VEÐURSTOFA ÍSLANDS

Report
03028

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A statistical model for predicting the probability of precipitation in Iceland

VÍ-ÞJ02
Reykjavík
August 2003

List of notation

BS: Half Brier score

BSS: Brier skill score

cdf: Cumulative distribution function

DMO: Direct Model Output

ECMWF: European Center for Medium range Forecast.

FAR: False Alarme Rate

GLM: Generalized Linear Model

HIT: Hit rate

IRLS: Iterative Reweighted Least Squares

KSS: Kuipers skill score

MSLP: Mean Sea Level Pressure

NWP: Numerical Weather Prediction

pdf: Probability density function

POD: Probability of detection

PoP : Probability of precipitation

PPM: Perfect Prognostic Method

QPF: Quantitative Precipitation Forecast

ROC: Relative Operating Characteristic

TS: Threat score

A Statistical Model for Predicting the Probability of Precipitation in Iceland

Philippe Crochet

Abstract

A statistical model is developed for predicting the probability of precipitation (PoP) at specific locations in Iceland. A Perfect Prognostic Method (PPM) is adopted. The model parameters are calibrated with observations and then the method is applied to the output from the ECMWF NWP model up to 5 days ahead. In most cases, the predictions are reliable and can be considered as useful, and the categorical prediction of precipitation-no precipitation is improved when compared to the direct model output (DMO) forecast.

1 Introduction

The quantitative precipitation forecast (QPF) is usually derived by a spatial interpolation of the 4 closest neighbour grid points of a NWP model to the given location. Then, the simplest way to forecast if precipitation will occur or not above a threshold value is to directly transform the QPF into a categorical yes/no prediction. Quite frequently, the occurrence of precipitation is overestimated, partly because of the difficulty for the NWP models to describe local effects, and also because of the interpolation procedure itself in relation to the spacing of the model grid and the spatial intermittency of the precipitation process. In order to minimize these effects, a statistical model is developed for predicting the probability of precipitation (PoP) in Iceland. Section 2 presents the statistical modeling. Section 3 is devoted to the presentation of the data. In section 4 the model is tested for several locations and validated with the data from the ECMWF NWP model. Section 5 concludes this paper.

2 Modeling the probability of precipitation

2-1) Markov chains

This first approach identifies the statistical dependence of precipitation occurrence with its own past. Let R_t be the amount of precipitation accumulated during a 24h period ending a time t and let I_t define a binary variable describing the state wet (W) or dry (D) above a given precipitation threshold τ:

$$I_{\mathrm{t}} = \begin{Bmatrix} 1 \text{ or wet} & if \ \mathrm{R_t} > \tau \\ 0 \text{ or dry} & otherwise \end{Bmatrix} \qquad (1)$$

The transition probability from an initial state i wet or dry to a final state j wet or dry, in n days is defined by:

$$P_{ij}(n) = \Pr(I_t = j | I_{t-n} = i) \tag{2}$$

Using the Chapman-Kolmogorov equation, (see Ross 1992), $P_{ij}(n)$ is estimated as follows:

$$P_{ij}(n) = \sum_{k=0}^{1} P_{ik}(1) P_{kj}^{n-1}(1) \tag{3}$$

From (3), it can be shown that $P_{ij}(n)$ may be calculated by multiplying the matrix $P_{ij}(1)$ by itself n times:

$$P_{ij}(n) = P_{ij}^{n}(1) \tag{4}$$

2-2) Generalized linear model

In this approach, the probability $p_{(t)}$ that precipitation occurs within a 24h period is estimated by the following generalized linear model (GLM):

$$\log\left(\frac{p_{(t)}}{1 - p_{(t)}}\right) = \alpha_0 + \sum_{i=1}^{k} \alpha_i X_i(t) \tag{5}$$

or

$$p_{(t)} = \frac{\exp\left(\alpha_0 + \sum_{i=1}^{k} \alpha_i X_i(t)\right)}{1 + \exp\left(\alpha_0 + \sum_{i=1}^{k} \alpha_i X_i(t)\right)} \tag{6}$$

The proposed model (5) postulates that the logit of precipitation occurence is a linear combination of a set of explanatory variables. Early work by Brelsford and Jones, 1967, already describe probabilistic prediction of weather elements using logistic regression. In the present work, the α_i coefficients are estimated with an iterative reweighted least squares (IRLS) method provided by the S-PLUS® software. Details about GLM can be found in McCullagh and Nelder (1989). In the study presented here, the predictors X_i are limited to the two-metre dew point depression (T-Td), the 10 metre zonal (U_{10}) and meridional (V_{10}) wind components and the mean sea level pressure (MSLP). These parameters are potential predictors frequently selected in similar pre-existing models together with other predictors, see for instance Kumar et al. 1999, Raible et al. 1999, Fraedrich and Leslie 1987a and 1987b, Miller and Leslie, 1985. In the proposed framework, the goal is to select a small set of explanatory variables that have been measured at the considered sites for several years, and that are operationally forecasted by the NWP models up to the medium range. The use of a small number of parameters should limit the overall forecasting error of the input data and also make the physical interpretation of the equation easier.

2-3) Conditioning the GLM with the season and the initial state

In this approach, the probability that precipitation occurs within a 24h period is defined by the GLM model (6) conditioned by the season (s) and the initial state I_{t-n}, n days before, that is 8 equations per range n:

$$p\left(t \middle| s, I_{t-n}\right) = \frac{\exp\left(\alpha_0\left(s, I_{t-n}\right) + \sum_{i=1}^{k} \alpha_i\left(s, I_{t-n}\right) X_i(t)\right)}{1 + \exp\left(\alpha_0\left(s, I_{t-n}\right) + \sum_{i=1}^{k} \alpha_i\left(s, I_{t-n}\right) X_i(t)\right)} \tag{7}$$

2-4) PoP predictions using NWP data

Once the model coefficients α_i have been calibrated with real observations, the PoP can be predicted n days ahead by injecting the forecasts X_i^* given by a NWP model into (7). At the time the NWP forecasts are available, the initial state (wet or dry) is known.

$$PoP(t+n) = \hat{P}\left(t+n \middle| s, I_t\right) \tag{8}$$

where $\hat{p}\left(t+n \middle| s, I_t\right)$ is predicted with the conditional GLM model (7) and output X_i^* from a NWP model:

$$X_1^* = \frac{1}{k} \sum_{h=24(n-1)}^{24n} T^*(t+h) - Td^*(t+h) \tag{9-1}$$

$$X_2^* = \frac{1}{k} \sum_{h=24(n-1)}^{24n} U10^*(t+h) \tag{9-2}$$

$$X_3^* = \frac{1}{k} \sum_{h=24(n-1)}^{24n} V10^*(t+h) \tag{9-3}$$

$$X_4^* = \frac{1}{k} \sum_{h=24(n-1)}^{24n} MSLP^*(t+h) \tag{9-4}$$

where h is the forecast range in hours and k is the number of forecast ranges belonging to the interval [24(n -1); 24n].

2-5) Statistical scores

Let $\psi(PoP|n)$ and $\Psi(PoP|n)$ denote respectively the probability density function (pdf) and cumulative distribution function (cdf) of the PoP predictions for a given forecast range n:

$$\Psi(PoP = \delta|n) = \Pr(PoP \le \delta|n) = \int_0^{\delta} \psi(PoP|n) dPoP \tag{10}$$

The unconditional pdf can be written as follows:

$$\psi(PoP|n) = \sum_k \psi_k(PoP|n) p(\mathrm{I}_{t+n} = k) \quad (\mathrm{k} = 1{,}0 \ \text{ or } \mathrm{W,D}) \tag{11}$$

where

$$\psi_k(PoP|n) = \psi(PoP|I_{t+n} = k, n) \quad (k = 1{,}0 \ \text{ or } \mathrm{W,D}) \tag{12}$$

is the conditional pdf of the PoP predictions valid n days ahead given that the day is either wet or dry, and $p(\mathrm{I}_{t+n} = k)$ is the marginal probability that the day is either wet or dry, i.e. the sample climatology. The corresponding conditional cdfs are given by:

$$\Psi_k(\delta|n) = \Pr(PoP \le \delta|I_{t+n} = k, n) = \int_0^{\delta} \psi_k(PoP|n) dPoP \quad (k = 1{,}0 \text{ or } \mathrm{W,D}) \tag{13}$$

From the two conditional pdfs $\psi_k(PoP|n)$ (or cdfs $\Psi_k(\delta|n)$), a discrimination diagram can be built to judge the capacity of the prediction model to delineate the two states wet and dry for a given PoP prediction (see Murphy and Winkler 1987 and Wilks 1995). The PoP predictions are skillful if they have the ability to discriminate correctly the two states wet and dry. This will be the case if $\psi_D(PoP|n)$ is positively skewed and if $\psi_W(PoP|n)$ is negatively skewed. In the perfect case, $\psi_D(PoP|n)$ displays a spike at PoP=0 and $\psi_W(PoP|n)$ displays a spike at PoP=1.

From the PoP prediction, a categorical yes/no (or wet/dry) prediction can be defined by applying a cutoff δ. Let Z_{t+n} represents the categorical prediction of the two possible states valid at time (t+n):

$$Z_{\mathrm{t+n}} = \begin{cases} 1 \text{ or W} & \text{if } \mathrm{PoP}_{\mathrm{t+n}} > \delta \\ 0 \text{ or D} & \text{otherwise} \end{cases} \tag{14}$$

Using the contingency table 1, the following statistical scores can be defined for any cutoff δ:

- Probability of detection:

$$POD(\delta|n) = \frac{a}{a+c} \tag{15}$$

- False alarm rate:

$$FAR(\delta|n) = \frac{b}{a+b} \tag{16}$$

and the Relative Operating Characteristic (ROC) curve can be built :

$$POD(\delta|n) = g(FAR(\delta|n)) \tag{17}$$

The ROC curve gives the POD and FAR levels to be expected for a given PoP cutoff δ. This curve can be used to define the most suitable cutoff to apply to the PoP predictions with respect to the type of decision problem the user is dealing with. The area under the ROC curve gives a measure of forecast accuracy. A perfect forecast will get an area of 1 and a useless forecast will get an area of 0.5. According to Buizza et al., 1999, it is common practice to consider an area under the ROC curve of 0.7 as the limit for a useful prediction, and an area of more than 0.8 as indicative of a good prediction.

The quality of the PoP predictions can also be evaluated with the following statistical scores (see Wilks, 1995):

- The half Brier score (Brier, 1950), i.e the mean-squared error of the probability forecast:

$$BS(n) = \frac{1}{k}\sum_{t=1}^{k}\left(PoP_{t+n} - I_{t+n}\right)^2 \tag{18}$$

This score can be decomposed as follows:

$$BS(n) = BS_{\text{reliability}} - BS_{\text{resolution}} + BS_{\text{uncertainty}} \tag{19}$$

where

$$BS_{\text{reliability}} = \frac{1}{k}\sum_{i=1}^{m} N_i\left(PoP_i - E[I_i]\right)^2 \tag{20}$$

is related to the reliability of the prediction.

$$BS_{resolution} = \frac{1}{k}\sum_{i=1}^{m} N_i \left(E[I_i] - E[I]\right)^2 \qquad (21)$$

is related to the ability of the prediction to discriminate between precipitation and no precipitation.

$$BS_{\text{uncertainty}} = E[I](1 - E[I]) \qquad (22)$$

is independent of the prediction and depends only on the climatological occurrence of precipitation of the sample.

N_i is the sample size for the class i and $k = \sum_{i=1}^{m} N_i$ is the total sample size

The lower the BS, the better.

- The Brier skill score :

$$BSS(n) = \frac{BS(n)_{Markov} - BS(n)}{BS(n)_{Markov}} \qquad (23)$$

defines the percentage improvement of the Brier score with respect to climatology estimated here by the Markov PoP prediction.

- The Hit rate:

$$HIT(\delta|n) = \frac{a+d}{a+b+c+d} \qquad (24)$$

gives the relative number of correctly predicted wet and dry situations.

- The Threat score:

$$TS(\delta|n) = \frac{a}{a+b+c} \qquad (25)$$

The best threat score receives a value of 1 and the worst one gets a value of 0.

- The Bias:

$$Bias(\delta|n) = \frac{a+b}{a+c} \qquad (26)$$

If the bias is lower than one, the model is underforecasting the precipitation occurence, if the bias is greater than 1, the model is overforecasting the precipitation occurence, and if the bias is 1, the model is unbiased.

- The Kuipers skill score:

$$KSS(\delta|n) = \frac{ad - bc}{(a+c)(b+d)} \tag{27}$$

This score measures the forecast skill. A perfect forecast will get a KSS of one, random forecast will get a KSS of zero and forecast worse than the random forecast will get a KSS < zero.

Contingency table 1: with the sample size

	$I_{t+n} = 1$ (wet)	$I_{t+n} = 0$ (dry)
$Z_{t+n} = 1$ (wet)	a	b
$Z_{t+n} = 0$ (dry)	c	d

3 Data

The statistical PoP model (7) described in section 2 is calibrated individually for 11 stations located around Iceland (Appendix 1). A day is defined to be wet if at least 0.1 mm of precipitation is measured in 24h (from 09h00 to 09h00 UTC), and dry otherwise. The transition probabilities $P_{ij}(n)$ are estimated with a 10 year period sample (01/01/1990 to 31/12/1999). The GLM equations are calibrated with measured surface parameters for the period 01/12/1994 to 01/12/1999. Each predictor is measured every 6 hours at 00h00, 06h00, 12h00 and 18h00 UTC and then averaged over the 24h period during which precipitation is accumulated. The model validation is first made for a two year period (01/12/1999 to 01/12/2001) using ground measurements. Then the data from the ECMWF NWP model 12h00 UTC run are used to study the predictive skills of the model in an operational environment, for the same period. The data used in this study have a spatial resolution of 1.5° lat × 1.5° long. The local forecast of a given parameter is derived by a bi-linear interpolation of the DMO forecasts at the 4 nearest grid points.

4 Results

4-1) Markov chains

The transition probabilities $P_{ij}(1)$ have been estimated for each station and each season and then $P_{ij}(n)$ was derived using (4) for $1 < n \leq 10$ days. Appendix 2 presents these transition probabilities for 4 different locations. The seasonal dependence is well marked. The stationarity is reached when two events distant of k days are independent. It corresponds to the climatological probability of precipitation for a given season. Although there is a marked difference from station to station for the values of $P_{ij}(n)$, the results indicate strong evidence that the sequence of wet and dry days are dependent up to 3 to 4 days. The Markov chains will be used as the climatological reference to predict the PoP.

4-2) GLM equations

The GLM equations have been estimated for each station. The seasonal variability of the coefficients is marked. The initial state is influencing the value of the coefficients as well. The relative importance of each predictor can be clearly identified. In most cases, the most important parameter is the dew point depression. The associated coefficient α_1 is negative in all cases (with some exceptions for Egilsstadir), meaning that the PoP will increase if the dew point depression decreases. Then, the second most important parameter is quite frequently the MSLP. The associated coefficient α_4 is negative in all cases meaning that an increase in the MSLP will decrease the PoP. The third and fourth most frequent important parameters are the zonal or the meridional wind speed component, depending on the geographical location of the station. The sign of the associated coefficients α_2 and α_3 depends on the station and the season. The predominant wind direction for each station is quite obvious. Roughly speaking, all the stations located in the West and South of Iceland are under the main influence of southerly winds, the station located in the East is mainly influenced by easterly winds, the stations in the North and NE are under the influence of northerly winds.

4-3) Validation using observations

The ability of the statistical model (7) to estimate the PoP is first evaluated with an independent sample of observations. This validation defines the reference to be compared later with validations using forecast data from the ECMWF NWP model. The quality of the PoP forecasts is first investigated by studying the reliability and the discrimination diagrams. These diagrams were estimated by averaging the PoP-predictions over 10 probability intervals of 10% width. A successful attempt to model the empirical pdfs $\psi_k(PoP|n)$ has also been made using Beta distributions (Appendix 3).
Then the ROC curves were computed for 19 PoP cutoff values δ ranging from 0.05 to 0.95. Appendix 4 presents the different diagrams for 4 stations.

The statistical model is reliable at all locations. The discrimination between precipitation and no-precipitation is satisfactory for most stations except in the North (Akureyri and Blonduos). The area under the ROC curves is usually larger than 0.7 and decreases slowly with the number of days n used to define the initial state I_{t-n}. This shows the gain of information expected by conditioning the PoP model with the initial state.

The BS is usually quite high, because of the uncertainty term (22). The highest possible value for the uncertainty term is 0.25, and it corresponds to a climatological occurrence of precipitation of 0.5. One can see that the sample used in this study is close to that value at all locations. The BS displays a geographical dependence directly related to the resolution term with an increase from the South to the North.

4-4) Validation using NWP data

The ability of the statistical model (7) to predict the PoP several days ahead is now evaluated with forecast data from the ECMWF NWP model for the same period. The two-metre temperature and dew-point forecasts are first post-processed with an adaptive Kalman filtering procedure (Crochet 2002). For the other parameters, the DMO values are used.

The quality of the PoP forecasts is first investigated by studying the reliability and discrimination diagrams and the ROC curves. Appendix 5 presents the different diagrams for 4 stations. The categorical yes/no prediction was derived for a PoP cutoff δ = 0.5. The results are presented in Appendix 6.

The GLM and the Markov chain predictions are reliable at all stations and all forecast ranges while the DMO predictions are clearly overforecasting the occurrence of precipitation. The area under the ROC curves decreases with the forecast range as expected showing the link between the forecast accuracy and the quality of the GLM-PoP predictions. The area under the ROC curves is usually lower than the one corresponding to the reference values. According to this criteria, the PoP predictions are useful at all locations except for Akureyri, Blonduos and Egilsstadir.

The discrimination diagrams show that the ability to discriminate between precipitation and no-precipitation is decreasing mainly from the South to the North. These diagrams also show that for Akureyri, Blonduos and Egilsstadir, the GLM-PoP predictions are not skillful to clearly identify the situations with precipitation but are successful to identify the situations without precipitation. These results explain the low values for the area under the ROC curves.

The value of the BS increases slowly with the forecast range and from the South to the North as a consequence of a decrease in the resolution term, i.e. the reduction in the ability to discriminate between precipitation and no-precipitation. At all locations, the lowest BS corresponds to the GLM-PoP predictions, then the Markov-chain predictions and last the ECMWF-DMO predictions.

When a PoP cutoff $\delta = 0.5$ is considered, the statistical scores computed for the categorical yes/no forecasts show the superiority of the statistical model against the DMO forecasts except for the threat score and the POD. The FAR is reduced at the expense of a reduction in the POD. This cutoff can be optimized for each station according to the needs of the users.

5 Conclusion

The statistical model presented in this study provides an objective and reliable prediction of the probability of precipitation in Iceland. This model combines a few meaningful surface parameters through a GLM. The usefulness of the prediction was observed to depend on the geographical location. The predictions are quite reliable up to 5 days ahead. The discrimination between occurrence and non-occurrence is satisfactory at most forecast ranges except for two locations in the North (Blonduos and Akureyri) and one in the East (Egilsstadir) where the model is skillful to predict days with no-precipitation but not with precipitation.

Acknowledgements

I wish to thank Trausti Jónsson for helpful comments on the draft of this paper.

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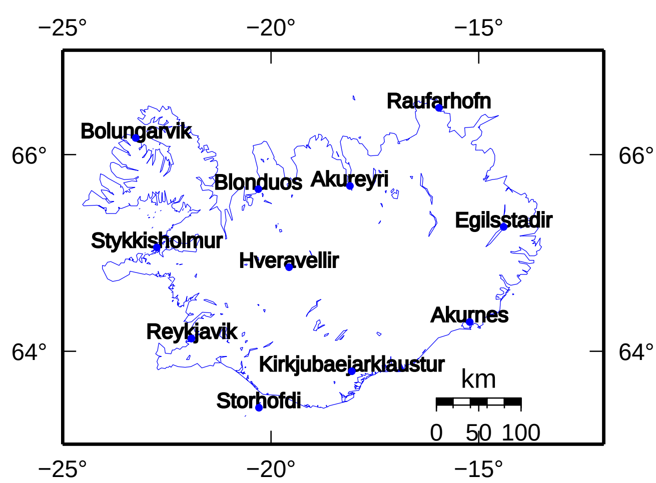
Appendix 1

Location map

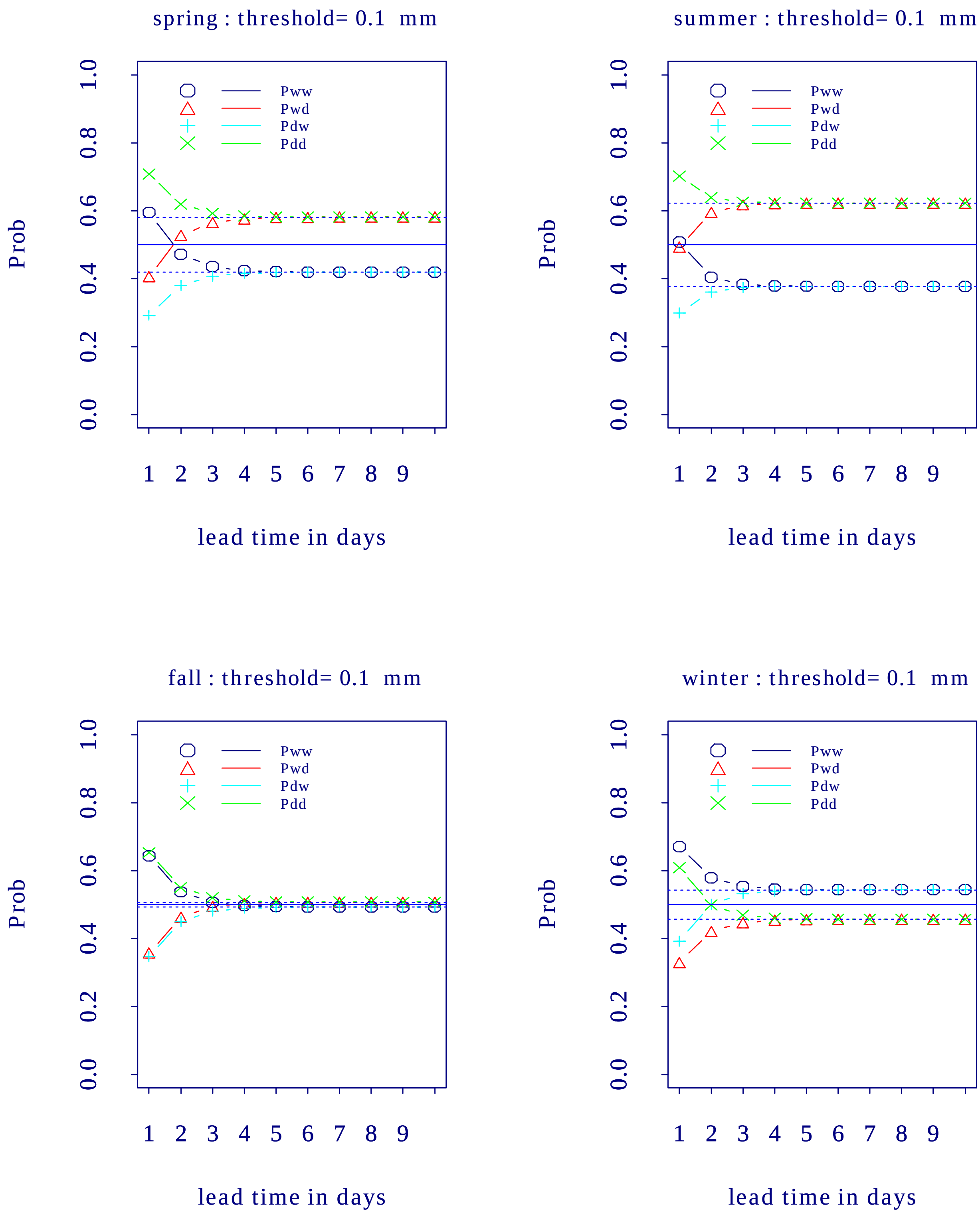
Figure 1


−25°
−20°
−15°
66°
64°
Raufarhofn
Bolungarvik
Blonduos
Akureyri
Egilsstadir
Stykkisholmur
Hveravellir
Akurnes
Reykjavik
Kirkjubaejarklaustur
Storhofdi
km
0
50
100

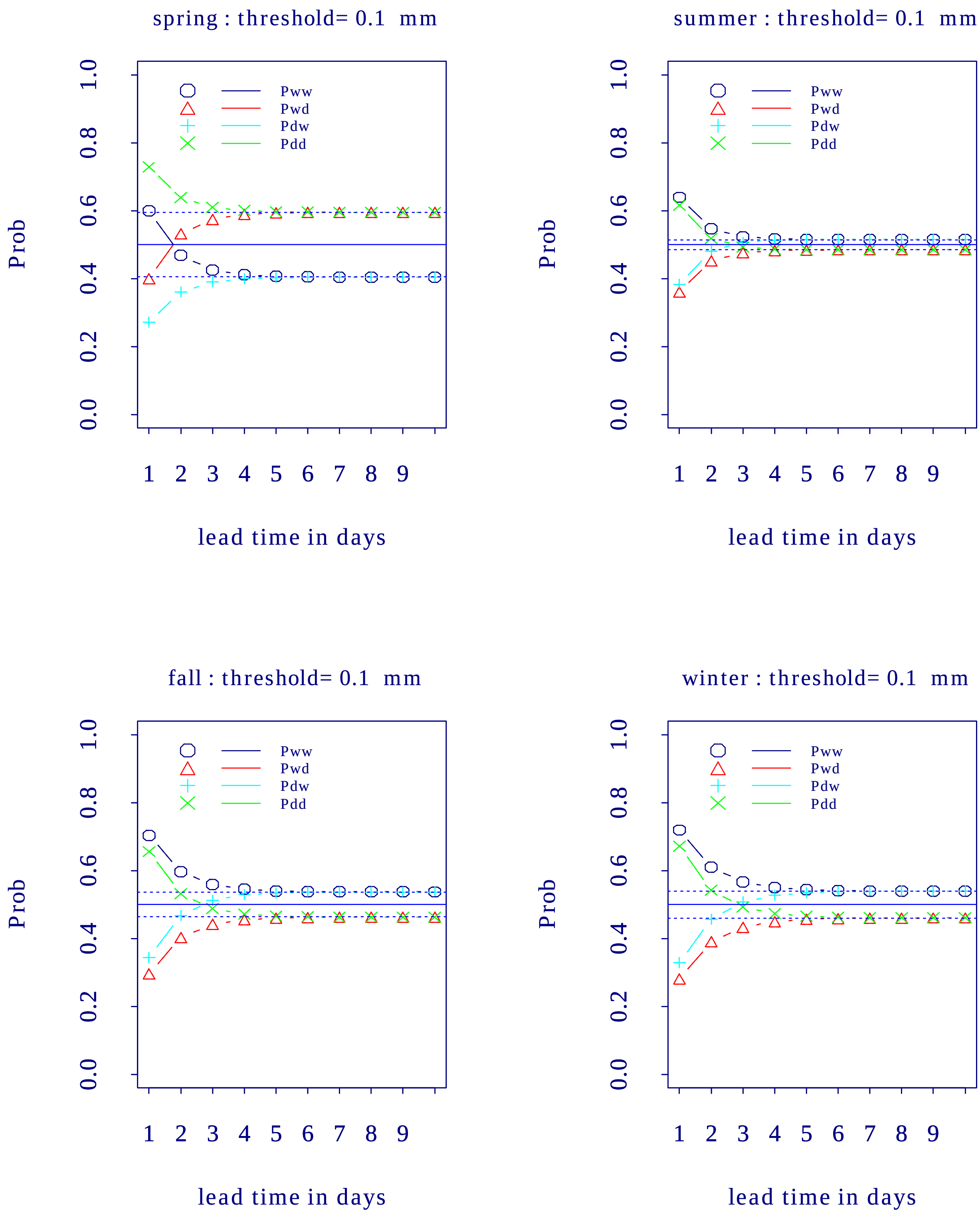
Appendix 2

Transition probabilities

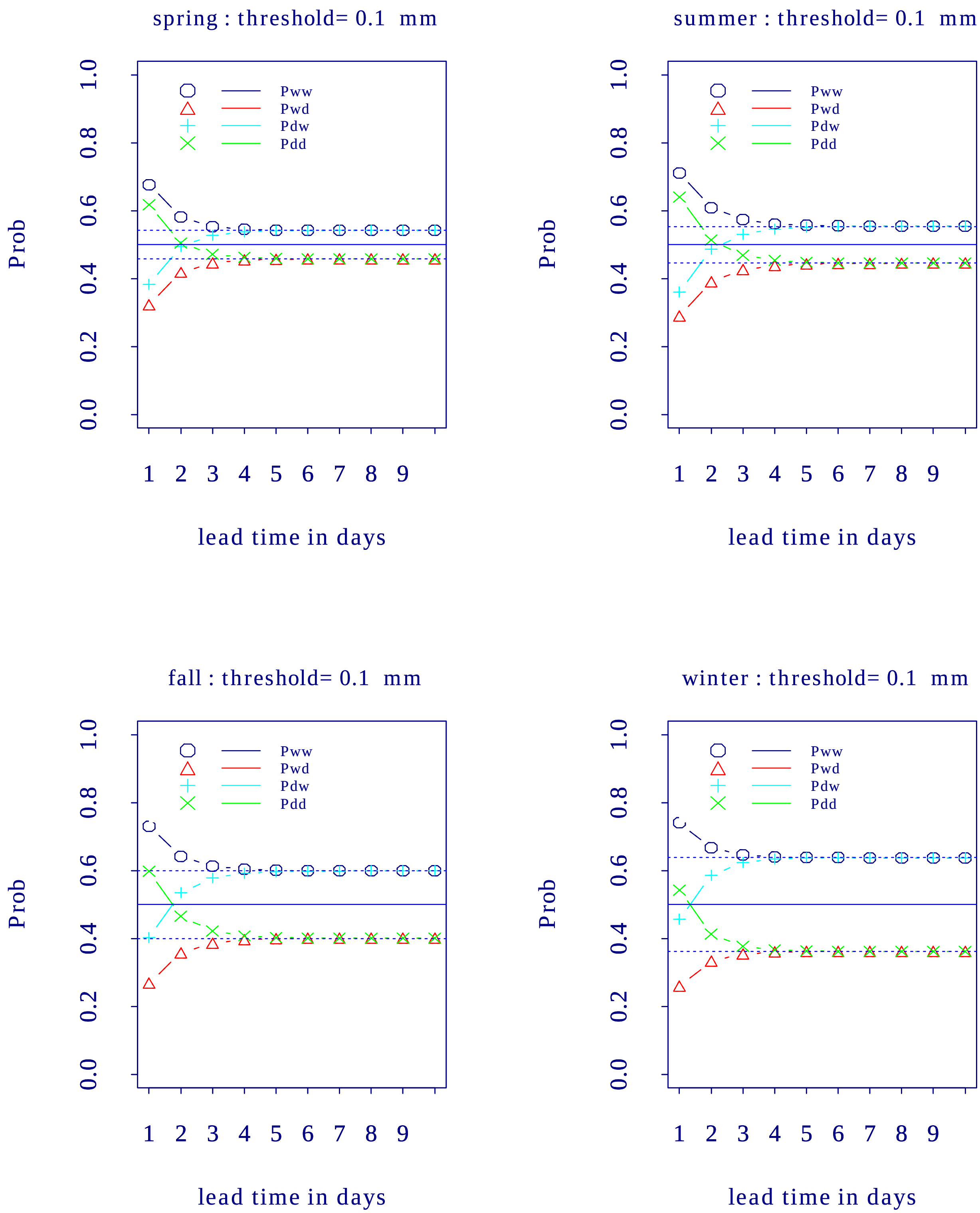
Akureyri : Markov chain for daily precipitation
transition probabilities for several lead times



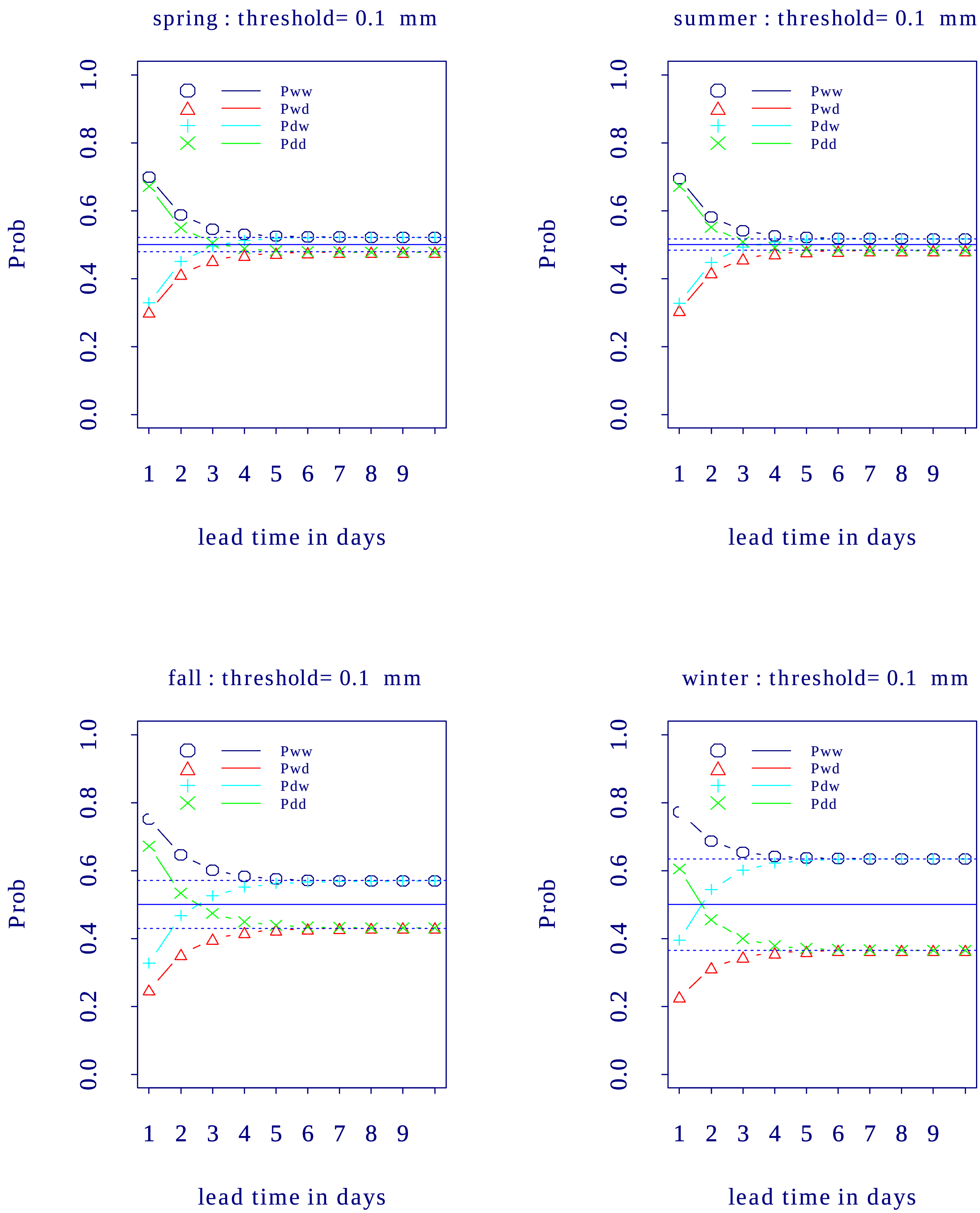
Akurnes : Markov chain for daily precipitation
transition probabilities for several lead times



Hveravellir : Markov chain for daily precipitation transition probabilities for several lead times



Reykjavik : Markov chain for daily precipitation
transition probabilities for several lead times



Appendix 3

Beta-distribution

The empirical pdfs $\psi_k(PoP|n)$ are modeled using a Beta distribution:

$$\psi_k(PoP|n) = \left[\frac{\Gamma(a_k + b_k)}{\Gamma(a_k)\Gamma(b_k)}\right] PoP^{a_k - 1}(1 - PoP)^{b_k - 1} \qquad \text{(A-1)}$$

where the parameters a_k and b_k are estimated as follows:

$$a_k = \frac{E\left[PoP|I_{t+n} = k\right]^2 \left(1 - E\left[PoP|I_{t+n} = k\right]\right)}{Var\left(PoP|I_{t+n} = k\right)} - E\left[PoP|I_{t+n} = k\right] \qquad \text{(A-2)}$$

and

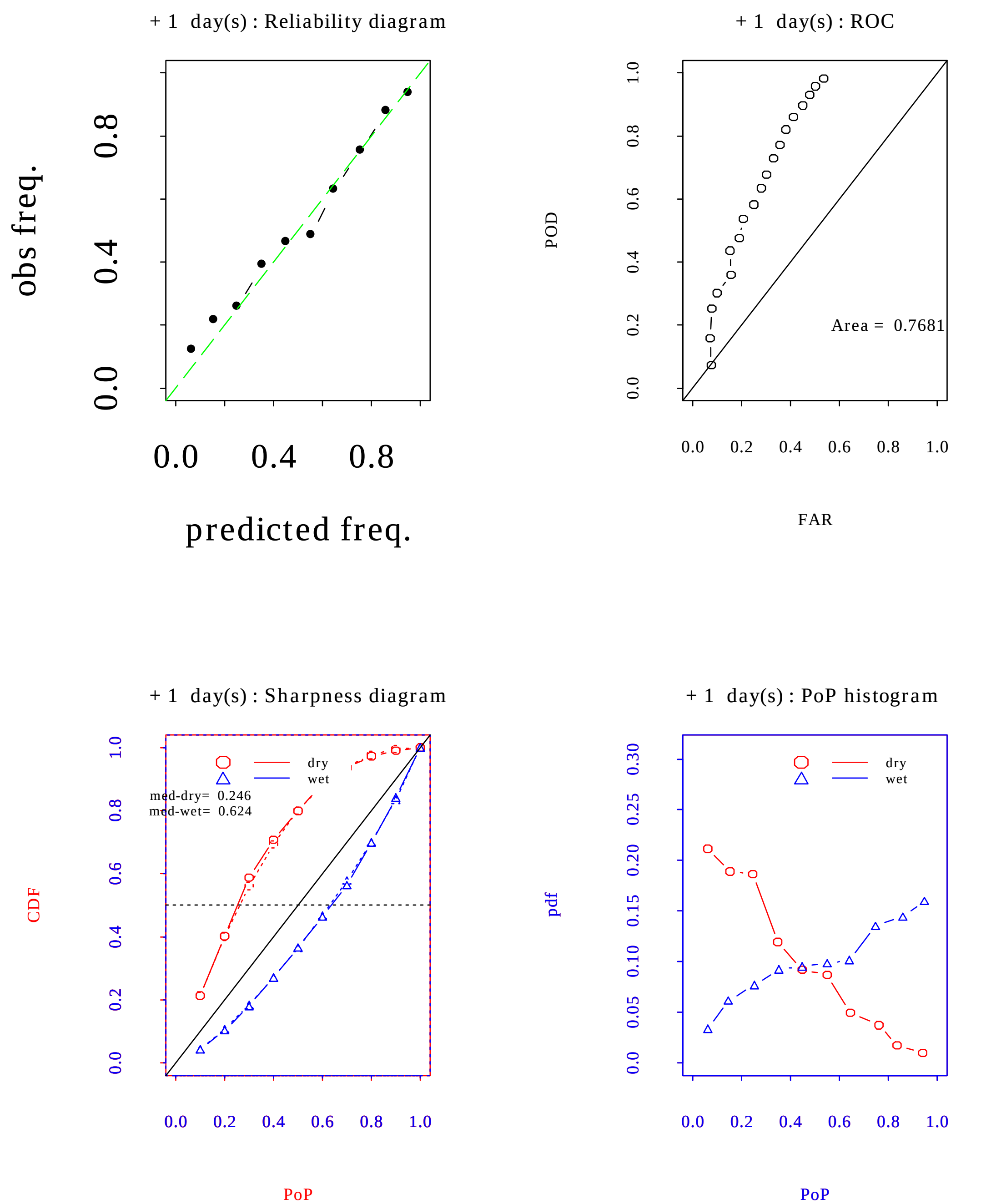
$$b_k = \frac{a_k\left(1 - E\left[PoP|I_{t+n} = k\right]\right)}{E\left[PoP|I_{t+n} = k\right]} \qquad \text{(A-3)}$$

Appendix 4

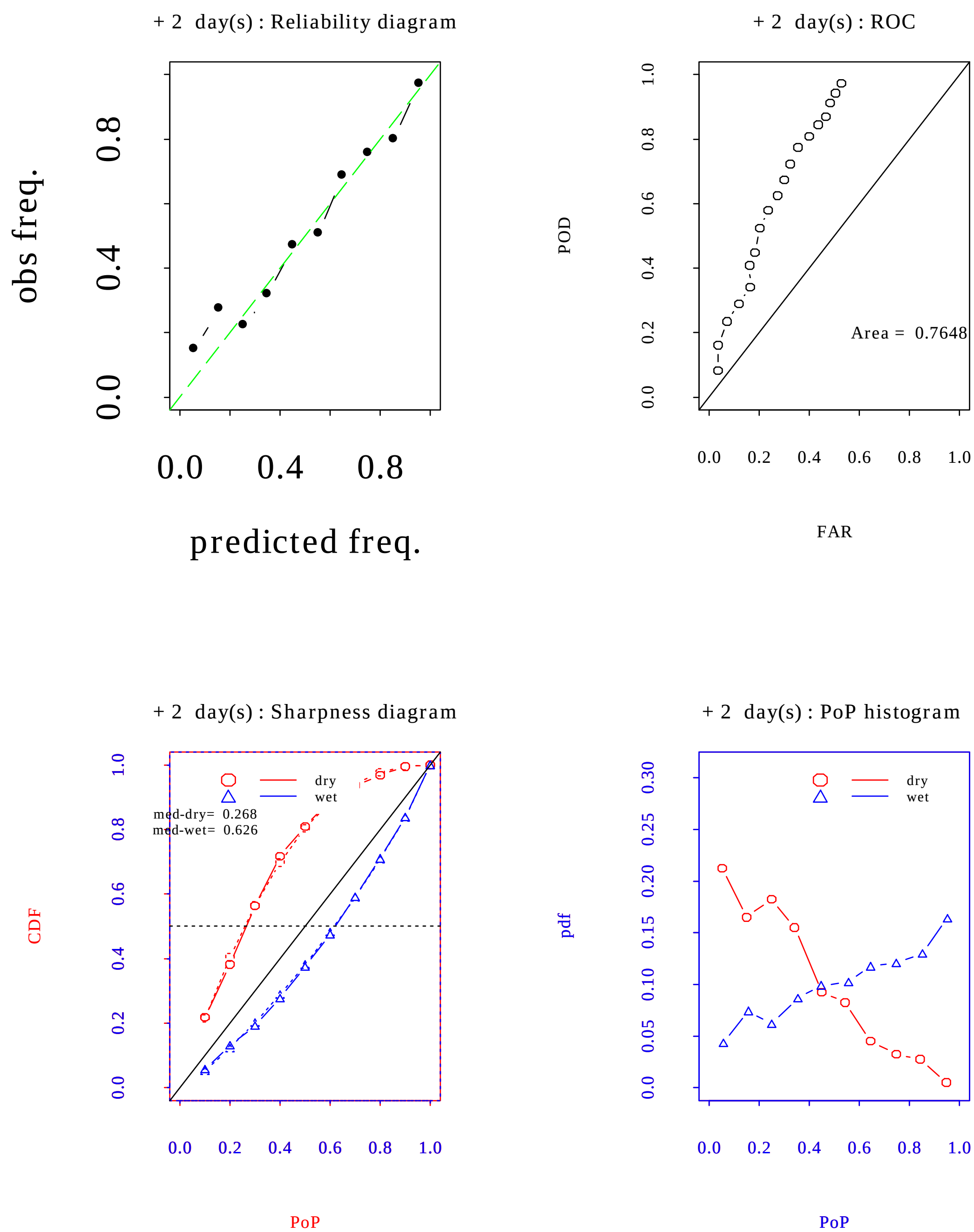
GLM-PoP

Statistical scores with real observations

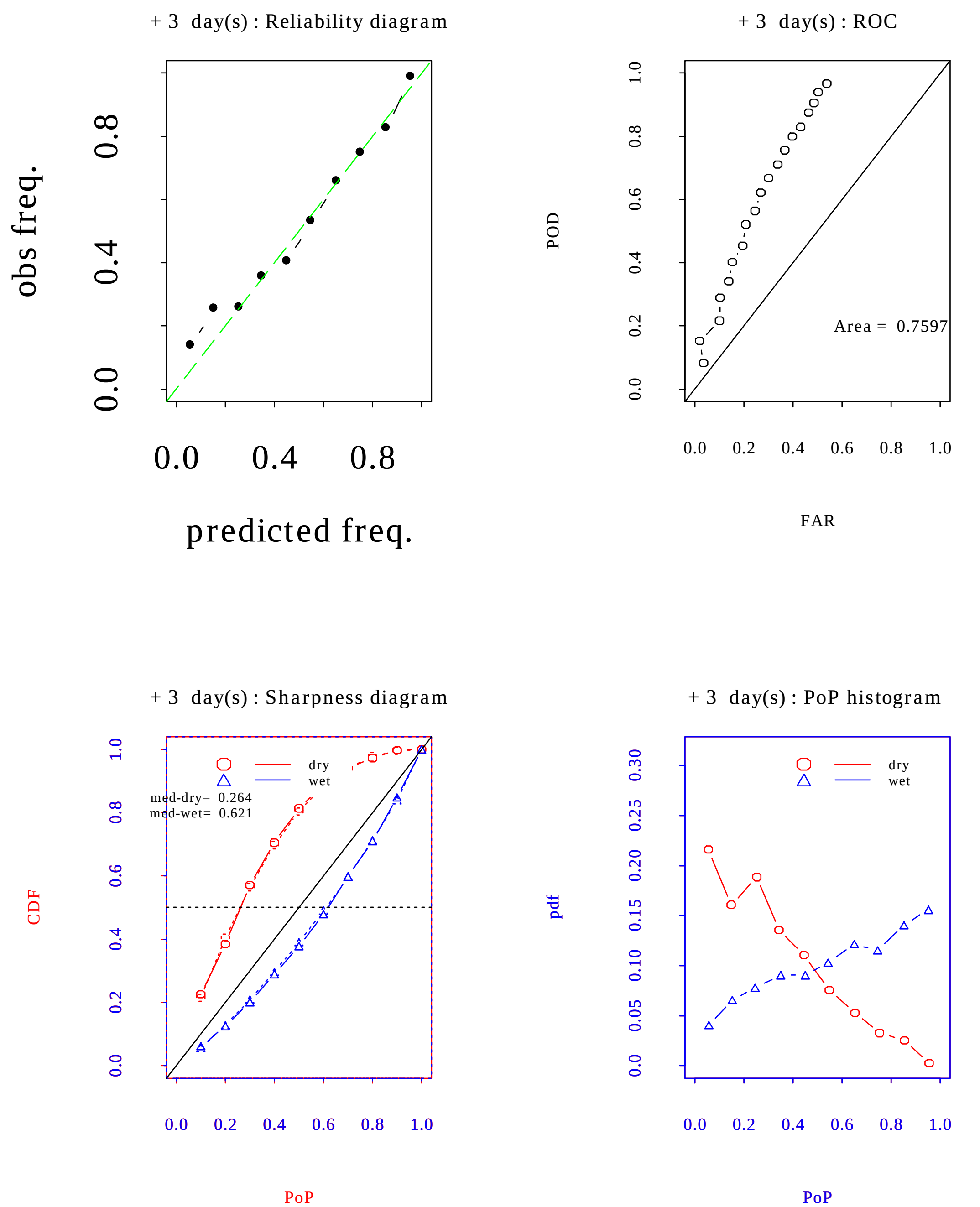
Akureyri : Verification diagrams for MOS PoP, threshold= 0.1 mm



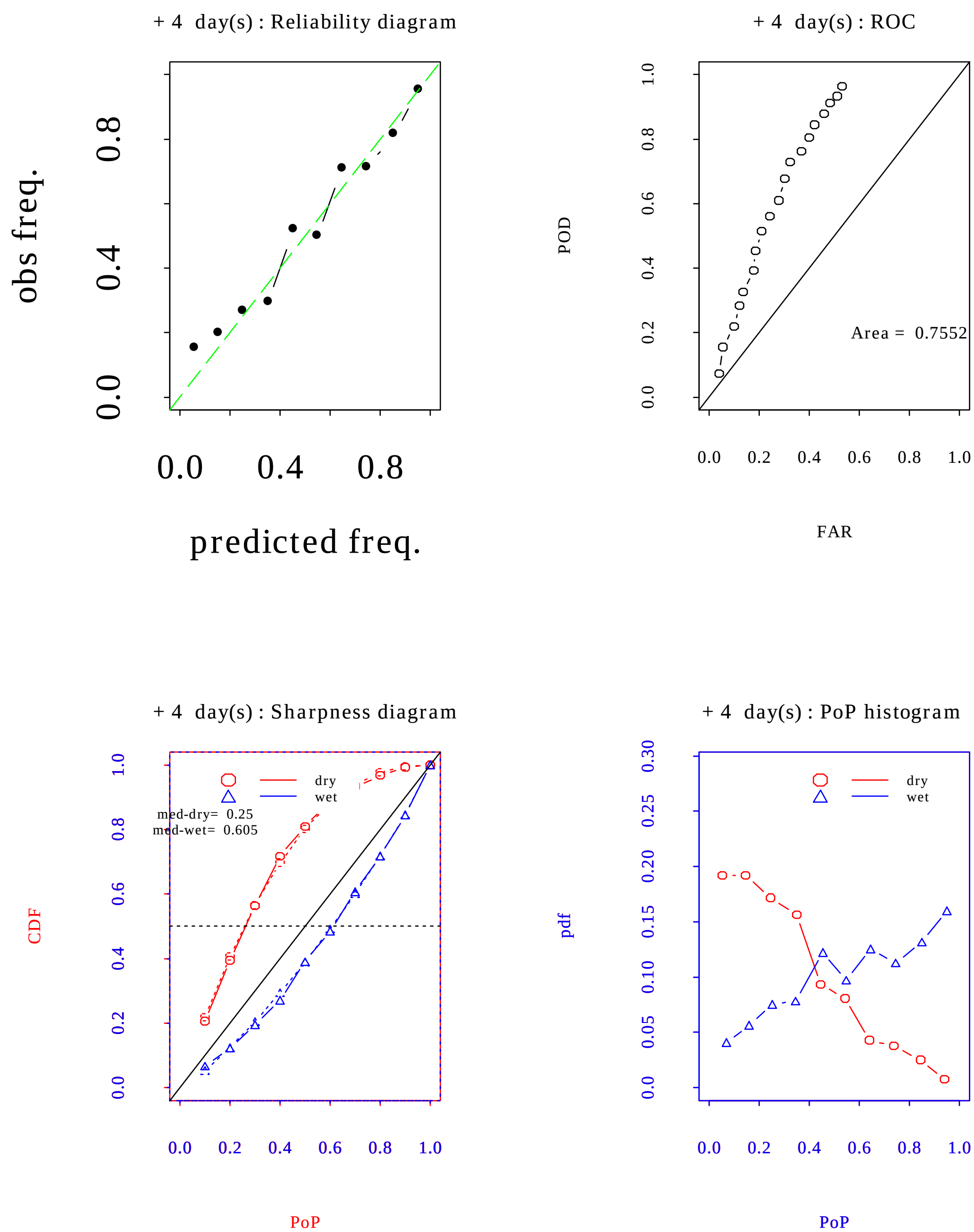
Akureyri : Verification diagrams for MOS PoP, threshold= 0.1 mm



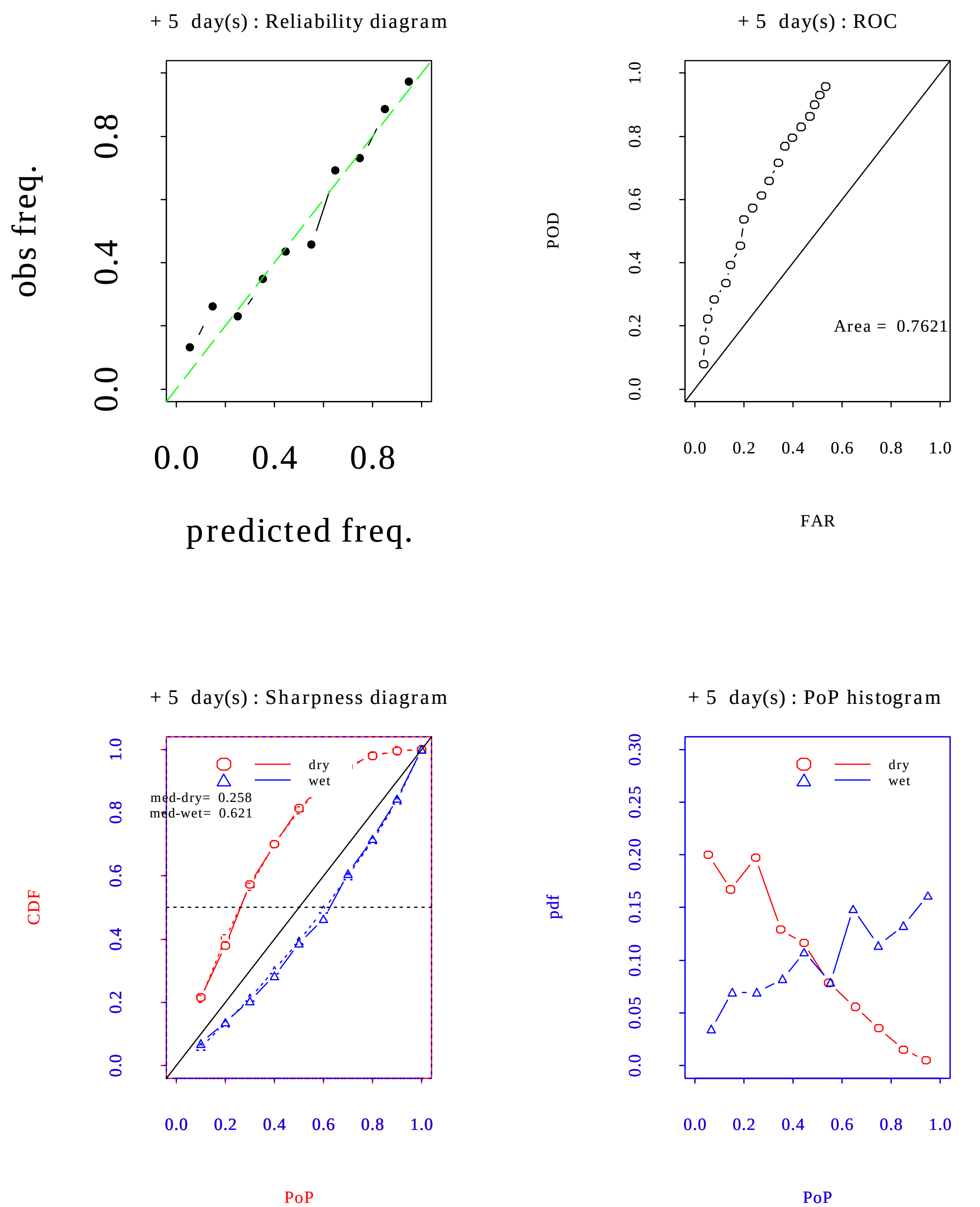
Akureyri : Verification diagrams for MOS PoP, threshold= 0.1 mm

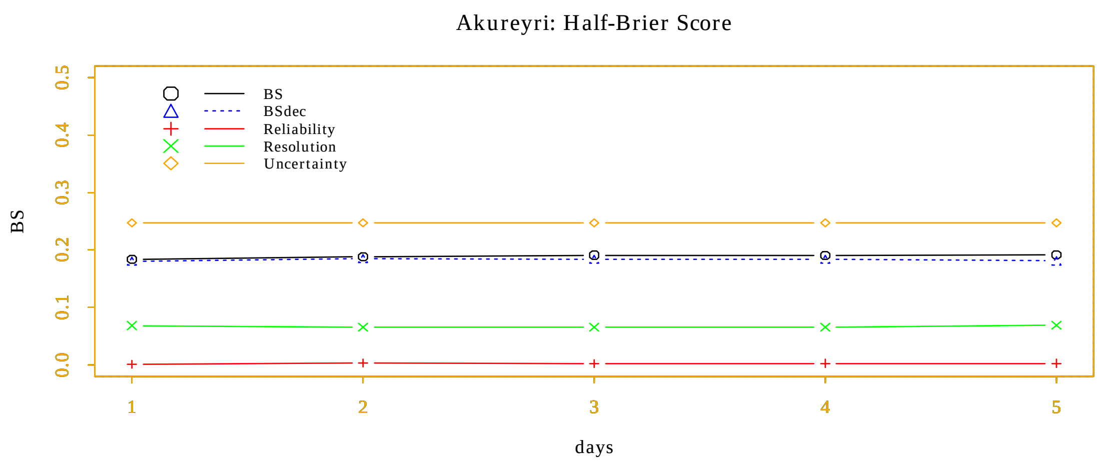


Akureyri : Verification diagrams for MOS PoP, threshold= 0.1 mm

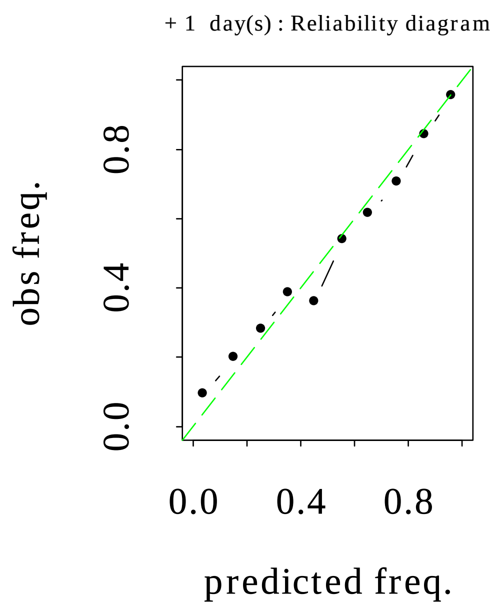


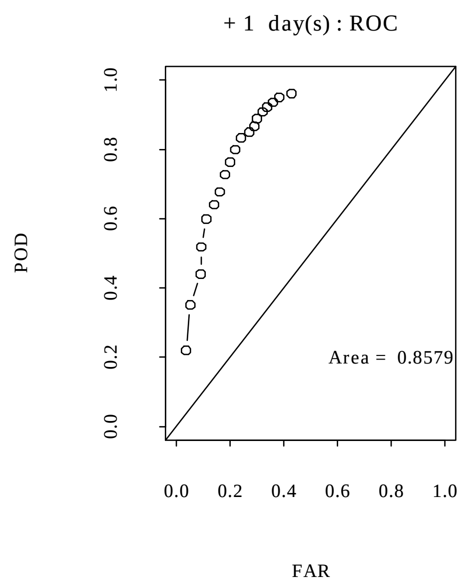
Akureyri : Verification diagrams for MOS PoP, threshold= 0.1 mm

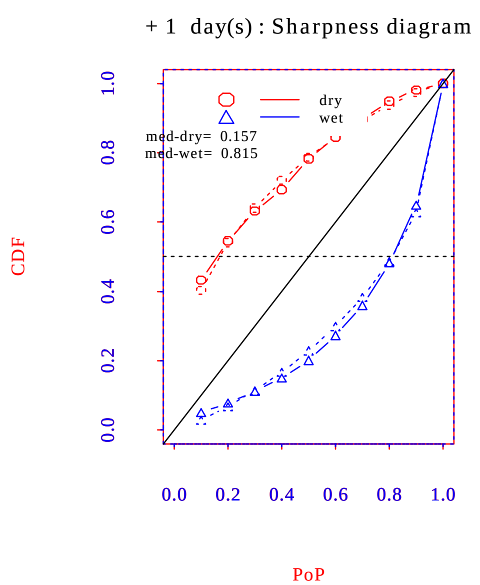


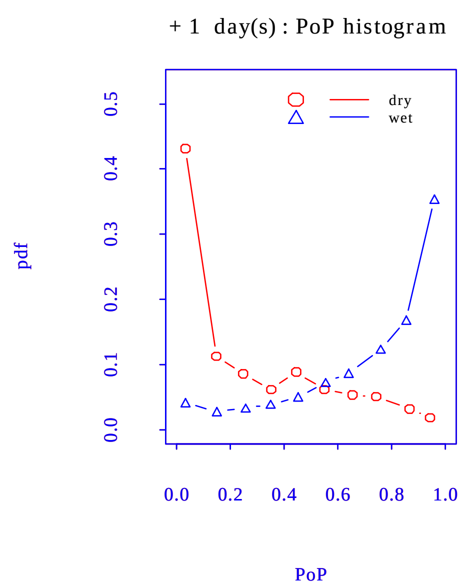

Akureyri: Half-Brier Score
BS
days
BS
BSdec
Reliability
Resolution
Uncertainty
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5

Akurnes : Verification diagrams for MOS PoP, threshold= 0.1 mm

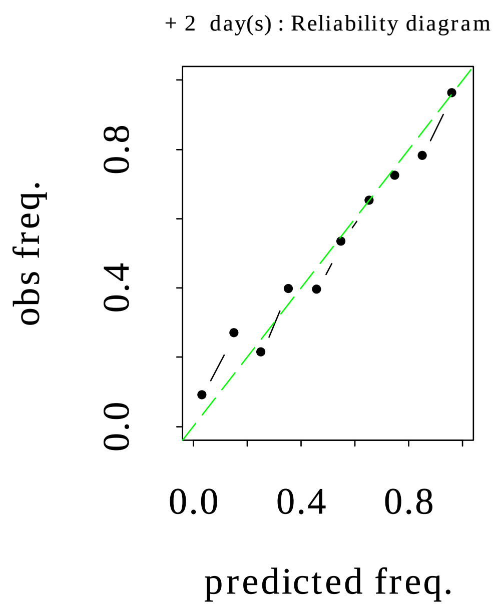


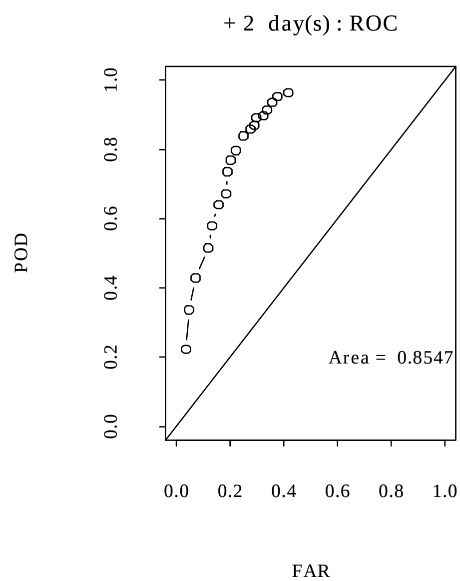


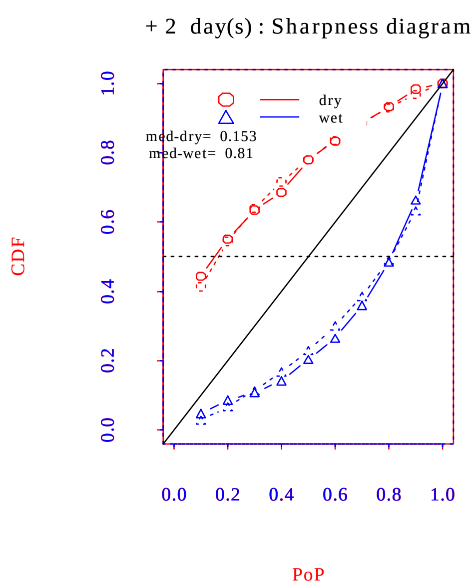


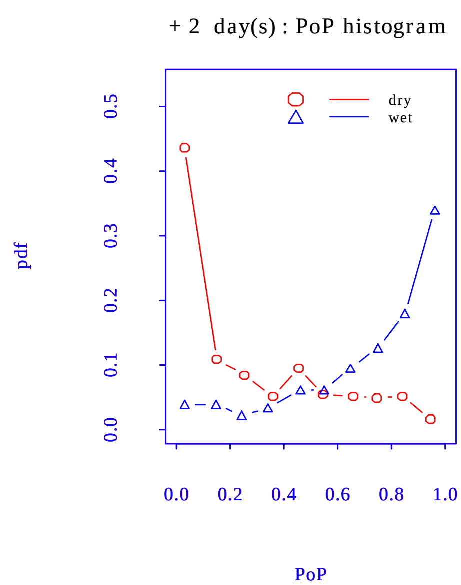


Akurnes : Verification diagrams for MOS PoP, threshold= 0.1 mm

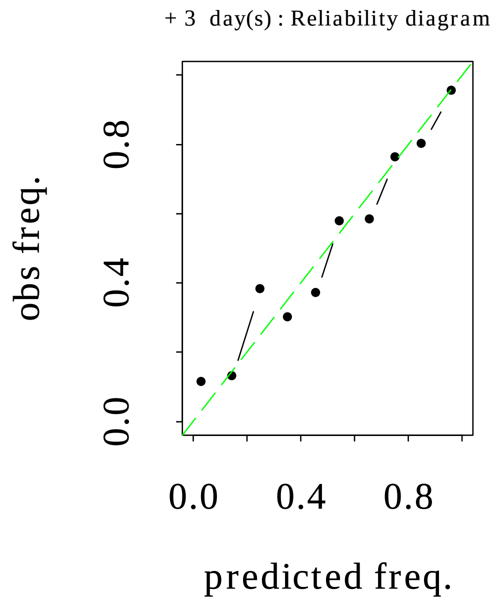


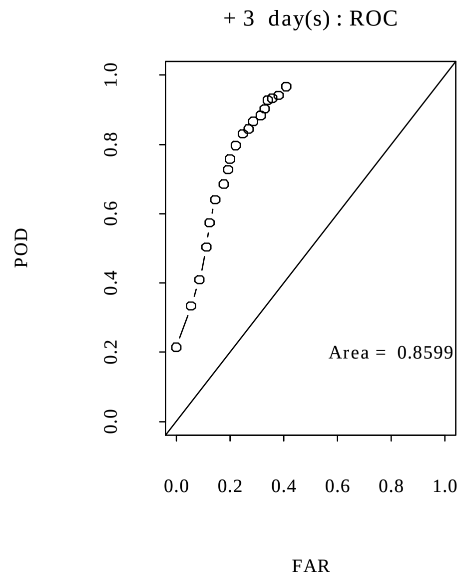


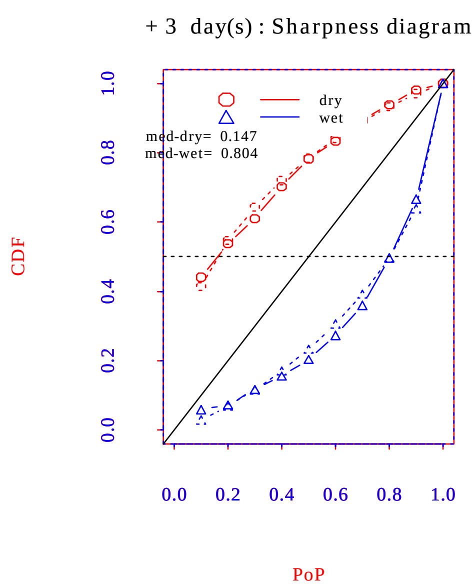


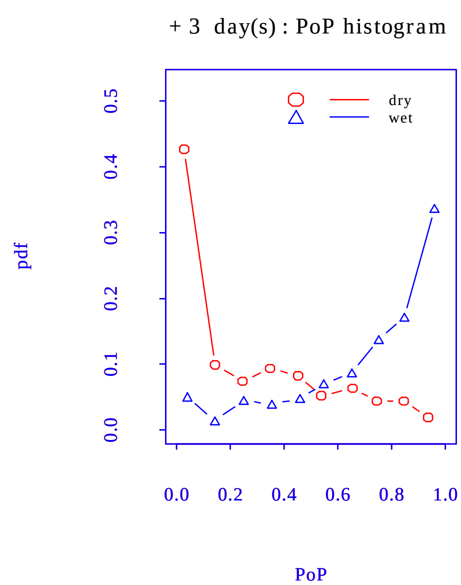


Akurnes : Verification diagrams for MOS PoP, threshold= 0.1 mm

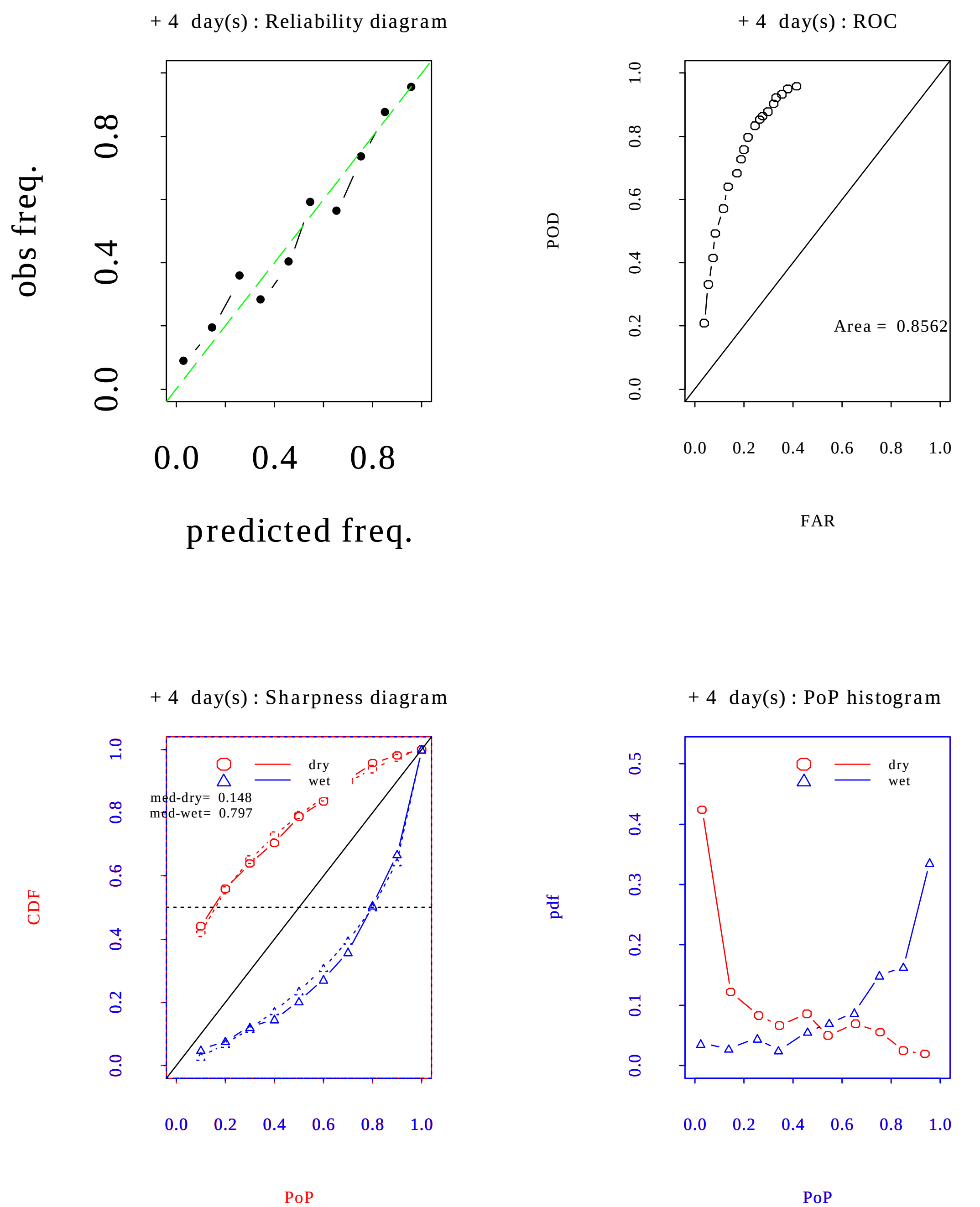




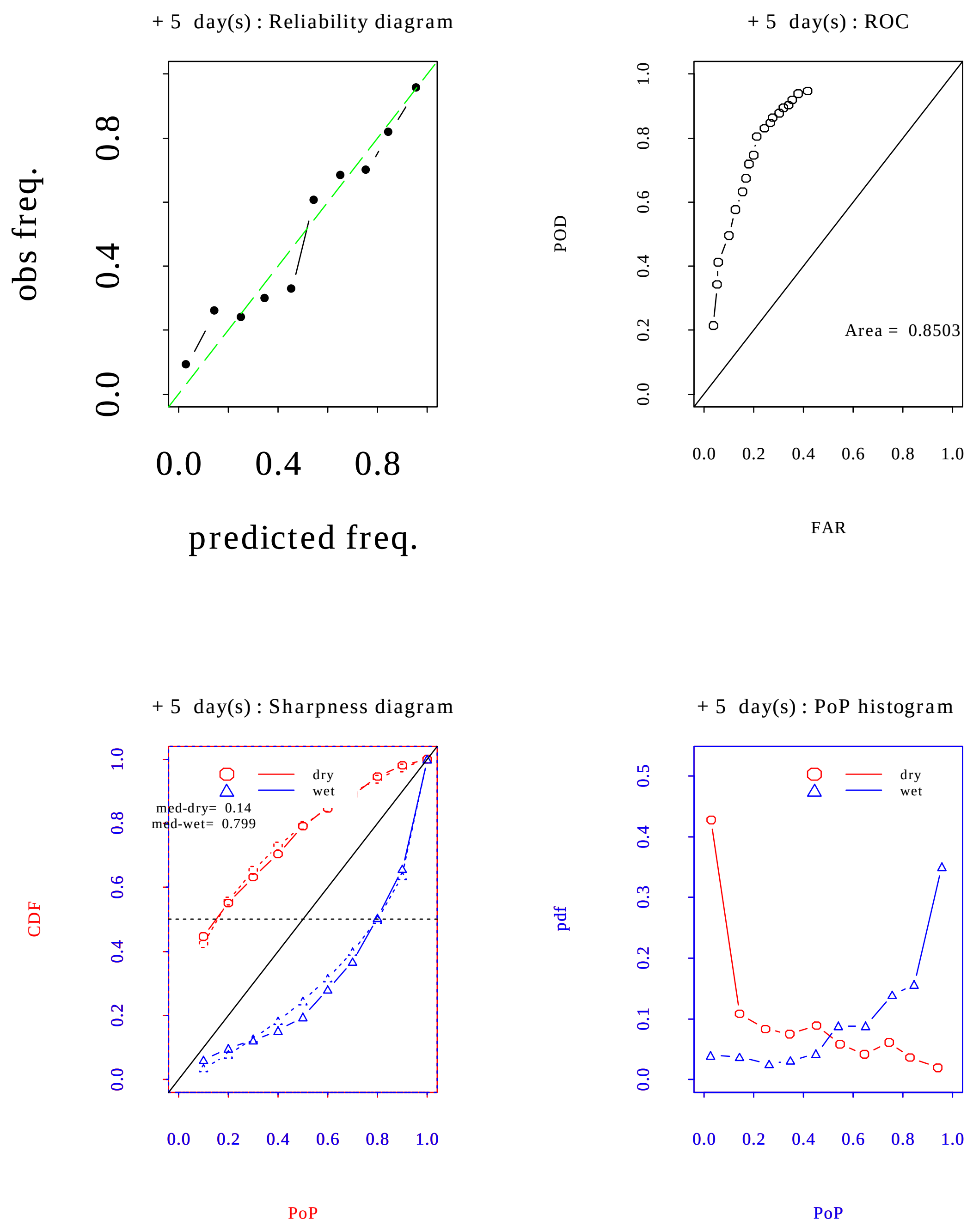


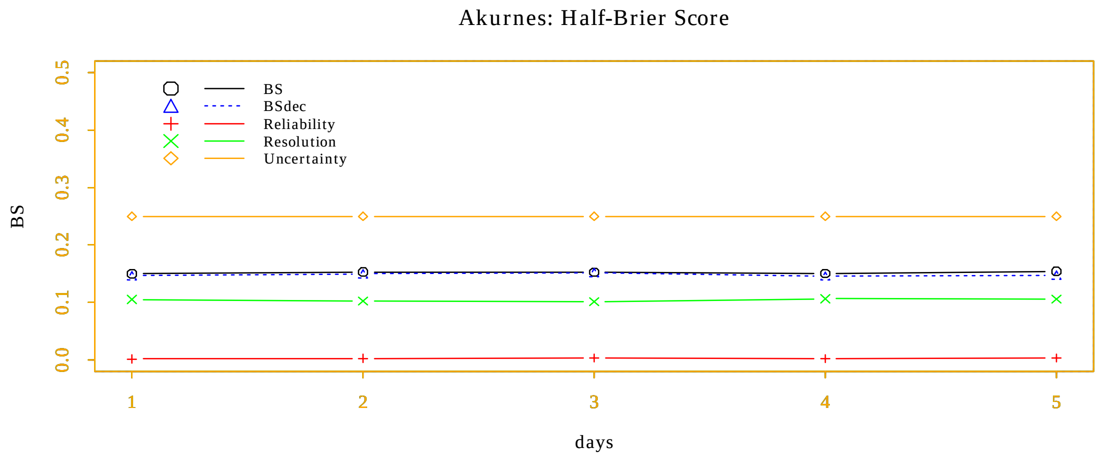


Akurnes : Verification diagrams for MOS PoP, threshold= 0.1 mm

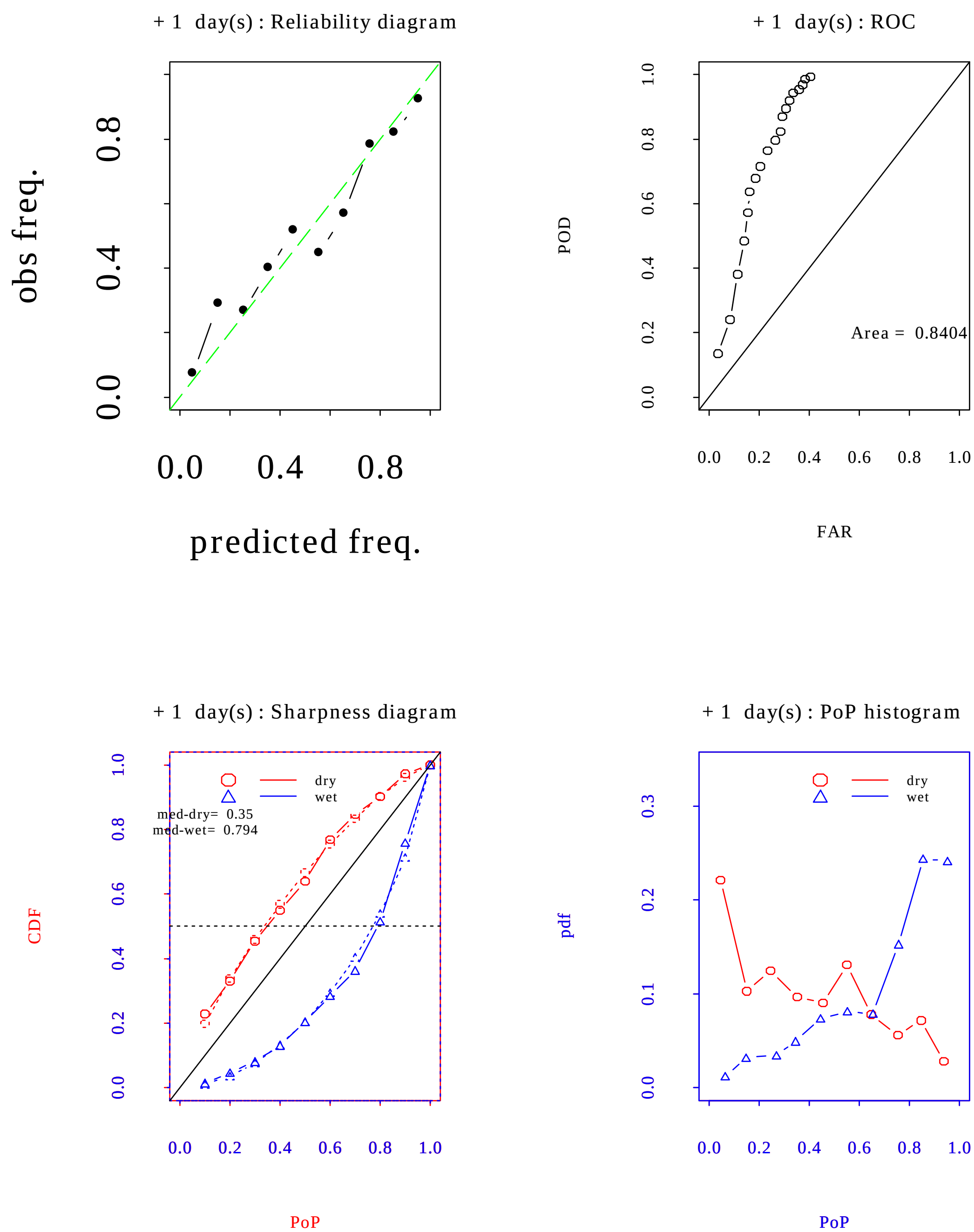


Akurnes : Verification diagrams for MOS PoP, threshold= 0.1 mm

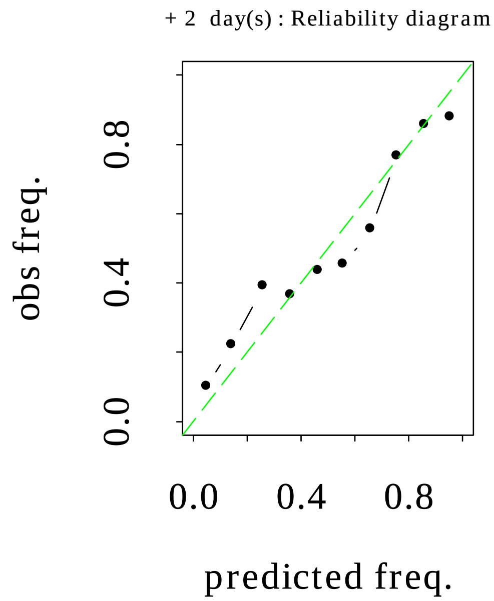


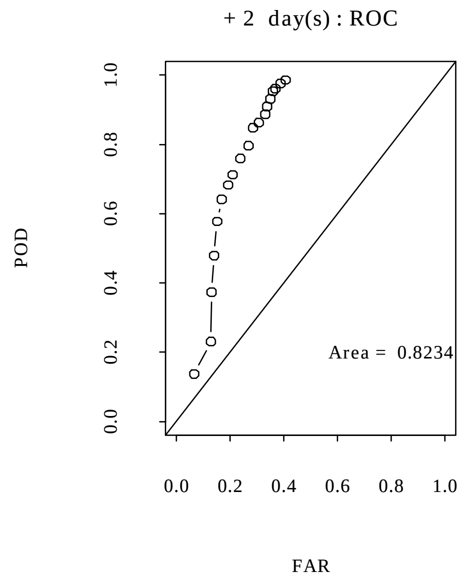

Akurnes: Half-Brier Score
BS
BSdec
Reliability
Resolution
Uncertainty
BS
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
days

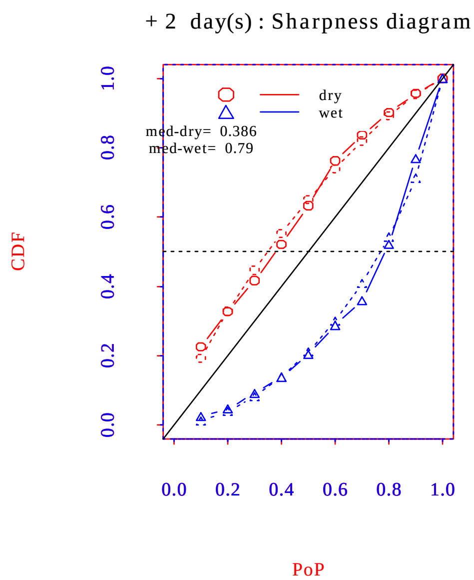
Hveravellir : Verification diagrams for MOS PoP, threshold= 0.1 mm

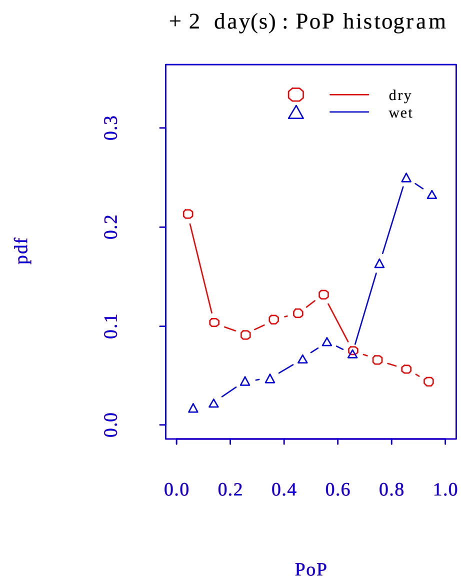


Hveravellir : Verification diagrams for MOS PoP, threshold= 0.1 mm

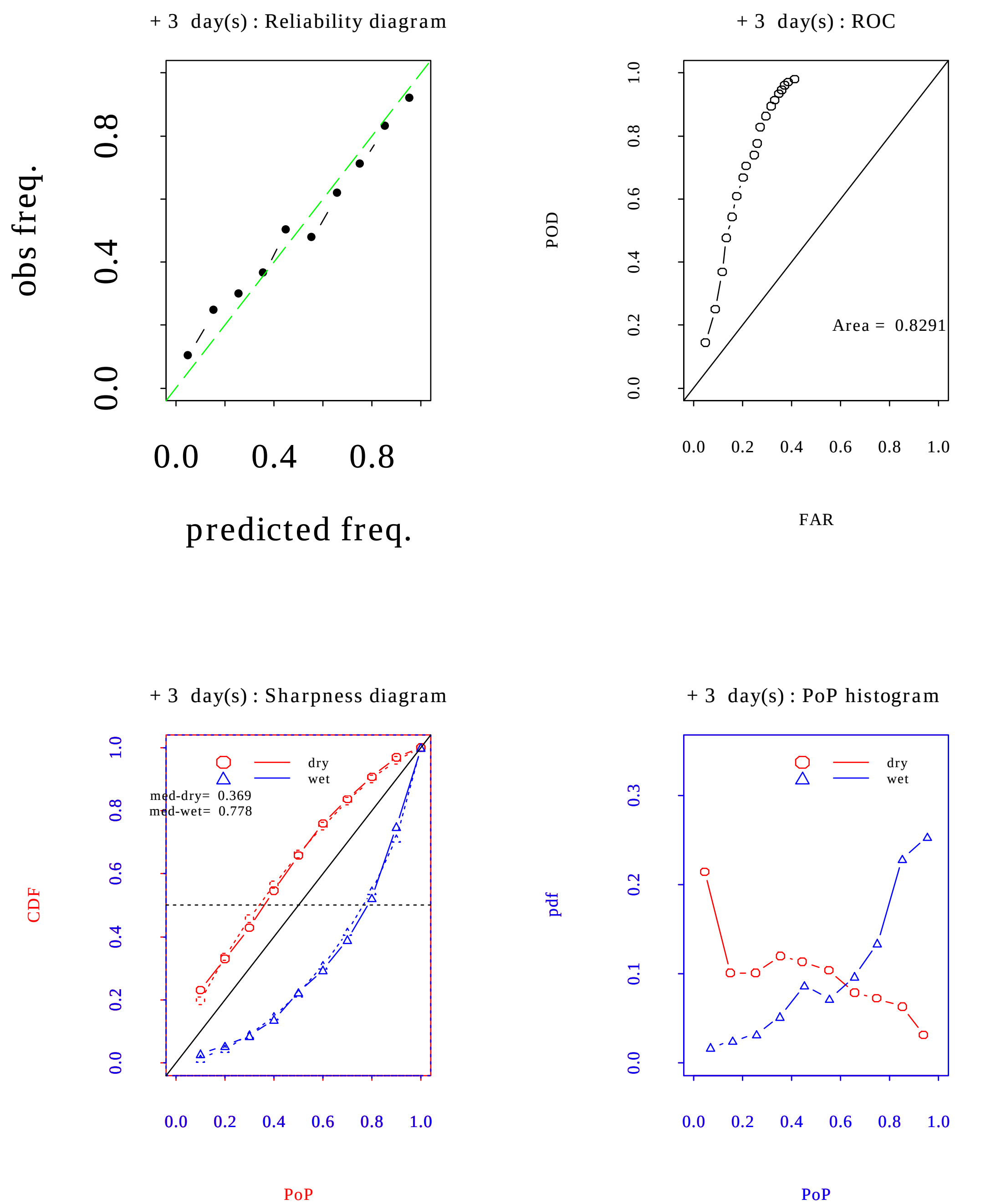




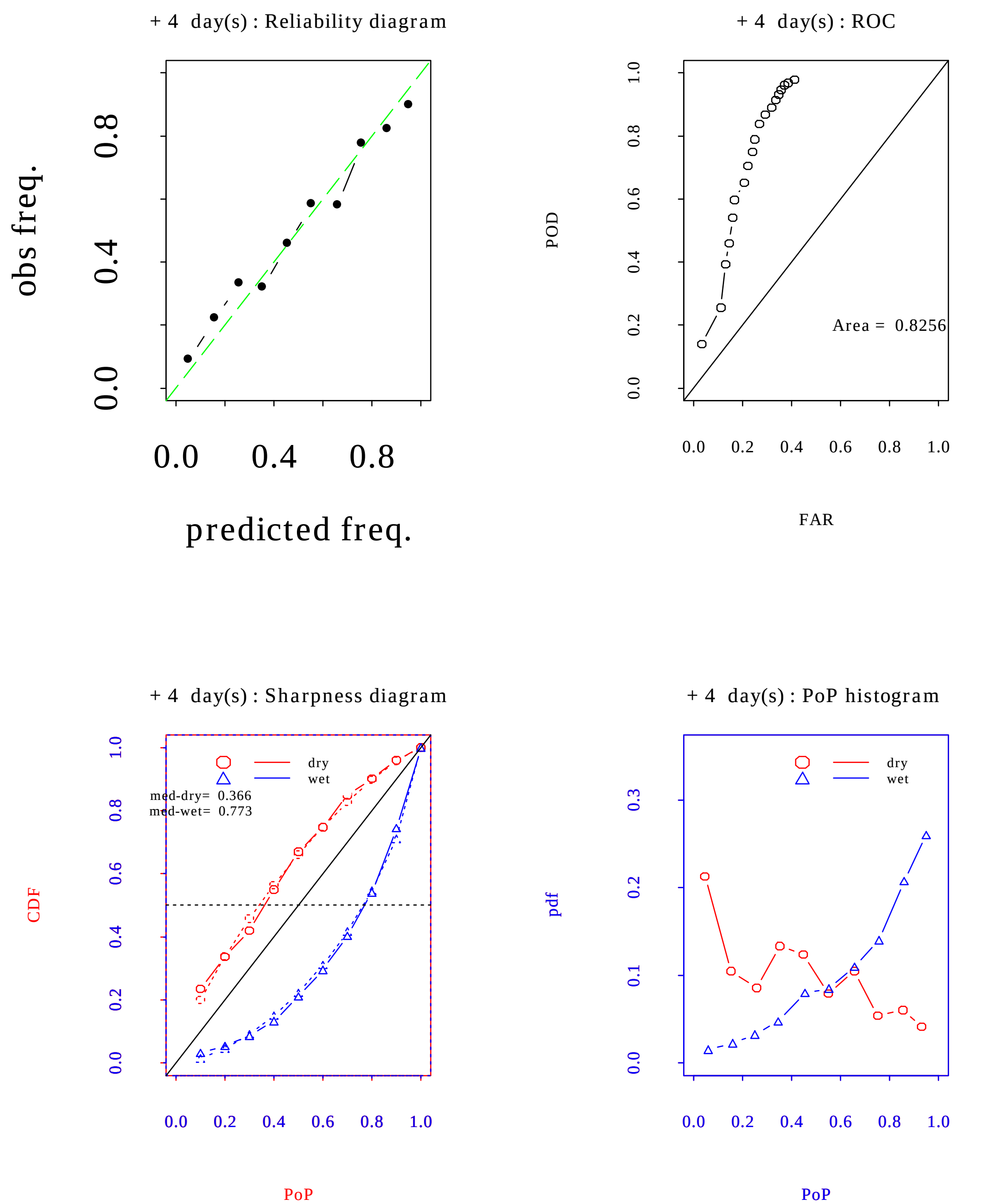




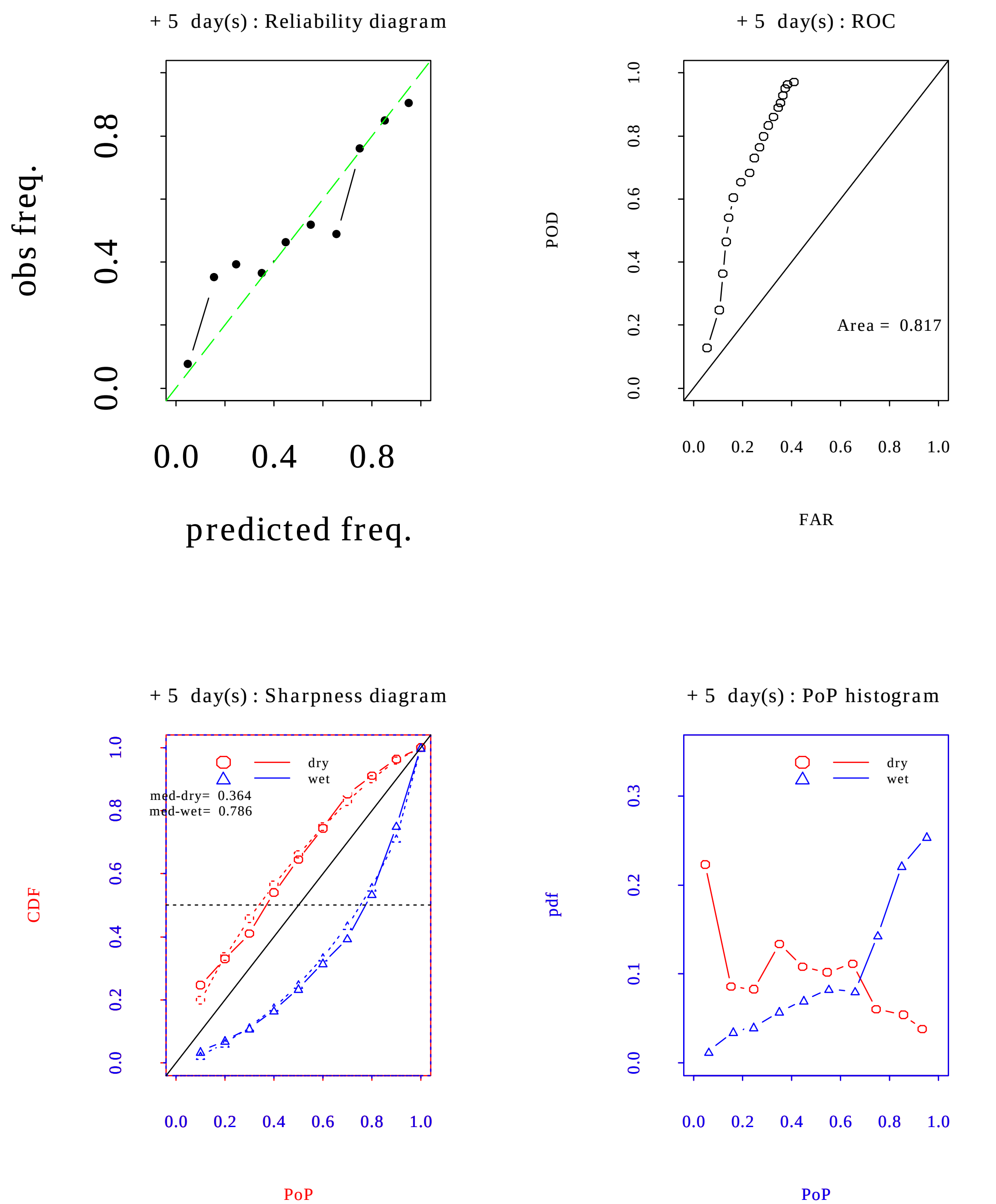
Hveravellir : Verification diagrams for MOS PoP, threshold= 0.1 mm

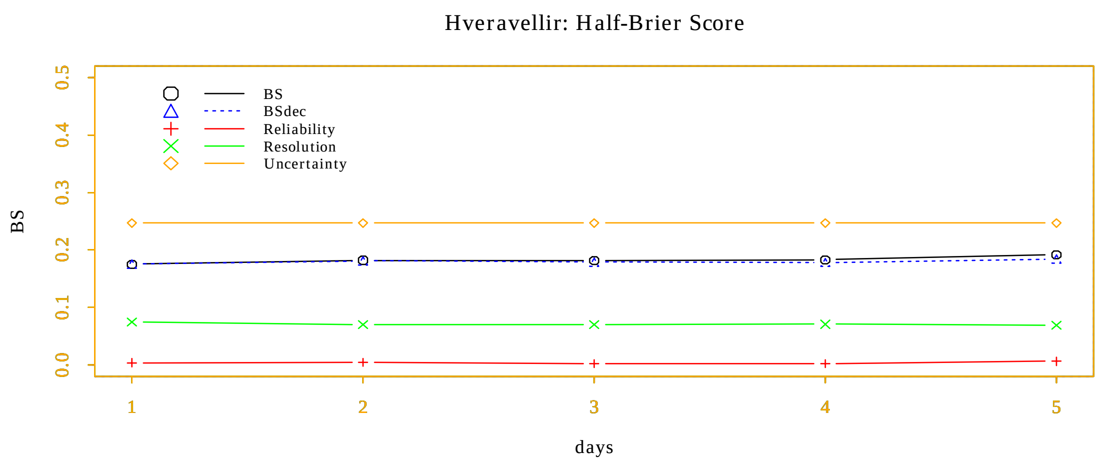


Hveravellir : Verification diagrams for MOS PoP, threshold= 0.1 mm

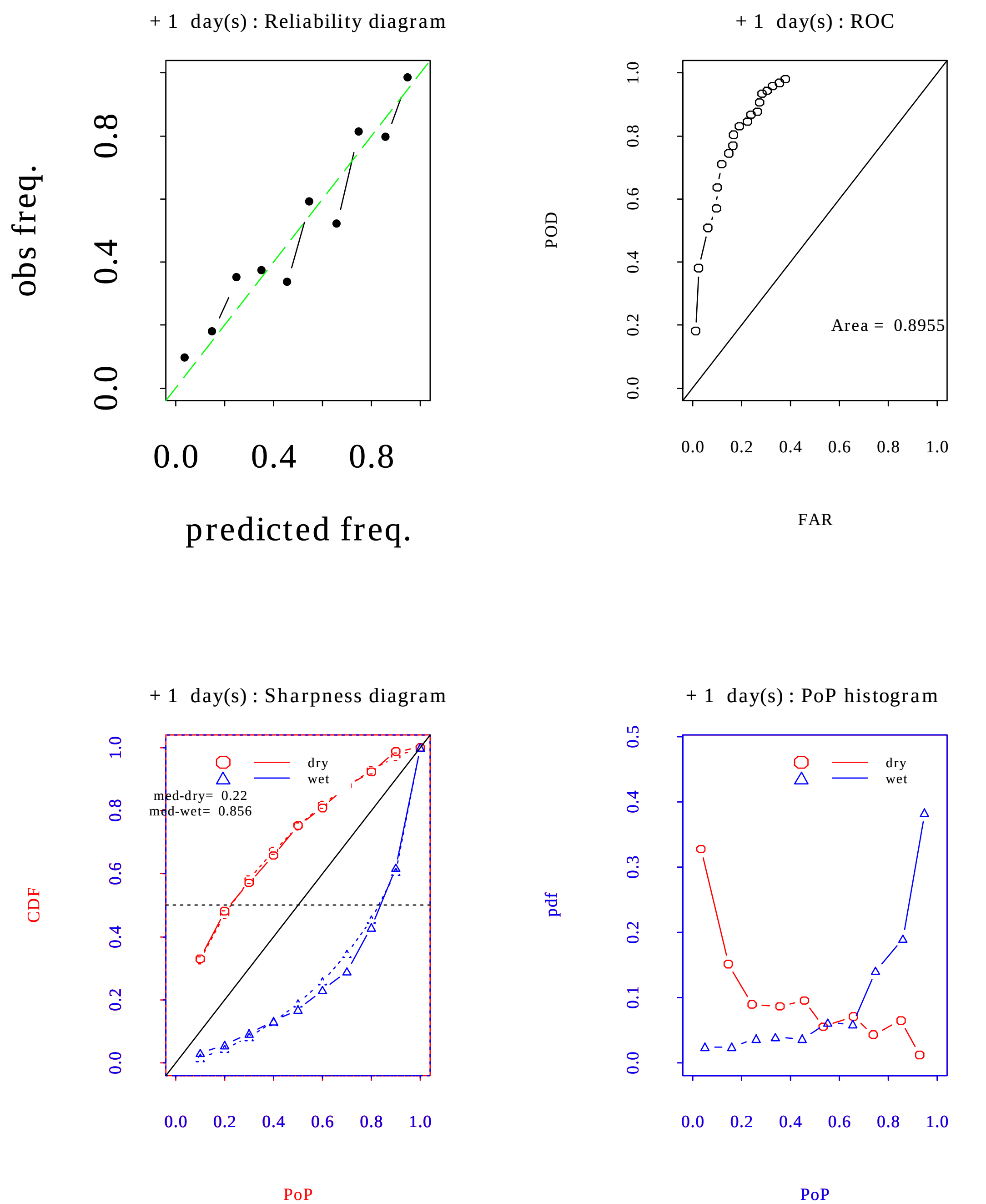


Hveravellir : Verification diagrams for MOS PoP, threshold= 0.1 mm

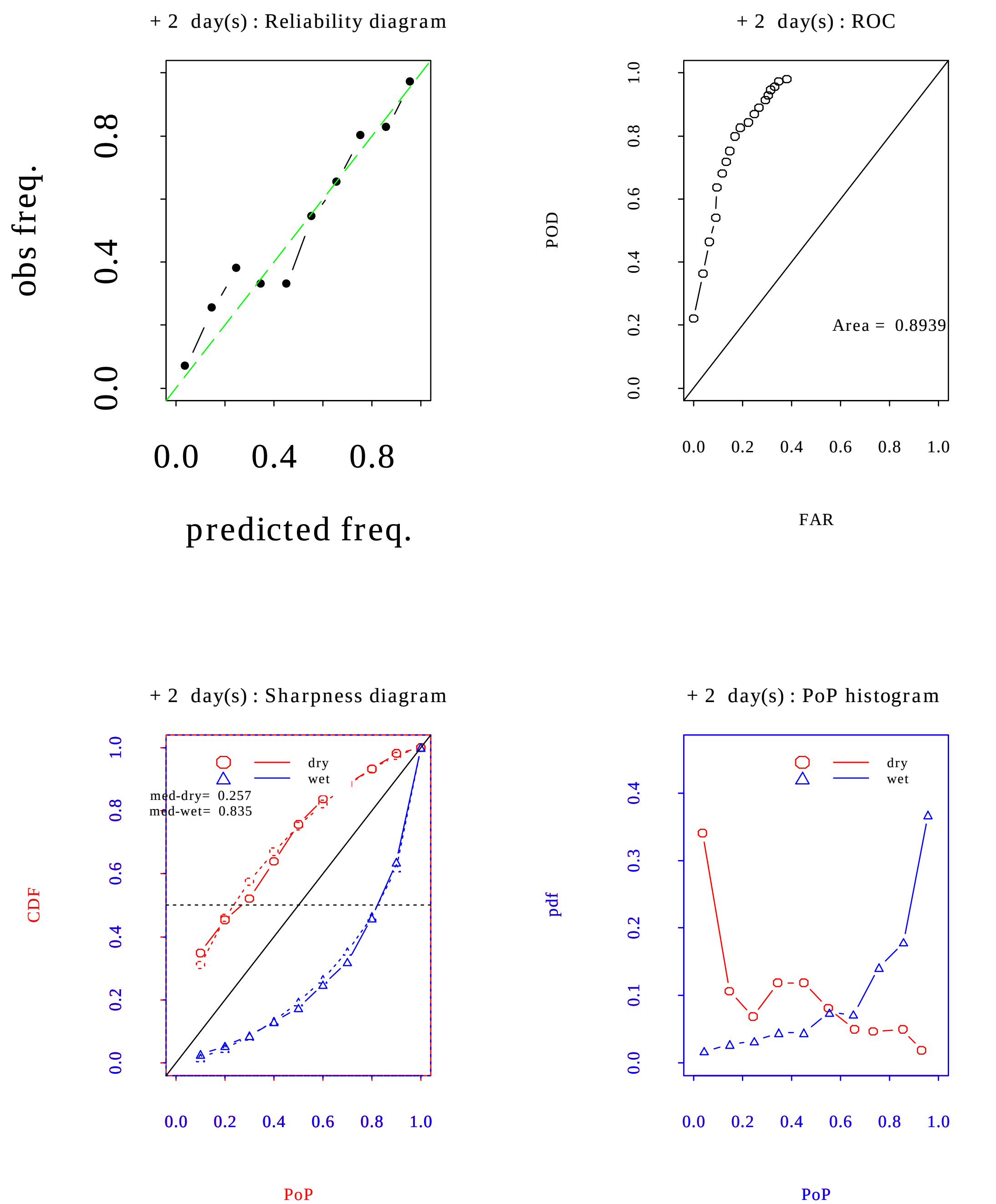



Hveravellir: Half-Brier Score
BS
BSdec
Reliability
Resolution
Uncertainty
BS
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
days

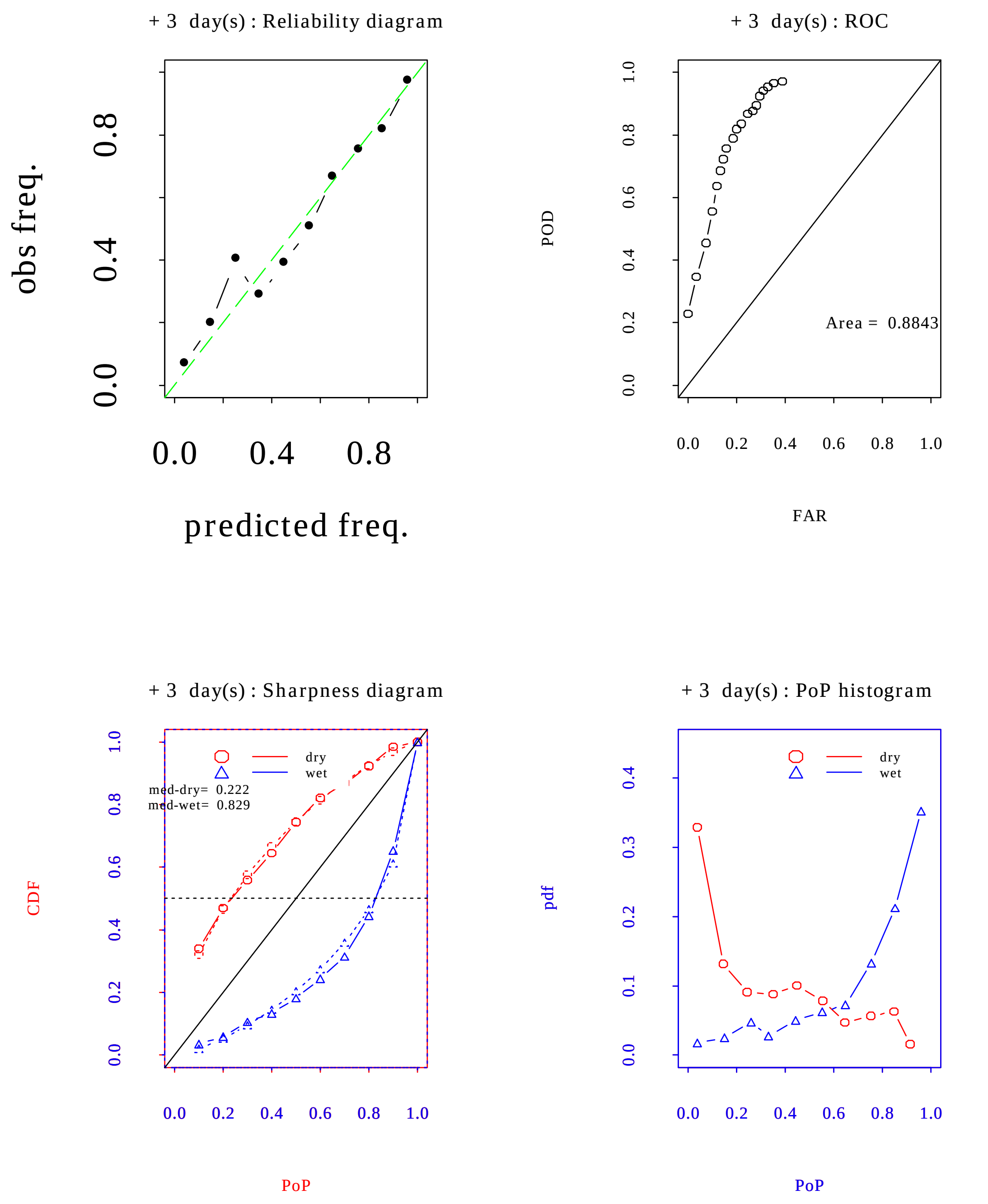
Reykjavik : Verification diagrams for MOS PoP, threshold= 0.1 mm



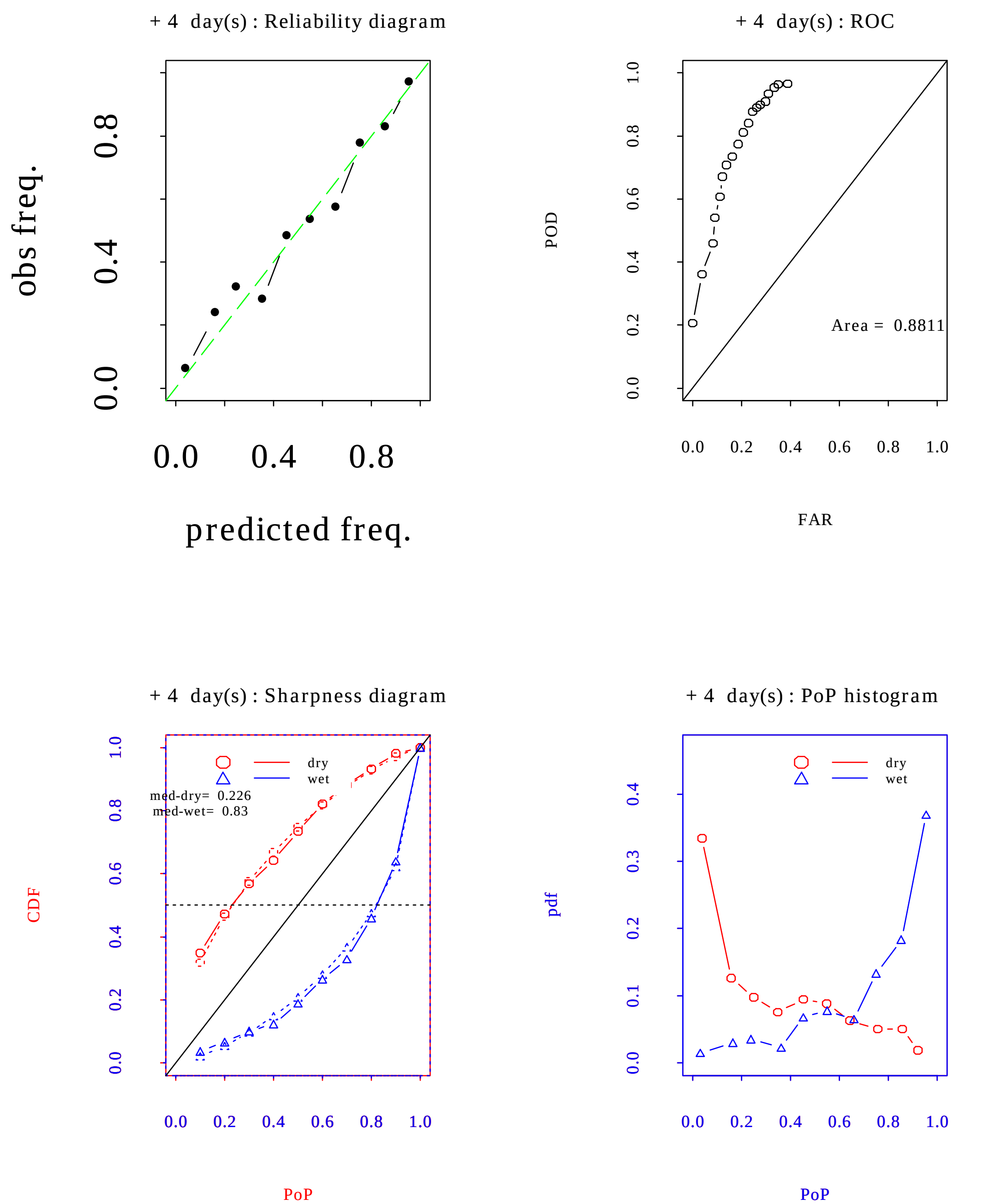
Reykjavik : Verification diagrams for MOS PoP, threshold= 0.1 mm



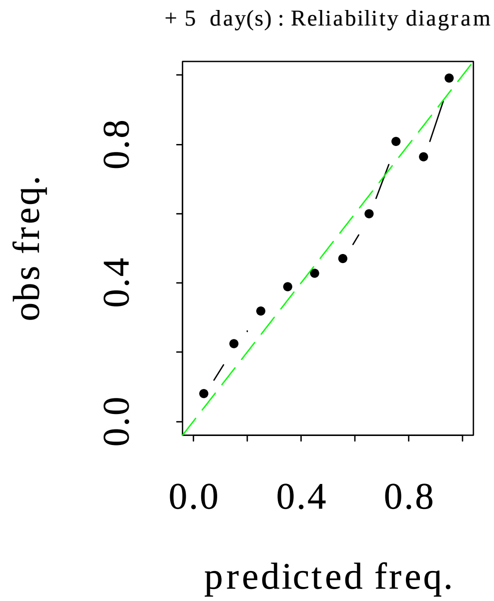
Reykjavik : Verification diagrams for MOS PoP, threshold= 0.1 mm

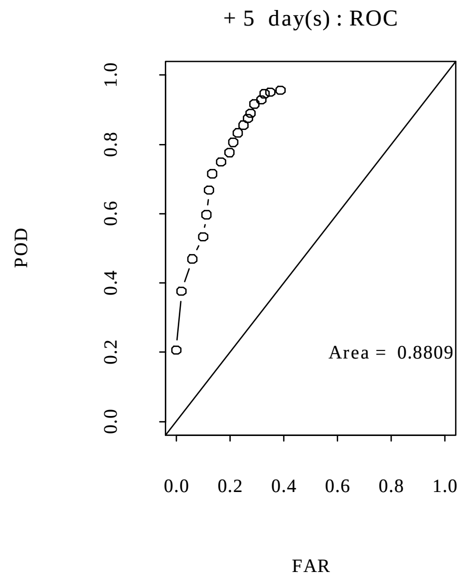


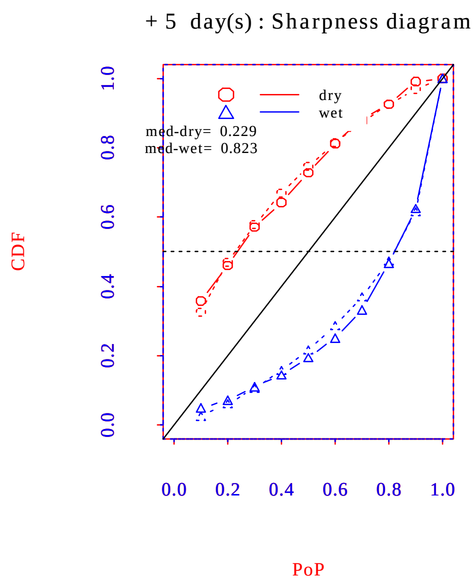
Reykjavik : Verification diagrams for MOS PoP, threshold= 0.1 mm

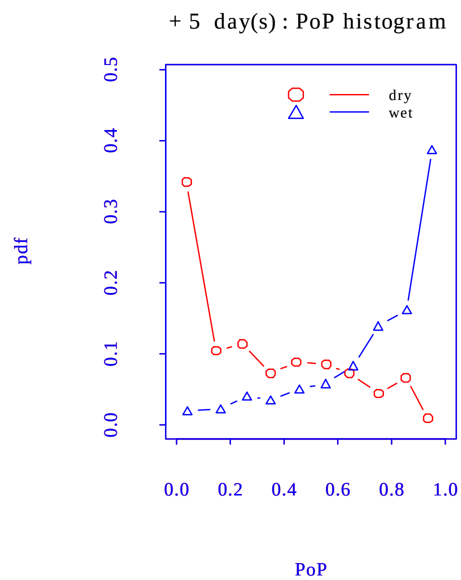


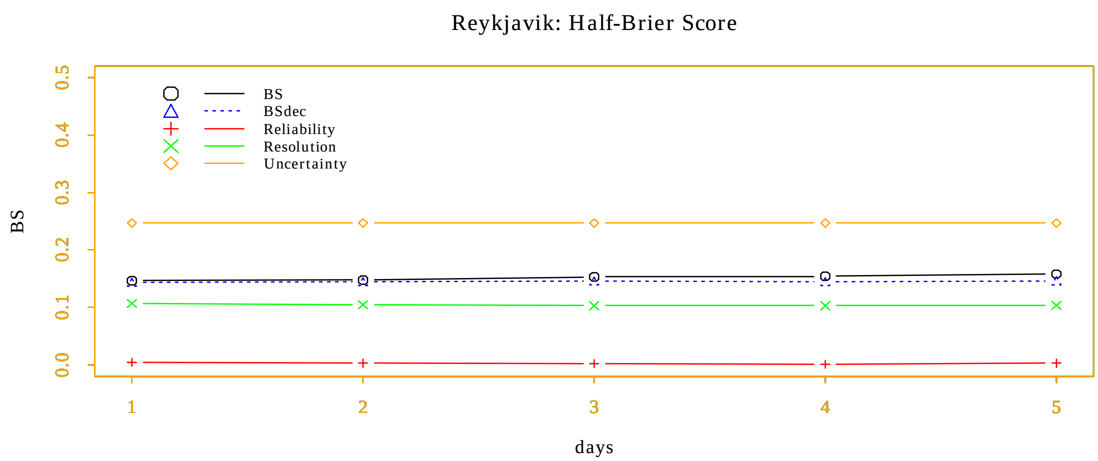
Reykjavik : Verification diagrams for MOS PoP, threshold= 0.1 mm



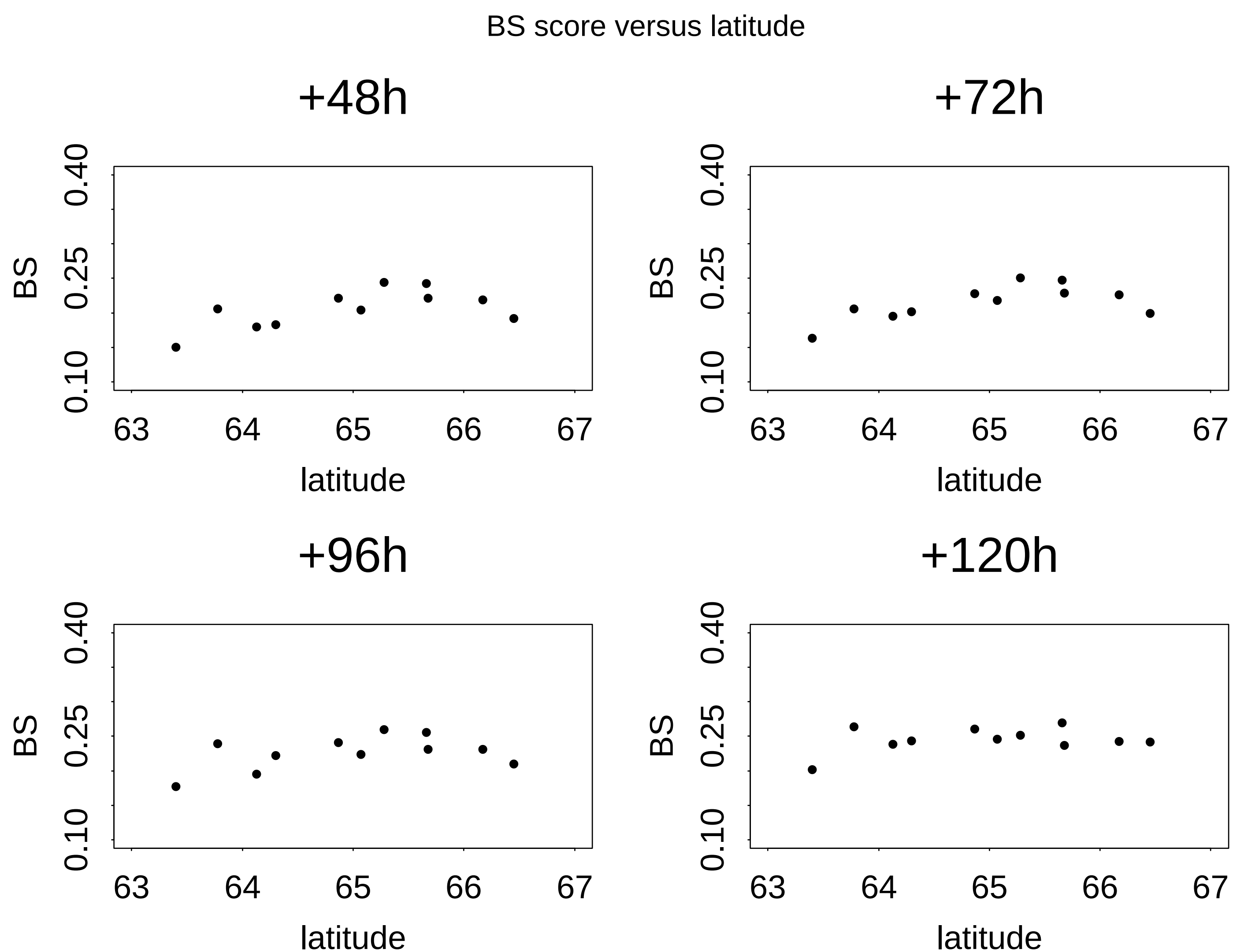








Reykjavik: Half-Brier Score
BS
BSdec
Reliability
Resolution
Uncertainty
0.0
0.1
0.2
0.3
0.4
0.5
BS
1
2
3
4
5
days

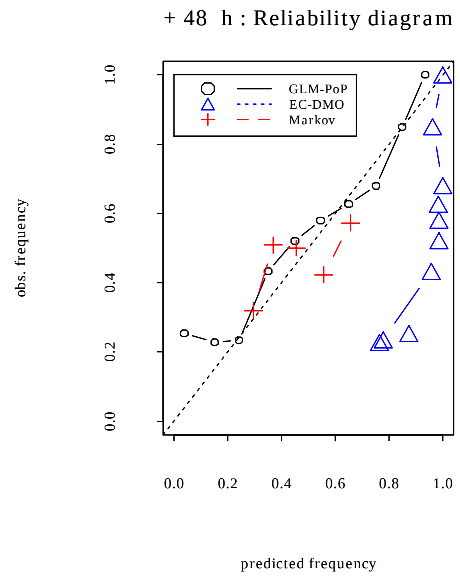

BS score versus latitude
+48h
+72h
+96h
+120h
BS
0.10
0.25
0.40
63
64
65
66
67
latitude

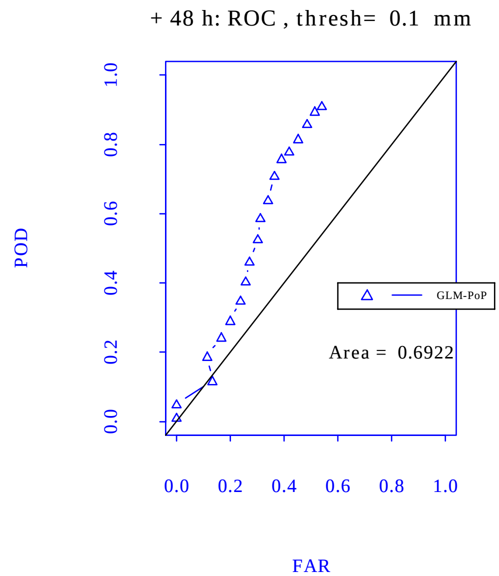
Appendix 5

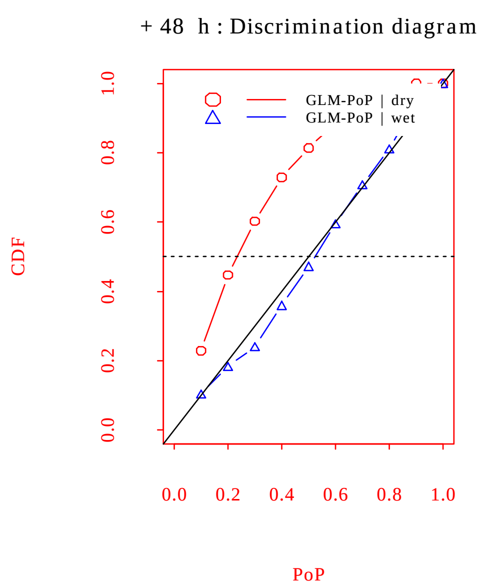
GLM-PoP

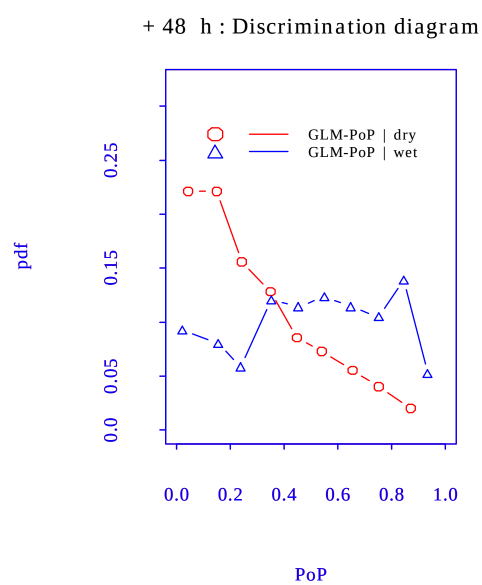
Statistical scores with ECMWF forecasts

Akureyri : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

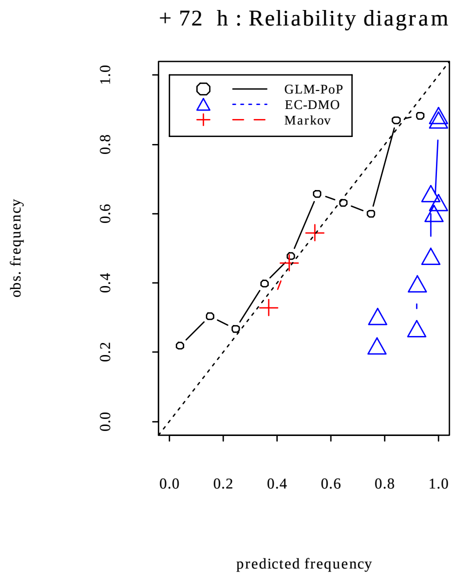


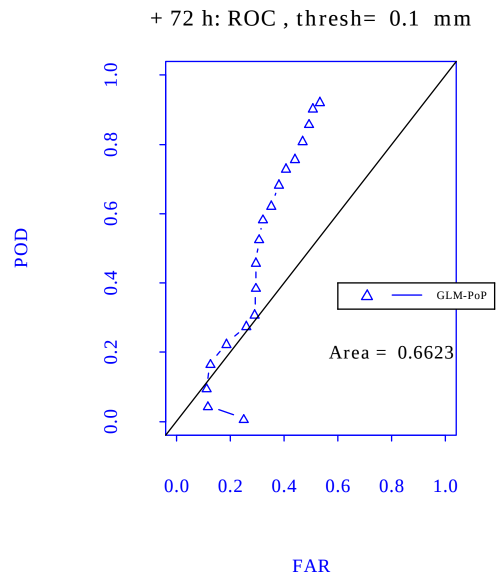


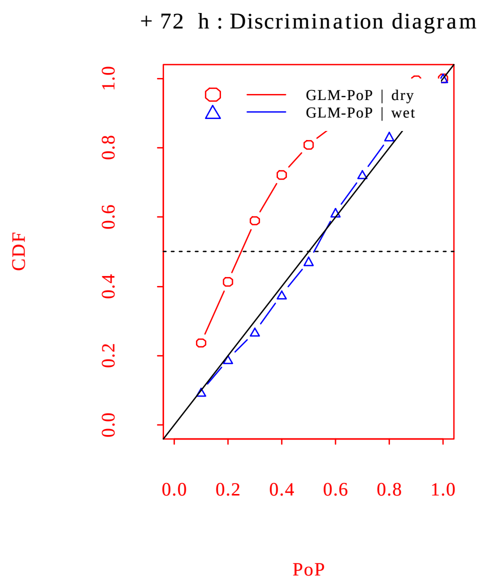


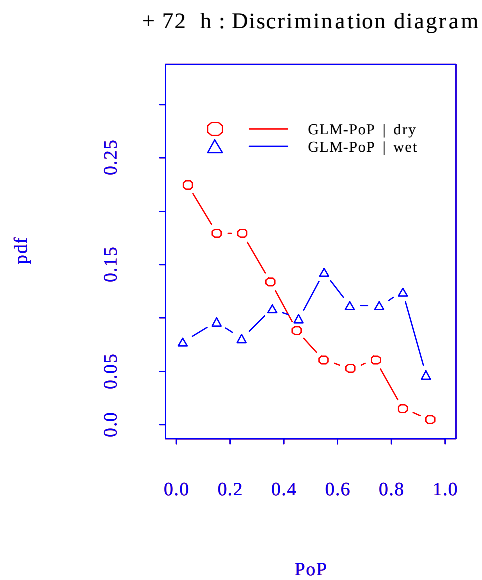


Akureyri : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

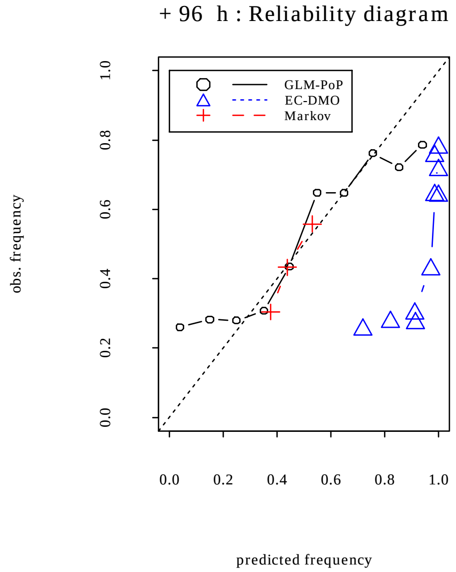


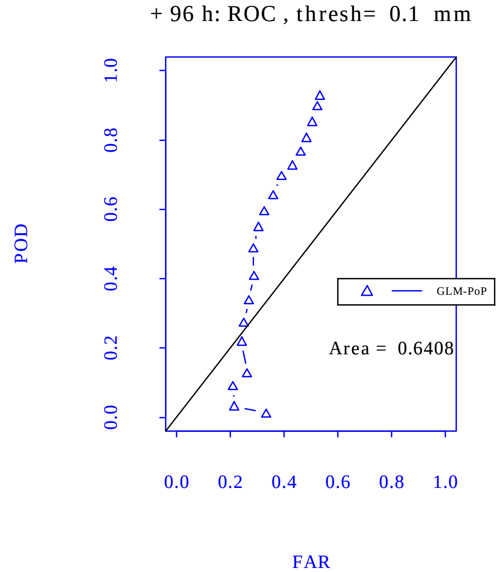


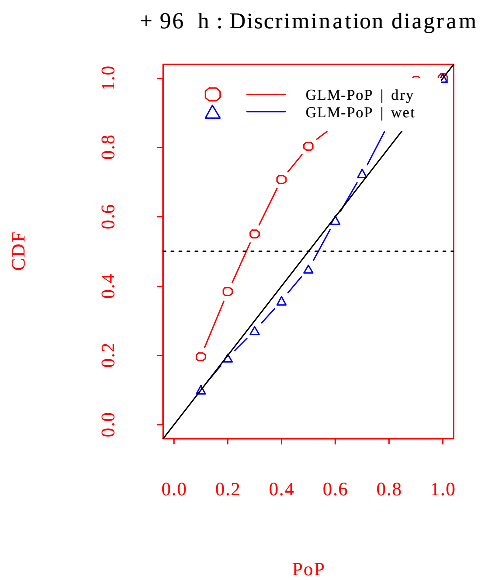


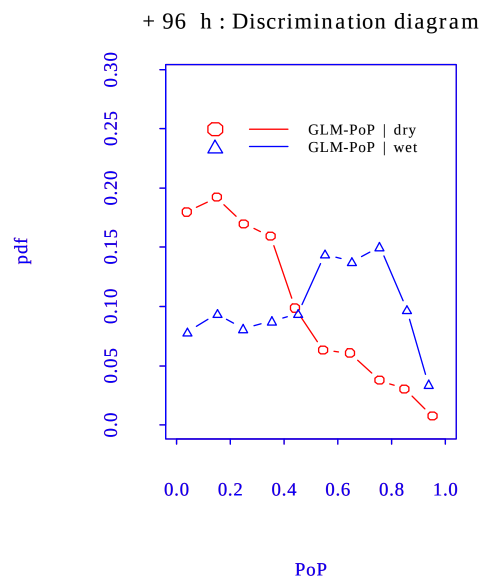


Akureyri : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

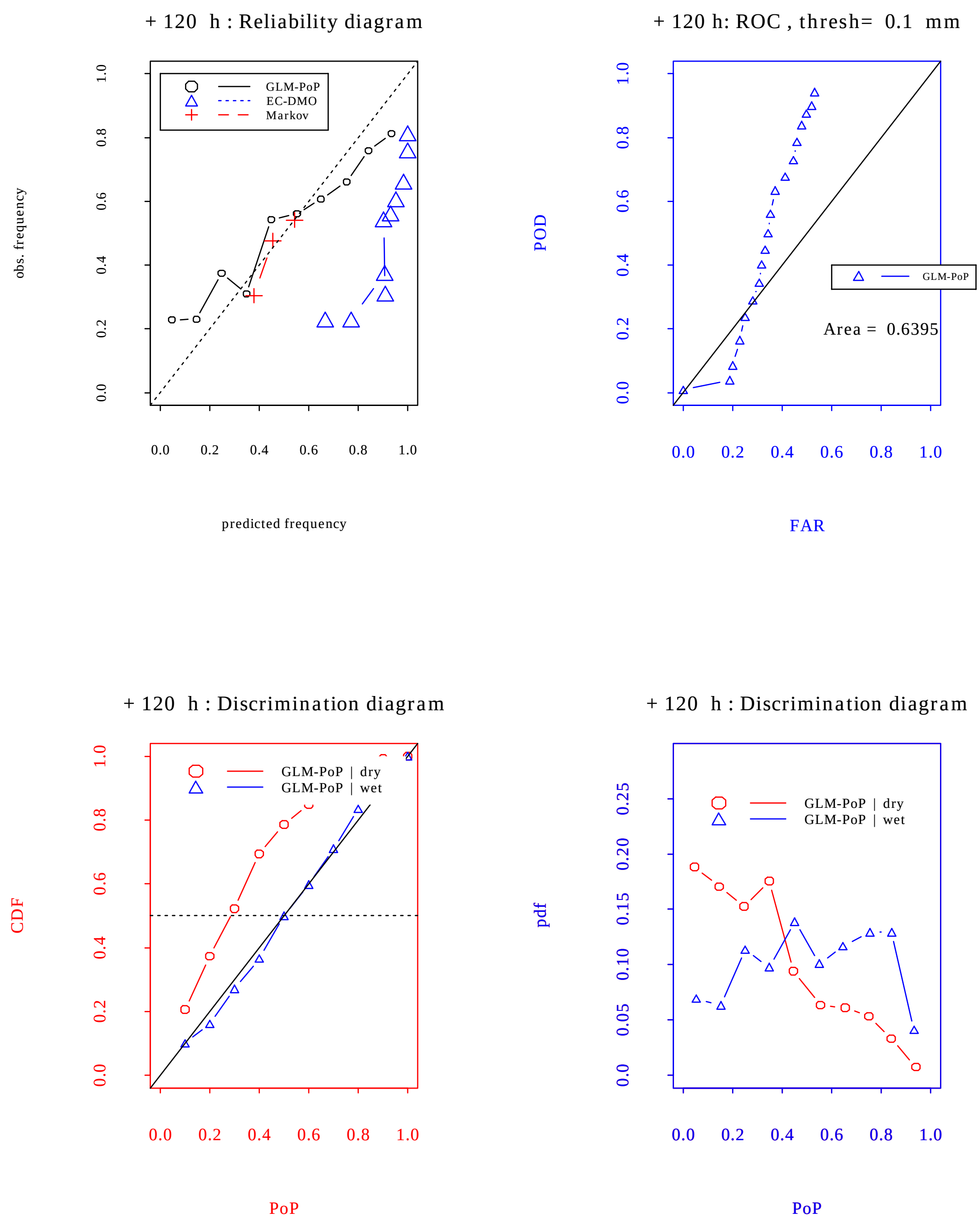




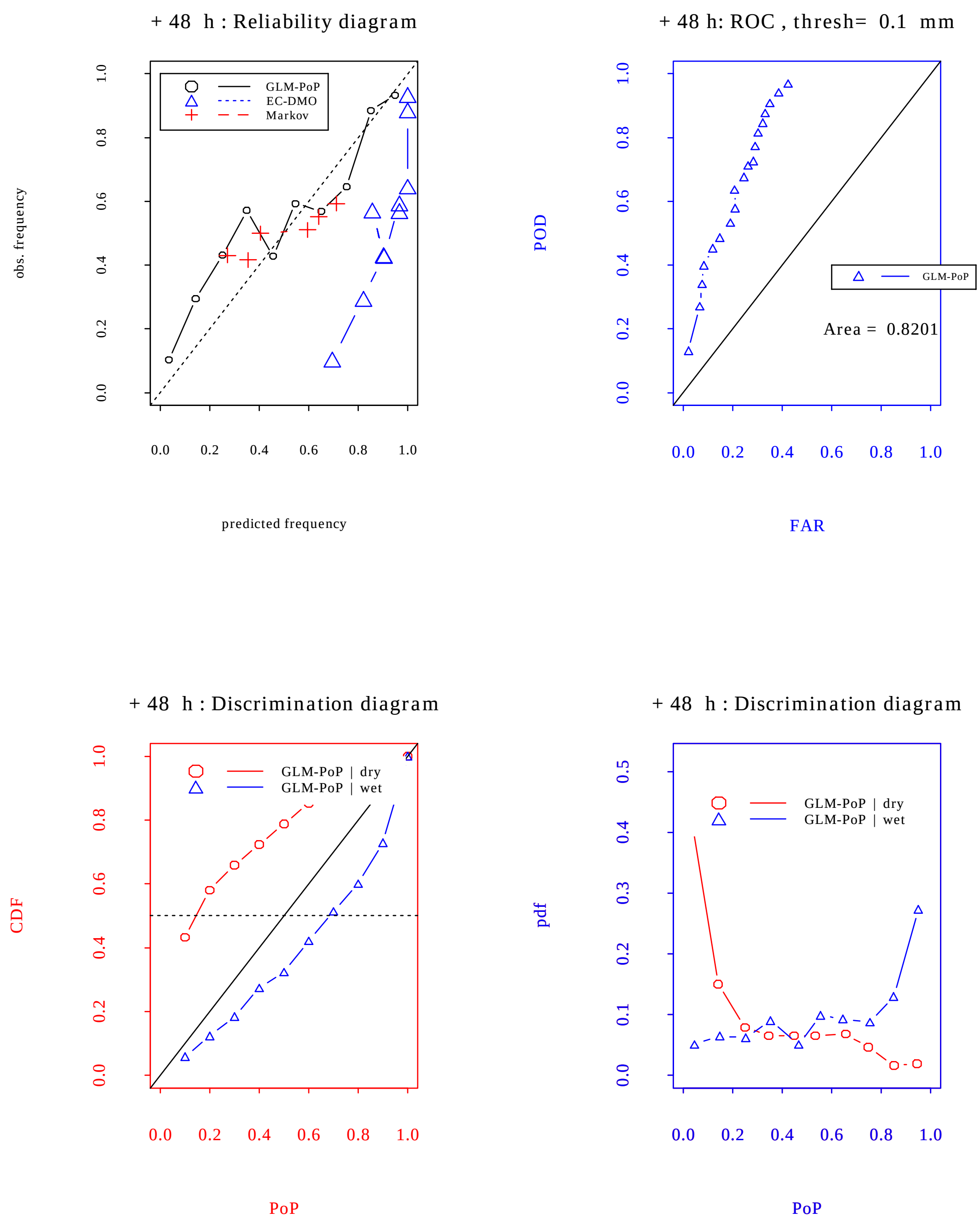




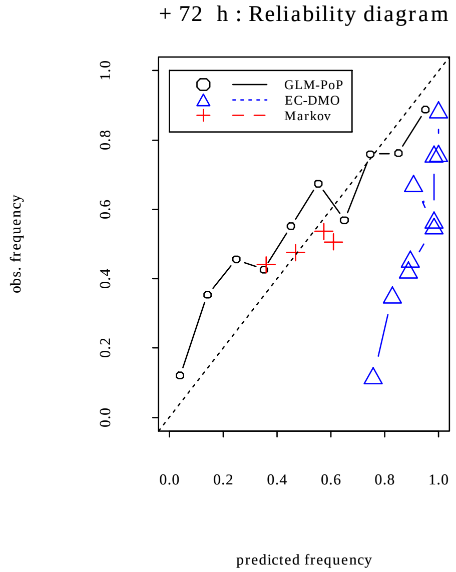
Akureyri : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

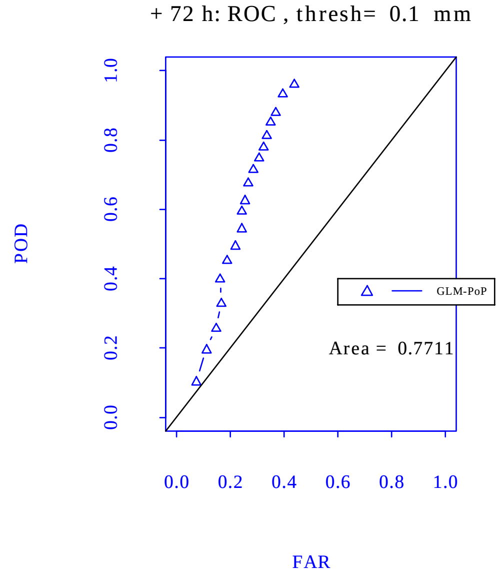


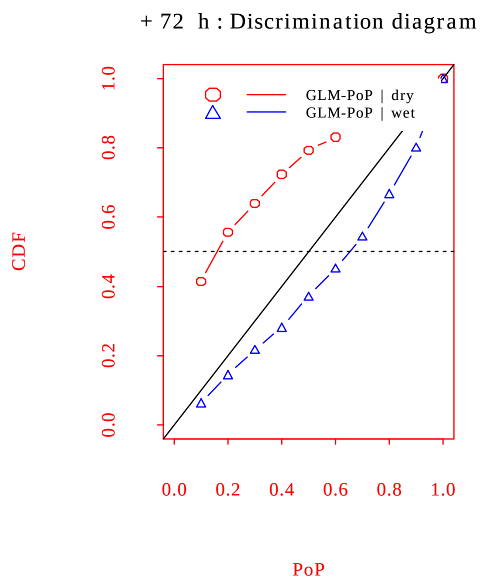
Akurnes : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

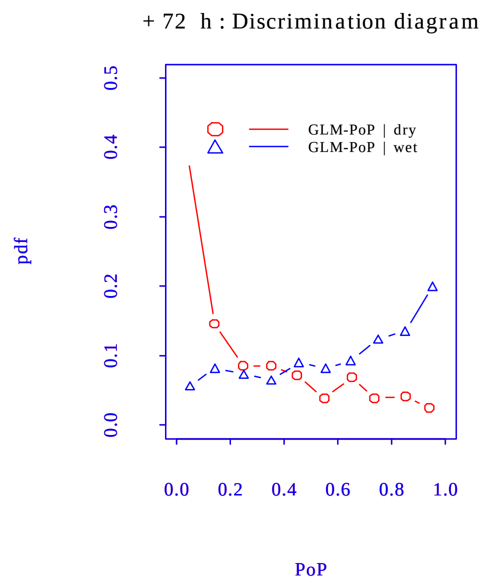


Akurnes : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

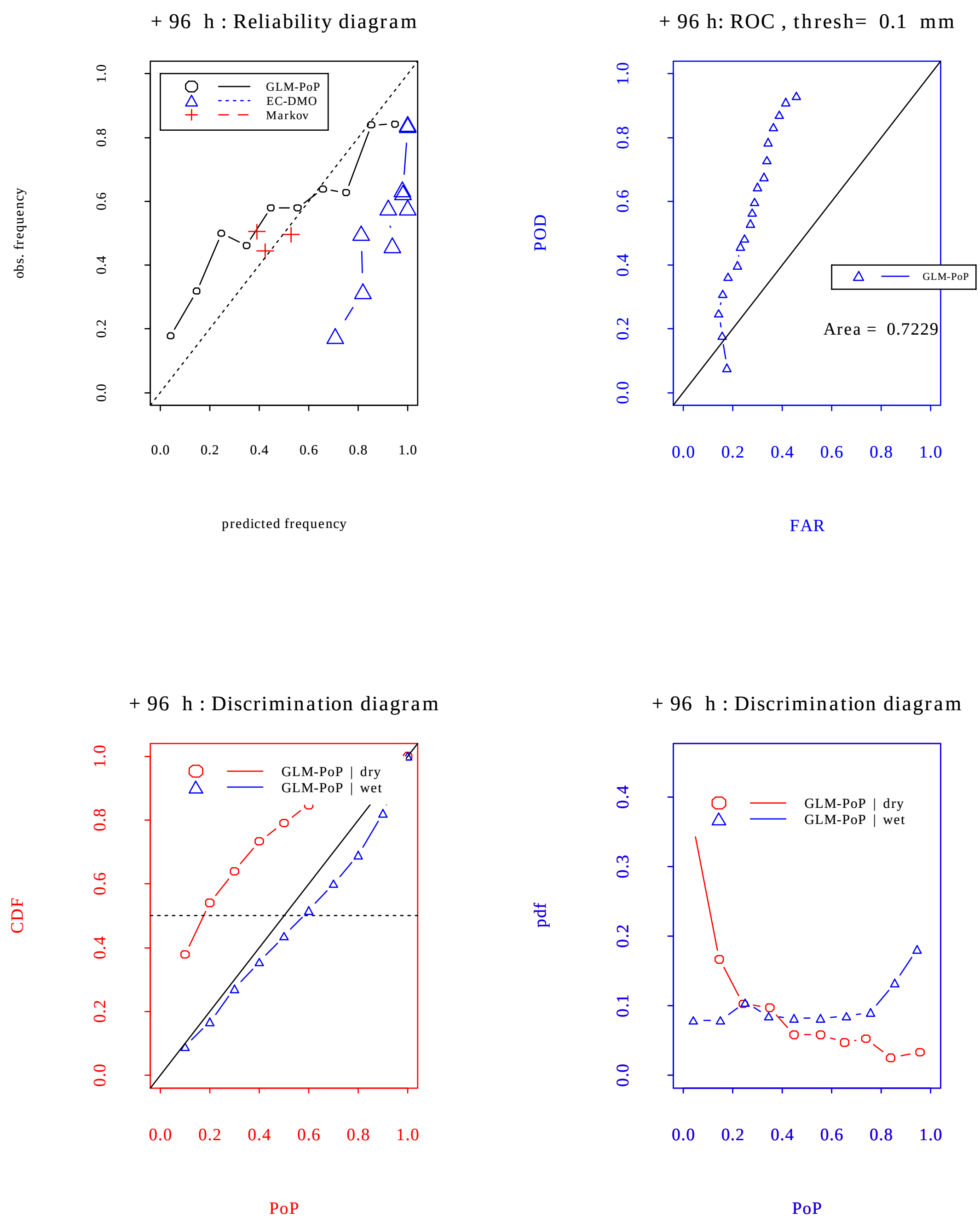




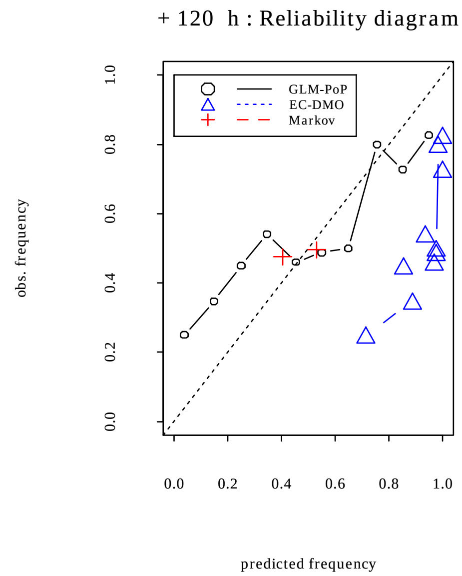


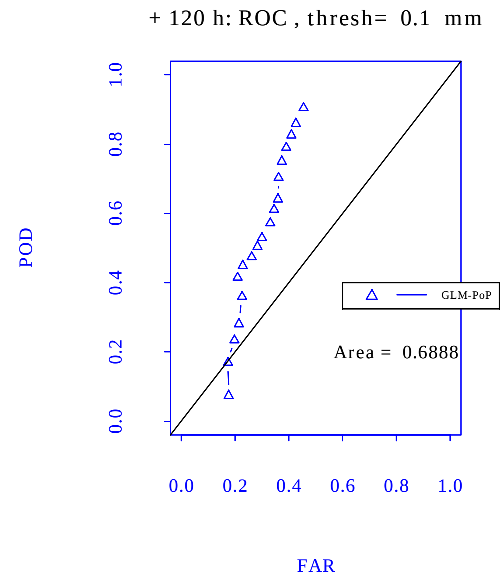


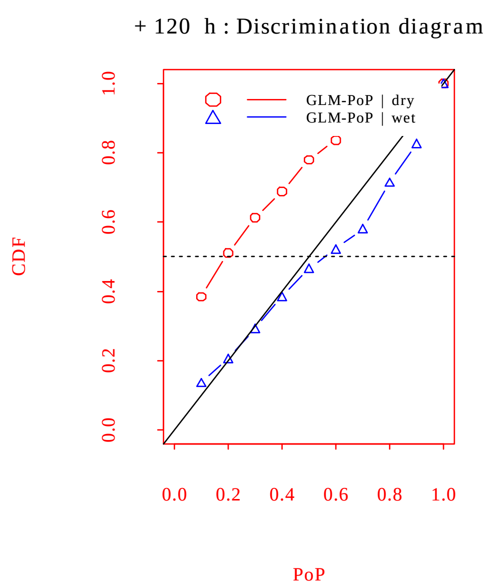
Akurnes : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

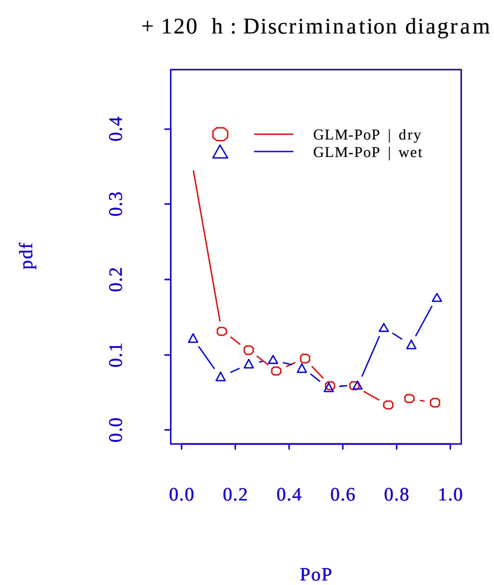


Akurnes : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

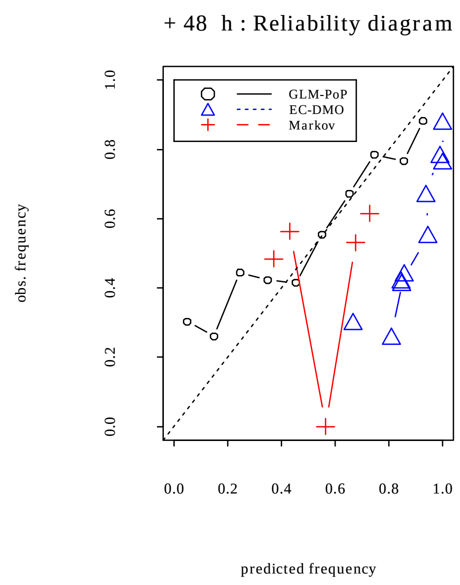


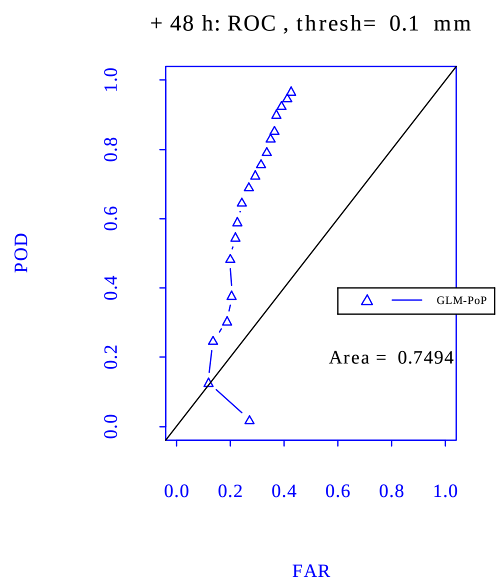


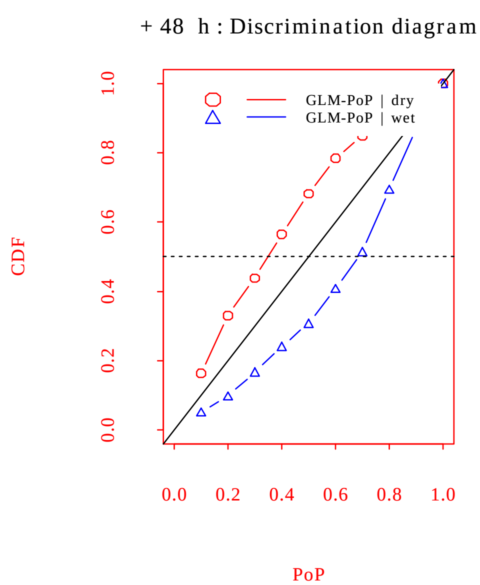


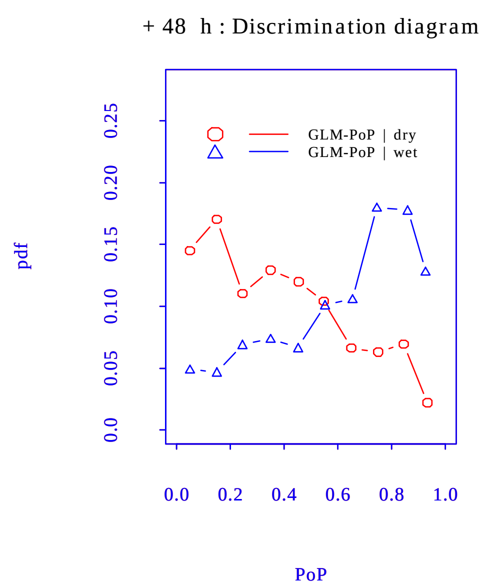


Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

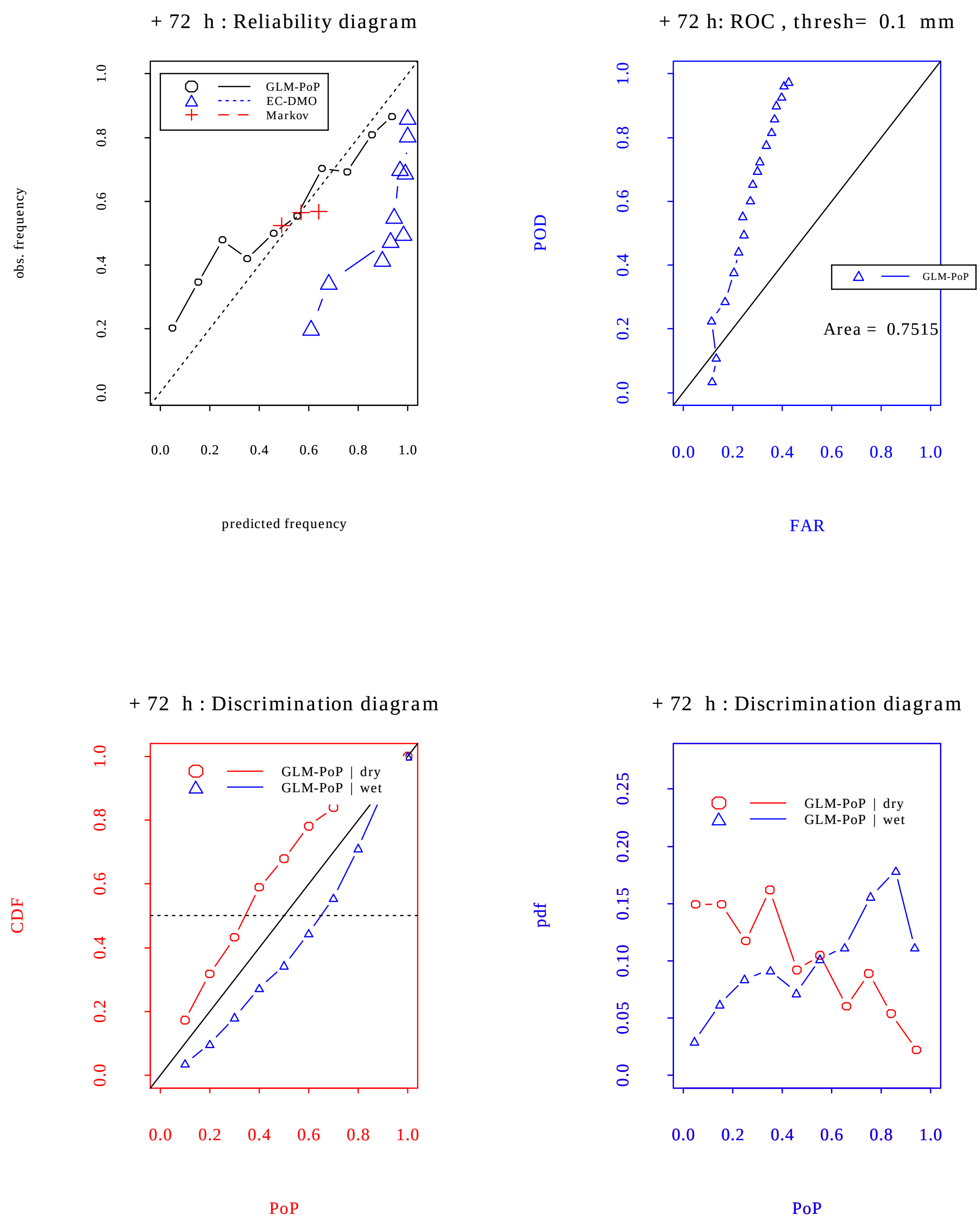




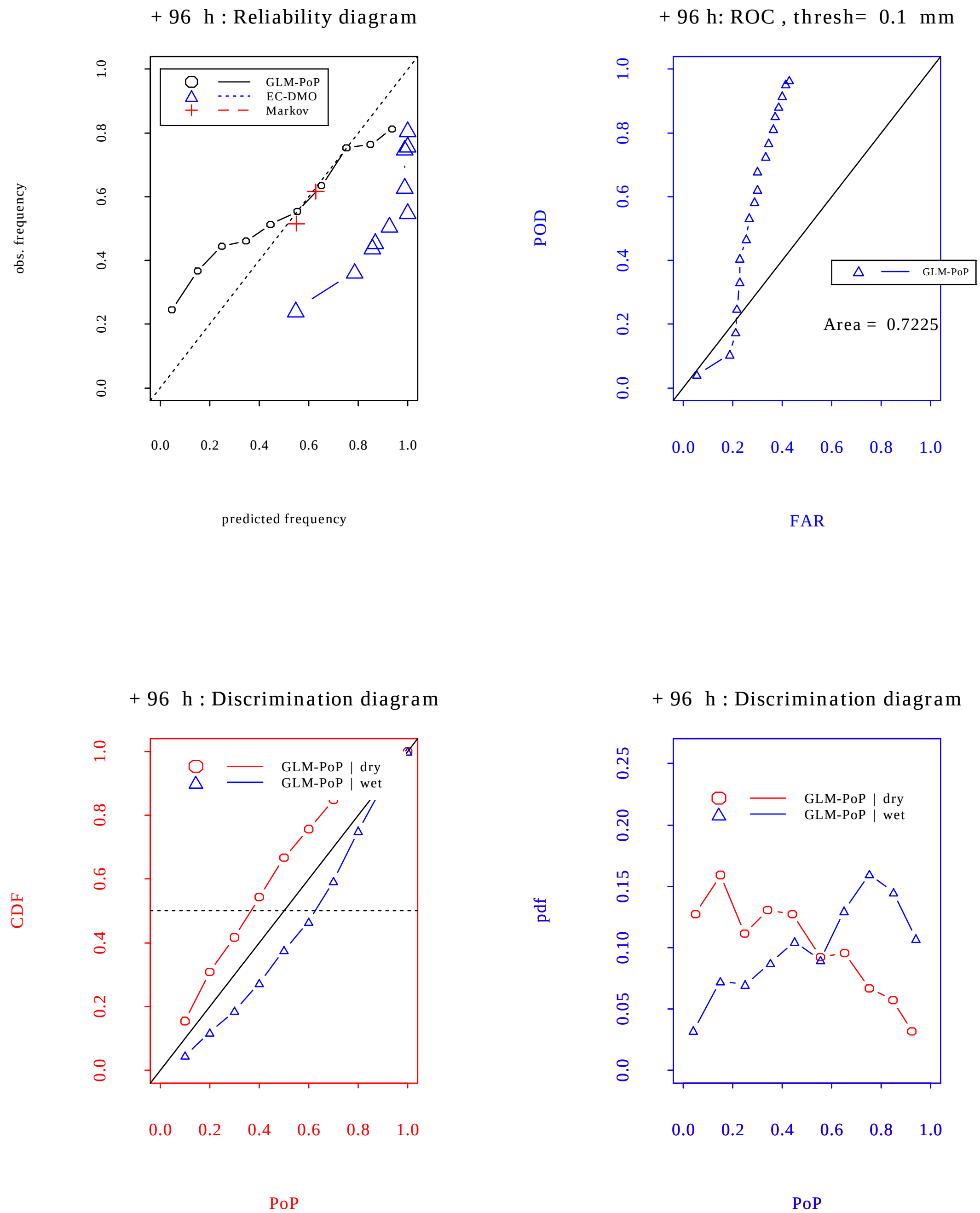




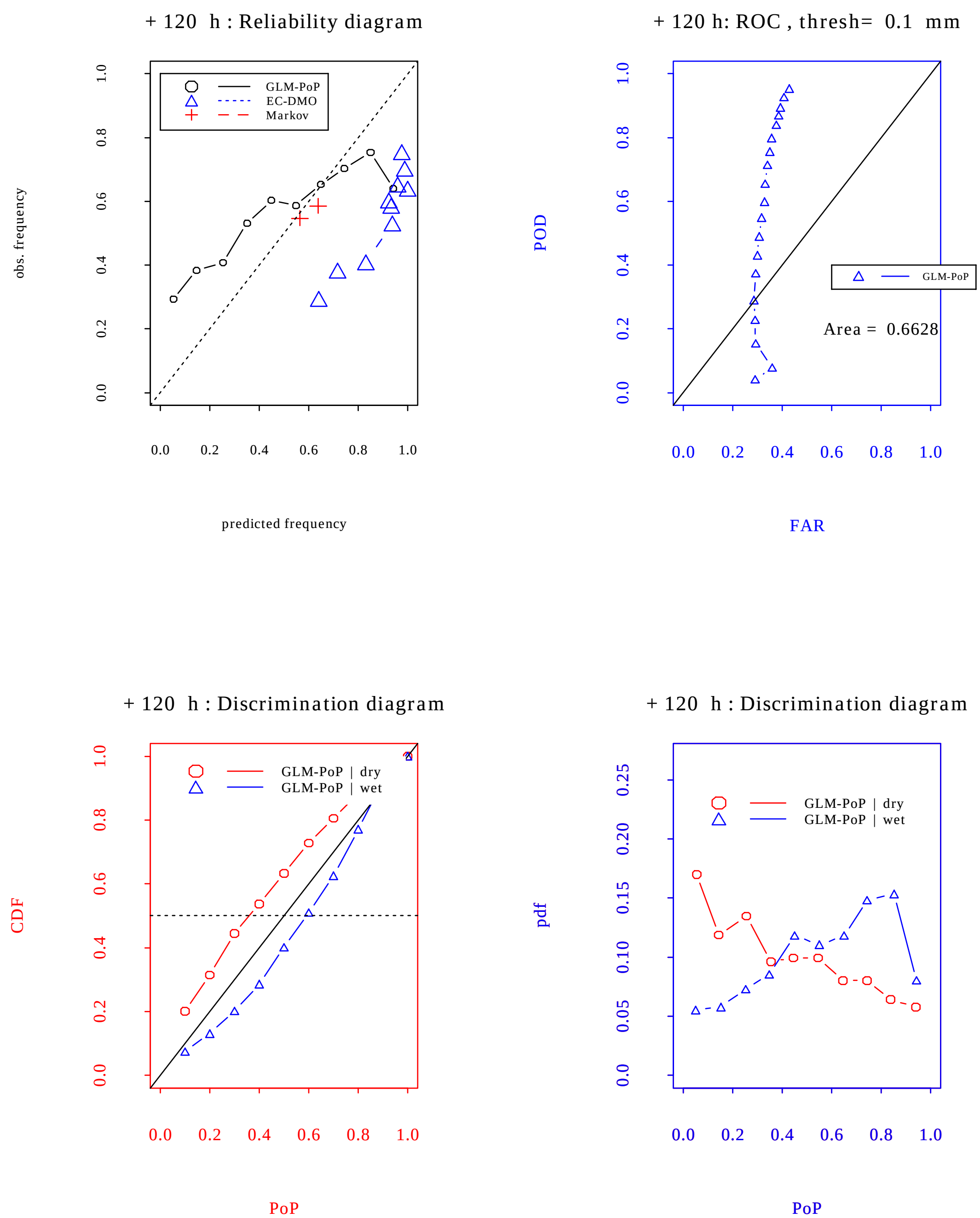
Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112



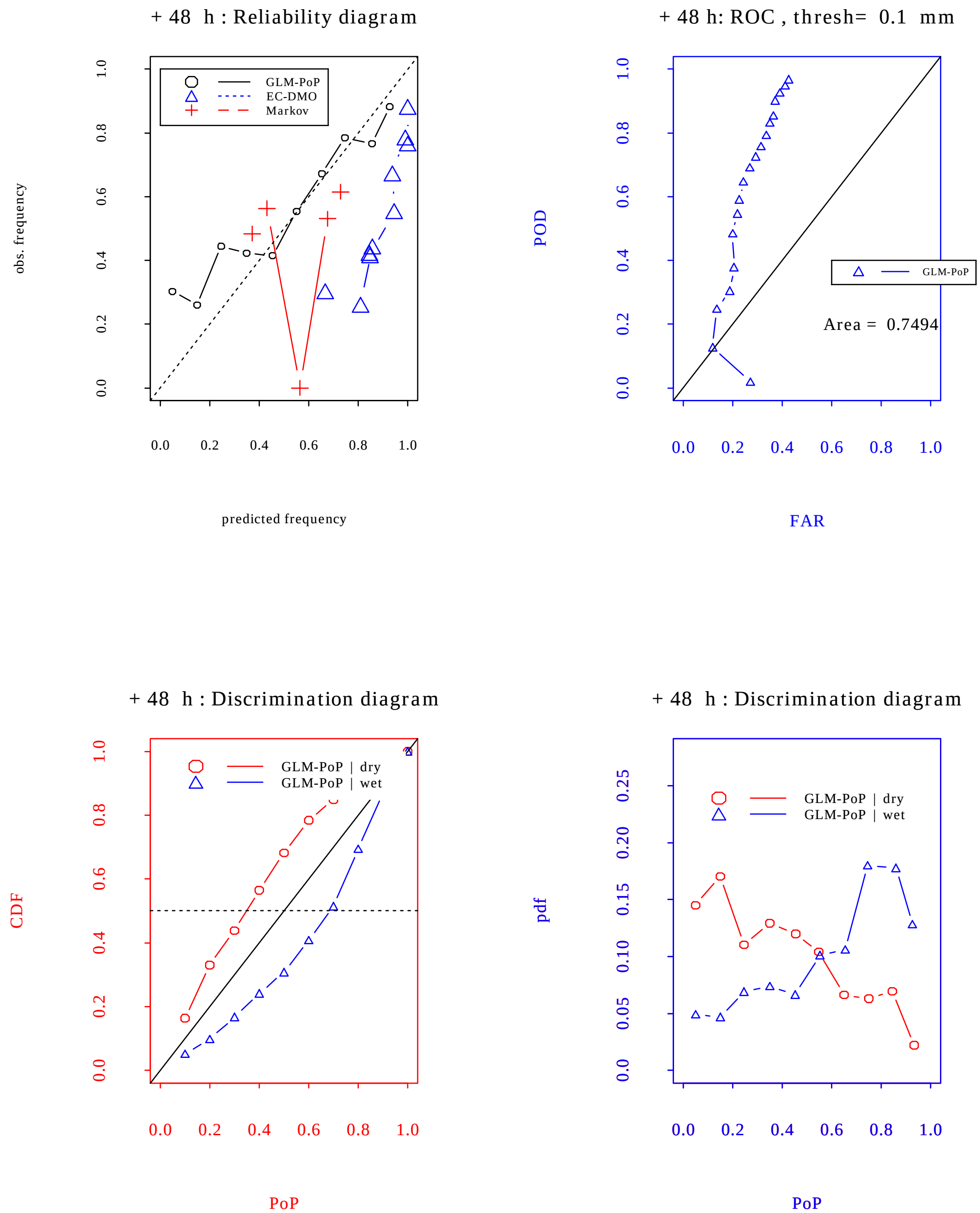
Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112



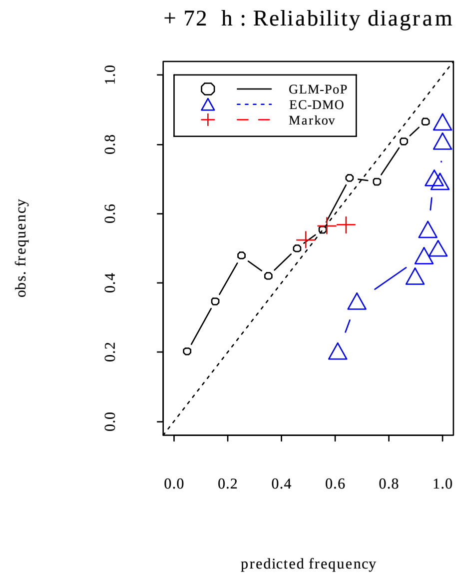
Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

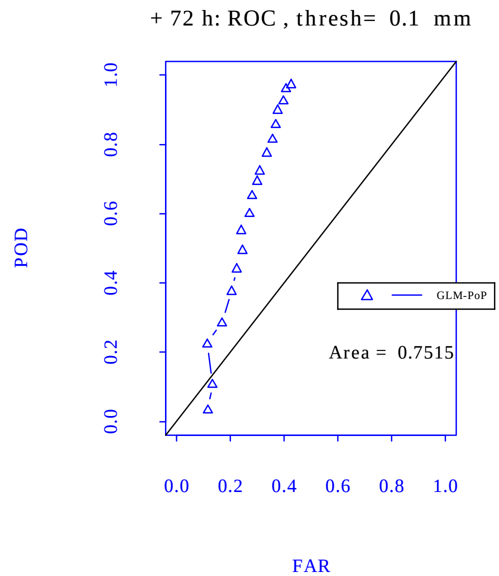


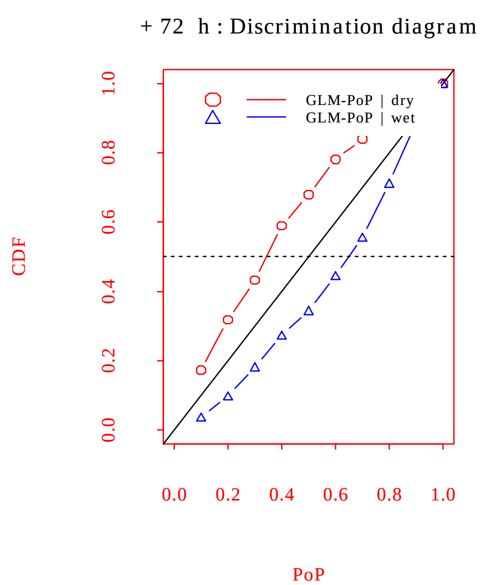
Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

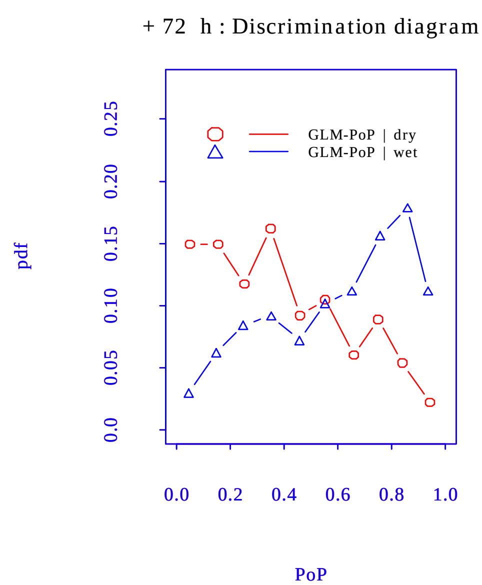


Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

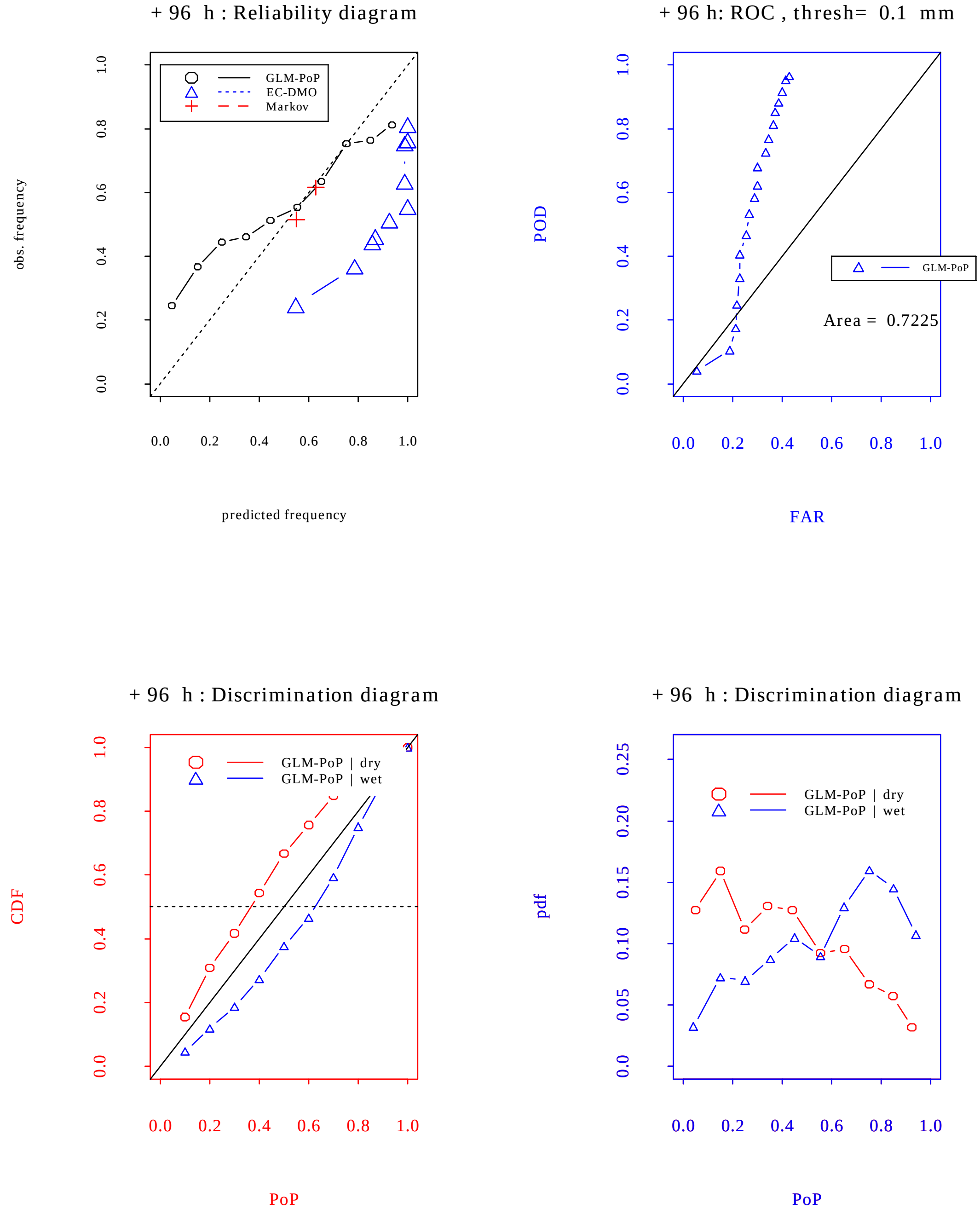




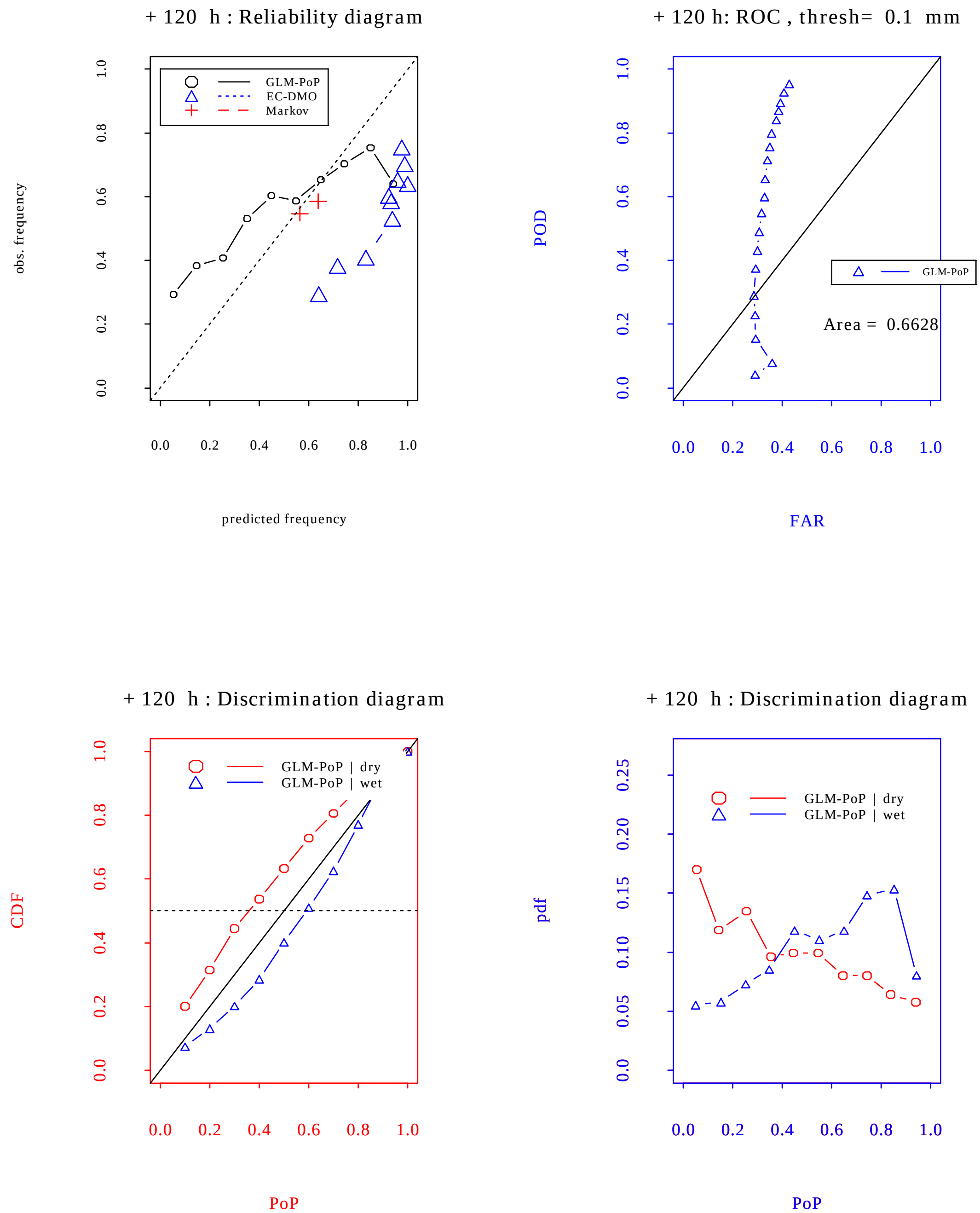




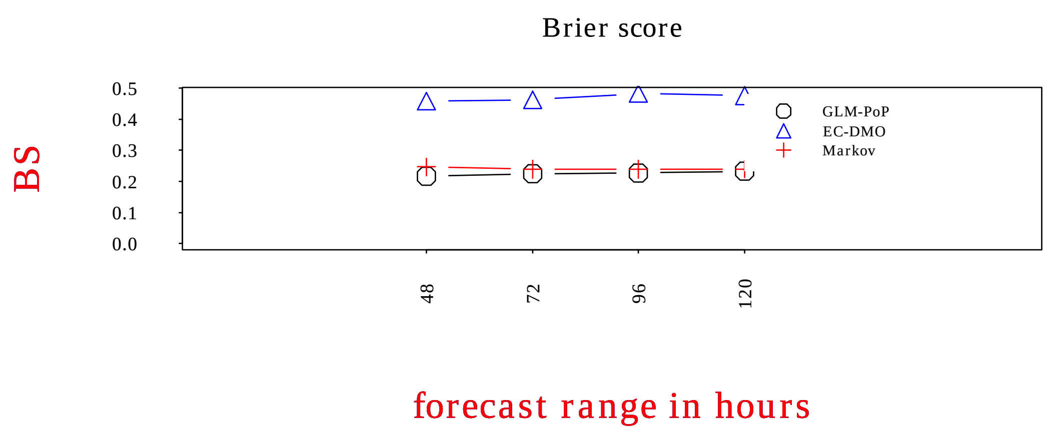
Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

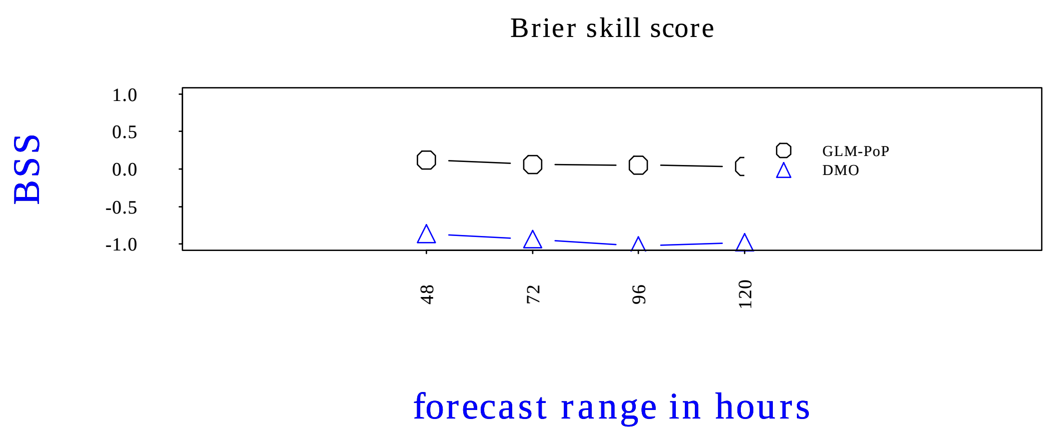


Hveravellir : Verification diagrams for ECMWF MOS PoP
Period : 1999120112 - 2001120112

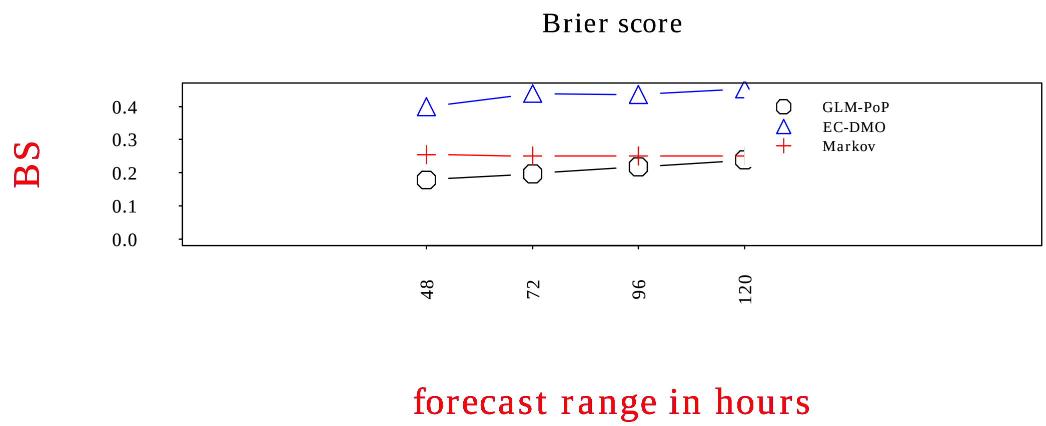


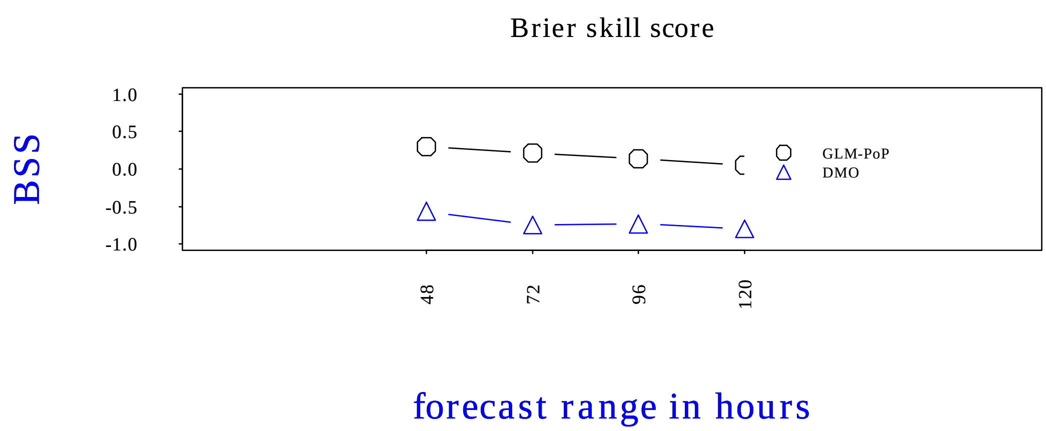
Akureyri : statistical scores for ECMWF PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112



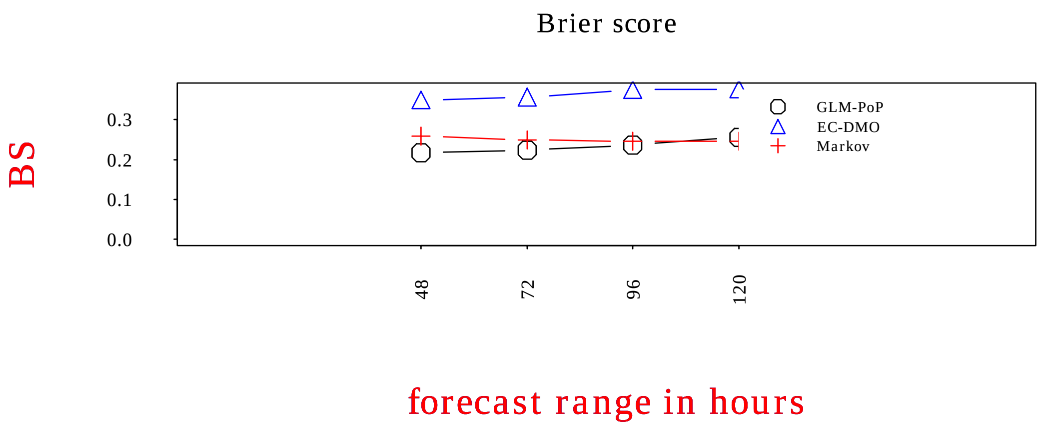


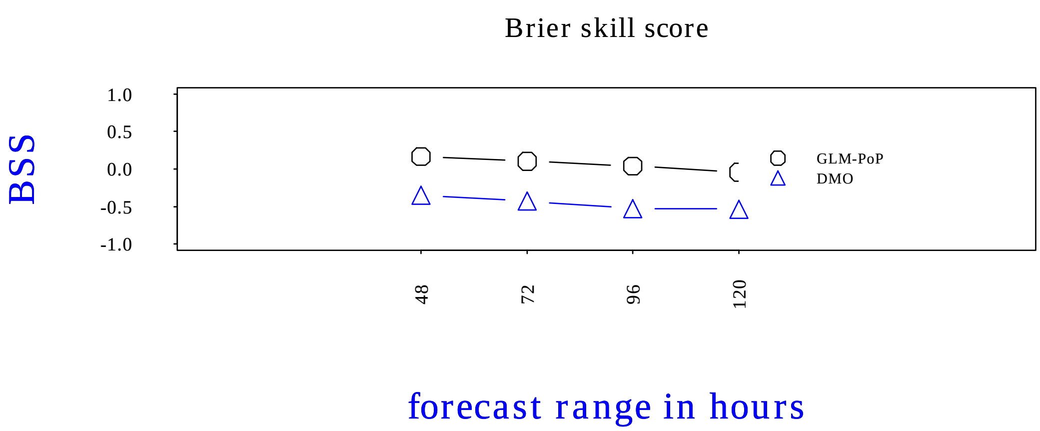
Akurnes : statistical scores for ECMWF PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112



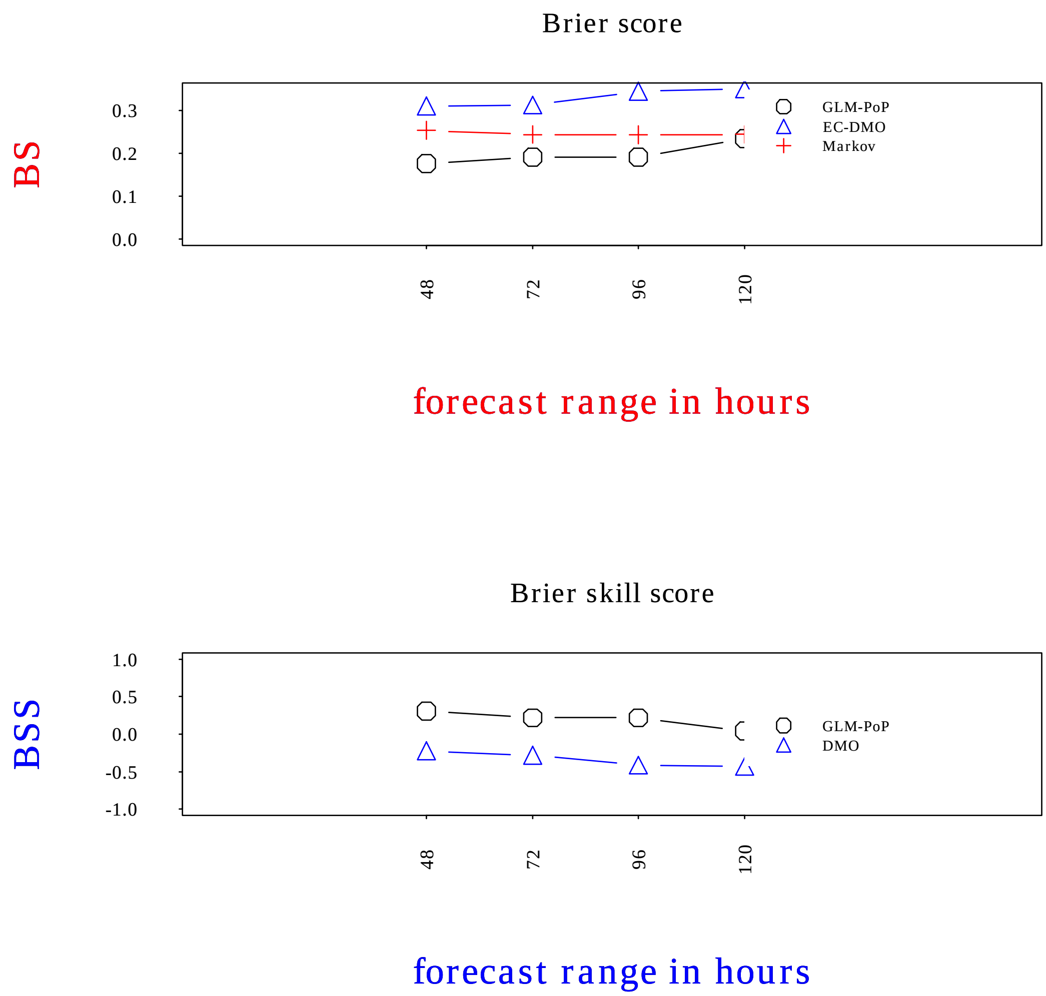


Hveravellir : statistical scores for ECMWF PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112





Reykjavik : statistical scores for ECMWF PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112

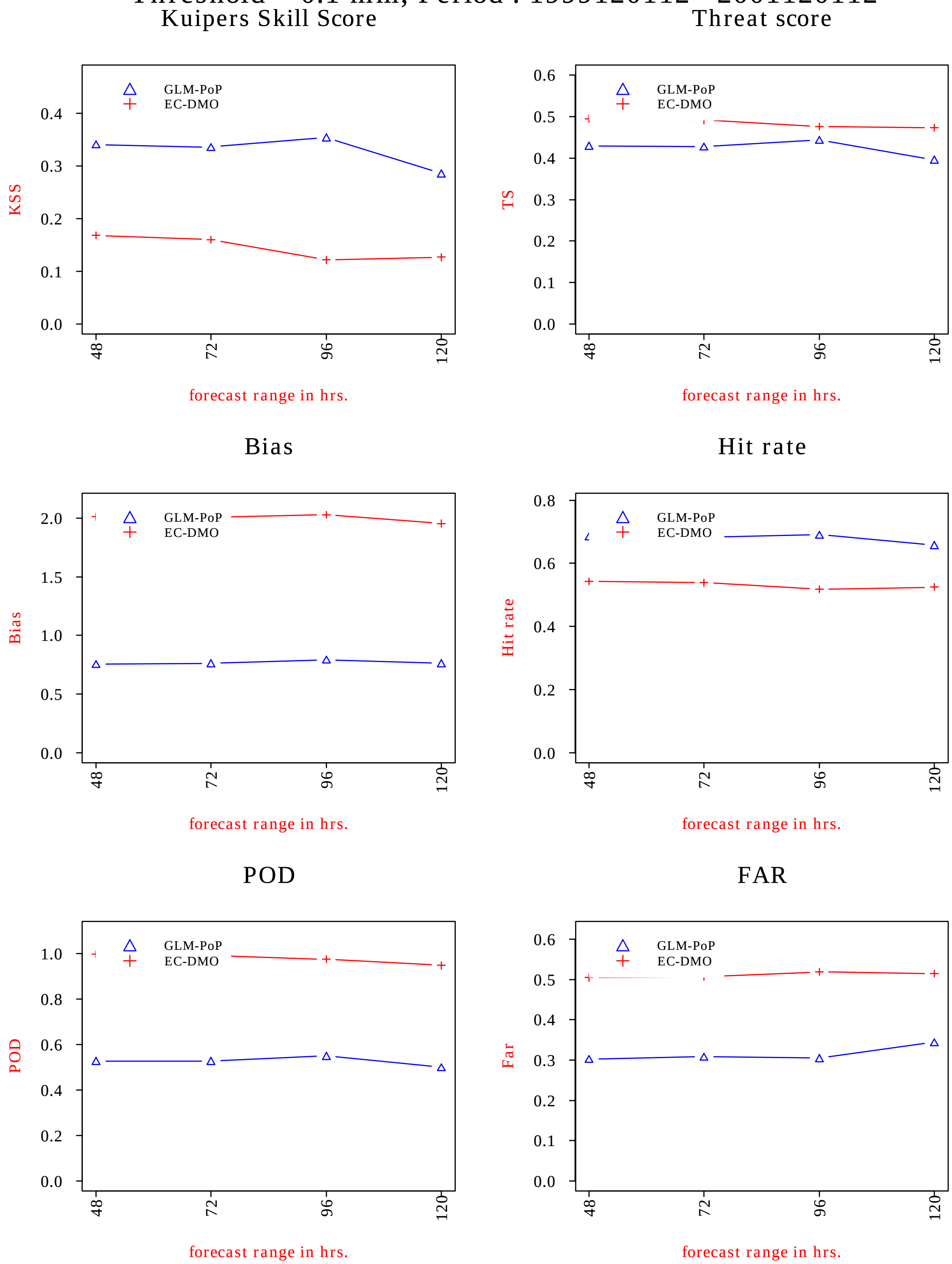


Appendix 6

GLM-PoP

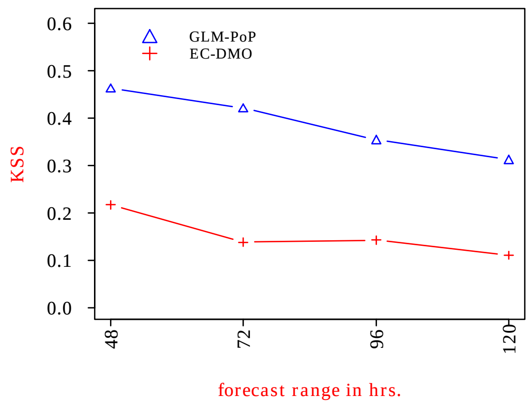
Statistical scores for a categorical prediction with ECMWF forecasts

Akureyri : statistical scores for ECMWF MOS PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112

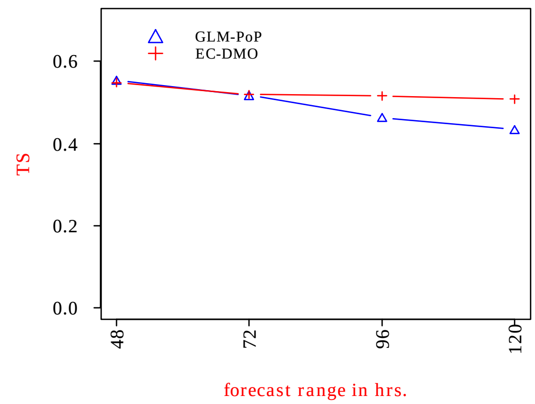


Akurnes : statistical scores for ECMWF MOS PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112

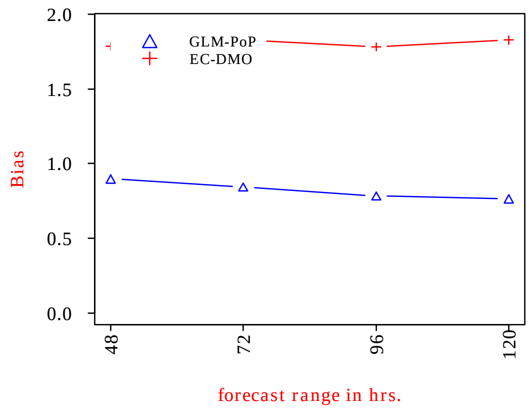
Kuipers Skill Score



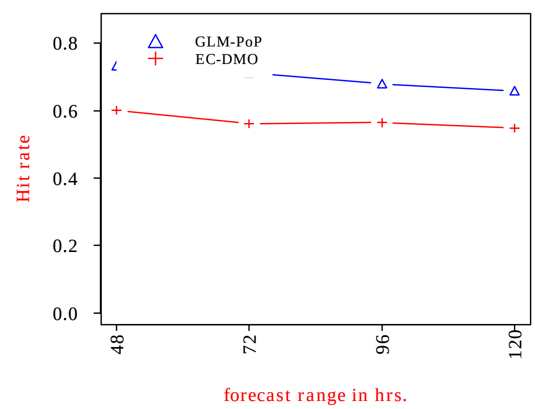
Threat score



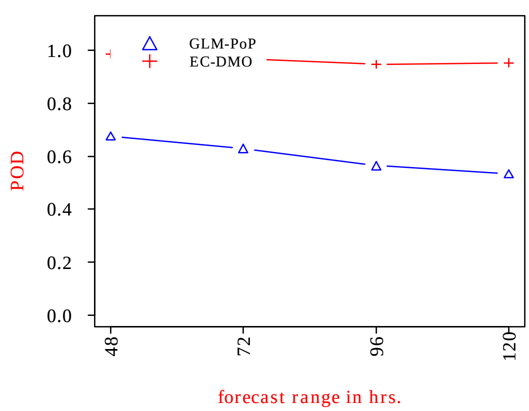
Bias



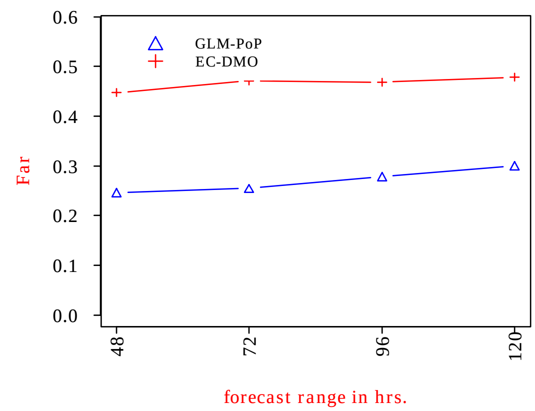
Hit rate



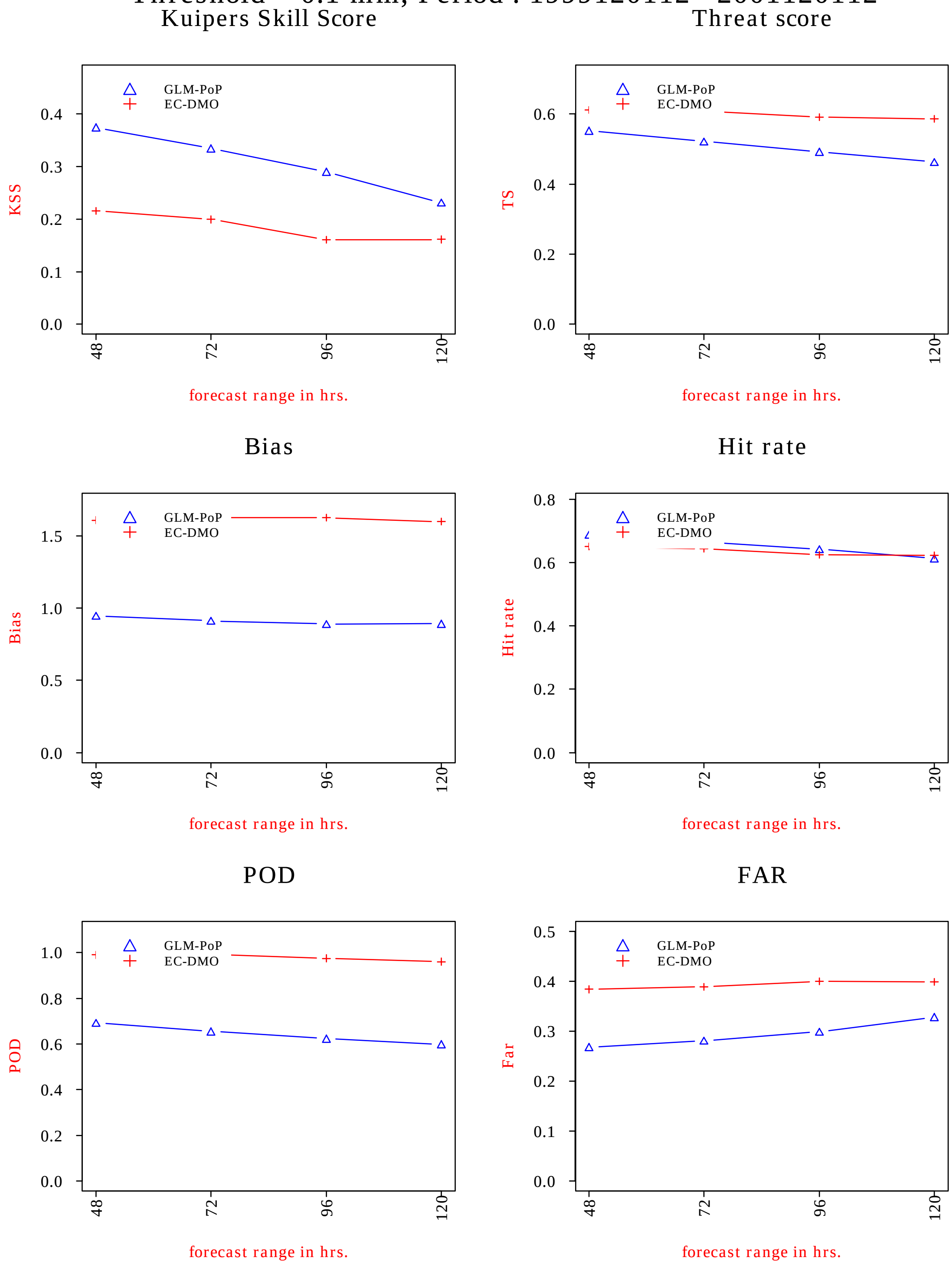
POD



FAR



Hveravellir : statistical scores for ECMWF MOS PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112



Reykjavik : statistical scores for ECMWF MOS PoP
Threshold= 0.1 mm, Period : 1999120112 - 2001120112