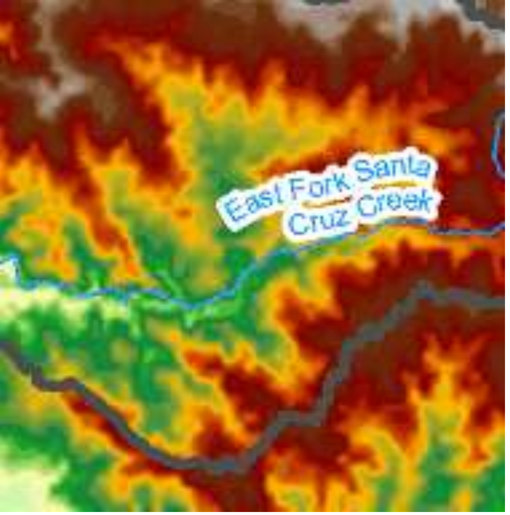

How major disturbances and climate contribute to water supply risk: Data analytics and modeling

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Alain N. Rousseau, Rua S. Mordecai, Zhengxiang Yu, and Steven G. McNulty

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Southern Research Station, Research Triangle Park, North Carolina

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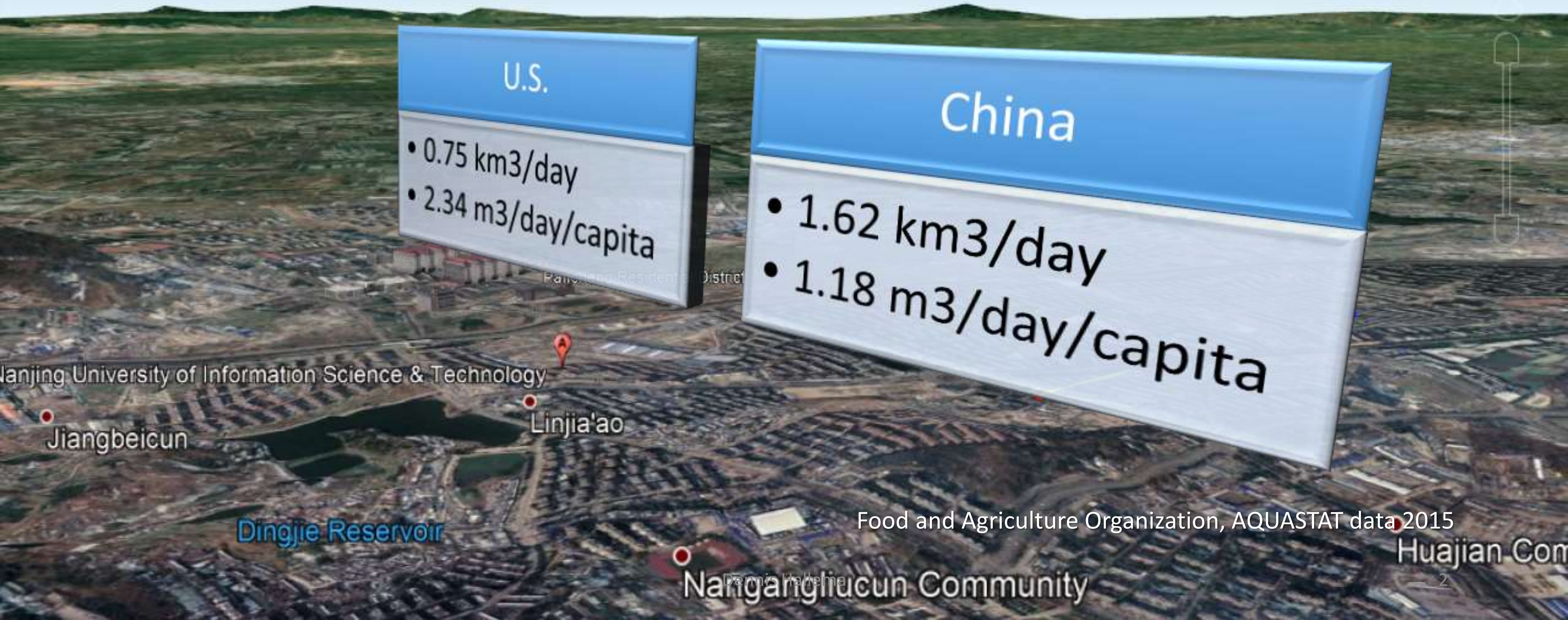
Surface water withdrawals

U.S.

- 0.75 km3/day
- 2.34 m3/day/capita

China

- 1.62 km3/day
- 1.18 m3/day/capita

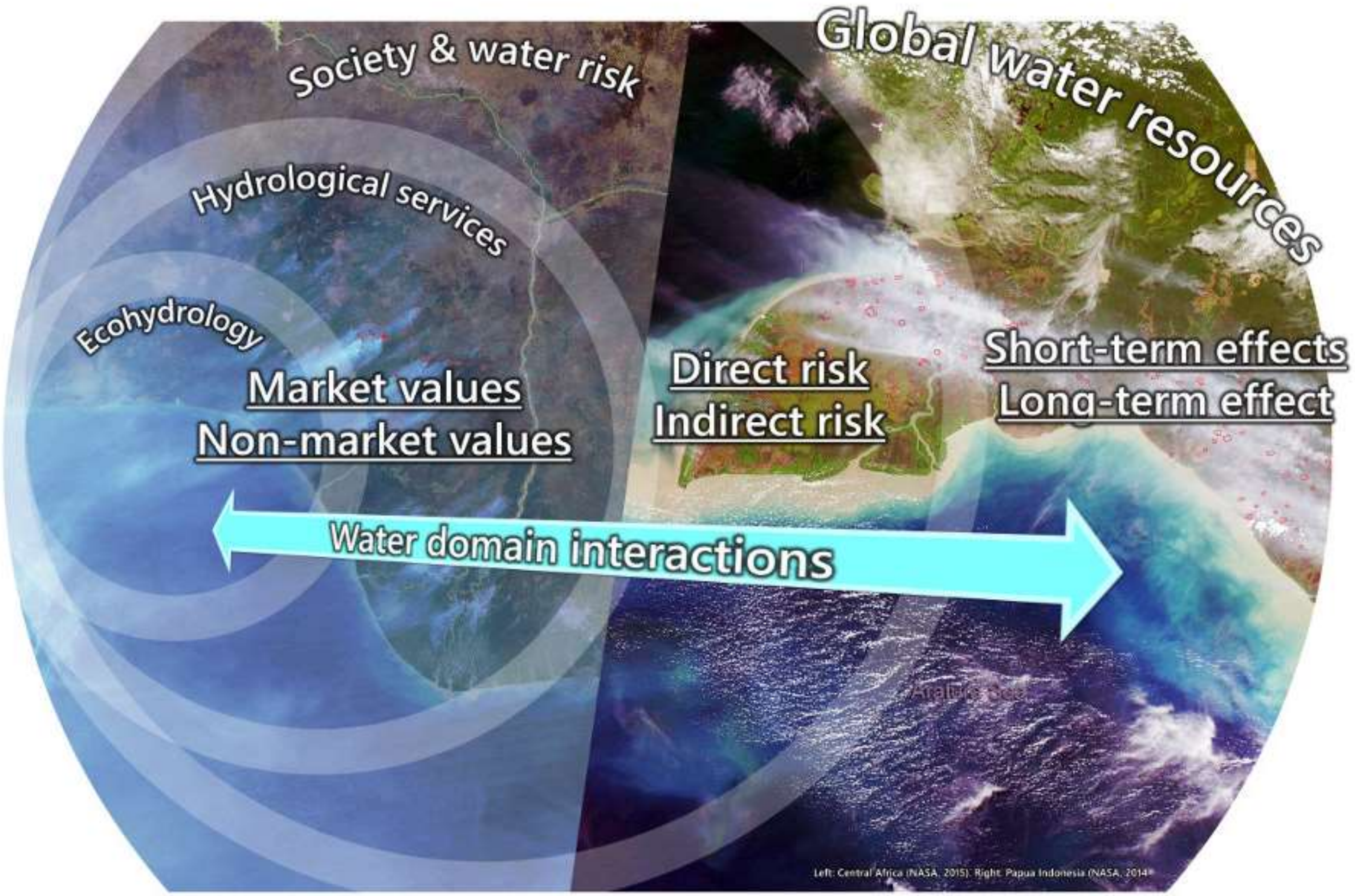


Food and Agriculture Organization, AQUASTAT data 2015

Why water supply risk matters

Reduce economic cost of:

- Water treatment
- Reservoir management
- Flood insurance
- Disaster aid



Scope

- How do major disturbances vs. climate contribute to water supply risk over multiple years?
- <u>Show what data methods and computational modeling can do for the assessment of water resources and related risks</u>

Approach

1. Use machine learning to detect environmental and climate thresholds when wildfire disturbance impacts river flow
2. Integrate thresholds in large scale water yield model (WaSSI)

Machine learning

- Construction of algorithms that can learn from data
- Formalized by Arthur Samuel in 1959 paper:

  Some Studies in Machine Learning Using the Game of Checkers

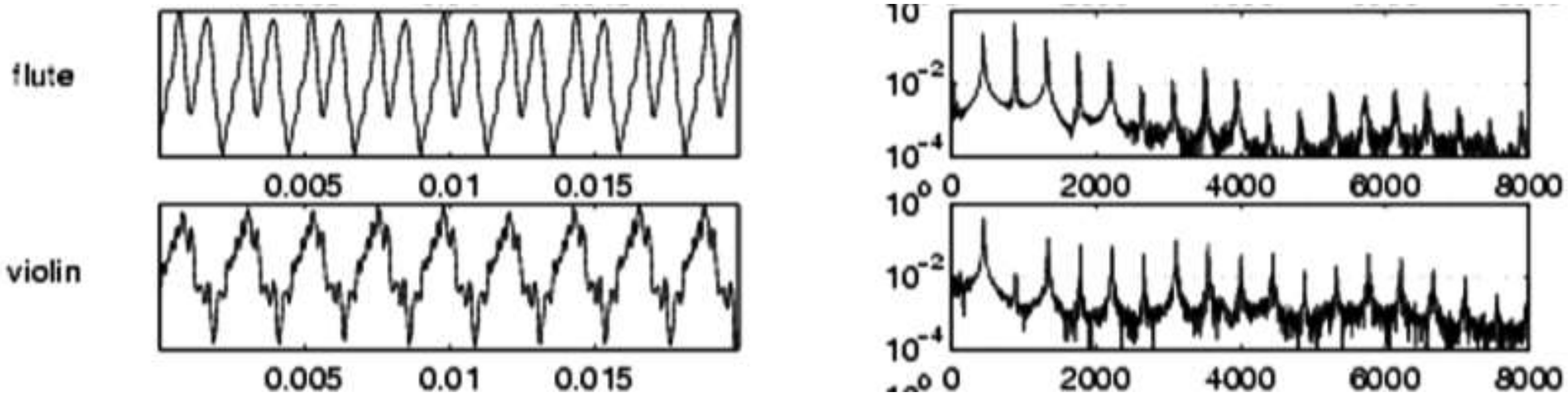
  "it can learn to do this in a remarkably short period of time (8 or 10 hours of machine-playing time)"

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. IBM Journal of Research and Development, 3(3), 210-229.

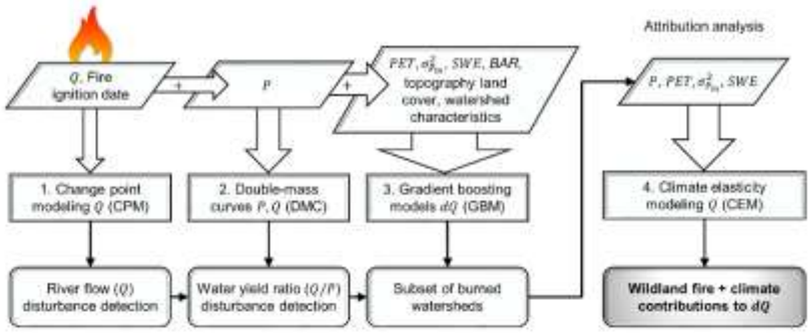
How machine learning works

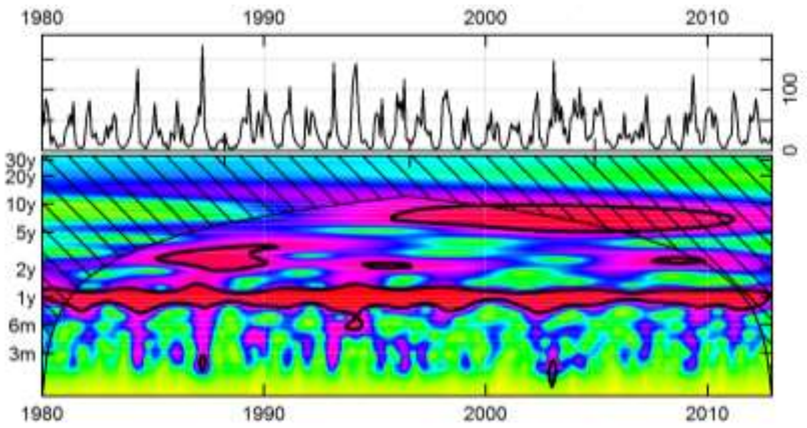
Machine learning analogous to a synthesizer

- Combines harmonics to emulate an instrument
- Frequency oscillators, transistors & filters



Machine learning analogous to a synthesizer





- Combines <u>time series data</u> to simulate <u>hydrologic response e.g. river flow</u>
- Environmental data, switches & filters

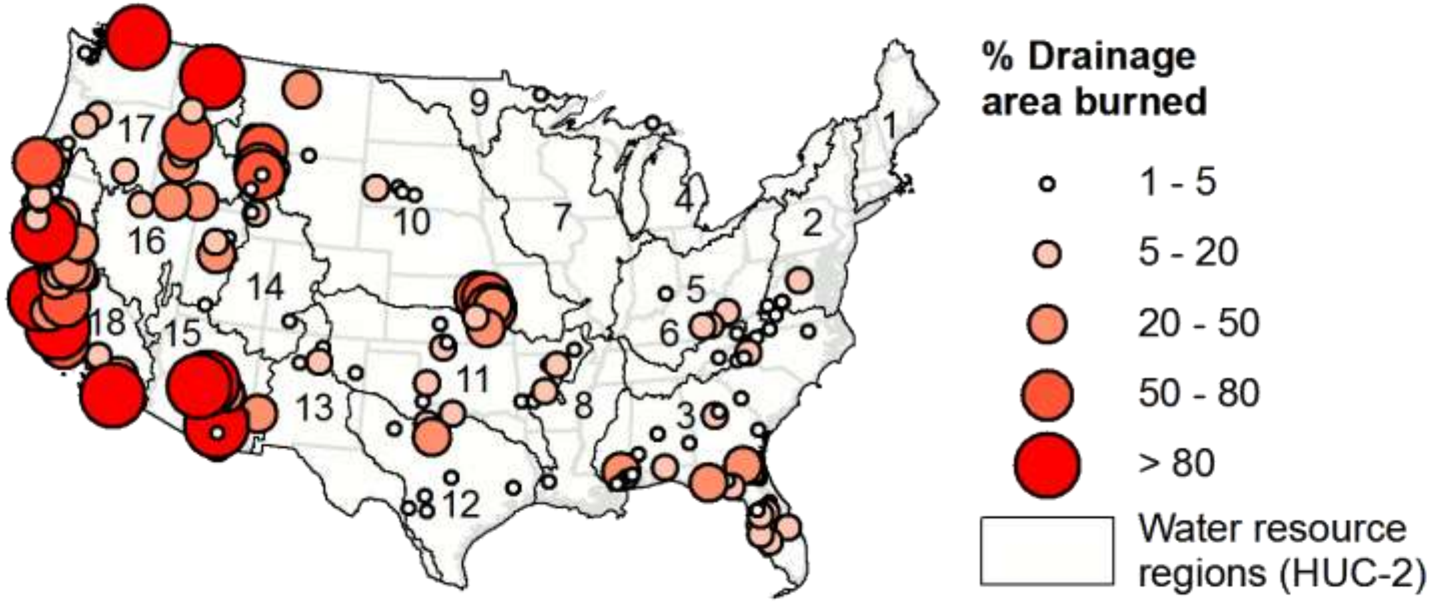
http://amath.colorado.edu/pub/matlab/music/

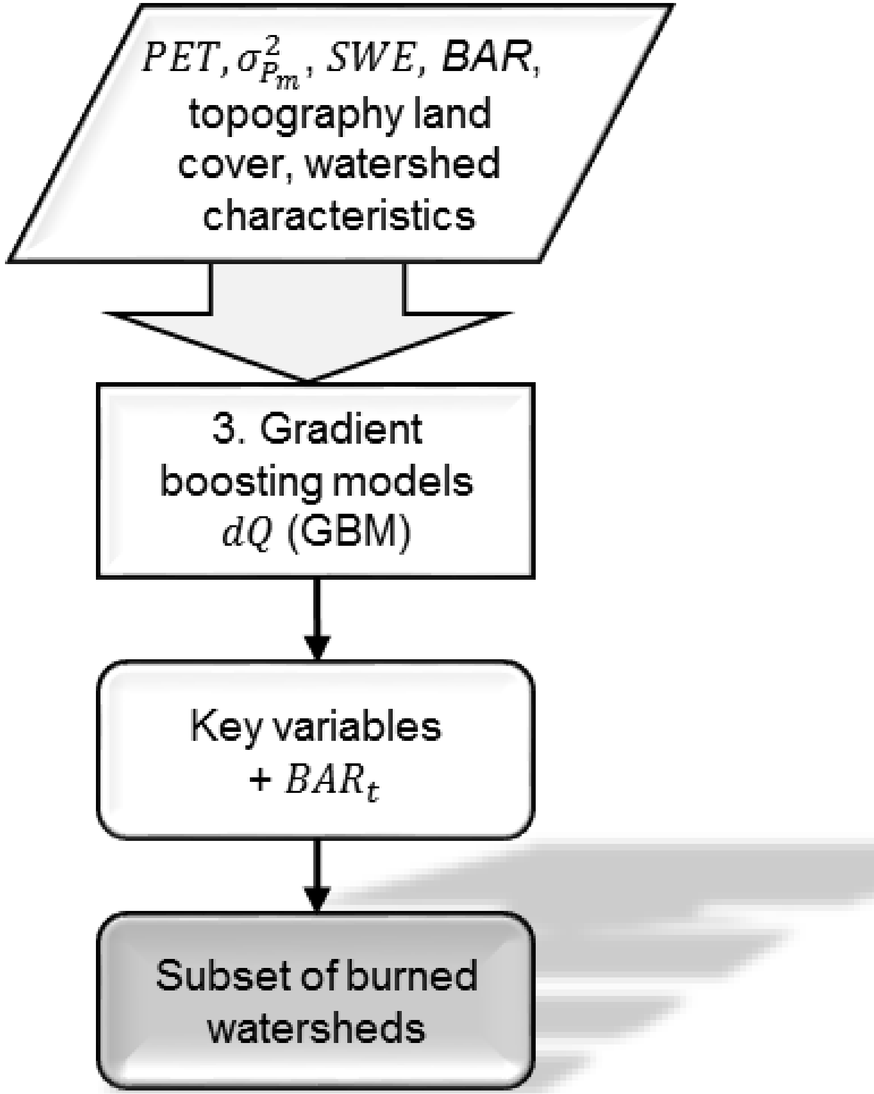
Machine learning

- Identify influential variables we do not (yet) understand at the national/regional scale
- Allows you to use all your data
- Detecting environmental thresholds
- Extremely useful for formulating/refining hypotheses

Application

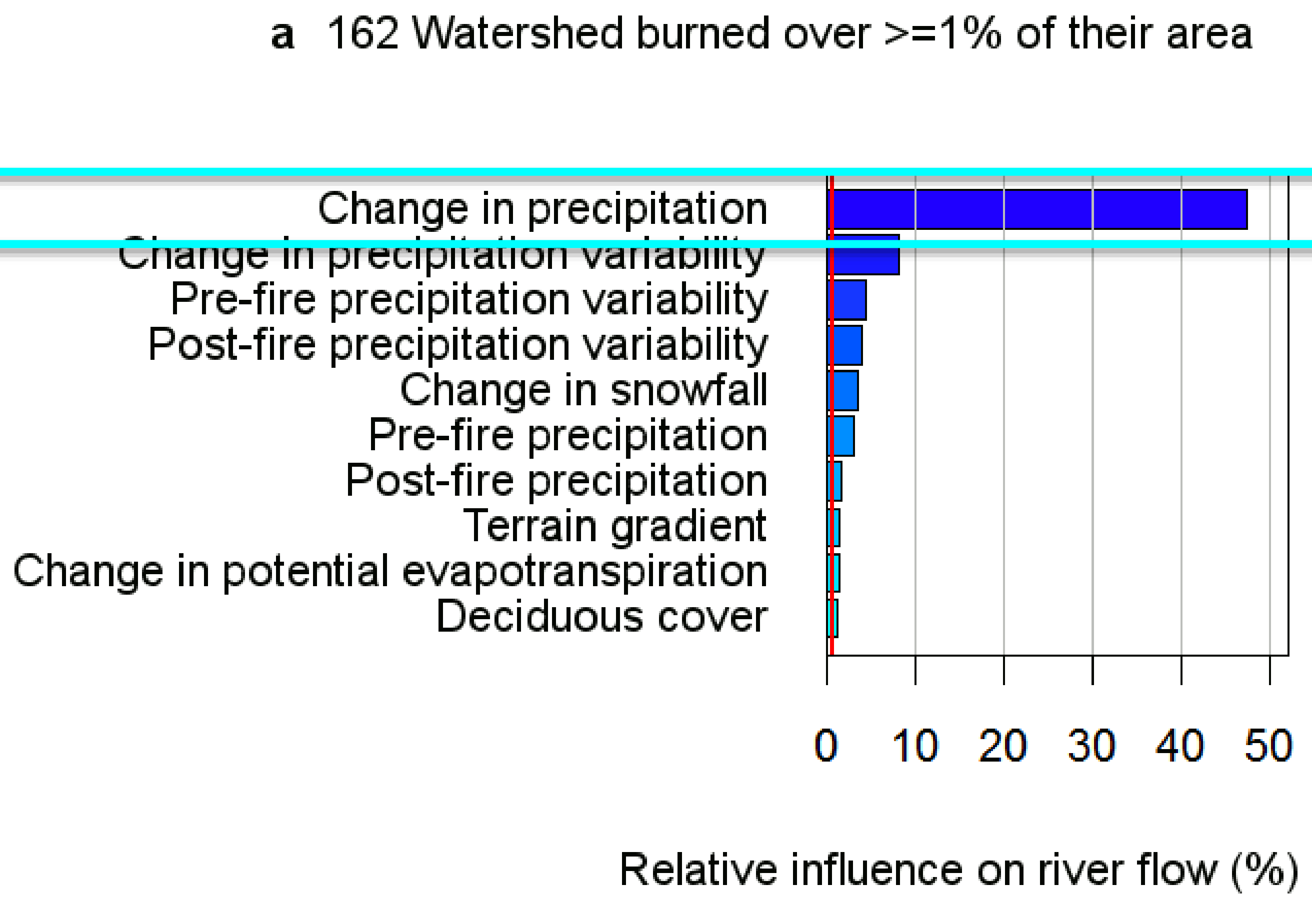
Identify U.S. gaged watersheds where wildland fires affected river flow between 1984-2008.





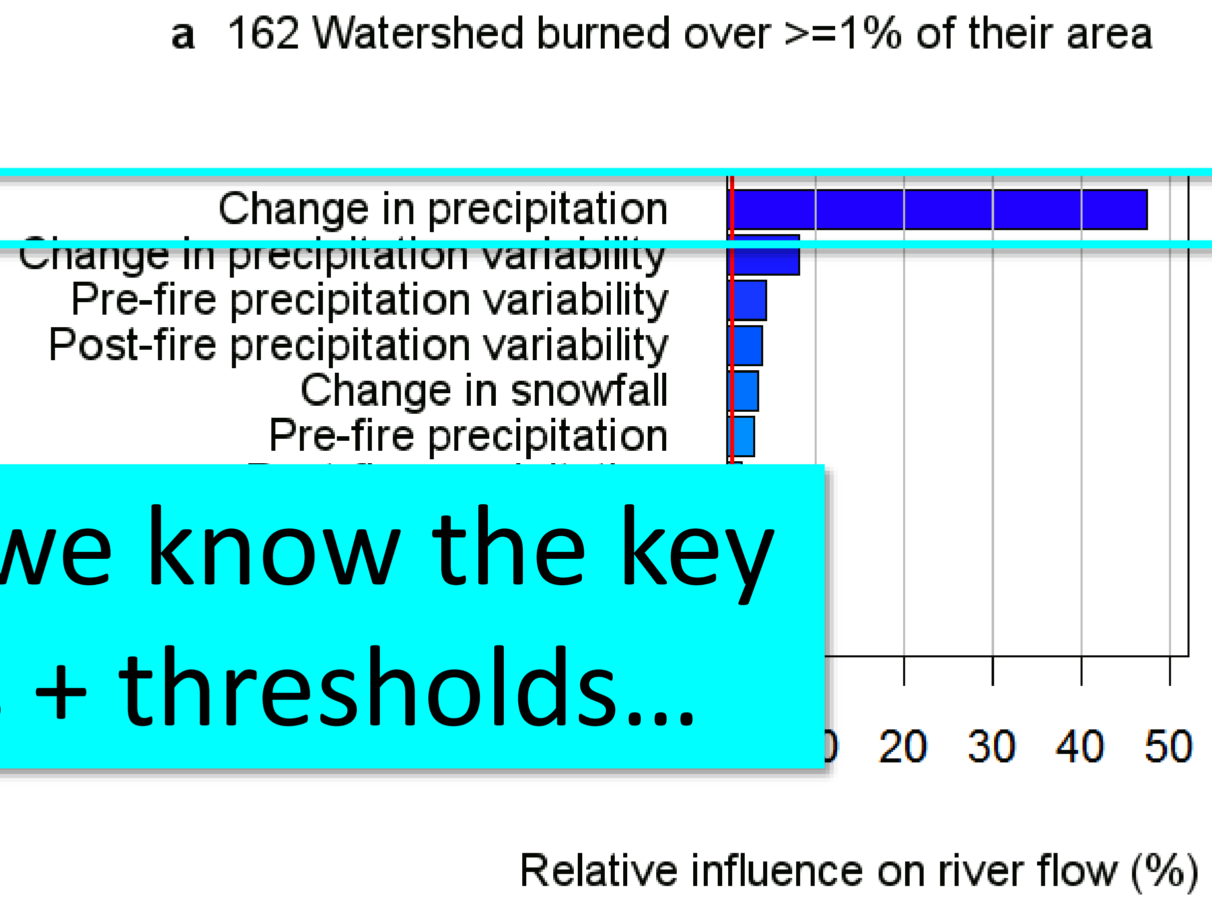
[Hallema & others, Nature Communications (2018)]

Key variables + thresholds for impact on river flows



[Hallema & others, Nature Communications (2018)]

Key variables + thresholds for impact on river flows

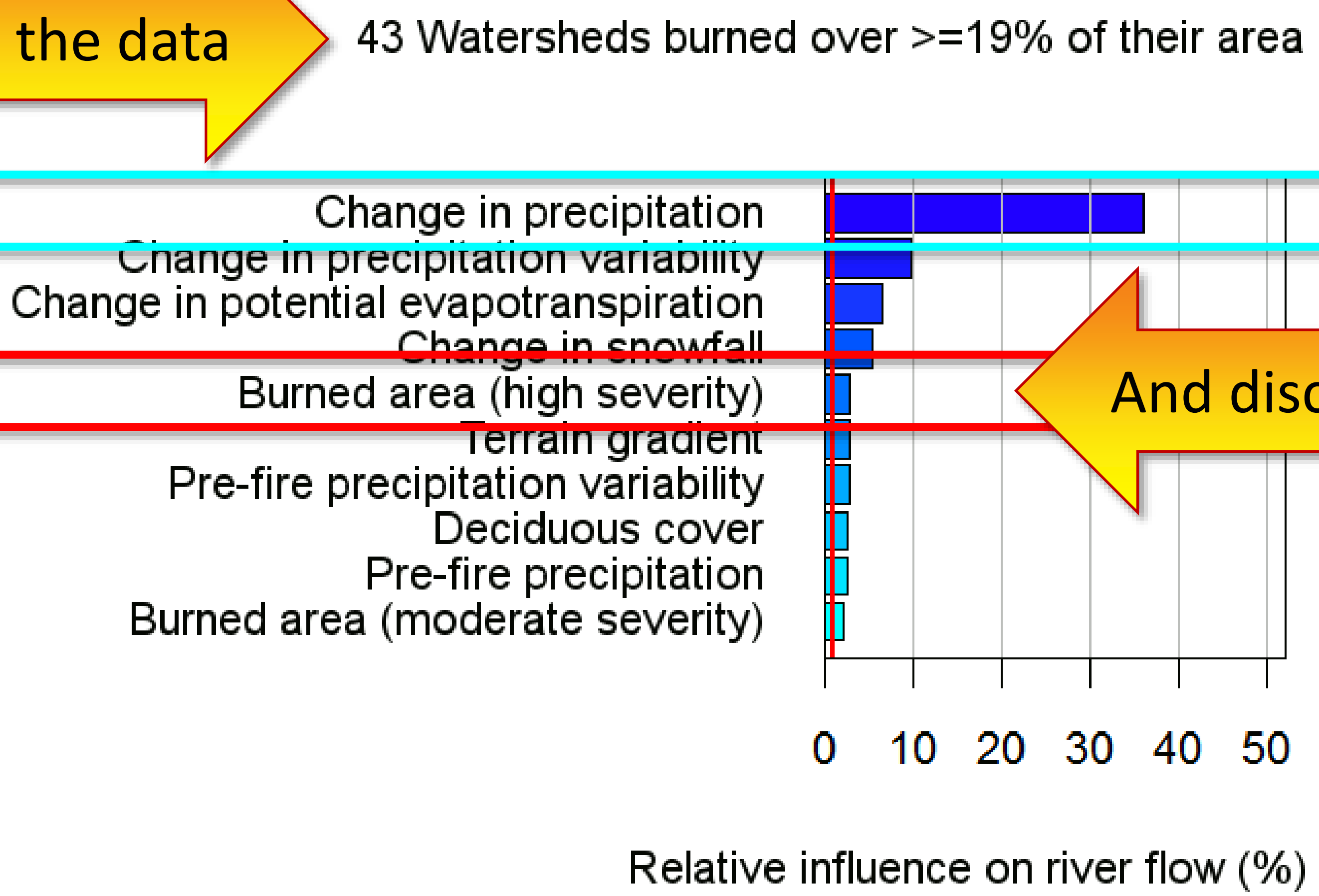


Now that we know the key variables + thresholds…

Key variables + thresholds for impact on river flows

…we can subset the data

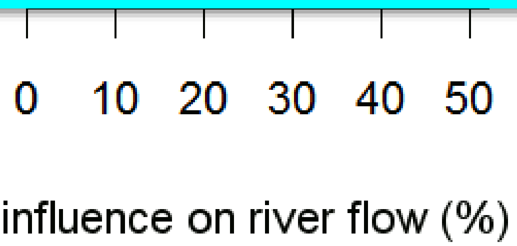
And discover new thresholds



Key variables + thresholds for impact on river flows

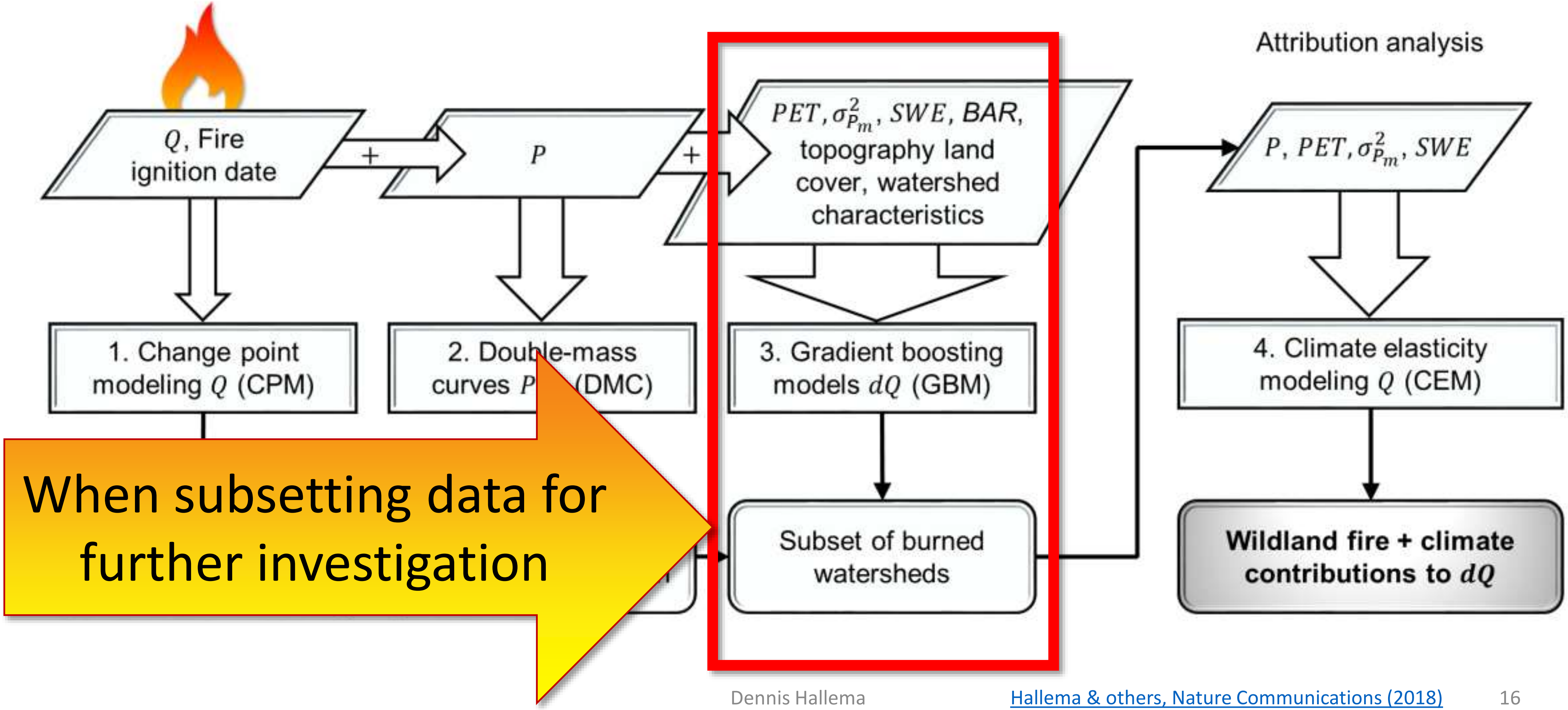
Again, why machine learning is useful here:

1. Identify influential variables we don't (yet) understand
2. Detect environmental thresholds
3. Extract maximum information from data
4. Extremely useful for formulating/refining hypotheses



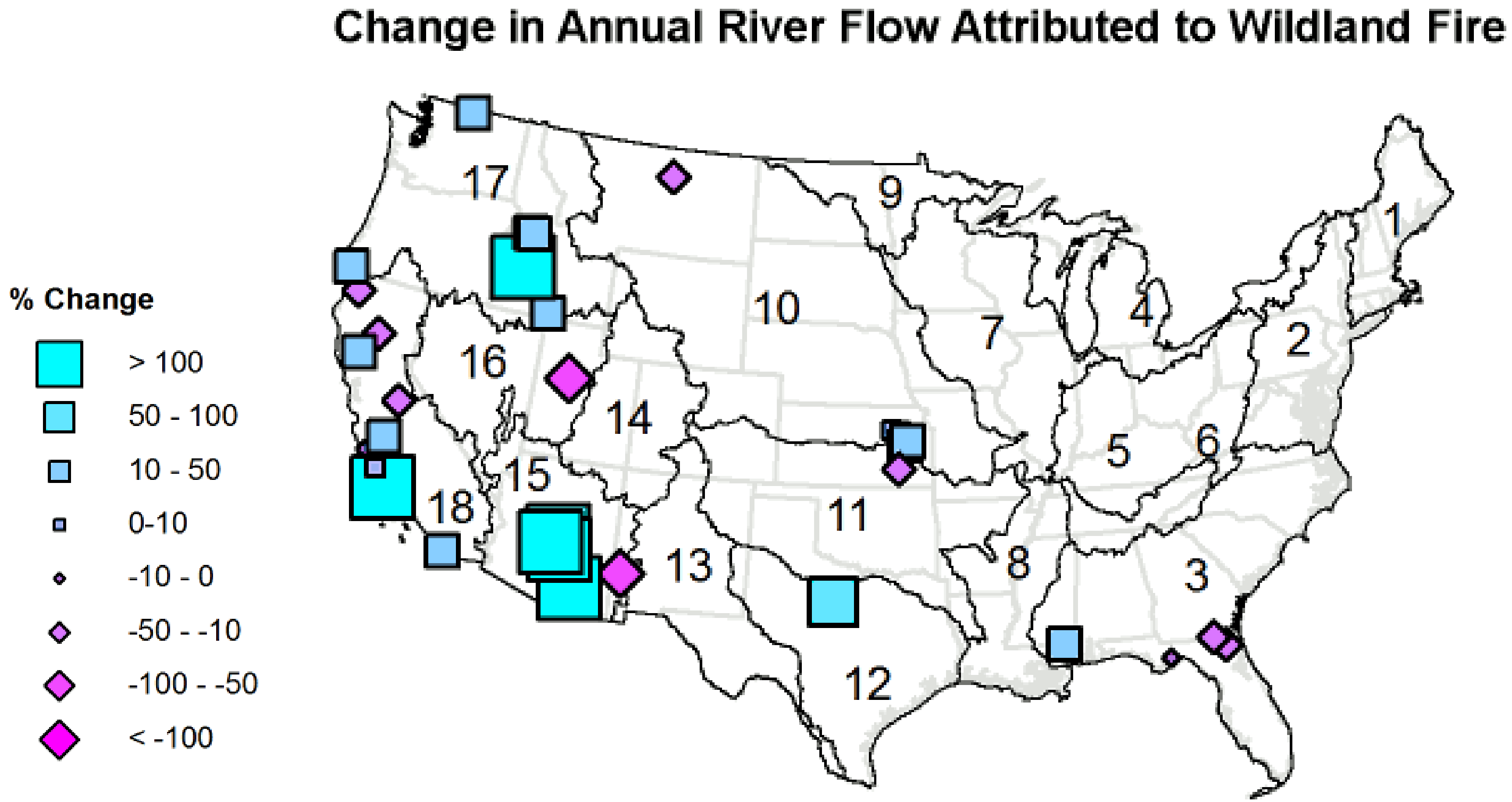
[Hallema & others, Nature Communications (2018)]

Where machine learning fits in complex work flows



Hallema & others, Nature Communications (2018)

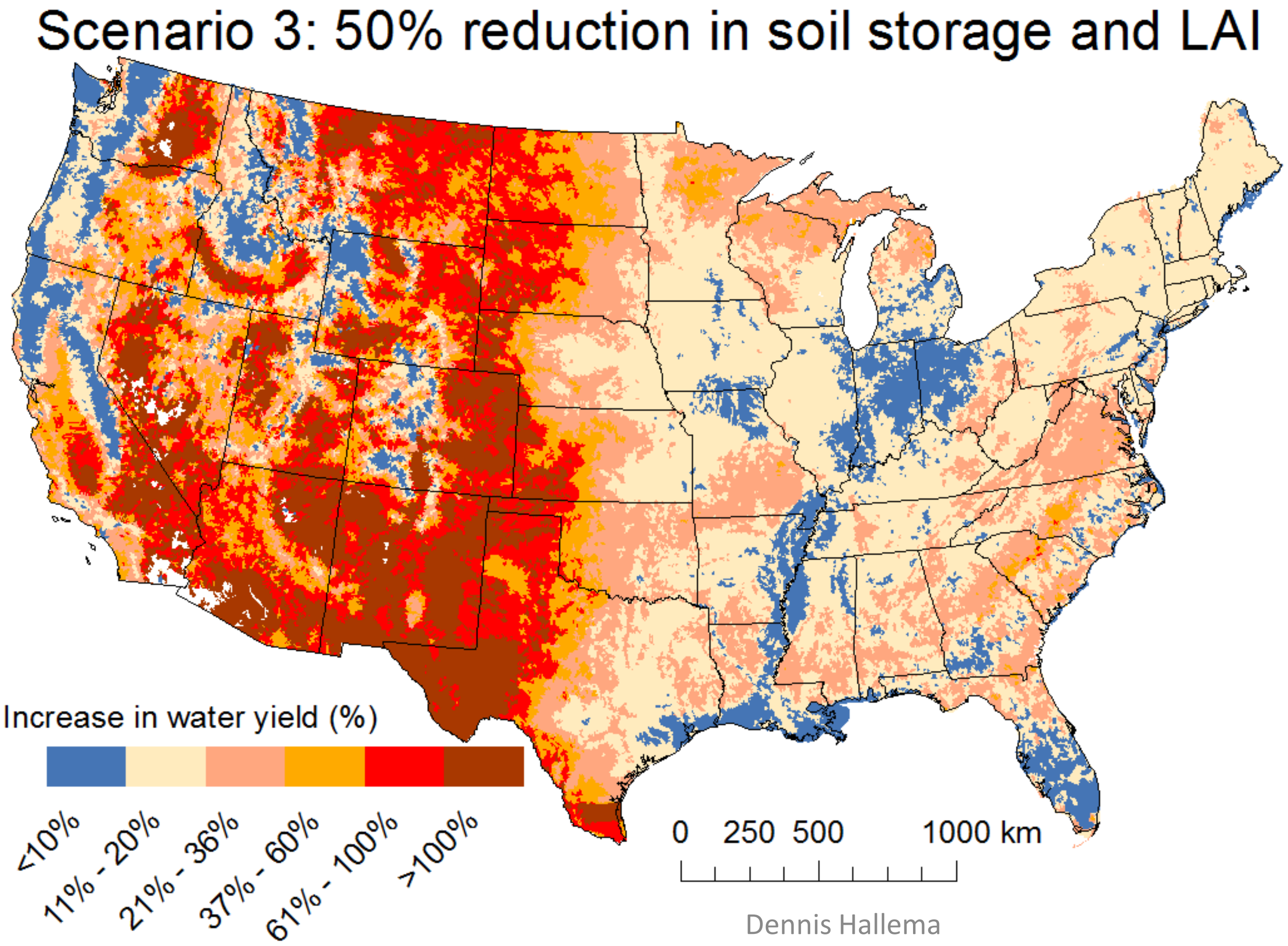
Use influential variables to model large scale disturbance impacts on water yields



- Observed postfire river flow increased by +43.3% on average (median +14.0%)
- But because precipitation generally declined, true wildfire impact was +57.5% (median +14.6%).

[Hallema & others, Nature Communications (2018)](#)

Use influential variables to model large scale disturbance impacts on water yields



- Full coverage in WaSSI
- 88,000 subwatersheds
- Potential impact of large wildfires on water yields
- Reduced soil storage increases runoff

Highlights

- Combine data analytics with hydrological models to estimate true disturbance impact
- Integrate future climate models to assess potential impacts
- Powerful tool for data-driven water risk management

Acknowledgement

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- Chinese Meteorological Society
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