

## **Suggested Readings for Breakout Session L: “Modern approaches to climate and hydrological data analysis and modeling”**

It is well established by now that the earth system is a highly interconnected system across processes (atmospheric, oceanic, and eco-hydrologic) and across scales (cloud microphysics to large scale dynamics). Improving modeling and prediction relies on using state-of-the-art methodologies for extracting from available data relevant information and hidden relationships, merging observations at different scales, advancing data assimilation methodologies, and identifying trends and patterns. Listed below are a few references on topics: (i) Modern spatial data analysis and reconstruction methods: from EOF regression to random forests, and dictionary learning; and (ii) Stochastic modeling approaches for the next generation of climate models: from self-similarity to connections between microscopic scales and global circulations scales.

### **EOF reconstruction and forecasting**

1. Shen, S.S.P., N. Tafolla, T.M. Smith, and P.A. Arkin, 2014: Multivariate regression reconstruction and its sampling error for the quasi-global annual precipitation from 1900-2011, *J. Atmospheric Sciences*, **71**, 3250-3268. doi: 10.1175/JAS-D-13-0301.1.
2. Shen, S.S.P., G. Behm, T.Y. Song, and T.D. Qu, 2017: A dynamically consistent reconstruction of ocean temperature, *Journal of Atmospheric and Oceanic Technology*, **34**, DOI: 10.1175/JTECH-D-16-0133.1.
3. Smith, T.M., S.S.P. Shen, and R. Ferraro, 2016: Super-ensemble statistical forecasting of monthly precipitation over the contiguous US, with improvements from ocean-area precipitation predictors, *Journal of Hydrometeorology*, **17**: 2699-2711. DOI: <http://dx.doi.org/10.1175/JHM-D-16-0018.1>

### **Random forests reconstruction and forecasting**

4. R project for random forests method:  
<https://cran.r-project.org/web/packages/randomForest/index.html>
5. Random forests method tutorial  
<http://www.math.usu.edu/adele/RandomForests/Ovronnaz.pdf>
6. Hutengs, C., and M. Vohland. 2016: Downscaling land surface temperatures at regional scales with random forest regression, *Remote Sensing of Environment* **178**, 127-141.

### **Dictionary learning for data reconstruction**

7. A tutorial for dictionary learning for reconstruction  
<http://www.irisa.fr/metiss/gribonval/Talks/2014/Gribonval-MLSP.pdf>
8. Fofoula-Georgiou, Efi, Ardeshir M. Ebtehaj, S. Q. Zhang, and A. Y. Hou, 2014: Downscaling Satellite Precipitation with Emphasis on Extremes: A Variational L1-Norm Regularization in the Derivative Domain." *Surveys in Geophysics* **35**, 765. doi:10.1007/s10712-013-9264-9, [http://efi.eng.uci.edu/papers/efg\\_135.pdf](http://efi.eng.uci.edu/papers/efg_135.pdf)
9. Ebtehaj, A.M., E. Fofoula-Georgiou, and G. Lerman, 2012: Sparse regularization for precipitation downscaling. *Journal of Geophysical Research: Atmospheres*, **117**(D8). DOI: 10.1029/2011JD017057, [http://efi.eng.uci.edu/papers/efg\\_119.pdf](http://efi.eng.uci.edu/papers/efg_119.pdf)

10. Ebtehaj, A.M., and E. Foufoula-Georgiou, On variational downscaling, fusion, and assimilation of hydrometeorological states: A unified framework via regularization, *Water Resour. Res.*, 49(9), 5944-5963, doi: 10.1002/wrcr.20424, 2013, [http://efi.eng.uci.edu/papers/efg\\_134.pdf](http://efi.eng.uci.edu/papers/efg_134.pdf)

### **Stochastic modeling**

11. Stechmann, S. N., and J. D. Neelin, 2011: A Stochastic model for the transition to strong convection, *J. Atmos. Sci.*, 68, 2955–2970.
12. Leung, K., M. Velado, A. Subramanian, G.J. Zhang, R.C.J. Somerville, and S.S.P. Shen, 2016: Simulation of high-resolution precipitable water data using a stochastic differential equation with a random trigger, *Advances in Data Science and Adaptive Analysis*, 8, No. 2, DOI: 10.1142/S2424922X16500066
13. Chen, N., and A.J. Majda, 2017: Simple stochastic dynamical models capturing the statistical diversity of El Niño Southern Oscillation. *Proceedings of the National Academy of Sciences*, 201620766.

### **Climate networks**

14. Ludescher, J., A. Gozolchiani, M. Bogachev, A. Bunde, S., Havlin, and H. Schellnhuber, 2013: Improved El Nino forecasting by cooperative detection, *PNAS*, 110, 11742–11745. doi: 10.1073/pnas.1309353110
15. Steinhäuser, N, Chawla, and A. Ganguly, An exploration of climate data using complex networks, *SIGKDD Explorations*, vol. 12, issue 1, and references therein. <https://www3.nd.edu/~nchawla/papers/SIGKDD10.pdf>
16. Tsonis, A., and K. Swanson, 2007: Topology and predictability of El Nino and La Nina networks, *Phys. Rev. Letters*, 34, L13705.