

Literatuur

1. Albers, J. R., & Newman, M. (2019). A Priori Identification of Skillful Extratropical Subseasonal Forecasts. *Geophysical Research Letters*, *46*(21), 12527–12536. <https://doi.org/10.1029/2019GL085270>
2. Albers, J. R., & Newman, M. (2021). Subseasonal predictability of the North Atlantic Oscillation. *Environmental Research Letters*, *16*(4). <https://doi.org/10.1088/1748-9326/abe781>
3. Baker, L. H., Shaffrey, L. C., Johnson, S. J., & Weisheimer, A. (2024). Understanding the Intermittency of the Wintertime North Atlantic Oscillation and East Atlantic Pattern Seasonal Forecast Skill in the Copernicus C3S Multi-Model Ensemble. *Geophysical Research Letters*, *51*(15). <https://doi.org/10.1029/2024GL108472>
4. Barnes, E. A., & Hartmann, D. L. (2010). Dynamical Feedbacks and the Persistence of the NAO. *Journal of the Atmospheric Sciences*, *67*(3), 851–865. <https://doi.org/10.1175/2009JAS3193.1>
5. Barnes, McCullen, N., & Kjeldsen, T. R. (2023). Forecasting seasonal to sub-seasonal rainfall in Great Britain using convolutional-neural networks. *Theoretical and Applied Climatology*, *151*(1–2), 421–432. <https://doi.org/10.1007/s00704-022-04242-x>
6. Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. In *Nature* (Vol. 525, Issue 7567, pp. 47–55). Nature Publishing Group. <https://doi.org/10.1038/nature14956>
7. Bloomfield, H. C., Brayshaw, D. J., Gonzalez, P. L. M., & Charlton-Perez, A. (2021). Pattern-based conditioning enhances sub-seasonal prediction skill of European national energy variables. *Meteorological Applications*, *28*(4), 1–16. <https://doi.org/10.1002/met.2018>
8. Bodnar, C., Bruinsma, W. P., Lucic, A., Stanley, M., Brandstetter, J., Garvan, P., Riechert, M., Weyn, J., Dong, H., Vaughan, A., Gupta, J. K., Tambiratnam, K., Archibald, A., Heider, E., Welling, M., Turner, R. E., & Perdikaris, P. (2024). *Aurora: A Foundation Model of the Atmosphere*. <http://arxiv.org/abs/2405.13063>
9. Bonev, B., Kurth, T., Hundt, C., Pathak, J., Baust, M., Kashinath, K., & Anandkumar, A. (2023). *Spherical Fourier Neural Operators: Learning Stable Dynamics on the Sphere*. <http://arxiv.org/abs/2306.03838>
10. Cai, M., Yu, Y., Deng, Y., Van Den Dool, H. M., Ren, R., Saha, S., Wu, X., & Huang, J. (2016). Feeling the pulse of the stratosphere an emerging opportunity for predicting continental-scale cold-air outbreaks 1 month in advance. *Bulletin of the American Meteorological Society*, *97*(8), 1475–1489. <https://doi.org/10.1175/BAMS-D-14-00287.1>
11. Chen, K., Bai, L., Ling, F., Ye, P., Chen, T., Luo, J.-J., Chen, H., Xiao, Y., Chen, K., Han, T., & Ouyang, W. (2023). *Towards an end-to-end artificial intelligence driven global weather forecasting system*. <http://arxiv.org/abs/2312.12462>
12. Chen, L., Zhong, X., Li, H., Wu, J., Lu, B., Chen, D., Xie, S.-P., Wu, L., Chao, Q., Lin, C., Hu, Z., & Qi, Y. (2024). A machine learning model that outperforms conventional global subseasonal forecast models. *Nature Communications*, *15*(1), 6425. <https://doi.org/10.1038/s41467-024-50714-1>

13. Dawson, A., & Palmer, T. N. (2015). Simulating weather regimes: impact of model resolution and stochastic parameterization. *Climate Dynamics*, 44(7–8), 2177–2193. <https://doi.org/10.1007/s00382-014-2238-x>
14. de Andrade, F. M., Young, M. P., MacLeod, D., Hiron, L. C., Woolnough, S. J., & Black, E. (2021). Subseasonal Precipitation Prediction for Africa: Forecast Evaluation and Sources of Predictability. *Weather and Forecasting*, 36(1), 265–284. <https://doi.org/10.1175/WAF-D-20-0054.1>
15. Feng, P. N., Lin, H., Derome, J., & Merlis, T. M. (2021). Forecast skill of the NAO in the subseasonal-to-seasonal prediction models. *Journal of Climate*, 34(12), 4757–4769. <https://doi.org/10.1175/JCLI-D-20-0430.1>
16. Ferranti, L., Magnusson, L., Vitart, F., & Richardson, D. S. (2018). How far in advance can we predict changes in large-scale flow leading to severe cold conditions over Europe? *Quarterly Journal of the Royal Meteorological Society*, 144(715), 1788–1802. <https://doi.org/10.1002/qj.3341>
17. Hausfather, Z., Drake, H. F., Abbott, T., & Schmidt, G. A. (2020). Evaluating the Performance of Past Climate Model Projections. *Geophysical Research Letters*, 47(1). <https://doi.org/10.1029/2019GL085378>
18. Horat, N., & Lerch, S. (2024). Deep Learning for Postprocessing Global Probabilistic Forecasts on Subseasonal Time Scales. *Monthly Weather Review*, 152(3), 667–687. <https://doi.org/10.1175/MWR-D-23-0150.1>
19. Kochkov, D., Yuval, J., Langmore, I., Norgaard, P., Smith, J., Mooers, G., Klöwer, M., Lottes, J., Rasp, S., Düben, P., Hatfield, S., Battaglia, P., Sanchez-Gonzalez, A., Willson, M., Brenner, M. P., & Hoyer, S. (2024). Neural general circulation models for weather and climate. *Nature*. <https://doi.org/10.1038/s41586-024-07744-y>
20. Lee, R. W., Woolnough, S. J., Charlton-Perez, A. J., & Vitart, F. (2019). ENSO Modulation of MJO Teleconnections to the North Atlantic and Europe. *Geophysical Research Letters*, 46(22), 13535–13545. <https://doi.org/10.1029/2019GL084683>
21. Lemburg, A., & Fink, A. H. (2024). Investigating the medium-range predictability of European heatwave onsets in relation to weather regimes using ensemble reforecasts. *Quarterly Journal of the Royal Meteorological Society*. <https://doi.org/10.1002/qj.4801>
22. Lorenz, E. N. (1969). The predictability of a flow which possesses many scales of motion. *Tellus*, 21(3), 289–307. <https://doi.org/10.3402/tellusa.v21i3.10086>
23. Mariotti, A., Baggett, C., Barnes, E. A., Becker, E., Butler, A., Collins, D. C., Dirmeyer, P. A., Ferranti, L., Johnson, N. C., Jones, J., Kirtman, B. P., Lang, A. L., Molod, A., Newman, M., Robertson, A. W., Schubert, S., Waliser, D. E., & Albers, J. (2020). Windows of Opportunity for Skillful Forecasts Subseasonal to Seasonal and Beyond. *Bulletin of the American Meteorological Society*, January 2020, 608–625. <https://doi.org/10.1175/bams-d-18-0326.1>
24. Mastrantonas, N., Furnari, L., Magnusson, L., Senatore, A., Mendicino, G., Pappenberger, F., & Matschullat, J. (2022). Forecasting extreme precipitation in the central Mediterranean: Changes in predictors' strength with prediction lead time. *Meteorological Applications*, 29(6). <https://doi.org/10.1002/met.2101>
25. Mouatadid, S., Orenstein, P., Flaspohler, G., Cohen, J., Oprescu, M., Fraenkel, E., & Mackey, L. (2023). Adaptive bias correction for improved subseasonal forecasting. *Nature Communications*, 14(1). <https://doi.org/10.1038/s41467-023-38874-y>

26. Nguyen, T., Brandstetter, J., Kapoor, A., Gupta, J. K., & Grover, A. (2023). *ClimaX: A foundation model for weather and climate*. <http://arxiv.org/abs/2301.10343>
27. Osman, M., Beerli, R., Büeler, D., & Grams, C. M. (2023). Multi-model assessment of sub-seasonal predictive skill for year-round Atlantic–European weather regimes. *Quarterly Journal of the Royal Meteorological Society*, 149(755), 2386–2408. <https://doi.org/10.1002/qj.4512>
28. Polkova, I., King, M., Ruggieri, P., Athanasiadis, P., Kretschmer, M., & Baehr, J. (2020). *Autumn Arctic predictors for winter marine cold air outbreaks over the Barents Sea*. 727852.
29. Rouges, E., Kretschmer, M., & Shepherd, T. G. (2024). *On the link between weather regimes and energy shortfall during winter for 28 European countries*. <https://doi.org/https://doi.org/10.31223/X5DM70>
30. Ruggieri, P., Benassi, M., Materia, S., Peano, D., Ardilouze, C., Batté, L., & Gualdi, S. (2022). On the role of Eurasian autumn snow cover in dynamical seasonal predictions. *Climate Dynamics*, 58(7–8), 2031–2045. <https://doi.org/10.1007/s00382-021-06016-z>
31. Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., & Teuling, A. J. (2010). Earth-Science Reviews Investigating soil moisture – climate interactions in a changing climate: A review. *Earth Science Reviews*, 99(3–4), 125–161. <https://doi.org/10.1016/j.earscirev.2010.02.004>
32. Smith, D. M., Eade, R., Scaife, A. A., Caron, L. P., Danabasoglu, G., DelSole, T. M., Delworth, T., Doblas-Reyes, F. J., Dunstone, N. J., Hermanson, L., Kharin, V., Kimoto, M., Merryfield, W. J., Mochizuki, T., Müller, W. A., Pohlmann, H., Yeager, S., & Yang, X. (2019). Robust skill of decadal climate predictions. *Npj Climate and Atmospheric Science*, 2(1). <https://doi.org/10.1038/s41612-019-0071-y>
33. Sun, X., Zhong, X., Xu, X., Huang, Y., Li, H., Feng, J., Han, W., Wu, L., & Qi, Y. (2024). *FuXi Weather: An end-to-end machine learning weather data assimilation and forecasting system*. <http://arxiv.org/abs/2408.05472>
34. Van Straaten, C., Whan, K., Coumou, D., van den Hurk, B., & Schmeits, M. (2023). Correcting Subseasonal Forecast Errors with an Explainable ANN to Understand Misrepresented Sources of Predictability of European Summer Temperatures. *Artificial Intelligence for the Earth Systems*, 2(3). <https://doi.org/10.1175/aies-d-22-0047.1>
35. Vaughan, A., Markou, S., Tebbutt, W., Requeima, J., Bruinsma, W. P., Andersson, T. R., Herzog, M., Lane, N. D., Chantry, M., Hosking, J. S., & Turner, R. E. (2024). *Aardvark weather: end-to-end data-driven weather forecasting*. <http://arxiv.org/abs/2404.00411>
36. Vijverberg, S., & Coumou, D. (2022). The role of the Pacific Decadal Oscillation and ocean-atmosphere interactions in driving US temperature predictability. *Npj Climate and Atmospheric Science*, 5(1), 18. <https://doi.org/10.1038/s41612-022-00237-7>
37. Vijverberg, S., Hamed, R., & Coumou, D. (2022). Skillful U.S. Soy Yield Forecasts at Presowing Lead Times. *Artificial Intelligence for the Earth Systems*, 2(3). <https://doi.org/10.1175/aies-d-21-0009.1>
38. WeatherBench2. (n.d.). *WeatherBench2*. Retrieved August 9, 2024, from <https://sites.research.google/weatherbench/>
39. Weyn, J. A., Durran, D. R., Caruana, R., & Cresswell-Clay, N. (2021). Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *Journal of Advances in Modeling Earth Systems*, 13(7). <https://doi.org/10.1029/2021MS002502>

40. Weyn, J. A., Kumar, D., Berman, J., Kazmi, N., Klocek, S., Lufarenko, P., & Thambiratnam, K. (2024). *An ensemble of data-driven weather prediction models for operational sub-seasonal forecasting*. <http://arxiv.org/abs/2403.15598>
41. Zhang, L., Wang, C., Han, W., Mcphaden, M. J., Hu, A., & Xing, W. (2023). *Emergence of the Central Atlantic Niño*. <https://www.science.org>