

Publikációs lista, Baran Sándor

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E) ELŐADÁS NEMZETKÖZI KONFERENCIÁN

1. *Optimal designs for complex Ornstein-Uhlenbeck processes*. Modern Stochastic: Theory and Applications V, Kyiv, Ukraine, June 1–4, 2021 (online, meghívott plenáris).

2. *Statistical calibration of ensemble forecasts of heat indices.* Joint SRNWP-EPS and Post-processing workshop 2020, October 27-30 2020, BlueJeans video-conference meeting (meghívott plenáris).
3. *Statistical methods in weather forecasting.* 11th International Conference on Applied Informatics, Eger, Hungary, January 29–31, 2020 (meghívott plenáris).
4. *Statistical post-processing of water level forecasts.* 12th International Conference of the ERCIM WG on Computational and Methodological Statistics (CMStatistics 2019), London, United Kingdom, December 14 – 16, 2019 (meghívott).
5. *Statistical post-processing of dual-resolution ensemble forecasts.* EGU General Assembly 2019, Vienna, Austria, April 8 – 12, 2019 (meghívott).
6. *Similarity-based semilocal estimation of post-processing models.* IX. International Workshop on Applied Probability (IWAP 2018), Budapest, Hungary, June 18 – 21, 2018.
7. *Combining predictive distributions for calibration of ensemble forecasts for precipitation accumulation.* 13th German Probability and Statistics Days, Freiburg, Germany, February 27 – March 2, 2018.
8. *Combining predictive distributions for calibration of ensemble forecasts for wind speed.* XXXIV. International Seminar on Stability Problems for Stochastic Models, Debrecen, Hungary, August 25–29, 2017.
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10. *Mixture EMOS model for calibrating ensemble forecasts of wind speed.* 12th German Probability and Statistics Days, Bochum, Germany, March 1–4, 2016.
11. *Bivariate BMA and EMOS models for joint calibration of temperature and wind speed forecasts.* Mini Symposium on Statistical Postprocessing of Ensemble Forecasts, HITS, Heidelberg, Germany, July 15, 2015 (meghívott).
12. *Log-normal distribution based EMOS models for probabilistic wind speed forecasting.* European Meeting of Statisticians, Amsterdam, The Netherlands, July 6–10, 2015.
13. *Joint calibration of temperature and wind speed forecasts using Bayesian Model Averaging.* 12th Workshop on Stochastic Models, Statistics and Their Applications, Wroclaw, Poland, February 16–20, 2015.
14. *Probabilistic methods in wind speed forecasting.* Latin American Congress of Statistical Societies (CLATSE2014), La Serena, Chile, October 20–23, 2014 (meghívott plenáris).

15. *Comparison of BMA and EMOS statistical calibration methods for ensemble weather prediction.* 3rd Stochastic Modeling Techniques and Data Analysis International Conference (SMTDA2014), Lisbon, Portugal, June 11–14, 2014.
16. *Statistical post-processing of ensemble forecasts.* ECMI workshop on “The mathematics of air pollution”, Budapest, Hungary, May 26–27, 2014 (meghívott plenáris).
17. *Probabilistic wind speed forecasting using Bayesian model averaging with truncated normal components.* 11th German Probability and Statistics Days, Ulm, Germany, March 4–7, 2014.
18. *Statistical calibration of ensemble forecasts.* 9th International Conference on Applied Informatics, Eger, Hungary, January 29–February 1, 2014.
19. *Probabilistic temperature forecasting with statistical calibration in Hungary.* 29th European Meeting of Statisticians, Budapest, Hungary, July 20–25, 2013.
20. *Optimal design for parameters of a shifted Ornstein-Uhlenbeck sheet.* XXXI. International Seminar on Stability Problems for Stochastic Models, Moscow, Russia, April 23–27, 2013.
21. *Parameter estimation and testing stability in a spatial unilateral autoregressive model.* Modern Stochastic: Theory and Applications III, Kyiv, Ukraine, September 10–14, 2012 (meghívott).
22. *Parameter estimation in linear regression driven by a Gaussian random field.* 8th World Congress in Probability and Statistics, Istanbul, Turkey, July 9–14, 2012.
23. *Probabilistic wind speed prediction in Hungary.* 10th German Probability and Statistics Days, Mainz, Germany, March 6–9, 2012.
24. *Calibrating forecast ensembles of the LAMEPS system of the Hungarian Meteorological Service using Bayesian Model Averaging.* Applied Mathematics and Scientific Computing, Trogir, Croatia, June 13–17, 2011.
25. *Parameter estimation in a spatial unit root autoregressive model.* Applied Stochastic Models and Data Analysis (ASMDA2011), Rome, Italy, June 7–10, 2011.
26. *Asymptotic inference of a spatial unit root autoregressive model.* Modern Stochastic: Theory and Applications II, Kyiv, Ukraine, September 7–11, 2010 (meghívott).
27. *Parameter estimation in a spatial unit root autoregressive model.* 10th International Vilnius Conference on Probability Theory and Mathematical Statistics, Vilnius, Lithuania, June 28–July 2, 2010.
28. *On the covariance structure of an unstable unilateral spatial autoregressive model.* 27th European Meeting of Statisticians, Toulouse, France, July 20–24, 2009.

29. *Parameter estimation in unstable unilateral spatial autoregressive models.* Probability and Statistics with Applications, Debrecen, Hungary, June 8–12, 2009.
30. *Risk estimation in Down's syndrome screening.* XXVIII. International Seminar on Stability Problems for Stochastic Models, Zakopane, Poland, May 31–June 5, 2009.
31. *Asymptotic inference for a one-dimensional simultaneous autoregressive model.* Barcelona Conference on Asymptotic Statistics, Barcelona, Spain, September 1–5, 2008.
32. *Asymptotic behaviour of the least squares estimator in a nearly unstable sequence of spatial AR models.* 8th German Open Conference on Probability and Statistics, Aachen, Germany, March 4–7, 2008.
33. *Mean estimation of a shifted Wiener sheet.* 5th International Conference on Levy Processes: Theory and Applications, Copenhagen, Denmark, August 13–17, 2007 (poszter).
34. *Prediction of macroeconomic quantities using stochastic models.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, July 9–13, 2007.
35. *An estimator for nonlinear regression models.* XXVI. International Seminar on Stability Problems for Stochastic Models, Sovata-Bai, Romania, August 27–September 2, 2006.
36. *Mean estimation of the Wiener sheet.* 26th European Meeting of Statisticians, Torun, Poland, July 24–28, 2006.
37. *Asymptotic inference for unstable spatial AR models.* 9th International Vilnius Conference on Probability Theory and Mathematical Statistics, Vilnius, Lithuania, June 25–30, 2006.
38. *Asymptotic inference for unit roots in spatial autoregression.* 25th European Meeting of Statisticians, Oslo, Norway, July 24–28, 2005.
39. *Prediction of Hungarian mortality rates using Lee-Carter method.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, June 19–24, 2005.
40. *A consistent estimator for nonlinear regression models.* COMPSTAT 2004, Prague, Czech Republic, August 23–27, 2004 (poszter).
41. *Asymptotic inference for a nearly unstable sequence of stationary spatial AR models.* Third Croatian Congress of Mathematics, Split, Croatia, June 16–18, 2004.
42. *Parameter estimation in linear measurement error models.* Workshop Risk Analysis and Other Applications of Statistics, Budapest, Hungary, April 13–14, 2004.
43. *Estimating the risk of a Down's syndrome term pregnancy using age and serum markers.* 6th International Conference on Applied Informatics, Eger, Hungary, January 27–31, 2004.

44. *Asymptotic inference for an unstable triangular spatial AR model.* Statistical Inference in Linear Models, Bedlewo, Poland, August 21–27, 2003.
45. *An application of stochastic optimization in earth sciences.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, June 23–27, 2003.
46. *A consistent estimator for linear measurement error models.* 24th European Meeting of Statisticians 2002, Prague, Czech Republic, August 19–23, 2002.
47. *Estimation of the mean of a Wiener sheet.* 23rd European Meeting of Statisticians 2001, Funchal, Madeira, Portugal, August 13–19, 2001.
48. *Estimation of the mean of Ornstein-Uhlenbeck processes and sheets.* XXI. International Seminar on Stability Problems for Stochastic Models, Eger, Hungary, January 28– February 3, 2001.
49. *A new estimator in linear measurement error models.* STAT'2000, International Conference on Mathematical Statistics, Szklarska Poreba, Poland, August 21–25, 2000.
50. *Estimation of the mean of Ornstein-Uhlenbeck processes.* Fourth Meeting of Austrian, Slovenian, Italian and Hungarian Young Statisticians, Pécs, Hungary, October 8–10, 1999 (meghívott).
51. *Asymptotic properties of an estimator in functional errors-in-variables models.* XX. International Seminar on Stability Problems for Stochastic Models, Lublin–Nałeczów, Poland, September 5–11, 1999.
52. *On the weak convergence of a continuous state space simulated annealing.* 4th International Conference on Applied Informatics, Eger–Noszvaj, Hungary, August 30–September 3, 1999.
53. *Application of limit theorems for errors-in-variables models.* Colloquium on Limit Theorems of Probability and Statistics, Balatonlelle, Hungary, June 28–July 2, 1999.
54. *On functionals of complex Ornstein-Uhlenbeck processes.* Austrian, Hungarian, and Slovenian Joint Meeting of Young Statisticians, Piran, Slovenia, October 9–11, 1998 (meghívott).
55. *An Application of simulated annealing to ML-estimation of a partially observed Markov Chain.* 3rd International Conference on Applied Informatics, Eger–Noszvaj, Hungary, August 24–28, 1997.
56. *Asymptotic properties in space and time of an estimator in errors-in-variables models in the presence of validation data.* 10th European Young Statistician Meeting, Warsaw, Poland, August 18–22, 1997 (meghívott).