Predictive Understanding of Compound and Cascading Extremes and Their Impacts

Moetasim Ashfaq[1], Amir AghaKouchak[2], Phu Nguyen[2]

[1]*Oak Ridge National Laboratory, Oak Ridge, TN, USA;* [2]*University of California, Irvine, Irvine, CA, USA*

Focal Areas

(2) Predictive modeling through the use of AI techniques.

Scientific Challenge

We seek to answer the following questions: What interactions across spatial and temporal scales drive multivariate compound and cascading water cycle extremes, and how can we leverage understanding of such interactions to improve predictive understanding of these events and quantification of their impacts?

Rationale

Extremes represent the upper or lower end of the range of spatiotemporal conditions in the Earth system that often have adverse socio-ecological consequences as natural and human systems are exposed to hazardous environments to which they are not well accustomed. These conditions can be a result of univariate outliers (e.g., precipitation/temperature extremes) or can be due to a confluence of two or more variables (e.g., drought, wildfires, heat waves, ocean-terrestrial flooding), which individually may be in their extreme states. The impacts of extremes particularly become exceptionally disproportionate when they compound or cascade one another. Some examples of compounding extremes include (i) drought and heatwave, (ii) extreme precipitation and strong winds or storm surge, (iii) hot, dry, and windy conditions, and (iv) extreme rain over burned areas causing debris flow. Compound extremes are often regarded as the co-occurrence of multiple environmental stressors over the same geographical region that collectively represent extreme hazardous conditions. However, concurrent extremes with common drivers can also be studied over multiple geographical regions with distinct but interconnected extremes (e.g., common drivers contributed to both the 2010 Russian heatwave and Pakistan floods (Lau and Kim, 2012)). Consecutive occurrence of extremes can also cascade in the form of a major disaster, such as the 2018 California mudflows that were a result of a chain of unconnected events (drought → extreme precipitation → vegetation (fuel) growth → hot summer → wildfires → extreme precipitation → debris flow; see Figure 1) over a period of several years (AghaKouchak et al., 2020). By design, such occurrences represent the worst conditions possible and have the greatest potential to disrupt regional-scale socioeconomic and ecosystem sustainability and the global food supply chain.

The research in the area of compound and cascading extremes is relatively new and therefore, robust frameworks for defining such extremes and evaluating their impacts on social-ecological systems are still a work in progress (e.g., Leonard et al., 2014; AghaKouchak et al., 2020). Currently, gaps in the analytical frameworks are used to characterize such extremes. Most of the research thus far has focused on temporally compounding extremes, whereas spatially compounding extremes (i.e., the concurrent occurrences of similar or distinct extremes across multiple regions) have received relatively limited attention. Given that interactions across spatiotemporal scales in the Earth system are complex, a complete understanding of the nature of interacting extremes or confluence of nonextreme states of Earth system variables that lead to

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compounding events is likely yet to be unraveled. Similarly, our knowledge of the extent to which the impacts of such extremes may cascade and of the resulting multi-sector vulnerability is currently limited. Likewise, no systematic understanding toward the role of regional and large-scale modes of natural and forced Earth system variability in driving such extremes exists (e.g., Steptoe et al., 2017) that can be leveraged to test the ability of Earth system models, and to improve their predictability at varying time scales.

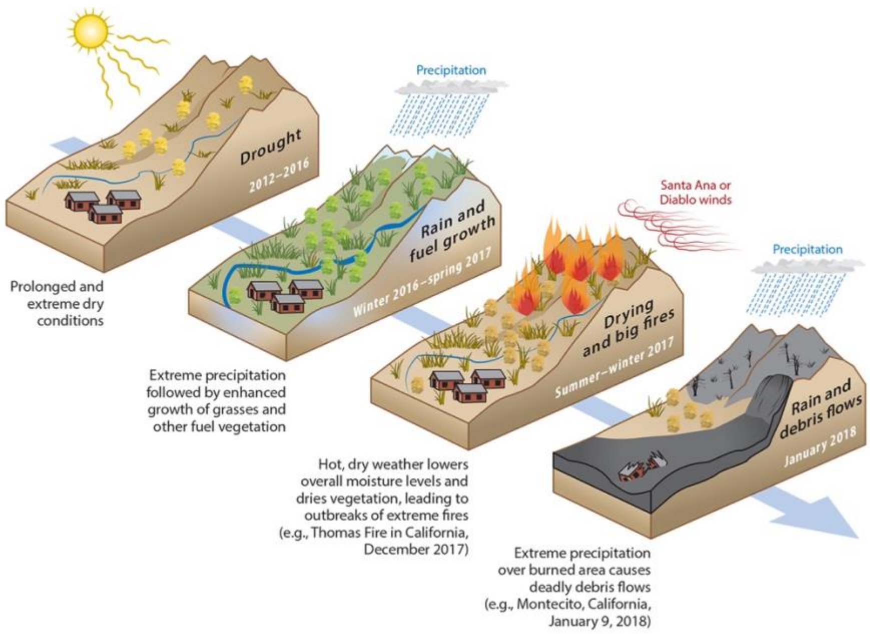

***Figure 1**. The following set of consecutive events resulted in significant human health and economic impacts in California: a prolonged extreme drought from 2012 to 2016; extreme precipitation during the winter of 2017, enhancing growth of fuels such as shrubs and grasses; a very dry, warm spring and summer, reducing moisture levels and drying existing vegetation; record-setting Diablo and Santa Ana winds (for sustained wind and low humidity); extreme fires occurring shortly thereafter (i.e., the Thomas Fire in December 2017); and extreme rainfall over the burned area in January 2018 (Source: AghaKouchak et al., 2020).*

Narrative

Improvements in the understanding of compound and cascading extremes and their impacts requires a multi-pronged approach of detection, attribution, and prediction, where machine/deep learning and artificial intelligence algorithms can aid and accelerate progress.

Development of robust analytical frameworks that can efficiently detect spatiotemporal environmental stressors causing compound and cascading extremes: Deep-learning, convolutional neural networks have been applied on large-scale modeled and observed data sets to efficiently identify individual extremes (e.g., Horton et al., 2015). Such machine learning and data analytics tools can be a promising solution to relatively more complex and interdependent or interacting states of the Earth system that lead to compounding or cascading events. Cascading events are particularly difficult to identify because they are often separated by space and time. For this reason, some common multivariate models designed for capturing statistical dependence fail to describe the relationship between cascading hazards (e.g., extreme rain and wildfires are typically statistically independent, but they can interact through their impacts). The development of such automated and highly efficient algorithms requires comprehensive training data sets, and powerful pattern recognition algorithms that "learn" the teleconnected relationships and associated time lags, which is challenging given the uncertainties across global hydrometeorological observations in representing spatiotemporal variations of interacting or interdependent extremes. To this end, machine learning–guided data assimilation can provide an objective way to combine observations, simulations, and remotely sensed data streams to improve on these limitations.

Attribution of the Earth system states that are precursors to compound and cascading events: The identification of processes that influence the occurrence of compound and cascading extremes is a key step to establishing their predictive capability. Characteristics of extremes in the Earth system are often related to the dynamics of planetary waves (Petoukhov et al., 2013). Wave patterns in jet streams, atmospheric blocking, and wave breaking are some of the leading causes of simultaneous or concurrent extremes (Kornhuber et al., 2020). Several factors can excite such atmospheric patterns, including anomalies in sea surface temperatures over the tropical/subtropical oceans and/or land surface conditions over the terrestrial regions. Atmospheric waves that originate along the tropical jet streams are also known to have associations with the genesis of tropical storms/hurricanes that subsequently can lead to significant compounding weather events. At monthly to seasonal timescales, large-scale modes of natural climate variability, such as the El Niño Southern Oscillation (ENSO), remotely exert their direct and indirect influence through the propagation of Rossby waves in the higher latitudes as a result of anomalies in the atmospheric diabatic heating over the oceanic basins. At sub-monthly scales, the interaction of air masses leads to the development of frontal boundaries, characterized by a sharp transition in moisture, temperature, and wind direction, which are often associated with significant weather events. Overall, patterns in the land-atmosphere-ocean continuum from the movement of air masses to the propagation of waves interact and intersect in ways that are fundamental to the formation of compound or cascading extremes. Machine learning and artificial intelligence algorithms can be used as cognitive tools to recognize, classify, and predict these patterns. Although the use of artificial neural networks for the classification of patterns in the Earth system is now quite common (e.g., Chattopadhyay et al., 2020; Kim et al., 2019), attribution of these patterns to specific physical causes remains a challenge, where deployment of explainable artificial intelligence techniques can be vital. Such analytical frameworks can subsequently guide the idealized Earth system modeling to elucidate the underlying physical mechanisms.

Prediction of compound and cascading extremes at sub-seasonal to multi-decadal time scales: Identification of precursors to compound and cascading extremes and the underlying physical mechanisms or modes of variability provides a pathway to improve the predictability of such events at varying time scales. ENSO is one of the major modes of natural variability and a dominant force in the spatiotemporal recurrence of compounding extremes (e.g., Mukhrjee et al., 2020). Information about the state of ENSO is useful for predictions on weekly to seasonal timescales and can substantially improve preparedness and response system capacities. Some evidence shows that statistical predictive modeling employing deep learning approaches can provide ENSO forecasts at sufficient lead times with skills at par or better than dynamical models (Ham et al., 2019), which should guide development of similar approaches for other modes of natural variability. Moreover, atmospheric teleconnections can vary at sub-seasonal scales because of complex inter-basin and land-atmosphere-ocean interactions (Abid et al., 2020; Cai et al., 2019), which need to be deciphered for the prediction of compounding extremes at shorter timescales. Machine learning techniques can identify geographical areas influencing the variability of these teleconnections and therefore can inform the effort to reduce uncertainties in dynamical modeling approaches. Furthermore, forced variability of the Earth system is partly responsible for an increase in the recurrence of extremes and, therefore, separation of these variations from naturally occurring transitory changes may be necessary. To this end, artificial neural networks, when trained on historical and future Earth system model simulations, can separate the forced signal from the natural variability. Overall, artificial intelligence techniques provide the promise of improved predictive understanding of water cycle extremes to cope with the emerging challenges posed by climate variability and change.

Suggested Experts

Ali Nazemi (ali.nazemi@concordia.ca)
Carlo De Michele (carlo.demichele@polimi.it)
Colin Raymond (colin.raymond@jpl.nasa.gov)
Felicia Chiang (chiangf@uci.edu)
Gianfausto Salvadori (gianfausto.salvadori@unisalento.it)
Hamed Moftakhari (hmoftakhari@eng.ua.edu)
Ivan Haigh (i.d.haigh@soton.ac.uk)
Jakob Zscheischler (jakob.zscheischler@climate.unibe.ch)
Kate Marvel (kdm2144@columbia.edu)
Kathleen White (kathleen.d.white@usace.army.mil)
Marleen de Ruiter (m.c.de.ruiter@vu.nl)
Moji Sadegh (mojtabasadegh@boisestate.edu)
Philip Ward (philip.ward@vu.nl)
Rolf Olsen (j.rolf.olsen@usace.army.mil)
Soroosh Sorooshian (soroosh@uci.edu)
Thomas Wahl (t.wahl@ucf.edu)

References

Abid, M. A., Ashfaq, M., Kucharski, F., Evans, K. J., and Almazroui, M. 2020. Tropical Indian Ocean mediates ENSO influence over Central Southwest Asia during the wet season. *Geophys. Res. Lett.*, **47,** e2020GL089308, https://doi.org/10.1029/2020GL089308

AghaKouchak A., Chiang, F., Huning, L. S., Love C. A., Mallakpour, I., Mazdiyasni, O., Moftakhari, H., Papalexiou, S. M., Ragno, E., and Sadegh, M. 2020. Climate Extremes and Compound Hazards in a Warming World, *Annual Review of Earth and Planetary Sciences*, **48,** 519-548, doi: https://doi.org/10.1146/annurev-earth-071719-055228

Cai, W., et al. 2019. Pantropical climate interactions. Science, **363**(6430), 944. doi: https://doi.org/10.1126/science.aav4236

Chattopadhyay, A., Hassanzadeh, P., and Pasha, S. 2020. Predicting clustered weather patterns: A test case for applications of convolutional neural networks to spatio-temporal climate data. *Sci Rep* **10,** 1317. doi: https://doi.org/10.1038/s41598-020-57897-9

Ham, Y. G., Kim, J. H., and Luo, J. J. 2019. Deep learning for multi-year ENSO forecasts. *Nature* **573,** 568–572. doi: https://doi.org/10.1038/s41586-019-1559-7

Kim, S., Kim, H., Lee, J., Yoon, S., Kahou, S. E., Kashinath, K., and Prabhat, M. 2019. Deep-Hurricane-Tracker: Tracking and Forecasting Extreme Climate Events. In Proceedings of the 2019 IEEE Winter Conference on Applications of Computer Vision, Waikoloa Village, HI, USA, January 7–11, 2019; 1761–1769.

Kornhuber, K., et al. 2020. Amplified Rossby waves enhance risk of concurrent heatwaves in major breadbasket regions. *Nat. Clim. Chang.* **10,** 48–53. doi: https://doi.org/10.1038/s41558-019-0637-z

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., Risbey, J., Schuster, S., Jakob, D., and Stafford-Smith, M. 2014. A compound event framework for understanding extreme impacts. *WIRES Climate Change* **5**(1), 113–128.

Mukherjee, S., Ashfaq, M., and Mishra, A. K. 2020. Compound drought and heatwaves at a global scale: The role of natural climate variability-associated synoptic patterns and land-surface energy budget anomalies. *Journal of Geophysical Research: Atmsospheres* **125**, e2019JD031943.

Petoukhov, V., Rahmstorf, S., Petri, S., and Schellnhuber, H. J. 2013. Quasiresonant amplification of planetary waves and recent Northern Hemisphere weather extremes. *Proc Natl Acad Sci USA* **110**(14), 5336–5341.

Steptoe, H., Jones, S. E. O., and Fox, H. 2018. Correlations between extreme atmospheric hazards and global teleconnections: Implications for multihazard resilience. *Rev. Geophys.* 56, 50–78. doi: https://doi.org/10.10