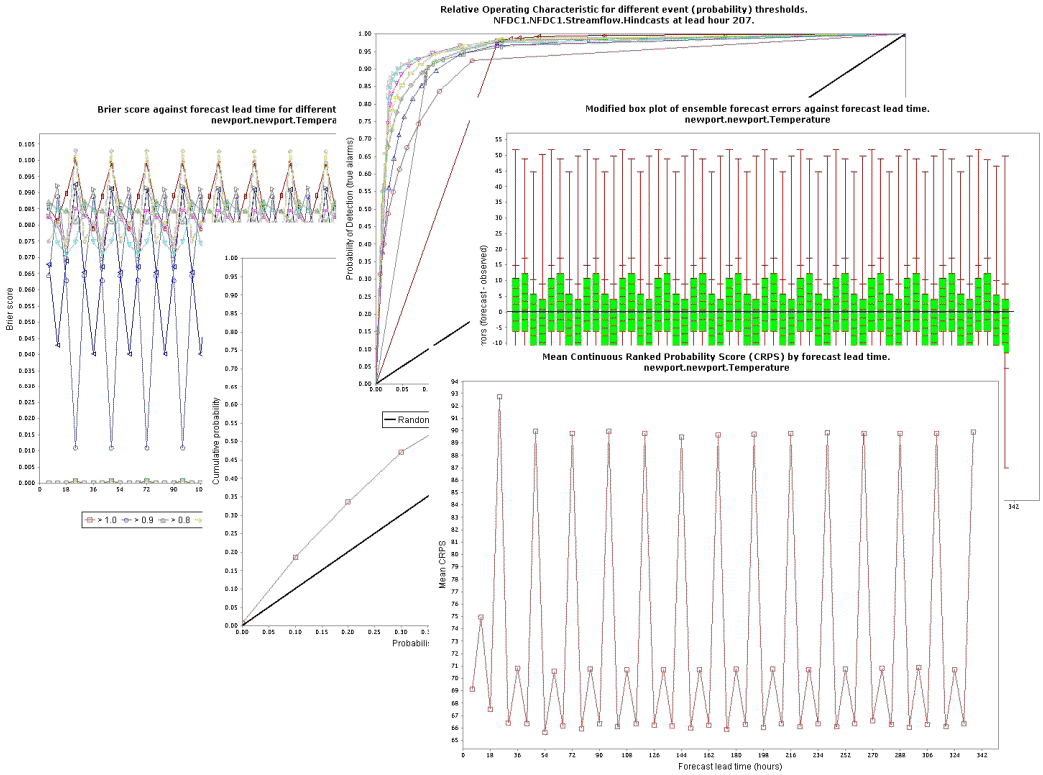
Ensemble Verification System (EVS)

Version 3.0



User's Manual

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Preface

The Ensemble Verification System (EVS) is an experimental prototype developed by the Hydrological Ensemble Prediction (HEP) group of the US National Weather Service's Office of Hydrologic Development (OHD). It is designed for verifying ensemble forecasts of hydrologic and hydrometeorological variables, such as temperature, precipitation, streamflow and river stage. EVS is intended to be flexible, modular and open to accommodate enhancements and additions, not only by its developers but also by its users. As such, we welcome your participation in the continuing development of the EVS toward a versatile and standardized tool for ensemble verification.

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1. INTRODUCTION

Ensemble forecasting is widely used in meteorology and, increasingly, in hydrology to quantify and propagate modeling uncertainty (Stensrud et al., 1999; Brown and Heuvelink, 2007; Park and Xu, 2009). Uncertainties in model predictions originate from the inputs, structure and parameters of a model, among other things (Brown and Heuvelink, 2005; Gupta et al., 2005). In practice, ensemble forecasts cannot account for all of these uncertainties, and some uncertainties are difficult to quantify accurately (NRC, 2006). Thus, ensemble forecasts are subject to errors. These errors are manifest as differences between the forecast probabilities and the corresponding observed probabilities over a large sample of forecasts and verifying observations (subject to sampling and observational uncertainty; Jolliffe and Stephenson, 2003; Hashino et al., 2006; Wilks, 2006). Unlike single-valued forecasts, ensemble forecasts cannot be verified with deterministic measures, such as the mean error or the root mean square error (RMSE). Rather, each ensemble member, and thus each error, is associated with only a partial probability of occurrence. Many of the techniques used to verify ensemble forecasts were pioneered in meteorology (Wilks, 2006). For example, the Brier Score (BS; Brier, 1950) was developed to verify probability forecasts of discrete weather events, such as tornados. The BS measures the average squared difference between the forecast probability of an event and its observed probability (which is 1 if the event occurred and 0 otherwise). With the growth of probabilistic forecasting, ensemble verification is increasingly used in other disciplines, such as hydrology (Bradley et al., 2004), oceanography (Park and Xu, 2009), ecology (Araújo and New, 2007) and volcanology (Bonadonna et al., 2005).

The basic attributes of ensemble forecast quality are broadly applicable, since they are concerned with probability distributions or measures on probability distributions. However, the specific approach to verification will depend on the forecast variables and their temporal and spatial scales, as well as the intended applications and users of the forecasts (e.g. research versus operational forecasting). In order to support ensemble verification for a wide range of applications in hydrology and beyond, flexible and user-friendly software is required. This is illustrated with an example from the National Weather Service (NWS). The River Forecast Centers (RFCs) of the NWS produce ensemble forecasts of temperature, precipitation and streamflow at a variety of lead times (Schaake et al., 2007; Demargne et al., 2007; Demargne et al., 2009, Wu et al., 2010). In one experimental operation, ensemble traces of

precipitation and temperature are generated from single-valued forecasts using an Ensemble Pre-Processor (EPP; Schaake et al., 2007, Wu et al., 2010). These traces are input into the Ensemble Streamflow Prediction (ESP) subsystem of the NWS River Forecast System (NWSRFS; NWS, 2005), from which ensemble traces of streamflow are output. There is a need to verify these forecasts and to identify the factors responsible for model error and skill in different situations. Verification is required at multiple temporal and spatial scales, ranging from minutes and kilometers (e.g. for flash flood guidance) to years and entire regions (e.g. for water resource planning and national verification). Furthermore, there is a need to support both operational forecasting within the RFCs and hydrologic research and development within the NWS. In order to meet these needs, work on ensemble verification is separated into two themes (see Demargne et al., 2009 for further details); 1) verification and bias-correction of real-time ensemble forecasts, which should *directly* improve decisions that rely on forecast probabilities ("real-time verification"; see Brown and Seo, 2010a); and 2) verification of archived operational forecasts and hindcasts, which should *indirectly* improve decision making via enhanced techniques for generating ensemble forecasts ("diagnostic verification").

The Ensemble Verification System (EVS) is a flexible, user-friendly, software tool that is designed to verify ensemble forecasts of continuous numeric variables, such as temperature, precipitation and streamflow (Brown et al., 2010b). The EVS can be applied to forecasts from any number of geographic locations (points or areas) and issued with any frequency and lead time. It can also aggregate forecasts in time, such as daily precipitation totals based on hourly forecasts, and can aggregate verification statistics across several discrete locations. However, it does not support the verification of uncertain spatial fields, such as gridded atmospheric pressure, or uncertain spatial objects, such as storm cells.

A verification study with the EVS is separated into three stages (Brown et al., 2010b), namely: 1) Verification; 2) Aggregation; and 3) Output. In the Verification stage, one or more Verification Units (VUs) are defined. Each VU comprises a set of forecasts and verifying observations for one environmental variable at one geographic location. The ensemble forecasts and observations are provided in an XML or ASCII format. The Verification stage also requires one or more verification metrics to be selected. The forecasts and observations are then paired by forecast lead time and the verification metrics computed. The results are written to the Output dialog, where the metrics can be plotted in an internal viewer or written to file in a variety of graphical

formats or in XML. The Aggregation stage allows for the averaging of verification statistics across multiple VUs.

The verification metrics in the EVS comprise both deterministic metrics, which verify the ensemble mean forecast, and probabilistic metrics, which verify the forecast probabilities. The probabilistic metrics comprise distribution-oriented metrics, which verify the joint probability distribution of the forecasts and observations (or its factors), and measure-oriented statistics, which summarize the forecast quality in a score. Their combination allow for specific attributes of forecast quality, such as reliability and discrimination, to be examined in varying levels of detail. This is important, as the EVS is intended for a wide range of applications and users, including both scientific researchers and operational forecasters in the National Weather Service (NWS). In addition to implementing standard measures of forecast quality, the EVS provides a platform for testing new verification metrics.

The EVS is currently being used by operational forecasters at several of the NWS RFCs. It is also used routinely to support scientific research and development within the NWS (e.g. Demargne et al., 2007; Wu et al., 2010; Brown et al., 2010b). In future, the EVS will be expanded to allow for the verification of both single-valued and probabilistic forecasts issued by the RFCs. Such verification is needed to identify the nature and sources of forecasting error, document forecast performance as a function of changing practices, and to support targeted improvements in forecast models and field data collection. These topics are being pursued by the NWS in collaboration with Environment Canada, the European Center for Medium Range Weather Forecasting (ECMWF), the Verification Testbed of the Hydrologic Ensemble Prediction Experiment (HEPEX), and with several universities. It is hoped that the introduction of verification standards, supported by a common verification tool, will allow for inter-comparisons of forecasting models and methods in different regions and over extended periods of time, contributing to the better use of uncertain weather and water forecasts, as outlined in NRC (2006).

The EVS is free to use, distribute, and modify, but is provided without technical support.

2. INSTALLATION INSTRUCTIONS AND START-UP

2.1 Contents of the full distribution

Currently, the full distribution of the EVS can be downloaded from:

http://www.nws.noaa.gov/oh/evs.html

The full distribution comprises (** are required to run the EVS):

Item	Description
EVS.jar**	The main executable and associated libraries
EVS_3.0_MANUAL.pdf	This manual
EVS_3.0_RELEASE_NOTES.pdf	The release notes, including changes and bug-fixes
EVS_3.0_TEST_DATA.zip	An example dataset for running the EVS
Bug_and_enhance_template.txt	A template for reporting bugs and suggested enhancements
EVS_3.0_SOURCE.zip	A directory containing the Java source-code for the EVS
/javadoc	A directory containing "Javadoc" source code documentation
/resources/rscripts/	A series of scripts for generating custom verification plots in R
EVS.bat	Example of a Windows batch file w/ command to use more RAM

2.2 Requirements

No formal installation of the EVS is required. However, in order to run the EVS you will need:

1. The Java™ Runtime Environment (JRE) version 6.0 (1.6) or higher. You can check your current version of Java by opening a command prompt and typing java –version. If the command is not recognized, you do not have a version of the JRE installed. If the installed version is older than 1.6, you should update the JRE. The JRE is free software and may be downloaded from the Sun website:

   http://java.sun.com/javase/downloads/index.jsp

2. The EVS executable, `EVS.jar`, and associated resources in `EVS_3.0.zip`;

3. Microsoft Windows 98/2000/NT/XP/Vista Operating System (OS) or Linux. In addition, you will need:

   - A practical minimum of 256MB of Random-Access Memory (RAM) and ~50MB of hard-disk space free (not including the associated datasets).
   - For many applications of the EVS, involving verification of large datasets more RAM and disk space will be required. A minimum of 1GB of RAM and 2GB of disk space is recommended.

2.3 Unpacking and running the EVS

Once you have obtained the EVS software, unpack the zipped archive to any directory of your computer (e.g. `C:/Program Files/EVS_3.0/`) using, for example, WinZip™ on Windows or the `unzip` command in Linux/Unix:

```
unzip EVS_3.0.zip
```

There are two possible ways of running the EVS, namely: 1) by executing the Graphical User Interface (GUI); and 2) by executing the EVS from the command line with a pre-defined project file.

Executing the EVS with the GUI:

Once you have unpacked the software, you may run the EVS by double-clicking on "EVS.jar" in Windows or by opening a command prompt, navigating to the root directory, and typing a java command that references the EVS jar file, such as:

```
java –jar EVS.jar.
```

Executing the EVS without the GUI:

In order to execute the EVS without the GUI, you must have one or more pre-defined EVS projects available. The EVS projects are specified in XML (see *Appendix A2*) and may be created with or without the GUI. For example, a base project may be created with the GUI and then altered manually or with a script outside of the GUI (e.g. changing the input and output data sources). One or more EVS projects may

be invoked from a command prompt by typing a java command with the paths to the project(s) listed afterwards, for example:

```
java –jar EVS.jar project_1.evs
```

where `project_1.evs` is an EVS project (the project need not be located in the root directory, but should be referenced by its full path otherwise). By default, the graphical and numerical results are written to the output directories specified in the projects.

2.4 Troubleshooting the installation

<u>List of typical problems and actions:</u>

– **"Nothing happens when executing EVS.jar"**

Ensure that the Java Runtime Environment (JRE) is installed on your machine and is in your PATH. The JRE should be version 6.0 (1.6) or higher. To check that a suitable version of the JRE is installed and in your PATH, open a command prompt and type:

```
java -version
```

If the command is not recognized, the JRE is not installed and in your PATH. If the version is below 6.0 (1.6), update the JRE (see above).

If this does not help, check the root directory of your installation for a log file named `evs.log`. Send the error message to the authors for advice on how to proceed (James.D.Brown@noaa.gov).

– **"An error message is thrown when executing EVS.jar"**

If an error message is thrown by the JRE (i.e. a java error appears in the message), the error may be caused by the local installation of Java.

2.5 Altering memory settings

By default, the amount of RAM memory available to the EVS is restricted by the Java Virtual Machine. In order to perform ensemble verification with large datasets, it may be necessary to change this default and increase the amount of memory available. This is achieved by executing the EVS on the command line, whether invoking the GUI or running a project without the GUI. To execute the GUI with altered memory settings, navigate to the installation directory of the EVS, and type:

```
java -Xmx1000m -jar EVS.jar
```

where `1000` is the maximum amount of memory (in megabytes) allocated to the EVS in this example. The maximum memory allocation should be significantly lower than the total amount of RAM available on your machine, as other programs, including the OS, will require memory to run. For example, on a 32-bit Windows OS with 4000 megabtyes of memory, around 1200 megabytes of memory will typically be available for the EVS. The EVS will only start with an increased memory setting if the Java Virtual Machine can actually allocate the desired amount of memory.

2.6 Source code and documentation

The Java source code for the EVS can be found in the `src.zip` archive in the root directory of your installation. The Application Programming Interface (API) is described in the html documentation, which accompanies the software (in the `/javadoc` directory).

2.7 Computer resource considerations

The time required to execute an EVS project, as well as the amount of RAM and hard-disk space required, will depend on a wide range of factors, including:

- The number of forecast locations;
- The number of paired forecasts and observations for each location, which itself depends on the forecast frequency, the forecast horizon or number of “lead times”, the number of ensemble members etc;

- The verification metrics required and the number of thresholds at which they are computed;
- Whether the forecasts and observations are already paired (quicker) or need to be paired and written to an associated paired file (slower);
- When performing conditional verification (i.e. with a subset of the overall pairs), whether those pairs should also be written to file (slower, and the default) or not written (quicker);
- When aggregating across several forecast locations, whether the verification metrics should be computed by averaging the values of the verification metrics at the individual locations (quicker, and the default) or by pooling the pairs and then computing the metrics for the pooled pairs (much slower); and
- The computer resources available.

All floating point numbers used within the EVS are double-precision (64-bit) numbers. Thus, a single observed or forecast (ensemble member) value will consume 8 bytes of RAM. The EVS requires more RAM than implied by the data, as some duplication of data is necessary, and the EVS itself has an overhead of ~15 megabytes. In the absence of sufficient memory to complete a calculation, an `OutOfMemoryError` will be thrown. To save disk space, the default maximum precision for writing floating point numbers (the forecasts and observations) to the EVS paired file is *five* decimal places, with fewer decimal places written as required. The maximum precision may be controlled via the `<paired_write_precision>` tag within the EVS project file (see *Appendix A2*, but note that calculations are always performed in double-precision).

3. OVERVIEW OF FUNCTIONALITY

3.1 Summary of functionality in the EVS Version 3.0

A complete list of the enhancements, changes in default behavior, and bug fixes between successive versions of the EVS can be found in the release notes that accompany this distribution (`EVS_3.0_RELEASE_NOTES.pdf`).

The functionality currently supported by the EVS includes:

- Pairing of observed and ensemble forecast values, which may be provided in a variety of file formats, to perform verification for a given forecast point or area. The observed and forecast values may be in different time systems or at different temporal scales, the times and scales being defined by the user;

- Computation of multiple verification metrics for arbitrary numeric forecast variables (e.g. precipitation, temperature, streamflow, river stage) at a single forecast point or area. The verification metrics are computed for each of the forecast lead times available. The available metrics include:
    - For verification of the ensemble mean forecast: correlation coefficient, mean error, root mean square error, mean absolute error;
    - For verification of the ensemble-derived forecast probabilities: Brier Score and its decomposition into reliability, resolution and uncertainty; Brier Skill Score; Continuous Ranked Probability Score and its decomposition into reliability, resolution and uncertainty; Continuous Ranked Probability Skill Score; Relative Operating Characteristic; Relative Operating Characteristic Score; and the reliability diagram. Several newly-developed metrics are also provided.

- Conditional verification with a reduced set of pairs. Two forms of conditional verification are supported by the EVS, namely 1) the identification of "pre-conditions" to sub-select pairs; and 2) verification with respect to thresholds (for metrics that verify discrete events, such as flooding, these thresholds are compulsory, as they define the events). The pre-conditions include: 1) a restricted set of dates (e.g. months, days, weeks, hours of the day, or some combination of these); 2) a restricted set of observed or forecast values (e.g. ensemble mean exceeding some threshold, maximum observed values within a 90 day window,

forecast probability of exceeding some threshold greater than 0.95, observed values of another variable not exceeding some threshold). When verifying the remaining pairs against particular thresholds, the thresholds may be defined with respect to the climatological probability distribution (based on a specified sample of observed data), such as the 95th percentile flow, or in real values, such as flood stage;

- Aggregation of verification results across a group of forecast locations, either by averaging the verification metrics from the individual locations (possibly weighed) or by pooling the pairs and computing the verification metrics for the pooled pairs. When aggregating in space, the individual locations must have common properties (e.g. common variables, units and scales); and

- Generation of graphical and numerical products, which may be written to file in various formats (e.g. png, jpeg, svg files) or plotted within EVS. In addition, several R scripts are provided in the `/resources/rscripts` directory for importing and plotting data in the R statistical environment (R Development Core Team, 2008).

3.2 Planned functionality

The additional functionalities planned for future versions of the EVS includes, in no particular order:

- The ability to compute measures of sampling uncertainty, such as confidence intervals, for the verification statistics;

- The addition of options for combining several metrics into one plot and for increasing the flexibility of plotting more generally;

- Functionality for verifying joint distributions; that is, the statistical dependencies in space and time, as well as the marginal distributions (e.g. to verify the reliability of the correlations associated with forecast values across several lead times);

- The ability to compute forecast skill for several reference forecasts at once, such as climatology, persistence or raw model output (e.g. before data assimilation or

manual adjustment). Currently, only one reference forecast may be defined for each combination of forecast point and skill score;

- The development of a batch language to support generation of verification products without running the GUI. For example, it should be possible to create a template point and apply this to a wider group of forecast points, changing only the observed and forecast data sources via a batch processor; and

- The ability to separate errors in hydrologic forecasts into phase (timing) and amplitude errors.

4. GETTING STARTED

As indicated above, there are two possible ways to use the EVS, namely: 1) with the Graphical User Interface (GUI); and 2) from the command line with a pre-defined project. The GUI provides a structured interface for defining an ensemble verification study and is considered in some detail below. Once familiar with the software, or when conducting verification at a large number of forecast points, execution via the command line with a pre-defined project may be preferred.

4.1 Structure of the GUI

A verification study with the EVS is separated into three stages:

1. **Verification:** identification of one or more Verification Units (VUs), pairing of forecasts and observations, and computation of verification metrics. Each VU comprises a set of forecasts and verifying observations for one environmental variable at one geographic location, together with a list of verification metrics to be computed;

2. **Aggregation:** identification of one or more Aggregation Units (AUs). Each aggregation unit comprises two or more VUs and is used to measure the average performance across these VUs. This is an optional stage;

3. **Output:** production of graphical and numerical outputs of the verification statistics for one or more previously defined VUs and AUs.

These stages are separated into “tabbed panes” in the GUI, which also contains a taskbar for administrative operations, such as creating, opening, and saving projects (*Fig. 1*). Initially, a verification study may involve linearly navigating through these tabbed panes until one or more VUs and AUs have been defined, the verification statistics generated, and the results written to file. However, once a VU has been defined and saved, the point of entry into the software may vary. For example, an existing project may be modified, a new AU identified from a set of pre-existing VUs, or new graphical outputs generated. Project files, which are written in an XML format (see *Section 4.4* for file data formats), can be created or edited manually and then executed from a command prompt (e.g. in DOS or Linux) rather than from the GUI, thereby allowing simple batch processing of VUs and AUs through shell scripting.

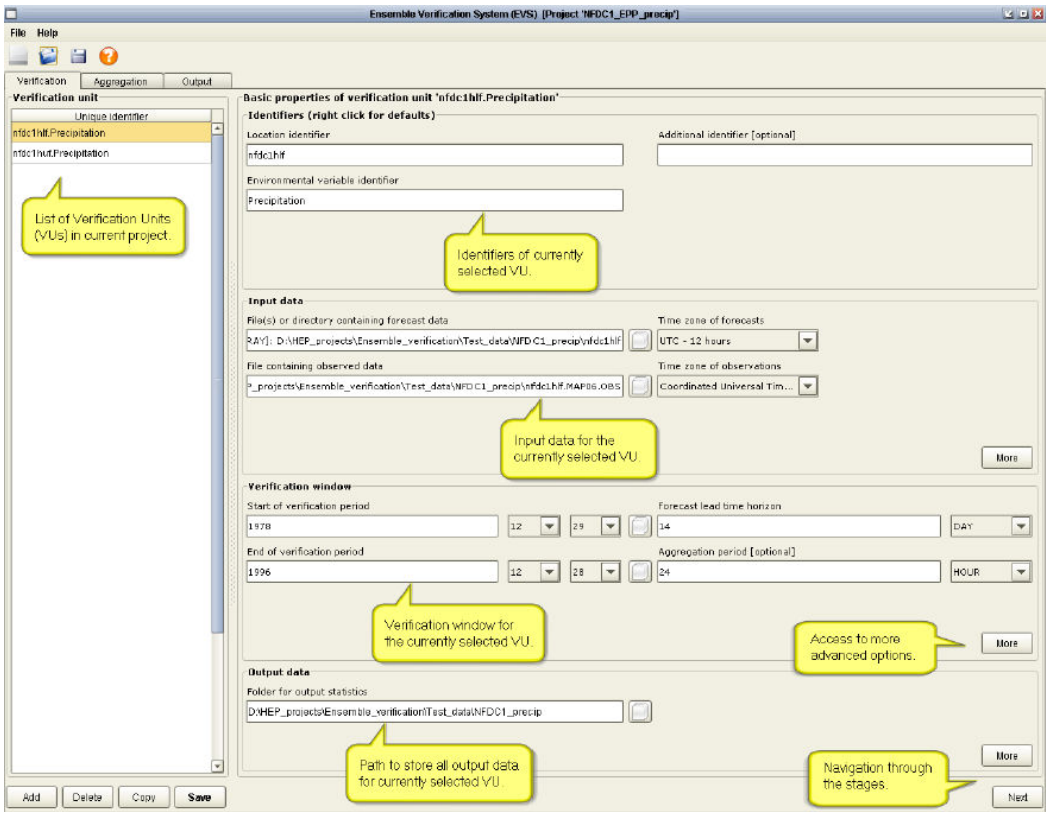
Each tabbed pane within the GUI comprises one or more panels, which correspond to intermediate steps within the current stage, such as the specification of data sources (one panel in Stage 1) and the selection of verification statistics to compute (another panel in Stage 1). At each stage, "basic options", such as the identification of observed and forecast data, are separated from more "advanced options", such as the selection of specific months over which to verify the forecasts. The latter are accessible via pop-up dialogs.

4.2 Stage 1: Verification

The first stage of a verification study in the EVS involves the identification of a VU, followed by the selection and computation of verification metrics (*Fig. 1*). The basic attributes of a VU are:

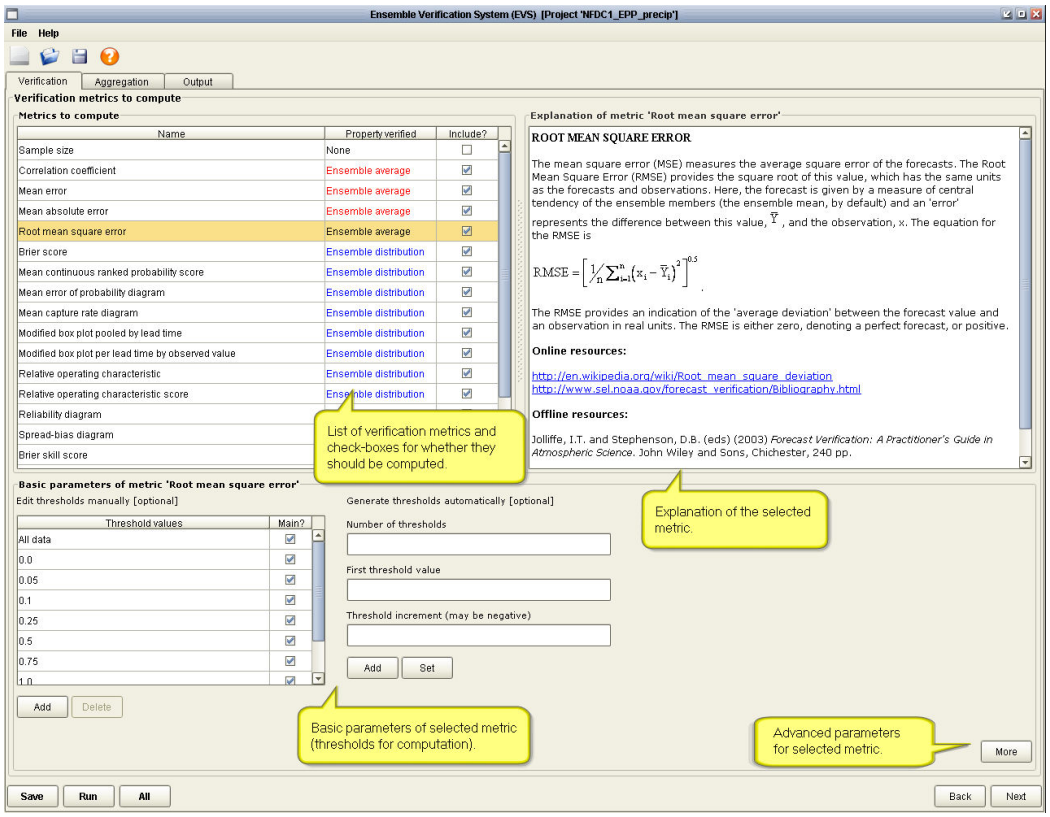
- a unique identifier, which is built from a 'location identifier', an 'environmental variable identifier' and, optionally, an 'additional identifier', which can be used to distinguish between forecasts from several modeling systems, among other things;
- the paths to the observed and forecast data (see *Section 4.4* on data formats);
- the time systems in which the forecasts and observations are stored (e.g. UTC);
- the temporal and spatial 'support' of the forecasts and observations (i.e. space-time scale) and their associated measurement units;
- the period for which verification statistics should be computed;
- the forecast lead times for which verification statistics should be computed; and
- the location where verification outputs should be written.

Fig. 1: The opening panel in the "Verification" stage



In addition to the basic attributes of a VU, several refinements are possible. For example, the verification period may be refined to include only winter months or specific days of the week. Similarly, the analysis may be restricted to a subset of the observed and forecast values, such as temperature forecasts whose ensemble mean is below freezing. Collectively, these "pre-conditions" lead to some of the pairs being ignored when computing the verification results. Another common requirement is to verify the forecasts at aggregated temporal scales. For example, six-hourly precipitation totals may be aggregated to daily totals before conducting verification. Temporal aggregation is achieved by applying an aggregation function (e.g. the sum) to each ensemble trace within the period of aggregation, and then collating the traces into an aggregated ensemble forecast. This ensures that any statistical dependencies between forecast lead times are preserved in the aggregated traces. Temporal disaggregation is not supported by the EVS.

Fig. 2: The second panel in the "Verification" stage



Once a VU has been defined, one or more verification metrics are selected from a tabular display for calculation (*Fig. 2*). The metrics are grouped into 'deterministic metrics', which evaluate the quality of the ensemble average forecast (e.g. mean or median), 'probabilistic metrics', which measure errors in the forecast probabilities, and 'skill scores', which measure the relative performance of two forecasting systems in terms of a given, probabilistic, metric. When selecting a particular metric (*Fig. 2*), a description of that metric, including links to further reading (online and offline), appear in the adjacent dialog (*Fig. 2*). Many of the probabilistic metrics are formulated for discrete events, such as the occurrence of precipitation or flooding, rather than the forecast probability distribution as a whole, which comprises an infinite number of possible events. Here, the forecast events are verified *after* applying any pre-conditions to remove pairs (see above). Thus, in designing a verification study, the identification of discrete events should be considered jointly with the specification of any pre-conditions to remove pairs. The metrics may be computed for several discrete events (conditions), for which event thresholds and associated logical conditions must be defined (e.g. <, >). The event thresholds may be given in real units, such as flow in m^3 s^{-1}, or in observed climatological probabilities. Real units

are useful when an event threshold is physically meaningful, such as exceedence of a flood threshold. Climatological probabilities are useful when the aim is to verify the full range of forecast conditions or when the verification results will be averaged across several locations with different observed climatologies. However, the climatological probabilities are computed from a limited sample of observations and are, therefore, subject to sampling uncertainty. For convenience, the option to verify against thresholds is also provided for the deterministic metrics and for those probabilistic metrics that do not require discrete events. While these metrics depend continuously on the data, they may be computed for subsets of the overall dataset (selected by thresholds) in order to evaluate the ensemble forecast quality in a conditional sense. The thresholds may be input manually or generated semi-automatically using a combination of: 1) the number of thresholds; 2) the first threshold; and 3) a constant increment between thresholds, which may be positive (increasing from the first threshold) or negative (decreasing). The thresholds may be identified as “main” thresholds or “auxiliary” thresholds. Currently, this distinction affects plotting only; the verification results for “main” thresholds are plotted within the EVS and the results for both “main” and “auxiliary” thresholds are written to file, allowing more complex plots to be generated outside of the EVS (e.g. plots of verification scores as a “continuous” function of threshold value).

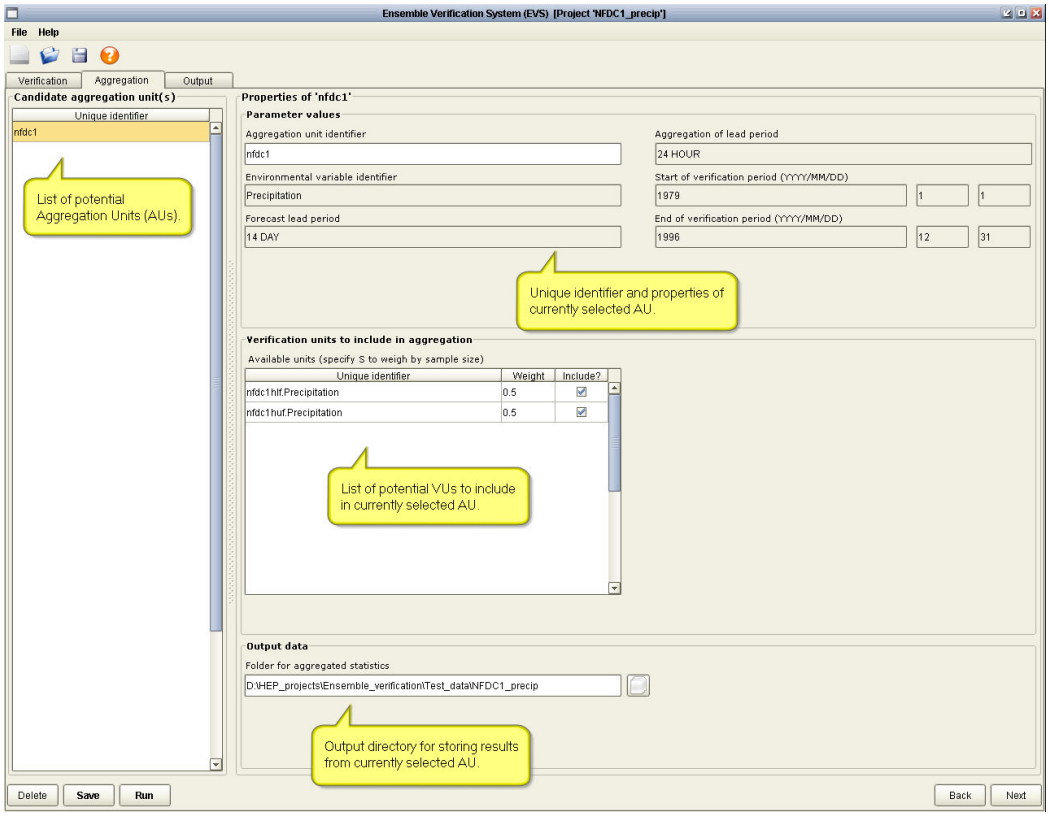
Depending on the chosen verification metric, other parameters may be modified (see *Section 5.3* also). For example, the reliability of the forecast probabilities may be computed by grouping the forecast probabilities into smaller bins (with finer resolution, but fewer samples per bin) or larger bins (coarser resolution, but more samples per bin).

On executing a VU for the first time, the forecasts and observations are paired together by forecast valid time and lead time. Verification is conducted separately for each forecast lead time, as forecasting errors depend strongly on lead time. The paired data are then written to file (*Section 4.4*), both to enable quality control and to improve the speed of execution when modifying and re-running VUs. Since all of the outputs from the EVS are based on the paired data, they should be checked to ensure that the forecasts and observations were read and interpreted correctly (e.g. that the time systems were correctly specified).

4.3 Stage 2: Aggregation

In order to evaluate the aggregate performance of a forecasting system across a range of forecast locations, two or more VUs may be aggregated. This is conducted in the Aggregation panel of the EVS, where an Aggregation Unit (AU) is defined (*Fig. 3*). The potential AUs are determined automatically by the GUI upon adding or editing VUs. A potential AU is added to the Aggregation panel for each set of VUs that are completely defined and comparable. Two VUs are comparable if they share forecast variables with common temporal support (after temporal aggregation), common measurement units, and verification statistics with common parameter values.

Fig. 3: The only panel in the "Aggregation" stage



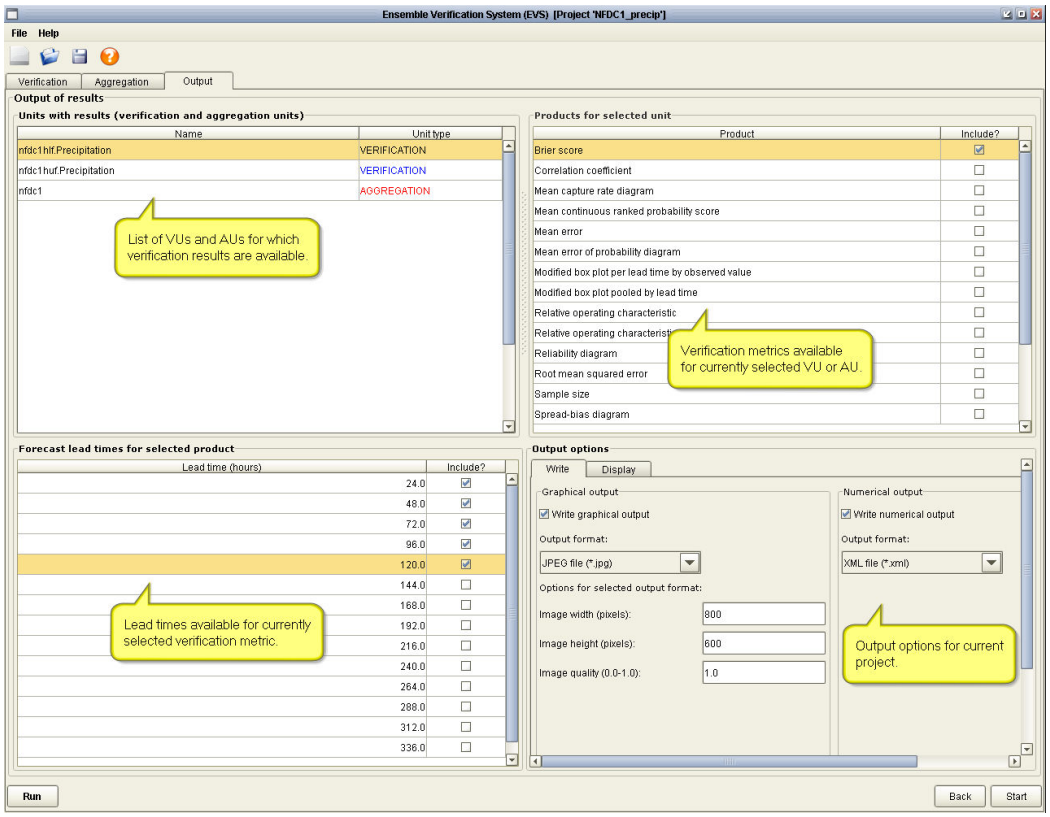
By default, the verification results for an AU comprise a weighed average of the verification results from the component VUs. An advanced option exists within the EVS project file (not the GUI) to pool the pairs from the individual locations rather than averaging the verification results (this is rarely feasible for large datasets). Once a potential AU has been determined in the GUI, four attributes are user-defined

(*Fig. 3*): 1) a unique identifier for the AU; 2) the component VUs, which are selected from a list of candidates; 3) the weight associated with each VU in the aggregation; and 4) the output directory for the aggregated statistics. On executing an AU, the verification metrics from the component VUs are collated and their weighed averages determined. For verification metrics that comprise binned statistics (e.g. the reliability diagram; see below), the sample means are computed for each bin in turn. For verification statistics that are conditional upon one or more event thresholds, the statistics are averaged across the same thresholds at each location. In order to have a meaningful spatial aggregation, the threshold must have a consistent physical interpretation in space and time, such as the exceedence of a local flood threshold rather than a fixed river stage. The weights assigned to each VU must be within [0,1] and the sum of all weights must be equal to 1. By default, equal weights are assigned to each VU, but unequal weights may be input manually or the character 'S' specified to weigh by the relative sample size at the first forecast lead time (maintaining constant weights across lead times).

4.4 Stage 3: Output

The Output panel of the EVS stores the verification results for each of the VUs and AUs in the current project. The results are organized by the unique identifier of the VU or AU, the name of the verification metric, and by forecast lead time (*Fig. 4*). The VUs and AUs available for plotting are shown in the top left table and are colored blue and red, respectively (*Fig. 4*). On selecting a particular VU or AU, a list of metrics with available results appears in the right-hand table. On selecting a particular metric, the bottom left table displays a list of lead times (in hours) for which the metric results are available. The basic options for plotting and writing metrics are shown in the bottom-right dialog. Options are provided on the tables for selecting particular combinations of metric and lead time. The options are provided in menus, which are displayed by right-clicking on one of the tables. For example, by right-clicking on the table of metrics (top right in *Fig. 4*), an option appears for selecting all metrics and lead times. The metrics can be plotted in an internal graphing tool, which includes basic functionality for animating metrics across a sequence of lead times, or written to file in a variety of graphical formats (*Section 4.4*). Also, the underlying statistics can be written to file in an XML format and viewed in a text editor or web browser.

Fig. 4: The only panel in the "Output" stage



4.5 File data formats supported by the EVS

The file data formats supported by the EVS are summarized in *Table 1*. Further details can be found in *Appendix A2*. They are separated into: 1) input data, comprising the ensemble forecasts and verifying observations for each VU; 2) paired data, comprising the paired forecasts and observations for a specific VU; 3) output data, comprising the verification statistics for a particular VU or AU in a graphical or numerical format; and 4) a project file, containing the parameter values of one or more VUs and AUs.

As indicated above, a VU is defined for each forecast variable and location. The input data for a single VU comprises the ensemble forecasts, which may be provided in one or multiple files, and the single-valued observations, which are provided in a single file.

Table 1: main file formats supported by the EVS

Data store	Format	Extension	Description
Project data	XML	evs	Stores VUs and AUs and their parameters
Paired data	XML	xml	Stores paired forecasts and observations
Input data	ASCII	fcst	Stores ensemble forecasts
	ASCII	obsvd	Stores observed data
	XML	xml	Stores observed data (XML format)
	XML	xml	Stores forecast data (XML format)
Graphical output	JPEG	jpg	Plots of verification metrics in raster format
	PNG	png	Plots of verification metrics in raster format
	SVG	svg	Plots of verification metrics in vector format
Numerical output	XML	xml	Numerical output of verification metrics

The forecasts and observations can be provided in XML or ASCII formats. Various internal formats are used by the NWS for storing and exchanging ensemble forecasts and observations. These can also be read by the EVS, but are not described here. The ASCII format for storing the ensemble forecasts comprises one forecast per line (*Fig. 5a* shows sixteen forecasts). Each forecast requires the forecast valid date and time, the forecast lead time, and the forecast ensemble members *in trace-order* (this is important to preserve any temporal statistical dependencies when aggregating forecasts in time). Adjacent entries are separated by a whitespace or comma. The ASCII format for storing the single-valued observations also comprises one instance per line, and includes the date and time of the observation, together with the observed value (*Fig. 5b*). Again, adjacent entries can be separated by a whitespace or comma. The XML format for storing the observed and forecast data (as opposed to paired data: see below) follows the Published-Interface (PI-) XML format used in the Flood Early Warning System (FEWS). The XML format is described in detail here:

http://public.deltares.nl/display/FEWSDOC/The+Delft-Fews+Published+interface+(PI)

Several NWS formats are also supported by the EVS, including the “OHD datacard format” and the “CS binary” format. The OHD datacard format is described here:

http://www.nws.noaa.gov/ohd/hrl/nwsrfs/users_manual/part7/_pdf/72datacard.pdf

Fig. 5: The ASCII format for ensemble forecasts (upper) and observations (lower)

```
1/1/2000   12   12.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
1/2/2000   0   24.0   0.0   0.0040   0.028   0.02   0.016   0.0080   0.024   0.028   0.024   0.031   0.024
1/2/[illegible]   0.0   0.047   0.024   0.035   0.031   0.031   0.016   0.028   0.043   0.063
1/[illegible].0   0.0080   0.0040   0.0040   0.0080   0.0080   0.0   0.012   0.0040   0.02
1/[illegible]0.0   0.0   0.0040   0.0080   0.0040   0.0   0.0   0.0   0.0   0.0
1/[illegible]0.0040   0.012   0.0   0.051   0.[illegible]0   0.059   0.012
1/[illegible]0.0   0.0080   0.0   0.02   0.028[illegible]6   0.0
1/5/2000   0   96.0   0.05   0.0   0.0040   0.0   0.24   0.0[illegible]9   0.0
1/5/2000   12   108.0   0.0   0.0   0.0080   0.0   0.055   0.0[illegible]   0.094   0.0
1/6/2000   0   120.0   0.0[illegible]   0.031   0.0080   0.0040   0.012   0.063   0.02   0.02
1/6/2000   12   132.0   0.[illegible]   0.028   0.0080   0.028   0.031   0.031   0.0   0.02
1/7/2000   0   144.0[illegible]02   0.024   0.039   0.02   0.043   0.0040   0.024
1/7/2000   12   156.0   0.[illegible]24   0.035   0.055   0.012   0.0040   0.028   0.028
1/8/2000   0   168.0   0.0   0.02   0.012   0.016   0.016   0.043   0.051   0.0   0.059   0.031   0.059
1/8/2000   12   180.0   0.0   0.0   0.0   0.02   0.0080   0.012   0.012   0.0   0.063   0.028   0.063
1/9/2000   0   192.0   0.0   0.0   0.0   0.016   0.016   0.0   0.0080   0.0   0.039   0.0   0.016
```

Forecast valid date and time (UTC).

Ensemble member values.

Forecast lead time (hours)

```
1/1/2000   12   0.0
1/2/2000   0   0.0
1/[illegible]
1/[illegible]
1/[illegible]
1/[illegible]
1/5/2000   0   0.05
1/5/2000   12   0.0
1/6/2000   0   0.0
1/6/2000   12   0.0
1/7/2000   0   0.0
1/7/2000   12   0.0
1/8/2000   0   0.0
1/8/2000   12   0.0
1/9/2000   0   0.0
```

Forecast valid date and time (UTC).

Observed values.

Once a VU has been executed in the EVS, the forecasts and observations are written to a paired file in an XML format. The paired file stores each ensemble forecast together with its verifying observation. Each pair contains the date and time in Coordinated Universal Time (UTC), the forecast lead time, the observed value and the ensemble members, in trace-order, separated by commas (*Fig. 6*). The pairs are organized by forecast valid time, from the earliest forecast to the latest, and by forecast lead time, from the shortest lead time to the longest.

Fig. 6: The paired file format

```
- <!--
    Paired data file for the Ensemble Verification System (EVS).  Each pair comprises one or more
    forecasts and one observation, and is stored under a 'pr' tag.  Each pair has a readable date in UTC, a
    lead time in hours ('ld_h'), an observation ('ob'), one or more forecast values ('fc'), and an internal
    time in hours (in_h) used by EVS to read the pairs (in preference to the UTC date).  The internal time
    is incremented in hours from the forecast start time (represented in internal hours) to the end of the
    forecast lead period.  When multiple forecasts are present, each forecast represents an ensemble member,
    and each ensemble member is listed in trace-order, from the first trace to the last.
  -->
- <pairs>
    <pair_count>448</pair_count>
  - <pr>
    - <dt>
        <y>1980</y>
        <m>1</m>
        <d>1</d>
        <h>18.0</h>
      </dt>
      <ld_h>6.0</ld_h>
      <ob>0.0</ob>
      <fc>0.768, 5.776, 4.01, 6.331, -9.657, -9.458, 1.036, -0.9, 4.846, 1.075, -2.918, 4.4, 0.438, -7.681, 1.788, -4.665,
        0.538, 0.784, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903,
        1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903, 1.903</fc>
      <in_h></in_h>
    </
  - <pr>
    - <dt>
        <y>1980</y>
        <m>1</m>
        <d>2</d>
        <h>0.0</h>
      </dt>
      <ld_h>12.0</ld_h>
      <ob>0.0</ob>
      <fc>5.944, 8.705, 8.689, 11.596, -4.421, -5.36, 4.965, 2.633, 8.159, 4.382, 0.213, 8.413, 4.487, -4.377, 7.068,
        0.193, -1.029, 4.304, 5.552, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83,
        4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83, 4.83</fc>
      <in_h>87672.0</in_h>
    </pr>
```

Total pairs in file.

Explanation of file contents.

First pair.

Date and time (UTC).

Lead time (hours).

Observed value.

Ensemble members.

Second pair.

The output files from the EVS comprise the verification statistics for a specific VU or AU in one of several graphical formats, and corresponding numerical results in an XML format (see Appendix A2). The supported graphical formats include two raster formats: the Portable Network Graphic (PNG) format (a lossless format) and the Joint Photographic Experts Group (JPEG) format (a lossy format). The Scalable Vector Graphics (SVG) format is also supported by the EVS, as this allows for verification plots to be rescaled without loss of quality. Scripts are also available to import and plot the numerical results in R (R Development Core Team, 2008), where many more output formats and plotting options are available. Example scripts are provided in the `evs\resources\rscripts` directory of the installation.

Finally, the parameters of each VU and AU are saved in a project file in an XML format. The project files are ordinarily written by the EVS, but may be produced or edited outside of the EVS (e.g. with a script, to enable batch processing). The XML is organized by VU and AU, with entries for each input required in the GUI (*Fig. 7*).

Fig. 7: The project file format


```
<?xml version="1.0" standalone="yes" ?>
- <verification>
  - <verification_unit>
    - <identifiers>
        <location_id>NFDC1HUF</location_id>
        <environmental_variable_id>MAT</environmental_variable_id>
        <additional_id />
      </identifiers>
    - <input_data>
      - <forecast_data_location>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001011200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001021200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001031200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001041200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001051200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001061200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001071200_NFDC1_ESPForcing_Clim.XML</file>
          <file>S:\OHD-1\HEP\Ens_VV\CHPS-
            XEFS_Tests\Exported_ensemble_files\Exported_forcing\198001081200_NFDC1_ESPForcing_Clim.XML</file>
        </forecast_data_location>

        <observed_data_location>F:\NOAA_work\NOAA_D\HEP_projects\Ensemble_verification\Test_data\NFDC1_EPP_
        \nfdc1hlf.MAP06.OBS.ZT.101960-092003</observed_data_location>
        <forecast_time_system>Coordinated Universal Time (UTC)</forecast_time_system>
        <observed_time_system>Coordinated Universal Time (UTC)</observed_time_system>
      - <forecast_support>
          <statistic>INSTANTANEOUS</statistic>
          <existing_attribute_units>DEGREE (FAHRENHEIT)</existing_attribute_units>
          <notes />
        </forecast_support>
      - <observed_support>
          <statistic>INSTANTANEOUS</statistic>
          <existing_attribute_units>DEGREE (CELSIUS)</existing_attribute_units>
          <target_attribute_units>DEGREE (FAHRENHEIT)</target_attribute_units>
          <notes />
        </observed_support>
        <use_all_observations_for_climatology>false</use_all_observations_for_climatology>
      </input_data>
    - <verification_window>
```


First VU.

Some of the parameters of the first VU.

5. A DETAILED GUIDE TO THE OPTIONS IN EACH WINDOW OF THE GUI

This section provides a guide to the options available in each window of the GUI.

5.1 Administrative functions in the main window

The opening window of the GUI, together with the Taskbar, is shown in *Fig 1*. The opening window displays the verification units loaded into the software. The Taskbar is visible throughout the operation of the GUI and is used for administrative tasks, such as creating, opening, closing and saving a project. The Taskbar options are explained in *table 2*. Shortcuts are provided on the Taskbar for some common operations, but all operations are otherwise accessible through the dropdown lists.

Table 2: Menu items

Menu	Function	Use
File	New project	Creates a new project
	Open project	Opens a project file (*.evs)
	Close project	Closes a project
	Save project	Updates or creates a project file (*.evs)
	Save project as	Updates or creates a named project file (*.evs)
	Exit	Exits EVS
Help	Messages on/off	Displays/hides tool tips
	Console	Shows the details of errors thrown
	About	Credits

All work within the EVS can be saved to a project file with the .evs extension. A new project is created with the **New project** option under the **File** dialog. An existing project is saved using the **Save** or **Save As**… options. These options are also available on the Taskbar. Project files are stored in an XML format and may be opened in a web browser or text editor. An example is given in *Fig. 7*.

5.2 The first window in the Verification stage

The first stage of an ensemble verification study requires one or more Verification Units (VUs) to be defined (*Fig. 1*). In this context, a VU comprises a time-series of a single variable at one location. The spatial scale or support of the variable is not identified in the EVS, but is assumed to be consistent for the observed and forecast

data. For example, observations from a rain gauge should not, in general, be compared with precipitation forecasts averaged over a large grid cell. The actual spatial support may be arbitrarily small or large, but should be comparable for the forecasts and observations. A VU is uniquely identified by a location ID and a variable ID. These IDs must be entered in the first window, and are then displayed in the table and identifiers panel. A new VU may be added to the current project by clicking "**Add**" in the bottom left corner of the window (*Fig 1.*). This adds a VU with some default values for the identifiers. On entering multiple VUs, the basic properties of the *selected* VU (i.e. the item highlighted in the table) will be shown in the panels on the right. Existing units may be deleted or copied by selecting an existing unit in the table and clicking "**delete**" or "**copy**", respectively. On copying a unit, all of the properties of the unit are copied *except* the identifiers, which must be unique. This provides a convenient way to specify multiple units with the same verification properties (multiple segments to be verified for the same variable with the same temporal parameters).

The VU is defined by four different dialogs: Identifiers, Input data, Verification window, and Output data.

Identifiers dialog:

- Location ID: an identifier denoting the location of the forecast point;
- Environmental variable identifier: an identifier denoting the environmental variable to be verified;
- Additional identifier: arbitrary additional ID. For example, this may be used to distinguish between forecasts from different models for a common variable and location.

The names of the location and environmental variable are unrestricted (aside from a blank name or a name containing the illegal character '.' used to separate the identifiers). Several default names for environmental variables are provided by right-clicking on the variable identifier box (*Fig. 1*).

Input data dialog:

- Files or folder containing forecast data: path to the folder containing the ensemble forecast files (and no other file types), or a file array chosen

through the associated file dialog. ***If possible, when the ensemble forecasts are distributed across multiple files, only those files that contain relevant forecasts should be selected, as all files must be processed before being checked against verification conditions*** (e.g. if the files are separated by date, and a limited set of dates is subsequently defined);

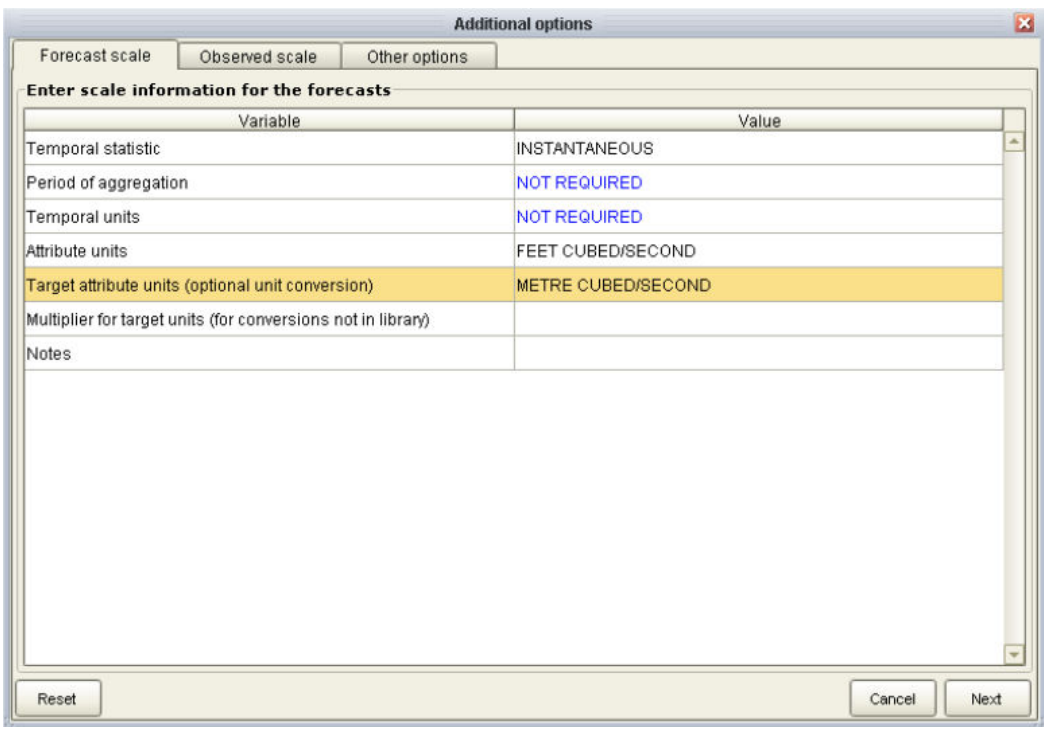
- File containing observed data: path to concurrent observations of the forecast variable, which are used to verify the forecasts;
- Time systems: the time systems for the observations and forecasts. The time systems of the forecasts and observations are required for pairing these data (on the basis of time);

The paths to the observed and forecast data may be entered manually or by clicking on the adjacent button, which opens a file dialog.

When conducting verification for the first time, the observations and forecasts are paired. These pairs are used to compute the differences between the observed and forecast values (i.e. the forecast 'errors') at concurrent times, i.e. the valid times. For subsequent work with the same unit, no pairing is necessary unless some of the input parameters that affect the pairs have changed (at which point, the pairs are deleted). The paired data are stored in an XML format, which may be opened in a web browser or text editor. Each forecast-observation pair is stored with a date in UTC (year, month, day, and hour), the forecast lead time in hours, the observed value, and the corresponding forecast ensemble members. A detailed explanation is also provided in the paired file header. An example of a paired file is given in *Fig. 6*. One paired file is always written by the EVS, namely a file containing the "raw pairs" (with extension `_pairs_raw.xml`), and one file is written optionally, namely a file containing the "conditional pairs" (with extension `_pairs_cond.xml`). The raw pairs comprise the paired forecasts and observations **after** any required change in support but **before** any changes in measurement units, temporal aggregation (of the pairs), or any other conditioning. The values should match those contained in the original observed and forecast files (after any change of support). The conditional pairs comprise the paired forecasts and observations from which the verification metrics will be computed. By default, the conditional pairs are also written to file, but this may be time-consuming (especially if few or no conditions were defined), and can be switched off (see the Output data options below).

In the EVS GUI, basic verification options are separated from more 'advanced' options, which are accessible through pop-up windows. For example, the "**More**" button within the Input data dialog opens a window for entering information about the scales at which the forecasts and observations are defined, among other things (*Fig. 8*). Scale information includes the units of measurement (e.g. cubic feet/second) and temporal support at which the forecasts and observations are recorded (e.g. instantaneous vs. time-averaged). The forecasts and observations must be defined at equivalent temporal (and spatial) scales for a meaningful comparison between them. In the absence of user-defined information on the temporal scales, a warning message will be presented on conducting verification. This warning message is avoided if the temporal scale information is entered explicitly.

Fig. 8: The Additional options dialog, accessed from the input data dialog



In most cases, changes of scale should be conducted before using the EVS, but some options are provided internally. In particular, the measurement or "attribute" units of the forecasts or observations may be changed with some restrictions:

- Changes in attribute units are achieved by either: 1) specifying a named change from the current "`Attribute units`" to the "`Target attribute units`"

(*Fig. 8*); or 2) specifying a factor by which to multiply the current "`Attribute units`", in order to arrive at the "`Target attribute units`". Named changes of units (without specifying a multiplier) are currently limited to:

- `DEGREES (CELCIUS) <--> DEGREES (FAHRENHEIT);`
- `MILLIMETRE <--> INCH`
- `METRE <--> FEET`
- `METRE CUBED/SECOND <--> FEET CUBED/SECOND`

In addition to changes in attribute units, there is some flexibility for verifying forecasts and observations with different temporal support *when the verification is desired at an aggregated level of support* (see the discussion below on temporal aggregation, and *Fig. 9c*). This is only possible under the following conditions:

1. The temporal support is `INSTANTANEOUS`, and the desired temporal aggregation involves a supported function (e.g. mean) over a period that is exactly divisible by the frequency of the data;
2. The temporal support is the `TOTAL` over a specified period and the desired level of aggregation is a total over a longer period that is an exact multiple of the shorter period and the frequency of the data (e.g. verifying at a daily timestep when the observations are six-hourly totals, available every six hours).

The "Other options" tab of the "Additional options" dialog (*Fig. 8*) contains further options for interpreting the input data, namely: 1) the identifier for 'null' or missing values (i.e. values ignored throughout a verification study including metric calculation; by default, the null value is -999.000); and 2) the option `Use all observations for climatology (not just paired observations)`. This controls how the "observed climatology" is determined from the observed data, specifically for deriving real-valued thresholds from the climatological probability distribution (an option described later; see *Fig. 10*). By default, the climatological distribution is determined from the paired observations (i.e. the conditional pairs). Optionally, it may be determined from the full period of observations (again, after applying any changes in attribute units, temporal aggregation and pre-conditions *except* for a limited verification period; see below).

Verification window:

- Start of verification period: the start date for verification purposes. This may occur before or after the period for which data are available. Missing periods will be ignored. The verification period is defined in UTC hours from 00 UTC on the input start date. The start date may be entered manually or via a calendar utility accessed through the adjacent button;
- End of verification period: as above, but defines the last date to consider. The end date is also defined as 00 UTC on the specified date (i.e. add one day if the input date should be included in the verification window);
- Forecast lead time horizon: at each forecast time, a prediction is made for a period into the future. This duration is referred to as the lead time horizon or lead period. For example, if the forecasts are issued every 6 hours and extend 14 days into the future, the lead time horizon is 14 days. The lead time horizon may comprise several different lead times (14*6=84 in this example) and may be shorter than the period covered by the input data;
- Aggregation period: when evaluating long-term ensemble forecasts (e.g. with a one-year forecast horizon), verification results may be confused by short-term variability, which is not relevant for the types of decisions that inform long-term forecasting, such as water supply forecasting. Aggregation of the forecasts and observations allows short-term variability to be removed by averaging over the period that *does* matter for decision making purposes. For example, daily forecasts may be aggregated into ninety-day averages (assuming that the forecast time horizon is at least ninety days). When the temporal support of the forecasts and observations is different, verification may still be possible at an aggregated temporal support (see above).

The verification window may be refined using various "pre-conditions" on the dates considered, as well as the size of the observed and forecast values included in the verification study. These options are accessed via the "**More**" button in the Verification window. For example, verification may be restricted to 'winter months' within the overall verification period, or may be limited to forecasts whose ensemble mean is below a given threshold (e.g. zero degrees for temperature forecasts). When conditioning on variable value, conditions may be built for the current unit (selected in the main verification window) using the values of another unit (e.g. select streamflow when precipitation is non-zero), providing the variables have the same prediction dates and intervals. Such conditioning may be relatively simple or

arbitrarily complex depending on how many conditions are imposed simultaneously. However, there is a trade-off between the specificity of a verification study, which is increased by conditioning, and the number of samples available to compute the verification statistics, which is reduced by conditioning (i.e. sampling uncertainty is increased). The dialog for conditioning on date and variable value is shown in *Fig. 9a* and *9b*, respectively. The conditions on dates or variable values entered in the verification window apply to all verification metrics computed for that VU. Alongside these pre-conditions, the individual metrics may be computed with respect to one or more threshold values, such as flows exceeding flood stage (see below). When designing a verification study, the pre-conditions used to sub-select pairs should be compatible with any discrete events that might be verified later. For example, it would *not* make sense to assess the quality of Probability of Precipitation (PoP) forecasts when all (non-) precipitation events had been removed via pre-conditions on the pairs. In contrast, it may make sense to eliminate "blown" forecasts (identified by conditions on variable values) before computing *any* verification metrics, including those for particular events.

Fig. 9a: Dialog for refining verification window: conditioning with dates

Categories for refining dates considered

Consider only specific months

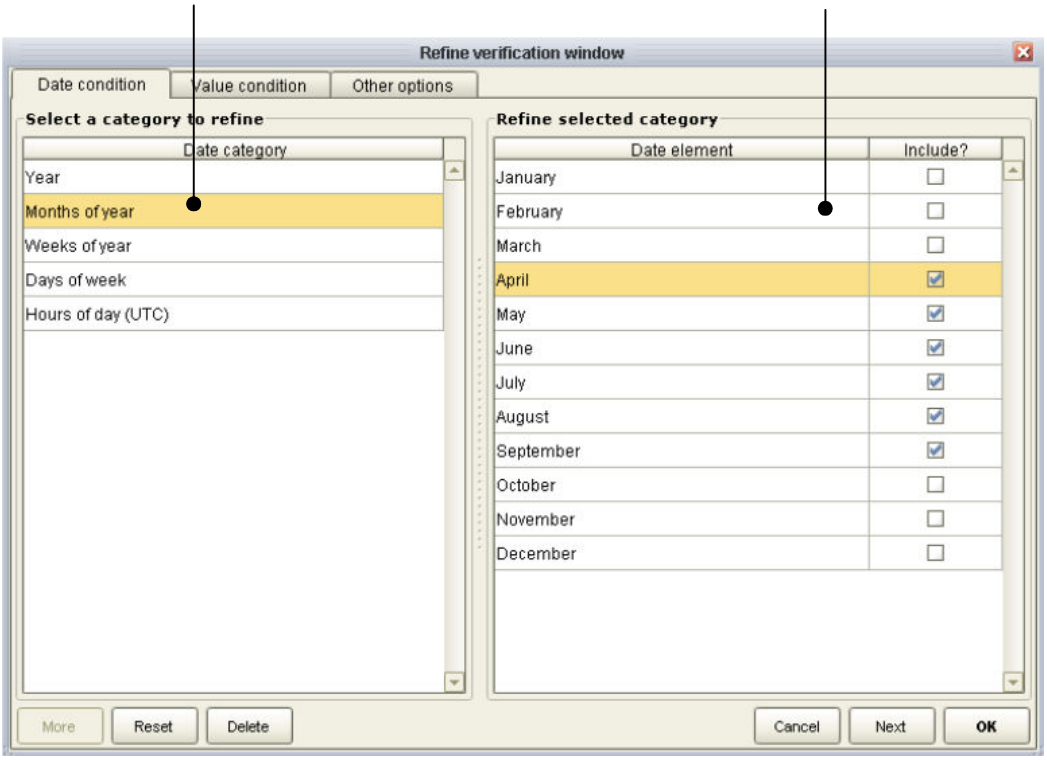
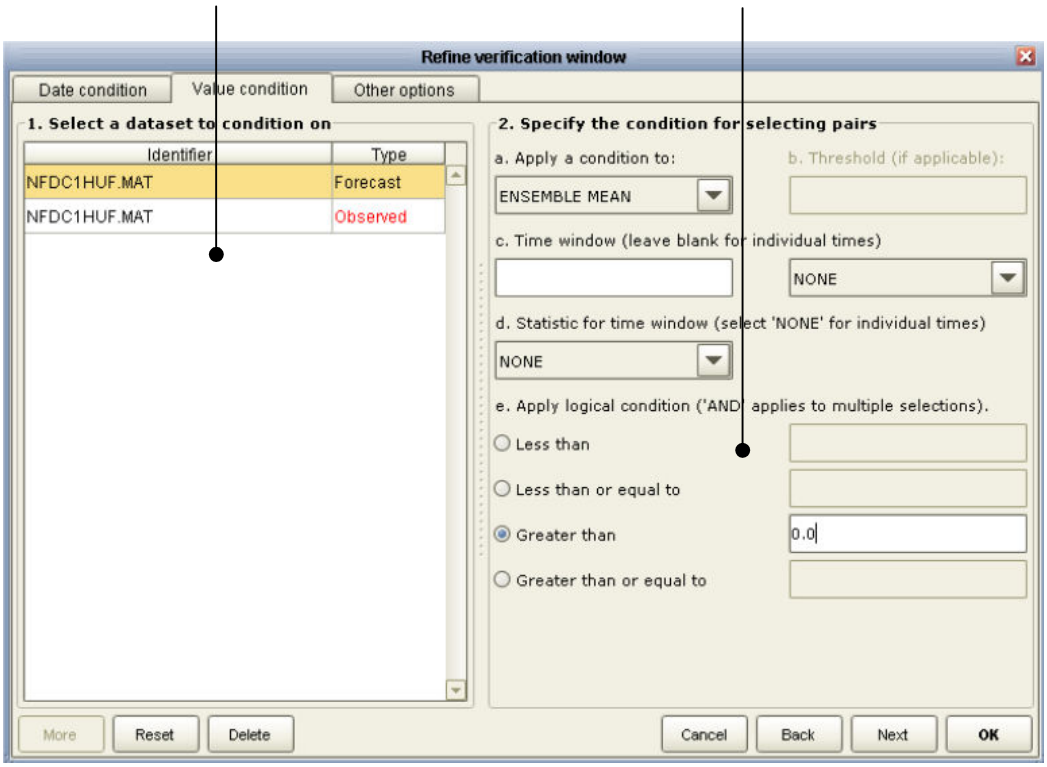


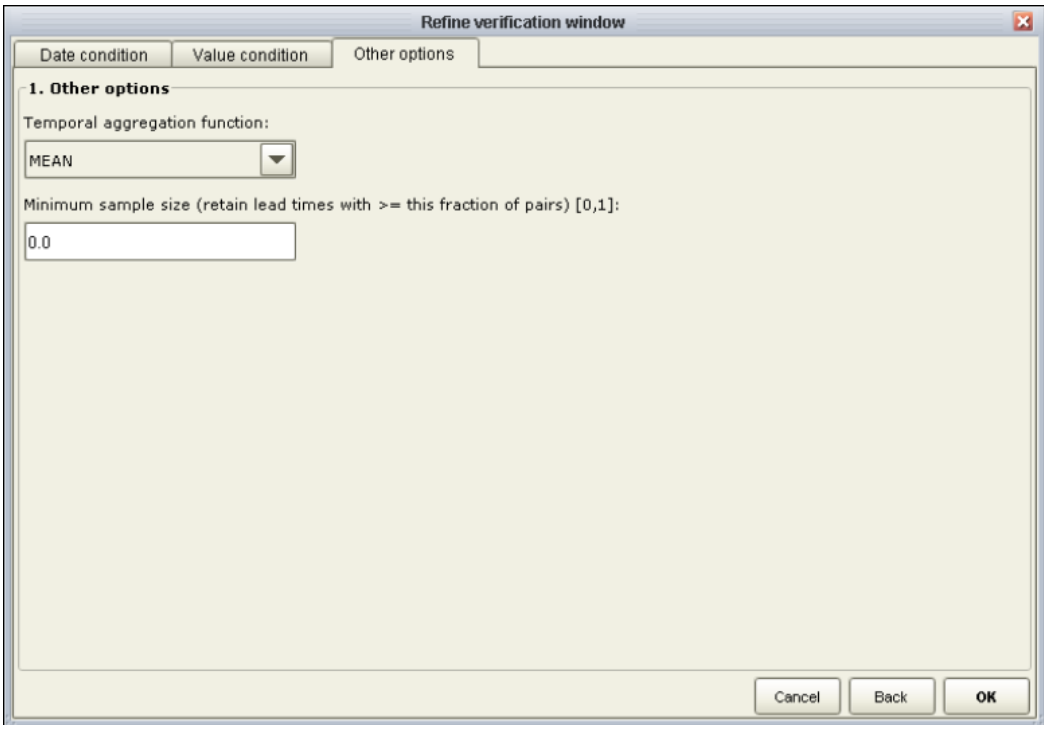
Fig. 9b: Dialog for refining verification window: conditioning with variable value

Variables available for conditioning Forecast ensemble mean > 0



Additional refinement options are available in the "Other options" section of the refinement dialog. Currently, there are two additional options. The first allows for a temporal aggregation function to be defined. By default, aggregations requested in the main verification window involve a mean average over the specified period. This may be changed to a total (i.e. accumulation), minimum or maximum value, among others (*Fig. 9c*). The second option allows for the specification of a minimum sample size per forecast lead time for computing verification results. The sample size constraint is set by a fraction in the range [0,1]. The fraction is multiplied by the average number of pairs across all lead times to determine the minimum sample size as a numbers of pairs. For example, a fraction of 0.5 implies that verification results will *not* be computed for any lead time with fewer than 50% of the average number of pairs across all lead times.

Fig. 9c: Dialog for refining the verification window: other options



Output data dialog:

- Folder for output statistics: path to the folder for writing the paired files and the verification output data generated by the system, if written output is requested (see below).
- A "**More**" button, which opens an advanced options dialog. The dialog contains an option to write the conditional pairs (true, by default).

5.3 The second window in the Verification stage

The second window in the Verification stage is shown in *Fig. 2* and is accessed by clicking "**Next**" from the first window (*Fig. 1*). The second window shows the verification metrics available for the VU selected in the first window.

The EVS includes single-valued error statistics, which can be used to verify the ensemble average forecast (mean, median or mode), and statistics that measure the quality of the forecast probabilities. While deterministic metrics cannot verify the forecast probabilities, they are useful for comparing single-valued forecasts with the "best estimate" from the ensemble forecast (such as the ensemble mean),

particularly if the ensemble forecasts were derived from single-valued forecasts (e.g. via Model Output Statistics). Currently, the deterministic measures available in the EVS include the mean error, the RMSE, the mean absolute error, and the coefficient of correlation between the ensemble mean forecast and observed outcome. *Table 3* lists the metrics available in the EVS, which contain varying levels of detail about the forecasting errors. Some of the ensemble verification metrics verify discrete events, such as the (non-)exceedence of a flood threshold, whereas other metrics evaluate the forecasting errors across all possible thresholds (see below). Further information about the metrics available in the EVS can be found in *Section 6* and *Appendix A1*. Examples of their interpretation can be found in *Section 7*.

Table 3: summary of the verification metrics available in the EVS

Metric name	Quality attribute tested	Discrete events?	Detail
Sample size	None	N/A	N/A
Mean error	Ensemble average (deterministic)	No	Lowest
RMSE	Ensemble average (deterministic)	No	Lowest
Mean absolute error	Ensemble average (deterministic)	No	Lowest
Correlation coefficient	Ensemble average (deterministic)	No	Lowest
Brier Score	Lumped error score	Yes	Low
Brier Skill Score	Lumped error score vs. reference	Yes	Low
Mean CRPS	Lumped error score	No	Low
Mean CRPS reliability	Lumped reliability score	No	Low
Mean CRPS resolution	Lumped resolution score	No	Low
CRPSS	Lumped error score vs. reference	No	Low
ROC score	Lumped discrimination score	Yes	Low
Mean error of prob.	Reliability (unconditional bias)	No	Low
MCRD	Probability of real-valued error	No	High
Spread-bias diagram	Reliability (conditional bias)	No	High
Reliability diagram	Reliability (conditional bias)	Yes	High
ROC diagram	Discrimination	Yes	High
Modified box plots	Error visualization	No	Highest

On selecting a given metric in the table, information about that metric is provided in the top right dialog, and the parameters of the metric are displayed for entering/editing in the bottom-left panel. A metric is included, and its parameter values are enabled for editing, by checking the box adjacent to the metric in the top left table. The parameters of each metric are listed in *table 4*. After modifying the verification statistics and their parameters, the new information is saved to the current unit by clicking "**Save**".

Table 4: Parameters for each verification metric

Metric	Parameter (and type)	Meaning
Mean Error	Thresholds **(basic)**	Produces the metric for each subset of data specified by the threshold. The thresholds may be defined in real units or in probabilities. By default, they refer to non-exceedence probabilities from the observed climatology.
	Ignore conditions on variable value **(advanced)**	Any conditions on the observed or forecast values used to subset pairs (an advanced option in the verification window) will be ignored for this metric.
	Average of ensemble members **(advanced)**	Select the desired average of the ensemble member values to verify. Options include the ensemble mean, median and mode values. By default, the ensemble mean is verified.
	Threshold values are observed probabilities **(advanced)**	If this parameter is true (checked; the default option), the threshold parameter (above) will refer to probabilities in the observed probability distribution. For example, a threshold value of 0.2 would select pairs in relation to the real value corresponding to probability 0.2 in the observed probability distribution. The form of the relationship will depend on the logical condition for the threshold (below). If this parameter is false (unchecked), the thresholds are interpreted as real-values in observed units (e.g. cubic feet per second).
	Logical condition for event threshold **(advanced)**	Changes the logical condition for any thresholds used to subset data. For example, if the logical condition is "greater than", only those forecast - observation pairs whose observed values are greater than the threshold will be used.

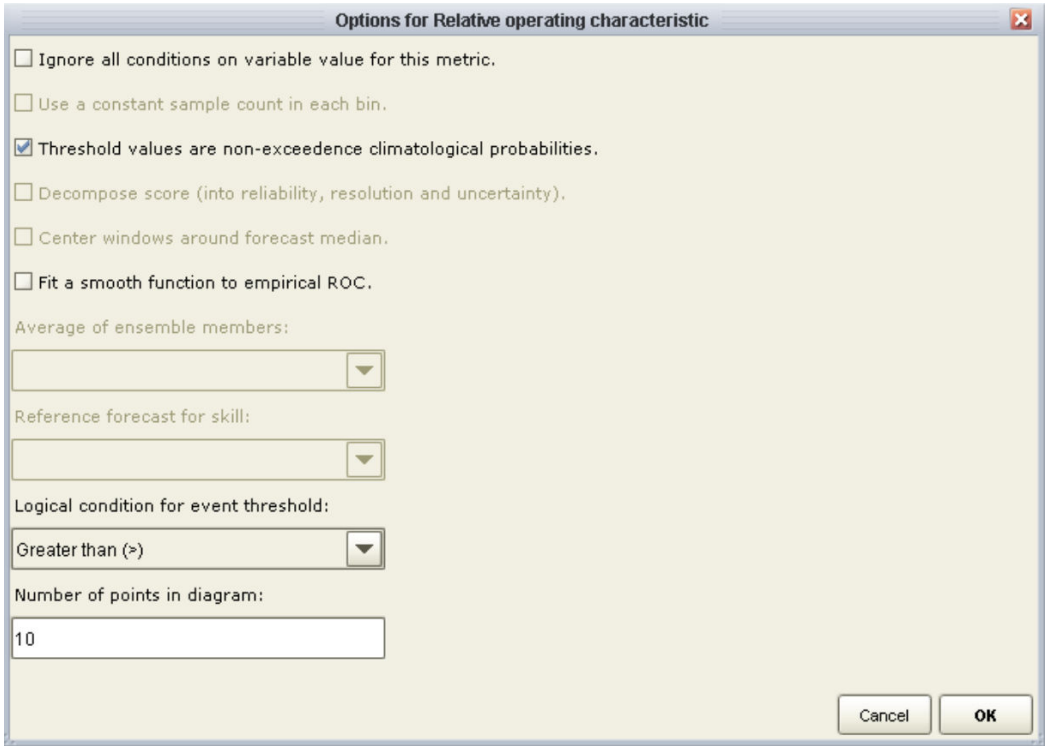
Root Mean Square Error	Same as mean error.	Same as mean error.
Mean Absolute Error	Same as mean error.	Same as mean error.
Correlation Coefficient	Same as mean error.	Same as mean error.
Brier score	Same as mean error.	Same as mean error.
Brier Skill Score	Same as mean error.	Same as mean error.
	Reference forecast for skill.	Allows a reference forecast to be selected for use in the skill calculation. The reference forecast must be loaded into the EVS as another VU.
Mean Continuous Ranked Probability Score	Same as mean error.	Same as mean error.
	Decompose score (into reliability, resolution and uncertainty) **(advanced)**	Decomposes the overall score into contributions due to (lack of) reliability, resolution and uncertainty (climatological variability). The overall score comprise reliability - resolution + uncertainty.
Mean Continuous Ranked Probability Skill Score	Same as Brier Skill Score.	Same as Brier Skill Score.
Mean Error of Probability diagram	Same as mean error.	Same as mean error.
	Number of points in diagram **(advanced)**	Sets the number of equally-spaced probability values (from 0-1) for which the metric will be computed and plotted.
Mean Capture Rate Diagram.	Same as Mean Error of Probability diagram.	Same as Mean Error of Probability diagram.
Modified box plot pooled by lead time.	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Number of points in diagram **(advanced)**.	Sets the number of equally-spaced probability values (from 0-1) at which the boxes will be computed and plotted. The middle thresholds form the boxes and outer thresholds form the whiskers.
Modified box plot per lead time by observed value.	Same as modified box plot pooled by lead time.	Same as modified box plot pooled by lead time.

Relative Operating Characteristic	Same as Mean Error of Probability diagram.	Same as Mean Error of Probability diagram.
Relative Operating Characteristic Score	Same as Mean Error of Probability diagram.	Same as Mean Error of Probability diagram.
Reliability Diagram	Ignore conditions on variable value **(advanced)**	Same as parameter for mean error.
	Use a constant sample count in each bin **(advanced)**.	If this parameter is false (unchecked; the default option), the forecasts probability bins for which the reliability values are computed will take a fixed width in the range 0-1 depending on the number of points requested for the diagram (below). If this parameter is true (checked), the forecast probability bins for which the reliability values are computed will vary in width such that each bin captures the same number of forecasts.
	Threshold values are observed probabilities **(advanced)**.	Same as parameter for mean error.
	Logical condition for event threshold **(advanced)**.	Same as parameter for mean error.
	Number of points in diagram **(advanced)**.	Sets the number of probability bins (from 0-1) for which the metric will be computed and plotted. These bins may capture an equal sample count (see above) or may be equally spaced.
Spread-Bias Diagram	Ignore conditions on variable value **(advanced)**.	Same as parameter for mean error.
	Threshold values are observed probabilities **(advanced)**.	Same as parameter for mean error.
	Center windows around forecast median **(advanced)**.	If this parameter is false (unchecked; the default option), the probability of an observation falling within a forecast bin is determined for bins separated by probabilities within the forecast distribution. For example, if the parameter for the 'Number of points in the diagram' (see below) is 10, probabilities will be determined for bins representing deciles of the forecast. If this parameter is true (checked), probabilities of the observation falling within a forecast bin will be determined for symmetric forecast bins defined with respect to the forecast median.
	Logical condition for event threshold **(advanced)**.	Same as parameter for mean error.
	Number of points in diagram **(advanced)**.	Defines the number of forecast bins for which the probability of an observation falling within that bin is determined.

Most of the ensemble verification metrics compare the observed and forecast values at specific thresholds. In some cases, these thresholds define a subset of data from which the metric is calculated. Most of the metrics can be computed from *all* data, as well as subsets of data defined by the thresholds. Other metrics verify only discrete events within the continuous forecast distributions. For example, the reliability diagram, relative operating characteristic and the Brier score, *require* one or more thresholds to be defined, and cannot be computed from all data. For these metrics, the thresholds represent cutoff values from which discrete events are computed. By default, the thresholds refer to non-exceedence probabilities within the climatological probability distribution and must, therefore, cover an interval of [0,1]. For example, a threshold of 0.2 would refer to all pairs whose observed values have an eighty percent chance of being exceeded, on average. The climatological probability distribution is computed from the observed (sample) data provided in the first verification window and is, therefore, subject to sampling uncertainty. The thresholds can be edited and added or deleted manually, via the table of thresholds, or semi-automatically by specifying a positive number of thresholds, the first threshold, and a non-zero increment between thresholds (positive to increase from the first threshold, negative to decrease). The types of thresholds may be modified via the "**More**" button, which displays an advanced options dialog. For example, the thresholds may be changed to real-values, rather than probabilities (e.g. flood stage) and the logical condition can be changed to non-exceedence, among others (see below also).

Depending on the selected verification metric, there are additional, advanced, parameters that can be altered. These parameters are available through the **"More"** button when a particular metric is selected. For example, when computing ensemble metrics using thresholds, the thresholds may be treated as non-exceedence (<, <=) or exceedence (>, >=) thresholds, which may be useful for exploring low- versus high-flow conditions, respectively (*Fig. 10*). The parameter options for each metric are summarized in *table 2*. A 'basic' parameter is accessed through the main window in EVS, while an 'advanced' parameter is accessed through the "**More**" button (as in *Fig. 10*).

Fig. 10: Advanced parameter options for a selected metric (ROC in this case)



All of the information necessary to verify the ensemble forecasts is now available, and the verification may be executed by clicking "**Run**" for the current VU or "**All**" to execute verification for all VUs in the current project. A progress dialog is then displayed. The progress dialog provides options to cancel processing, to minimize (iconify) the GUI, and to show further details of any errors thrown during processing. Processing may take several minutes or longer, depending on the size of the datasets involved. If not already available, the paired files are created (see above) and the selected metrics are then computed for each unit. No products are displayed or written at this stage; instead the numerical results are stored in memory, in preparation for generating these products in the Output window (see *Section 5.5*).

5.4 The Aggregation window

Alongside verification of ensemble forecasts from a single point or area, it is possible to aggregate verification statistics across multiple river segments. This is achieved in the aggregation window (*Fig. 3*). Only those points for which aggregation is possible will be displayed in the aggregation window. If no aggregation units (AUs) are displayed, no comparable VUs have been defined. Two VUs are comparable if they

share the same variable, temporal support (after any requested aggregation), and forecast time horizon.

The properties of an AU may be viewed or edited by selecting the unit in the table. Each AU is given a default identifier, which may be altered by the user. Multiple AUs may be defined in one project to generate aggregate statistics on various groups of VUs with common verification parameters.

Using the EVS GUI, aggregation is achieved by averaging the verification results from the input metrics. For verification metrics that comprise binned statistics (e.g. the reliability diagram; see below), the sample means are computed for each bin in turn. For verification statistics that are conditional upon one or more event thresholds, the statistics are averaged across the same thresholds at each location. The weights assigned to each VU must be within [0,1] and the sum of all weights must be equal to 1. By default, equal weights are assigned to each VU, but unequal weights may be input manually or a value of 'S' defined to weigh by the relative sample size at the first forecast lead time (maintaining constant weights across lead times). The default approach to spatial aggregation adopted in the EVS is somewhat pragmatic. In general, computing the average of a set of metrics (outputs) will not produce the same results as computing the metric from the pooled inputs, i.e. the pooled pairs. Averaging of the outputs is preferred over pooling of the inputs for reasons of computational efficiency, but pooling of pairs is preferred when the verification metrics are not a simple (linear) function of the data. The option to pool pairs, rather than average metrics, is available via the EVS project file using the `<pool_pairs>true</pool_pairs>` XML tag for a particular AU, where `true` will pool pairs and `false` will conduct averaging of metrics (the default). However, pooling of pairs is rarely practical for large datasets.

On selecting a particular AU, a list of candidate VUs appears under "Verification units to include in aggregation" and the common properties of those VUs appear under "Common parameter values". Two or more VUs must be selected to perform aggregation. The output folder in which the aggregated statistics will be written appears under "Output data". After defining one or more AUs, aggregation is performed by clicking "**Run**."

Editing of the VUs upon which one or more AUs is based will result in a warning message and the option to either remove the edited VU from each of the AUs to which it belongs or to cancel the edits.

5.5 The Output window

The Output window of the EVS allows for plotting of the verification statistics from one or more VUs or AUs. The units available for plotting are shown in the top left table, with VUs colored blue and AUs colored red (see *Fig. 4*). On selecting a particular unit under "Units with results", a list of metrics with available results appears in the right-hand table. On selecting a particular metric, the bottom left table displays a list of lead times (in hours) for which the metric results are available.

When verifying or aggregating the paired data, the sample from which verification metrics are computed is generated by pooling pairs from equivalent lead times. Products may be generated for some or all of these lead times, and will vary with the metric selected. For example, in selecting ten lead times for the modified box plot, it is possible to produce one graphic with ten boxes showing the (pooled) errors across those ten lead times. In contrast, for the reliability diagram, one graphic is produced for each lead time, with reliability curves for all thresholds specified in each graphic. The units, products, and lead times and are selected by checking the adjacent boxes in the last column of each table. In addition, when the product and lead time tables are populated, right clicking on these tables will provide additional options for selecting multiple products and lead times.

Products are generated with default options by clicking "**Run**". The default options are to write the numerical results in an XML format and the corresponding graphics in png format to the predefined output folder. The file naming convention is `unit_identifiers.metric_name.lead_time` for plots that comprise a single lead time and `unit_identifiers.metric_name` for the plots that comprise multiple lead times and for the numerical results.

As indicated above, the default output options are defined for each project, and comprise writing of numerical results to an XML file and writing of graphical results to a PNG file. These options are displayed in the bottom right dialog of the main Output window (*Fig 4.*). *Fig. 11* and *Fig. 12* show the writing and display options in more detail. The image parameters and formats for writing image files may be modified,

and include the PNG and JPEG raster formats and the SVG vector format (which writes much larger files, but maintains line quality with re-scaling). The graphical result may be plotted, edited (re-titled etc.) and saved using an internal viewer, and the numerical results can be shown within the default web-browser. When plotting results for multiple graphics in the internal viewer, a warning is given when more than five graphics will be plotted. A tabbed pane is used to collect plots together for metrics that have one plot for each lead time (*Fig. 13*). For rapid viewing, these plots may be animated by pressing the "**Animate**" button.

Fig. 11: product writing options

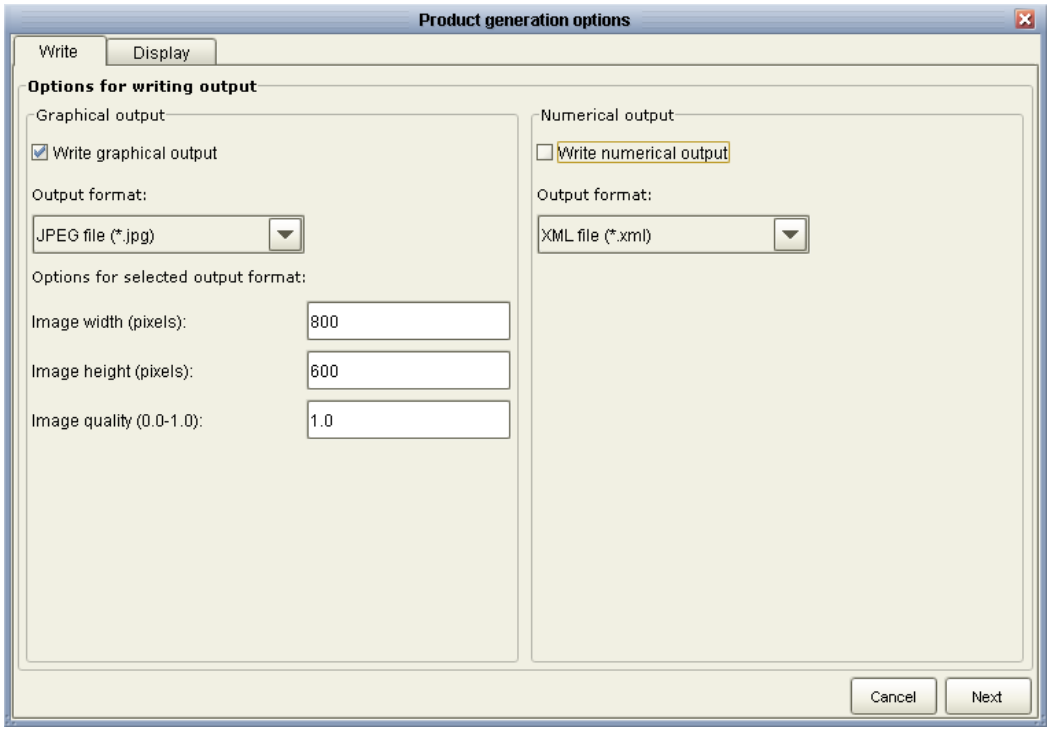


Fig. 12: product display options

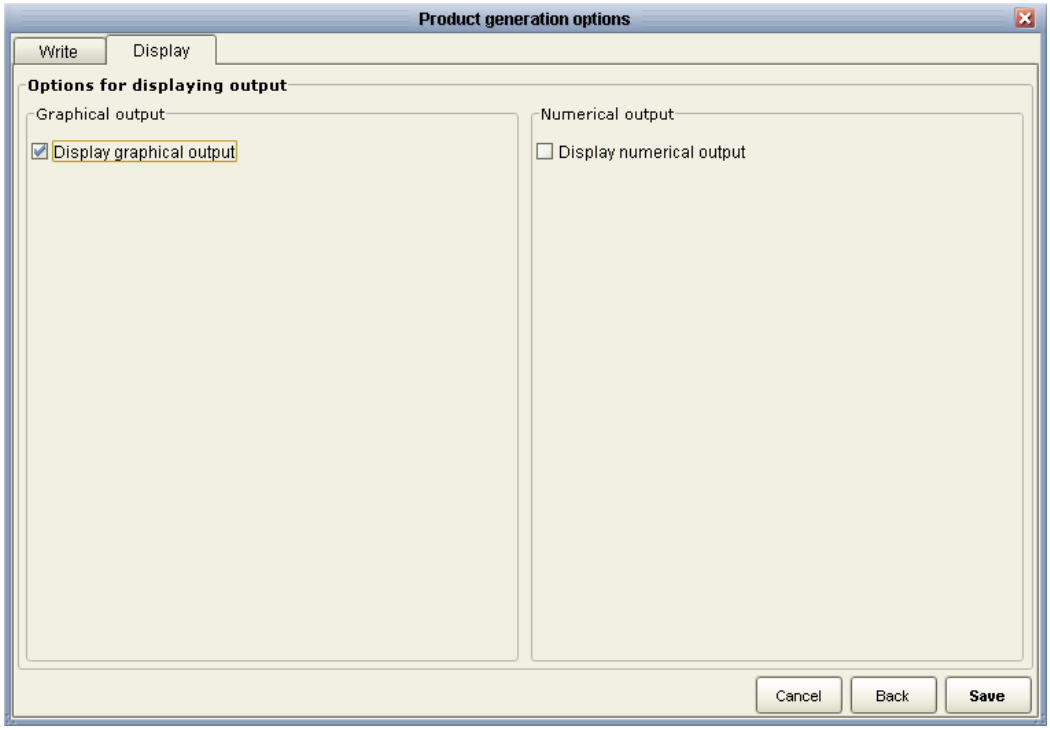
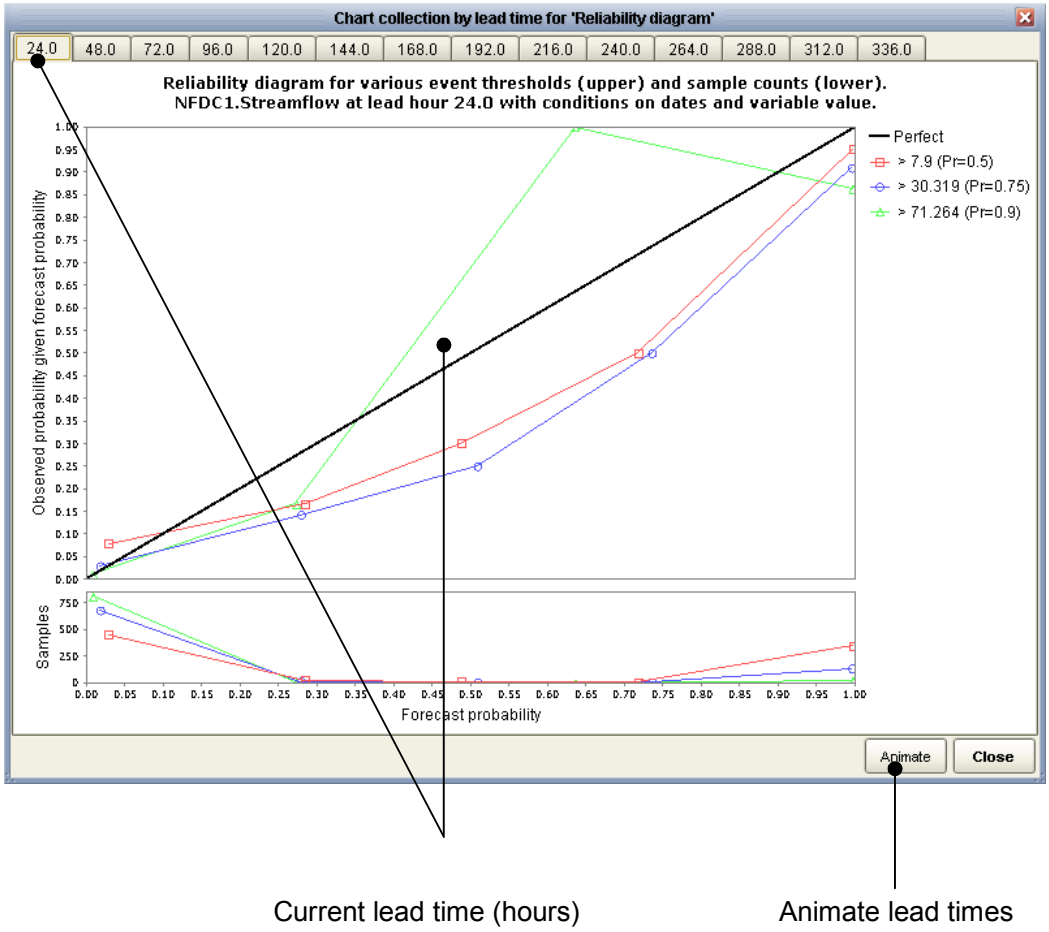


Fig. 13: plot collection for a metric with one plot for each lead time

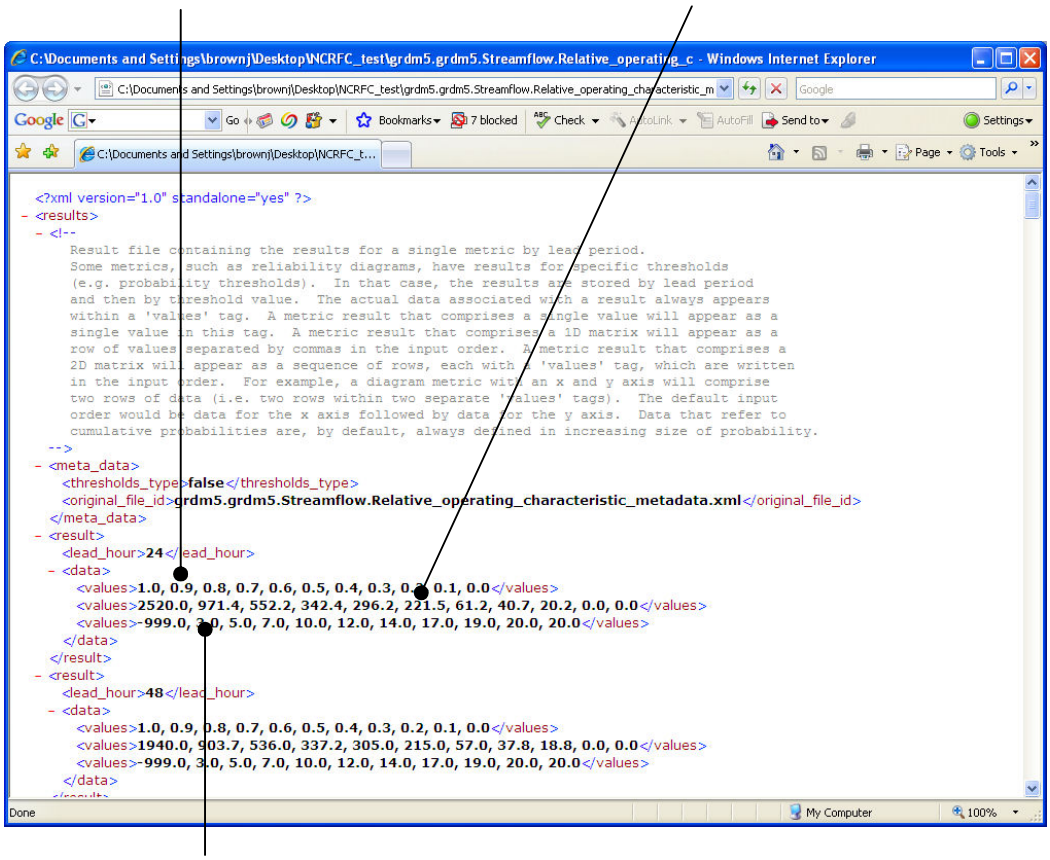


When writing numerical outputs for metrics that are based on one or more thresholds of the observations, such as the Brier Score, Relative Operating Characteristic and Reliability diagram, information about these thresholds is written to an XML file with the `_metadata.xml` extension. Specifically, the probability thresholds are written for each time step, together with their values in real units (of the observations) and the numbers of samples selected by those thresholds. An example is given in *Fig. 14*.

Fig. 14: example of a metadata file for metrics based on observed thresholds

Probability thresholds used at first lead time

Real values of thresholds



Sample counts for each threshold

6. THE VERIFICATION METRICS AVAILABLE IN THE EVS

6.1 Classes of verification metric and attributes of forecast quality

Detailed reviews of ensemble forecast quality can be found in Wilks (2006) and Jolliffe and Stephenson (2003). This section focuses on the verification metrics available in the EVS and the attributes of forecast quality to which they refer. In this context, "attribute" refers to a specific dimension of quality, such as the unbiasedness or "reliability" of the forecast probabilities. Important attributes of forecast quality are obtained by examining the joint probability distribution function (pdf) of the forecasts, *Y*, and observations, *X*, $f_{XY}(x,y)$. The joint distribution can be factored into $f_{X|Y}(x|y)\cdot f_Y(y)$, which is known as the "calibration-refinement" factorization or $f_{Y|X}(y|x)\cdot f_X(x)$, which is known as the "likelihood-base rate" factorization (Murphy and Winkler, 1987). Differences between $f_X(x)$ and $f_Y(y)$ describe the unconditional biases in the forecast probabilities. The conditional pdf, $f_{X|Y}(x|y)$, describes the conditional reliability of the forecast probabilities when compared to $f_Y(y)$ and "resolution" when only its sensitivity to $f_Y(y)$ is considered. For a given level of reliability, forecasts that contain less uncertainty, i.e. "sharp forecasts", may be preferred over "unsharp" ones, as they contribute less uncertainty to decision making (Gneiting et al., 2007). By way of illustration, a flood forecasting system is "reliable", or conditionally unbiased in its forecast probabilities, if flooding is observed twenty percent of the time when it is forecast with probability 0.2 (repeated for all forecast probabilities). A flood forecasting system has "resolution" if small changes in the forecast probabilities are associated with different observed outcomes, whether or not the forecast probabilities are reliable. In contrast, $f_{Y|X}(y|x)$ measures the ability of the forecasts to "discriminate" between different observed outcomes. An ensemble forecasting system is discriminatory with respect to an event if it consistently forecasts the event's (observed) occurrence with a probability higher than chance (i.e. climatology) and consistently forecasts its (observed) non-occurrence with a probability lower than chance. In general, the utility of a forecasting system will depend on several attributes of forecast quality (Jolliffe and Stephenson, 2003). However, for a particular application of the forecasts, some attributes of forecast quality may be more important than others. For example, when issuing flood warnings, it is particularly important that observed flood flows and non-

flood flows are discriminated between, because flood warnings are only effective if they are consistently correct and do not “cry wolf”.

For any given attribute of forecast quality, there are several possible metrics or measures of quality. For example, summary statistics for reliability and resolution can be obtained from quadratic error statistics, such as the BS (Brier, 1950), which contains a summed contribution from these two components (Murphy, 1996). When more details are required, specific events may be defined, such as flooding or the occurrence of precipitation, and forecast quality determined over specific ranges of forecast probability (as in the reliability diagram; Hsu and Murphy, 1986). Only those metrics thought to convey significantly different aspects of forecast quality are included in the EVS, which includes metrics that convey specific attributes of quality at various levels of detail (see *Table 3*). The flexibility to consider different attributes of forecast quality at various levels of detail is important, as the EVS is intended for a wide range of applications and users.

The EVS includes single-valued error statistics, which can be used to verify the ensemble mean forecast, and statistics that measure the quality of the forecast probabilities. While deterministic metrics cannot verify the forecast probabilities, they are useful for comparing single-valued forecasts with the “best estimate” from the ensemble forecast (such as the ensemble mean), particularly if the ensemble forecasts were derived from single-valued forecasts (e.g. via Model Output Statistics; Gneiting et al., 2005). However, caution should be exercised when using deterministic measures to verify the ensemble mean forecast, because the ensemble spread adds potential skill to the ensemble forecast and is not verified by a deterministic measure. Currently, the deterministic measures available in the EVS include the mean error, the mean absolute error, the RMSE, and the coefficient of correlation between the ensemble mean forecast and observed outcome (*Table 3*). Other measures of central tendency applied to an ensemble forecast, such as the median, or measures of high probability, such as the mode, may be included in future. *Table 3* lists the verification metrics that are currently available in the EVS, which contain varying levels of detail about the forecasting errors. The verification scores, such as the BS and the Continuous Ranked Probability Score (CRPS) are integral measures of forecast quality and are less sensitive to sampling uncertainty. Sampling uncertainty is an important concern when verifying forecast probabilities (Jolliffe and Stephenson, 2003; Wilks, 2006), particularly for extreme events (Bradley

et al., 2003). Also, the BS and CRPS may be decomposed into summed contributions from (lack of) reliability and resolution (Murphy 1996, Hersbach 2000).

As indicated above, reliability and discrimination are two key attributes of ensemble forecast quality. Both unconditional and conditional biases contribute to a lack of reliability in the forecast probabilities. If the forecasting system is conditionally unbiased, it is also unconditionally unbiased, but the reverse may not hold. The conditional biases are often considered alongside the forecast spread or "sharpness", because sharp forecasts are more informative, but not necessarily more reliable (Gneiting et al., 2007). For example, a forecast that issues the climatological probability of an event is unconditionally unbiased, because the average observed and forecast probabilities are, by definition, the same. However, it is conditionally biased, because hydrologic events are conditional upon several factors, such as precipitation amount and antecedent soil conditions. The conditional bias corresponds to the difference between a forecast issued from a perfectly reliable forecasting system (the diagonal line in the reliability diagram; Hsu and Murphy, 1986) and the climatological probability of occurrence (a horizontal line in the reliability diagram). Several metrics are available in the EVS for assessing the unconditional and conditional biases that contribute to unreliable forecast probabilities. In order of increasing detail, these include; 1) the reliability component of the mean CRPS ($\overline{CRPS}$; Matheson and Winkler, 1976; Hersbach, 2000); 2) a plot of the unconditional biases in the forecast probabilities (the mean error of probability diagram, MEPD); 3) a plot of the conditional biases in the forecast probabilities (the spread-bias diagram, SBD), which that is similar to the cumulative rank histogram (Anderson, 1996; Hamill, 1997; Talagrand, 1997); and 4) the reliability diagram, which plots the conditional biases in the forecast probabilities of a discrete event, such as flooding, and includes a plot of sharpness (Hsu and Murphy, 1986).

The reliability component of the $\overline{CRPS}$ measures the average reliability of the ensemble forecasts across all possible events (Hersbach, 2000). Specifically, it shows whether the observed outcome falls below the *j*th of *m* ranked ensemble members, $\{z_{j-1} \leq z_j;\ j=2,\ldots,m\}$, in proportion to j/m, on average. The MEPD shows the frequency with which an observed outcome falls below a probability threshold in the unconditional or "climatological" forecast distribution (*Section 6.2*). The SBD is closely related to the reliability component of the $\overline{CRPS}$. It shows the frequency with which an observed outcome falls below a probability threshold in the (conditional)

forecast distribution (see *Section 6.2*). The MEPD, the SBD, and the reliability diagram all measure bias in probability and have a common graphical interpretation. In each case, a deviation from the diagonal line represents to a lack of calibration in the forecast probabilities, whether unconditional (the MEPD) or conditional upon the forecast ensemble (the SBD) or specific forecast events (the reliability diagram). The reliability diagram plots the conditional probability that an event is observed to occur, *given the forecast*, against its forecast probability of occurrence (Hsu and Murphy, 1986; Bröcker and Smith, 2007a). It is useful to distinguish between the unconditional and conditional biases in the forecast probabilities, because the unconditional biases are more easily removed (e.g. through post-processing; Hashino et al., 2006), and may originate from different sources.

One measure of resolution and two measures of discrimination are currently available in the EVS, namely: 1) the resolution component of the $\overline{CRPS}$ (Hersbach, 2000); 2) the Relative Operating Characteristic (ROC) score (Mason and Graham, 2002; Fawcett, 2006); and; 3) the ROC curve (Green and Swets, 1966; Mason and Graham, 2002). The resolution component of the $\overline{CRPS}$ measures the average ability of the forecasts to distinguish between different observed outcomes, whether or not they were forecast reliably (Hersbach, 2000). The forecasting system has positive resolution if it performs better than the climatological probability forecast. The ROC score and ROC curve measure the ability of the forecasts to discriminate between observed events and non-events, such as flooding versus no flooding. In this context, there is a trade-off between the correct prediction of occurrences and the correct prediction of non-occurrences, or the probability level at which actions are triggered. For example, if a flood warning is triggered by only a small probability of flooding, there is a smaller chance that a flood event will evade detection, but there is a concomitantly higher chance that a non-event will be forecast incorrectly (i.e. of "crying wolf"; other factors being equal). Thus, the ROC curve plots the probability of detection against the probability of false detection for a range of forecast probability levels (Green and Swets, 1966). The ROC score measures the average gain over climatology for all probability levels (based on the integral of the ROC curve).

In addition to measures of reliability and discrimination, there are several composite measures of forecasting error provided in the EVS. In order of increasing information content, these include: 1) the BS; 2) the $\overline{CRPS}$; 3) the Mean Capture Rate Diagram (MCRD); and 4) box plots of errors in the forecast ensemble members. The BS and

the $\overline{CRPS}$ quantify the mean square error of the forecast probabilities for a single threshold and for all thresholds, respectively. In contrast, the MCRD and box plots show the forecasting errors in linear units (see *Section 6.2*). The quadratic form of the BS and the $\overline{CRPS}$ allows for their decomposition into reliability, resolution, and uncertainty (Murphy, 1996). However, this also complicates their use in operational forecasting, where low-probability, high-impact, events are crucial, but the square errors of probability in the forecasts are necessarily small (see *Section 6.2* also). In order to support comparisons between forecasting systems and across hydroclimatic regimes, the Brier Skill Score (BSS) and the Continuous Ranked Probability Skill Score (CRPSS) are also provided in the EVS. In both cases, the reference forecast is user-defined, and is introduced by defining an additional VU in the EVS.

6.2 Metrics developed for the EVS with an emphasis on operational forecasting

In addition to the standard metrics for reliability, resolution and discrimination, the EVS provides a platform for testing new metrics. Currently, these include the mean error of probability diagram (MEPD), which measures the unconditional biases in the forecast probabilities, the spread-bias diagram (SBD), which is similar to the (cumulative) rank histogram and tests the forecasts for conditional reliability (Anderson, 1996; Hamill, 1997; Talagrand, 1997), the Mean Capture Rate Diagram (MCRD), which is based on the Probability Score of Wilson et al. (1999), and modified box plots of the ensemble forecast errors versus observed amount. An important aim in developing these metrics was to provide operational forecasters with more application-oriented measures of ensemble forecast quality.

The MEPD measures the reliability of an ensemble forecasting system in an unconditional sense. Let z_{ij} denote the *j*th of *m* ensemble members from the *i*th of *n* ensemble forecasts and let x_i^o denote the observed outcome associated with the *i*th ensemble forecast. The forecast climatology has an empirical distribution function, $\hat{F}_{nm}(v)$, which is computed from the *n* ensemble forecasts as

$$\hat{F}_{nm}(v) = \frac{1}{n}\sum_{i=1}^{n}\hat{F}_{m_i}(v) \quad where \quad \hat{F}_{m_i}(v) = \frac{1}{m}\sum_{j=1}^{m}\mathbf{1}\{z_{ij} \le v\}, \tag{1}$$

and $\mathbf{1}\{\cdot\}$ is a step function that assumes value 1 if the condition is met and 0 otherwise. Let $H = [a,b \mid a,b \in [0,1]]$ denote an interval of fixed width on the

support of $\hat{F}_{nm}(v)$. The MEPD counts the fraction of observations that fall within the interval, *H*, namely

$$MEPD(H) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{nm}(x_i^o) \in H\}. \tag{2}$$

An ensemble forecasting system is unconditionally reliable or marginally calibrated over the interval, *H*, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty} \left\{ \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{nm}(x_i^o) \in H\} \right\} = b - a. \tag{3}$$

The MEPD shows $MEPD(H)$ against the width of *H* for each of *k* windows that span the unit interval. In practice, the *k* windows may cover any subintervals of the unit interval. The MEPD is similar to the quantile-quantile (Q-Q) plot (Wilks, 2006) and the probability-probability (P-P) plot (Shorack and Wellner, 1986; Gneiting et al., 2007). The Q-Q plot compares the order statistics of two samples, or the order statistics of one sample against the values of a theoretical distribution at corresponding quantiles (Wilks, 2006). The P-P plot compares the quantiles corresponding to these order statistics. Indeed, the MEPD is equivalent to a P-P plot of the climatological distributions of *X* and *Y* when evaluated for the *n* intervals, $\left\{ H_j = [0, b_j] \mid b_j = \frac{j}{n+1}, j = 1,\ldots,n \right\}$. As indicated above, the MEPD assumes asymptotic convergence of $MEPD(H)$ as $n\to\infty$. In practice, this may be evaluated by comparing the $MEPD(H)$ for *g* subsamples of the *n* available data.

For continuous random variables, such as temperature and streamflow, the SBD provides a simple measure of conditional reliability. It involves counting the fraction of observations, $SBD(I)$, that fall within an interval of fixed width on the support of the *i*th forecast, $I = [c, d \mid c, d \in [0,1]]$

$$SBD(I) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{m_i}(x_i^o) \in I\}. \tag{4}$$

An ensemble forecasting system is reliable over the interval, *I*, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty}\left\{ {}^{1}\!/_{n} \sum_{i=1}^{n} \mathbf{1}\{\hat{F}_{m_i}(x_i^o) \in I\}\right\} = d - c. \tag{5}$$

By defining *k* windows on the unit interval, $\left\{I_j = [c_j, d_j] \mid c_j, d_j \in [0,1]; j = 1,...,k\right\}$, the reliability can be determined for the entire range of forecast probabilities. In practice, the *k* windows may cover any subintervals of the unit interval. Certain windows may be preferred for some applications or for sampling reasons. For example, if the forecasts are uncertain in the tails, windows centered on the forecast median may be preferred. The SBD shows the observed frequency, $SBD(I)$, against the expected frequency, *d-c*. Any deviation from the diagonal line represents a lack of reliability in the forecast probabilities. More specifically, the ensemble forecasts are unreliable if the observed frequency, $SBD(I)$, deviates from the expected frequency by more than the sampling uncertainty of $SBD(I)$. If the *k* windows each cover a probability interval of *1/k*, the expected frequency has a uniform probability distribution, and the actual reliability can be tested for its goodness-of-fit to a uniform distribution (e.g. using the one-sided Cramer von Mises test; Anderson, 1962; Elmore, 2005; Bröcker, 2008).

For continuous random variables, the expected $SBD(I)$ is equal to the width of the interval, *I*, and is, therefore, strictly increasing as the width increases (see above). However, for mixed random variables, such as precipitation and wind-speed, the discrete portion of the probability distribution comprises an infinite number of intervals of different width. Although the window definition could be adapted for this case (see Hamill and Colucci, 1997 for a similar discussion), the reliability diagram may be preferred for mixed random variables.

While the SBD is analogous to the cumulative rank histogram, it explicitly defines the width of the interval, *I*, into which observations fall. When these windows are based on non-exceedence probabilities and are uniform in width (as well as non-overlapping and exhaustive), the SBD is also analogous to the Probability Integral Transform (PIT) (Casella and Berger, 1990), although the latter involves fitting a parametric cdf to the ensemble forecast distribution prior to evaluating the PIT (Gneiting et al., 2005). In that case, the SBD, the cumulative rank histogram and the

PIT can also be summarized with the reliability component of the $\overline{CRPS}$ (Hersbach, 2000), which tests whether an observation falls below a threshold with a frequency proportional to the cumulative probability of that threshold (averaged across all thresholds).

Integral measures of forecasting error are widely used in ensemble verification and include the BS and CRPS. As indicated above, the BS and CRPS may be decomposed into a reliability component, a resolution component, and an uncertainty component (Hersbach, 2000). In addition, they have the important property of being "strictly proper" (Bröcker and Smith, 2007b; Gneiting et al., 2007). A scoring rule is "proper" if it is maximized for a forecaster's true belief and is "strictly proper" if its maximum is unique (Gneiting et al., 2007). While linear scores are improper, quadratic scores, such as the BS and CRPS, are strictly proper. Nevertheless, if the user has a strong risk aversion towards extreme events, quadratic scores may not be desirable. The Probability Score (PS) of Wilson et al. (1999) is not strictly proper but has some appeal in operational forecasting (see also, Mason, 2008). The PS integrates the forecast probability distribution, $f_Y(y)$, over a symmetric window of width, *w*, around the observed outcome, x^o, and is defined as $PS(f_Y, x^o, w)$

$$PS(f_Y, x^o, w) = \int_{x^o - 0.5w}^{x^o + 0.5w} f_Y(y)dy. \tag{6}$$

As with the $\overline{CRPS}$, the $PS(f_Y, x^o, w)$ is averaged over *n* pairs of forecasts and verifying observations to form the $\overline{PS}(w)$

$$\overline{PS}(w) = \frac{1}{n}\sum_{i=1}^{n} PS(f_{Y_i}, x_i^o, w). \tag{7}$$

On average, the probability that a forecast value (or ensemble member) will fall within *w* of the observed value is $\overline{PS}(w)$. The expected PS of a perfect forecasting system is 1, because any given window around x^o will fully capture $f_Y(y)$. The $\overline{PS}(w)$ may be separated into an unconditional bias term, $\overline{PS_U}(w)$, and a conditional bias term, $\overline{PS_C}(w)$, where $\overline{PS}(w) = \overline{PS_U}(w) + \overline{PS_C}(w)$. The $\overline{PS_U}(w)$ stems from a lack of reliability in the forecast climatology, $\overline{f_Y}$, relative to the observed climatology, $\overline{f_X}$,

and is given by the absolute difference in the $\overline{PS}(w)$ for the forecasts $\overline{f_Y}$ and $\overline{f_X}$, i.e. $\overline{PS_U}(w) = \left| \frac{1}{n} \sum_{i=1}^{n} PS(\overline{f_{Y_i}}, x_i^o, w) - \frac{1}{n} \sum_{i=1}^{n} PS(\overline{f_{X_i}}, x_i^o, w) \right|$. The conditional bias may be deduced from $\overline{PS_C}(w) = \overline{PS}(w) - \overline{PS_U}(w)$.

When basing decisions on the $\overline{PS}(w)$, *w* may be interpreted as a "significant operating error". For example, when forecasting dam inflows, a high probability of realizing an error greater than *w* (i.e. 1-$\overline{PS}(w)$), on average, may have some practical implications for regulating dam outflows. In other cases, there may be no single *w* on which to base decisions. The Mean Capture Rate Diagram (MCRD) plots 1-$\overline{PS}(w)$ for all possible *w* (see *Section 5* for an example). The integral of the MCRD for the perfect forecasting system is 0, since *E*[*1-PS*]=*0* for all real values of *w*. While the PS is not strictly proper, there is an analytical relationship between the integral of the MCRD, denoted IPS, where $IPS = \int\int_{x^o - 0.5w}^{x^o + 0.5w} f_Y(y)\,dy\,dw$, and the strictly proper CRPS

$$IPS = CRPS + 2E[X \cdot F_Y(y)] - E[X]. \tag{8}$$

Thus, the integral of the MCRD is directly related to the $\overline{CRPS}$. However, of greater practical significance, the IPS is more sensitive to errors in the tails of the forecast probability distribution than the $\overline{CRPS}$.

7. EXAMPLE APPLICATIONS OF THE EVS

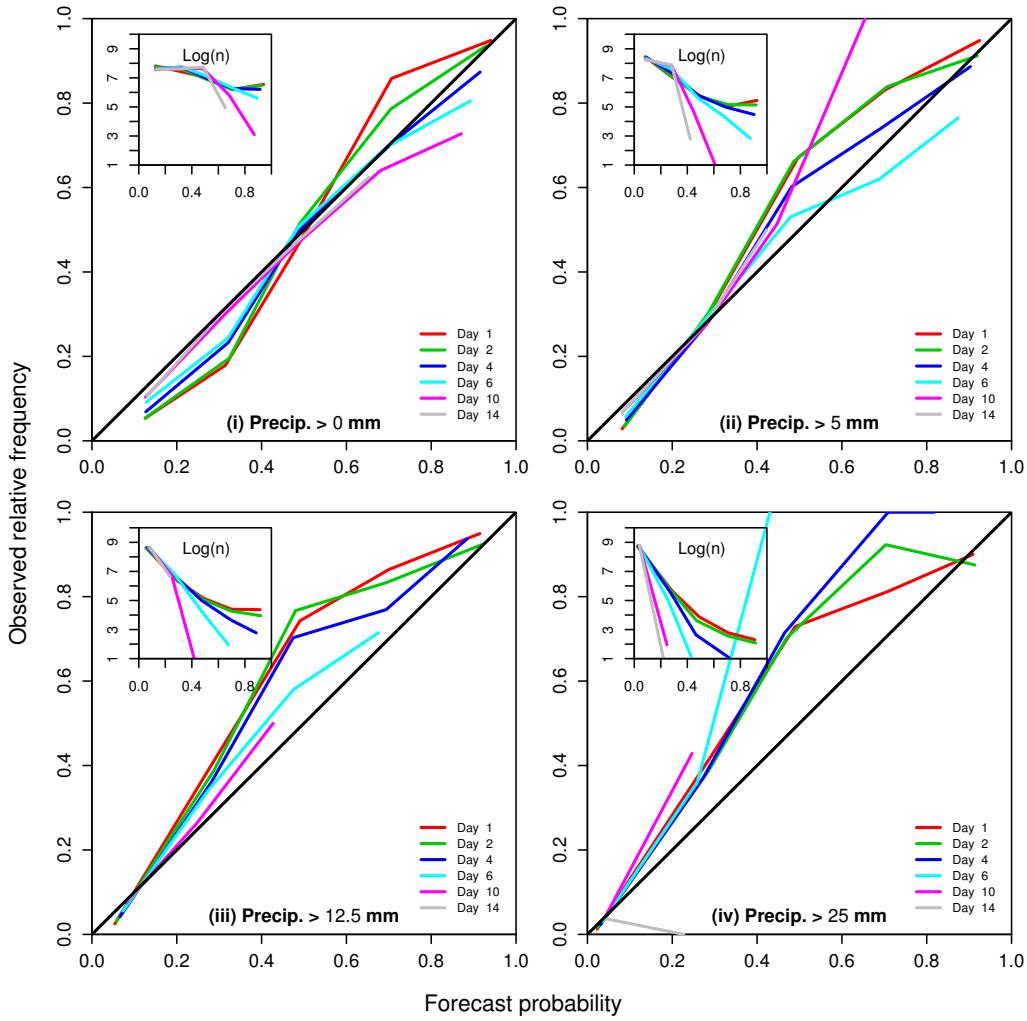
7.1 Precipitation forecasts from the NWS Ensemble Pre-Processor (EPP)

Six-hourly mean areal precipitation (MAP) totals were hindcast for a 17 year period between 1 January 1979 and 31 December 1996 for the North Fork of the American River above the North Fork Dam (USGS stream gauge station 11427000, NWS forecast point NFDC1), near Sacramento, California. The hindcasts were produced with the NWS Ensemble Pre-Processor (EPP; Schaake et al., 2007) for two MAP areas that contribute to streamflow at NFDC1. The EPP uses a form of Model Output Statistics (MOS) to generate ensemble forecasts of precipitation from single-valued forecasts. The technique is based on a linear regression of the single-valued forecasts and observations in normal probability space. Ensemble traces are then sampled from the conditional probability distribution of the observations, given the single-valued precipitation forecast (Schaake et al., 2007). When sampling from the conditional probability distribution at different lead times, the temporal correlations are reconstructed approximately using the Schaake Shuffle technique (Clark et al., 2003). In the current application, the single-valued forecasts were obtained from the frozen version of the Global Forecast System (GFS; frozen circa 1998) of the National Centers for Environmental Prediction (NCEP) and comprise the ensemble mean of the GFS forecasts (Toth et al., 1997; Hamill et al., 2006; Schaake et al. 2007; Wei et al., 2008). The GFS-EPP precipitation ensembles comprise a continuous record of six-hourly forecasts, with lead times ranging from 6 to 336 hours in six-hourly increments. Each GFS-EPP forecast contains 40 ensemble members, and each member represents an equally likely prediction of the total precipitation within the six-hour period. Using the EVS, the forecasts were aggregated from six-hourly totals to daily totals, and the verification statistics were averaged across the two MAP areas.

Fig. 15 shows the reliability of the GFS-EPP forecasts for daily precipitation totals exceeding 0.0 (i.e. probability of precipitation, PoP), 5.0, 12.5, and 25 mm at lead times of 1, 2, 4, 6, 10 and 14 days. The sampling uncertainties were too large to evaluate forecast reliability at thresholds exceeding 25 mm. As indicated in *Fig. 15*, the forecast probabilities are reliable for PoP and low precipitation amounts (e.g. >5.0 mm), particularly at lead times of 4 and 6 days, and are reasonably reliable for other precipitation amounts. At moderate (>12.5 mm) and high (>25 mm) precipitation thresholds, there is a tendency for the forecast probabilities to fall below the

observed relative frequencies. This is associated with a low-bias in the ensemble mean forecast for large precipitation amounts (see the upper-right plot in *Fig. 17*, together with *Fig. 18*). Also, as the event thresholds and lead times increase, the number of forecasts issued with high probability, i.e. the "sharpness", declines rapidly.

Fig. 15: Reliability diagrams for the EPP precipitation forecasts



ROC measures the ability of an ensemble forecasting system to discriminate predefined events, such as the occurrence versus non-occurrence of precipitation, and is insensitive to reliability. The ROC curves in *fig. 16* show the Probability of Detection (POD) versus the Probability of False Detection (POFD) for varying probability levels of the GFS-EPP forecasts. Here, an event is defined for daily

precipitation totals exceeding 0.0, 5.0, 12.5 or 25 mm at lead times of 1, 2, 4, 6, 10 or 14 days. The POD and POFD are plotted for twelve, equally spaced, probability thresholds. The diagonal line in each plot represents the climatological probability forecast or "zero skill" line. At short lead times, the ensemble forecasts are much more skilful than the climatological probability forecast across all precipitation amounts. Notably, while the ROC area declines consistently with forecast lead time, it increases slightly with precipitation threshold at lead times of 1 and 2 days. This is contrary to the expectation that forecast skill declines with increasing precipitation amount. However, NFDC1 lies on the upslope of the Sierra Nevada mountain range, where significant precipitation events are often enhanced by orographic lifting and are, therefore, relatively predictable at short lead times.

Fig. 16: Empirical ROC curves for the EPP precipitation forecasts

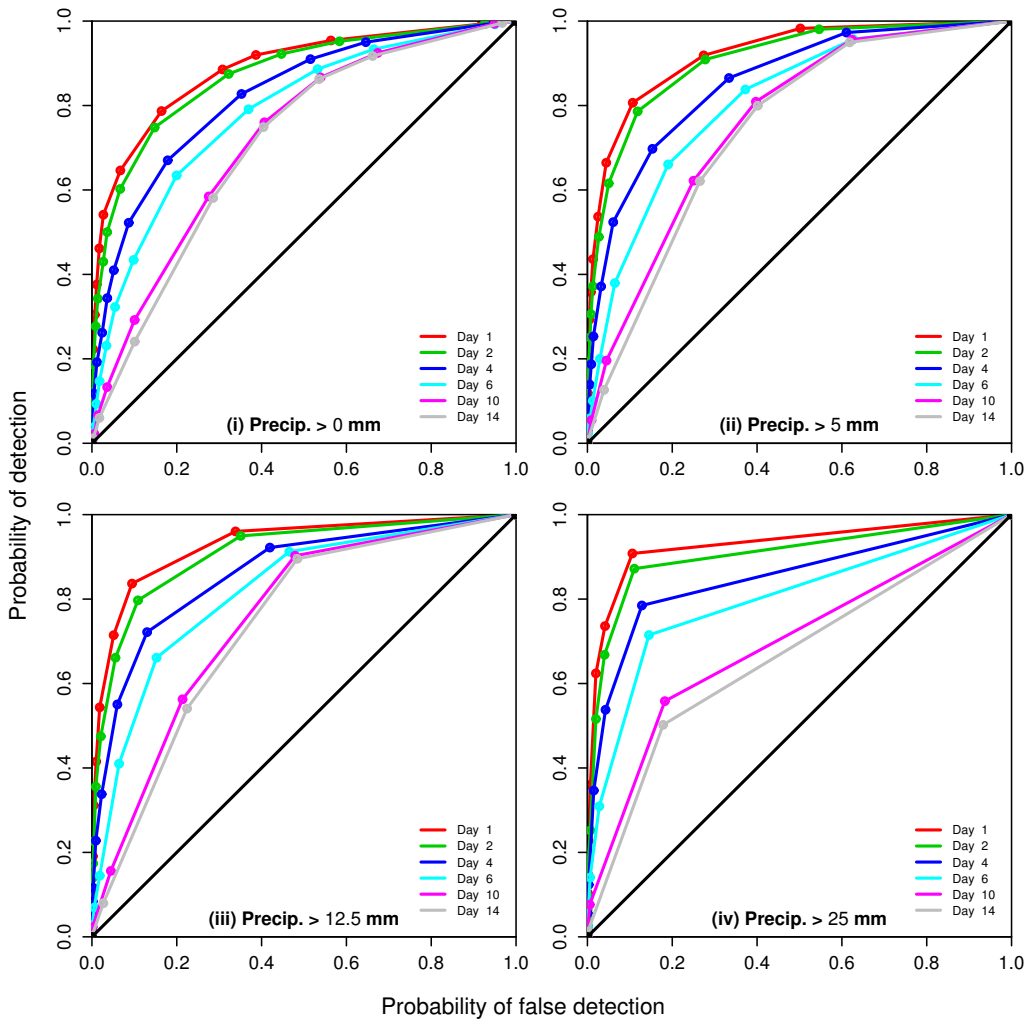


Fig. 17: Deterministic error statistics and $\overline{CRPS}$ for the EPP precipitation forecasts

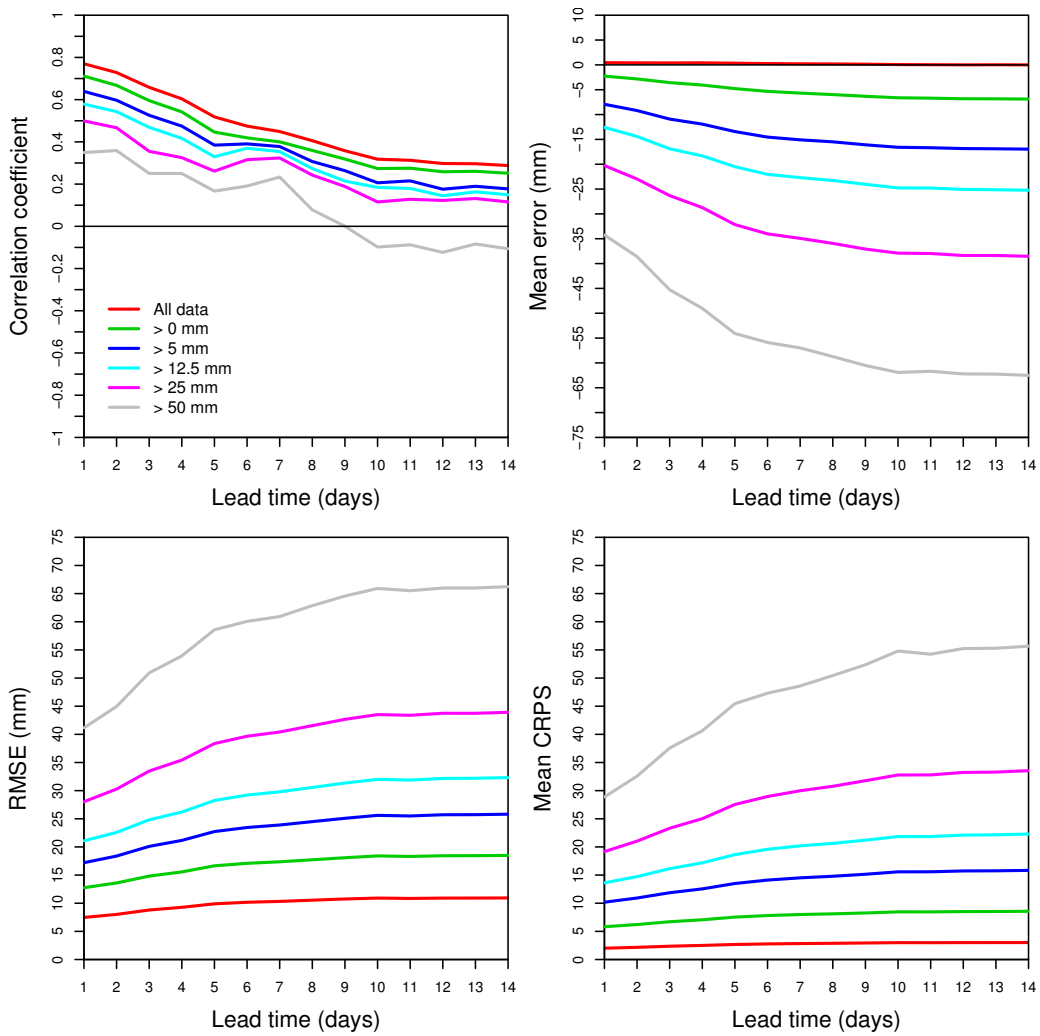
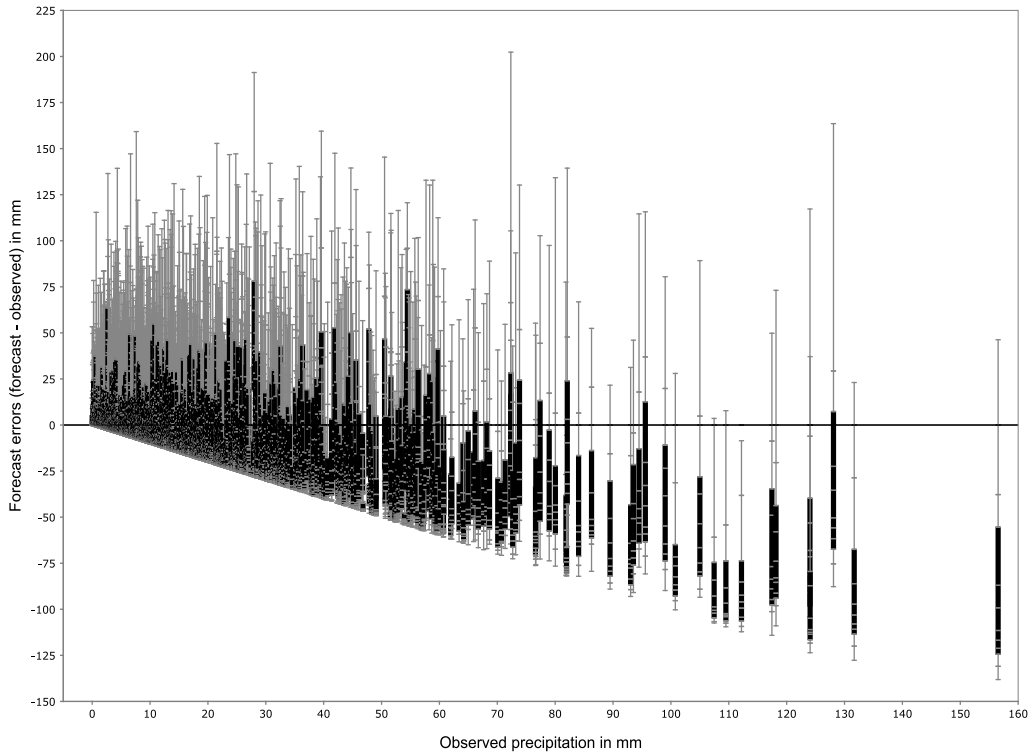


Fig. 17 shows the quality of the ensemble mean forecast in terms of mean error, RMSE and correlation with the observed amount, together with the $\overline{CRPS}$, which provides a lumped measure of error in the forecast probabilities. The statistics were computed for all forecast-observation pairs and for subsets whose observed values exceeded a threshold. As indicated in *Fig. 17*, there is a progressive decline in forecast quality with increasing lead time and observed precipitation amount, both in terms of the ensemble mean forecast (correlation coefficient, mean error, RMSE) and the overall forecast probabilities ($\overline{CRPS}$). The mean error is similar in magnitude to the RMSE, which suggests that much of the forecasting error at high precipitation thresholds stems from a conditional bias in the ensemble mean forecast. This is confirmed in the "modified box plots" of ensemble forecasting errors by observed

precipitation amount, which are shown in *Fig. 18* for lead day 1. Here, the forecasting errors (ensemble member – observed value) are plotted with box-and-whisker diagrams, where the whiskers are drawn at quantiles of the forecast error distribution (deciles in this case) and the middle quantiles are shaded (the middle six deciles in this case). The-box-and-whisker diagrams are then arranged by observed value in ascending order. The conditional bias in the ensemble mean forecast is readily apparent in *Fig. 18*, and shows over-forecasting of low precipitation amounts and under-forecasting of high amounts.

Fig. 18: Box plots for the EPP precipitation forecasts on lead day 1



7.2 Streamflow forecasts from the NWS Ensemble Streamflow Prediction system

Mean daily inflows were hindcast for a 17 year period between 1 January 1979 and 31 December 1996 at the North Fork Dam, California (NFDC1). The hindcasts were produced with the NWS Hydrologic Ensemble Hindcaster, which implements part of the NWSRFS in an ensemble framework, known as the Ensemble Streamflow Prediction (ESP) system (Demargne et al., 2007). The NWSRFS was forced with temperature and precipitation ensembles from the GFS-EPP (as described in *Section 7.1*). The streamflow hindcasts should only be considered illustrative of the EVS and not representative of the operational streamflow forecasts for NFDC1, which are forced with short-range QPF rather than the frozen GFS. These QPFs originate from the NWS Hydrometeorological Prediction Center and may be modified by the RFC forecasters to reflect the real-time streamflow conditions (a form of manual data-assimilation, known as run-time MODs). In general, the modified QPFs are much more skilful than the ensemble means of the frozen GFS. The hindcasts were aggregated from a six-hourly timestep to daily averages for comparison with the observed flows, which were only available as daily averages. The observed flows are based on stage observations, which were converted to flows using measured stage-discharge relations (Kennedy, 1983).

Fig. 19 shows the reliability of the forecasts at selected lead times. The results are shown for flow thresholds corresponding to climatological non-exceedence probabilities of 0.5 (10 $m^3 s^{-1}$), 0.75 (32 $m^3 s^{-1}$), 0.95 (85 $m^3 s^{-1}$) and 0.99 (210 $m^3 s^{-1}$). As indicated in *Fig. 19*, the forecast probabilities are reliable across a wide range of flow exceedence thresholds and lead times. However, they are slightly overconfident at moderately high flows, as evidenced by the higher forecast probabilities than observed relative frequencies. The forecasts are also consistently less reliable but sharper on lead day 1. This is understandable because the current version of the ESP system ignores uncertainties in the hydrologic model, including those in its initial conditions, structure and parameter values (Seo et al. 2006). Noise in the sharpness and reliability curves for streamflows that were forecast to exceed 210 $m^3 s^{-1}$ with high probability (0.8-1.0) reflects the small sample size and correspondingly high sampling uncertainty for such forecast events. *Fig. 20* shows the spread-bias plots for the ESP flow forecasts. These plots show the reliability of the forecast probabilities for all forecast-observation pairs and for subsets of pairs whose observed values exceed a probability threshold in the observed climatological

distribution. As indicated in *Fig. 20*, the forecasts are reasonably reliable across all flow exceedence thresholds and lead times, but tend to underpredict the observed streamflows at the highest flow threshold. *Fig. 21* shows the mean error of the ensemble mean forecast, the correlation of the ensemble mean flow with the observed flow, the ROC score, and the mean error of probability diagram (MEPD). While the forecasts are marginally well-calibrated (see the MEPD in *Fig. 21*), there is a loss of conditional reliability at the highest flow threshold across all forecast lead times (*Fig. 19*). This conditional bias originates from the conditional bias in the ensemble mean flow (*Fig 21.*). Overall, the conditional biases in the ESP streamflow forecasts (*Fig. 21*) are consistent with the conditional biases in the GFS-EPP precipitation forecasts (*Fig. 17*), which comprise over-forecasting of low precipitation amounts and under-forecasting of high amounts (*Fig. 18*).

Fig. 19: Reliability diagrams for the ESP forecasts

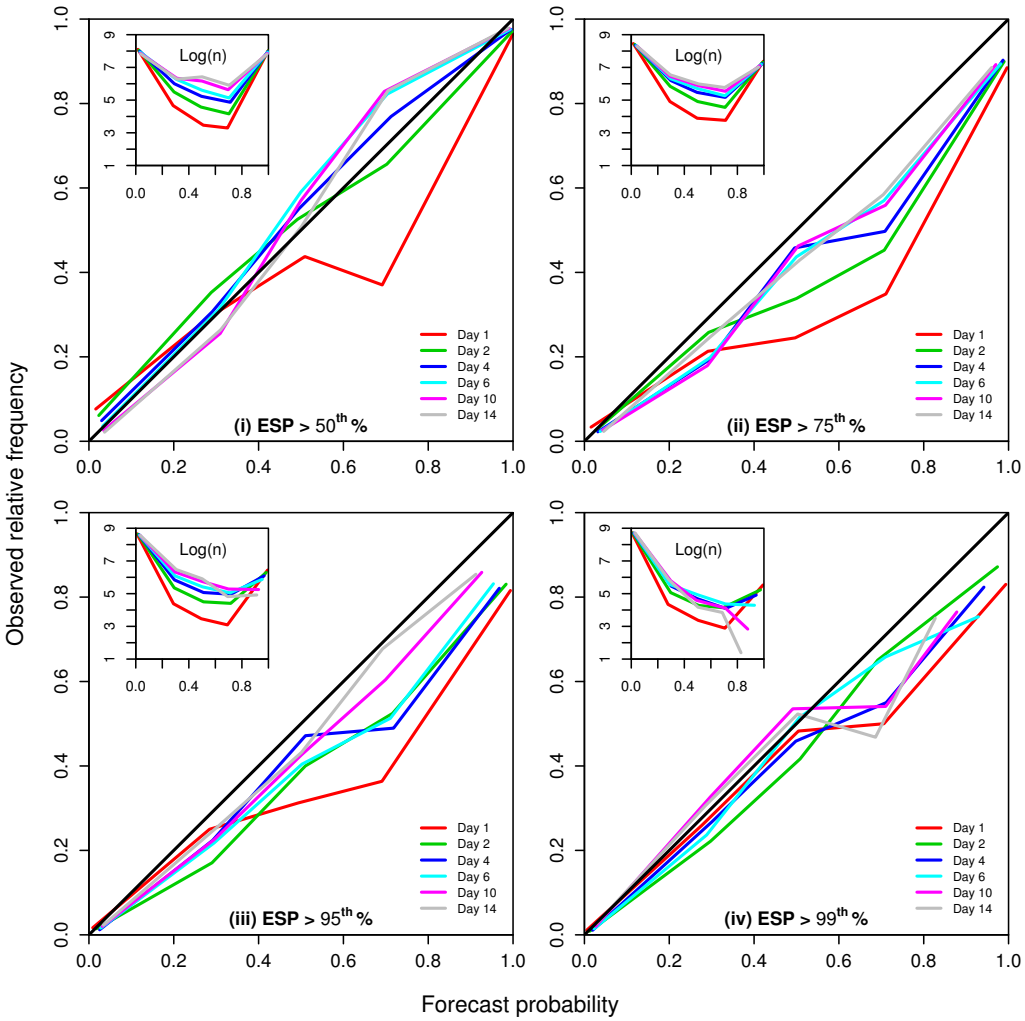


Fig. 20: Spread-bias plot for the ESP forecasts

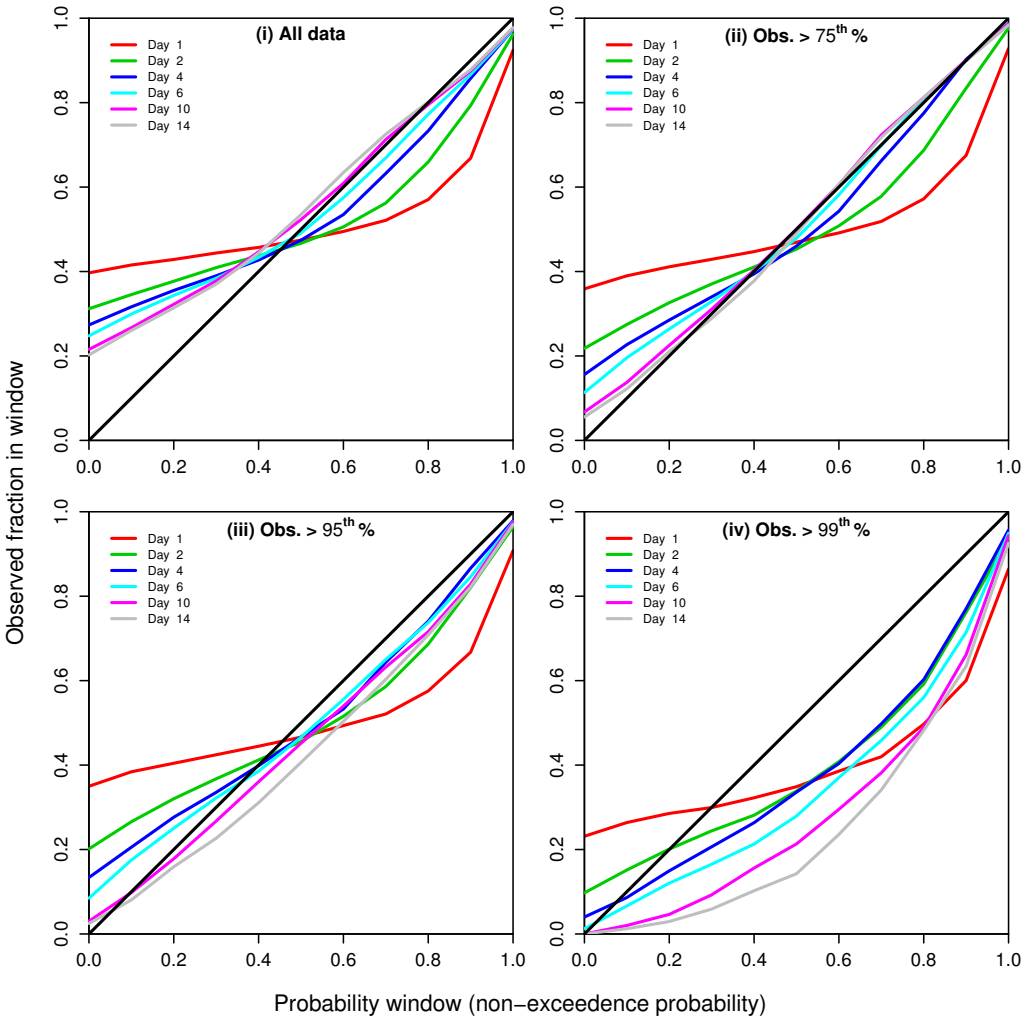


Fig. 21: Deterministic error statistics, ROC score and MEPD for the ESP forecasts

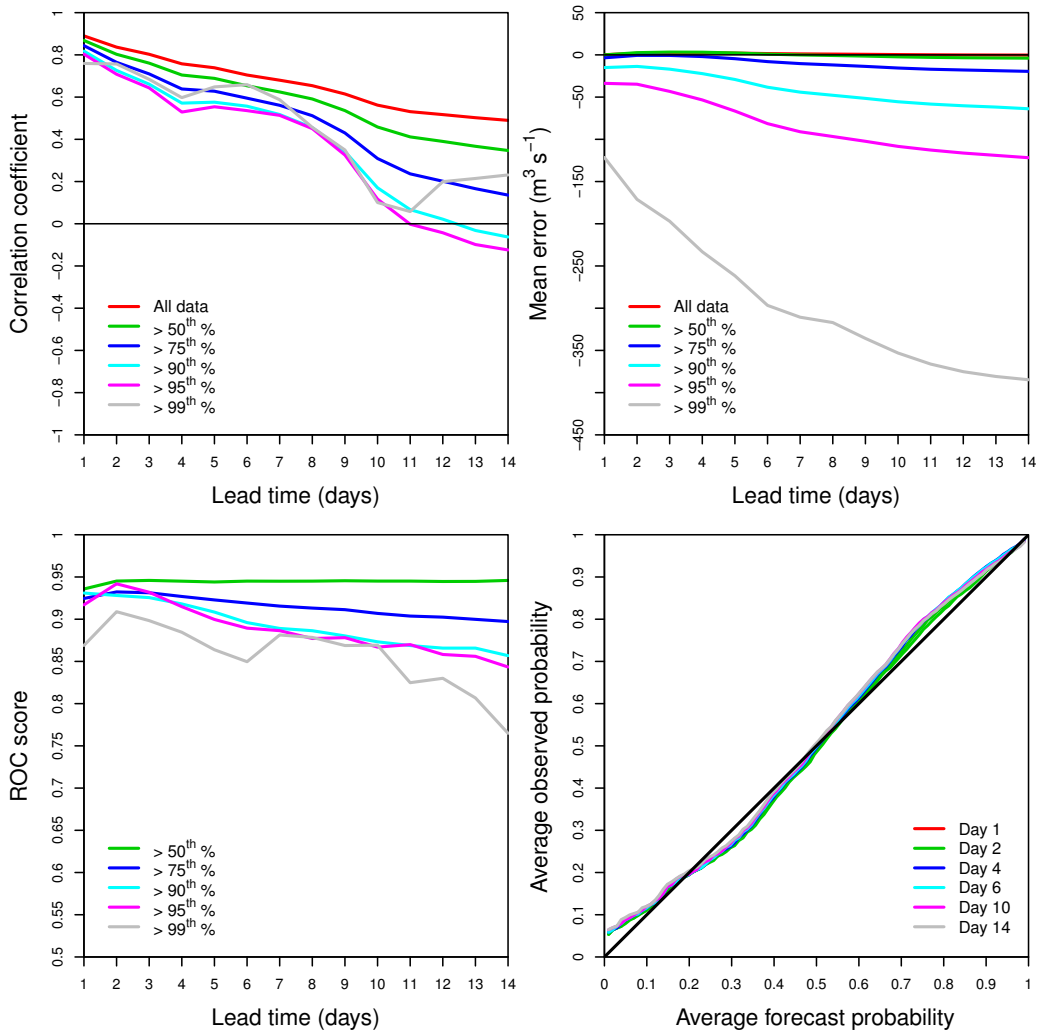


Fig. 22 shows the ROC curves for mean daily flows that correspond to climatological non-exceedence probabilities of 0.5, 0.75, 0.95 and 0.99. In comparison to the precipitation hindcasts, there is more consistent decline in discrimination with increasing forecast lead time and event threshold. Also, the flow forecasts are substantially more skillful than the climatological probability forecast for all forecast lead times and event thresholds. The MCRDs in *Fig. 23* show a rapid increase in the mean error of any given ensemble member over lead times of 1 and 2 days and a much slower decline in forecast quality over lead times of 4 to 14 days.

Fig. 22: Empirical ROC curves for the ESP flow forecasts

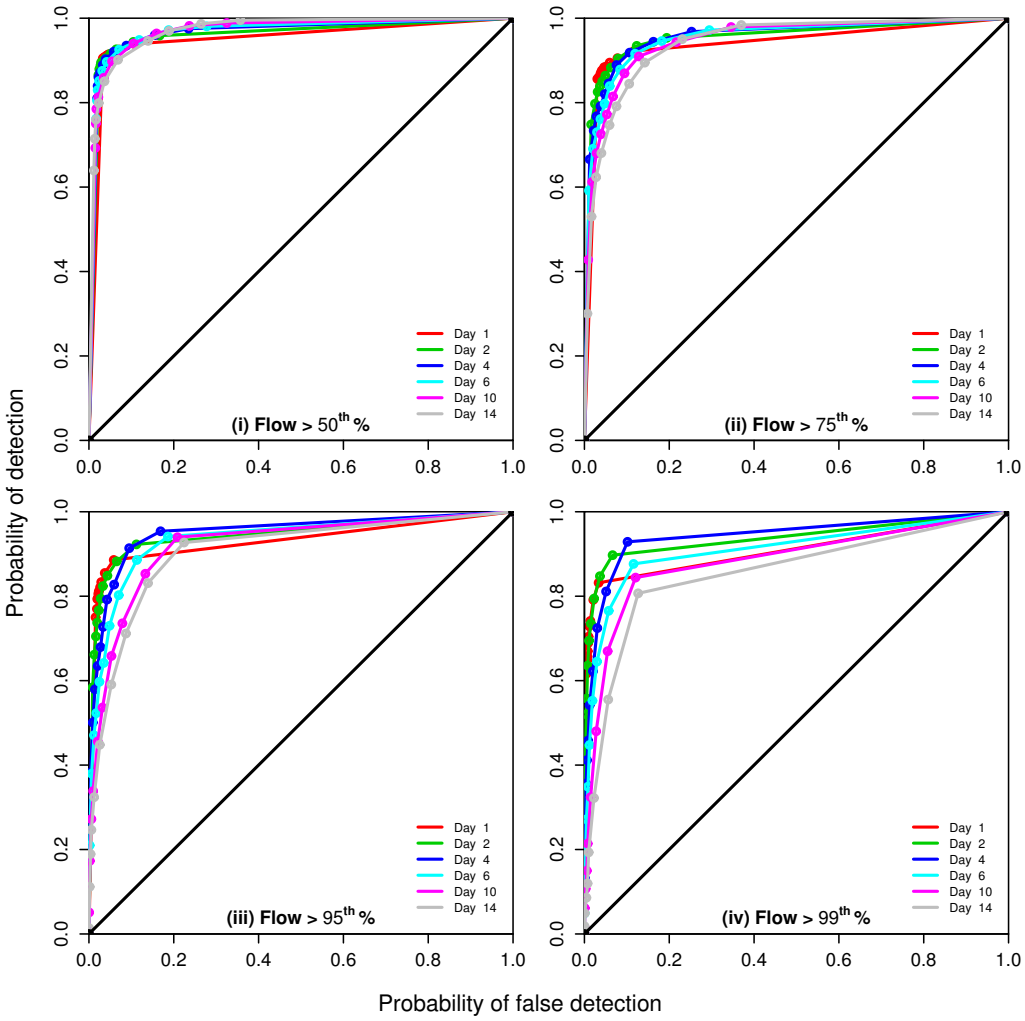
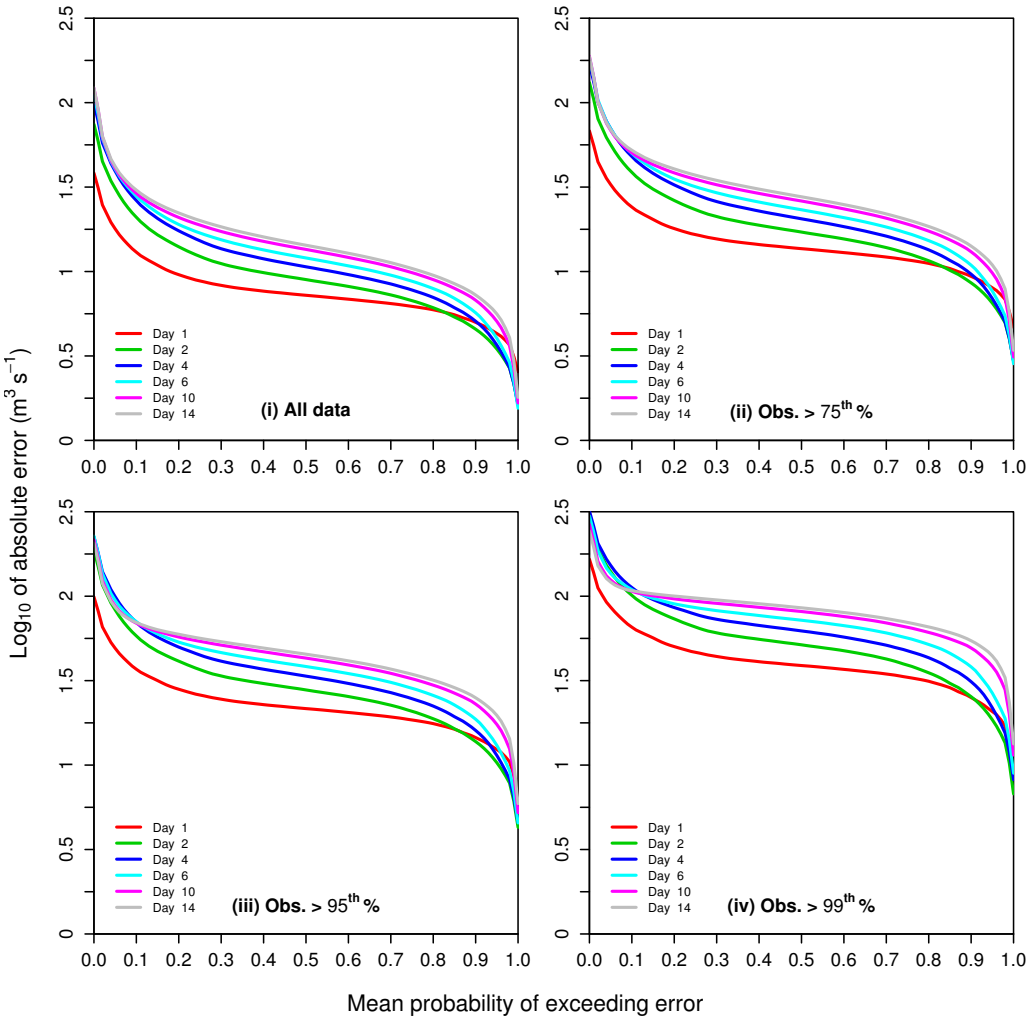


Fig. 23: Mean Capture Rate Diagrams for the ESP flow forecasts



8. THE APPLICATION PROGRAMMERS INTERFACE (API)

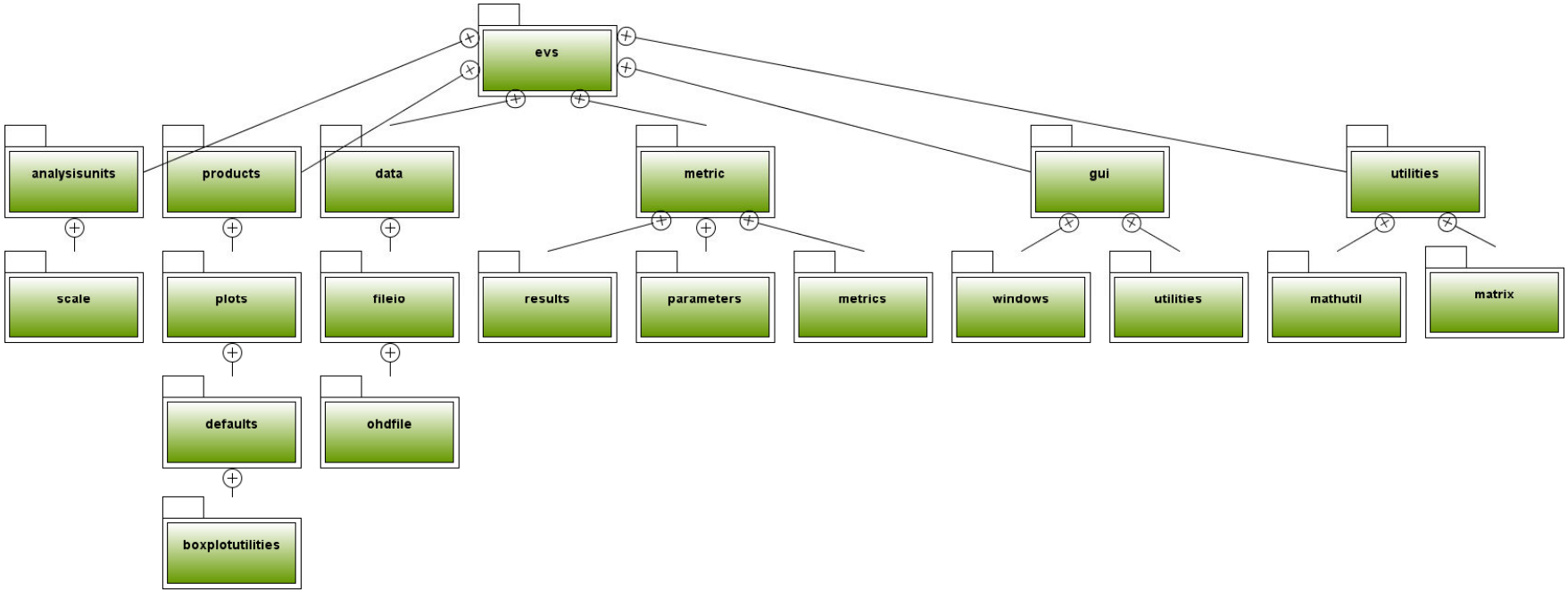
8.1 Overview

This section provides a brief overview of the API for the EVS and the procedure for adding a new verification metric. Detailed documentation of the code is provided in the hyperlinked html documentation that accompanies the software distribution. Developers may contact the authors for additional information about the source code (development support is not provided).

The EVS is written in Java, which is a simple, object-oriented, programming language (Flanagan, 2005). The Java platform comprises the language itself, a library of classes, and a Virtual Machine (VM), which runs on a specific operating system (OS). The VM allows for the "platform-independence" of Java applications, such as the EVS. A popular class library and one set of VMs are implemented by Sun Microsystems as the Java Runtime Environment (JRE). The EVS requires the JRE for execution (version 1.6 or higher), which is freely available from the Sun website for Java (http://java.sun.com/).

In object-oriented programming, the source code is separated into *classes*, each of which provides the blueprint for a particular *object*. For example, a class that computes the BS for a verification dataset, *a*, at an event threshold, *b*, provides the template for a BrierScore object with specific values of *a* and *b*. A class also contains methods, which determine the behavior of an object. For example, the BrierScore class contains the method getThreshold(), which returns the event threshold associated with a particular BrierScore object. Similarities among objects are exploited by linking classes together. This leads to a family tree in which children inherit and extend the functionality of their parents. For example, the BrierScore class inherits the functionalities of the EnsembleMetric, ScoreMetric, and ThresholdMetric classes. Groups of classes that have similar functions are stored in packages. For example, the BrierScore class is stored in the metrics package. The EVS comprises ~40,000 lines of code, which are separated into in 224 classes and stored in a hierarchy of 29 packages. *Fig. 24* shows the main package hierarchy in the EVS using UML. The API is fully documented in hyperlinked HTML, and the code itself is extensively commented (~25,000 lines).

Fig. 24: A UML description of the package heirachy in the EVS



8.2 Procedure for adding a new metric to the EVS

Due to its modular design, the procedure for adding a new metric to the EVS is tightly structured and requires little code development (beyond that required for the metric calculation). Indeed, much of the code required to implement a new metric in the EVS is dictated by, or already implemented in, a more general class of metric. This is illustrated by adding the logarithmic scoring rule or 'Ignorance Score' to the EVS. The Ignorance Score measures the quality of a probabilistic forecasting system with a numeric score (Good, 1952). A new metric, IgnoranceScore, is created in the package metrics and instructed to inherit from two general classes of which the IgnoranceScore is a specific case, EnsembleMetric and ScoreMetric. In order to satisfy the requirements of being an EnsembleMetric and a ScoreMetric, it is forced to implement several methods, including:

- getID(), returns a unique identifier for the metric [one line of code];

- getResultID(), returns an identifier from the list of identifiers in the MetricResult class that indicates the data type of the result [one line of code];

- deepCopy(), returns an independent copy of the metric object. Changes to the parameter values of the copied object are not reflected in the original object [approximately three lines of code, for which a template can be found in similar metrics, such as the BS].

- compute(), computes the metric for each forecast lead time and stores the result [several lines of code].

In order to display the Ignorance Score in the EVS, a default plot must also be created. By adding a class to the plots.defaults package (e.g. IgnoranceScorePlot) and associating the plot with the IgnoranceScore class, the Ignorance Score will be plotted in the EVS. The IgnoranceScorePlot extends the class DefaultXYPlotByLeadTime to plot the Ignorance Score by forecast lead time. A single method, getDefaultChart(), is then implemented to return an IgnoranceScorePlot with the correct y-axis dimension for the Ignorance Score (0-1), and any other information specific to the plotting of this score (e.g. axis and chart titles) [approximately five lines of code]. The plots themselves are created with the JFreeChart library (available from www.jfree.org/jfreechart/). Once the

IgnoranceScorePlot is associated with the results from an IgnoranceScore, the new metric can be displayed in the Output dialog of the EVS (*Section 5.5*). Descriptive information about the Ignorance Score can also be displayed in the GUI. This is achieved by setting the descriptionURL parameter of the IgnoranceScore class (which was inherited from the Metric class via EnsembleMetric) to the URL of a stable resource with descriptive information. For example, it may point to an html file in the statsexplained package, which contains descriptive information for the other metrics in the EVS.

APPENDIX A1 VERIFICATION STATISTICS COMPUTED IN THE EVS

Table 3 provides a list of the verification metrics supported by the EVS. Below is a short description of each metric, which is also available in the GUI.

Deterministic metrics for the ensemble mean forecast

Mean error

The mean error (ME) measures the average difference between a set of forecasts and corresponding observations. Here, it measures the average difference between the center of the ensemble forecast (the mean average, by default) and observation.

The ME of the ensemble average forecast, $\overline{Y}$, given the observation, x, is:

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{Y}_i\right) \tag{A1}$$

The ME provides a measure of first-order bias in the forecasts, and may be positive, zero, or negative. A positive mean error denotes overforecasting and a negative mean error denotes underforecasting. A mean error of zero (in the ensemble mean forecast) denotes an absence of bias.

Mean absolute error

The mean absolute error (MAE) measures the mean absolute difference between a set of forecasts and corresponding observations. Here, it measures the mean absolute difference between the center of the ensemble forecast (the mean average, by default) and the observation.

The MAE of the ensemble mean forecast, $\overline{Y}$, given the observation, x, is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - \overline{Y}_i\right| \tag{A2}$$

The MAE provides a measure of error spread in the center of the forecast distribution. It is similar to the Root Mean Square Error (RMSE), except the RMSE

employs square deviations, such that large errors contribution proportionally more to the overall score. The MAE generalizes to the Continuous Ranked Probability Score (CRPS) for ensemble or probability forecasts.

Root mean square error

The mean square error (MSE) measures the average square error of the forecasts. The Root Mean Square Error (RMSE) provides the square root of this value, which has the same units as the forecasts and observations. Here, the forecast corresponds to the ensemble average value (the mean, by default) and an 'error' represents the difference between the ensemble average, $\overline{Y}$, and the observation, x. The equation for the RMSE is:

$$\mathrm{RMSE} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(x_i - \overline{Y}_i \right)^2 \right]^{0.5} \qquad \text{(A3)}$$

The RMSE provides an indication of the ‘average deviation’ between the forecast value and an observation in real units. The RMSE is either zero, denoting a perfect forecast, or positive.

Correlation coefficient

The correlation coefficient measures the strength of linear association between two variables. Here, it measures the linear relationship between n pairs of ensemble average forecasts and corresponding observations. A correlation coefficient of 1.0 denotes a perfect linear relationship between the forecasts and observations. A correlation coefficient of -1.0 denotes a perfect inverse linear relationship (i.e. the observed values increase when the forecasts values decline and vice versa). The ensemble average forecast may be perfectly correlated with the observations and still contain biases, because the correlation coefficient is normalized by the overall mean of each variable. A correlation coefficient of 0.0 denotes the absence of any linear association between the forecasts and observations. However, a low correlation coefficient may occur in the presence of a strong non-linear relationship, because the correlation coefficient measures linear association only.

EVS computes the Pearson product-moment correlation coefficient, r, which is given by

$$r = \frac{\mathrm{Cov}(x, \bar{Y})}{\mathrm{Std}(x) \cdot \mathrm{Std}(\bar{Y})} \tag{A4}$$

where $\mathrm{Cov}(x, \bar{Y})$ is the sample covariance between the ensemble average forecasts and their corresponding observations. The sample standard deviations of the forecasts and observations are denoted $\mathrm{Std}(\bar{Y})$ and $\mathrm{Std}(x)$, respectively. The sample covariance between the n pairs of forecasts and observations is

$$\mathrm{Cov}(x, \bar{Y}) = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu_x)(\bar{Y}_i - \mu_{\bar{Y}}) \tag{A5}$$

where $\mu_{\bar{Y}}$ and μ_x are the overall sample means of the (ensemble average) forecasts and observations, respectively.

<u>Brier Score</u>

The Brier Score (BS) measures the average square error of a probability forecast. It is analogous to the mean square error of a deterministic forecast, but the forecasts, and hence error units, are given in probabilities. The Brier Score measures the error with which a discrete event, such as 'flooding', is predicted. For continuous forecasts, such as the amount of water flowing through a river, one or more discrete events must be defined from the continuous forecasts. There are several ways in which an event may be defined, depending on the verification problem. For an event that involves not exceeding some threshold, t, the Brier Score is computed from the forecast probability, $F_Y(t)$, and the corresponding observed outcome, x, whose cumulative probability is 1 if t is exceeded by the observation and 0 otherwise, as defined by the step function, $\mathbf{1}\{\cdot\}$

$$\mathrm{BS}(t) = \frac{1}{n} \sum_{i=1}^{n} \left(F_{Y_i}(t) - \mathbf{1}\{t \geq x_i\} \right)^2. \tag{A6}$$

A set of forecasts and observations of a binary event match exactly in terms of the BS if the mean square difference in the forecast probability and the corresponding (perfectly sharp) observed probability is zero. Optionally, the BS may be

decomposed into contributions due to (lack of) reliability, resolution and uncertainty, namely

$$\mathrm{BS} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncertainty}. \tag{A7}$$

Brier Skill Score

The Brier Skill Score (BSS) measures the performance of one forecasting system relative to another in terms of the Brier Score (BS). The BS measures the average square error of a probability forecast of a dichotomous event. The BSS comprises a ratio of the BS for the forecasting system to be evaluated (the "main forecasting system"), $\mathrm{BS}_{\mathrm{MAIN}}$, over the BS for the reference forecasting system, $\mathrm{BS}_{\mathrm{REF}}$

$$\mathrm{BSS} = 1 - \frac{\mathrm{BS}_{\mathrm{MAIN}}}{\mathrm{BS}_{\mathrm{REF}}}. \tag{A8}$$

As a measure of average square error in probability, values for the BS approaching zero are preferred. It follows that a BSS closer to 1 is preferred, as this indicates a low BS of the main forecasting system relative to the BS of the reference forecasting system. Unlike the BS, the BSS is not "strictly proper" (i.e. it can be hedged). Also, the BSS may behave erratically for forecasts of rare events because their errors of probability are necessarily small and their sampling uncertainties are likely high.

Mean Continuous Ranked Probability Score

The Continuous Ranked Probability Score (CRPS) summarizes the quality of a continuous probability forecast with a single number (a score). It measures the integrated square difference between the cumulative distribution function (cdf) of the forecast variable, $F_Y(y)$, and the corresponding cdf of the observed variable, $\mathbf{1}\{y \geq x\}$

$$\mathrm{CRPS} = \int_{-\infty}^{\infty} \left(F_Y(y) - \mathbf{1}\{y \geq x\} \right)^2 dy, \tag{A9}$$

where $\mathbf{1}\{y \geq x\}$ is a step function that assumes probability 1.0 for values greater than or equal to the observation, and 0.0 otherwise.

In practice, the CRPS is averaged across n of pairs of forecasts and observations, which leads to the mean CRPS

$$\overline{\mathrm{CRPS}} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{CRPS}_i. \tag{A10}$$

The numeric value of the mean CRPS will vary with application and is difficult to interpret in absolute terms (e.g. in terms of specific forecast errors). However, the CRPS has some desirable mathematical properties, including its insensitivity to hedging (i.e. the expected value of the score cannot be improved, *a priori*, by adopting a particular forecasting strategy). Other scores, such as the Probability Score of Wilson et al. (1999), may be hedged (in this case by issuing sharper forecasts).

Optionally, the mean CRPS may be decomposed into contributions due to (lack of) reliability, resolution and uncertainty (Hersbach, 2000), namely

$$\overline{\mathrm{CRPS}} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncertainty}. \tag{A11}$$

<u>Mean Continuous Ranked Probability Skill Score</u>

The mean Continuous Ranked Probability Skill Score ($\overline{\mathrm{CRPSS}}$) measures the performance of one forecasting system relative to another in terms of the mean Continuous Ranked Probability Score ($\overline{\mathrm{CRPS}}$). The $\overline{\mathrm{CRPS}}$ measures the average square error of a probability forecast across all possible event thresholds. The $\overline{\mathrm{CRPSS}}$ comprises a ratio of the $\overline{\mathrm{CRPS}}$ for the forecasting system to be evaluated (the "main forecasting system"), $\overline{\mathrm{CRPS}}_{\mathrm{MAIN}}$, and the $\overline{\mathrm{CRPS}}$ for a reference forecasting system, $\overline{\mathrm{CRPS}}_{\mathrm{REF}}$

$$\overline{\mathrm{CRPSS}} = \frac{\overline{\mathrm{CRPS}}_{\mathrm{REF}} - \overline{\mathrm{CRPS}}_{\mathrm{MAIN}}}{\overline{\mathrm{CRPS}}_{\mathrm{REF}}}. \tag{A12}$$

As a measure of average square error in probability, values for the $\overline{\mathrm{CRPS}}$ approaching zero are preferred. It follows that a $\overline{\mathrm{CRPSS}}$ closer to 1 is preferred, as this indicates a low $\overline{\mathrm{CRPS}}$ of the main forecasting system relative to the $\overline{\mathrm{CRPS}}$ of

the reference forecasting system. Unlike the $\overline{\mathrm{CRPS}}$, the $\overline{\mathrm{CRPSS}}$ is not "strictly proper" (i.e. it can be hedged). Also, the $\overline{\mathrm{CRPSS}}$ may behave erratically for forecasts of rare events because their errors of probability are necessarily small and their sampling uncertainties are likely high.

Mean Capture Rate

A key aspect of forecast quality is the probability of making a given error in real terms. The Probability Score (PS) of Wilson et al. (1999) is useful here because it identifies the probability with which a given, real-valued, error is exceeded. The PS is defined for a symmetric window, w, around the observation, x

$$\mathrm{PS}(w) = \int_{x-0.5w}^{x+0.5w} f_Y(y)dy. \tag{A13}$$

It conveys the extent to which an observation is captured by the forecast, where a high probability implies greater forecast performance. The disadvantages of the PS include its subjectivity and sensitivity to hedging, whereby the expected value of the PS is maximized for sharp forecasts.

By averaging the PS over a set of n ensemble forecasts and repeating for all possible windows, w, the probability of exceeding a given acceptable error can be determined and is referred to as the Mean Capture Rate (MCR)

$$\mathrm{MCR}(w) = \frac{1}{n}\sum_{i=1}^{n} 1 - \mathrm{PS}(w) \quad \forall w \in \mathbb{R} \tag{A14}$$

It should be noted that sensitivity to hedging does not apply to the MCR, as it is not a score. The resulting curve may be separated into errors of over-prediction and under-prediction by computing the MCR for ensemble members that exceed the observation and fall below the observation, respectively.

Modified box plots

Box plots (or box-and-whisker diagrams) provide a discrete representation of a continuous empirical probability distribution (Tukey, 1977).

Building on this idea, an empirical probability distribution function (pdf) may be summarized with an arbitrary set of percentile bins of which an arbitrary proportion may be shaded (e.g. the middle 60%), to convey the outer and inner probability densities, respectively. The modified box plots show the forecasting errors (ensemble member – observed value) by forecast lead time. Forecasts with common lead times are pooled before computing the errors and displaying them as a box.

Modified box plots by observed value

Constructs a set of modified boxes and organizes each box by the size of the corresponding observed value (from which the forecast errors were computed). If more than one forecast has the same observed value, the errors associated with those boxes are pooled and displayed in a single box (with a larger sample size).

Reliability diagram

The reliability diagram measures the accuracy with which a discrete event is forecast by an ensemble or probabilistic forecasting system. The discrete event may be defined in several ways. For example, flooding is a discrete event that involves the exceedence of a flow threshold. According to the reliability diagram, an event should be observed to occur with the same relative frequency as its forecast probability of occurrence over a large number of such forecast-observation pairs. For example, over a large number of cases where flooding is forecast to occur with a probability of 0.95, it should be observed to occur roughly 95% of the time. However, the calculation of the observed relative frequency is subject to sampling uncertainty. For example, their may be few cases in the historic record where flooding is forecast to occur with probability 0.95. In practice, the forecasts are binned into discrete probability intervals and the observed relative frequencies are plotted against the average forecast probability within each bin. The sampling uncertainty will decline as the width of the bin increases, but the precision of the diagram will also decline.

The Reliability diagram plots the average forecast probability within each bin on the x-axis. For a forecast event defined by the non-exceedence of some threshold, t, the average probability of the forecasts that fall in the kth forecast bin, B_k is given by

$$\frac{1}{\#I_k}\sum_{i\in I_k} F_{Y_i}(t), \tag{A15}$$

where I_k denotes the set of all indices, $I_k = \{i : i \in B_k\}$, whose forecasts (and associated paired observations) fall in the kth bin and $\#I_k$ denotes the number of elements in that set. The y-axis shows the corresponding fraction of observations that fall in the kth bin

$$\frac{1}{\#I_k}\sum_{i\in I_k} \mathbf{1}\{t \geq x_i\}, \tag{A16}$$

where $\mathbf{1}\{t \geq x_i\}$ is a step function that assumes value 1 if the ith observation, x_i, exceeds the threshold, t, and 0 otherwise. If the forecast is perfectly reliable, the observed fraction within each bin will equal the average of the associated forecast probabilities, forming a diagonal line on the reliability diagram. Deviation from the diagonal line represents bias in the forecast probabilities, notwithstanding sampling uncertainty. The reliability diagram may be computed for several discrete events. Each event is represented by a separate reliability curve.

The number of forecasts that fall in the kth bin, $\#I_k$, is referred to as the 'sharpness' of the forecasts and is displayed as a histogram for each of the forecast bins. Ideally, the forecast probabilities will be sharp, i.e. issued with little uncertainty, but also reliable.

Relative Operating Characteristic

The Relative Operating Characteristic (ROC; also known as the Receiver Operating Characteristic) measures the quality of a forecast for the occurrence of a discrete event, such as rainfall or flooding. For a probability forecast, the ROC curve measures the quality of a binary prediction or “decision” based on the forecast probability. A binary prediction is generated from the forecast by defining a probability threshold above which the discrete event is considered to occur. For example, a decision maker might issue a flood warning when the forecast probability of a flood exceeds 0.9. The ROC curve plots the forecast quality for several probability thresholds. Each threshold corresponds to a different level of risk aversion. For example, given a decision on whether to issue a flood warning, a probability

threshold of 0.7 corresponds to a higher level of risk aversion (i.e. a lower threshold for warning) than a probability of 0.9. As the threshold declines, the probability of correctly detecting an event (the Probability of Detection or POD) will increase, but the probably of “crying wolf” (the probability of False Detection or POFD) will also increase. The ROC curve plots the trade off between POD and POFD on two axes:

- Y-axis: the POD or probability with which an event is correctly forecast to occur. The POD is estimated from n sample data as the total number of correct forecasts divided by the total number of occurrences. For an event defined by the exceedance of a real-valued threshold, t, which is forecast to occur when the forecast probability exceeds a probability threshold, p_t, the POD is given by

$$\mathrm{POD}(t, p_t) = \frac{\sum_{i=1}^{n} \mathbf{1}\{1 - F_{Y_i}(t) > p_t \mid x_i > t\}}{\sum_{i=1}^{n} \mathbf{1}\{x_i > t\}}, \qquad \text{(A17)}$$

  where $\mathbf{1}\{\cdot\}$ is a step function that assumes the value 1 if the condition, $\{\cdot\}$, is met and 0 otherwise.

- X-axis: the POFD or probability with which an event is incorrectly forecast to not occur (i.e. the event occurs, but the forecast was for non-occurrence). The POFD is estimated from n sample data as the total number of incorrect forecasts divided by the total number of non-occurrences

$$\mathrm{POFD}(t, p_t) = \frac{\sum_{i=1}^{n} \mathbf{1}\{1 - F_{Y_i}(t) > p_t \mid x_i \le t\}}{\sum_{i=1}^{n} \mathbf{1}\{x_i \le t\}}. \qquad \text{(A18)}$$

These values are computed for probability thresholds that exhaust the unit interval, which is normally defined by a number of plotting points, q, that separate the unit interval, [0,1], into q thresholds at equal intervals. Additionally, the curve is forced to intersect (0,0), and (1,1).

For an ensemble forecasting system to perform well in terms of ROC, the POD must be high relative to the POFD. An ensemble forecasting system that produces forecasts in line with climatological expectation will have as many "successful"

predictions as the climatological probability of the event implies. A skillful forecasting system will always produce a ROC curve that lies above the diagonal line.

Practical applications of the ROC in the medical, atmospheric, and other sciences frequently fit a smooth curve to the empirical POD and POFD data. A common approach is to fit a binormal model, which assumes that the POD and POFD are normally distributed, each with given mean and variance (standard deviation). Experience has shown that the binormal model typically provides a good fit to the empirical POD and POFD, even when they are "significantly" non-normal (i.e. the binormal approximation is robust). The binormal model is given by

$$\begin{aligned} &\mathrm{POD} = \Phi(a + b\Phi^{-1}(\mathrm{POFD})) \quad \text{where} \\ &a = \frac{\mu_{\mathrm{POD}} - \mu_{\mathrm{POFD}}}{\sigma_{\mathrm{POD}}} \quad \text{and} \\ &b = \frac{\sigma_{\mathrm{POFD}}}{\sigma_{\mathrm{POD}}}. \end{aligned} \tag{A19}$$

Here, Φ is the cumulative distribution function of the standard normal distribution, μ_{POD} and μ_{POFD} are, respectively, the means of the POD and POFD, and σ_{POD} and σ_{POFD} are their corresponding standard deviations.

There are several approaches to estimating the parameters of the binormal model, a and b (or the means and standard deviations from which they are derived; for example, see Cai and Moskowitz, 2004). The simplest and most direct approach stems from the observation that

$$\Phi^{-1}(\mathrm{POD}) = a + b\Phi^{-1}(\mathrm{POFD}). \tag{A20}$$

Hence, the parameters, a and b, are the intercept and slope, respectively, of a linear (regression) relationship between the POD and POFD *following* their transformation to the probit scale. The EVS estimates these parameters through ordinary least squares regression. While the resulting model fit is mathematically correct, the standard errors of the model (or confidence intervals for the associated ROC Score) cannot be computed in this way, and are not reported by the EVS. Since the parameters of the binormal model are estimated from the empirical POD and POFD,

the model fit will depend on the number of probability thresholds used to compute the ROC curve. The number of thresholds cannot (usefully) exceed the number of ensemble members, m, (or m+1 thresholds) from which the POD and POFD are derived, as the ensemble forecast only contains information at these thresholds (members). However, the binormal curve is plotted for a large number of points in between these thresholds, in order to convey the smoothness of the fitted model.

The ROC Score is derived from the Area Under the Curve (AUC), and is an analytical function of the binormal model parameters

$$\mathrm{AUC} = \Phi\left(\frac{a}{\sqrt{1+b^2}}\right). \tag{A21}$$

Upon request, the binormal approximation to the ROC Score is also provided by the EVS. Since the model fit depends on the number of thresholds used to compute the ROC curve, the number of thresholds must be defined when computing the binormal approximation to the ROC Score. For an exact comparison between the binormal ROC curve and the binormal ROC Score (or AUC), the same number of thresholds, q, must be used for each metric.

Relative Operating Characteristic Score

The Relative Operating Characteristic (also known as the Receiver Operating Characteristic) measures the quality of a forecast for the occurrence of a discrete event, such as rainfall or flooding. It does not consider the quality of forecasts that predict no occurrence of the event defined (e.g. no rainfall or no flooding).

The ROC Score is based on the area underneath the ROC curve or AUC (Mason and Graham, 2002). The climatological probability forecast (i.e. an unskilled forecast) has an AUC of 0.5, which corresponds to the diagonal line in the ROC plot. The ROC Score rescales the AUC so that the climatological probability forecast has a score of 0 and a perfect forecast has a ROC Score of 1

$$\mathrm{ROC\,score} = \left(2 \cdot \mathrm{AUC}\right) - 1. \tag{A22}$$

As discussed under the Relative Operating Characteristic, practical applications of ROC analysis in the medical, atmospheric, and other sciences frequently fit a smooth curve to the paired values of the Probability of Detection (POD) and Probability of False Detection (POFD) derived from the sample data. A common approach is to fit a binormal model, which assumes that the POD and POFD are normally distributed, each with given mean and variance (standard deviation). Experience has shown that the binormal model typically provides a good fit to the empirical POD and POFD, even when the sample data are "significantly" non-normal (i.e. the binormal approximation is robust). The binormal approximation to the AUC (and hence the ROC Score) is given by

$$\mathrm{AUC} = \Phi\left(\frac{a}{\sqrt{1+b^2}}\right). \tag{A23}$$

Here, a and b are the parameters of the binormal model, and Φ is the cumulative distribution function of the standard normal distribution. The parameters a and b are, respectively, the intercept and slope of the (assumed) linear relationship between the POD and POFD *following* their transformation to the probit scale (see the discussion under the Relative Operating Characteristic). Unlike the empirical AUC (Mason and Graham, 2002), which bypasses the calculation of the ROC curve, the binormal approximation to the AUC (and ROC Score) is based on the q pairs of (POD, POFD) data from which the empirical ROC curve is computed (where q is the number of probability thresholds). Thus, for an exact comparison between the binormal ROC curve and the binormal ROC Score, the same number of thresholds, q, must be used for each metric. However, the binormal ROC Score will be closest to the empirical ROC Score when the ROC curve is constructed from m+1 probability thresholds, where m is the (fixed) number of ensemble members in each forecast. Put differently, the empirical AUC, described by Mason and Graham (2002), approximates the area under the ROC curve when constructed with as many probability thresholds as the (fixed) number of ensemble members in each forecast.

<u>Spread-bias diagram</u>

For continuous random variables, such as temperature and streamflow, the SBD provides a simple measure of conditional reliability. It involves counting the fraction

of observations, $\mathrm{SBD(I)}$, that fall within an interval of fixed width on the support of the ith forecast, $\mathrm{I} = [\mathrm{c}, \mathrm{d} \mid \mathrm{c}, \mathrm{d} \in [0,1]]$

$$\mathrm{SBD(I)} = \frac{1}{n} \sum_{i=1}^{n} 1\{\hat{F}_{m_i}(x_i^o) \in I\}. \tag{A24}$$

An ensemble forecasting system is reliable over the interval, I, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty} \left\{ \frac{1}{n} \sum_{i=1}^{n} 1\{\hat{F}_{m_i}(x_i^o) \in I\} \right\} = d - c. \tag{A25}$$

By defining k windows on the unit interval, $\left\{ I_j = [c_j, d_j] \mid c_j, d_j \in [0,1]; j = 1, ..., k \right\}$, the reliability can be determined for the entire range of forecast probabilities. In practice, the k windows may cover any subintervals of the unit interval. Certain windows may be preferred for some applications or for sampling reasons. For example, if the forecasts are uncertain in the tails, windows centered on the forecast median may be preferred. The SBD shows the observed frequency, $\mathrm{SBD(I)}$, against the expected frequency, $\mathrm{d\text{-}c}$. Any deviation from the diagonal line represents a lack of reliability in the forecast probabilities. More specifically, the ensemble forecasts are unreliable if the observed frequency, $\mathrm{SBD(I)}$, deviates from the expected frequency by more than the sampling uncertainty of $\mathrm{SBD(I)}$. If the k windows each cover a probability interval of $1/\mathrm{k}$, the expected frequency has a uniform probability distribution, and the actual reliability can be tested for its goodness-of-fit to a uniform distribution (e.g. using the one-sided Cramer von Mises test; Anderson, 1962; Elmore, 2005; Bröcker, 2008).

For continuous random variables, the expected $\mathrm{SBD(I)}$ is equal to the width of the interval, I, and is, therefore, strictly increasing as the width increases (see above). However, for mixed random variables, such as precipitation and wind-speed, the discrete portion of the probability distribution comprises an infinite number of intervals of different width. Although the window definition could be adapted for this case (see Hamill and Colucci, 1997 for a similar discussion), the reliability diagram may be preferred for mixed random variables.

While the SBD is analogous to the cumulative rank histogram, it explicitly defines the width of the interval, I, into which observations fall. When these windows are based on non-exceedence probabilities and are uniform in width (as well as non-overlapping and exhaustive), the SBD is also analogous to the Probability Integral Transform (PIT) (Casella and Berger, 1990), although the latter involves fitting a parametric cdf to the ensemble forecast distribution prior to evaluating the PIT (Gneiting et al., 2005). In that case, the SBD, the cumulative rank histogram and the PIT can also be summarized with the reliability component of the $\overline{\mathrm{CRPS}}$ (Hersbach, 2000), which tests whether an observation falls below a threshold with a frequency proportional to the cumulative probability of that threshold (averaged across all thresholds).

<u>Mean error of probability diagram</u>

The mean error of probability diagram (MEPD) measures the reliability of an ensemble forecasting system in an unconditional sense. Let z_{ij} denote the jth of m ensemble members from the ith of n ensemble forecasts and let x_i^o denote the observed outcome associated with the ith ensemble forecast. The forecast climatology has an empirical distribution function, $\hat{F}_{nm}(v)$, which is computed from the n ensemble forecasts as

$$\hat{F}_{nm}(v) = \frac{1}{n}\sum_{i=1}^{n}\hat{F}_{m_i}(v) \quad \text{where} \quad \hat{F}_{m_i}(v) = \frac{1}{m}\sum_{j=1}^{m}1\{z_{ij} \le v\}, \tag{A26}$$

and $\mathbf{1}\{\cdot\}$ is a step function that assumes value 1 if the condition is met and 0 otherwise. Let $H = [a, b \mid a, b \in [0,1]]$ denote an interval of fixed width on the support of $\hat{F}_{nm}(v)$. The MEPD counts the fraction of observations that fall within the interval, H, namely

$$\mathrm{MEPD}(H) = \frac{1}{n}\sum_{i=1}^{n}1\{\hat{F}_{nm}(x_i^o) \in H\}. \tag{A27}$$

An ensemble forecasting system is unconditionally reliable or marginally calibrated over the interval, H, if it captures observations in proportion to the width of that interval

$$\lim_{n,m\to\infty}\left\{\frac{1}{n}\sum_{i=1}^{n}1\{\hat{F}_{nm}(x_i^o)\in H\}\right\}=b-a. \tag{A28}$$

The MEPD shows $\mathrm{MEPD}(H)$ against the width of H for each of k windows that span the unit interval. In practice, the k windows may cover any subintervals of the unit interval. The MEPD is similar to the quantile-quantile (Q-Q) plot (Wilks, 2006) and the probability-probability (P-P) plot (Shorack and Wellner, 1986; Gneiting et al., 2007). The Q-Q plot compares the order statistics of two samples, or the order statistics of one sample against the values of a theoretical distribution at corresponding quantiles (Wilks, 2006). The P-P plot compares the quantiles corresponding to these order statistics. Indeed, the MEPD is equivalent to a P-P plot of the climatological distributions of X and Y when evaluated for the n intervals, $\left\{H_j=[0,b_j]\,|\,b_j=\frac{j}{n+1},j=1,...,n\right\}$. As indicated above, the MEPD assumes asymptotic convergence of $\mathrm{MEPD}(H)$ as $n\to\infty$. In practice, this may be evaluated by comparing the $\mathrm{MEPD}(H)$ for g subsamples of the n available data.

APPENDIX A2 XML OUTPUT FORMATS

EVS produces three types of XML file, namely: 1) project files, which store previously defined VUs and AUs; 2) paired data files, which store the paired forecasts and observations associated with a single VU; and 3) product files containing the numerical results for particular verification metrics.

Project files

Project files store all of the parameters required to close and restart EVS without loss of information. A project file is produced or updated by clicking "**Save**" or "**Save as…**" at any point during the operation of EVS. The data are stored in XML format and are, therefore, human readable, and may be produced separately from EVS (e.g. for batch calculations in the future).

The XML contains the following tags, in hierarchical order:

Level 1 (top level):

<verification> //Top level tag
<verification_unit> //Tag for a single verification unit (see *Level 2*)
<aggregation_unit> //Tag for a single aggregation unit (see *Level 3*)

Level 2 (verification unit, VU):

<verification_unit>
    <identifiers> //Identifiers for the VU (see *Level 2a*)
    <input_data> //Input data, including forecasts and observations (see *Level 2b*)
    <verification_window> //Verification window (see *Level 2c*)
    <output_data_location> //Path to output data folder
    <paired_data> //Paired data file [only when defined] (see *Level 2d*)
    <metrics> //Verification metrics selected (see *Level 2e*)

Level 2a (VU identifiers):

<identifiers> //Identifiers for the VU
    <location_id> //Identifier for the forecast point
    <environmental_variable_id> //Variable id (e.g. streamflow)
    <additional_id> // Additional id (e.g. forecast_model_1) [only when defined]

Level 2b (VU input data sources):

```
<input_data>  //Identifiers for the VU
    <forecast_data_location>  //Forecast data
        <file>  //Path to first file/folder (e.g. first file in a file array or a folder)
        <file>  //Path to second file in a file array [only when defined]
        <file>  //Etc.
        …
    <observed_data_location>   //Path to observed data file
    <forecast_time_system>   //Name of forecast time system
    <observed_time_system>   //Observed time system]
    <forecast_support>  //Scale of forecasts
        <statistic> //E.g. “instantaneous”
        <period>  //E.g. “1” [only when defined: blank when statistic = instantaneous]
        <period_units>  //E.g. “DAY” [only when defined: as above]
        <existing_attribute_units> //E.g. “feet cubed/second”
        <target_attribute_units> //E.g. “meter cubed/second”
        <attribute_units_function>  //Multiplier to arrive at stated attribute units [1.0]
        <notes>   //Additional textual info. [only when defined]
    <observed_support>  //Scale of observations [see forecast_support]
```

Level 2c (verification window for a given VU):

```
<verification_window>  //Window parameters
    <start_date>  //Start date (in UTC)
        <year>  //Start year
        <month>  //Start month of year
        <day>  //Start day of month
    <end_date>   //See start date
    <forecast_lead_period>   //Maximum lead time considered
    <forecast_lead_units>   //Units for the maximum lead time
    <aggregation_lead_period> //Average X consec. leads U [only when defined]
    <aggregation_lead_units>   //Period units for averaging (U) [only when defined]
    <aggregation_function>   //Function used to aggregate pairs [only when defined]
    <sample_size_constraint>   //Constraint on minimum sample size per lead time
    <date_conditions>   //Date conditions (see Level 2c_1) [only when defined]
    <value_conditions>   //Value conditions (see Level 2c_2) [only when defined]
```

Level 2c_1 (date conditions on the verification window) [only when defined]:

```
<date_conditions>   //Date conditions
    <exclude_years>  //Integer years to exclude from the overall range
```

```
    <exclude_months>  //Integer months to exclude from the overall range
    <exclude_weeks>  //Integer weeks to exclude from the overall range
    <exclude_days_of_week>  //Integer days to exclude from the overall range
    <exclude_hours_of_day_UTC>  //Integer [0,23] to exclude UTC hours of day
```

Level 2c_2 (value conditions on the verification window) [only when defined]:

```
<value_conditions>   //Value conditions.
    <condition>  //First of n possible conditions
        <unit_id>  //Identifier of the VU on which the condition is built
        <forecast_type>  //True for forecasts, false for observed values
        <statistic>  //Name of statistic, e.g. mean
        <statistic_constant>  //Constant associated with statistic [only when defined]
        <consecutive_period> //Window size [only when defined]
        <consecutive_period_units> //Window time units [only when defined]
        <consecutive_period_statistic> //Window statistic [only when defined]
        <logical_conditions> //Set of n possible logical arguments
                <function>  //First logical argument
                        <name>  //Unary function name, e.g. isLessThan (<)
                        <value>   //Unary function threshold, e.g. 0.5 means "< 0.5"
                …
    …
```

Level 2d (paired data for a given VU) [only when defined]:

```
<paired_data>   //Start of paired data specification
    <paired_data_location>  //Path to paired data
    <eliminate_duplicates>  //Is true to eliminate pairs with the same valid/lead times
    <write_conditional_pairs>  //Is true to write the conditional pairs
    <paired_write_precision>  //Integer number of decimal places for writing pairs > 0
    <strip_nulls_from_paired_file>  //Is true to not write null member values
    …
```

Level 2e (verification metrics for a given VU):

```
<metrics>   //Set of n possible metrics to compute
    <metric>  //First of n metrics
        <name>  //Name of metric
        Storage of parameters follows: varies by metric
    …
```

Level 3 (aggregation unit, AU) [only when defined]:

<aggregation_unit> //Aggregation unit

<name> //The aggregation unit name

<unit_id> //First of n possible VU identifiers associated with the aggregation unit

…

<weights> //Weights to assign to each of the n units identified above [sum to 1]

<output_data_location> //Path to where output data should be written for the AU

<pool_pairs> //Is true to pool pairs from the VUs rather than average metrics

An example of a full EVS project file is given below:


```
<?xml version="1.0" standalone="yes"?>
<verification>
<verification_unit>
	<identifiers>
		<location_id>NFDC1</location_id>
		<environmental_variable_id>Streamflow</environmental_variable_id>
		<additional_id></additional_id>
	</identifiers>
	<input_data>
		<forecast_data_location>
			<file>D:\HEP_projects\Test_data\NFDC1_flow\GFS_mean_hindcasts</file>
		</forecast_data_location>
		<observed_data_location>D:\HEP_projects\Ensemble_verification\Test_data\NFDC1_flow\nfdc1
		_cms.qme</observed_data_location>
		<forecast_time_system>UTC - 12 hours</forecast_time_system>
		<observed_time_system>UTC - 12 hours</observed_time_system>
		<forecast_support>
			<statistic>INSTANTANEOUS</statistic>
			<existing_attribute_units>METER CUBED/SECOND</existing_attribute_units>
			<notes></notes>
		</forecast_support>
		<observed_support>
			<statistic>MEAN</statistic>
			<period>24.0</period>
			<period_units>HOUR</period_units>
			<attribute_units>METER CUBED/SECOND</attribute_units>
			<notes></notes>
		</observed_support>
	</input_data>
	<verification_window>
		<start_date>
			<year>1976</year>
			<month>0</month>
			<day>1</day>
		</start_date>
		<end_date>
			<year>1996</year>
			<month>11</month>
			<day>31</day>
		</end_date>
		<forecast_lead_period>14</forecast_lead_period>
		<forecast_lead_units>DAY</forecast_lead_units>
		<aggregation_lead_period>24</aggregation_lead_period>
		<aggregation_lead_units>HOUR</aggregation_lead_units>
		<aggregation_function>MEAN</aggregation_function>
		<sample_size_constraint>0.0</ sample_size_constraint>
	</verification_window>
	<output_data_location>D:\HEP_papers\EVS_paper\EVS_projects\Results</output_data_location>
	<paired_data>
		<paired_data_location>D:\HEP_papers\NFDC1_Streamflow_pairs.xml</paired_data_location>
		<eliminate_duplicates>true</ eliminate_duplicates>
		<write_conditional_pairs>true</ write_conditional_pairs>
		<paired_write_precision>5</ paired_write_precision>
		<strip_nulls_from_paired_file>true</ strip_nulls_from_paired_file>
```

```
</paired_data>
<metrics>
        <metric>
                <name>BrierScore</name>
                <probability_array_parameter>0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <decompose_parameter>false</decompose_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>Correlation</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <vector_function_parameter>MEAN</ vector_function_parameter>
        </metric>
        <metric>
                <name>MeanAbsoluteError</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <vector_function_parameter>MEAN</ vector_function_parameter>
        </metric>
        <metric>
                <name>MeanCaptureRateDiagram</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <mcr_points_parameter>100</mcr_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>MeanContRankProbScore</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <decompose_parameter>false</decompose_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>MeanError</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <vector_function_parameter>MEAN</ vector_function_parameter>
        </metric>
        <metric>
                <name>MeanErrorOfProbabilityDiagram</name>
                <probability_array_parameter>-Infinity</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <mep_points_parameter>100</mep_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>ModifiedBoxPlotUnpooledByLeadObs</name>
                <box_unpooled_obs_points_parameter>10</box_unpooled_obs_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>ModifiedBoxPlotPooledByLead</name>
                <box_pooled_lead_points_parameter>10</box_pooled_lead_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>RelativeOperatingCharacteristic</name>
                <probability_array_parameter>0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <roc_points_parameter>10</roc_points_parameter>
```

```
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>ROCScore</name>
                <probability_array_parameter>0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <roc_score_points_parameter>10</roc_score_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>ReliabilityDiagram</name>
                <probability_array_parameter>0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <equal_samples_parameter>false</equal_samples_parameter>
                <reliability_points_parameter>5</reliability_points_parameter>
        </metric>
        <metric>
                <name>RootMeanSquaredError</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <vector_function_parameter>MEAN</ vector_function_parameter>
        </metric>
        <metric>
                <name>SampleSize</name>
                <probability_array_parameter>-Infinity,0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
        </metric>
        <metric>
                <name>SpreadBiasDiagram</name>
                <probability_array_parameter>-Infinity, 0.9, 0.95, 0.99</probability_array_parameter>
                <threshold_condition>isGreater</threshold_condition>
                <spread_bias_points_parameter>10</spread_bias_points_parameter>
                <forecast_type_parameter>regular</forecast_type_parameter>
                <unconditional_parameter>false</unconditional_parameter>
                <central_spread_bias_parameter>false</central_spread_bias_parameter>
        </metric>
    </metrics>
</verification_unit>
</verification>
```


Paired data files

A paired data file stores the pairs of forecasts and observations for a single VU in XML format. The file name corresponds to the VU identifier with a `_pairs.xml` extension.

Each pair comprises one or more forecasts and one observation, and is stored under a `<pr>` tag. Each pair has a readable date in Coordinated Universal Time (UTC or GMT), a lead time in hours (`<ld_h>`), an observation (`<ob>`), one or more forecast values (`<fc>`), and an internal time in hours (`<in_h>`) used by EVS to read the pairs (in preference to the UTC date). The internal time is incremented in hours from the forecast start time (represented in internal hours) to the end of the forecast time horizon. When multiple forecasts are present, each forecast represents an ensemble

member, and each ensemble member is listed in trace-order, from the first trace to the last. An example of the first few lines of a pair within a paired file is given below:

```
<pairs>   //Denotes start of paired data
<pair_count>448<pair_count>     //Total number of pairs on file
<pr>    //First pair
      <dt>   //Date tag
            <y>2005</y>   //Year
            <m>11</m>   //Month
            <d>31</d>   //Day
            <h>18</h>   //Hour
      </dt>   //End of date tag
      <ld_h>6.0</ld_h>   //Lead time in hours
      <ob>150.625</ob>   //Observed value
      <fc>   //Forecast values: in this case 49 ensemble members
            157.31567,157.31598,157.31627,157.3342,157.3148,
            157.31598,157.31509,157.31509,157.31572,157.31567,
            157.31538,157.31598,157.31598,157.3148,157.31627,
            157.31393,157.31567,157.31598,157.31595,
            157.31627,157.32852,157.31569,157.3148,157.34517,
            157.34586,157.34148,157.31664,157.31538,
            157.31509,157.31644,157.31509,157.31567,
            157.31639,157.31598,157.31598,157.31627,
            157.31598,157.31567,157.3161,157.31538,157.34439,
            157.3148,157.31627,157.3148,157.31598,157.31598,
            157.31657,157.3156,157.31567
      </fc>
      <in_h>315570</in_h>   //Internal hour incremented from start time
</pr>    //End of first pair tag
...
...
...

</pairs>   //Denotes end of paired data
```

Product files

Product files include the numerical and graphical results associated with verification metrics.

Numerical results are written in XML format. One file is written for each metric. The file name comprises the unique identifier of the VU or AU, together with the metric name (e.g. `Aggregation_unit_1.Modified_box_plot.xml`). Some metrics, such as reliability diagrams, have results for specific thresholds (e.g. probability thresholds). In that case, the results are stored by lead time and then by threshold value. The actual data associated with a result always appears within a 'values' tag.

A metric result that comprises a single value will appear as a single value in this tag. A metric result that comprises a 1D matrix will appear as a row of values separated by commas in the input order. A metric result that comprises a 2D matrix will appear as a sequence of rows, each with a <values> tag, which are written in the input order. For example, a diagram metric with an x and y axis will comprise two rows of data (i.e. two rows within two separate <values> tags). The default input order would be data for the x axis followed by data for the y axis. Data that refer to cumulative probabilities are, by default, always defined in increasing size of probability. If available, sample counts are given in the last <values> tag. Sample counts are also printed out in a separate XML file for each threshold used in the ROC, Reliability and Brier Score metrics (thresholds are compulsory for these metrics). This information is written to a file with the VU identifier, metric name and a `_metadata.xml` extension.

An example of the first few lines of a numerical result file for one metric, namely the 'modified box plot', is given below:

```
<results>        //Denotes start of the results data
<meta_data>      //Tag for metadata on the results

            //Next tag indicates that results are not available for separate
            thresholds of the observed variable

            <thresholds_type>false</thresholds_type>
            <original_file_id>Aggregation_unit_1.Modified_box_pl
            ot.xml</original_file_id >  //Original file
</meta_data>   //End of metadata
<result>   //First of n possible results
      <lead_hour>6</lead_hour>     //Result applies to lead hour 6
      <data>   //Start of data
            <values>0.0,0.1,…</values>   //Probs. drawn in box diagram
            <values>-1102,-233.5,…</values>   //Real values of probs.
            …
            …
            …

      </data>   //End of data
</result>   //End of first result
……
……
</results>        //Denotes end of the results data
```

APPENDIX A3 REFERENCES

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