A Fire Community Observatory: Interdisciplinary, AI-informed Post-Fire Rapid Response for Improved Water Cycle Science at Watershed Scale

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Scientific Challenges

Wildfire is an ecological disturbance that disrupts the hydrological cycle (*1*, *2*). In the past few years, a record number of multiple-and-compounding fires have occurred across urban-wildland gradients in the Western United States (*3*, *4*). Changes to watershed hydrological partitioning in response to fires (infiltration, runoff, evapotranspiration) presents unprecedented challenges to "Water-in-the-West" through negative impacts to water supply and its quality (*5*), and is a direct threat to downstream communities, groundwater, and drinking water supply infrastructure (*6*, *7*). While much work is being done to advance Artificial Intelligence and Machine Learning (AI/ML) use *during* fires for emergency response (i.e. predict fire movement, direct evacuations)(*8*), significant potential exists to use AI/ML to address three **scientific grand** challenges that are rarely addressed in a convergent science context (*9*)**:** 1) how to enhance the potential resiliency of a landscape *before* fire(s), 2) how to cost-effectively and optimally monitor watershed changes *after* fires, and 3) how to predict *future* hydrological and biogeochemical trajectories in fire-impacted watershed given climate change. This whitepaper addresses DOE Focal Area 1: Data acquisition and assimilation enabled by machine learning, AI, and advanced methods.

Despite the threats posed by fires to national questions of water security, a cross-scale and integrated model-observation-AI/ML framework does not exist to systematically evaluate the impacts of spatially heterogeneous disturbances like wildfire on hydrology, organisms, and ecosystems (wildlands and mixed human systems)(*10*, *11*) and how these changes feedback to potentially enhance climate change trends through CO_2 emissions (Figure 1).

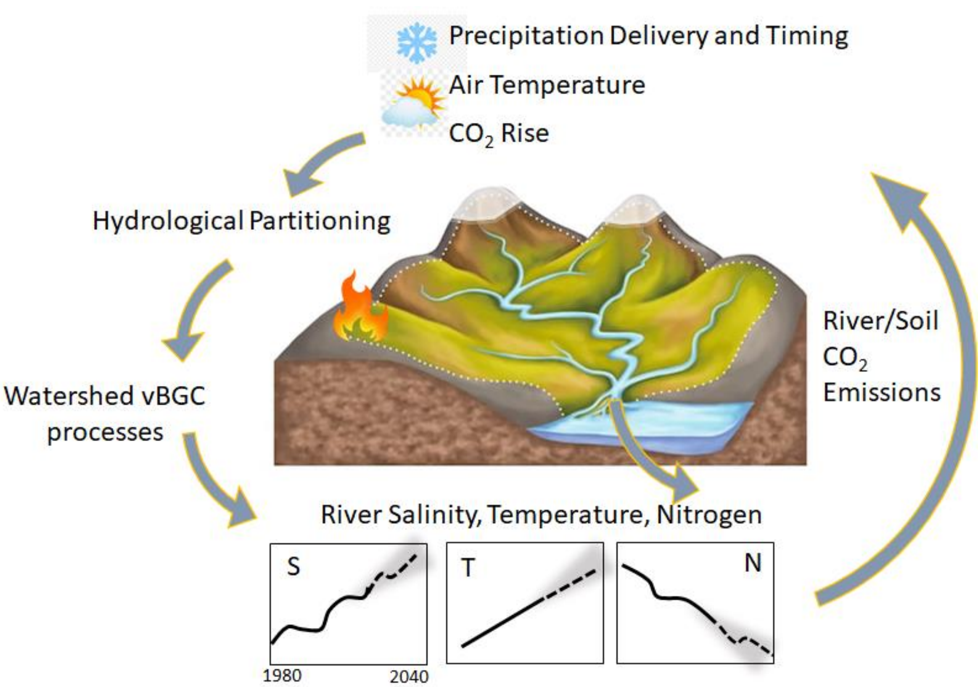

Figure 1: Climate and fire induced changes in hydrological partitioning across a watershed can lead to unknown and cascading impacts on downstream water supply and water quality. The biogeochemical processes supporting these changes directly feedback and supply CO_2 emissions back to the atmosphere (*12*, *13*).

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The lack of a cross-scale and integrated model-observation-AI/ML framework limits our ability to understand the interconnected roles between humans, fire, watersheds, ecosystems, and the resulting water cycle. Without such a systematic understanding, the potential impacts from a changing climate and human-development patterns cannot be predicted. Such a framework needs to consider not only the patterns of the built-environment, fire regime (i.e., patterns of burn severity, periodicity, intensity, and spread rates) and watershed hydrology, but the interconnected relationships and feedbacks that impact people, ecosystems, and resilience (*14*). This framework also needs to consider how to engage multidisciplinary teams of scientists quickly to rapidly-respond to fire events as they occur, and teams that have the ability to collectively assess diverse data types across whole ecosystems including hydrology, genomes, geochemistry, landscape vegetation, soils, and deep groundwater(*10*, *14*, *15*).

Six hurdles emerge in the development of an AI-informed framework that addresses pre- and post-wildfire response. Specifically, there remains: 1) limited agreement on relevant fire-related model benchmark data types and model evaluation metrics to perform model inter-comparisons (hydrological, geochemical, genomic, and biological) (*16*); 2) lack of historical benchmark data to utilize such appropriate models and evaluation metrics (i.e. genomics, metabolomics); 3) uncertainty about how the water cycle changes across the coupled atmosphere-surface-groundwater continuum; 4) nascent water-biogeochemical cycle couplings in watershed and earth system physically-based models that allow for surface and groundwater flow/solute/microbial exchange (*17*, *18*); 5) substantial model limitations for integrating spatially-heterogeneous and complex fire distribution and temporally-complex fire timing; and 6) limited ability for multidisciplinary teams to rapidly converge their science on new locations that experience fire.

Our vision is to shift how science is conducted both *before* and *after* fires to overcome these challenges. This vision will leverage AI/ML to engineer a "Fire Community Observatory" built upon a foundation of domain scientists to guide and implement AI/ML methods to optimize a rapid-response monitoring network *before*, *during*, and *after* fires. Our vision has the potential to foster substantial and paradigm-changing improvements in earth system predictability by advocating for new frameworks in how fire-science is conducted.

A framework is needed that allows for unprecedented community collaboration to collectively assess fire impacts from genomes to watershed scales, with a level of readiness needed to rapidly-respond and evaluate these events to improve predictability in response to climate change.

Mission

In order to improve earth system predictability in response to future fires, our "Fire Community Observatory" mission is to develop a coordinated, dedicated research team of different domain scientists to improve process-understanding and predictability of fire impacts on watersheds and their resiliency by tackling grand challenges *before* and *after* fires.

While the foundations for our mission are at a nascent stage, we envision a workshop to co-produce solutions to tackle these challenges and converge on methods and next steps thereby enabling a programmatic shift in water cycle science in a data intensive world. The Fire Community Observatory will enable improved predictability of water cycling ad watershed resilience under a changing climate with increased likelihood of fire disturbances. Specifically, multidisciplinary convergence will enable us to answer water-cycle science questions like:

1. How will water supply (surface and groundwater) and water quality shift when impacted by multiple-and compounding fire events?
2. What are the appropriate pre-fire stakeholder activities to help enhance watershed resilience?
3. How will these fires and their resulting hydrobiogeochemical changes feedback on CO_2 fluxes to the atmosphere?

4. What are the appropriate benchmark metrics to evaluate model predictions post-fire?
5. What is the most efficient and optimal monitoring network strategy to converge interdisciplinary teams post-fire?
6. How can we take advantage of the vast amount of diverse data available to understand pre-fire conditions that promote resilience to fire? Is there a difference in fire management strategies that promote resilience?

Methods

A workshop would bring traditionally disparate disciplines together to co-produce methodologies for collecting, analyzing, and assimilating data for post-fire rapid response to improve water cycle science at the watershed scale. Specifically, by assessing and converging as a multidisciplinary community, many new AI/ML methods arise:

1. **AI-Informed Post-Fire Rapid Response Data Collection:** Use of AI to inform strategic and optimal rapid *in situ* biological and hydrogeochemical sampling to enable scalable and interpretable datasets to draw appropriate conclusions across confounding factors. Require an unprecedented level of cooperation amongst interdisciplinary science teams, and participation by Local and Federal Agencies.
2. **Model-Data Assimilation:** AI assisted model-data assimilation would foster radical improvements to predictive capabilities because disturbances impact landscapes in spatially heterogeneous ways and introduce cascading effects in hydrology and biogeochemistry. Machine learning can directly inform raster data integration into process-based, spatially-explicit models. By using machine learning to aggregate remote sensing raster data for assimilation into process-based, integrated models, we can examine how patterns impact hydrological processes. Additionally, previously unusable geochemical or raster datasets such as those that are temporally or spatially sparse can be mined by leveraging AI/ML gap-filling techniques.
3. **Advancing hybrid models:** Adapting coupled models to include previously unrealized processing capability using AI/ML. Processes such as microbial metabolism, biotic interactions, vegetation change, and biogeochemistry respond directly to hydrological excursions however their traditional inclusion in models is computationally expensive at watershed scales. Hybrid models can overcome this problem by using AI/ML to simulate microbial metabolism, vegetation, and biogeochemistry and supplement the AI/ML prediction for the numerical process-based model mechanisms.
4. **Novel pattern recognition and process discovery:** Link genomic point scale data through raster scale remote sensing datasets to quantify resiliency within a landscape. In these non-numerical approaches, diverse, large datasets are ingested into AI/ML models to mine for patterns and processes that contribute to unique watershed steady-states that promote resilience and help identify key processes that could trigger "tipping-points" in watershed hydrology.
5. **Optimized "co-design" approach**: Foster multidisciplinary convergent science teams to assimilate data, refine model design, leverage new untapped datasets, and further promote preemptive and rapid-response data collection (#1). Pilot simulation-guided adaptive sampling, experimental design, and uncertainty propagation, to ultimately improve model prediction breadth and accuracy.

Leveraging the power of AI/ML techniques to engineer paradigm shifting improvements in earth system predictability will require not only new models, codes, and data analysis methods, but will also require converging science from teams, who also need to bridge vastly different spatial and temporal resolutions.

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References

1. G. Boisramé, S. Thompson, B. Collins, S. Stephens, Managed Wildfire Effects on Forest Resilience and Water in the Sierra Nevada. *Ecosystems*. **20**, 717–732 (2017).
2. F. Z. Maina, E. R. Siirila-Woodburn, *Hydrol. Process.*, in press, doi:10.1002/hyp.13568.
3. E. N. Stavros, J. T. Abatzoglou, D. McKenzie, N. K. Larkin, Regional projections of the likelihood of very large wildland fires under a changing climate in the contiguous Western United States. *Clim. Change*. **126**, 455–468 (2014).
4. A. L. Westerling, Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. *Science*. **313**, 940–943 (2006).
5. K. D. Bladon, M. B. Emelko, U. Silins, M. Stone, Wildfire and the Future of Water Supply. *Environ. Sci. Technol.* **48**, 8936–8943 (2014).
6. A. Mishra, A. Alnahit, B. Campbell, Impact of land uses, drought, flood, wildfire, and cascading events on water quality and microbial communities: A review and analysis. *J. Hydrol.*, 125707 (2020).
7. C. R. Proctor, J. Lee, D. Yu, A. D. Shah, A. J. Whelton, Wildfire caused widespread drinking water distribution network contamination. *AWWA Water Sci.* **2** (2020), doi:10.1002/aws2.1183.
8. X. Zhao, R. Lovreglio, E. Kuligowski, D. Nilsson, Using Artificial Intelligence for Safe and Effective Wildfire Evacuations. *Fire Technol.*, s10694-020-00979–x (2020).
9. P. Jain, S. C. P. Coogan, S. G. Subramanian, M. Crowley, S. Taylor, M. D. Flannigan, A review of machine learning applications in wildfire science and management. *Environ. Rev.* **28**, 478–505 (2020).
10. S. R. Holden, B. M. Rogers, K. K. Treseder, J. T. Randerson, Fire severity influences the response of soil microbes to a boreal forest fire. *Environ. Res. Lett.* **11**, 035004 (2016).
11. K. K. McLauchlan, P. E. Higuera, J. Miesel, B. M. Rogers, J. Schweitzer, J. K. Shuman, A. J. Tepley, J. M. Varner, T. T. Veblen, S. A. Adalsteinsson, J. K. Balch, P. Baker, E. Batllori, E. Bigio, P. Brando, M. Cattau, M. L. Chipman, J. Coen, R. Crandall, L. Daniels, N. Enright, W. S. Gross, B. J. Harvey, J. A. Hatten, S. Hermann, R. E. Hewitt, L. N. Kobziar, J. B. Landesmann, M. M. Loranty, S. Y. Maezumi, L. Mearns, M. Moritz, J. A. Myers, J. G. Pausas, A. F. A. Pellegrini, W. J. Platt, J. Roozeboom, H. Safford, F. Santos, R. M. Scheller, R. L. Sherriff, K. G. Smith, M. D. Smith, A. C. Watts, Fire as a fundamental ecological process: Research advances and frontiers. *J. Ecol.* **108**, 2047–2069 (2020).

12. D. Butman, S. Stackpoole, E. Stets, C. P. McDonald, D. W. Clow, R. G. Striegl, Aquatic carbon cycling in the conterminous United States and implications for terrestrial carbon accounting. *Proc. Natl. Acad. Sci.* **113**, 58–63 (2016).
13. C. Duvert, D. E. Butman, A. Marx, O. Ribolzi, L. B. Hutley, CO2 evasion along streams driven by groundwater inputs and geomorphic controls. *Nat. Geosci.* **11**, 813–818 (2018).
14. D. B. McWethy, T. Schoennagel, P. E. Higuera, M. Krawchuk, B. J. Harvey, E. C. Metcalf, C. Schultz, C. Miller, A. L. Metcalf, B. Buma, A. Virapongse, J. C. Kulig, R. C. Stedman, Z. Ratajczak, C. R. Nelson, C. Kolden, Rethinking resilience to wildfire. *Nat. Sustain.* **2**, 797–804 (2019).
15. R. B. MacNeille, K. A. Lohse, S. E. Godsey, J. N. Perdrial, C. V. Baxter, Influence of Drying and Wildfire on Longitudinal Chemistry Patterns and Processes of Intermittent Streams. *Front. Water*. **2**, 563841 (2020).
16. N. Collier, F. M. Hoffman, D. M. Lawrence, G. Keppel-Aleks, C. D. Koven, W. J. Riley, M. Mu, J. T. Randerson, The International Land Model Benchmarking (ILAMB) System: Design, Theory, and Implementation. *J. Adv. Model. Earth Syst.* **10**, 2731–2754 (2018).
17. J. Golaz, P. M. Caldwell, L. P. Van Roekel, M. R. Petersen, Q. Tang, J. D. Wolfe, G. Abeshu, V. Anantharaj, X. S. Asay-Davis, D. C. Bader, S. A. Baldwin, G. Bisht, P. A. Bogenschutz, M. Branstetter, M. A. Brunke, S. R. Brus, S. M. Burrows, P. J. Cameron-Smith, A. S. Donahue, M. Deakin, R. C. Easter, K. J. Evans, Y. Feng, M. Flanner, J. G. Foucar, J. G. Fyke, B. M. Griffin, C. Hannay, B. E. Harrop, M. J. Hoffman, E. C. Hunke, R. L. Jacob, D. W. Jacobsen, N. Jeffery, P. W. Jones, N. D. Keen, S. A. Klein, V. E. Larson, L. R. Leung, H. Li, W. Lin, W. H. Lipscomb, P. Ma, S. Mahajan, M. E. Maltrud, A. Mametjanov, J. L. McClean, R. B. McCoy, R. B. Neale, S. F. Price, Y. Qian, P. J. Rasch, J. E. J. Reeves Eyre, W. J. Riley, T. D. Ringler, A. F. Roberts, E. L. Roesler, A. G. Salinger, Z. Shaheen, X. Shi, B. Singh, J. Tang, M. A. Taylor, P. E. Thornton, A. K. Turner, M. Veneziani, H. Wan, H. Wang, S. Wang, D. N. Williams, P. J. Wolfram, P. H. Worley, S. Xie, Y. Yang, J. Yoon, M. D. Zelinka, C. S. Zender, X. Zeng, C. Zhang, K. Zhang, Y. Zhang, X. Zheng, T. Zhou, Q. Zhu, The DOE E3SM Coupled Model Version 1: Overview and Evaluation at Standard Resolution. *J. Adv. Model. Earth Syst.* **11**, 2089–2129 (2019).
18. J. Tang, W. J. Riley, Predicted Land Carbon Dynamics Are Strongly Dependent on the Numerical Coupling of Nitrogen Mobilizing and Immobilizing Processes: A Demonstration with the E3SM Land Model. *Earth Interact.* **22**, 1–18 (2018).
19. J. C. Underwood, M. E. Newcomer, T. Schram, P. Bliznik, D. A. Roth, T. I. Plowman, M. Smedt, R. W. Harvey, S. S. Hubbard, M. Trotta, D. Seymour, J. Jasperse, Water Quality of the Russian River Watershed After Sonoma and Napa County Fires: U.S. Geological Survey, (2018), (available at https://doi.org/10.5066/F73B5ZF9).
20. R. Meyer, E. E. Curd, T. Schweizer, Z. Gold, D. Ruiz Ramos, S. Shirazi, G. Kandlikar, W.-Y. Kwan, M. Lin, A. Friese, J. Moberg-Parker, M. Munguia Ramos, B. Shapiro, J. Sexton, L. Pipes, A. Garcia Vedrenne, M. Palacios Mejia, E. Aronson, T. Moore, R. Nielsen, H. Lewin, P. Barber, J. Wall, N. Kraft, R. Wayne, “The California Environmental DNA ‘CALeDNA’ Program” (preprint, Scientific Communication and Education, 2019), , doi:10.1101/503383.
21. J. Stegen, A. Goldman, S. Blackburn, R. Chu, R. Danczak, V. Garayburu-Caruso, E. Graham, C. Grieshauber, X. Lin, J. Morad, H. Ren, L. Renteria, C. Resch, M. Tfaily, N. Tolic, J. Toyoda, J. Wells, K. Znotinas, S. Brooks, N. Bouskill, M. E. Newcomer, A. Rowe, A. Saify, G. Smith, M. Soltanian, L. Trustschel, A. Turetcaia, WHONDRS Surface Water Sampling for Metabolite Biogeography (2018), , doi:10.15485/1484811.