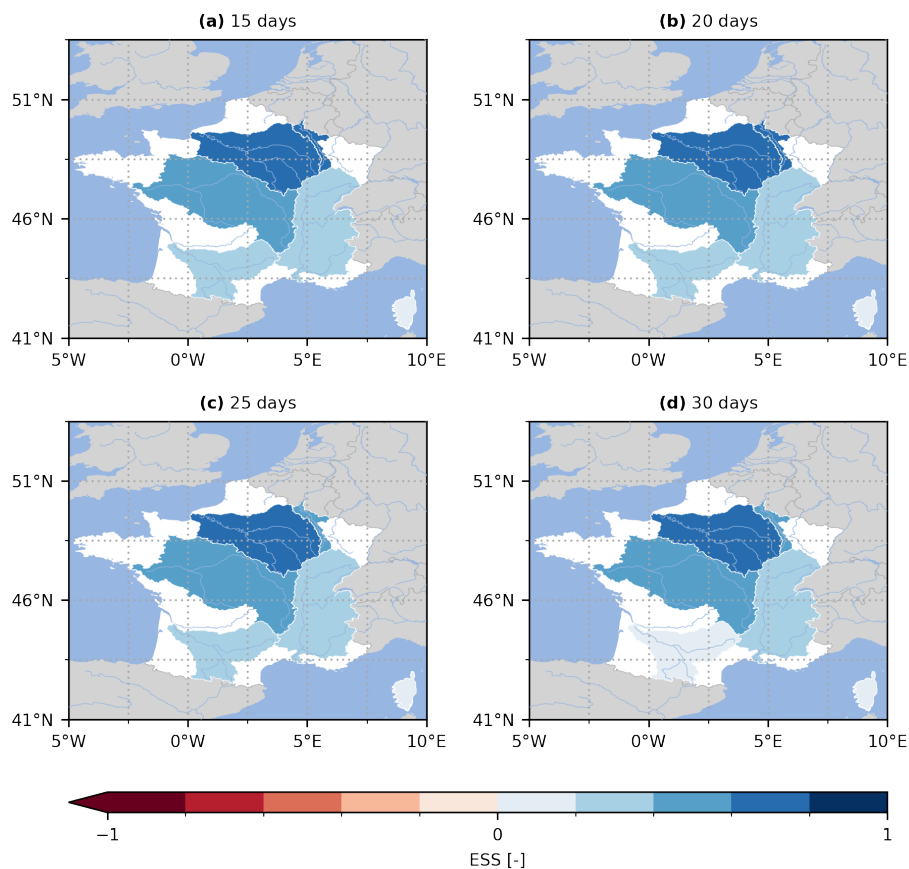
Figure 7. Energy Skill Score (ESS) for the GloFAS reforecasts (v2.2) against the persistence benchmark. The ESS is computed using the multi-dimensional design of `evalhyd` for six main French hydrographic basins (from North to South, Meuse, Seine, Loire, Rhône, Garonne, Corse), and for four lead times (i.e. **(a)** 15 d, **(b)** 20 d, **(c)** 25 d, and **(d)** 30 d).

7 Limitations of the tool

Some limitations in the current version of `evalhyd` exist. In a hydro-meteorological context, streamflow forecasts are often produced as deterministic forecasts or as ensemble forecasts to estimate the predictive probability distributions. However, they can also be issued as continuous predictive probability distributions. `evalhyd` only offers a solution for the first two situations, and the third situation is not currently supported.

As part of the design process, there was a focus on computational efficiency. This lead to the decision to rely on a compiled language and to resort to memoisation. Arguably, the former complicates the development effort compared with interpreted languages. In addition, the latter complicates the algorithms because the metric computations need to be decomposed, and the temporal reduction needs to be delayed for the masking functionality. Together, these design decisions hamper contributions

from the hydrological community, e.g. the inclusion of additional metrics. We believe that this is an unavoidable compromise for the sake of efficiency. Nevertheless, beyond efficiency considerations, relying on a compiled language also offers easier and cleaner options for exposing the metrics and the functionalities to several interpreted languages, instead of calling one interpreted language from another, for instance.

260   Furthermore, another design decision was to focus on the numerical aspect of streamflow evaluation, leaving aside its visualisation aspect (e.g. plotting rank histograms, reliability diagrams, and so on), unlike existing tools such as EVS, which offers a graphical user interface (Brown et al., 2010). Beyond a healthy separation of concerns, this is also partly influenced by the fact that the compiled core is intended to feature all of the functionalities presented here, and that visualisation capabilities are more accessible in interpreted languages. Nonetheless, the data necessary to plot such figures can be provided as numerical

265   values to limit the effort on the user's side. This is already the case in `evalhyd` with the rank histogram (using the metric `RANK_HIST`) and the reliability diagram (using the metric `REL_DIAG`).

8   Conclusions and perspectives

In this article, a new evaluation tool for streamflow predictions, named `evalhyd`, was presented. A first version of this tool gives hydrologists access to a large variety of evaluation metrics, commonly used to analyse streamflow predictions. It also

270   offers convenient and hydrologically-relevant functionalities such as sample stratification or metric uncertainty estimation. The tool is readily available to a diversity of users, as it is distributed as a C++ library, as a Python package, as an R package, and as a command line tool. These packages come with extensive online documentation, accessible at https://hydrogr.github.io/evalhyd (last access: 22 May 2023).

   Some of the developments envisaged for future versions of the tool include the addition of other evaluation metrics, especially

275   multivariate ones, the implementation of additional bindings for other open source languages (e.g. Julia, Octave), and the support of configuration files common across the software stack to further simplify collaboration and reproducibility.

   Through its polyglot character, this tool is aimed at the hydrological community as a whole, and we hope that it can foster collaborations amongst its users without a programming language barrier. For example, through the organisation of user workshops, new evaluation metrics and new evaluation strategies could emerge that could be implemented in the tool to directly

280   benefit our community at large.

Code availability. The package used for the illustrative example is `evalhyd-python`. It is available from HAL (https://hal.science/hal-04088473, last access: 11 May 2023) (Hallouin and Bourgin, 2023). The scripts used to produce the figures in the illustrative example are available upon request from the corresponding author.

Data availability. The observation data used in this study, i.e. the GloFAS-ERA5 v2.1 river discharge reanalysis data, can be downloaded

285   from Copernicus' Climate Data Store (https://doi.org/10.24381/cds.a4fdd6b9, last access: 10 May 2023) (Harrigan et al., 2021). The predic-

tion data used in this study, i.e. the GloFAS v2.2 river discharge reforecast data, can also be downloaded from Copernicus' Climate Data Store (https://doi.org/10.24381/cds.2d78664e, last access: 10 May 2023) (Zsoter et al., 2020).

Author contributions. CP, FB, MHR, and VA were responsible for the funding acquisition. All co-authors contributed to the conceptuali-sation. TH and FB developed the software. TH performed the data curation and the formal analysis. TH prepared the original draft of the
290 manuscript. All co-authors contributed to the review and editing of the manuscript.

Competing interests. The authors declare that none of them has any competing interests.

Acknowledgements. The authors acknowledge the financial support of the French Ministry of Environment (DGPR/SNRH/SCHAPI) for this work. The authors would like to thank Shaun Harrigan from ECMWF for the help with pre-processing the GloFAS reforecasts, Antoine Prou-vost and Johan Mabille from QuantStack for the help with using the `xtensor` software stack, and Guillaume Thirel, Laurent Strohmenger,
295 and Léonard Santos from INRAE for their feedback on this paper.

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(a) C++ interface

```cpp
#include <xtensor/xtensor.hpp>
#include <evalhyd/evalp.hpp>

xt::xtensor<double, 2> obs =
    {{4.7, 4.3, 5.5, 2.7, 4.1}};
xt::xtensor<double, 4> prd =
    {{{{5.3, 4.2, 5.7, 2.3, 3.1},
       {4.3, 4.2, 4.7, 4.3, 3.3},
       {5.3, 5.2, 5.7, 2.3, 3.9}}}};
xt::xtensor<double, 2> thr = {{4., 5.}};

auto res = (
    evalhyd::evalp(obs, prd, {"BS"}, thr, "high")
);
```

(b) Python interface

```python
import numpy
import evalhyd

obs = numpy.array([[4.7, 4.3, 5.5, 2.7, 4.1]])
prd = numpy.array([[[[5.3, 4.2, 5.7, 2.3, 3.1],
                     [4.3, 4.2, 4.7, 4.3, 3.3],
                     [5.3, 5.2, 5.7, 2.3, 3.9]]]])
thr = numpy.array([[4., 5.]])

res = (
    evalhyd.evalp(obs, prd, ["BS"], thr, "high")
)
```

(c) R interface

```r
obs ← rbind(c(4.7, 4.3, 5.5, 2.7, 4.1))
prd ← array(
    rbind(c(5.3, 4.2, 5.7, 2.3, 3.1),
          c(4.3, 4.2, 4.7, 4.3, 3.3),
          c(5.3, 5.2, 5.7, 2.3, 3.9)),
    dim=c(1, 1, 3, 5)
)
thr ← rbind(c(4., 5.))

res ← (
    evalhyd::evalp(obs, prd, c("BS"), thr, "high")
)
```

(d) Command line interface

./obs/site_a.csv

```
4.7,4.3,5.5,2.7,4.1
```

./prd/leadtime_1/site_a.csv

```
5.3,4.2,5.7,2.3,3.1
4.3,4.2,4.7,4.3,3.3
5.3,5.2,5.7,2.3,3.9
```

./thr/site_a.csv

```
4.,5.
```

```
./evalhyd evalp \
    "./obs/" "./prd/" "BS" \
    --thr "./thr/" --events "high"
```

Figure A1. Comparison of the interfaces for the probabilistic entry point `evalp` across the `evalhyd` software stack through a simple example evaluating ensemble predictions (`prd`, of shape $\{sites: 1, \ lead\ times: 1, \ ensemble\ members: 3, \ time: 5\}$) against observations (`obs`, of shape $\{sites: 1, \ time: 5\}$) using the Brier score (BS) based on streamflow thresholds (`thr`, of shape $\{sites: 1, \ thresholds: 2\}$) for flood events (i.e. high flows): **(a)** C++ interface fed with `xtensor` data structures, **(b)** Python interface fed with `numpy` data structures, **(c)** R interface fed with R data structures, and **(d)** command line interface fed with data in CSV files in structured directories.
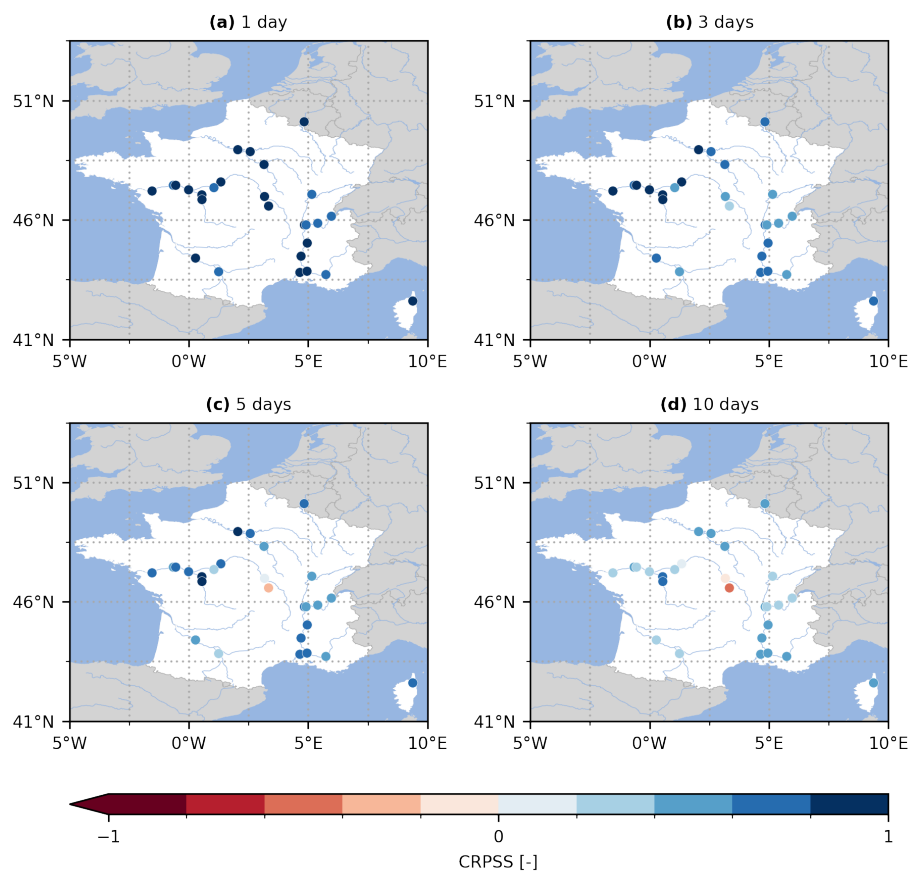
Figure A2. Continuous Rank Probability Skill Score (CRPSS) for the GloFAS reforecasts (v2.2) against the persistence benchmark. The CRPSS is computed with `evalhyd` for all 23 GloFAS stations located in France, and for four lead times (i.e. **(a)** 1 d, **(b)** 3 d, **(c)** 5 d, and **(d)** 10 d), mirroring a zoomed-in version of Figure 6 in Harrigan et al. (2023).
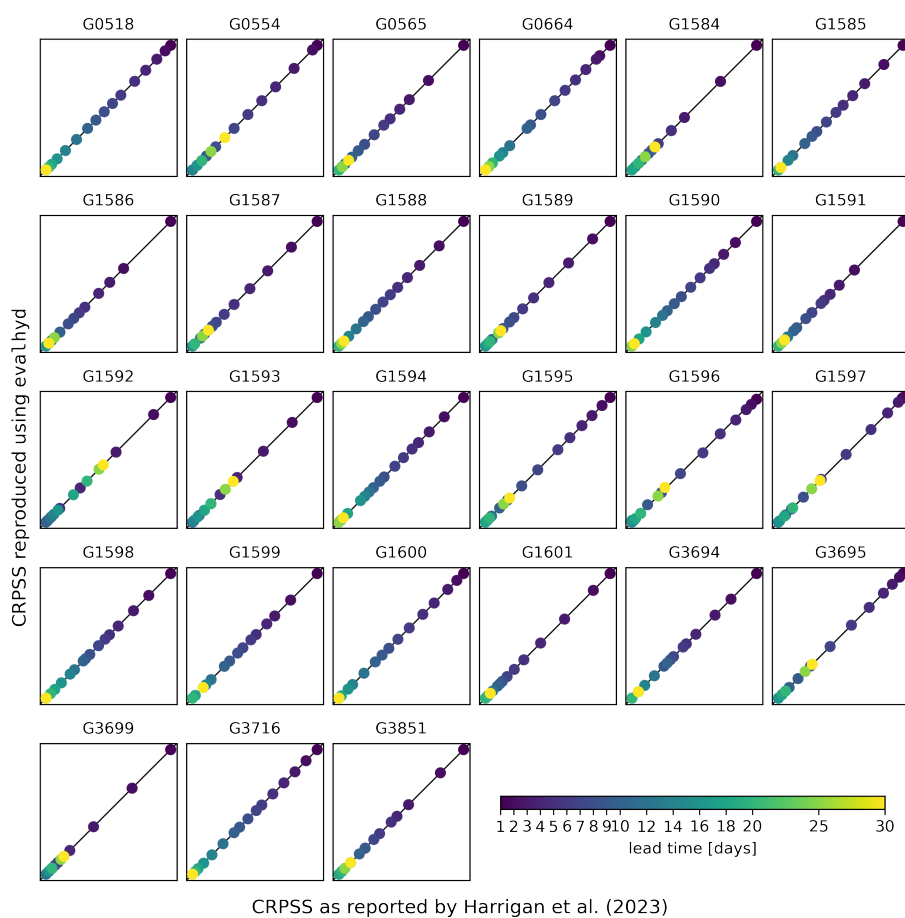
Figure A3. Comparison between the CRPSS reported in Harrigan et al. (2023) (x-axis) and the CRPSS computed using `evalhyd` (y-axis) against the persistence benchmark. Each panel represents one of the 23 GloFAS stations located in France, and in each panel, the diagonal represents the 1:1 line, and each data point represents one of the 17 lead times in the GloFAS reforecasts (v2.2).