References:

GAN:

Miralles, O., D. Steinfeld, O. Martius, and A. C. Davison, 2022: Downscaling of historical wind fields over Switzerland using generative adversarial networks. *Artif. Intell. Earth Syst.*, **1**, e220018, https://doi.org/10.1175/AIES-D-22-0018.1.

Annau, N. J, Cannon, A. J., Monahan, A. H, 2023: Algorithmic hallucinations of near-surface winds: Statistical downscaling with generative adversarial networks to convection-permitting scales. *Artif. Intell. Earth Syst.*, **2,** e230015, https://doi.org/10.1175/AIES-D-23-0015.1

Watson, C. D., Wang, C., Lynar, T., & Weldemariam, K., 2020: Investigating two super-resolution methods for downscaling precipitation: ESRGAN and CAR. *34th Conference on Neural Information Processing Systems (NeurIPS 2020), Vancouver, Canada.* Retrieved from https://arxiv.org/abs/2012.01233.

Harris, L., McRae, A. T. T., Chantry, M., Dueben, P. D., Palmer, T. N., 2022: A generative deep learning approach to stochastic downscaling of precipitation forecasts. *J. Adv. Model. Earth Syst.,* **14,** e2022MS003120. https://doi.org/10.1029/2022MS003120

Oyama, N., Ishizaki, N.N., Koide, S., 2023: Deep generative model super-resolves spatially correlated multiregional climate data. *Sci. Rep.,* **13**, 5992. https://doi.org/10.1038/s41598-023-32947-0

RC:

Tanaka, G., Yamane, T., Héroux, J. B., Nakane, R., Kanazawa, N., Takeda, S., Numata, H., Nakano, D., Hirose, A., 2019: Recent advances in physical reservoir computing: A review. *Neural Networks*, **115,** 100-123. https://doi.org/10.1016/j.neunet.2019.03.005

Gauthier, D. J., Bollt, E., Griffit, A., Wendson A. S., Barbosa, W. A. S., 2021: Next generation reservoir computing. *Nature Communications*, **12,** 5564. https://doi.org/10.1038/s41467-021-25801-2

ML Model Surrogates:

Rasp, S., Dueben, P. D., Scher, S., Weyn, J. A., Mouatadid, S., Thuerey, N., 2020: WeatherBench: A benchmark data set for data-driven weather forecasting. *J. Adv. Model. Earth Syst.*, 12, e2020MS002203. https://doi.org/10.1029/2020MS002203

Weyn, J. A., Durran, D. R., Caruana, R., 2019: Can machines learn to predict weather? Using deep learning to predict gridded 500-hPa geopotential height from historical weather data. *J. Adv. Model. Earth Syst.*, **11,** 2680–2693. https://doi.org/10.1029/2019MS001705

Weyn, J. A., Durran, D. R., Caruana, R., 2020: Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. *J. Adv. Model. Earth Syst.*, **12,** e2020MS002109. https://doi.org/10.1029/2020MS002109

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. *J. Adv. Model. Earth Syst.*, **13,** e2021MS002502. https://doi.org/10.1029/2021MS002502

Pathak, J., and co-authors, 2022: FourCastNet: A global data-driven high-resolution weather model using adaptive Fourier neural operators. *ArXiv, abs/2202.11214.* https://doi.org/10.48550/arXiv.2202.11214

Bi, K., L. Xie, H. Zhang, X. Chen, X. Gu, Q. Tian, Pangu-Weather: A 3D high-resolution model for fast and accurate global weather forecast. *arXiv:2211.02556 [physics.ao-ph],* https://doi.org/10.48550/arXiv.2211.0255

Lam, R., and co-authors, 2023: GraphCast: Learning skillful medium-range global weather forecasting. *arXiv:2212.12794 [cs.LG],* https://doi.org/10.48550/arXiv.2212.12794

Oskarsson, J., Landelius, T., Linsten, F., 2023: Graph-based neural weather prediction limited area modeling. *arXiv:2309.17370v2 [cs.LG] 14 Nov 2023,* https://arxiv.org/abs/2309.17370