Science-integrated Artificial-intelligence for Flooding and precipitation Extremes (SAFE)

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FOCAL AREA(s)

- **Primary: 3** ("Insights gleaned from complex data … physics- or knowledge-guided AI")
- **Secondary: 2** ("Predictive modeling through the use of AI … hierarchy of models")

This white paper focuses on methods that blend AI and science (e.g., physics, biogeochemistry) by (a) guiding AI cost functions, trajectories and representations with science knowledge and/or with context-specific data-driven insights in a Bayesian-inspired framework; (b) framing AI models in the context of physics-informed dynamic, causal networks; (c) merging AI-enhanced science models with science-guided explainable AI; (d) focusing on statistics/processes related to extremes and translations to risks in a changing world; & (e) identifying model parameterizations or components that must be improved to minimize risks and add maximum value to stakeholders.

SCIENCE CHALLENGE

A grand challenge [1-10] in hydrologic science is to understand why signals of climate change and variability, which are often visible in precipitation extremes at aggregate scales, are not consistently observed in the case of extreme flooding. However, a solution to this challenge may prove elusive unless the water cycle is viewed in an integrative manner. Thus, for riverine flooding, while Hortonian (infiltration excess) runoff may have stronger correlation with precipitation extremes and hence perhaps to warming trends or climate oscillators, Dunne (saturation excess) runoff may have a more complex relationships with time series of precipitation and with evaporation and transpiration, but rain-on-snow and snowmelt events may depend on land-surface and atmospheric temperatures. Atmospheric rivers [11] and tropical cyclones [12] lead to precipitation or flooding and are impacted by climate. Flooding assessments need to consider long-term baselines [13], evolving risk factors [14], coupled natural-human systems [15-16], and novel adaptation such as nature-inspired design [17-18].

RATIONALE

The urgency of stakeholder needs pertaining to precipitation and flooding extremes requires transformative advances in long-standing challenges within earth systems sciences. Challenges for which emerging AI solutions have started to make a difference include (a) cloud physics and subgrid processes [19-24]; (b) spatiotemporal patterns and dependencies [25-29; 44]; (c) climate oscillations and teleconnections with regional hydrology [30-35]; (d) pattern search across multiple ensembles [35-36]; and (e) statistical downscaling [37-40; 45]. The AI solutions cited have ranged from machine learning (including Deep Learning), network-based approaches, and

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spatiotemporal data mining with machine learning. The successful AI solutions [41-42] have mostly evolved along two categories: first, where process knowledge guides and informs AI methods to various degrees for analyzing observed and model-simulated data; and second, where AI gets embedded in computational models as data-driven equivalents of 'parameterizations'.

However, to be able to make a breakthrough in hydrologic (precipitation and flooding) extremes, three major barriers (among others) need to be overcome:

(1) Hydrologic and hydroclimate processes operate in highly heterogeneous environments, the properties of which are imprecisely known, causing scale-dependence of parameterizations; but as better/more data emerges, fine-tuning AI to address these challenges may be feasible.
(2) Physics-based computer models of precipitation and flooding extremes rely too heavily on calibration parameters that do not generalize well under extrapolation; the ability of AI to address this challenge by considering a wider set of data and relations needs to be explored.
(3) Predictability in hydrology or hydroclimate is limited by a combination of long-standing gaps in process knowledge, human management, and internal variability; this limitation is further compounded by changes in risk elements such as vulnerability and exposure. Methodological and diagnostic understanding of spatiotemporal extremes generation processes, along with better appreciation of stakeholder risks, may suggest avenues for targeted improvements.

Our proposed "Focal Area(s)" described on the previous page, especially the three principled approaches indicated therein, are designed to directly target the three barriers discussed above.

NARRATIVE

A suite of science/knowledge integrated artificial intelligence (AI) methods may be needed to advance predictive understanding of precipitation and flooding extremes over 2 to 30-year projection horizons at stakeholder-relevant spatiotemporal resolutions. These methods may advance climate science and earth system modeling, develop credible projections, and lead to fundamental insights, and enable risk-informed decisions with a focus on precipitation and flooding extremes in the near term. Our overarching hypothesis is that intelligent blends of AI and physics can improve predictive understanding of crucial – yet long-standing – challenges.

Our team members are among the pioneers [62-80] in developing integrated science–AI models for earth systems: we will build upon our foundational work to inform workshops and plans for DOE that will inspire the development of a suite of solutions in *physics-guided AI (PGAI), AI-enhanced physics (AIEP), including generative models, causal and interpretable AI, as well as uncertainty or risk assessments*. Here we define 'physics' broadly to include biogeochemistry and process knowledge. We group the proposed advances under an umbrella phrase: **Structure-Agnostic Process Models** (SAPM). Rather than making a priori assumptions about the structural forms of the (parameterized) physics-based or AI-based models, SAPM will let the (ensemble of) structures (whether AIEP or PGAI) to evolve in a data-driven and physically (or scientifically) consistent manner. SAPM can therefore be thought of as a more general class of solutions that encapsulates both AIEP and PGAI, as well as their hybrid blends. One challenge in earth systems models (both physics and AI) is generalizability under changing conditions. Spatiotemporal analogues [37; 46-49] for model development and evaluation can be explored. Interpretability is crucial, a balance with accuracy may be possible by exploring manifolds of physically plausible hypotheses spaces. A combination of implicit and physics-guided explicit regularization will further advance generalizability. Evaluation will entail embedding process models within Earth System Models (ESMs) of differing complexity, as well as via spatiotemporal analogues (which will be extracted by mining historical space-time data that probabilistically resemble plausible future climate) to infer generalizability under ('non-stationary') change [43].

Uncertainty assessments (UA), including intrinsic variability and knowledge gaps [50-52], may rely on large-ensemble runs, what-ifs, and AI-based emulations of processes embedded in the latest-generation of ESMs along with adaptations of recent developments in information theory. We will discuss model-based ensembles (such as ESM large-ensembles) and observation-based ensembles to discuss a falsifiable theory for initial-condition and multi-parameter variability, in a way that balances skills, convergence and the ability to reproduce observed data associations and tail behavior. We will focus on how to bridge the gap between researchers in nonlinear physics and information theory who tend to work with relatively simplified models and computational climate modelers working with the latest ESMs [53-60]. Lessons learned with simplified models, from Lorenz and Held-Suarez to reduced-order ESM, will be adapted to more complex ESMs.

AI-inspired **risk quantification and prediction** methods based on fundamental principles of operational research, data-driven science, and machine learning may characterize and quantify hazards, vulnerability, and exposure [13-18], with observations, model-simulations, and what-if scenarios. Diagnostic and prognostic insights on extremes generation processes in space-time can be combined with assessments of critical stakeholder needs (e.g., for adaptation or mitigation), which in turn may identify targeted model improvement goals while also informing decisions.

A **hypothesis-driven evaluation** strategy needs to rely on experiments to examine causal interpretability and generalizability of the hybrid physics-AI methods under changing climate conditions. We will develop a causal-AI system for methods in parameter estimation, prediction, and uncertainty quantification. We propose a simulation-observation experimental testbed, where structure-agnostic hybrid physics-AI methods will be compared with observations (including those based on spatiotemporal analogues and observation-based ensembles) and examined by embedding within models of disparate complexity, e.g., from reduced order or constrained models to the latest generation of ESMs for multi-parameter and initial condition ensembles.

Organizing Principles for Workshops and a Five to Ten Year Vision

The workshops will characterize the state-of-the-art, develop requirements and specifications for novel methods (e.g., compare with [61]), and generate 5- to 10-year guidelines for future ESMs. We propose workshop organizing principles along 5 mutually supporting areas ***(a)*** understanding processes relevant for ESMs (Years 1-4), ***(b)*** SAPM methods and their evaluation (Years 2-5), ***(c)*** iterative feedback among: ***a–b*** (Years 3-6), ***(d)*** research into integration/evaluation of human system models (Year 1-6), ***(e)*** incorporation of human dynamics into future ESMs (Years 6-10). The timelines will be adjusted as physics-integrated AI and human system models mature.

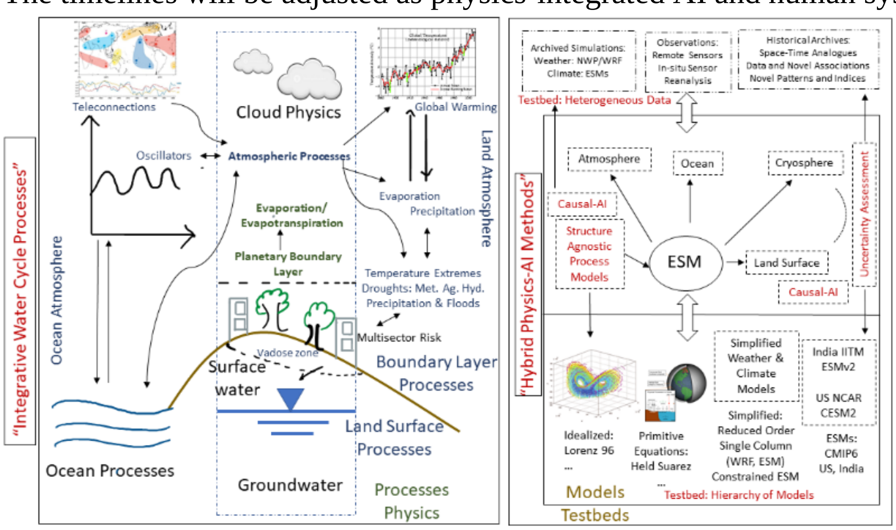

Figure 1: *The integrative water cycle, with core processes relevant for precipitation and flooding extremes, are shown on the left. The SAPM approach, including science-integrated AI and associated evaluation testbeds, risks and uncertainty, and ESM improvements, are on the right. Workshop organizing principles (a)–(c) relate to this figure. Research into human systems (e.g., lifelines, policy) and their integration into ESMs, (d)–(e), are not shown.*

SUGGESTED PARTNERS / EXPERTS

Our 12-member core team is listed under Authors / Affiliations. In addition, we plan to select our invitees from the following other experts and specialists (with many of whom our team members have a long history of collaboration):

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REFERENCES *(Publications by the members of this team in blue)*

1. Sharma, A., Wasko, C. and Lettenmaier, D.P., 2018. If precipitation extremes are increasing, why aren't floods? Water Resources Research, 54(11), 8545-8551.
2. Wasko, C., Sharma, A. and Lettenmaier, D.P., 2019. Increases in temperature do not translate to increased flooding. Nature Communications, 10, 5676.
3. Blöschl, G., Hall, J., Parajka, J., Perdigão, R.A., Merz, B., Arheimer, B., Aronica, G.T., Bilibashi, A., Bonacci, O., Borga, M. and Čanjevac, I., 2017. Changing climate shifts timing of European floods. Science, 357(6351), 588-590.
4. Blöschl, G. et al., 2019. Changing climate both increases and decreases European river floods. Nature, 573(7772), 108-111.
5. Kao, S.C. and Ganguly, A.R., 2011. Intensity, duration, and frequency of precipitation extremes under 21st-century warming scenarios. Journal of Geophysical Research: Atmospheres, 116(D16).
6. Min, S.K., Zhang, X., Zwiers, F.W. and Hegerl, G.C., 2011. Human contribution to more-intense precipitation extremes. Nature, 470(7334), 378-381.
7. Sankarasubramanian, A. and Lall, U., 2003. Flood quantiles in a changing climate: Seasonal forecasts and causal relations. Water Resources Research, 39(5).
8. O'Gorman, P.A. and Schneider, T., 2009. The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. Proceedings of the National Academy of Sciences, 106(35), 14773-14777.
9. Kodra, E., Bhatia, U., Chatterjee, S., Chen, S. and Ganguly, A.R., 2020. Physics-guided probabilistic modeling of extreme precipitation under climate change. Scientific Reports, 10, 10299.
10. Kumar, D. and Ganguly, A.R., 2018. Intercomparison of model response and internal variability across climate model ensembles. Climate dynamics, 51(1), 207-219.
11. Payne, A.E., Demory, M.E., Leung, L.R., Ramos, A.M., Shields, C.A., Rutz, J.J., Siler, N., Villarini, G., Hall, A. and Ralph, F.M., 2020. Responses and impacts of atmospheric rivers to climate change. Nature Reviews Earth & Environment, 1(3), 143-157.
12. Lin, N. and Emanuel, K., 2016. Grey swan tropical cyclones. Nature Climate Change, 6(1), 106-111.
13. Rao, M.P., Cook, E.R., Cook, B.I., D'Arrigo, R.D., Palmer, J.G., Lall, U., Woodhouse, C.A., Buckley, B.M., Uriarte, M., Bishop, D.A. and Jian, J., 2020. Seven centuries of reconstructed Brahmaputra River discharge demonstrate underestimated high discharge and flood hazard frequency. Nature Communications, 11(1).
14. Merz, B., Aerts, J.C.J.H., Arnbjerg-Nielsen, K., Baldi, M., Becker, A., Bichet, A., Blöschl, G., Bouwer, L.M., Brauer, A., Cioffi, F. and Delgado, J.M., 2014. Floods and climate: emerging perspectives for flood risk assessment and management. Natural Hazards and Earth System Sciences, 14(7), 1921-1942.
15. Serre, D. and Heinzlef, C., 2018. Assessing and mapping urban resilience to floods with respect to cascading effects through critical infrastructure networks. International Journal of Disaster Risk Reduction, 30, 235-243.
16. Yadav, N., Chatterjee, S. and Ganguly, A.R., 2020. Resilience of urban transport network-of-networks under intense flood hazards exacerbated by targeted attacks. Scientific Reports, 10, 10350.

17. Sutton-Grier, A.E., Wowk, K. and Bamford, H., 2015. Future of our coasts: The potential for natural and hybrid infrastructure to enhance the resilience of our coastal communities, economies and ecosystems. Environmental Science & Policy, 51, 137-148.
18. Jones, H.P., Hole, D.G. and Zavaleta, E.S., 2012. Harnessing nature to help people adapt to climate change. Nature Climate Change, 2(7), 504-509.
19. Zelinka, M.D., Myers, T.A., McCoy, D.T., Po-Chedley, S., Caldwell, P.M., Ceppi, P., Klein, S.A. and Taylor, K.E., 2020. Causes of higher climate sensitivity in CMIP6 models. Geophysical Research Letters, 47(1), e2019GL085782.
20. Schneider, T., Lan, S., Stuart, A. and Teixeira, J., 2017. Earth system modeling 2.0: A blueprint for models that learn from observations and targeted high-resolution simulations. Geophysical Research Letters, 44(24), 12-396.
21. Yuval, J. and O'Gorman, P.A., 2020. Stable machine-learning parameterization of subgrid processes for climate modeling at a range of resolutions. Nature Communications, 11(1), 3295.
22. Rasp, S., Pritchard, M.S. and Gentine, P., 2018. Deep learning to represent subgrid processes in climate models. Proceedings of the National Academy of Sciences, 115(39), 9684-9689, DOI: 10.1073/pnas.1810286115.
23. Yadav, N., Ravela, S. and Ganguly, A.R., 2020. Machine Learning for Robust Identification of Complex Nonlinear Dynamical Systems: Applications to Earth Systems Modeling. Fragile Earth Workshop, ACM KDD 2020, arXiv preprint arXiv:2008.05590.
24. Gagne II, D.J., Haupt, S.E., Nychka, D.W. and Thompson, G., 2019. Interpretable deep learning for spatial analysis of severe hailstorms. Monthly Weather Review, 147(8), 2827-2845.
25. Das, D., Ganguly, A.R. and Obradovic, Z., 2015. A Bayesian sparse generalized linear model with an application to multiscale covariate discovery for observed rainfall extremes over the United States. IEEE Transactions on Geoscience and Remote Sensing, 53(12), 6689-6702.
26. Chang, W., Stein, M.L., Wang, J., Kotamarthi, V.R. and Moyer, E.J., 2016. Changes in spatiotemporal precipitation patterns in changing climate conditions. Journal of Climate, 29(23), 8355-8376.
27. Steinhaeuser, K., Chawla, N.V. and Ganguly, A.R., 2011. Complex networks as a unified framework for descriptive analysis and predictive modeling in climate science. Statistical Analysis and Data Mining: The ASA Data Science Journal, 4(5), 497-511.
28. Steinhaeuser, K., Ganguly, A.R. and Chawla, N.V., 2012. Multivariate and multiscale dependence in the global climate system revealed through complex networks. Climate Dynamics, 39(3-4), pp.889-895.
29. Chatterjee, S., Steinhaeuser, K., Banerjee, A., Chatterjee, S. and Ganguly, A., 2012, April. Sparse group lasso: Consistency and climate applications. In Proceedings of the 2012 SIAM International Conference on Data Mining (pp. 47-58). Society for Industrial and Applied Mathematics.
30. Ham, Y.G., Kim, J.H. and Luo, J.J., 2019. Deep learning for multi-year ENSO forecasts. Nature, 573(7775), 568-572.
31. Kawale, J., Liess, S., Kumar, A., Steinbach, M., Snyder, P., Kumar, V., Ganguly, A.R., Samatova, N.F. and Semazzi, F., 2013. A graph-based approach to find teleconnections in

climate data. Statistical Analysis and Data Mining: The ASA Data Science Journal, 6(3), 158-179.

32. Liess, S., Kumar, A., Snyder, P.K., Kawale, J., Steinhaeuser, K., Semazzi, F.H., Ganguly, A.R., Samatova, N.F. and Kumar, V., 2014. Different modes of variability over the Tasman Sea: Implications for regional climate. Journal of Climate, 27(22), 8466-8486.
33. Agrawal, S., Steinbach, M., Boley, D., Chatterjee, S., Atluri, G., Dang, A.T., Liess, S. and Kumar, V., 2019. Mining novel multivariate relationships in time series data using correlation networks. IEEE Transactions on Knowledge and Data Engineering, 32(9), 1798-1811.
34. Lu, M., Lall, U., Kawale, J., Liess, S. and Kumar, V., 2016. Exploring the predictability of 30-day extreme precipitation occurrence using a global SST–SLP correlation network. Journal of Climate, 29(3), pp.1013-1029.
35. Kim, S., Kim, H., Lee, J., Yoon, S., Kahou, S.E., Kashinath, K. and Prabhat, M., 2019, January. Deep-hurricane-tracker: Tracking and forecasting extreme climate events. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1761-1769). IEEE.
36. Racah, Evan, Christopher Beckham, Tegan Maharaj, Samira Ebrahimi Kahou, and Christopher Pal. "Extreme weather: a large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events." In Proceedings of the 31st International Conference on Neural Information Processing Systems, pp. 3405-3416. 2017.
37. Salvi, K., Ghosh, S. and Ganguly, A.R., 2016. Credibility of statistical downscaling under nonstationary climate. Climate Dynamics, 46(5-6), 1991-2023.
38. Vandal, T., Kodra, E., Ganguly, S., Michaelis, A., Nemani, R. and Ganguly, A.R., 2017, August. DeepSD: Generating high resolution climate change projections through single image super-resolution. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1663-1672).
39. Vandal, T., Kodra, E., Dy, J., Ganguly, S., Nemani, R. and Ganguly, A.R., 2018, July. Quantifying uncertainty in discrete-continuous and skewed data with Bayesian deep learning. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2377-2386).
40. Liu, Y., Ganguly, A.R. and Dy, J., 2020, August. Climate Downscaling Using YNet: A Deep Convolutional Network with Skip Connections and Fusion. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 3145-3153).
41. Jones, N., 2017. How machine learning could help to improve climate forecasts. Nature News, 548(7668), 379.
42. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J. and Carvalhais, N., 2019. Deep learning and process understanding for data-driven Earth system science. Nature, 566(7743), 195-204.
43. Haupt, S.E., J. Copeland, W.Y.Y. Cheng, C. Amman, Y. Zhang, and P. Sullivan, 2016: Quantifying the Wind and Solar Power Resource and their Inter-annual Variability over the United States under Current and Projected Future Climate, Journal of Applied Meteorology and Climatology, 55, pp. 345-363.

44. Giffard-Roisin S, Yang M, Charpiat G, Kumler Bonfanti C, Kégl B, Monteleoni C., 2020. Tropical Cyclone Track Forecasting Using Fused Deep Learning from Aligned Reanalysis Data. Frontiers in Big Data.
45. Groenke, B. Madaus, L, and Monteleoni, C., 2020. ClimAlign: Unsupervised statistical downscaling of climate variables via normalizing flows. Proceedings of the 10th International Conference on Climate Informatics (CI 2020), Association for Computing Machinery, 60–66.
46. Zorita, E. and Von Storch, H., 1999. The analog method as a simple statistical downscaling technique: Comparison with more complicated methods. Journal of Climate, 12(8), 2474-2489.
47. Fitzpatrick, M.C., Dunn, R.R., 2019. Contemporary climatic analogs for 540 North American urban areas in the late 21st century. Nat Communications, 10, 614.
48. McLeman, R.A. and Hunter, L.M., 2010. Migration in the context of vulnerability and adaptation to climate change: insights from analogues. Wiley Interdisciplinary Reviews: Climate Change, 1(3), 450-461.
49. Bos, S.P., Pagella, T., Kindt, R., Russell, A.J. and Luedeling, E., 2015. Climate analogs for agricultural impact projection and adaptation—a reliability test. Frontiers in Environmental Science, 3, 65.
50. Lehner, F., Deser, C., Maher, N., Marotzke, J., Fischer, E.M., Brunner, L., Knutti, R. and Hawkins, E., 2020. Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. Earth System Dynamics, 11(2), 491-508.
51. Deser, C., Lehner, F., Rodgers, K.B., Ault, T., Delworth, T.L., DiNezio, P.N., Fiore, A., Frankignoul, C., Fyfe, J.C., Horton, D.E. and Kay, J.E., 2020. Insights from Earth system model initial-condition large ensembles and future prospects. Nature Climate Change, 10(4), 277-286.
52. Aerts, J.C., Botzen, W.J., Clarke, K.C., Cutter, S.L., Hall, J.W., Merz, B., Michel-Kerjan, E., Mysiak, J., Surminski, S. and Kunreuther, H., 2018. Integrating human behaviour dynamics into flood disaster risk assessment. Nature Climate Change, 8(3), 193-199.
53. Runge, J., Bathiany, S., Bollt, E., Camps-Valls, G., Coumou, D., Deyle, E., Glymour, C., Kretschmer, M., Mahecha, M.D., Muñoz-Marí, J. and van Nes, E.H., 2019. Inferring causation from time series in Earth system sciences. Nature Communications, 10, 2553.
54. Sapsis, T.P. and Majda, A.J., 2013. Statistically accurate low-order models for uncertainty quantification in turbulent dynamical systems. Proceedings of the National Academy of Sciences, 110(34), 13705-13710.
55. Nowack, P., Runge, J., Eyring, V. and Haigh, J.D., 2020. Causal networks for climate model evaluation and constrained projections. Nature Communications, 11, 1415.
56. Dorheim, K., Link, R., Hartin, C., Kravitz, B. and Snyder, A., 2020. Calibrating simple climate models to individual Earth system models: Lessons learned from calibrating Hector. Earth and Space Science, 7(11), p.e2019EA000980.
57. Stevens, B. and Bony, S., 2013. What are climate models missing? Science, 340(6136), 1053-1054.

58. Clark, M.P., Fan, Y., Lawrence, D.M., Adam, J.C., Bolster, D., Gochis, D.J., Hooper, R.P., Kumar, M., Leung, L.R., Mackay, D.S. and Maxwell, R.M., 2015. Improving the representation of hydrologic processes in Earth System Models. Water Resources Research, 51(8), 5929-5956.
59. Lauer, A., Eyring, V., Bellprat, O., Bock, L., Gier, B.K., Hunter, A., Lorenz, R., Pérez-Zanón, N., Righi, M., Schlund, M. and Senftleben, D., 2020. Earth System Model Evaluation Tool (ESMValTool) v2. 0–diagnostics for emergent constraints and future projections from Earth system models in CMIP. Geoscientific Model Development, 13(9), 4205-4228.
60. Zhao, L., Oleson, K., Bou-Zeid, E., Krayenhoff, E.S., Bray, A., Zhu, Q., Zheng, Z., Chen, C. and Oppenheimer, M., 2021. Global multi-model projections of local urban climates. Nature Climate Change, 11, 152–157.
61. Peter Düben, Umberto Modigliani, Alan Geer, Stephan Siemen, Florian Pappenberger, Peter Bauer, Andy Brown, Martin Palkovic, Baudouin Raoult, Nils Wedi, Vasileios Baousis (January 2021) Machine learning at ECMWF: A roadmap for the next 10 years, ECMWF Technical Memoranda n. 878.
62. Karpatne, A., Atluri, G., Faghmous, J.H., Steinbach, M., Banerjee, A., Ganguly, A., Shekhar, S., Samatova, N. and Kumar, V., 2017. Theory-guided data science: A new paradigm for scientific discovery from data. IEEE Transactions on knowledge and data engineering, 29(10), 2318-2331.
63. A.R. Ganguly, E.A. Kodra, A. Agrawal, A. Banerjee, S. Boriah, Sn. Chatterjee, So. Chatterjee, A. Choudhary, D. Das, J. Faghmous, P. Ganguli, S. Ghosh, K. Hayhoe, C. Hays, W. Hendrix, Q. Fu, J. Kawale, D. Kumar, V. Kumar, W. Liao, S. Liess, R. Mawalagedara, V. Mithal, R. Oglesby, K. Salvi, P. K. Snyder, K. Steinhaeuser, D. Wang, and D. Wuebbles (2014): Toward enhanced understanding and projections of climate extremes using physics-guided data mining techniques, Nonlinear Processes in Geophysics, 21, 777-795, 2014.
64. Read, J.S., Jia, X., Willard, J., Appling, A.P., Zwart, J.A., Oliver, S.K., Karpatne, A., Hansen, G.J., Hanson, P.C., Watkins, W. and Steinbach, M., 2019. Process-guided deep learning predictions of lake water temperature. Water Resources Research, 55(11), 9173-9190.
65. Daw, A., Thomas, R.Q., Carey, C.C., Read, J.S., Appling, A.P. and Karpatne, A., 2020. Physics-guided architecture (PGA) of neural networks for quantifying uncertainty in lake temperature modeling. In Proceedings of the 2020 SIAM international conference on data mining (pp. 532-540). Society for Industrial and Applied Mathematics.
66. Kodra, E., Bhatia, U., Chatterjee, S., Chen, S. and Ganguly, A.R., 2020. Physics-guided probabilistic modeling of extreme precipitation under climate change. Scientific Reports, Nature Publishing Group, 10, 10299.
67. Das, D., Dy, J., Ross, J., Obradovic, Z. and Ganguly, A.R., 2014. Non-parametric Bayesian mixture of sparse regressions with application towards feature selection for statistical downscaling. Nonlinear Processes in Geophysics, 21(6), 1145-1157.
68. Faghmous, J.H., Banerjee, A., Shekhar, S., Steinbach, M., Kumar, V., Ganguly, A.R. and Samatova, N., 2014. Theory-guided data science for climate change. Computer, 47(11), 74-78.
69. Zhuang, Y., Small, D.L., Shu, X., Yu, K., Islam, S. and Ding, W., 2018, November. Galaxy: Towards Scalable and Interpretable Explanation on High-Dimensional and Spatio-Temporal

Correlated Climate Data. In 2018 IEEE International Conference on Big Knowledge (ICBK) (pp. 146-153). IEEE.

70. Yadav, N. and Ganguly, A.R., 2020, September. A Deep Learning Approach to Short-Term Quantitative Precipitation Forecasting. In Proceedings of the 10th International Conference on Climate Informatics (pp. 8-14).
71. Ganguly, A.R. and Bras, R.L., 2003. Distributed quantitative precipitation forecasting using information from radar and numerical weather prediction models. Journal of Hydrometeorology, 4(6), 1168-1180.
72. Yadav, N., Ravela, S. and Ganguly, A.R., 2020. Machine Learning for Robust Identification of Complex Nonlinear Dynamical Systems: Applications to Earth Systems Modeling. Fragile Earth Workshop (Best student paper), ACM KDD 2020, arXiv preprint arXiv:2008.05590.
73. Rojo Hernández, J.D., Mesa, Ó.J. and Lall, U., 2020. ENSO dynamics, trends, and prediction using machine learning. Weather and Forecasting, 35(5), 2061-2081.
74. Kodra, E. and Ganguly, A.R., 2014. Asymmetry of projected increases in extreme temperature distributions. Scientific Reports, Nature Publishing Group, 4, 5884.
75. Schlef, K.E., Moradkhani, H. and Lall, U., 2019. Atmospheric circulation patterns associated with extreme United States floods identified via machine learning. Scientific Reports, Nature Publishing Group, 9, 7171.
76. Conticello, F.R., Cioffi, F., Lall, U. and Merz, B., 2020. Synchronization and delay between circulation patterns and high streamflow events in Germany. Water Resources Research, 56(4), p.e2019WR025598.
77. Haupt, S.E., Pasini, A. and Marzban, C. eds., 2008. Artificial intelligence methods in the environmental sciences. Springer Science & Business Media, 424 pages.
78. Haupt, S.E., McCandless, T.C., Lee, J.C., Kosović, B., Alessandrini, S., Dettling, S., Hussain, T. and Al-Rasheedi, M., 2020, June. Combining Physical Modeling with Artificial Intelligence for Solar Power Forecasting. In 2020 47th IEEE Photovoltaic Specialists Conference (PVSC) (pp. 2051-2053). IEEE.
79. Vandal, T., Kodra, E., Ganguly, S., Michaelis, A., Nemani, R. and Ganguly, A.R., 2018, July. Generating high resolution climate change projections through single image super-resolution: An abridged version. In International Joint Conferences on Artificial Intelligence Organization. IJCAI 2018.
    Highlighted in Nature Perspective on Deep Learning and Process Understanding by Reichstein et al.: see Reference 42).
80. Moss, R.H., Avery, S., Baja, K., Burkett, M., Chischilly, A.M., Dell, J., Fleming, P.A., Geil, K., Jacobs, K., Jones, A., Knowlton, K., Koh, J., Lemos, M.C., Melillo, J., Pandya, R., Richmond, T.C., Scarlett, L., Snyder, J., Stults, M., Waple, A.M., Whitehead, J., Zarrilli, D., Ayyub, B.M., Fox, J., Ganguly, A., Joppa, L., Julius, S., Kirshen, P., Kreutter, R., McGovern, A., Meyer, R., Neumann, J., Solecki, W., Smith, J., Tissot, P., Yohe, G., and Zimmerman, R., 2019. Evaluating knowledge to support climate action: A framework for sustained assessment. Report of an independent advisory committee on applied climate assessment. Weather, Climate, and Society, 11(3), 465-487.
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    More details available from SCAN website: climateassessment.org