



UNIVERSITÀ
DEGLI STUDI
DI UDINE

Università degli studi di Udine

Confidence predictive distributions: an application to temperature forecasting in Veneto

Original

Availability:

This version is available <http://hdl.handle.net/11390/1252484> since 2023-08-24T08:29:10Z

Publisher:

Published

DOI:

Terms of use:

The institutional repository of the University of Udine (<http://air.uniud.it>) is provided by ARIC services. The aim is to enable open access to all the world.

Publisher copyright

(Article begins on next page)

PROCEEDINGS

Edited By: Giada Adelfio and Antonino Abbruzzo

GRASPA 2023



GRASPA-SIS BIENNIAL CONFERENCE

The Researcher Group for Environmental Statistics of The Italian Statistical Society

TIES EUROPEAN REGIONAL MEETING

The International Environmetrics Society

Palermo, 10-11 July, 2023

Dipartimento di Scienze Economiche Aziendali e Statistiche, Università degli Studi di Palermo



**Università
degli Studi
di Palermo**

Proceedings of the GRASPA 2023 Conference
Palermo, 10-11 July 2023
Edited by: Giada Adelfio and Antonino Abbruzzo

—
Palermo: Università degli Studi di Palermo.

ISBN: 979-12-210-3389-2

Questo volume è rilasciato sotto licenza Creative Commons
Attribuzione - Non commerciale - Non opere derivate 4.0



© 2023 The Authors

Sponsored by:



Stazione
Zoologica
Anton Dohrn
Napoli



Contents

1	Keynote Sessions	9
1.1	Modeling Extremal Streamflow using Deep Learning Approximations and a Flexible Spatial Process. <i>R. Majumder, B. J. Reich and B. A. Shaby</i>	9
1.2	Estimating Covid-19 transmission time using Hawkes point processes. <i>F. P. Schoenberg</i>	11
2	Complex data and models	13
2.1	O2S2 for uncertainty quantification in natural background level concentrations. <i>A. Menafoglio, L. Guadagnini, A. Guadagnini and P. Secchi</i>	13
2.2	Penalized multivariate hidden semi-Markov models for time series environmental data. <i>M. Mingione, P. Alaimo Di Loro, F. Lagona and A. Maruotti</i>	16
2.3	Statistical analysis of complex networks. <i>N. Pronello, A. Cucco, R. Ignaccolo and L. Ippoliti</i>	22
3	Statistical Methods and Environmental Studies	27
3.1	ARPA Sicily: collection of environmental data, for an integrated vision of the regional territory and to support the "One Health" approach. <i>G. Cuffari and A. Conti</i>	27
3.2	Exploring the effects of temperature on demersal fish communities in the Central Mediterranean Sea using INLA-SPDE modeling approach. <i>C. Rubino, G. Adelfio, A. Abbruzzo, M. Bosch-Belmar, F. Colloca, M. Di Lorenzo, F. Fiorentino, V. Gancitano and G. Milisenda</i>	33

3.3	Analytical Methods of the Respiratory Epidemiological Surveys carried out by the National Research Council. <i>G. Viegi, S. Maio, G. Sarno, S. La Grutta and S. Baldacci</i>	39
4	Measuring and modelling of environmental	45
4.1	A Bayesian Time Series Model for Reconstructing Hydroclimate from Multiple Proxies. <i>N. Cahill, J. Croke, M. Campbell, K. Hughes, J. Vitkovsky, J. E. Kilgallen and A. Parnell</i>	45
4.2	Some empirical results on nearest neighbour pseudo-populations for re-sampling from spatial populations. <i>R.M. Di Biase, A. Marcelli, S. Franceschi and L. Fattorini</i>	52
4.3	Kriging Riemannian data for environmental applications. <i>A. Menafoglio, D. Pigoli and P. Secchi</i>	58
5	Spatio-temporal modelling for urban	61
5.1	Stochastic reconstruction of a spatio-temporal Hawkes process with isotropic excitation: an application to road accidents. <i>P. Alaimo Di Loro and M. Mingione</i>	61
5.2	ARPALData: retrieving and analyzing air quality and weather data of Lombardy (Italy). <i>P. Maranzano and A. Algieri</i>	68
5.3	Mechanistic spatio-temporal modeling of infectious diseases and crime data on urban environments. <i>J. Mateu and A. Brizi</i>	74
6	Advances in statistical ecology	81
6.1	Spatial occurrence models using Integrated Nested Laplace Approximation. <i>S. Martino, J. Belmont Osuna, J. Illian and H. Rue</i>	81
6.2	Data analysis of photogrammetry-based mapping: the seacucumbers in the Giglio Island as a case study. <i>G. Mastrantonio, D. Ventura, E. Casoli, A. Rakaj, G. Jona Lasinio and A. Pollice</i>	83
6.3	A species distribution modelling framework for combining citizen science data from different monitoring schemes. <i>J. Belmont Osuna, S. Martino, G. Panunzi, and J. Illian</i>	84
7	Controlling for unmeasured confounding	85
7.1	On the effect of spatial confounding: an approach based on the theory of quadratic forms. <i>F. Greco and M. Narcisi</i>	85
7.2	A Flexible Bayesian Time-varying Coefficient Regression Model in Health Applications. <i>C. Zaccardi, P. Valentini and L. Ippoliti</i>	92
7.3	Confounder-Dependent Bayesian Mixture Model: Characterizing Heterogeneity of Causal Effects in Air Pollution Epidemiology. <i>D. Zorzetto, F. J. Bargagli-Stoffi, A. Canale and F. Dominici</i>	98
8	Posters	99
8.1	Spatio-temporal analysis of the distribution of larval round sardinella in Mediterranean coastal area. <i>A. Abbruzzo, A. Granata, B. Patti, A. Cuttitta and M. Torri</i>	100

8.2	A Novel Spatio-Temporal Estimation Method for Occurrences Over Planar and Curved Regions . <i>B. Begu , S. Panzeri , E. Arnone and L. M. Sangalli</i>	107
8.3	Addressing Sequestration Bias in Estimating Malaria Parasite Age Distribution: A Bayesian Statistical Model. <i>E. Bortolato, P. E. Jacob, and J. A. Watson</i>	113
8.4	Accounting for Misreporting in Spatial Zero-Inflated Poisson Models. <i>C. Cal-culli, S. Arima and A. Pollice</i>	118
8.5	Penalized quantile regression for spatial distributed data. <i>C. Castiglione, E. Arnone, M. Bernardi, A. Farcomeni, L. M. Sangalli</i>	124
8.6	Sign-Flip tests for the nonparametric component in Spatial Regression with PDE regularization. <i>M. Cavazzutti, E. Arnone, F. Ferraccioli, L. Finos, C. Gal-imberti, L.M. Sangalli</i>	130
8.7	Environmental exposure indicators and respiratory health in asthmatic chil-dren: a case study. <i>G. Cilluffo, G. Ferrante, S. Fasola , V. Malizia, L. Montal-bano, A. Ranzi , C. Badaloni, G. Viegi and S. La Grutta</i>	135
8.8	Non-parametric density estimation over linear networks. <i>A. Clemente, E. Arnone, J. Mateu and L. M. Sangalli</i>	141
8.9	Selecting the Kth nearest-neighbour for clutter removal in spatial point pro-cesses through segmented regression models . <i>N. D'Angelo and G. Adelfio</i>	146
8.10	Modeling linkage errors in species diversity estimates: an ABC approach. <i>D. Di Cecco, and A. Tancredi</i>	152
8.11	The effect of deforestation on infant health: a multilevel mediation analysis. <i>C. Di Maria</i>	158
8.12	Geostatistical methods comparison: an application on the concentration of PM2.5 in Lombardy. <i>A. Fassò, J. Rodeschini and A. Fusta Moro</i>	164
8.13	Application of the hierarchical variance decomposition approach to an ecological case study with mixed effects. <i>L. Ferrari, M. Ventrucci and A. Laini</i>	170
8.14	Variables selection in a P-spline regression model for flood frequency anal-ysis. <i>A. Gardini</i>	176
8.15	Assessment of death risk for asbestos cancers using functional regression models among dockworkers exposed to asbestos in northeastern Italy. <i>P. Girardi, V. Comiati, V. Casotto, C. Gaetan, M.N. Ballarin, E. Merler and U. Fedeli</i>	182
8.16	Confidence predictive distributions: an application to temperature fore-casting in Veneto. <i>F. Giummolè and V. Mameli</i>	188
8.17	Particulate matter PM10 assessment by meteorological conditions to mon-itor extractive activities' impact: a case of study. <i>E. Iakimova, F. Condino and F. Domma</i>	193
8.18	Health and environmental risk perception measurement and classification: a case study in Gela (Sicily). <i>G. Ilardo, A. Pandolfo, V. Malizia, G. Cilluffo, S. Fasola, A. Bonomolo, G. Piva, L. Cori, G. Viegi and S. La Grutta</i>	199
8.19	Severe storms events' reproduction in the United States of America: evalua-tion from the marked self-exciting point processes point of view. <i>F. Lagona and M. Mingione</i>	205

- 8.20 A parametric hidden semi-Markov model for toroidal time-series. *G. Lo Galbo, G. Adelfio and M. Chiodi* 211
- 8.21 Design-based mapping of land use/land cover classes with bootstrap estimation of precision by nearest-neighbour interpolation. *A. Marcelli, R.M. Di Biase, P. Corona, S.V. Stehman and L. Fattorini* 217
- 8.22 BayesSizeAndShape: a Julia package for Bayesian estimation of Size and Shape data regression models. *G. Mastrantonio and G. Jona Lasinio* 223
- 8.23 Space-time clustering of seismic events in Chile. *O. Nicolis, L. Delgado, B. Peralta and M. Díaz* 228
- 8.24 Forecasting Air Pollutants through Artificial Neural Networks. *E. Nissi and L. Saliaj* 234
- 8.25 Functional principal component analysis for space-time data. *A. Palummo, E. Arnone, L. Formaggia and L. M. Sangalli* 239
- 8.26 Association between vegetation index and asthma in children and adolescents in North-Central Europe. *A. Pandolfo, G. Ilardo, V. Malizia, G. Squillacioti, S. Fasola, F. Ghelli, G. Ferrante, S. La Grutta, G. Viegi and R. Bono* 245
- 8.27 A taxonomy for Random Forest in the spatial regression framework. *L. Patelli, M. Cameletti, N. Golini and R. Ignaccolo* 251
- 8.28 Fish characteristics and microplastic ingestion: a mediation analysis of fish length and trophic level in Western Mediterranean pelagic demersal fish. *M. Sciandra, A. Albano, A. Plaia, C. Di Maria, C. Andolina, S. Vizzini and M.C. Fossi* 257
- 8.29 UAV plant image Classification Using Combined Machine Learning And Deep Learning Models. *A. Simonetto, G. Tariku and G. Gilioli* 262
- 8.30 A Bayesian study of temporal changes in seismicity. *E. Varini and R. Rotondi* 268
- 8.31 On time lag detection between time series sampled by eddy covariance systems. *D. Vitale and D. Papale* 273

Confidence predictive distributions: an application to temperature forecasting in Veneto

F. Giummolè¹ and V. Mameli^{2,*}

¹ Department of Environmental Sciences, Informatics and Statistics, Ca' Foscari University of Venice; giummolè@unive.it,

² Department of Economics and Statistics, Udine; valentina.mameli@uniud.it

*Corresponding author

Abstract. Post-processing techniques are nowadays frequently used in order to reduce the impact of errors in ensemble forecasts of meteorological variables. Ensemble model output statistics (EMOS) are a widely spread post-processing approach built on a heteroscedastic linear regression model. After replacing unknown parameters with suitable estimates, an estimative EMOS distribution function for prediction is obtained. However, it is well known that forecasts based on estimative EMOS may lack calibration, particularly when the number of ensembles is large compared to the number of historical observations. Here, we suggest overcoming this drawback by applying in the EMOS context a predictive approach based on the concept of confidence distribution. The result is a new predictive distribution that takes the form of a variance correction of the classical estimative EMOS distribution. The performance of the confidence EMOS distribution is tested on a real-data application for temperature forecasting. It can be seen that our proposal performs better than the classical estimative EMOS, both in terms of coverage probabilities and log-score.

Keywords. Confidence distribution; Coverage probabilities; EMOS.

1 Introduction

Forecasting the weather is an essential component of support to decision making in many different situations. Forecasts have gradually improved over the past few decades, in part as a consequence of advancements in numerical weather prediction (NWP) ([1]). The forecasts produced by physics-based models, which are typically provided as forecast ensembles, still exhibit systematic bias and are frequently under-dispersive despite these advances ([2]). Today, it is common practice to further refine, enhance, and calibrate NWP using statistical post-processing techniques. One of the most widely used methods for post-processing ensemble forecasts is ensemble model output statistics (EMOS, [4]).

Classic EMOS is nothing but a linear heteroscedastic regression model with Gaussian errors, where the ensembles play the role of explanatory variables and their sample variance contributes to the variance component. Unknown parameters are estimated on the basis of past observations by minimising some suitable scoring rules. After substituting parameter estimates in the Gaussian distribution function of the variable of interest, a so-called estimative distribution is obtained. Estimative EMOS distribution functions are commonly used to forecast the variable of interest and, in particular, to obtain prediction

intervals or limits with the desired level of confidence. Unfortunately, even if this procedure is able to correct for bias and under-dispersion of the ensemble, it is not fully calibrated, and the actual coverage of its quantiles may consistently differ from the nominal one.

Ad-hoc techniques, useful for modelling specific datasets, have been proposed in the literature to overcome this problem. A method that can be applied in the general context of EMOS, as well as with distributions that differ from the normal case, is considered in [5], where an easy bootstrap procedure is used for calibrating estimative EMOS distributions. Here, we consider the approach to prediction based on confidence distributions, presented by [6], and capable to include frequentist, Bayesian, and fiducial predictive inference within a unique framework. With this method, unknown parameters are eliminated by integration with respect to a so-called confidence distribution. Depending on the features of the model and of the chosen confidence distribution, the resulting confidence predictive distribution is, at least approximately, well-calibrated, giving quantiles with the correct coverage probability.

This work is a seminal attempt to use confidence predictive distributions in the context of EMOS. Using data about maximum daily temperatures in the Veneto region, north of Italy, we show the potentiality of this method for improving the usual estimative approach. In the next section, we present some basic concepts on EMOS and confidence-based prediction and obtain the confidence EMOS predictive distribution. In the last section, we apply the result to the problem of forecasting temperatures in the Veneto region. In particular, we use data regarding Cavallino-Treporti station, located in the Venice lagoon. We show the superiority of the new predictive distribution on the usual estimative distribution, both with respect to the log-score and the coverage of predictive quantiles.

2 EMOS prediction with confidence

The simplest version of EMOS is just a regular linear regression model with heteroscedastic normal errors. The ensemble members are combined linearly to form the EMOS mean, with the contribution of ensemble members to the relevant weather variable represented by unknown coefficients. The EMOS variance, which considers the spread relationship, is a linear function of the ensemble variance. To set the notation, consider that $\{Y_i\}_{i \geq 1}$ is a sequence of independent continuous random variables. $Y^n = (Y_1, \dots, Y_n)$, $n > 1$, is observable while $Z = Y_{n+1}$ is a future or not yet observed variable. In the classic EMOS all the Y_i 's, $i \geq 1$, are normally distributed with mean and variance depending on m ensemble members. Let $X^{n+1} = (1, X_{1,n+1}, \dots, X_{m,n+1})^T$ include 1 for the intercept of the model and the ensembles associated with the future variable Z , and let S_{n+1}^2 be the variance of the ensembles $(X_{1,n+1}, \dots, X_{m,n+1})$. The full distribution of Z is given by

$$Z | X_{1,n+1}, \dots, X_{m,n+1} \sim \Phi \left(\frac{z - \mu_{n+1}}{\sigma_{n+1}} \right), \quad (1)$$

where $\Phi(\cdot)$ denotes the standard normal distribution function and $\mu_{n+1} = \beta_0 + \beta_1 X_{1,n+1} + \dots + \beta_m X_{m,n+1} = \beta X^{n+1}$ and $\sigma_{n+1}^2 = \gamma_0 + \gamma_1 S_{n+1}^2$, see [4]. The parameters $\beta = (\beta_0, \dots, \beta_m)$, γ_0 and γ_1 are non-negative unknown coefficients. Log-score and CRPS are two appropriate scoring rules that are typically minimised in order to estimate unknown EMOS parameters. An estimative distribution for the future weather quantity Z is obtained by substituting the estimated parameters in the full distribution of Z :

$$\Phi \left(\frac{z - \hat{\mu}_{n+1}}{\hat{\sigma}_{n+1}} \right), \quad (2)$$

with $\hat{\mu}_{n+1} = \hat{\beta} X^{n+1}$, and $\hat{\sigma}_{n+1}^2 = \hat{\gamma}_0 + \hat{\gamma}_1 S_{n+1}^2$, where $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_m)$, $\hat{\gamma}_0$, and $\hat{\gamma}_1$ are suitable estimates of β , γ_0 , and γ_1 , respectively, based on an observed sample from Y^n , $y^n = (y_1, \dots, y_n)$.

Unfortunately, estimative distributions occasionally exhibit poor performance, particularly when there are few historical observations in comparison to the size of the ensemble. In order to improve the estimative EMOS (2) we consider the method proposed in [6] based on the concept of confidence distribution. According to [6] a whole predictive distribution function for the variable Z can be obtained by integrating (1) with respect to a confidence distribution for the unknown parameters. The properties of the resulting predictive distribution for Z are strictly related to those of the used confidence distribution. Let X be the $n \times (m+1)$ design matrix, namely, $X = [X^1, \dots, X^n]^T$ with $X^i = (1, X_{1,i}, \dots, X_{m,i})^T$ for $i = 1, \dots, n$. Following [6], we choose a confidence distribution for β derived from the asymptotic distribution of $\hat{\beta}$:

$$\Phi_{m+1} \left((X^T \Sigma^{-1} X)^{1/2} (\hat{\beta} - \beta) \right), \quad (3)$$

where Φ_{m+1} denotes a $(m+1)$ -dimensional normal distribution with zero mean vector and unit covariance matrix, $\Sigma = \text{diag}(\gamma_0 + \gamma_1 S^2)$ with $S^2 = (S_1^2, \dots, S_n^2)$, $S_i^2 = \frac{1}{m-1} \sum_{j=1}^m (X_{ij} - \bar{X}_i)^2$ denoting the variance of the i -th observation of the ensemble and $\bar{X}_i = \frac{1}{m} \sum_{j=1}^m X_{ij}$ its mean, $i = 1, \dots, n$.

By integrating (1) with respect to (3) and replacing Σ with $\hat{\Sigma} = \text{diag}(\hat{\gamma}_0 + \hat{\gamma}_1 S^2)$ and σ_{n+1}^2 with $\hat{\sigma}_{n+1}^2 = \hat{\gamma}_0 + \hat{\gamma}_1 S_{n+1}^2$ we obtain the corresponding confidence predictive distribution:

$$Q(z; y^n) = \Phi \left(\frac{z - \hat{\mu}_{n+1}}{\sqrt{\hat{\sigma}_{n+1}^2 + (X^{n+1})^T (X^T \hat{\Sigma}^{-1} X)^{-1} X^{n+1}}} \right). \quad (4)$$

The new confidence predictive distribution (4) is nothing but a variance adjustment of the estimative EMOS distribution (2). It corresponds to the exact predictive distribution in heteroscedastic regression models, for the case when the variance-covariance matrix of the errors is known, see for instance [3]. Indeed, our procedure accounts for the additional uncertainty in the estimates of the regression parameters but not in the estimate of the variance component. Thus, the resulting predictive distribution is not fully calibrated. Nonetheless, as shown in the next section, it provides prediction limits with a coverage probability very close to the nominal one.

3 Real case study

In this study, we focus on forecasts for the maximum daily temperatures at stations located in the Veneto region, northern Italy. We have a three-year period of interest that runs from August 16, 2009, to August 17, 2012. The dataset was previously analysed in [5] by using the classical EMOS and a bootstrap calibrated modification of it. Historical maximum daily temperature forecasts are available from <http://www.scia.isprambiente.it/>. While the ensemble forecasts are provided by the World Climate Research Programme. We examine the maximum daily temperatures for the Venetian lagoon station Cavallino-Treporti (Longitude: 12.48642, Latitude: 45.45805). In accordance with [4], we use a sliding window of 50 observations as our training set and the remaining 1039 days as our test set. Estimates of the EMOS parameters are obtained by optimizing the log-score (namely, minus the log-likelihood) over the sliding training period. Then, we consider the estimative EMOS in (2), the bootstrap predictive distribution obtained in [5], as well as the predictive distribution (4) produced by the suggested methodology. We compare the performances of the three distributions for each of the 1039 observations in terms of coverage probability and log-score. The mean and standard deviation of the log-score for the three predictive models are summarised in Table 1. Note that the confidence predictive distribution improves

on the estimative distribution, since the lower the score the better the method. We have also obtained coverage probabilities and mean lengths of level 66.7% central intervals to properly assess the calibration and concentration of the various predictive models (Table 2). It can be seen that the confidence predictive distribution performs much better than the bootstrap predictive distribution in terms of coverage probability of the central prediction interval. The increased length of the interval is in fact justified by the higher and more precise coverage. Additionally, the coverage probabilities of the upper prediction limits of 90%, 95%, and 99% are derived and represented in Figure 1. In relation to the estimative distributions, it should be noted that the coverage probabilities obtained from the proposed predictive distribution are closer to nominal levels, and to those of the Bootstrap predictive distribution. The PIT histograms for the three considered predictive models are finally shown in Figure 2. We can see that the histogram produced by the suggested methodology is very similar to the uniform one, indicating good calibration. The excessive under-dispersion of the estimative EMOS distribution gives the PIT histogram its particular U shape.

As we have seen, in terms of all the considered measures, the confidence predictive distribution performs similar to the Bootstrap predictive distribution discussed in [5], but it has the advantage of not requiring any time-consuming computational process like the bootstrap itself.

	Est	Boot	Conf
Log-score	2.98	2.51	2.55
	(0.08)	(0.03)	(0.03)

Table 1: Log-score values of the three predictive distributions. Est denotes the estimative EMOS, Boot the Bootstrap predictive distribution obtained in [5], while Conf denotes the confidence predictive distribution in (4).

	Est	Boot	Conf
mean length	3.53	5.42	6.18
	(0.02)	(0.04)	(0.05)
coverage	0.451	0.641	0.692
	(0.015)	(0.015)	(0.014)

Table 2: Coverage probabilities and mean lengths of the central prediction interval of level 0.67 for the three predictive distributions. Est denotes the estimative EMOS, Boot the Bootstrap predictive distribution obtained in [5], while Conf denotes the confidence predictive distribution in (4). Standard errors in brackets.

References

- [1] Bauer, P., Thorpe, A., Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, **525**, 47–55.
- [2] Buizza, R. (1997). Potential forecast skill of ensemble prediction and spread and skill distributions of the ECMWF ensemble prediction system. *Monthly Weather Review*, **125**, 99–119.
- [3] Faraway, J.J. (2005). *Linear Models with R*. Chapman & Hall.

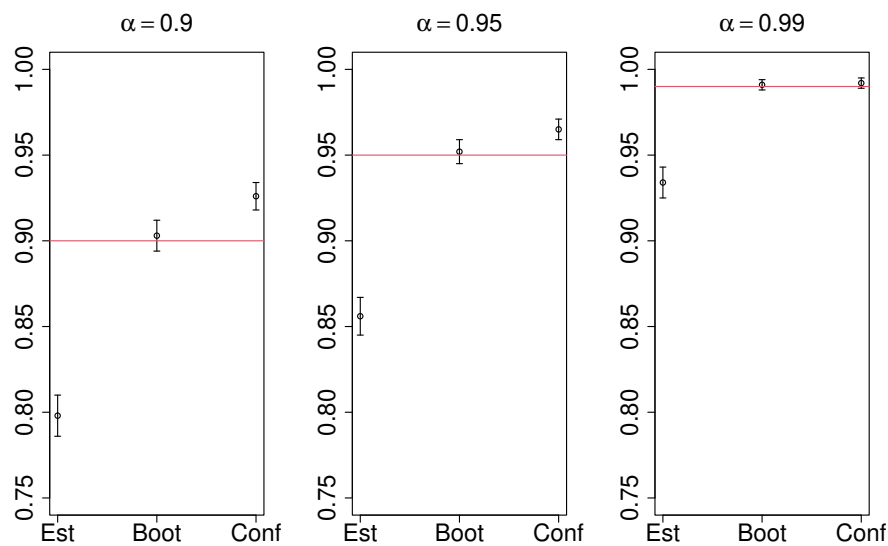


Figure 1: Coverage probabilities of upper prediction limits for the three predictive distributions. Left panel $\alpha = 0.90$, middle panel $\alpha = 0.95$, right panel $\alpha = 0.99$. Est denotes the estimative EMOS, Boot the Bootstrap predictive distribution obtained in [5], while Conf denotes the confidence predictive distribution in (4).

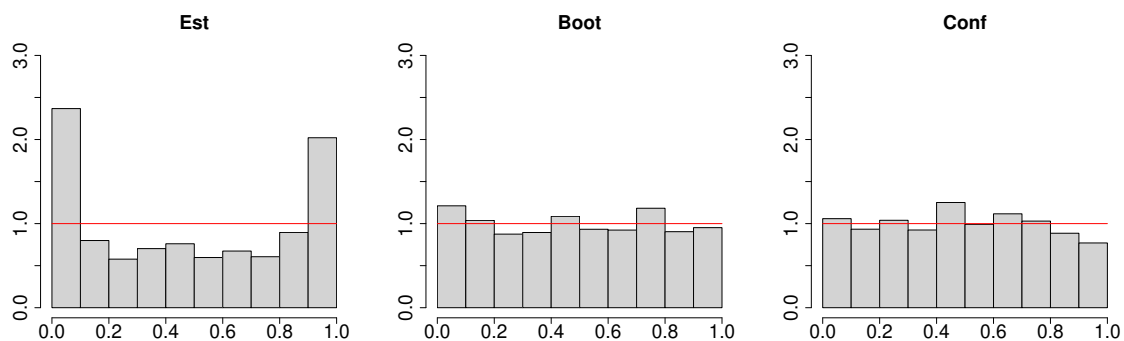


Figure 2: PIT histograms of the three predictive distributions. Est denotes the estimative EMOS, Boot the Bootstrap predictive distribution obtained in [5], while Conf denotes the confidence predictive distribution in (4).

- [4] Gneiting, T., Raftery, A.E., Westveld III, A.H., Goldman, T. (2005). Calibrated Probabilistic Forecasting Using Ensemble Model Output Statistics and Minimum CPRS Estimation. *Monthly Weather Review*, **133**(5), 1098–1118.
- [5] Gaetan, C., Giummolè, F., Mameli, V., Siad, S. (2022). Ensemble model output statistics for temperature forecasts in Veneto. Book of short papers of the 51st scientific meeting of the Italian Statistical Society, 1253–1258.
- [6] Shen, J., Liu, R.Y., Xie, M. (2018). Prediction with confidence-A general framework for predictive inference. *Journal of Statistical Planning and Inference*, **195**, 126–140.