Publikációs lista, Baran Sándor

A) Referált folyóiratcikk

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

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

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

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.

7. Szabó, M., Gascón, E., Baran, S., Parametric post-processing of dual-resolution precipitation forecasts. *Wea. Forecasting* **38** (2023), no. 8, 1313–1322. (IF: 2.900; SJR: Q1)

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)

    1. Sharma, K., Lee, J. C. K., Porson, A., Chandramouli, K., Roberts, N., Boyd, D., Zhang, H., Barker, D. M., Adaptive selection of members for convective-permitting regional ensemble prediction over the western Maritime Continent. *Front. Environ. Sci.* **11** (2023), paper 1281265, doi:10.3389/fenvs.2023.1281265.
    2. Allen, S., Ziegel, J., Ginsbourger, D., Assessing the calibration of multivariate probabilistic forecasts. *Q. J. R. Meteorol. Soc.* (2024), doi:10.1002/qj.4647.

9. Baran, S., Baran, Á., Calibration of wind speed ensemble forecasts for power generation. *Időjárás* **125** (2021), no. 4, 609–624. (IF: 0.869; SJR: Q4)

1. Schultz, B., Lerch, S., Machine learning methods for postprocessing ensemble forecasts of wind gusts: A systematic comparison. *Mon. Weather Rev.* **150** (2022), 235–257.
2. Casciaro, G., Ferrari, F., Cavaiola, M., Mazzino, A., Novel strategies of Ensemble Model Output Statistics (EMOS) for calibrating wind speed/power forecasts. *Energy Convers. Manag.* **271** (2022), paper 116297, doi:10.1016/j.enconman.2022.116297.
3. Krechowicz, A., Krechowicz, M., Poczeta, K., Machine learning approaches to predict electricity production from renewable energy sources. *Energies* **15** (2022), paper 9146, doi:10.3390/en15239146.
4. Ghazvinian, M., Zhang, Y., Hamill, T. M., Seo, D.-J., Fernando, N., Improving probabilistic quantitative precipitation forecasts using short training data through artificial neural networks. *J. Hydrometeorol.* **23** (2022), 1365–1382.
5. Gneiting, T., Lerch, S., Schultz, B., Probabilistic solar forecasting: Benchmarks, post-processing, verification. *Sol. Energy* **252** (2023), 72–80.

10. Baran, S., Szokol, P., Szabó, M., Truncated generalized extreme value distribution based EMOS model for calibration of wind speed ensemble forecasts. *Environmetrics* **32** (2021), paper e2678, (IF: 1.527; SJR: Q1/Q2)

    1. Taillardat, M. Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere* **12** (2021), paper 966, doi:10.3390/atmos12080966.
    2. Kosana, V., Madasthu, S., Teeparthi, K., A novel hybrid framework for wind speed forecasting using autoencoder-based convolutional long short-term memory network. *Int. Trans. Electr. Energ. Syst.* (2021), paper e13072, doi:10.1002/2050-7038.13072.
    3. Schultz, B., Lerch, S., Machine learning methods for postprocessing ensemble forecasts of wind gusts: a systematic comparison. *Mon. Weather Rev.* **150** (2022), 235–257.
    4. Najib, M. K., Nurdiati, S., Sopaheluwakan, A., Multivariate fire risk models using copula regression in Kalimantan, Indonesia. *Nat. Hazards* **113** (2022), 1263–1283.
    5. Bhat, C. R., A new closed-form two-stage budgeting-based multiple discrete-continuous model. *Transport. Res. B-Meth.* **164** (2022), 162–192.
    6. Murphy-Barltrop, C. J. R., Wadsworth, J. L., Eastoe, E. F., New estimation methods for extremal bivariate return curves. *Environmetrics* (2023), paper e2797, doi:10.1002/env.2797.
    7. Chiodo, E., Diban, B., Mazzanti, G., De Angelis, F. A., Review on wind speed extreme values modeling and Bayes estimation for wind power plant design and construction. *Energies* **16** (2023), paper 5456, doi:10.3390/en16145456.

11. Díaz, M., Nicolis, O., Marín, J. C., Baran, S., Post-processing methods for calibrating the wind speed forecasts in central regions of Chile. *Ann. Math. Inform.* **53** (2021), 93–108. (SJR: Q3/Q4)

12. Schulz, B., El Ayari, M., Lerch, S., Baran, S., Post-processing numerical weather prediction ensembles for probabilistic solar irradiance forecasting. *Sol. Energy* **220** (2021), 1016–1031. (IF: 7.188; SJR: Q1/Q1)

    1. Singla, P., Duhan, M., Saroha, S., Review of different error metrics: A case of solar forecasting. *AIUB J. Sci. Eng.* **20** (2021), 158–165.
    2. Taillardat, M. Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere* **12** (2021), paper 966, doi:10.3390/atmos12080966.
    3. Wang, L., Shi, J., A comprehensive application of machine learning techniques for short-term solar radiation prediction. *Appl. Sci.* **11** (2021), paper 5808, doi:10.3390/app11135808.
    4. Lin, B., Shi, L., New understanding of power generation structure transformation, based on a machine learning predictive model. *Sustain. Energy Technol. Assess.* **51** (2022), paper 101962, doi:10.1016/j.seta.2022.101962.
    5. Khajeh, H., Laaksonen, H., Applications of probabilistic forecasting in smart grids: A review. *Appl. Sci.* **12** (2022), paper 1823, doi:10.3390/app12041823.
    6. Gao, Y., Miyata, S., Akashi, Y., Multi-step solar irradiation prediction based on weather forecast and generative deep learning model. *Renew. Energy* **188** (2022), 637–650.
    7. Yang, D., Wang, W., Gueymard, C. A., Hong, T., Kleissl, J., Huang, J., Perez, M. J., Perez, R., Bright, J. M., Xia, X., van der Meer, D., Peters, I. M., A review of solar forecasting, its dependence on atmospheric sciences and implications for grid integration: Towards carbon neutrality. *Renew. Sustain. Energy Rev.* **161** (2022), paper 112348, doi:10.1016/j.rser.2022.112348.
    8. Mayer, M. J., Impact of the tilt angle, inverter sizing factor and row spacing on the photovoltaic power forecast accuracy. *Appl. Energy* **323** (2022), paper 119598, doi:10.1016/j.apenergy.2022.119598.
    9. Lin, F., Zhang, Y., Wang, K., Wang, J., Zhu, M., Parametric probabilistic forecasting of solar power with fat-tailed distributions and deep neural networks. *IEEE Trans. Sustain. Energy* **13** (2022), 2133–2147.
    10. Wang, W., Yang, D., Hong, T., Kleissl, J., An archived dataset from the ECMWF Ensemble Prediction System for probabilistic solar power forecasting. *Sol. Energy* **248** (2022), 64–75.
    11. Borunda, M., Ramírez, A., Garduno, R., Ruíz, G., Hernandez, S., Jaramillo, O. A., Photovoltaic power generation forecasting for regional assessment using machine learning. *Energies* **15** (2022), paper 8895, doi:10.3390/en15238895.

12. Rekha, M. P., Perumal, K., Reducing dimensions in time series data using Remora Optimization Algorithm. *International Journal of Engineering Trends and Technology* **70** (2022), 108–121.
13. Pappa, A., Theodoropoulos, I., Galmarini, S., Kioutsioukis, I., Analog versus multi-model ensemble forecasting: A comparison for renewable energy resources. *Renew. Energy* **205** (2023), 563–573.
14. Mayer, M. J., Yang, D., Pairing ensemble numerical weather prediction with ensemble physical model chain for probabilistic photovoltaic power forecasting. *Renew. Sustain. Energy Rev.* **175** (2023), paper 113171, doi:10.1016/j.rser.2023.113171.
15. Mayer, M. J., Biró, B., Szücs, B., Aszódi, A., Probabilistic modeling of future electricity systems with high renewable energy penetration using machine learning. *Appl. Energy* **336** (2023), paper 120801, doi:10.1016/j.apenergy.2023.120801.
16. Banik, R., Biswas, A., Improving solar PV prediction performance with RF-CatBoost ensemble: A robust and complementary approach. *Renew. Energy Focus* **46** (2023), 207–221.
17. Cerna, F. V., Coêlho, J. K., Fantesia, M. P., Naderi, E., Marzband, M., Contreras, J., Load factor improvement of the electricity grid considering distributed energy resources operation and regulation of peak load. *Sustain. Cities Soc.* **98** (2023), paper 104802, doi:10.1016/j.scs.2023.104802.
18. Backes, J., Renz, W., Improving wind speed uncertainty forecasts using recurrent neural networks. *Proceedings of the Northern Lights Deep Learning Workshop, Vol 4.* 2023, paper 6806, doi:10.7557/18.6806.
19. Chen, Y., Bai, M., Zhang, Y., Liu, J., Yu, D., Error revision during morning period for deep learning and multi-variable historical data-based day-ahead solar irradiance forecast: towards a more accurate daytime forecast. *Earth Sci. Inform.* **16** (2023), 2261–2283.
20. Wang, J.-T., Nguyen, T. A. T., Guo, Y.-H., Hsu, C.-Y., Xie, H.-J., An innovative cluster-based prediction approach for mass solar site management. *Energy Environ.* (2023), paper 0958305X231164676, doi:10.1177/0958305X231164676.
21. Gao, Y., Miyata, S., Akashi, Y., Interpretable deep learning for hourly solar radiation prediction: A real measured data case study in Tokyo. *J. Build. Eng.* **79** (2023), paper 107814, doi:10.1016/j.jobe.2023.107814.
22. Yin, H., Wang, Q., Xing, Y., Power prediction of parabolic trough power system based on BP neural network. In *Proceedings of the 3rd International Conference on Energy Engineering and Power Systems (EEPS).* IEEE, 2023, pp. 1014–1019, doi:10.1109/EEPS58791.2023.10256732.
23. Del Pozo, F. E., Jr., Kim, C. K., Kim, H.-G., Refining the selection of historical period in analog ensemble technique. *Energies* **16** (2023), paper 7630, doi:10.3390/en16227630.

13. Baran, Á, Lerch, S., El Ayari, M., Baran, S., Machine learning for total cloud cover prediction. *Neural. Comput. Appl.* **33** (2021), 2605–2620. (IF: 5.102; SJR: Q2/Q1)

    1. Krinitskiy, M., Aleksandrova, M., Verezemskaya, P., Gulev, S., Sinitsyn, A., Kovaleva, N., Gavrikov, A., On the generalization ability of data-driven models in the problem of total cloud cover retrieval. *Remote Sens.* **13** (2021), paper 326, doi:10.3390/rs13020326.
    2. Grönquist, P., Yao, C., Ben-Nun, T., Dryden, N., Dueben, P., Li, S., Hoefler, T., Deep learning for post-processing ensemble weather forecasts. *Phil. Trans. R. Soc. A* **379** (2021), paper 20200092, doi:10.1098/rsta.2020.0092.
    3. Dupuy, F., Mestre, O., Serrurier, M., Kivachuk Burdá, V., Zamo, M., Cabrera-Gutiérrez, M. C., Bakkay, M. C., Jouhaud, J-C., Mader, M-A., Oller, G., ARPEGE cloud cover forecast postprocessing with convolutional neural network. *Wea. Forecasting* **36** (2021), 567–586.
    4. Bączkiewicz, A., Wątróbski, J., Sałabun, W., Kołodziejczyk, J. An ANN model trained on regional data in the prediction of particular weather conditions. *Appl. Sci.* **11** (2021), paper 4757, doi:10.3390/app11114757.
    5. Sonnewald, M., Lguensat, R., Jones, D. C., Dueben, P. D., Brajard, J., Balaji, V., Bridging observations, theory and numerical simulation of the ocean using machine learning. *Environ. Res. Lett.* **16** (2021), paper 073008, doi:10.1088/1748-9326/ac0eb0.
    6. Dai, Y., Hemri, S., Spatially coherent postprocessing of cloud cover ensemble forecasts. *Mon. Weather Rev.* **149** (2021), 3923–3937.
    7. Hensel, S., Marinov, M. B., Koch, M., Arnaudov, D., Evaluation of deep learning-based neural network methods for cloud detection and segmentation. *Energies* **14** (2021), paper 6156, doi:10.3390/en14196156.
    8. Dehmolaie, M., Rezazadeh, M., Azadi, M., Evaluation of deterministic wind speed forecasting output of two ensemble post-processing methods. *Iran. J. Geophys.* **15** (2021), 93–117.
    9. Bandara, I., Zhang, L., Mistry, K., Deep learning based short-term total cloud cover forecasting. In *Proceedings of the 2022 International Joint Conference on Neural Networks (IJCNN).* IEEE, 2022, pp. 1–8, doi:10.1109/IJCNN55064.2022.9892773.
    10. Kesornsit, W., Sirisathitkul, Y., Hybrid machine learning model for electricity consumption prediction using random forest and artificial neural networks. *Appl. Comput. Intell. Soft Comput.* **2022** (2022), paper 1562942, doi:10.1155/2022/1562942.
    11. Shakya, D., Deshpande, V., Agarwal, M., Kumar, B., Standalone and ensemble-based machine learning techniques for particle Froude number prediction in a sewer system. *Neural. Comput. Appl.* **34** (2022), 15481–15497.

12. Asilevi Junior, P., Opoku, N. K., Martey, F., Setsoafia, E., Ahafianyo, F., Quansah, E., Dogbey, F., Amankwah, S., Padi, M., Development of high resolution cloud cover climatology databank using merged manual and satellite datasets over Ghana, West Africa. *Atmos. Ocean* **60** (2022), 566–579.

13. Deo, R. C., Masrur Ahmed, A. A., Casillas-Pérez, D., Ali Pourmousavi, S., Segal, G., Yu, Y., Salcedo-Sanz, S., Cloud cover bias correction in numerical weather models for solar energy monitoring and forecasting systems with kernel ridge regression. *Renew. Energ.* **203** (2023), 113-130.

14. Rust, F. M., Evans, G. R., Ayliffe, B. A., Improving the blend of multiple weather forecast sources by Reliability Calibration. *Meteorol. Appl.* **30** (2023), paper: e2142, doi:10.1002/met.2142.

15. Deng, X., Da, F., Shao, H., Wang, X., A survey of the researches on grid-connected solar power generation systems and power forecasting methods based on ground-based cloud atlas. *Energy Engineering* **120** (2023), 385–408.

16. Jobst, D., Möller, A., Groß, J., D-vine copula based postprocessing of wind speed ensemble forecasts. *Q. J. R. Meteorol. Soc.* **149** (2023), 2575–2597.

17. Ludwig, M., Arora, S., Taylor, J. W., Probabilistic load forecasting using post-processed weather ensemble predictions. *J. Oper. Res. Soc.* **74** (2023), 1008–1020.

18. Shuvalova, J., Chubarova, N., Shatunova, M., Cloud characteristics and their effects on solar irradiance according to the ICON model, CLOUDNET and BSRN observations. *Atmosphere* **14** (2023), paper 1769, doi:10.3390/atmos14121769.

19. Khojasteh-Leylakoohi, F., Mohit, R., Khalili-Tanha, N., Asadnia, A., Naderi, H., Pourali, G., Yousefli, Z., Khalili-Tanha, G., Khayaei, M., Maftooh, M., Nassiri, M., Hassanian, S. M., Ghayour-Mobarhan, M., Ferns, G. A., Shahidsales, S., Lam, A. K.-y., Giovannetti, E., Nazari, E., Batra, J., Avan, A., Down regulation of Cathepsin W is associated with poor prognosis in pancreatic cancer. *Sci. Rep.* **13** (2023), paper 16678, doi:10.1038/s41598-023-42928-y.

14. Giacomelli Sobrinho, V., Lagutov, V., Baran, S., Green with savvy? Brazil's climate pledge to the Paris Agreement and its transition to the Green Economy. *Energy and Climate Change* **1** (2020), paper 100015, doi:10.1016/j.egycc.2020.100015.

    1. Wei, T., Wu, J., Chen, S., Keeping track of greenhouse gas emission reduction progress and targets in 167 cities worldwide. *Front. Sustain. Cities* **3** (2021), paper 696381, doi:10.3389/frsc.2021.696381.

    2. Zeng, S., Liu, R., Zhou, Y., He, X., Research on provincial forestry investment efficiency in China. *Advances in Management and Applied Economics* **11** (2021), 1–24.

3. Santos, V. O., Araujo, R. O., Ribeiro, F. C. P., Colpani, D., Lima, V. M. R., Tenório, J. A. S., Coleti, J.,; Falcão, N. P. S., Chaar, J. S., de Souza, L. K. C., Analysis of thermal degradation of peach palm (Bactris gasipaes Kunth) seed using isoconversional models. *Reac. Kinet. Mech. Cat.* **135** (2022), 367–387.
4. Akrofi, M. M., Okitasari, M., Kandpal, R., Recent trends on the linkages between energy, SDGs and the Paris Agreement: a review of policy-based studies. *Discover Sustainability* **3** (2022), paper 32, doi:10.1007/s43621-022-00100-y.
5. Okorie, D. I., Wesseh, P. K. Jr., Climate agreements and carbon intensity: Towards increased production efficiency and technical progress? *Struct. Change Econ. Dyn.* **66** (2023), 300–313.
6. Mondragon, M., Peyerl, D., Regulatory pathways for the decentralisation of the Brazilian electricity system. Chapter 7. In: Da Silva, V., Relva, S., Peyerl, D. (eds.) *Energy Transition in Brazil* Springer Nature Switzerland, Cham, Switzerland, 2023, 111–123.

15. Baran, S., Baran, Á., Pappenberger, F., Ben Bouallègue, Z., Statistical post-processing of heat index ensemble forecasts: is there a royal road? *Q. J. R. Meteorol. Soc.* **146** (2020), no. 732, 3416–3434. (IF: 3.739; SJR: Q1)

    1. Meng, X., Taylor, J. W., Comparing probabilistic forecasts of the daily minimum and maximum temperature. *Int. J. Forecast.* **38** (2022), 267–281.

16. Sikolya, K., Baran, S., On the optimal designs for the prediction of complex Ornstein-Uhlenbeck processes. *Comm. Statist. Theory Methods* **49** (2020), no. 20, 4859–4870. (IF: 0.893; SJR: Q3)

    1. Dasgupta, S., Mukhopadhyay, S., Keith, J., Optimal designs for some bivariate cokriging models. *J. Stat. Plan. Inference* **221** (2022), 9–28.

17. Lerch, S., Baran, S., Möller, A., Groß, J., Schefzik, R., Hemri, S., Graeter, M., Simulation-based comparison of multivariate ensemble post-processing methods. *Nonlinear Process. Geophys.* **27** (2020), no. 2, 349–371. (IF: 1.740; SJR: Q2/Q2/Q2)

    1. Narajewski, M., Ziel, F., Ensemble forecasting for intraday electricity prices: Simulating trajectories. *Appl. Energy* **279** (2020), paper 115801, doi:10.1016/j.apenergy.2020.115801.
    2. Perrone, E., Schicker, I., Lang, M. N., A case study of empirical copula methods for the statistical correction of forecasts of the ALADIN-LAEF system. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 277–288.
    3. Petropoulos, F., Apiletti, D., Assimakopoulos, V. *et al.* Forecasting: theory and practice. *Int. J. Forecast.* **38** (2022), 705–871.

4. Roksvåg, T., Lenkoski, A., Scheuerer, M., Heinrich-Mertsching, C., Thorarinsdottir, T. L., Probabilistic prediction of the time to hard freeze using seasonal weather forecasts and survival time methods. *Q. J. R. Meteorol. Soc.* **149** (2023), 211–230.
5. Li, L., Yun, Z., Liu, Y., Wang, Y., Zhao, W., Kang, Y., Gao, R., Improving categorical and continuous accuracy of precipitation forecasts by integrating Empirical Quantile Mapping and Bernoulli-Gamma-Gaussian distribution. *Atmos. Res.* **298** (2024), paper 107133, doi:10.1016/j.atmosres.2023.107133.

18. Stehlík, M., Kiselák, J., Bukina, E., Lu, Y., Baran, S., Fredholm integral relation between compound estimation and prediction (FIRCEP). *Stoch. Anal. Appl.* **38** (2020), no. 3, 427–459. (IF: 1.530; SJR: Q2/Q3/Q3)
    1. Mansouri, D. E. K., Kaddar, B., Benkabou, S.-E., Benabdeslem, K., The Mode-Fisher pooling for time complexity optimization in deep convolutional neural networks. *Neural. Comput. Appl.* **33** (2021), 6443–6465.
    2. Aghajary, M. M., Gharehbaghi, A., A novel adaptive control design method for stochastic nonlinear systems using neural network. *Neural. Comput. Appl.* **33** (2021), 9259–9287.

19. Díaz, M., Nicolis, O., Marín, J. C., Baran, S., Statistical post-processing of ensemble forecasts of temperature in Santiago de Chile. *Meteorol. Appl.* **27** (2020), paper e1818, doi:10.1002/met.1818. (IF: 2.119; SJR: Q3)
    1. Li, X., Chen, J., Xu, C.-Y., Chen, H., Guo, S., Intercomparison of multiple statistical methods in post-processing ensemble precipitation and temperature forecasts. *Meteorol. Appl.* **27** (2020), paper e1935, doi:10.1002/met.1935.
    2. Ylinen, K., Räty, O., Laine, M., Operational statistical postprocessing of temperature ensemble forecasts with stationspecific predictors. *Meteorol. Appl.* **27** (2020), paper e1971, doi:10.1002/met.1971.
    3. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.
    4. Jin, W., Zhang, W., Hu, J., Weng, B., Huang, T., Chen, J., Using the residual network module to correct the sub-seasonal high temperature forecast. *Front. Earth Sci.* **9** (2022), paper 760766, doi:10.3389/feart.2021.760766.

20. Baran, S., Hemri, S., El Ayari, M., Statistical post-processing of water level forecasts using Bayesian model averaging with doubly-truncated normal components. *Water Resour. Res.* **55** (2019), 3997–4013. (IF: 4.309; SJR: D1)

1. Muharsyah, R., Hadi, T. W., Indratno, S. W., Implementation of Bayesian model averaging method to calibrate monthly rainfall ensemble prediction over Java island. *Agromet* **34** (2020), 20–33.
2. Awol, F. S., Coulibaly, P., Tsanis, I., Identification of combined hydrological models and numerical weather predictions for enhanced flood forecasting in a semiurban watershed. *J. Hydrol. Eng.* **26** (2021), paper 04020057, doi:10.1061/(ASCE)HE.1943-5584.0002018.
3. Liu, W., Yang, T., Sun, F., Wang, H., Feng, Y., Du, M., Observation-constrained projection of global flood magnitudes with anthropogenic warming. *Water Resour. Res.* **27** (2021), paper e2020WR028830, doi:10.1029/2020WR028830.
4. Baharvand, S., Jozaghi, A., Fatahi-Alkouhi, R., Karimzadeh, S., Nasiri, R., Lashkar-Ara, B., Comparative study on the machine learning and regression-based approaches to predict the hydraulic jump sequent depth ratio. *Iran. J. Sci. Technol. Trans. Civ. Eng.* **45** (2021), 2719–2732.
5. Lu, P., Lin, K., Xu, C-Y., Lan, T., Liu, Z., He, Y., An integrated framework of input determination for ensemble forecasts of monthly estuarine saltwater intrusion. *J. Hydrol.* **598** (2021), paper 126225, doi:10.1016/j.jhydrol.2021.126225.
6. Siguera, V. A., Weerts, A., Klein, B., Fan, F. M., Paiva, R. C. D., Collischonn, W., Postprocessing continental-scale, medium-range ensemble streamflow forecasts in South America using Ensemble Model Output Statistics and Ensemble Copula Coupling. *J. Hydrol.* **600** (2021), paper 126520, doi:10.1016/j.jhydrol.2021.126520.
7. Barczy, M., A new example for a proper scoring rule. *Comm. Statist. Theory Methods* **51** (2022), 3705–3712.
8. Xie, J., Liu, L., Wang, Y., Xu, Y-P., Chen, H., Changes in actual evapotranspiration and its dominant drivers across the Three-River Source Region of China during 1982–2014. *Hydrology Research* **53** (2022), 297–313.
9. Ran, J., Cui, Y., Xiang, K., Song, Y. Improved runoff forecasting based on time-varying model averaging method and deep learning. *PLoS One* **17** (2022), paper e0274004, doi:10.1371/journal.pone.0274004.
10. Zhou, X., Huang, G., Fan, Y., Wang, X., Li, Y., A mixed-level factorial inference approach for ensemble long-term hydrological projections over the Jing River Basin. *J. Hydrometeorol.* **23** (2022), 1807–1830.
11. Abdallah, M., Mohammadi, B., Zaroug, M. A. H., Omer, A., Cheraghalizadeh, M., Eldow, M. E. E., Duan, Z., Reference evapotranspiration estimation in hyper-arid regions via D-vine copula based-quantile regression and comparison with empirical approaches and machine learning models. *J. Hydrol. Reg. Stud.* **44** (2022), paper 101259, doi:10.1016/j.ejrh.2022.101259.

12. Qi, P., Tang, X., Xu, Y. J., Cui, Z., Sun, J., Zhang, G., Wu, Y., Jiang, M., Optimizing environmental flow based on a new optimization model in balancing objectives among river ecology, water supply and power generation in a high-latitude river. *J. Environ. Manage.* **342** (2023), paper 118261, doi:10.1016/j.jenvman.2023.118261.
13. Kang, S., Yin, J., Gu, L., Yang, Y., Liu, D., Slater, L., Observation-constrained projection of flood risks and socioeconomic exposure in China. *Earth's Future* **11** (2023), paper e2022EF003308, doi:10.1029/2022EF003308.
14. Lu, M., Hou, Q., Qin, S., Zhou, L., Hua, D., Wang, X., Cheng, L., A stacking ensemble model of various machine learning models for daily runoff forecasting. *Water* **15** (2023), paper 1265, doi:10.3390/w15071265.
15. Li, G., Liu, Z., Zhang, J., Han, H., Shu, Z., Bayesian model averaging by combining deep learning models to improve lake water level prediction. *Sci. Total Environ.* **906** (2024), paper 167718, doi:10.1016/j.scitotenv.2023.167718. 167718, doi:10.1016/j.scitotenv.2023.167718.
16. Yang, Y., Chen, R., Ding, Y., Qing, W., Li, H., Han, C., Liu, Y., Liu, J., Evaluation of 12 precipitation products and comparison of 8 multi-model averaging methods for estimating precipitation in the Qilian Mountains, Northwest China. *Atmos. Res.* **296** (2023), paper 107075, doi:10.1016/j.atmosres.2023.107075.

21. Baran, S., Leutbecher, M., Szabó, M., Ben Bouallègue, Z., Statistical post-processing of dual-resolution ensemble forecasts. *Q. J. R. Meteorol. Soc.* **145** (2019), 1705–1720. (IF: 3.471; SJR: D1)

    1. Alessi, M. J., DeGaetano, A. T., A comparison of statistical and dynamical downscaling methods for short-term weather forecasts in the US Northeast. *Meteorol. Appl.* **28** (2021), paper e1976, doi:10.1002/met.1976.

22. Baran, S., Lerch, S., Combining predictive distributions for statistical post-processing of ensemble forecasts. *Int. J. Forecast.* **34** (2018), 477–496. (IF: 3.386; SJR: D1)

    1. Wilks, D. S., Chapter 3 – Univariate Ensemble Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 49–89.
    2. Bremnes, J. B., Constrained quantile regression splines for ensemble postprocessing. *Mon. Weather Rev.* **147** (2019), 1769–1780.
    3. Taillardat, M., Fougères, A.-L., Naveau, P., Mestre, O., Forest-based and semi-parametric methods for the postprocessing of rainfall ensemble forecasting. *Wea. Forecasting* **34** (2019), 617–634.
    4. Serafin, T., Uniejewski, B., Weron, R., Averaging predictive distributions across calibration windows for day-ahead electricity price forecasting. *Energies*, **12** (2019), paper 2561, doi:10.3390/en12132561.

5. Tyralis, H., Papacharalampous, G., Burnetas, A., Langousis, A., Hydrological post-processing using stacked generalization of quantile regression algorithms: Large-scale application over CONUS. *J. Hydrol.* **577** (2019), paper 123957, doi:10.1016/j.jhydrol.2019.123957.
6. Yang, D., Zhang, A. N., Impact of information sharing and forecast combination on fast-moving-consumer-goods demand forecast accuracy. *Information* **10** (2019), paper 260, doi:10.3390/info10080260.
7. Wu, Y., Yang, X., Zhang, W., Kuang, Q., Mixture probabilistic model for precipitation ensemble forecasting. *Q. J. R. Meteorol. Soc.* **145** (2019), 3516–3534.
8. Liu, H., Duan, Z., A vanishing moment ensemble model for wind speed multi-step prediction with multi-objective base model selection. *Appl. Energy* **261** (2020), paper 114367, doi:10.1016/j.apenergy.2019.114367.
9. Lu, P., Ye, L., Zhong, W., Qu, Y., Zhai, B., Tang, Y., Zhao, Y., A novel spatio-temporal wind power forecasting framework based on multi-output support vector machine and optimization strategy. *J. Clean. Prod.* **254** (2020), paper 119993, doi:10.1016/j.jclepro.2020.119993.
10. Möller, A., Groß, J., Probabilistic temperature forecasting with a heteroscedastic autoregressive ensemble postprocessing model. *Q. J. R. Meteorol. Soc.* **146** (2020), 211–224.
11. Schaumann, P., de Langlard, M., Hess, R., James, P., Schmidt, V., A calibrated combination of probabilistic precipitation forecasts to achieve a seamless transition from nowcasting to very short-range forecasting. *Wea. Forecasting* **35** (2020), 773–791.
12. Taillardat, M., Mestre, O., From research to applications – examples of operational ensemble post-processing in France using machine learning. *Nonlin. Processes Geophys.* **27** (2020), 329–347.
13. Allen, S., Ferro, C. A. T., Kwasniok, F., Recalibrating wind speed forecasts using regime-dependent Ensemble Model Output Statistics. *Q. J. R. Meteorol. Soc.* **146** (2020), 2576-2596.
14. McAndrew, T., Wattanachit, N., Gibson, G. C., Reich, N. G., Aggregating predictions from experts: A review of statistical methods, experiments, and applications. *Wiley Interdiscip. Rev. Comput. Stat.* (2020), paper e1514, doi:10.1002/wics.1514.
15. Le Gal La Salle, J., Badosa, J., David, M., Pinson, P., Lauret, P., Added-value of ensemble prediction system on the quality of solar irradiance probabilistic forecasts. *Renew. Energy* **162** (2020), 1321–1339.
16. Ghazvinian, M., Zhang, Y., Seo, D.-J., A nonhomogeneous regression-based statistical postprocessing scheme for generating probabilistic quantitative precipitation forecast. *J. Hydrometeorol.* **21** (2020), 2275–2291.

17. Li, J., Hao, J., Feng, Q., Sun, X., Liu, M., Optimal selection of heterogeneous ensemble strategies of time series forecasting with multi-objective programming. *Expert Syst. Appl.* **166** (2021), paper 114091, doi:10.1016/j.eswa.2020.114091.

18. Liu, H., Yang, R., Wang, T., Zhang, L., A hybrid neural network model for short-term wind speed forecasting based on decomposition, multi-learner ensemble, and adaptive multiple error corrections. *Renew. Energy* **165** (2021), 573–594.

19. Thorgeirsson, A. T., Gauterin, F., Probabilistic predictions with federated learning. *Entropy* **23** (2021), paper 41, doi:10.3390/e23010041.

20. Allen, S., Evans, G. R., Buchanan, P., Kwasniok, F., Incorporating the North Atlantic Oscillation into the post-processing of MOGREPS-G wind speed forecasts. *Q. J. R. Meteorol. Soc.* **147** (2021), 1403–1418.

21. Ghazvinian, M., Zhang, Y., Seo, D.-J., He, M., Fernando, N., A novel hybrid artificial neural network - parametric scheme for postprocessing medium-range precipitation forecasts. *Adv. Water Resour.* **151** (2021), paper 103907, doi:10.1016/j.advwatres.2021.103907.

22. Contreras-Lisperguer, R., Muñoz-Cerón, E., Aguilera, J., de la Casa, J., A set of principles for applying Circular Economy to the PV industry: Modeling a closed-loop material cycle system for crystalline photovoltaic panels. *Sustain. Prod. Consum.* **28** (2021), 164–179.

23. Taillardat, M. Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere* **12** (2021), paper 966, doi:10.3390/atmos12080966.

24. Hamill, T. M., Comparing and combining deterministic surface temperature postprocessing methods over the US. *Mon. Weather Rev.* **149** (2021), 3289–3298.

25. Le Gal La Salle, J., *Qualité et valeur des prévisions solaires probabilistes.* PhD thesis, Université de La Réunion, 2021.

26. Huang, Y., Liu, G.-P., Hu, W., Theory-guided output feedback neural network (Tg-OFNN) for short-term wind power forecasting. In *Proceedings of the 40th Chinese Control Conference (CCC).* Shanghai Systems Science Press, 2021, pp. 5951–5956, doi:10.23919/CCC52363.2021.9550331.

27. Meng, X., Taylor, J. W., Comparing probabilistic forecasts of the daily minimum and maximum temperature. *Int. J. Forecast.* **38** (2022), 267–281.

28. World Meteorological Organization, *Guidelines on Ensemble Prediction System Post-processing.* WMO-No. 1254, WMO, Switzerland, 2021.

29. Ghazvinian, M., Zhang, Y., Hamill, T. M., Seo, D.-J., Fernando, N., Improving probabilistic quantitative precipitation forecasts using short training data through artificial neural networks. *J. Hydrometeorol.* **23** (2022), 1365–1382.

    30. Pic, R., Dombry, C., Naveau, P., Taillardat, M., Distributional regression and its evaluation with the CRPS: Bounds and convergence of the minimax risk. *Int. J. Forecast.* **39** (2023), 1564–1572.
    31. Gilbert, C., Browell, J., Stephen, B., Probabilistic load forecasting for the low voltage network: Forecast fusion and daily peaks. *Sustain. Energy, Grids Netw.* **34** (2023), paper 100988, doi:10.1016/j.segan.2023.100998.
    32. Hu, W., Ghazvinian, M., Chapman, W. E., Sengupta, A., Ralph, F. M., Delle Monache, L., Deep learning forecast uncertainty for precipitation over the western United States. *Mon. Weather Rev.* **151** (2023), 1367–1385.
    33. Wang, X., Hyndman, R. J., Li, F., Kang, Y., Forecast combinations: An over 50-year review. *Int. J. Forecast.* **39** (2023), 1518–1547.
    34. Ludwig, M., Arora, S., Taylor, J. W., Probabilistic load forecasting using post-processed weather ensemble predictions. *J. Oper. Res. Soc.* **74** (2023), 1008–1020.
    35. Nikhil Teja, K., Manikanta, V., Das, J., Umamahesh, N. V., Enhancing the predictability of flood forecasts by combining Numerical Weather Prediction ensembles with multiple hydrological models. *J. Hydrol.* **625** (2023), paper 130176, doi:10.1016/j.jhydrol.2023.130176.
    36. Wattanachit, N., Ray, E. L., McAndrew, T. C., Reich, N. G., Comparison of combination methods to create calibrated ensemble forecasts for seasonal influenza in the U.S. *Stat. Med.* **42** (2023), 4696–4712.

23. Baran, S., Szák-Kocsis, Cs., Stehlík, M., D-optimal designs for complex Ornstein-Uhlenbeck processes. *J. Stat. Plan. Inference* **197** (2018), 93–106. (IF: 0.756; SJR: Q2/Q1/Q2)
    1. Sykulski, A., Olhede, S., Sykulska-Lawrence, H., The elliptical Ornstein-Uhlenbeck process. *Stat. Interface* **16** (2023), 133–146.

24. Baran, S., K-optimal designs for parameters of shifted Ornstein-Uhlenbeck processes and sheets. *J. Stat. Plan. Inference* **186** (2017), 28–41. (IF: 0.814; SJR: Q2/Q1/Q2)
    1. Yan, L., Duan, X., Liu, B., Xu, J., Bayesian optimization based on K-optimality. *Entropy* **20** (2018), paper 594, doi:10.3390/e20080594.

25. Baran, S., Möller, A., Bivariate ensemble model output statistics approach for joint forecasting of wind speed and temperature. *Meteorol. Atmos. Phys.* **129** (2017), no. 1, 99–112. (IF: 1.356; SJR: Q3)
    1. Schefzik, R., Combining parametric low-dimensional ensemble postprocessing with reordering methods. *Q. J. R. Meteorol. Soc.* **142** (2016), 2463–2477.
    2. Wendt, R. D. T., *A hierarchical multivariate Bayesian approach to ensemble model output statistics in atmospheric prediction.* PhD thesis, Naval Postgraduate School, Monterey, California, 2017.

3. Li, W., Duan, Q., Miao, C., Ye, A., Gong, W., Di, Z., A review on statistical post-processing methods for hydrometeorological ensemble forecasting. *Wiley Interdiscip. Rev. Water* **4** (2017), paper e1246, doi:10.1002/wat2.1246.

4. Bellier, J., Bontron, G., Zin, I., Using meteorological analogues for reordering post-processed precipitation ensembles in hydrological forecasting. *Water Resour. Res.* **53** (2017), 10085–10107.

5. Dai, K., Zhu, Y., Bi, B., The review of statistical post-process technologies for quantitative precipitation forecast of ensemble prediction system. *Acta Meteorol. Sin.* **76** (2018), 493–510.

6. Schepen, A., Everingham, Y., Wang, Q. J., On the joint calibration of multivariate seasonal climate forecasts from GCMs. *Mon. Weather Rev.* **148** (2020), 437–456.

7. Lang, M. N., Lerch, S., Mayr, G. J., Simon, T., Stauffer, R., Zeileis, A., Remember the past: a comparison of time-adaptive training schemes for non-homogeneous regression. *Nonlin. Processes Geophys.* **27** (2020), 23–34.

8. Muharsyah, R., Hadi, T. W., Indratno, S. W., Implementation of Bayesian model averaging method to calibrate monthly rainfall ensemble prediction over Java island. *Agromet* **34** (2020), 20–33.

9. Wang, Z.-w., Zhang, W.-m., Tian, G.-m., Liu, Z., Joint values determination of wind and temperature actions on long-span bridges: Copula-based analysis using long-term meteorological data. *Eng. Struct.* **219** (2020), paper 110866, doi:10.1016/j.engstruct.2020.110866.

10. Zhang, W.-m., Wang, Z.-w., Liu, Z., Joint distribution of wind speed, wind direction, and air temperature actions on long-span bridges derived via trivariate metaelliptical and plackett copulas. *J. Bridge Eng.* **25** (2020), paper 04020069, doi:10.1061/(ASCE)BE.1943-5592.0001608.

11. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.

12. Perrone, E., Schicker, I., Lang, M. N., A case study of empirical copula methods for the statistical correction of forecasts of the ALADIN-LAEF system. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 277–288.

13. Liu, Y., Solar GHI ensemble prediction based on a meteorological model and method Kalman filter. *Adv. Meteorol.* **2022** (2022), paper 1523198, doi:10.1155/2022/1523198.

14. Ma, R., Chen, N., Ge, B., Hu, X., Chen, A., Probabilistic modeling of wind characteristics for long-span cable-stayed bridges based on field measurements considering deck disturbance effects. *Measurement* **222** (2023), paper 113617, doi:10.1016/j.measurement.2023.113617.

26. Lerch, S., Baran, S., Similarity-based semi-local estimation of EMOS models. *J. R. Stat. Soc. Ser. C Appl. Stat.* **66** (2017), no. 1, 29–51. (IF: 1.750; SJR: Q1/Q1)

    1. Schefzik, R., A similarity-based implementation of the Schaake shuffle. *Mon. Weather Rev.* **144** (2016), 1909–1921.
    2. Hemri, S., *Probabilistic forecasting based on hydrometeorological ensembles.* PhD thesis, Karlsruhe Institute of Technology, 2016.
    3. Hemri, S., Klein, B., Analog based post-processing of navigation-related hydrological ensemble forecasts. *Water Resour. Res.* **53** (2017), 9059–9077.
    4. Hamill, T., Engle, E., Myrick, D., Peroutka, M., Finan, C., Scheuerer, M., The US national blend of models statistical post-processing of probability of precipitation and deterministic precipitation amount. *Mon. Weather Rev.* **145** (2017), 3441–3463.
    5. Hamill, T. M., Chapter 7 – Practical Aspects of Statistical Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 187–217.
    6. van Straaten, C., Whan, K., Schmeits, M., Statistical postprocessing and multivariate structuring of high-resolution ensemble precipitation forecasts. *J. Hydrometeorol.* **19** (2018), 1815–1833.
    7. Holman, B. P., Lazarus, S. M., Splitt M. E., Statistically and dynamically downscaled, calibrated, probabilistic 10-m wind vector forecasts using ensemble model output statistics. *Mon. Weather Rev.* **146** (2018), 2859–2880.
    8. Scheuerer, M., Hamill, T. M., Probabilistic forecasting of snowfall amounts using a hybrid between a parametric and an analog approach. *Mon. Weather Rev.* **147** (2019), 1047–1064.
    9. Ben Bouallègue, Z., Magnusson, L., Haiden, T., Richardson, D. S., Monitoring trends in ensemble forecast performance focusing on surface variables and high-impact events. *Q. J. R. Meteorol. Soc.* **145** (2019), 1741–1755.
    10. Feldmann, K., Richardson, D. S., Gneiting, T., Grid- vs. station-based postprocessing of ensemble temperature forecasts. *Geophys. Res. Lett.* **46** (2019), 7744–7751.
    11. Gascón, E., Lavers, D., Hamill, T. M., Richardson, D. S., Ben Bouallègue, Z., Leutbecher, M., Pappenberger, F., Statistical post-processing of dual-resolution ensemble precipitation forecasts across Europe. *Q. J. R. Meteorol. Soc.* **145** (2019), 3218–3235.
    12. Barnes, C., Chandler, R. E., Brierley, C. M., New approaches to postprocessing of multi-model ensemble forecasts. *Q. J. R. Meteorol. Soc.* **145** (2019), 3479–3498.
    13. Dabernig, M., Schicker, I., Kann, A., Wang, Y., Lang, M. N., Statistical post-processing with standardized anomalies based on a 1 km gridded analysis. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 265–275.

14. Li, X., Chen, J., Xu, C.-Y., Chen, H., Guo, S., Intercomparison of multiple statistical methods in post-processing ensemble precipitation and temperature forecasts. *Meteorol. Appl.* **27** (2020), paper e1935, doi:10.1002/met.1935.
15. Ylinen, K., Räty, O., Laine, M., Operational statistical postprocessing of temperature ensemble forecasts with stationspecific predictors. *Meteorol. Appl.* **27** (2020), paper e1971, doi:10.1002/met.1971.
16. Allen, S., Evans, G. R., Buchanan, P., Kwasniok, F., Accounting for skew when postprocessing MOGREPS-UK temperature forecast fields. *Mon. Weather Rev.* **149** (2021), 2835–2852.
17. Ratri, D. N., Whan, K., Schmeits, M., Calibration of ECMWF seasonal ensemble precipitation reforecasts in Java (Indonesia) using bias-corrected precipitation and climate indices. *Wea. Forecasting* **36** (2021), 1375–1386.
18. Godahewa, R., Bandara, K., Webb, G. I., Smyl, S., Bergmeir, C., Ensembles of localised models for time series forecasting. *Knowl.-Based Syst.* **233** (2021), paper 107518, doi:10.1016/j.knosys.2021.107518.
19. Skøien, J. O., Bogner, K., Salamon, P., Wetterhall, F., On the implementation of postprocessing of runoff forecast ensembles. *J. Hydrometeorol.* **22** (2021), 2731–2749.
20. Yagli, G. M., Yang, D., Srinivasan, D., Ensemble solar forecasting and post-processing using dropout neural network and information from neighboring satellite pixels. *Renew. Sustain. Energy Rev.* **155** (2022), paper 111909, doi:10.1016/j.rser.2021.111909.
21. Zhang, H., Wang, Y., Chen, D., Feng, D., You, X., Wu, W., Temperature forecasting correction based on operational GRAPES-3km model using machine learning methods. *Atmosphere* **13** (2022), paper 362, doi:10.3390/atmos13020362.
22. Ghazvinian, M., Zhang, Y., Hamill, T. M., Seo, D.-J., Fernando, N., Improving probabilistic quantitative precipitation forecasts using short training data through artificial neural networks. *J. Hydrometeorol.* **23** (2022), 1365–1382.

27. Baran, S., Nemoda, D., Censored and shifted gamma distribution based EMOS model for probabilistic quantitative precipitation forecasting. *Environmetrics* **27** (2016), no. 5, 280–292. (IF: 1.532; SJR: Q2/Q2)

    1. Sansom, P. G., Ferro, C. A. T., Stephenson, D. B., Goddard, L., Mason, S. J., Best practices for post-processing ensemble climate forecasts, Part I: Selecting appropriate recalibration methods. *J. Climate.* **29** (2016), 7247–7264.
    2. Li, W., Duan, Q., Miao, C., Ye, A., Gong, W., Di, Z., A review on statistical post-processing methods for hydrometeorological ensemble forecasting. *Wiley Interdiscip. Rev. Water* **4** (2017), paper e1246.

3. Taillardat, M., Fougères, A.-L., Naveau, P., Mestre, O., Forest-based methods and ensemble model output statistics for rainfall ensemble forecasting. arXiv:1711.10937.

4. Taillardat, M., *Non-parametric methods of post-processing for ensemble forecasting.* PhD thesis, Université Paris-Saclay, 2017.

5. Wright, D. B., Kirschbaum, D. B., Yatheendradas, S., Satellite precipitation characterization, error modeling, and error correction using censored shifted gamma distributions. *J. Hydrometeorol.* **18** (2017), 2801–2815.

6. Hamill, T., Engle, E., Myrick, D., Peroutka, M., Finan, C., Scheuerer, M., The US national blend of models statistical post-processing of probability of precipitation and deterministic precipitation amount. *Mon. Weather Rev.* **145** (2017), 3441–3463.

7. Ma, Q., Xiong, L., Xu, C.-Y., Guo, S., Assessing the adequacy of bias corrected IMERG satellite precipitation estimates using extended mixture distribution mapping method over Yangtze River basin. *MATEC Web Conf.* **246** (2018), paper 01096.

8. Wilks, D. S., Chapter 3 – Univariate Ensemble Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 49–89.

9. Friederichs, P., Wahl, S., Busch, S., Chapter 5 – Postprocessing for Extreme Events. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 127–154.

10. Whan, K., Schmeits, M., Comparing area probability forecasts of (extreme) local precipitation using parametric and machine learning statistical postprocessing methods. *Mon. Weather Rev.* **146** (2018), 3561–3673.

11. Wilks, D. S., Enforcing calibration in ensemble postprocessing. *Q. J. R. Meteorol. Soc.* **144** (2018), 76–84.

12. Papayiannis, G. I., Galanis, G. N., Yannacopoulos, A. N., Model aggregation using optimal transport and applications in wind speed forecasting. *Environmetrics* **29** (2018), paper e2531, doi:10.1002/env.2531.

13. Ji, L., Zhi, X., Zhu, S., Fraedrich, K., Probabilistic precipitation forecasting over East Asia using Bayesian model averaging. *Wea. Forecasting* **34** (2019), 377–392.

14. Schlosser, L., Hothorn, T., Stauffer, R., Zeileis, A., Distributional regression forests for probabilistic precipitation forecasting in complex terrain. *Ann. Appl. Stat.* **13** (2019), 1564–1589.

15. Taillardat, M., Fougères, A.-L., Naveau, P., Mestre, O., Forest-based and semiparametric methods for the postprocessing of rainfall ensemble forecasting. *Wea. Forecasting* **34** (2019), 617–634.

16. Ma, Q., Xiong, L., Xia, J., Xiong, B., Yang, H., Xu, C.-Y., A censored shifted mixture distribution mapping method to correct the bias of daily IMERG satellite precipitation estimates. *Remote Sens.* **11** (2019), paper 1345, doi:10.3390/rs11111345.

17. Li, X.-Q., Chen, J., Xu, C.-Y., Li., L., Chen, H., Performance of post-processed methods in hydrological predictions evaluated by deterministic and probabilistic criteria. *Water Resour. Manag.* **33** (2019), 3289–3302.

18. Gascón, E., Lavers, D., Hamill, T. M., Richardson, D. S., Ben Bouallègue, Z., Leutbecher, M., Pappenberger, F., Statistical post-processing of dual-resolution ensemble precipitation forecasts across Europe. *Q. J. R. Meteorol. Soc.* **145** (2019), 3218–3235.

19. Nousu, J.-P., Lafaysse, M., Vernay, M., Bellier, J., Evin, G., Joly, B., Statistical post-processing of ensemble forecasts of the height of new snow. *Nonlin. Processes Geophys.* **26** (2019), 339–357.

20. Wu, Y., Yang, X., Zhang, W., Kuang, Q., Mixture probabilistic model for precipitation ensemble forecasting. *Q. J. R. Meteorol. Soc.* **145** (2019), 3516–3534.

21. Zhong, Y., Guo, S., Xiong, F., Liu, D., Ba, H., Wu, X., Probabilistic forecasting based on ensemble forecasts and EMOS method for TGR inflow. *Front. Earth Sci.* **14** (2020), 188–200.

22. Wu, W., Emerton, R., Duan, Q., Wood, A. W., Wetterhall, F., Robertson, D. E., Ensemble flood forecasting: Current status and future opportunities. *Wiley Interdiscip. Rev. Water* (2020), paper e1432, doi:10.1002/wat2.1432.

23. Rustam, F., Reshi, A. A., Mehmood, A., Ullah, S., On, B., Aslam, W., Choi, G. S., COVID-19 future forecasting using supervised machine learning models. *IEEE Access* **8** (2020), 101489–101499.

24. Li, X., Chen, J., Xu, C.-Y., Chen, H., Guo, S., Intercomparison of multiple statistical methods in post-processing ensemble precipitation and temperature forecasts. *Meteorol. Appl.* **27** (2020), paper e1935, doi:10.1002/met.1935.

25. Ben Bouallègue, Z., Haiden, T., Weber, N. J., Hamill, T. M., Richardson, D. S., Accounting for representativeness in the verification of ensemble precipitation forecasts. *Mon. Weather Rev.* **148** (2020), 2049–2062.

26. Scheuerer, M., Switanek, M. B., Worsnop, R. P., Hamill, T. M., Using artificial neural networks for generating probabilistic subseasonal precipitation forecasts over California. *Mon. Weather Rev.* **148** (2020), 3489–3506.

27. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.

28. Ghazvinian, M., Zhang, Y., Seo, D.-J., A nonhomogeneous regression-based statistical postprocessing scheme for generating probabilistic quantitative precipitation forecast. *J. Hydrometeorol.* **21** (2020), 2275–2291.

29. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.
30. Ji, L., Luo, Q., Ji, Y., Zhi, X., Probabilistic forecasting of the 500 hPa geopotential height over the Northern Hemisphere using TIGGE multi-model ensemble forecasts. *Atmosphere* **12** (2021), paper 253, doi:10.3390/atmos12020253.
31. Ghazvinian, M., Zhang, Y., Seo, D.-J., He, M., Fernando, N., A novel hybrid artificial neural network - parametric scheme for postprocessing medium-range precipitation forecasts. *Adv. Water Resour.* **151** (2021), paper 103907, doi:10.1016/j.advwatres.2021.103907.
32. Friedli, L., Ginsbourger, D., Bhend, J., Area-covering postprocessing of ensemble precipitation forecasts using topographical and seasonal conditions. *Stoch. Environ. Res. Risk. Assess.* **35** (2021), 215–230.
33. Siguera, V. A., Weerts, A., Klein, B., Fan, F. M., Paiva, R. C. D., Collischonn, W., Postprocessing continental-scale, medium-range ensemble streamflow forecasts in South America using Ensemble Model Output Statistics and Ensemble Copula Coupling. *J. Hydrol.* **600** (2021), paper 126520, doi:10.1016/j.jhydrol.2021.126520.
34. Ratri, D. N., Whan, K., Schmeits, M., Calibration of ECMWF seasonal ensemble precipitation reforecasts in Java (Indonesia) using bias-corrected precipitation and climate indices. *Wea. Forecasting* **36** (2021), 1375–1386.
35. Sura, R., Kumar, S., A detailed analysis of Covid-19 using supervised machine learning models. *AIP Conference Proceedings* **2417** (2021), paper 070001, doi:10.1063/5.0072634.
36. Li, Y., Tian, D., Medina, H., Multimodel subseasonal precipitation forecasts over the contiguous United States: skill assessment and statistical postprocessing. *J. Hydrometeorol.* **22** (2021), 2581–2600.
37. Li, D., Marshall, L., Liang, Y., Sharma, A., Hydrologic multi-model ensemble predictions using variational Bayesian deep learning. *J. Hydrol.* **604** (2022), paper 127221, doi:10.1016/j.jhydrol.2021.127221.
38. Li, W., Pan, B., Xie, J., Duan, Q., Convolutional neural network-based statistical post-processing of ensemble precipitation forecasts. *J. Hydrol.* **605** (2022), paper 127301, doi:10.1016/j.jhydrol.2021.127301.
39. Paria, A., Jana, S., *Prediction of Crops Production Using Random Forest Regression.* Balas, V. E., Tavares, J. M. R. S., Mandal, L. (eds) *Proceedings of International Conference on Computational Intelligence, Data Science and Cloud Computing: IEM-ICDC 2021,* Kolkata, India, December 22–24, 2021, Springer Nature Singapore,
40. Ghazvinian, M., Zhang, Y., Hamill, T. M., Seo, D.-J., Fernando, N., Improving probabilistic quantitative precipitation forecasts using short training data through artificial neural networks. *J. Hydrometeorol.* **23** (2022), 1365–1382.

    41. Ji, Y., Zhi, X., Ji, L., Zhang, Y., Hao, C., Peng, T., Deep-learning-based post-processing for probabilistic precipitation forecasting. *Front. Earth Sci.* **10** (2022), paper 978041, doi:10.3389/feart.2022.978041.
    42. Chen, P., Buis, K., Zhao, X., A comprehensive toolbox for the gamma distribution: The gammadist package. *J. Qual. Technol.* **55** (2023), 75–87.
    43. Zhang, T., Liang, Z., Wang, H., Wang, J., Hu, Y., Li, B., Merging multisatellite precipitation products using stacking method and the censored-shifted gamma ensemble model output statistics in China's Beimiaoji basin. *J. Hydrol.* **618** (2023), paper 129263, doi:10.1016/j.jhydrol.2023.129263.
    44. Hu, W., Ghazvinian, M., Chapman, W. E., Sengupta, A., Ralph, F. M., Delle Monache, L., Deep learning forecast uncertainty for precipitation over the western United States. *Mon. Weather Rev.* **151** (2023), 1367–1385.
    45. Ji, Y., Zhi, X., Ji, L., Peng, T., Conditional ensemble model output statistics for postprocessing of ensemble precipitation forecasting. *Wea. Forecasting* **38** (2023), 1701–1718.
    46. Jiang, X., Zhang, L., Liang, Z., Fu, X., Wang, J., Xu, J., Zhang, Y., Zhong, Q., Study of early flood warning based on postprocessed predicted precipitation and Xinanjiang model. *Weather Clim. Extrem.* (2023), paper 100611, doi:10.1016/j.wace.2023.100611.
    47. Wang, G., Tong, K., Chen, A., Qi, H., Xu, X., Ma, S., Impacts of the least perceived travel cost on the Weibit network equilibrium. *Transportmetrica A* **19** (2023), paper 1980131, doi:10.1080/23249935.2021.1980131.
    48. Muschinski, T., Mayr, G. J., Zeileis, A., Simon, T., Robust weather-adaptive post-processing using model output statistics random forests. *Nonlinear Process. Geophys.* **30** (2023), 503–514.
    49. Li, L., Yun, Z., Liu, Y., Wang, Y., Zhao, W., Kang, Y., Gao, R., Improving categorical and continuous accuracy of precipitation forecasts by integrating Empirical Quantile Mapping and Bernoulli-Gamma-Gaussian distribution. *Atmos. Res.* **298** (2024), paper 107133, doi:10.1016/j.atmosres.2023.107133.
    50. Banerjee, S., Gowrisankar, A. (eds.) *Fractal Signatures in the Dynamics of an Epidemiology An Analysis of COVID-19 Transmission.* CRC Press, Boca Raton, 2024.

28. Baran, S., Lerch, S., Mixture EMOS model for calibrating ensemble forecasts of wind speed. *Environmetrics* **27** (2016), no. 2, 116–130. (IF: 1.532; SJR: Q2/Q2)

    1. Eide, S. S., *Statistical postprocessing of ensemble forecasts of wind.* Master thesis, Norwegian University of Science and Technology, 2016.
    2. Taillardat, M., Fougères, A.-L., Naveau, P., Mestre, O., Forest-based methods and ensemble model output statistics for rainfall ensemble forecasting. arXiv:1711.10937.

3. Taillardat, M., *Non-parametric methods of post-processing for ensemble forecasting.* PhD thesis, Université Paris-Saclay, 2017.
4. Wilks, D. S., Chapter 3 – Univariate Ensemble Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 49–89.
5. Sharpe, M. A., Bysouth, C. E., Stretton, R. E., How well do Met Office post-processed site-specific probabilistic forecasts predict relative-extreme events? *Meteorol. Appl.* **25** (2018), 23–32.
6. Papayiannis, G. I., Galanis, G. N., Yannacopoulos, A. N., Model aggregation using optimal transport and applications in wind speed forecasting. *Environmetrics* **29** (2018), paper e2531, doi:10.1002/env.2531.
7. Nowotarski, J., Weron, R., Recent advances in electricity price forecasting: A review of probabilistic forecasting. *Renew. Sust. Energ. Rev.* **81** (2018), 1548–1568.
8. Amaro, V., Cavuoti, S., Brescia, M., Vellucci, C., Longo, G., Bilicki, M., de Jong, J. T. A., Tortora, C., Radovich, M., Napolitano, N. R., Buddelmeijer, H., Statistical analysis of probability density functions for photometric redshifts through the KiDS-ESO-DR3 galaxies. *Mon. Notices Royal Astron. Soc.* **482** (2019), 3116–3134.
9. Bessac, J., Constantinescu, E. M., Anitescu, M., Stochastic simulation of predictive space-time scenarios of wind speed using observations and physical model outputs. *Ann. Appl. Stat.* **12** (2018), 432–458.
10. Whan, K., Schmeits, M., Comparing area probability forecasts of (extreme) local precipitation using parametric and machine learning statistical postprocessing methods. *Mon. Weather Rev.* **146** (2018), 3561–3673.
11. Lin, Y. Yang, M., Wan, C., Wang, J., Song, Y., A multi-model combination approach for probabilistic wind power forecasting. *IEEE Trans. Sustain. Energy* **10** (2019), 226–237.
12. Bremnes, J. B., Constrained quantile regression splines for ensemble postprocessing. *Mon. Weather Rev.* **147** (2019), 1769–1780.
13. Vargas, S. A., Esteves, G. R. T., Macaira, P. M., Bastos, B. Q., Cyrino Oliveira, F. L., Souza, R. C. Wind power generation: A review and a research agenda. *J. Clean. Prod.* **218** (2019), 850–870.
14. Lang, M. N., Mayr, G. J., Staufer, R., Zeileis, A., Bivariate Gaussian models for wind vectors in a distributional regression framework. *Adv. Stat. Clim. Meteorol. Oceanogr.* **5** (2019), 115–132.
15. Taillardat, M., Fougères, A.-L., Naveau, P., Mestre, O., Forest-based and semi-parametric methods for the postprocessing of rainfall ensemble forecasting. *Wea. Forecasting* **34** (2019), 617–634.

16. Allen, S., Ferro, C. A. T., Kwasniok, F., Regime-dependent statistical post-processing of ensemble forecasts. *Q. J. R. Meteorol. Soc.* **145** (2019), 3535–3552..

17. Zhao, J., Wang, J., Guo, Z., Guo, Y., Lin, W., Lin, Y., Multi-step wind speed forecasting based on numerical simulations and an optimized stochastic ensemble method. *Appl. Energy* **255** (2019), paper 113833, doi:10.1016/j.apenergy.2019.113833.

18. Nousu, J.-P., Lafaysse, M., Vernay, M., Bellier, J., Evin, G., Joly, B., Statistical post-processing of ensemble forecasts of the height of new snow. *Nonlin. Processes Geophys.* **26** (2019), 339–357.

19. Jahn, D. E., Gallus, Jr. W. A., Nguyen, P. T. T., Pan, Q., Cetin, K., Byon, E., Manuel, L., Zhou, Y., Jahani, E., Projecting the most likely annual urban heat extremes in the central United States. *Atmosphere* **10** (2019), paper 727; doi:10.3390/atmos10120727.

20. Möller, A., Groß, J., Probabilistic temperature forecasting with a heteroscedastic autoregressive ensemble postprocessing model. *Q. J. R. Meteorol. Soc.* **146** (2020), 211–224.

21. Bremnes, J. B., Ensemble postprocessing using quantile function regression based on neural networks and Bernstein polynomials. *Mon. Weather Rev.* **148** (2020), 403–414.

22. Allen, S., Ferro, C. A. T., Kwasniok, F., Recalibrating wind speed forecasts using regime-dependent Ensemble Model Output Statistics. *Q. J. R. Meteorol. Soc.* **146** (2020), 2576-2596.

23. Dabernig, M., Schicker, I., Kann, A., Wang, Y., Lang, M. N., Statistical post-processing with standardized anomalies based on a 1 km gridded analysis. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 265–275.

24. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.

25. Che, J., Wang, B., Chen, S., Analysis of data mining method for short-term wind measurement of wind farm based on multi-technology fusion. *Int. J. Inf. Commun. Technol.* **17** (2020), 211–225.

26. Ghazvinian, M., Zhang, Y., Seo, D.-J., A nonhomogeneous regression-based statistical postprocessing scheme for generating probabilistic quantitative precipitation forecast. *J. Hydrometeorol.* **21** (2020), 2275–2291.

27. Zhao, J., Guo, Z., Guo, Y., Lin, W., Zhu, W., A self-organizing forecast of day-ahead wind speed: selective ensemble strategy based on numerical weather predictions. *Energy* **218** (2021), paper 119509, doi:10.1016/j.energy.2020.119509.

28. Allen, S., Evans, G. R., Buchanan, P., Kwasniok, F., Incorporating the North Atlantic Oscillation into the post-processing of MOGREPS-G wind speed forecasts. *Q. J. R. Meteorol. Soc.* **147** (2021), 1403–1418.

29. Ghazvinian, M., Zhang, Y., Seo, D.-J., He, M., Fernando, N., A novel hybrid artificial neural network - parametric scheme for postprocessing medium-range precipitation forecasts. *Adv. Water Resour.* **151** (2021), paper 103907, doi:10.1016/j.advwatres.2021.103907.
30. Zamo, M., Bel, L., Mestre, O., Sequential aggregation of probabilistic forecasts–Application to wind speed ensemble forecasts. *J. R. Stat. Soc. Ser. C Appl. Stat.* **70** (2021), 202–225.
31. Doubleday, K., Jascourt, S., Kleiber, W., Hodge, B.-M., Probabilistic solar power forecasting using Bayesian model averaging. *IEEE Trans. Sustain. Energy* **12** (2021), 325–337.
32. Veldkamp, S., Whan, K., Dirksen, S., Schmeits, M., Statistical postprocessing of wind speed forecasts using convolutional neural networks. *Mon. Weather Rev.* **149** (2021), 1141–1152.
33. Taillardat, M. Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere* **12** (2021), paper 966, doi:10.3390/atmos12080966.
34. Hyvärinen, O., Laurila, T. K., Räty, O., Korhonen, N., Vajda, A., Gregow, H., Winter subseasonal wind speed forecasts for Finland from ECMWF. *Adv. Sci. Res.* **18** (2021), 127–134.
35. Tinsi, L., *Modeling and optimal strategies in short-term energy markets.* PhD thesis, Institut Polytechnique de Paris, 2021.
36. Abedinia, O., Bagheri, M., Execution of synthetic Bayesian model average for solar energy forecasting. *IET Renew. Power Gener.* **16** (2022), 1134–1147.
37. Koliander, G., El-Laham, Y., Djurić, P. M., Hlawatsch, F., Fusion of probability density functions. *Proc. IEEE* **110** (2022), 404–453.
38. Darbandsari, P., Coulibaly, P., Assessing entropy-based Bayesian model averaging method for probabilistic precipitation forecasting. *J. Hydrometeorol.* **23** (2022), 421–440.
39. Tankov, P., Tinsi, L., Stochastic optimization with dynamic probabilistic forecasts. *Ann. Oper. Res.* (2022), doi:10.1007/s10479-022-04913-y.
40. Yang, D., Kleissl, J., Summarizing ensemble NWP forecasts for grid operators: Consistency, elicitability, and economic value. *Int. J. Forecast.* **39** (2023), 1640–1654.
41. Bolin, D., Wallin, J., Local scale invariance and robustness of proper scoring rules. *Stat. Sci* **38** (2023), 140–159.
42. Phipps, K., Meisenbacher, S., Heidrich, B., Turowski, M., Mikut, R., Hagenmeyer, V., Loss-customised probabilistic energy time series forecasts using automated hyperparameter optimisation. *Proceedings of the 14th ACM International Conference on Future Energy Systems.* Association for Computing Machinery (ACM), New York, 2023, 271–286.

43. Abedinia, O., Sobhani, B., Bagheri, M., A new hybrid forecasting model for solar energy output. *2023 IEEE International Conference on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe*, Madrid, Spain, 2023, doi: 10.1109/EEEIC/ICPSEurope57605.2023.10194845.
44. Wattanachit, N., Ray, E. L., McAndrew, T. C., Reich, N. G., Comparison of combination methods to create calibrated ensemble forecasts for seasonal influenza in the U.S. *Stat. Med.* **42** (2023), 4696–4712.
45. Van Poecke, A., Tabari, H., Hellinckx, P., Unveiling the backbone of the renewable energy forecasting process: Exploring direct and indirect methods and their applications. *Energy Rep.* **11** (2024), 544–557.

29. Baran, S., Pap, G., Sikolya, K., Testing stability in a spatial unilateral autoregressive model. *Comm. Statist. Theory Methods* **45** (2016), 933–949. (IF: 0.311; SJR: Q3)

30. Baran, S., Lerch, S., Log-normal distribution based EMOS models for probabilistic wind speed forecasting. *Q. J. R. Meteorol. Soc.* **141** (2015), 2289–2299. (IF: 3.669; SJR: D1)

    1. Junk, C., Delle Monache, L., Alessandrini, S. Analog-based ensemble model output statistics. *Mon. Weather Rev.* **143** (2015), 2909–2917.
    2. Junk, C., Späth, S., von Braman, L., Delle Monache, L., Comparison and combination of regional and global ensemble prediction systems for probabilistic predictions of hub-height wind speed. *Wea. Forecasting* **30** (2015), 1234–1253.
    3. Klein, B., Meißner, D., Hemri, S., Lisniak, D., Ermittlung der prädiktiven Unsicherheit von hydrologischen Ensemblevorhersagen. Bundesanstalt für Gewässerkunde, Bericht BfG-1853, 2015.
    4. Schefzik, R., *Physically coherent probabilistic weather forecasts using multivariate discrete copula-based ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2015.
    5. Jo, S., Seok, I., Choi, T., A nonparametric Bayesian seemingly unrelated regression model. *Korean J. Appl. Stat.* **29** (2016), 627–641.
    6. Taillardat, M., Mestre, O., Zamo, M. and Naveau, P., Calibrated ensemble forecasts using quantile regression forests and ensemble model output statistics. *Mon. Weather Rev.* **144** (2016), 2375–2393.
    7. Schefzik, R., Combining parametric low-dimensional ensemble postprocessing with reordering methods. *Q. J. R. Meteorol. Soc.* **142** (2016), 2463–2477.
    8. Hemri, S., *Probabilistic forecasting based on hydrometeorological ensembles.* PhD thesis, Karlsruhe Institute of Technology, 2016.
    9. Eide, S. S., *Statistical postprocessing of ensemble forecasts of wind.* Master thesis, Norwegian University of Science and Technology, 2016.

10. Ahn, K.-H., Palmer, R., Steinschneider, S., A hierarchical Bayesian model for regionalized seasonal forecasts: Application to low flows in the northeastern United States. *Water Resour. Res.* **53** (2017), 503–521.

11. Li, M., Chen, W., Zhang, T., Application of MODWT and log-normal distribution model for automatic epilepsy identification. *Biocybern. Biomed. Eng.* **37** (2017), 679–689.

12. Zhao, T., Bennett, J., Wang, Q., Schepen, A., Wood, A., Robertson, D., Ramos, M., How suitable is quantile mapping for post-processing GCM precipitation forecasts? *J. Climate.* **30** (2017), 3185–3196.

13. Dai, J., Tan, Y., Yang, W., Wen, L., Shen, X., Investigation of wind resource characteristics in mountain wind farm using multiple-unit SCADA data in Chenzhou: A case study. *Energ. Convers. Manage.* **148** (2017), 378–393.

14. Taillardat, M., *Non-parametric methods of post-processing for ensemble forecasting.* PhD thesis, Université Paris-Saclay, 2017.

15. Bogner, K., Liechti, K., Zappa, M., Technical note: Combining quantile forecasts and predictive distributions of stream-flows. *Hydrol. Earth Syst. Sci.* **21** (2017), 5493–5502.

16. Sun, X. G., Yin, J. F., Zhao, Y., Using the inverse of expected error variance to determine weights of individual ensemble members: application to temperature prediction. *J. Meteor. Res.* **31** (2017), 502–513.

17. Castro Arjona, S., *Análisis de la dispersión en la predicción meteorológica proporcionada por ECMWF-EPS.* Master thesis, Universidad de Sevilla, 2018.

18. Harrou, F., Sun, Y., Madakyaru, M., Bouyedou, B., An improved multivariate chart using partial least squares with continuous ranked probability score. *IEEE Sensors J.* **18** (2018), 6715–6726.

19. Wilks, D. S., Chapter 3 – Univariate Ensemble Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 49–89.

20. Han, K., Choi, J., Kim, C., Comparison of statistical post-processing methods for probabilistic wind speed forecasting. *Asia-Pacific J. Atmos. Sci.* **54** (2018), 91–101.

21. Wilks, D. S., Enforcing calibration in ensemble postprocessing. *Q. J. R. Meteorol. Soc.* **144** (2018), 76–84.

22. Zamo, M., Naveau, P., Estimation of the continuous ranked probability score with limited information and applications to ensemble weather forecasts. *Math. Geosci.* **50** (2018), 209–234.

23. Masseran, N., Integrated approach for the determination of an accurate wind-speed distribution model. *Energy Convers. Manag.* **173** (2018), 56–64.

24. Kamnińska, J. A., Probabilistic forecasting of nitrogen dioxide concentrations at an urban road intersection. *Sustainability* **10** (2018), paper 4213; doi:10.3390/su10114213.

25. Bessac, J., Constantinescu, E. M., Anitescu, M., Stochastic simulation of predictive space-time scenarios of wind speed using observations and physical model outputs. *Ann. Appl. Stat.* **12** (2018), 432–458.

26. Bremnes, J. B., Constrained quantile regression splines for ensemble postprocessing. *Mon. Weather Rev.* **147** (2019), 1769–1780.

27. Avati, A., Duan, T., Jung, K., Shah, N. H., Ng, A., Countdown regression: sharp and calibrated survival predictions. In: Adams, R. P., Gogate, V. (eds) *Proceeding of the Conference on Uncertainty in Artificial Intelligence UAI 2019*, Curran Associates, (2019) Paper: 151391.

28. Cevallos-Torres L., Botto-Tobar M., Case study: logistical behavior in the use of urban transport using the Monte Carlo simulation method. In: *Problem-Based Learning: A Didactic Strategy in the Teaching of System Simulation.* Studies in Computational Intelligence, vol 824. Springer, 2019, pp. 97–110.

29. Ba, H., Guo, S., Zhong, Y., Liu, Z., Wu, X., He, S., Comparative study on probabilistic ensemble flood forecasting considering precipitation forecasts for the Three Gorges Reservoir. *Shuikexue Jinzhan/Advances in Water Science* **30** (2019), 186–197.

30. Chai, S., Xu, Z., Jia, Y., Conditional density forecast of electricity price based on ensemble ELM and logistic EMOS. *IEEE T. Smart. Grid* **10** (2019), 3031–3043.

31. McDermott, P. L., Wikle, C. K., Deep echo state networks with uncertainty quantification for spatio-temporal forecasting. *Environmetrics* **30** (2019), paper e2553, doi:10.1002/env.2553.

32. Vargas, S. A., Esteves, G. R. T., Macaira, P. M., Bastos, B. Q., Cyrino Oliveira, F. L., Souza, R. C. Wind power generation: A review and a research agenda. *J. Clean. Prod.* **218** (2019), 850–870.

33. Lang, M. N., Mayr, G. J., Staufer, R., Zeileis, A., Bivariate Gaussian models for wind vectors in a distributional regression framework. *Adv. Stat. Clim. Meteorol. Oceanogr.* **5** (2019), 115–132.

34. Allen, S., Ferro, C. A. T., Kwasniok, F., Regime-dependent statistical post-processing of ensemble forecasts. *Q. J. R. Meteorol. Soc.* **145** (2019), 3535–3552.

35. Nousu, J.-P., Lafaysse, M., Vernay, M., Bellier, J., Evin, G., Joly, B., Statistical post-processing of ensemble forecasts of the height of new snow. *Nonlin. Processes Geophys.* **26** (2019), 339–357.

36. Jahn, D. E., Gallus, Jr. W. A., Nguyen, P. T. T., Pan, Q., Cetin, K., Byon, E., Manuel, L., Zhou, Y., Jahani, E., Projecting the most likely annual urban

heat extremes in the central United States. *Atmosphere* **10** (2019), paper 727, doi:10.3390/atmos10120727.

37. Zhong, Y., Guo, S., Xiong, F., Liu, D., Ba, H., Wu, X., Probabilistic forecasting based on ensemble forecasts and EMOS method for TGR inflow. *Front. Earth Sci.* **14** (2020), 188–200.

38. Möller, A., Groß, J., Probabilistic temperature forecasting with a heteroscedastic autoregressive ensemble postprocessing model. *Q. J. R. Meteorol. Soc.* **146** (2020), 211–224.

39. Bremnes, J. B., Ensemble postprocessing using quantile function regression based on neural networks and Bernstein polynomials. *Mon. Weather Rev.* **148** (2020), 403–414.

40. Steinhauer, J., Friedrichs, P., Vertical profiles of wind gust statistics from a regional reanalysis using multivariate extreme value theory. *Nonlin. Processes Geophys.* **27** (2020), 239–252.

41. Bevilacqua, M., Caamaño-Carrillo, C., Gaetan, C., On modeling positive continuous data with spatiotemporal dependence. *Environmetrics* **31** (2020), paper e2632, doi:10.1002/env.2632.

42. Plenković, I. O., Schicker, I., Dabernig, M., Horvath, K., Keresturi, E., Analog-based post-processing of the ALADIN-LAEF ensemble predictions in complex terrain. *Q. J. R. Meteorol. Soc.* **146** (2020), 1842–1860.

43. Constantinescu, E. M., Petra, N., Bessac, J., Petra, C. G., Statistical treatment of inverse problems constrained by differential equations-based models with stochastic terms. *SIAM-ASA J. Uncertain.* **8** (2020), 170–197.

44. Allen, S., Ferro, C. A. T., Kwasniok, F., Recalibrating wind speed forecasts using regime-dependent Ensemble Model Output Statistics. *Q. J. R. Meteorol. Soc.* **146** (2020), 2576–2596.

45. Vema, V. K., Sudheer, K. P., Chaubey, I., Uncertainty of hydrologic simulation, and its impact on the design and the effectiveness of water conservation structures. *Stoch. Environ. Res. Risk Assess.* **34** (2020), 973–991.

46. Guan, J., Lin, J., Guan, J. J., Mokaramian, E., A novel probabilistic short-term wind energy forecasting model based on an improved kernel density estimation. *Int. J. Hydrog. Energy* **45** (2020), 23791–23808.

47. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.

48. Zhang, L., Xie, L., Han, Q., Wang, Z., Huang, C., Probability density forecasting of wind speed based on quantile regression and kernel density estimation. *Energies* **13** (2020), paper 6125, doi:10.3390/en13226125.

49. Perrone, E., Schicker, I., Lang, M. N., A case study of empirical copula methods for the statistical correction of forecasts of the ALADIN-LAEF system. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 277–288.

50. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.

51. Alessi, M. J., DeGaetano, A. T., A comparison of statistical and dynamical downscaling methods for short-term weather forecasts in the US Northeast. *Meteorol. Appl.* **28** (2021), paper e1976, doi:10.1002/met.1976.

52. Allen, S., Evans, G. R., Buchanan, P., Kwasniok, F., Incorporating the North Atlantic Oscillation into the post-processing of MOGREPS-G wind speed forecasts. *Q. J. R. Meteorol. Soc.* **147** (2021), 1403–1418.

53. Zamo, M., Bel, L., Mestre, O., Sequential aggregation of probabilistic forecasts–Application to wind speed ensemble forecasts. *J. R. Stat. Soc. Ser. C Appl. Stat.* **70** (2021), 202–225.

54. Zhao, Z., Huang, Q., Ming, B., Chen, J., Liu, D., Chen, X., Hydrological ensemble forecasting method based on stochastic combination of multiple models. *Journal of Hydroelectric Engineering* **40** (2021), 76–87.

55. Taillardat, M. Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere* **12** (2021), paper 966, doi:10.3390/atmos12080966.

56. Lee, Y.-G., Kim, C., Probabilistic forecast of low-level wind shear over Jeju international airport using non-homogeneous regression model. *Int. J. Electr. Eng. Educ.* (2021), doi:10.1177/0020720921997066.

57. Zhao, P., Wang, Q. J., Wu, W., Yang, Q., Extending a joint probability modelling approach for post-processing ensemble precipitation forecasts from numerical weather prediction models. *J. Hydrol.* **605** (2022), paper 127285, doi:10.1016/j.jhydrol.2021.127285.

58. Choi, H.-W., Kim, Y.-H., Han, K., Kim, C., Probabilistic forecast of low level wind shear of Gimpo, Gimhae, Incheon and Jeju International Airports using ensemble model output statistics. *Atmosphere* **12** (2021), paper 1643, doi:10.3390/atmos12121643.

59. Tinsi, L., *Modeling and optimal strategies in short-term energy markets.* PhD thesis, Institut Polytechnique de Paris, 2021.

60. Han, Q., Wang, T., Chu, F., Nonparametric copula modeling of wind speed-wind shear for the assessment of height-dependent wind energy in China. *Renew. Sustain. Energy Rev.* **161** (2022), paper 112319, doi:10.1016/j.rser.2022.112319.

61. Casciaro, G., Ferrari, F., Lagomarsino-Oneto, D., Lira-Loarca, A., Mazzino, A., Increasing the skill of short-term wind speed ensemble forecasts combining forecasts

and observations via a new dynamic calibration. *Energy* **251** (2022), paper 123894, doi:10.1016/j.energy.2022.123894.

62. Oreluk, J., Sheps, L., Najm, H., Bayesian model calibration for vacuum-ultraviolet photoionisation mass spectrometry. *Combust. Theory Model.* **26** (2022), 513–540.
63. Zhao, P., Wang, Q. J., Wu, W., Yang, Q., Spatial mode-based calibration (SMoC) of forecast precipitation fields from numerical weather prediction models. *J. Hydrol.* **613** (2022), paper 128432, doi:10.1016/j.jhydrol.2022.128432.
64. Casciaro, G., Ferrari, F., Cavaiola, M., Mazzino, A., Novel strategies of Ensemble Model Output Statistics (EMOS) for calibrating wind speed/power forecasts. *Energy Convers. Manag.* **271** (2022), paper 116297, doi:10.1016/j.enconman.2022.116297.
65. Tankov, P., Tinsi, L., Stochastic optimization with dynamic probabilistic forecasts. *Ann. Oper. Res.* (2022), doi:10.1007/s10479-022-04913-y.
66. Khan, T., Ahmad, I., Wang, Y., Salam, M., Shahzadi, A., Batool, M., Comparison approach for wind resource assessment to determine the most precise approach. *Energy Environ.* (2022), doi:10.1177/0958305X221135981.
67. Yang, D., Yang, G., Liu, B., Combining quantiles of calibrated solar forecasts from ensemble numerical weather prediction. *Renew. Energy* **215** (2023), paper 118993, doi:10.1016/j.renene.2023.118993.
68. Younis, A., Elshiekh, H., Osama, D., Shaikh-Eldeen, G., Elamir, A., Yassin, Y., Omer, A., Biraima, E., Wind speed forecast for Sudan using the two-parameter Weibull distribution: The case of Khartoum city. *Wind* **3** (2023), 213–231.
69. Diaaeldin, I. M., Attia, M. A., Khamees, A. K., Omar, O. A. M., Badr, A. O., A novel multiobjective formulation for optimal wind speed modeling via a mixture probability density function. *Mathematics* **11** (2023), paper 1463, doi:10.3390/math11061463.
70. Zhao, P., Wang, Q. J., Wu, W., Yang, Q., Spatial mode-based calibration (SMoC) of forecast precipitation fields with spatially correlated structures: An extended evaluation and comparison with gridcell-by-gridcell postprocessing. *J. Hydrometeorol.* **24** (2023), 1509–1525.
71. Jobst, D., Möller, A., Groß, J., D-vine copula based postprocessing of wind speed ensemble forecasts. *Q. J. R. Meteorol. Soc.* **149** (2023), 2575–2597.
72. Chen, K. R., Zhou, Y., Wang, P., Wang, P., Yang, X., Zhang, N., Wang, D., Improving wind forecasts using a gale-aware deep attention network. *J. Meteor. Res.* **37** (2023), 775–789.

31. Baran, S., Sikolya, K., Stehlík, M., Optimal designs for the methane flux in troposphere. *Chemometr. Intell. Lab.* **146** (2015), 407–417. (IF: 2.217; SJR: Q2/Q2/Q2/Q2/Q2

    1. Garcia-Papani, F., Leiva, V., Uribe-Opazo, M. A., Aykroyd, R. G., Birnbaum-Saunders spatial regression models: Diagnostics and application to chemical data, *Chemometr. Intell. Lab.* **177** (2018), 114–128.

2. de la Calle Arroyo, C., López-Fidalgo, J., Rodríguez-Aragón, L. J., Optimal Experimental Design for Physicochemical Models: A Partial Review. In Pardo, M. C., Morales, D., Martín, N., Gil, M. Á., Balakrishnan, N. (eds.) *Trends in Mathematical, Information and Data Sciences: A Tribute to Leandro Pardo.* Springer, 2023, pp. 319–328.

32. Baran, S., Möller, A., Joint probabilistic forecasting of wind speed and temperature using Bayesian model averaging. *Environmetrics* **26** (2015), no. 2, 120–132. (IF: 1.160; SJR: Q2/Q2)

1. Schefzik, R., *Physically coherent probabilistic weather forecasts using multivariate discrete copula-based ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2015.
2. Schefzik, R., A similarity-based implementation of the Schaake shuffle. *Mon. Weather Rev.* **144** (2016), 1909–1921.
3. Schefzik, R., Combining parametric low-dimensional ensemble postprocessing with reordering methods. *Q. J. R. Meteorol. Soc.* **142** (2016), 2463–2477.
4. Lerch, S., *Probabilistic forecasting and comparative model assessment, with focus on extreme events.* PhD thesis, Karlsruhe Institute of Technology, 2016.
5. Li, W., Duan, Q., Miao, C., Ye, A., Gong, W., Di, Z., A review on statistical postprocessing methods for hydrometeorological ensemble forecasting. *Wiley Interdiscip. Rev. Water* **4** (2017), paper e1246, doi:10.1002/wat2.1246.
6. Weijenborg, C., Chagnon, J. M., Friederichs, P., Gray, S. L., Hense, A., Coherent evolution of potential vorticity anomalies associated with deep moist convection. *Q. J. R. Meteorol. Soc.* **143** (2017), 1254–1267.
7. Bellier, J., Bontron, G., Zin, I., Using meteorological analogues for reordering postprocessed precipitation ensembles in hydrological forecasting. *Water Resour. Res.* **53** (2017), 10085–10107.
8. Papayiannis, G. I., Galanis, G. N., Yannacopoulos, A. N., Model aggregation using optimal transport and applications in wind speed forecasting. *Environmetrics* **29** (2018), paper e2531, doi:10.1002/env.2531.
9. Schepen, A., Everingham, Y., Wang, Q. J., On the joint calibration of multivariate seasonal climate forecasts from GCMs. *Mon. Weather Rev.* **148** (2020), 437–456.
10. Bertin, M., Marin, S., Millet, C., Berge-Thierry, C., Using Bayesian model averaging to improve ground motion predictions. *Geophys. J. Int.* **220** (2020), 1368–1378.
11. Muharsyah, R., Hadi, T. W., Indratno, S. W., Implementation of Bayesian model averaging method to calibrate monthly rainfall ensemble prediction over Java island. *Agromet* **34** (2020), 20–33.

12. Wang, Z.-w., Zhang, W.-m., Tian, G.-m., Liu, Z., Joint values determination of wind and temperature actions on long-span bridges: Copula-based analysis using long-term meteorological data. *Eng. Struct.* **219** (2020), paper 110866, doi:10.1016/j.engstruct.2020.110866.
13. Zhang, W.-m., Wang, Z.-w., Liu, Z., Joint distribution of wind speed, wind direction, and air temperature actions on long-span bridges derived via trivariate metaelliptical and plackett copulas. *J. Bridge Eng.* **25** (2020), paper 04020069, doi:10.1061/(ASCE)BE.1943-5592.0001608.
14. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.
15. Perrone, E., Schicker, I., Lang, M. N., A case study of empirical copula methods for the statistical correction of forecasts of the ALADIN-LAEF system. *Meteorol. Z. (Contrib. Atm. Sci.)* **29** (2020), 277–288.
16. Dong, B., Widjaja, R., Wu, W., Zhou, Z., Review of onsite temperature and solar forecasting models to enable better building design and operations. *Build. Simul.* **14** (2021), 885–907.
17. Zhao, P., Wang, Q. J., Wu, W., Yang, Q., Spatial mode-based calibration (SMoC) of forecast precipitation fields from numerical weather prediction models. *J. Hydrol.* **613** (2022), paper 128432, doi:10.1016/j.jhydrol.2022.128432.
18. Zhou, Y., Wu, Z., Xu, H., Wang, H., Prediction and early warning method of inundation process at waterlogging points based on Bayesian model average and data-driven. *J. Hydrol. Reg. Stud.* **44** (2022), paper 101248, doi:10.1016/j.ejrh.2022.101248.
19. Zhao, P., Wang, Q. J., Wu, W., Yang, Q., Spatial mode-based calibration (SMoC) of forecast precipitation fields with spatially correlated structures: An extended evaluation and comparison with gridcell-by-gridcell postprocessing. *J. Hydrometeorol.* **24** (2023), 1509–1525.

33. Baran, S., Stehlík, M., Optimal designs for parameters of shifted Ornstein-Uhlenbeck sheets measured on monotonic sets. *Statist. Probab. Lett.* **99** (2015), 114–124. (IF: 0.506; SJR: Q2/Q2)

    1. Singh, R., Mukhopadhyay, S., Exact Bayesian designs for count time series. *Comput. Stat. Data. Anal.* **134** (2019), 157–170.
    2. Dasgupta, S., Mukhopadhyay, S., Keith, J., Optimal designs for some bivariate cokriging models. *J. Stat. Plan. Inference* **221** (2022), 9–28.

34. Gál, Z., Almási, B., Dabóczi, T., Vida, R., Oniga, S., Baran, S., Farkas, I., Internet of things: application areas and research results of the FIRST project. *Infocomm. J.* **6** (2014), no. 3, 37–44. (SJR: Q4/Q4)

1. Lencse, G., Kovács, Á., Advanced measurements of the aggregation capability of the MPT network layer multipath communication library. *Int. J. Adv. Telecom. Elect. Sign. Syst.* **4** (2015), 41–48.
2. Szedmina, L., Molcer, P. S., Simon, J., Čović, Z., Clicking for business English success. In: *Proceedings of the IEEE 13th International Symposium on Intelligent Systems and Informatics (SISY 2015).* Subotica, Serbia, September 17–19, 2015. Institute of Electrical and Electronics Engineers (IEEE), 2016, pp. 313–317.
3. Baranyi, P., Csapó, Á., Sallai, G., Cognitive Capabilities in the Future Internet. In: *Cognitive Infocommunications (CogInfoCom).* Springer International Publishing, 2015, pp. 173–185.
4. Kovács, A., Comparing the aggregation capability of the MPT communications library and multipath TCP. In: *7th IEEE International Conference on Cognitive Infocommunications(CogInfoCom).* Wroclaw, Poland, October 16–18, 2016. Institute of Electrical and Electronics Engineers (IEEE), 2016, pp. 157–161.
5. Alohali, B., Security in cloud of things (CoT). In: *Managing Big Data in Cloud Computing Environments.* IGI Global, 2016. 46–70.
6. Simon, J., Čović, Z., Petkovics, I., Industrie 4.0 based customized mass production overview. *Proceedings of the 4th International Conference and Workshop Mechatronics in Practice and Education – MECHEDU 2017*, Subotica, Serbia, May 4–5, 2017. Subotica Tech – College of Applied Sciences, Subotica, 2017, 72–76.
7. Alohali, B., Vassilakis, V. G., Protecting data confidentiality in the cloud of things. *Int. J. Hyperconnect. Internet Things* **1** (2017), 29–46.
8. Kovács, Á., Evaluation of the aggregation capability of the MPT network layer multipath communication library and multipath TCP. *Acta. Polytech. Hung.* **16** (2019), 129–147.

35. Baran, S., Horányi, A., Nemoda, D., Comparison of the BMA and EMOS statistical methods in calibrating temperature and wind speed forecast ensembles. *Időjárás* **118** (2014), no. 3, 217–241. (IF: 0.500; SJR: Q3)

    1. Schefzik, R., *Physically coherent probabilistic weather forecasts using multivariate discrete copula-based ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2015.
    2. Lerch, S., *Probabilistic forecasting and comparative model assessment, with focus on extreme events.* PhD thesis, Karlsruhe Institute of Technology, 2016.
    3. Narendra, R. D. *Ensemble Model Output Statistics untuk Prakiraan Cuaca Jangka Pendek.* Master Thesis, Institut Teknologi Sepuluh Nopember, Surabaya, 2017.
    4. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.

5. Dehmolaie, M., Rezazadeh, M., Azadi, M., Evaluation of deterministic wind speed forecasting output of two ensemble post-processing methods. *Iran. J. Geophys.* **15** (2021), 93–117.
6. Phipps, K., Lerch, S., Andersson, M., Mikut, R., Hagenmeyer, V., Ludwig, N., Evaluating ensemble post-processing for wind power forecasts. *Wind Energy* **25** (2022), 1379–1405.

36. Baran, S., Horányi, A., Nemoda, D., Probabilistic temperature forecasting with statistical calibration in Hungary. *Meteorol. Atmos. Phys.* **124** (2014), no. 3-4, 129–142. (IF: 1.049; SJR: Q2)

    1. Schefzik, R., *Physically coherent probabilistic weather forecasts using multivariate discrete copula-based ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2015.
    2. Curceac, S., Ternynck, C., Quarda, T. B. M. J., Chebana, F., Niang, S. D., Short-term air temperature forecasting using Nonparametric Functional Data Analysis and SARMA models. *Environ. Modell. Softw.* **111** (2019), 394–408.
    3. Dong, B., Widjaja, R., Wu, W., Zhou, Z., Review of onsite temperature and solar forecasting models to enable better building design and operations. *Build. Simul.* **14** (2021), 885–904.
    4. Widjaja, R. F., Wu, W., Zhou, Z., Sun, R., Fontenot, H. C., Dong, B., A general spatial-temporal framework for short-term building temperature forecasting at arbitrary locations with crowdsourcing weather data. *Build. Simul.* **16** (2023), 963–982.

37. Baran, S., Probabilistic wind speed forecasting using Bayesian model averaging with truncated normal components. *Comput. Stat. Data. Anal.* **75** (2014), 227–238. IF: 1.400; SJR: Q1/Q1/Q1/Q1)

    1. Hemri, S., Lisniak, D., Klein, B., Ermittlung probabilistischer Abflussvorhersagen unter Berücksichtigung zensierter Daten. *HyWa* **58** (2014), no. 2, 84–94.
    2. Möller, A., *Multivariate and spatial ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2014.
    3. Jiang, P., Dong, Q., A new hybrid model based on an intelligent optimization algorithm and a data denoising method to make wind speed predication. *Math. Probl. Eng.* (2015), paper 714605.
    4. Wang, J., Hu, J., A robust combination approach for short-term wind speed forecasting and analysis – Combination of the ARIMA (Autoregressive Integrated Moving Average), ELM (Extreme Learning Machine), SVM (Support Vector Machine) and LSSVM (Least Square SVM) forecasts using a GPR (Gaussian Process Regression) model. *Energy* **93** (2015), 41–56.

5. Błazejowski, M., Kwiatkowski, J., Bayesian model averaging and jointness measures for gretl. *J. Stat. Softw.* **68** (2015), doi:10.18637/jss.v068.i05.

6. Liu, H., Tian, H., Liang, X., Li, Y., New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, Mind Evolutionary Algorithm and Artificial Neural Networks. *Renew. Energ.* **83** (2015), 1066–1075.

7. Schefzik, R., *Physically coherent probabilistic weather forecasts using multivariate discrete copula-based ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2015.

8. Wu, Y., Zhong, Y., Wang, D., Wu, W., Probabilistic precipitation forecasting over the Dongjiang Basin with BMA. *Tropical Geography* **35** (2015), 860–872.

9. Hu, J., Wang, J., Short-term wind speed prediction using empirical wavelet transform and Gaussian process regression. *Energy* **93** (2015), 1456–1466.

10. Nguefack-Tsague, G., Zucchini, W., A mixture-based Bayesian model averaging method. *Open Journal of Statistics* **6** (2016), 220–228.

11. Schefzik, R., Combining parametric low-dimensional ensemble postprocessing with reordering methods. *Q. J. R. Meteorol. Soc.* **142** (2016), 2463–2477.

12. Lerch, S., *Probabilistic forecasting and comparative model assessment, with focus on extreme events.* PhD thesis, Karlsruhe Institute of Technology, 2016.

13. Hemri, S., *Probabilistic forecasting based on hydrometeorological ensembles.* PhD thesis, Karlsruhe Institute of Technology, 2016.

14. Wang, M.-L., Liu, X.-T., Wang, Y.-S., Wang, X.-L., Guo, H., Xing, Y.-F., Research on assembly tolerance allocation and quality control based on fuzzy reliability. *P. I. Mech. Eng. C – J. Mec.* **230** (2016), 3755–3766.

15. Hemri, S., Klein, B., Analog based post-processing of navigation-related hydrological ensemble forecasts. *Water Resour. Res.* **53** (2017), 9059–9077.

16. Lan, S., Lina, X., Yuzhu, H., Application research on the multi-model fusion forecast of wind speed. *Plateau Meteorology* **36** (2017), 1022–1028.

17. Eide, S. S., Bremnes, J. B., Steinsland, I., Bayesian model averaging for wind speed ensemble forecasts using wind speed and direction. *Wea. Forecasting* **32** (2017), 2217–2227.

18. Wang, X.-D., Forecasting short-term wind speed using support vector machine with particle swarm optimization. In: Li, C., De Oliveira, J. V., Ding, P., Guo, W., Shi, J., Bai, Y. (eds.): 2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC). New York, IEEE, 2017. 241–245.

19. Dai, J., Tan, Y., Yang, W., Wen, L., Shen, X., Investigation of wind resource characteristics in mountain wind farm using multiple-unit SCADA data in Chenzhou: A case study. *Energ. Convers. Manage.* **148** (2017), 378–393.

20. Abaza, M., Anctil, F., Fortin, V., Perreault, L., On the incidence of meteorological and hydrological processors: effect of resolution, sharpness and reliability of hydrological ensemble forecasts. *J. Hydrol (Amst)* **555** (2017), 371–384.

21. Bogner, K., Liechti, K., Zappa, M., Technical note: Combining quantile forecasts and predictive distributions of stream-flows. *Hydrol. Earth Syst. Sci.* **21** (2017), 5493–5502.

22. Lan, S., Lina, X., Yuzhu, H., Wind power application research on the fusion of the determination and ensemble prediction. *Adv. Sci. Res.* **14** (2017), 227–230.

23. Li, C., Xiao, Z., Xia, X., Zou, W., Zhang, C., A hybrid model based on synchronous optimisation for multi-step short-term wind speed forecasting. *Appl. Energy* **215** (2018), 131–144.

24. Wilks, D. S., Chapter 3 – Univariate Ensemble Postprocessing. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 49–89.

25. Pinson, P., Messner, J. W., Chapter 9 – Application of Postprocessing for Renewable Energy. In Vannitsem, S., Wilks, D. S., Messner, J. W. (eds.), *Statistical Postprocessing of Ensemble Forecasts*, Elsevier, 2018, pp. 241–266.

26. Han, K., Choi, J., Kim, C., Comparison of statistical post-processing methods for probabilistic wind speed forecasting. *Asia-Pacific J. Atmos. Sci.* **54** (2018), 91–101.

27. Kim, C., Forecast of wind speed using quantile regression and non-homogeneous regression models. *Journal of Climate Research* **13** (2018), 37–49.

28. Bessac, J., Constantinescu, E. M., Anitescu, M. Stochastic simulation of predictive space-time scenarios of wind speed using observations and physical model outputs. *Ann. Appl. Stat.* **12** (2018), 432–458.

29. Liu, G., Zhou, J., Jia, B., He, F., Yang, Y., Sun, N., Advance short-term wind energy quality assessment based on instantaneous standard deviation and variogram of wind speed by a hybrid method. *Appl. Energy* **238** (2019), 643–667.

30. Lang, M. N., Mayr, G. J., Staufer, R., Zeileis, A., Bivariate Gaussian models for wind vectors in a distributional regression framework. *Adv. Stat. Clim. Meteorol. Oceanogr.* **5** (2019), 115–132.

31. Huang, N., Wu, Y., Cai, G., Zhu, H., Yu, C., Jiang, L., Zhang, Y., Zhang, J., Xing, E., Short-term wind speed forecast with low loss of information based on feature generation of OSVD. *IEEE Access* **7** (2019), 81027–81046.

32. Mazzeo, D., Oliveto, G., Marsico, A., A correction to the unimodal and bimodal truncated normal distributions for a more accurate representation of extreme and calm wind speeds. *Int. J. Energy Res.* **43** (2019), 7908–7941.

33. Zhao, J., Wang, J., Guo, Z., Guo, Y., Lin, W., Lin, Y., Multi-step wind speed forecasting based on numerical simulations and an optimized stochastic ensemble method. *Appl. Energy* **255** (2019), paper 113833, doi:10.1016/j.apenergy.2019.113833.

34. Zhao, J., Guo, Z., Guo, Y., Zhang, Y., Lin, W., Hu, J., Wind resource assessment based on numerical simulations and an optimized ensemble system. *Energy Convers. Manag.* **201** (2019), paper 112164, doi:10.1016/j.enconman.2019.112164.

35. Aminyavari, S., Saghafian, B., Probabilistic streamflow forecast based on spatial post-processing of TIGGE precipitation forecasts. *Stoch. Env. Res. Risk A.* **33** (2019), 1939–1950.

36. Chen, M.-R., Zeng, G.-Q., Lu, K.-D., Weng, J., A two-layer nonlinear combination method for short-term wind speed prediction based on ELM, ENN, and LSTM. *IEEE Internet Things J.* **6** (2019), 6997–7010.

37. Chu, F., Dai, B., Ma, X., Wang, F., Ye, B., A minimum-cost modeling method for nonlinear industrial process based on multimodel migration and Bayesian model averaging method. *IEEE Trans. Autom. Sci. Eng.* **17** (2020), 947–956.

38. Jiang, H., Shihua, L., Dong, Y., Multidimensional meteorological variables for wind speed forecasting in Qinghai Region of China: a novel approach. *Adv. Meteorol.* (2020), paper 5396473, doi:10.1155/2020/5396473.

39. Li, L.-L., Chang, Y.-B., Tseng, M.-L., Liu, J.-Q., Lim, M. K., Wind power prediction using a novel model on wavelet decomposition-support vector machines-improved atomic search algorithm. *J. Clean. Prod.* **270** (2020), paper 121817, doi:10.1016/j.jclepro.2020.121817.

40. Shen, R., Xing, R., Wang, Y., Hua, D., Ma, M., Ultra-short-term prediction method of photovoltaic electric field power based on ground-based cloud image segmentation. *E2S Web of Conferences* **185** (2020), paper 01052, doi:10.1051/e3sconf/202018501052.

41. Kisi, O., Alizamir, M., Trajkovic, S., Shiri, J., Kim, S., Solar radiation estimation in mediterranean climate by weather variables using a novel Bayesian model averaging and machine learning methods. *Neural Process. Lett.* **52** (2020), 2297–2318.

42. Ma, Z., Guo, S., Xu, G., Aziz, S., Meta learning-based hybrid ensemble approach for short-term wind speed forecasting. *IEEE Access* **8** (2020), 172859–172868.

43. Wilks, D. S., *Statistical Methods in the Atmospheric Sciences. Fourth Edition.* Elsevier, Amsterdam, 2020.

44. Zhang, L., Xie, L., Han, Q., Wang, Z., Huang, C., Probability density forecasting of wind speed based on quantile regression and kernel density estimation. *Energies* **13** (2020), paper 6125, doi:10.3390/en13226125.

45. Kim, S., Alizamir, M., Kim, N. W., Kisi, O., Bayesian Model Averaging: A unique model enhancing forecasting accuracy for daily streamflow based on different antecedent time series. *Sustainability* **12** (2020), paper 9720, doi:10.3390/su12229720.

46. Constantinescu, E. M., Petra, N., Bessac, J., Petra, C. G., Statistical treatment of inverse problems constrained by differential equations-based models with stochastic terms. *SIAM-ASA J. Uncertain.* **8** (2020), 170–197.
47. Rashid, H., Haider, W., Batunlu, C., Forecasting of wind turbine output power using machine learning. In: *2020 10th International Conference on Advanced Computer Information Technologies (ACIT)* (2020) pp. 396–399.
48. Cai, R., Xie, S., Wang, B., Yang, R., Xu, D., He, Y., Wind speed forecasting based on extreme gradient boosting. *IEEE Access* **8** (2020), 175063–175069.
49. Zhao, J., Guo, Z., Guo, Y., Lin, W., Zhu, W., A self-organizing forecast of day-ahead wind speed: selective ensemble strategy based on numerical weather predictions. *Energy* **218** (2021), paper 119509, doi:10.1016/j.energy.2020.119509.
50. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.
51. Xie, A., Yang, H., Chen, J., Sheng, L., Zhang, Q., A short-term wind speed forecasting model based on a multi-variable long short-term memory network. *Atmosphere* **12** (2021), paper 651, doi:10.3390/atmos12050651.
52. Doubleday, K., Jascourt, S., Kleiber, W., Hodge, B.-M., Probabilistic solar power forecasting using Bayesian model averaging. *IEEE Trans. Sustain. Energy* **12** (2021), 325–337.
53. Lee, Y.-G., Kim, C., Probabilistic forecast of low-level wind shear over Jeju international airport using non-homogeneous regression model. *Int. J. Electr. Eng. Educ.* (2021), doi:10.1177/0020720921997066.
54. Grün, B., Hofmarcher, P., Identifying groups of determinants in Bayesian model averaging using Dirichlet process clustering. *Scand. J. Stat.* **48** (2021), 1018–1045.
55. Tinsi, L., *Modeling and optimal strategies in short-term energy markets.* PhD thesis, Institut Polytechnique de Paris, 2021.
56. World Meteorological Organization, *Guidelines on Ensemble Prediction System Postprocessing.* WMO-No. 1254, WMO, Switzerland, 2021.
57. Mundu, M. M., Nnamchi, S. N., Ukagwu, K. J., Peter, B. A., Nnamchi, O. A., Ssempewo, J. I., Numerical modelling of wind flow for solar power generation in a case study of the tropical zones. *Model. Earth Syst. Environ.* **8** (2022), 4123–4134.
58. Tankov, P., Tinsi, L., Stochastic optimization with dynamic probabilistic forecasts. *Ann. Oper. Res.* (2022), doi:10.1007/s10479-022-04913-y.
59. Tanhapour, M., Soltani, J., Malekmohammadi, B., Hlavcova, K., Kohnova, S., Petrakova, Z., Lotfi, S., Forecasting the ensemble hydrograph of the reservoir inflow based on post-processed TIGGE precipitation forecasts in a coupled atmospheric-hydrological system. *Water* **15** (2023), paper 887, doi:10.3390/w15050887.

60. Li, M., Wang, X., Semiparametric model averaging method for survival probability predictions of patients *Comput. Stat. Data. Anal.* **185** (2023), paper 107759, doi:10.1016/j.csda.2023.107759.

61. Wu, J., Li, N., Impact of components number selection in truncated Gaussian mixture model and interval partition on wind speed probability distribution estimation. *Sci. Total Environ.* **883** (2023), paper 163709, doi:10.1016/j.scitotenv.2023.163709.

62. Saini, V. L., Kumar, R., Al-Sumaiti, A. S., Sujil, A., Heydarian-Forushani, E., Learning based short term wind speed forecasting models for smart grid applications: An extensive review and case study. *Electr. Power Syst. Res.* **222** (2023), paper 109502, doi:10.1016/j.epsr.2023.109502.

63. Wang, X., Hyndman, R. J., Li, F., Kang, Y., Forecast combinations: An over 50-year review. *Int. J. Forecast.* **39** (2023), 1518–1547.

64. Ahmad, T., Zhou, N., Ensemble methods for probabilistic solar power forecasting: A comparative study. In *Proceedings of the 2023 IEEE Power & Energy Society General Meeting (PESGM)*, IEEE, 2023, doi:10.1109/PESGM52003.2023.10253133.

65. Chen, M., Yang, H., Mao, B., Xie, K., Chen, C., Dong, Y., An ensemble forecast wind field correction model with multiple factors and spatio-temporal features. *Atmosphere* **14** (2023), paper 1650, doi:10.3390/atmos14111650.

38. Baran, S., Horányi, A., Nemoda, D., Statistical post-processing of probabilistic wind speed forecasting in Hungary. *Meteorol. Z.* **22** (2013), no. 3, 273–282. (IF: 1.160; SJR: Q2)

    1. Gneiting, T., Calibration of medium-range weather forecasts. *ECMWF Technical Memorandum* No. 719, 2014.

    2. Möller, A., *Multivariate and spatial ensemble postprocessing methods.* PhD thesis, Heidelberg University, 2014.

    3. El-gindy, A. A. H., El-nashar, Elham S., Probability modelling of wind velocity for assessment of wind energy at Alexandria coast. *Res. J. App. Sci. Eng. Technol.* **8** (2014), 2001–2015.

    4. Arató, M., Martinek, L., Comparison of reserving and spatial models in insurance. In: Montserrat, G. et al. (ed.) *Current Topics on Risk Analysis: ICRA6 and RISK 2015 Conference.* Barcelona, Spain, May 26–29, 2015. Fundación Mapfre, Madrid, 2015, 71–78.

    5. Scheuerer, M., Möller, D., Probabilistic wind speed forecasting on a grid based on ensemble model output statistics. *Ann. Appl. Stat.* **9** (2015), 1328–1349.

    6. Lerch, S., *Probabilistic forecasting and comparative model assessment, with focus on extreme events.* PhD thesis, Karlsruhe Institute of Technology, 2016.

7. Möller, A., Groß, J., Probabilistic temperature forecasting based on an ensemble autoregressive modification. *Q. J. R. Meteorol. Soc.* **142** (2016), 1385–1394.
8. Arató, M., Martinek, L., Mályusz, M., Simulation based comparison of stochastic claims reserving models in general insurance. *Stud. Sci. Math. Hung.* **54** (2017), 241–275.
9. Martinek, L., Analysis of stochastic reserving models by means of NAIC claims data. *Risks* **7** (2019), paper 62, doi:10.3390/risks7020062.
10. Arató, N. M., Martinek, L., The quality of reserve risk calculation models under Solvency II and IFRS 17. *Risks* **10** (2022), paper 204, doi:10.3390/risks10110204.

39. Baran, S., Sikolya, K., Stehlík, M., On the optimal designs for the prediction of Ornstein-Uhlenbeck sheets. *Statist. Probab. Lett.* **83** (2013), no. 6, 1580–1587. (IF: 0.531; SJR: Q3/Q2)

    1. Dasgupta, S., Mukhopadhyay, S., Keith, J., Optimal designs for some bivariate cokriging models. *J. Stat. Plan. Inference* **221** (2022), 9–28.

40. Baran, S., Sikolya, K., Veress, L., Estimating the risk of a Down's syndrome term pregnancy using age and serum markers: Comparison of various methods. *Comm. Statist. Simulation Comput.* **42** (2013), no. 7, 1654–1672. (IF: 0.288; SJR: Q3/Q3)

41. Baran, S., Sikolya, K., Parameter estimation in linear regression driven by a Gaussian sheet. *Acta Sci. Math. (Szeged)* **78** (2012), no. 3-4, 689–713. (SJR: Q4/Q3)

42. Baran, S., Sikolya, K., Parameter estimation in linear regression driven by a Wiener sheet. *Ann. Math. Inform.* **39** (2012), 3–15. (SJR: Q3/Q4)

43. Baran, S., Pap, G., Parameter estimation in a spatial unit root autoregressive model. *J. Multivariate Anal.* **107** (2012), 282–305. (IF: 1.063; SJR: Q1/D1/Q1)

    1. Hassan, A. R., *Stationarity and Unit Roots in Spatial Autoregressive Models.* PhD thesis. Universidad Nacional de Colombia, 2012.
    2. Mojiri, A., Waghei, Y., Nili Sani, H. R., Mohtashami Borzadaran, G. R., Spatial prediction by using unilateral autoregressive models in two-dimensional space. *J. of Stat. Sci.* **12** (2018), 189–208.

44. Kukush, A., Baran, S., Fazekas, I., Usoltseva, E., Simultaneous estimation of baseline hazard rate and regression parameters in Cox proportional hazards model with measurement error. *J. Statist Res.* **45** (2011), no. 2, 77–94.

    1. Chernova, O., Confidence regions in Cox proportional hazards model with measurement errors and unbounded parameter set. In Wiklund, T. (ed.), *Proceedings of the 20th European Young Statisticians Meeting*, Uppsala University, 2017, pp. 75–81.

2. Chernova, O., Hypothesis testing in Cox proportional hazards model with measurement errors. *Theory Probab. Math. Stat.* **100** (2019), 198–207.

45. Baran, S., On the variances of a spatial unit root model. *Lith. Math. J.* **51** (2011), no. 2, 122–140. (IF: 0.486; SJR: Q2)

46. Baran, S., Pap, G., Asymptotic inference for a one-dimensional simultaneous autoregressive model. *Metrika* **74** (2011), no. 1, 55–66. (IF: 0.674; SJR: Q3/Q2)

47. Baran, S., Pap, G., Zuijlen, M. v., Parameter estimation of a shifted Wiener sheet. *Statistics* **45** (2011), no. 4, 319–335. (IF: 0.724; SJR: Q3/Q3)

48. Baran, S., Pap, G., On the least squares estimator in a nearly unstable sequence of stationary spatial AR models. *J. Multivariate Anal.* **100** (2009), no. 4, 686–698. (IF: 1.017; SJR: Q2/Q1/Q2)

    1. Leonenko, N., Taufel, E., Disaggregation of spatial autoregressive processes. *Spatial Statistics* **3** (2013), no. 3, 1–20.
    2. Wang, J., Semiparametric nonlinear log-periodogram regression estimation for perturbed stationary anisotropic long memory random fields. *Comm. Statist. Simulation Comput.* (2021), doi:10.1080/03610918.2021.2006712.

49. Baran, S., Pap, G., Zuijlen, M. v., Asymptotic inference for unit roots in spatial triangular autoregression. *Acta Appl. Math.* **96** (2007), no. 1-3, 17–42. (IF: 0.366; SJR: Q3)

    1. Paulauskas, V., Zové, R., A note on self-normalization for a simple spatial autoregressive model. *Lithuanian Math. J.* **47** (2007), no. 2, 184–194.
    2. Paulauskas, V., On unit roots for spatial autoregressive models. *J. Multivariate Anal.* **98** (2007), no. 1, 209–226.
    3. Hu, H., QML estimators in linear regression models with functional coefficient autoregressive processes. *Math. Probl. Eng.* (2010), paper 956907, doi:10.1155/2010/956907.
    4. Hu, H., Pan, X., Xu, L., Maximum likelihood estimators in linear regression models with Ornstein-Uhlenbeck process. *J. Inequal. Appl.* **2014** (2014), paper 301, doi:10.1186/1029-242X-2014-301.

50. Baran, S., Gáll, J., Ispány, M., Pap, G., Forecasting Hungarian mortality rates using the Lee-Carter method. *Acta Oeconomica* **57** (2007), no. 1, 25–38. (SJR: Q4)

    1. Scherp, H., *Applying the Lee-Carter model to countries in Eastern Europe and the former Soviet Union.* Disseration for actuarial diploma. Swedish Society of Actuaries, 2007.

2. Arató, M., Bozsó, D., Elek, P., Zempléni, A., Forecasting and simulating mortality tables. *Math. Comput. Modelling* **49** (2009), no. 3-4, 805–813.
3. Pitacco, E., Denuit, M., Haberman, S., Olivieri, A., *Modelling longevity dynamics for pensions and annuity business.* Oxford University Press, Oxford, 2009.
4. Májer, I. Kovács, E., Élettartam-kockázat – a nyugdíjrendszerre nehezedő egyik teher. *Statisztikai Szemle* **89** (2011), no. 7-8, 709–812.
5. Bajkó, A., Maknics, A., Tóth, K., Vékás, P. A magyar nyugdíjrendszer fenntarthatóságáról. *Közgazdasági Szemle* **62** (2015), 1229–1257.
6. Li, H., *Managing Longevity Risk.* PhD Thesis, Tilburg University, 2015.
7. Li, H., De Waegenaere, A., Melenberg, B., The choice of sample size for mortality forecasting: a Bayesian learning approach. *Insur. Math. Econ.* **63** (2015), 153–168.
8. Safitri, L., Mardiyati, S., Rahim, H., Estimation of mortality rate in Indonesia with Lee-Carter model. *AIP Conference Proceedings* **2023** (2018), paper 020210.
9. Zili, A. H. A., Mardiyati, S., Lestari, D., Forecasting Indonesian mortality rates using the Lee-Carter model and ARIMA method. *AIP Conference Proceedings* **2023** (2018), paper 020212.
10. Safitri, L., Mardiyati, S., Rahim, H., Forecasting the mortality rates of Indonesian population by using neural network. *J. Phys.: Conf. Ser.* **974** (2018), paper 012030.
11. Cerda-Hernádez, J., Sikov, A., Lee-Carter method for forecasting mortality for Peruvian population. arXiv:1811.09622.
12. Vékás, P., Változások a halandóságjavulás mintázatában Magyarországon. *Biztosítás és Kockázat* **5** (2018), 34–47.
13. Safitri, L., Mardiyati, S., Rahim, H., Comparison of Lee-Carter's classic and general model for forecasting mortality rate in Indonesia. *International Journal of GEOMATE* **16** (2019), 119–124.
14. Vékás, P., *Az élettartam-kockázat modellezése.* Budapesti Corvinus Egyetem, Budapest, 2019.
15. Aji, N. P., Mardiyati, S., Malik, M., Forecasting Indonesian mortality rates using Lee-Carter model and regression linear model. *AIP Conference Proceedings* **2168** (2019), paper 020041.
16. Gogola, J., Vékás, P., Élettartam-kockázat Csehországban és Magyarországon. *Biztosítás és Kockázat* **7** (2020), 14–26.
17. Hunt, A., Blake, D., On the structure and classification of mortality models. *N. Am. Actuar. J.* **25** (2021), S215–S234.
18. Ibrahim, N. S. M., Lazam, N.,Shair, S. N., Forecasting Malaysian mortality rates using the Lee-Carter model with fitting period variants. *J. Phys.: Conf. Ser.* **1988** (2021), paper 012103.

19. Tóth, Cs. G., Multi-population models to handle mortality crises in forecasting mortality: A case study from Hungary. *Society and Economy* **43** (2021), 128–146.
20. Cheng, Z., Si, W., Xu, Z., Xiang, K., Prediction of China's population mortality under limited data. *Int. J. Environ. Res. Public Health* **19** (2022), paper 12371, doi:10.3390/ijerph191912371.
21. Fajar, M., Fajariyanto, E., Lee-Carter modeling for mortality in Indonesia with a Bayesian approach. *Barekeng: Jurnal Ilmu Matematika dan Terapan* **16** (2022), 1241–1248.

51. Csukás, A., Takai, S., Baran, S., Adolescent growth in main somatometric traits of Japanese boys: Ogi Longitudinal Growth Study. *HOMO* **57** (2006), no. 1, 73–86. (IF: 0.585; SJR: Q2/Q2)

    1. Whitley, E., Gunnell, D., Davey Smith, G., Holly, J. M. P. and Martin, R. M., Childhood circumstances and anthropometry: The Boyd Orr cohort. *Ann. Hum. Biol.* **35** (2008), no. 5, 518–534.
    2. Bralić, I., Sekularne promjene rasta i razvoja. *Paediatr Croat.* **52** (2008), no. 1, 25–35.
    3. Garlipp, D. C., *Estudo descritivo dos resultados de desenhos transversais, longitudinais e longitudinais mistos em variáveis do crescimento somático em uma mesma população de crianças jovens.* PhD thesis, Universidade Federal do Rio Grande do Sul, 2011.
    4. Smajić, M., Mihajlović, I., Tomić, B., Transverzalna dimenzionalnost skeleta mladih fudbalera. *Journal of the Anthropologycal Society of Serbia* **46** (2011), 229–235.
    5. Niskanen, M., Ruff, C. B., Holt, B., Sládek, V., Berner, M., Temporal and Geographic Variation in Body Size and Shape of Europeans from the Late Pleistocene to Recent Times. In *Skeletal Variation and Adaptation in Europeans: Upper Paleolithic to the Twentieth Century* (edited by Ruff, C. B.), John Wiley & Sons, Inc., Hoboken, NJ, USA, 2018, pp. 49–89.
    6. Kasai, T., Kamada, H., Tomaru, Y., Tsukagoshi, Y., Nishino, T., Yamazaki, M., Miyakawa, S., Shiraki, H., Longitudinal changes in musculoskeletal findings of elementary and junior high school students: a 1-year prospective study. *J. Phys. Fitness Sports Med.* **9** (2020), 53–64.
    7. Nakajima, R., Kamada, H., Kasai, T., Tomaru, Y., Waku, M., Yamaki, A., Ban, A., Miyakawa, S., Yamazaki, M., Shiraki, H., Effect of temporary school closure due to COVID-19 on musculoskeletal function in elementary school children. *J. Rural. Med.* **16** (2021), 154–159.

52. Baran, S., A consistent estimator for nonlinear regression models. *Metrika* **62** (2005), no. 1, 1–15. (IF: 0.451; SJR: Q3/Q3)

1. Ciuperca, G., Asymptotic behaviour of the LS estimator in a nonlinear model with long memory. *J. Korean Statist. Soc.* **40** (2011), no. 2, 193–203.

53. Baran, S., Pap, G., Zuijlen, M. v., Asymptotic inference for a nearly unstable sequence of stationary spatial AR models. *Statist. Probab. Lett.* **69** (2004), no. 1, 53–61. (IF: 0.284; SJR: Q3/Q3)

    1. Ojeda, S., Vallejos, R., Bustos, O., A new image segmentation algorithm with applications to image inpainting. *Comput. Statist. Data Anal.* **54** (2010), no. 9, 2082–2093.
    2. Martellosio, F., Efficiency of the OLS estimator in the vicinity of a spatial unit root. *Statist. Probab. Lett.* **81** (2011), no. 8, 1285–1291.
    3. Vallejos, R., Ojeda, S., Image segmentation and time series clustering based on spatial and temporal ARMA processes. In Pei-Gee Peter Ho (Ed.), *Advances in Image Segmentation.* ISBN: 978-953-51-0817-7, InTech, 2012.
    4. Ojeda, S., Britos, G. M., A new algorithm to represent texture images. *International Journal of Advanced Computer Science and Applications* **4** (2013), no. 6, 106–111.
    5. Britos, G. M., Ojeda, S., Robust estimation for spatial autoregressive processes based on bounded innovation propagation representations. *Comput. Stat.* **34** (2019), 1315–1335.

54. Baran, S., Pap, G., Zuijlen, M. v., Asymptotic inference for an unstable spatial AR model. *Statistics* **38** (2004), no. 6, 465–483. (IF: 0.323; SJR: Q3/Q3)

    1. Robinson, P. M., Vidal Sanz, J., Modified Whittle estimation of multilateral spatial models. *Cemmap Working Paper* CWP18/03, 2003.
    2. Mirzaev, T. S., Startsev, A. N., A new approach to parameter estimate in a spatial autoregression model of first order. In: *Computer Data Analysis and Modeling: Complex Stochastic Data and Systems.* Minsk, Belarus: 07.09.2010–11.09.2010.09.11. Publishing center BSU, Minsk, 2010, paper 94536.
    3. Hassan, A. R., *Stationarity and Unit Roots in Spatial Autoregressive Models.* PhD thesis. Universidad Nacional de Colombia, 2012.
    4. Arezki, O., Hamaz, A., On linear prediction for stationary random fields with non-symmetrical half-plane past. *Comm. Statist. Theory Methods* **51** (2022), 5298–5309.

55. Baran, S., A consistent estimator for linear models with dependent observations. *Comm. Statist. Theory Methods* **33** (2004), no. 10, 2469–2486. (IF: 0.186; SJR: Q3)

    1. Fan, G-L., Liang, H-Y., Wang, J-F., Xu, H-X., Asymptotic properties for LS estimators in EV regression model with dependent errors. *AStA Adv. Stat. Anal.* **89** (2010), no. 1, 89–103.

2. Miao, Y., Zhao, F., Wang, K., Central limit theorems for LS estimators in the EV regression model with dependent measurements. *J. Korean Statist. Soc.* **40** (2011), no. 3, 303–312.
3. Yang, Q., Asymptotic normality of LS estimators in the simple linear EV regression model with PA errors. *Comm. Statist. Theory Methods* **41** (2012), no. 23, 4276–4284.
4. Miao, Y., Zhao, F., Wang, K., Chen, Y., Asymptotic normality and strong consistency of LS estimators in the EV regression model with NA errors. *Stat. Papers* **54** (2013), no. 1, 193–206.
5. Xu, S-F., Li, N., Consistency for the LS estimator in the linear EV regression model with replicate observations. *J. Korean Statist. Soc.* **42** (2013), no. 4, 451–458.
6. Fan, G-L., Liang, H-Y., Wang, J-F., Empirical likelihood for heteroscedastic partially linear errors-in-variables model with α-mixing errors. *Stat. Papers* **54** (2013), no. 1, 85–112.
7. Hu, H., Pan, X., Asymptotic normality of Huber-Dutter estimators in a linear EV model with AR(1) processes. *J. Inequal. Appl.* (2014), 2014:474.
8. Wang, S., MDP for estimators in EV regression models with α -mixing errors. *Statistics* **49** (2015), 119–127.
9. Shen, A., Asymptotic properties of LS estimators in the errors-in-variables model with MD errors. *Stat. Papers* **60** (2019), 1193–1206.

56. Baran, S., Pap, G., Zuijlen, M. v., Estimation of the mean of a Wiener sheet. *Stat. Inference Stoch. Process.* **7** (2004), no. 3, 279–304.

57. Baran, S., Pap, G., Zuijlen, M. v., Estimation of the mean of stationary and nonstationary Ornstein–Uhlenbeck processes and sheets. *Comput. Math. Appl.* **45** (2003), no. 4-5, 563–579. (IF: 0.498; SJR: Q2/Q2/Q2)

1. Varga, K., *On statistical problems of discrete an continuous time autoregressive processes.* PhD thesis, University of Debrecen, 2003.
2. Leonenko, N., Taufer, E., Convergence of integrated superpositions of Ornstein-Uhlenbeck processes to fractional Brownian motion. *Stochastics* **77** (2005), no. 6, 477–499.
3. Rao, B. L. S. P., Estimation for translation of a process driven by fractional Brownian motion. *Stoch. Anal. Appl.* **23** (2005), no. 6, 1199-1212.
4. Taufer, E., Leonenko, N., Characteristic function estimation of non-Gaussian Ornstein-Uhlenbeck processes. *J. Statist. Plan. Inference* **139** (2009), no. 9, 3050–3063.
5. Puggioni, G., *Using Data Augmentation and Stochastic Differential Equations in Spatio Temporal Modeling.* PhD thesis, Duke University, 2009.

6. Rao, B. L. S. P., *Statistical inference for fractional diffusion processes.* John Wiley and Sons, Chichester, 2010.
7. Zufiria, P. J., A mathematical framework for new fault detection schemes in nonlinear stochastic continuous-time dynamical systems. *Appl. Math. Comput.* **218** (2012), no. 23, 11391–11403.
8. Taufer, E., Estimation of marginal parameters of SUP-OU processes with long range dependence. *Int. J. Adv. Stat. Probab.* **4** (2016), no. 2, 102–108.
9. Barczy, M., Examples of random fields that can be represented as space-domain scaled stationary Ornstein-Uhlenbeck fields. *Math. Slovaca* **68** (2018), 197–210.

58. Norberg, T., Rosén, L., Baran, Á. and Baran, S., On modelling discrete geological structures as Markov random fields. *Math. Geol.* **34** (2002), no. 1, 63–77. (IF: 0.527; SJR: Q1/Q2)

    1. Zhang, Y., Fogg, G. E., Simulation of multi-scale heterogeneity of porous media and parameter sensitivity analysis. *Sci. China Ser. E* **46** (2003), no. 5, 459–474.
    2. Li, W. D., Zhang, C. R., Burt, J. E., Zhu, A. X., Feyen, J., Two-dimensional Markov chain simulation of soil type spatial distribution. *Soil Sci. Soc. Am. J.* **68** (2004), no. 5, 1479–1490.
    3. Li, W. D., Zhang, C. R., Burt, J. E., Zhu, A. X., A Markov chain-based probability vector approach for modeling spatial uncertainties of soil classes. *Soil Sci. Soc. Am. J.* **69** (2005), no. 6, 1931–1942.
    4. Li, W. D., Zhang, C. R., Application of transiograms to Markov chain simulation and spatial uncertainty assessment of land-cover classes, *GIScience and Remote Sensing* **42** (2005), no. 4, 297–319.
    5. Zhang, C. R., Li, W. D., Markov chain modeling of multinomial land-cover classes, *GIScience and Remote Sensing* **42** (2005), no. 1, 1–18.
    6. Liu, Z. F., Hao, T. Y., Fang, H., Modeling of stochastic reservoir lithofacies with Markov chain model. *Acta Petrolei Sinica* **26** (2005), no. 5, 57–60.
    7. Li, W. D., Zhang, C. R., A generalized Markov chain approach for conditional simulation of categorical variables from grid samples. *Transactions in GIS* **10** (2006), no. 4, 651–669.
    8. Heuvelink, G. B. M., Brown, J. D., Towards a soil information system for uncertain soil data. In *Digital Soil Mapping: An Introductory Perspective (Developments in Soil Science, Volume 31)* (edited by Lagacherie, P., McBratney, A. B., Voltz, M.), Elsevier, 2007. Chapter 8, 97–106.
    9. Li, W. D., A fixed-path Markov chain algorithm for conditional simulation of discrete spatial variables. *Math. Geol.* **39** (2007), no. 2 159–176.

10. Heuvelink, G. B. M., Brown, J. D., van Loon, E. E., A probabilistic framework for representing and simulating uncertain environmental variables. *Int. J. Geogr. Inf. Sci.* **21** (2007), no. 5, 497–513.

11. Li, W. D., Zhang, C. R., A random-path Markov chain algorithm for simulating categorical soil variables from random point samples. *Soil Sci. Soc. Am. J.* **71** (2007), no. 3, 656–668.

12. Zhang, C. R., Li, W. D., Comparing a fixed-path Markov chain geostatistical algorithm with sequential indicator simulation in categorical variable simulation from regular samples, *GIScience and Remote Sensing* **44** (2007), no. 3, 251–266.

13. Albora, A. M., Ucan, O. N., Aydogan, D., Modelling potential field sources in the Gelibolu Peninsula (Western Turkey) using a Markov Random Field approach. *Pure Appl. Geophys.* **164** (2007), no. 5, 1057–1080.

14. Brown, J. D., Heuvelink, G. B. M., The Data Uncertainty Engine (DUE): A software tool for assessing and simulating uncertain environmental variables. *Computers & Geosciences* **33** (2007), no. 2, 172–190.

15. Li, W. D. Transiograms for characterizing spatial variability of soil classes. *Soil Sci. Soc. Am. J.* **71** (2007), no. 3, 881–893.

16. Güler, M. E., A review of management science applications of discrete time Markov chains. *Review of Social, Economic and Business Studies* **11/12** Fall 2008–2009.

17. Li, W. D., Zhang, C. R., A single-chain-based multidimensional Markov chain model for subsurface characterization. *Environ. Ecol. Stat.* **15** (2008), no. 2, 157–174.

18. Friedel, M. J., Hydrologic modeling strategy for the Islamic Republic of Mauritania, Africa. *U.S. Geological Survey Open-File Report* 2008-1173, 2008, 20 p.

19. Brown, J. D., Heuvelink, G. B. M., On the identification of uncertainties in spatial data and their quantification with probability distribution functions. In *The Handbook of Geographic Information Science* (edited by J. P. Wilson and A. Stewart), John Wiley and Sons, 2008, 94–107.

20. Cardiff, M., Kitanidis, P. K., Bayesian inversion for facies detection: An extensible level set framework. *Water Resour. Res.* **45** (2009), paper W10416, doi:10.1029/2008WR007675.

21. Knotters, M., Heuvelink, G. B. M., Hoogland, T., Walvoort, D. J. J., *A disposition of interpolation techniques.* Wageningen, Statutory Research Tasks Unit for Nature and the Environment, WOt-werkdocument 190, 2010.

22. Li, J., Xiong, L., Fang, S., Tang, L., Huo, H., Lithology stochastic simulation based on Markov chain models integrated with multi-scale data. *Acta Petrolei Sinica* **31** (2010), no. 1, 73–77.

23. Ma, R., Shi, J., Liu, J., Dealing with the spatial synthetic heterogeneity of aquifers in the North China Plain: A case study of Luancheng County in Hebei Province. *Acta Geologica Sinica* **86** (2012), no. 1, 226–245.
24. Ma, R., Shi, J.-S., Liu, J.-C., Zhang, Y.-L., Establishment and application of Cloud-Markov model based on aquifer hydraulic conductivity. *Journal of Hydraulic Engineering* **43** (2012), no. 7, 767–776.
25. Kempen, B., Brus, D. J., Heuvelink, G. B. M., Soil type mapping using the generalised linear geostatistical model: A case study in a Dutch cultivated peatland. *Geoderma* **189–190**, November 2012, 540–553.
26. Lee, J., Kitanidis, P. K., Bayesian inversion with total variation prior for discrete geologic structure identification. *Water Resour. Res.* **49** (2013), no. 11, 7658–7669.
27. van der Veer, G., Development and application of geospatial models for verifying the geographical origin of food. In *New Analytical Approaches for Verifying the Origin of Food* (edited by P. Brereton), Elsevier, 2013, 60–80.
28. Goldberg, D. A., Higher order Markov random fields for independent sets. arXiv: 1301.1762.
29. Tian, Y. K., Zhou, H., Yuan, S. Y., Lithologic discrimination method based on Markov random field. *Chinese J. Geophys.* **56** (2013), no. 4, 1360–1368.
30. Hartikainen, A., *Statistical analysis of geological space.* Master thesis, Aalto University, 2014.
31. Huang, X., Wang, Z., Modeling categorical random fields via linear Bayesian Updating. Preprints 2016, 2016070030, doi:10.20944/preprints201607.0030.v1.
32. Huang, X., Wang, Z., Guo, J., Prediction of categorical spatial data via Bayesian updating. *Int. J. Geogr. Inf. Sci.* **30** (2016), 1426–1449.
33. Wang, X., Li, Z., Wang, H., Rong, Q., Liang, R. Y., Probabilistic analysis of shield-driven tunnel in multiple strata considering stratigraphic uncertainty. *Struct. Saf.* **62** (2016), 88–100.
34. Li, Z., Wang, X., Wang, H., Liang, R. Y., Quantifying stratigraphic uncertainties by stochastic simulation techniques based on Markov random field. *Eng. Geol.* **201** (2016), 106–122.
35. Li, Z., *Subsurface simulation using stochastic modeling techniques for reliability based design of geo-structures.* PhD thesis, University of Akron, 2016.
36. Huang, X., Wang, Z., Guo, J., Theoretical generalization of Markov chain random field from potential function perspective. *J. Cent. South Univ.* **23** (2016), no. 1, 189–200.
37. Wang, H., Wellmann, J. F., Li, Z., Wang, X., Liang, R. Y., A segmentation approach for stochastic geological modeling using hidden Markov random fields. *Math. Geosci.* **49** (2017), 145–147.

38. Howarth, R. K., *Dictionary of Mathematical Geosciences.* Springer, 2017.

39. Wang, X., Wang, H., Liang, R. Y., Zhu, H., Di, H., A hidden Markov random field model based approach for probabilistic site characterization using multiple cone penetration test data. *Struct. Saf.* **70** (2018), 128–138.

40. Wang, X., Wang, H., Liang, R. Y., A method for slope stability analysis considering subsurface stratigraphic uncertainty. *Landslides* **15** (2018), 925–936.

41. Gong, W., Tang, H., Wang, H., Wang, X., Juang, C. H., Probabilistic analysis and design of stabilizing piles in slope considering stratigraphic uncertainty. *Eng. Geol.* **259** (2019), paper 105162, doi:10.1016/j.enggeo.2019.105162.

42. Li, W. D., Zhang, C. R., Markov chain random fields in the perspective of spatial Bayesian networks and optimal neighborhoods for simulation of categorical fields. *Computat. Geosci.* **23** (2019), 1087–1106.

43. Žukovič, M., Borovský, M., Lach, M., Hristopulos, D. T., GPU-accelerated simulation of massive spatial data based on the modified planar rotator model. *Math. Geosci.* **52** (2020), 123–143.

44. Gong, W., Zhao, C., Juang, C. H., Tang, H., Wang, H., Hu, X., Stratigraphic uncertainty modelling with random field approach. *Comput. Geotech.* **125** (2020), paper 103681, doi:10.1016/j.compgeo.2020.103681.

45. Zhao, C., Wong, W., Li, T., Juang, H., Tang, H., Wang, H., Probabilistic characterization of subsurface stratigraphic configuration with modified random field approach. *Eng. Geol.* **288** (2021), paper 106138, doi:10.1016/j.enggeo.2021.106138.

46. Ismagilov, N., Borovitskiy, V., Lifshits, M., Platonova, M., Boolean spectral analysis in categorical reservoir modeling. *Math. Geosci.* **53** (2021), 305–324.

47. Das, K., Samanta, S. K., Modelling and analysis of $D-BMAP/D-MSP/1$ queue using *RG*-factorization. *Qual. Technol. Quant. Manag.* **18** (2021), 355–381.

48. Samanta, S. K., Das, K., Computing stationary distributions of the $D\text{-}MAP/D\text{-}MSP^{(a,b)}/1$ queueing system. *J. Ambient Intell. Humaniz. Comput.* **13** (2022), 571–590.

49. Chakraborty, R., Dey, A., Probabilistic slope stability analysis: state-of-the-art review and future prospects. *Innov. Infrastruct. Solut.* **7** (2022), paper 177, doi:10.1007/s41062-022-00784-1.

50. Hsu, Y.-H., Lu, Y.-C., Khoshnevisan, S., Juang, H., Hwang, J., Influence of geological uncertainty on the design of OWTF monopiles. *Eng. Geol.* **303** (2022), paper 106621, doi:10.1016/j.enggeo.2022.106621.

51. Wang, H., Wei, X., Stochastic Stratigraphic Simulation and Uncertainty Quantification Using Machine Learning. In Lemnitzer, A., Stuedlein, A. W. (eds.) *Geo-Congress 2022: Site and Soil Characterization, Computational Geotechnics, Risk, and Lessons Learned.* ASCE, 2022, pp. 337–346.

52. Wei, X., Wang, H., Stochastic stratigraphic modeling using Bayesian machine learning. *Eng. Geol.* **307** (2022), paper 106789, doi:10.1016/j.enggeo.2022.106789.
53. Cardenas, I. C., A two-dimensional approach to quantify stratigraphic uncertainty from borehole data using non-homogeneous random fields. *Eng. Geol.* **314** (2023), paper 107001, doi:10.1016/j.enggeo.2023.107001.
54. Shuku, T., Phoon, K.-K., Data-driven subsurface modelling using a Markov random field model. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards* **17** (2023), 41–63.
55. Shuku, T., Data-Driven Site Characterization. In Phoon, K.-K., Shuku, T., Ching, J. (eds.) *Uncertainty, Modeling, and Decision Making in Geotechnics,* CRC Press, 2023, pp. 143–175.
56. Wang, F., Li, H., Li, G., You, Z-J., Chen, E. J., Characterization of geological uncertainties from limited boreholes using copula-based coupled Markov chains for underground construction. *Undergr. Space* **16** (2024), 94–105.

59. Baran, S., A new consistent estimator for linear errors-in-variables models. *Comput. Math. Appl.* **41** (2001), no. 7-8, 821–833. (IF: 0.383; SJR: Q3/Q3/Q2)

    1. Neng, J., Yafen, Y., Estimation of reporting tax errors for Chinese personal income based on errors-in-variables model. *Second International Conference on Innovative Computing, Information and Control, ICICIC 2007* (2008), art. no. 4428021.
    2. Wendelberger, J. R., Variation in controlled experimental variables. *Qual. Technol. Quant. M.* **12** (2015), no. 1, 29–40.

60. Baran, S., Asymptotic properties of an estimator in functional errors-in-variables models. *Theory Probab. Appl.* **45** (2001), no. 4, 701–703. (IF: 0.110; SJR: Q4/Q4)

61. Baran, S., A consistent estimator in general functional errors-in-variables models. *Metrika* **51** (2000), no. 2, 117–132. (IF: 0.212; SJR: Q4/Q4)

    1. Kukush, A., Zwanzig, S. On consistent estimators in nonlinear functional errors-in-variables models. In *Total Least Squares and Errors-in-Variables Modeling: Analysis, Algorithms and Applications* (edited by S. Van Huffel and P. Lemmerling), Kluwer Acad. Publ., Dordrecht, 2002, 145–154.
    2. Cheng, C-L., Schneeweiss, H., On the polynomial measurement error model. In *Total Least Squares and Errors-in-Variables Modeling: Analysis, Algorithms and Applications* (edited by S. Van Huffel and P. Lemmerling), Kluwer Acad. Publ., Dordrecht, 2002, 131–143.
    3. Kukush, A., Markovsky, I., Huffel, S. V., Consistent estimation in the bilinear multivariate errors-in-variables model. *Metrika* **57** (2003), no. 3, 253–285.

4. Balsamo, A., Mana, G., Pennecchi, F., On the best fit of a line to uncertain observation pairs. *Metrologia* **42** (2005), no. 5, 376–382.
5. Jun, B. E., Bernstein, D. S., Extended least-correlation estimates for errors-in-variables non-linear models. *Internat. J. Control* **82** (2007), no. 2, 256–267.
6. Taupin, M. L., *Déconvolution et Estimation dans les modèles avec erreurs sur les variables.* Habilitation thesis, Paris Descartes University, 2008.
7. Butucea, C., Taupin, M. L., New M-estimators in semi-parametric regression with errors in variables. *Ann. Inst. H. Poincaré Probab. Statist.* **44** (2008), no. 3, 393–421.
8. Piga, D., Tóth, R., A bias-corrected estimator for nonlinear systems with output-error type model structures. *Automatica* **50** (2014), no. 9, 2373–2380.

62. Fazekas, I., Baran, S., Lauridsen, J., Asymptotic properties of an estimator in errors-in-variables models in the presence of validation data. *Comput. Math. Appl.* **38** (1999), no. 5-6, 31–39. (IF: 0.314; SJR: Q2/Q3/Q2)

63. Arató, M., Baran, S., Ispány, M., Functionals of complex Ornstein-Uhlenbeck processes. *Comput. Math. Appl.* **37** (1999), no. 1, 1–13. (IF: 0.314; SJR: Q2/Q3/Q2)

1. Tsurkis, I. Ya., Spiridonov, E. A., On the applicability of the mathematical apparatus of Markovian processes to the description of the Chandler wobble. *Izvestiya Physics of the Solid Earth* **44** (2009), no. 4, 273–286.
2. Tsurkis, I. Ya., Spiridonov, E. A., Variations in the amplitude of the chandler wobble. *Izvestiya Physics of the Solid Earth* **45** (2009), no. 12, 1072–1080.
3. Tsurkis, I. Ya., Spiridonov, E. A., Kuchay, M. S., On the pole motion stochastic model in connection with the Chandler anomaly of the beginning of the XXth century. *Geophysical Research* **11** (2010), no. 4., 69–78.
4. Fernandez-Alcala, R. M., Navarro-Moreno, J., Ruiz-Molina, J. C., Prediction on widely factorizable signals. *EURASIP J. Adv. Sig. Pr.* (2012), 2012:96.
5. Navarro-Moreno, J., Fernandez-Alcala, R. M., Ruiz-Molina, J. C., A quaternion widely linear model for nonlinear Gaussian estimation *IEEE Trans. Signal Process.* **62** (2014), no. 24, 6414–6424.
6. Prior, A. F., *Estimação de parâmetros em modelos estocásticos de estruturas com comportamento dinâmico linear e quasi linear.* PhD thesis, University of Porto, 2015.
7. Otten, D., Exponentially weighted resolvent estimates for complex Ornstein-Uhlenbeck systems. *J. Evol. Eq.* **15** (2015), no. 4, 753–799.
8. Guillaumin, A. P., Sykulski, A. M., Olhede, S. C., Early, J. J., Lilly, J. M., Analysis of non-stationary modulated time series with applications to oceanographic surface flow measurements. *J. Time Ser. Anal.* **38** (2017), 668–710.

9. Lilly, J. M., Sykulski, A. M., Early, J. J., Olhede, S. C., Fractional Brownian motion, the Matérn process, and stochastic modeling of turbulent dispersion. *Nonlin. Processes Geophys.* **24** (2017), 481–514.
10. Freitas, M. M., *Monitorização de vibrações em estruturas: métodos de identificação modal no domínio do tempo.* Master Thesis, Instituto Superior de Engenharia de Lisboa, 2017.
11. Chen, Y., One dimensional complex Ornstein-Uhlenbeck operator. *Communications on Stochastic Analysis* **11** (2017), 357–372.
12. Guillaumin, A. P., *Quasi-likelihood inference for modulated non-stationary time series.* PhD thesis, University College London, 2018.
13. Trevizan, R. D., Ruben, C., Rossoni, A., Dhulipala, S. C., Bretas, A., Bretas, N. G., μPMU-based temporal decoupling of parameter and measurement gross error processing in DSSE. *Electricity* **2** (2021), 423–438.
14. Alliluev, A. D., Makarov, D. V., Dynamics of a nonlinear quantum oscillator under non-Markovian pumping. *J. Russ. Laser. Res.* **43** (2022), 71–81.

64. Fazekas, I., Baran, S., Kukush, A., Lauridsen, J., Asymptotic properties in space and time of an estimator in non-linear functional errors-in-variables models. *Random Oper. Stochastic Equations* **7** (1999), no. 4, 389–412. (SJR: Q4/Q3)

    1. Cheng, C-L., Schneeweiss, H., On the polynomial measurement error model. In *Total Least Squares and Errors-in-Variables Modeling: Analysis, Algorithms and Applications* (edited by S. Van Huffel and P. Lemmerling), Kluwer Acad. Publ., Dordrecht, 2002, 131–143.
    2. Gabrosek, J., Cressie, N., The effect of attribute prediction of location uncertainty in spatial data. *Geogr. Anal.* **34** (2002), no. 3, 262–285.
    3. Cressie, N., Kornak, J., Spatial statistics in the presence of location error with an application to remote sensing of the environment. *Statist. Sci.* **18** (2003), no. 4, 436–456.
    4. Taupin, M. L., *Déconvolution et Estimation dans les modèles avec erreurs sur les variables.* Habilitation thesis, Paris Descartes University, 2008.
    5. Butucea, C., Taupin, M. L., New M-estimators in semi-parametric regression with errors in variables. *Ann. Inst. H. Poincaré Probab. Statist.* **44** (2008), no. 3, 393–421.

65. Kozma, L., Baran, S., On metrical homogeneous connections of a Finsler point space. *Publ. Math. Debrecen* **49** (1996), no. 1-2, 59–68. (IF: 0.099)

    1. Tamássy, L., Area and metrical connections in Finsler spaces. In *Finsler Geometries* (edited by P. L. Antonelli), Kluwer Acad. Publ., 2000, 263–280.

2. Tamássy, L., Point Finsler spaces with metrical linear connections. *Publ. Math. Debrecen* **56** (2000), no. 3-4, 643–655.

3. Tamássy, L., Finsler spaces of Riemann-Minkowsky type. In *Finsler and Lagrange Geometries* (edited by M. Anastatiei and P. L. Antonelli), Kluwer Acad. Publ., 2003, 225–232.

4. Tamássy, L., Geometry of the point Finsler spaces. In *Non-Euclidean Geometries* (edited by A. Prékopa, E. Molnár), Springer, 2006, 445–461.

5. Park, H-S., Park, H-Y., Kim, B-D., On a Finsler space with (α, β)-metric and certain metrical non-linear connection. *Commun. Korean Math. Soc.* **21** (2006), no. 1, 177–183.

6. Tamássy, L., Finsler spaces with polynomial metric. In *Space-Time Structure. Algebra and Geometry* (edited by D. G. Pavlov, Gh. Atanasiu, V. Balan), Lilia-Print, Moscow, 2007, 311–319.

B) Konferencia-kiadvány

1. Baran, S., Veress, L., Estimating the risk of a Down's syndrome term pregnancy using age and serum markers. Csőke et al. (ed.) *Proceedings of the 6^{th} International Conference on Applied Informatics*, Eger, Hungary, January 27–31, 2004, Eszterházi Károly Főiskola, Eger, 2005, 75–84.

2. Baran, S., Pap, G., Zuijlen, M. v., Estimation of the mean of Ornstein-Uhlenbeck processes and sheets. Kovács, E., Winkler, Z. (ed.) *Proceedings of the 4^{th} International Conference on Applied Informatics*, Eger–Noszvaj, Hungary, August 30–September 3, 1999. Molnár és társa, Eger, 2001, 337–344.

3. Baran, Á., Baran, S., On the weak convergence of a continuous state space simulated annealing. Kovács, E., Winkler, Z (ed.) *Proceedings of the 4^{th} International Conference on Applied Informatics*, Eger–Noszvaj, Hungary, August 30–September 3, 1999. Molnár és társa, Eger, 2001, 231–240.

4. Fazekas, I., Lauridsen, J., Baran, S., Asymptotic properties of an estimator in spatial errors-in-variables models in the presence of validation data. Kovács, E. et al. (ed.) *Proceedings of the 3^{rd} International Conference on Applied Informatics*, Eger–Noszvaj, Hungary, August 25–28, 1997. Nyomda Kft., Eger, 1999, 59-68.

5. Baran, S., Szabó, Á., An application of simulated annealing to ML-estimation of a partially observed Markov chain. Kovács, E. et al. (ed.) *Proceedings of the 3^{rd} International Conference on Applied Informatics*, Eger–Noszvaj, Hungary, August 25–28, 1997. Nyomda Kft., Eger, 1999, 85–95.

1. Verdes, E., *The π^* index: computation, characterization and application of a new goodness of fit measure.* Ph.D. thesis, University of Debrecen, 2001.
2. Goldstein, P., Karaga, M., Kosor, M., Nizetić, I., Tadić, M., Vlah, D., Hidden Markov models and multiple alignments of protein sequences. In Drmać, Z. et al. (eds.), *Proceedings of the Conference on Applied Mathematics and Scientific Computing*, Springer, Dordrecht, 2005, pp. 187–196.

6. Baran, S., Estimating the transition matrix of a finite state space Markov chain with MATLAB. *Proc. of the Workshop on Statistics at Universities: Its Impact for Society*, Eötvös University Press, Budapest, 1997, 29–34.

C) Egyetemi jegyzet

1. Baran, S., *Feladatok a hipotézisvizsgálat témaköréből.* mobiDIÁK Könyvtár, Debreceni Egyetem, 2005. http://mobidiak.inf.unideb.hu.

2. Baran S., Fazekas I., Gelvitzky B., Iglói E., Ispány M., Kalmár I., Nagy M., Tar L., Verdes E., *Bevezetés a matematikai statisztikába.* Kossuth Egyetemi Kiadó, Debrecen, 1997, 523 oldal. (X. fejezet, 345–380 oldalak.)

    1. Óvári, M., Záray, Gy., Danzer, K. and Thiel, G., Investigation of distribution of beryllium, nickel and vanadium in subsoil of Csepel-Island. *Microchemical J.* **67** (2000), 249–256.

D) Szoftver

1. Yuen, R. A., Baran, S., Fraley, C., Gneiting, T., Lerch, S., Scheuerer, M., Thorarinsdottir, T. L., *R package ensembleMOS, Version 0.8.2: Ensemble Model Output Statistics* (2018). Available at: `https://cran.r-project.org/package=ensembleMOS`

    1. Barnes, C., Chandler, R. E., Brierley, C. M., New approaches to postprocessing of multi-model ensemble forecasts. *Q. J. R. Meteorol. Soc.* **145** (2019), 3479–3498.
    2. Le Gal La Salle, J., Badosa, J., David, M., Pinson, P., Lauret, P., Added-value of ensemble prediction system on the quality of solar irradiance probabilistic forecasts. *Renew. Energy* **162** (2020), 1321–1339.
    3. Wang, D., Wang, P., Wang, C., Zhuang, S., Shi, J., A conformal prediction inspired approach for distribution regression with random Fourier features. *Appl. Soft Comput.* **97** (2020), paper 106807, doi:10.1016/j.asoc.2020.106807.
    4. Medina, H., Tian, D., Comparison of probabilistic post-processing approaches for improving numerical weather prediction-based daily and weekly reference evapotranspiration forecasts. *Hydrol. Earth Syst. Sci.*, **24** (2020), 1011–1030.

5. Javanshiri, Z., Fathi, M., Mohammadi, S. A., Comparison of the BMA and EMOS statistical methods for probabilistic quantitative precipitation forecasting. *Meteorol. Appl.* **28** (2021), paper e1974, doi:10.1002/met.1974.
6. Le Gal La Salle, J., *Qualité et valeur des prévisions solaires probabilistes.* PhD thesis, Université de La Réunion, 2021.
7. World Meteorological Organization, *Guidelines on Ensemble Prediction System Post-processing.* WMO-No. 1254, WMO, Switzerland, 2021.
8. Yang, D., Yang, G., Liu, B., Combining quantiles of calibrated solar forecasts from ensemble numerical weather prediction. *Renew. Energy* **215** (2023), paper 118993, doi:10.1016/j.renene.2023.118993.
9. Yang, D., Kong, Y., Liu, B., Wang, J., Sun, D., Yang, G., Wang, W., Comparing calibrated analog and dynamical ensemble solar forecasts. *Solar Energy Advances* **4** (2024), paper 100048, doi:10.1016/j.seja.2023.100048.

E) Előadás nemzetközi konferencián

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 (meghívott).
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, meghívott).
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 (meghívott).
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, meghívott plenáris).

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 (meghívott plenáris).

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

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 (meghívott).

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

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.

14. *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.

15. *Statistical post-processing of ensemble forecasts for precipitation accumulation.* TIES-GRASPA 2017, Bergamo, Italy, July 24–26, 2017 (meghívott).

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 (meghívott).

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 (meghívott plenáris).

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 (meghívott plenáris).

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 (meghívott).

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 (meghívott).

33. *Parameter estimation in a spatial unit root autoregressive model.* 10^{th} International Vilnius Conference on Probability Theory and Mathematical Statistics, Vilnius, Lithuania, June 28–July 2, 2010.

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 (poszter).

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 (poszter).

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 (meghívott).

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 (meghívott).

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 (meghívott).