List of publications of Sándor Baran

A) Articles in journals

1. Leutbecher, M., Baran, S., Ensemble size dependence of the logarithmic score for forecasts issued as multivariate normal distributions. *Manuscript* (submitted).

2. Baran, S., Lakatos, M., Clustering-based spatial interpolation of parametric post-processing models. *arXiv:* 2401.14393 (submitted).

3. Baran, Á, Baran, S., Parametric model for post-processing visibility ensemble forecasts. *arXiv:* 2310.16824 (submitted).

4. Baran, Á, Baran, S., A two-step machine learning approach to statistical post-processing of weather forecasts for power generation. *Q. J. R. Meteorol. Soc.* **150** (2024), no. 759, 1029–1047. (IF: 8.900; SJR: D1)

5. Baran, S., Lakatos, M., Statistical post-processing of visibility ensemble forecasts. *Meteorol. Appl.* **30** (2023), no. 5, paper e2157, doi:10.1002/met.2157. (IF: 2.700; SJR: Q2)

6. Szépszó, G., Baran, Á., Baran, S., Jávorné Radnóczi, K., Kornyik, M., Tajti, D., Sugárzásra és magassági szélre vonatkozó rövidtávú előrejelzések operatív statisztikai utófeldolgozása. *Légkör* **68** (2023), 118–125.

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8. Lakatos, M., Lerch, S., Hemri, S., Baran, S., Comparison of multivariate post-processing methods using global ECMWF ensemble forecasts. *Q. J. R. Meteorol. Soc.* **149** (2023), no. 752, 856–877. (IF: 8.900; SJR: D1)

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C) Lecture notes

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D) Software

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E) Conference talks

1. *Discrete post-processing of visibility ensemble forecasts using machine learning* 16^{th} International Conference of the ERCIM WG on Computational and Methodological Statistics (CMStatistics 2023), Berlin, Germany, December 16–18, 2023 (invited).

2. *Optimal designs for complex Ornstein-Uhlenbeck processes with trend.* 16^{th} German Probability and Statistics Days, Essen, Germany, March 7–10, 2023.

3. *K-optimal designs for parameters of shifted Ornstein-Uhlenbeck processes and sheets.* 15^{th} International Conference of the ERCIM WG on Computational and Methodological Statistics (CMStatistics 2022), London, United Kingdom, December 17–19, 2022.

4. *K-optimal designs for regression models driven by Ornstein-Uhlenbeck processes and fields.* International Workshop "Statistics of Stochastic Processes in Discrete and Continuous Time", Kyiv, Ukraine, October 11–12, 2022 (online, invited).

5. *Machine learning-based approaches to statistical post-processing of weather forecasts for power generation.* HITS Workshop on Post-processing, HITS, Heidelberg, Germany, July 20, 2022 (invited).

6. *Calibration of wind speed ensemble forecasts for power generation.* EGU General Assembly 2022, Vienna, Austria, May 23–27, 2022.

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

8. *Statistical calibration of ensemble forecasts of heat indices.* Joint SRNWP-EPS and Post-processing workshop 2020, October 27–30 2020, BlueJeans video-conference meeting (invited plenary).

9. *Statistical methods in weather forecasting.* 11^{th} International Conference on Applied Informatics, Eger, Hungary, January 29–31, 2020 (invited plenary).

10. *Statistical post-processing of water level forecasts.* 12^{th} International Conference of the ERCIM WG on Computational and Methodological Statistics (CMStatistics 2019), London, United Kingdom, December 14–16, 2019 (invited).

11. *Statistical post-processing of dual-resolution ensemble forecasts.* EGU General Assembly 2019, Vienna, Austria, April 8–12, 2019 (invited).

12. *Similarity-based semilocal estimation of post-processing models.* IX. International Workshop on Applied Probability (IWAP 2018), Budapest, Hungary, June 18–21, 2018.

13. *Combining predictive distributions for calibration of ensemble forecasts for precipitation accumulation.* 13^{th} German Probability and Statistics Days, Freiburg, Germany, February 27–March 2, 2018.

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16. *Mixture EMOS model for calibrating ensemble forecasts of wind speed.* 12^{th} German Probability and Statistics Days, Bochum, Germany, March 1–4, 2016.

17. *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 (invited).

18. *Log-normal distribution based EMOS models for probabilistic wind speed forecasting.* European Meeting of Statisticians, Amsterdam, The Netherlands, July 6–10, 2015.

19. *Joint calibration of temperature and wind speed forecasts using Bayesian Model Averaging.* 12^{th} Workshop on Stochastic Models, Statistics and Their Applications, Wroclaw, Poland, February 16–20, 2015.

20. *Probabilistic methods in wind speed forecasting.* Latin American Congress of Statistical Societies (CLATSE2014), La Serena, Chile, October 20–23, 2014 (invited plenary).

21. *Comparison of BMA and EMOS statistical calibration methods for ensemble weather prediction.* 3^{rd} Stochastic Modeling Techniques and Data Analysis International Conference (SMTDA2014), Lisbon, Portugal, June 11–14, 2014.

22. *Statistical post-processing of ensemble forecasts.* ECMI workshop on "The mathematics of air pollution", Budapest, Hungary, May 26–27, 2014 (invited plenary).

23. *Probabilistic wind speed forecasting using Bayesian model averaging with truncated normal components.* 11^{th} German Probability and Statistics Days, Ulm, Germany, March 4–7, 2014.

24. *Statistical calibration of ensemble forecasts.* 9^{th} International Conference on Applied Informatics, Eger, Hungary, January 29–February 1, 2014.

25. *Probabilistic temperature forecasting with statistical calibration in Hungary.* 29^{th} European Meeting of Statisticians, Budapest, Hungary, July 20–25, 2013.

26. *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.

27. *Parameter estimation and testing stability in a spatial unilateral autoregressive model.* Modern Stochastic: Theory and Applications III, Kyiv, Ukraine, September 10–14, 2012 (invited).

28. *Parameter estimation in linear regression driven by a Gaussian random field.* 8^{th} World Congress in Probability and Statistics, Istanbul, Turkey, July 9–14, 2012.

29. *Probabilistic wind speed prediction in Hungary.* 10^{th} German Probability and Statistics Days, Mainz, Germany, March 6–9, 2012.

30. *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.

31. *Parameter estimation in a spatial unit root autoregressive model.* Applied Stochastic Models and Data Analysis (ASMDA2011), Rome, Italy, June 7–10, 2011.

32. *Asymptotic inference of a spatial unit root autoregressive model.* Modern Stochastic: Theory and Applications II, Kyiv, Ukraine, September 7–11, 2010 (invited).

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34. *On the covariance structure of an unstable unilateral spatial autoregressive model.* 27^{th} European Meeting of Statisticians, Toulouse, France, July 20–24, 2009.

35. *Parameter estimation in unstable unilateral spatial autoregressive models.* Probability and Statistics with Applications, Debrecen, Hungary, June 8–12, 2009.

36. *Risk estimation in Down's syndrome screeing.* XXVIII. International Seminar on Stability Problems for Stochastic Models, Zakopane, Poland, May 31–June 5, 2009.

37. *Asymptotic inference for a one-dimensional simultaneous autoregressive model.* Barcelona Conference on Asymptotic Statistics, Barcelona, Spain, September 1–5, 2008.

38. *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.

39. *Mean estimation of a shifted Wiener sheet.* 5th International Conference on Levy Processes: Theory and Applications, Copenhagen, Denmark, August 13–17, 2007 (poster).

40. *Prediction of macroeconomic quantities using stochastic models.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, July 9–13, 2007.

41. *An estimator for nonlinear regression models.* XXVI. International Seminar on Stability Problems for Stochastic Models, Sovata-Bai, Romania, August 27–September 2, 2006.

42. *Mean estimation of the Wiener sheet.* 26^{th} European Meeting of Statisticians, Torun, Poland, July 24–28, 2006.

43. *Asymptotic inference for unstable spatial AR models.* 9^{th} International Vilnius Conference on Probability Theory and Mathematical Statistics, Vilnius, Lithuania, June 25–30, 2006.

44. *Asymptotic inference for unit roots in spatial autoregression.* 25^{th} European Meeting of Statisticians, Oslo, Norway, July 24–28, 2005.

45. *Prediction of Hungarian mortality rates using Lee-Carter method.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, June 19–24, 2005.

46. *A consistent estimator for nonlinear regression models.* COMPSTAT 2004, Prague, Czech Republic, August 23–27, 2004 (poster).

47. *Asymptotic inference for a nearly unstable sequence of stationary spatial AR models.* Third Croatian Congress of Mathematics, Split, Croatia, June 16–18, 2004.

48. *Parameter estimation in linear measurement error models.* Workshop *Risk Analysis and Other Applications of Statistics*, Budapest, Hungary, April 13–14, 2004.

49. *Estimating the risk of a Down's syndrome term pregnancy using age and serum markers.* 6^{th} International Conference on Applied Informatics, Eger, Hungary, January 27–31, 2004.

50. *Asymptotic inference for an unstable triangular spatial AR model.* Statistical Inference in Linear Models, Bedlewo, Poland, August 21–27, 2003.

51. *An application of stochastic optimization in earth sciences.* Applied Mathematics and Scientific Computing, Brijuni, Croatia, June 23–27, 2003.

52. *A consistent estimator for linear measurement error models.* 24^{th} European Meeting of Statisticians 2002, Prague, Czech Republic, August 19–23, 2002.

53. *Estimation of the mean of a Wiener sheet.* 23^{rd} European Meeting of Statisticians 2001, Funchal, Madeira, Portugal, August 13–19, 2001.

54. *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.

55. *A new estimator in linear measurement error models.* STAT'2000, International Conference on Mathematical Statistics, Szklarska Poreba, Poland, August 21–25, 2000.

56. *Estimation of the mean of Ornstein-Uhlenbeck processes.* Fourth Meeting of Austrian, Slovenian, Italian and Hungarian Young Statisticians, Pécs, Hungary, October 8–10, 1999 (invited).

57. *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.

58. *On the weak convergence of a continuous state space simulated annealing.* 4^{th} International Conference on Applied Informatics, Eger–Noszvaj, Hungary, August 30–September 3, 1999.

59. *Application of limit theorems for errors-in-variables models.* Colloquium on Limit Theorems of Probability and Statistics, Balatonlelle, Hungary, June 28–July 2, 1999.

60. *On functionals of complex Ornstein-Uhlenbeck processes.* Austrian, Hungarian, and Slovenian Joint Meeting of Young Statisticians, Piran, Slovenia, October 9–11, 1998 (invited).

61. *An Application of simulated annealing to ML-estimation of a partially observed Markov Chain.* 3^{rd} International Conference on Applied Informatics, Eger–Noszvaj, Hungary, August 24–28, 1997.

62. *Asymptotic properties in space and time of an estimator in errors-in-variables models in the presence of validation data.* 10^{th} European Young Statistician Meeting, Warsaw, Poland, August 18–22, 1997 (invited).