The Prediction Lab

Predicting Harmful
Algal Blooms

The Problem

Toxins produced by Harmful Algal Blooms (HABs) are a health hazard to humans and animals, and incur a large financial burden to water utilities and other water quality stakeholders

Algae like cyanobacteria can create toxins

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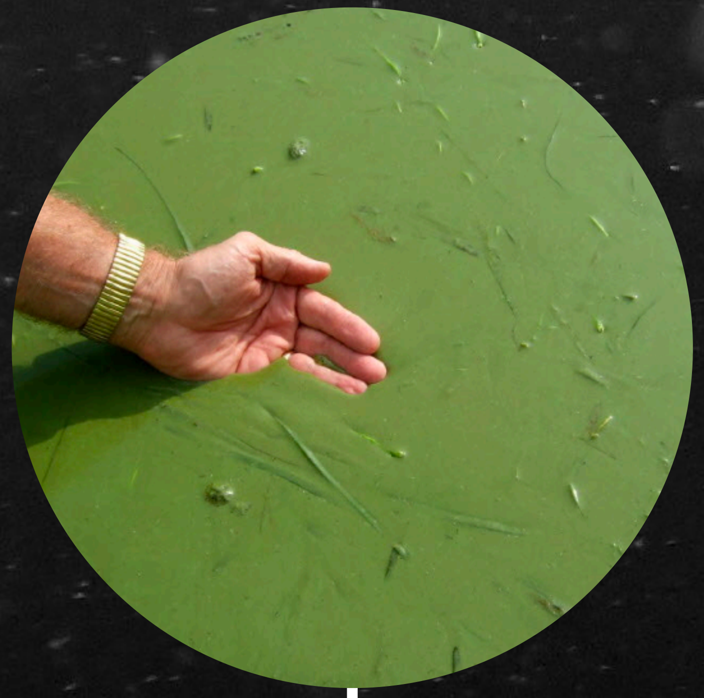

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Lots of data: water samples, CYAN, qPCR…etc

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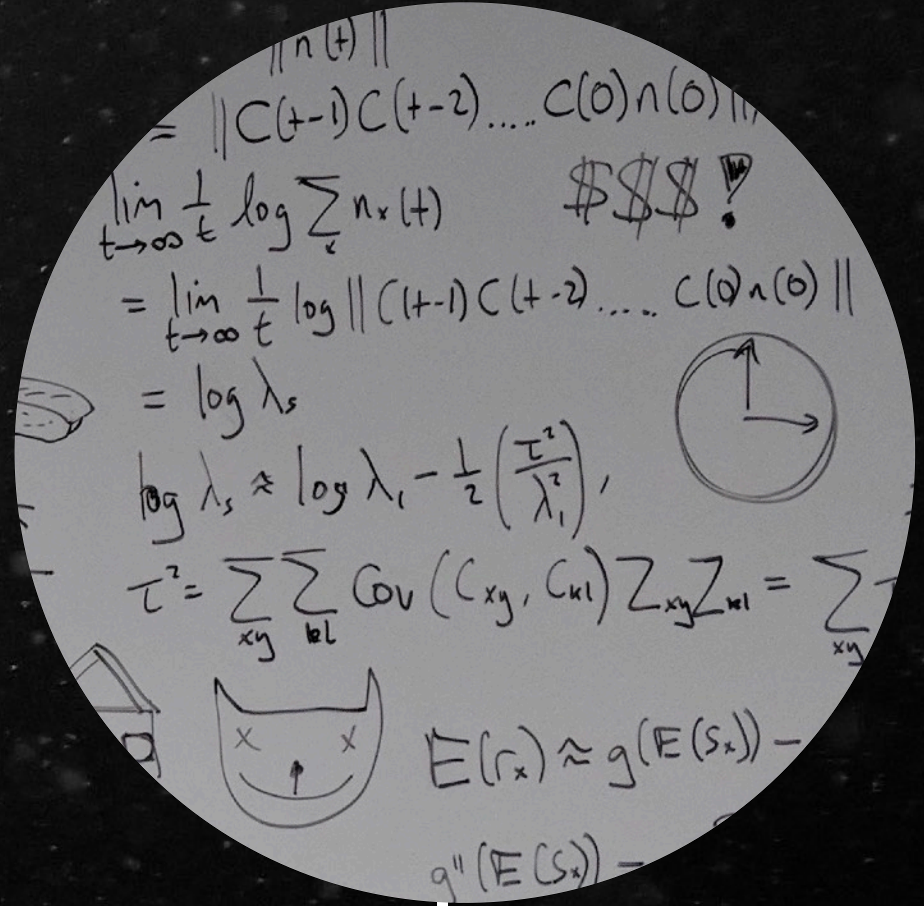

Then we use math and algorithms, but…

What's The Real Problem?

We collect a lot of data, we develop a lot of models… but how do we make the data we have actionable?

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LG SONIC
Leading in ultrasonic algae control

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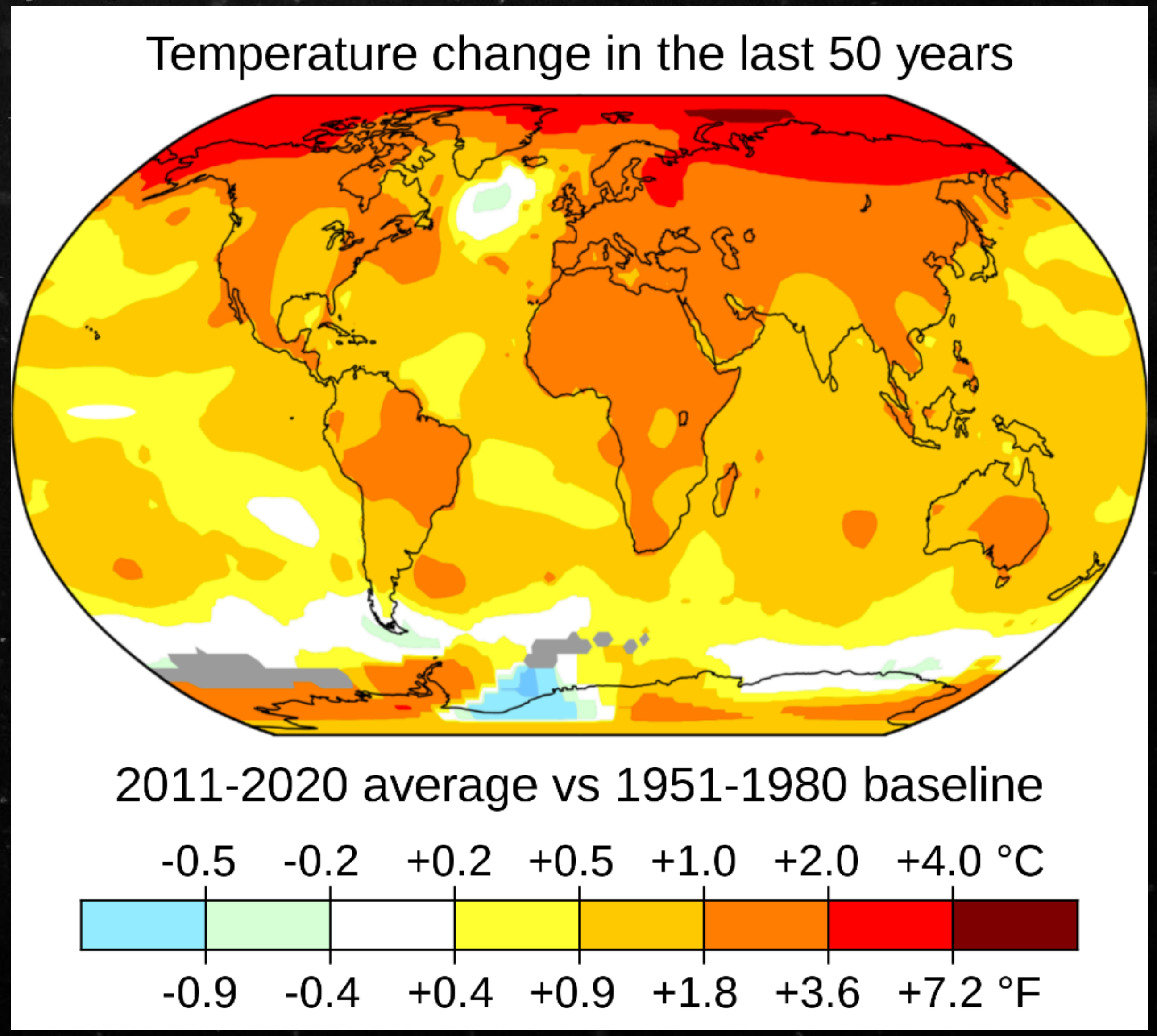

Timescales (weeks, months, years, decades)

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Solutions

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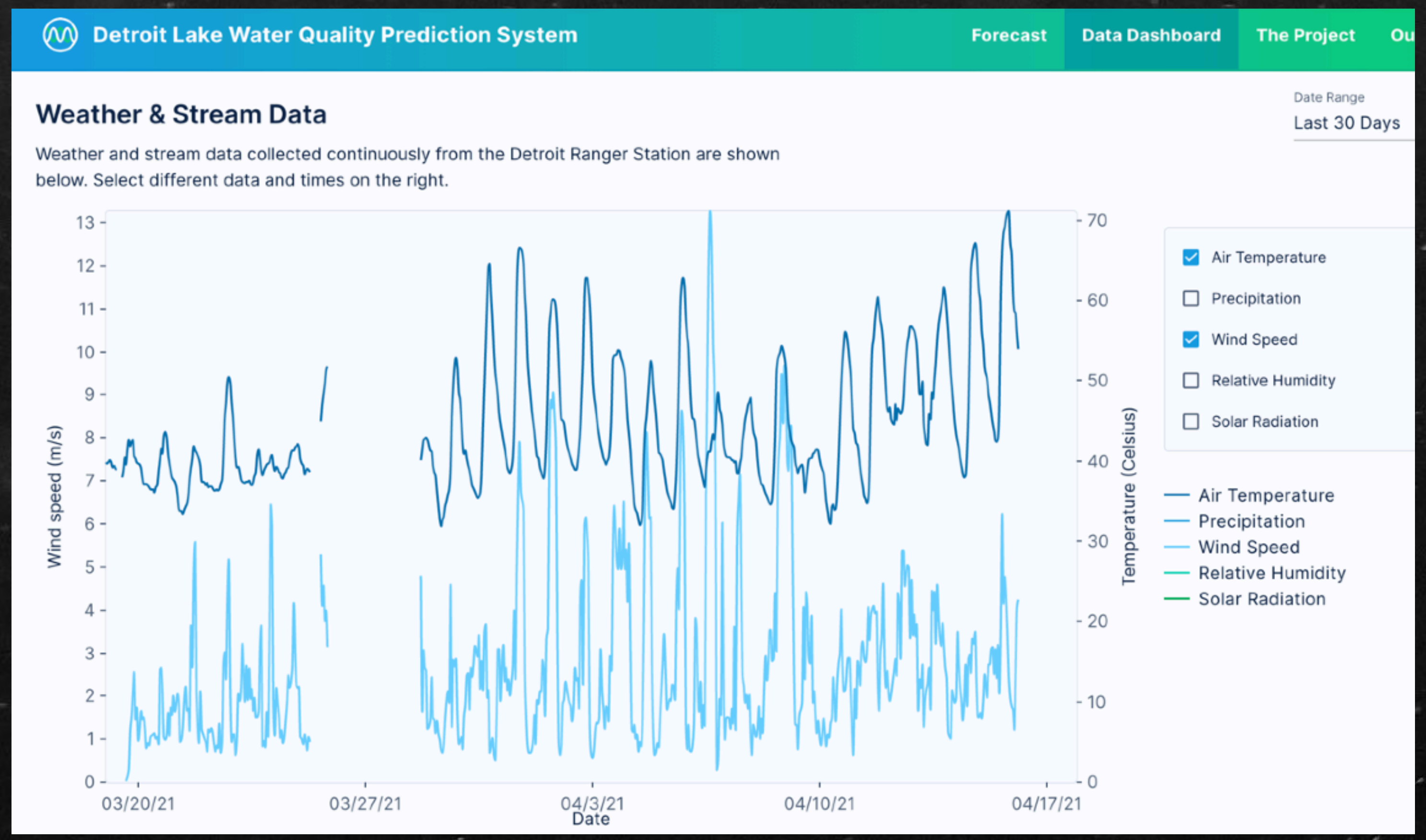

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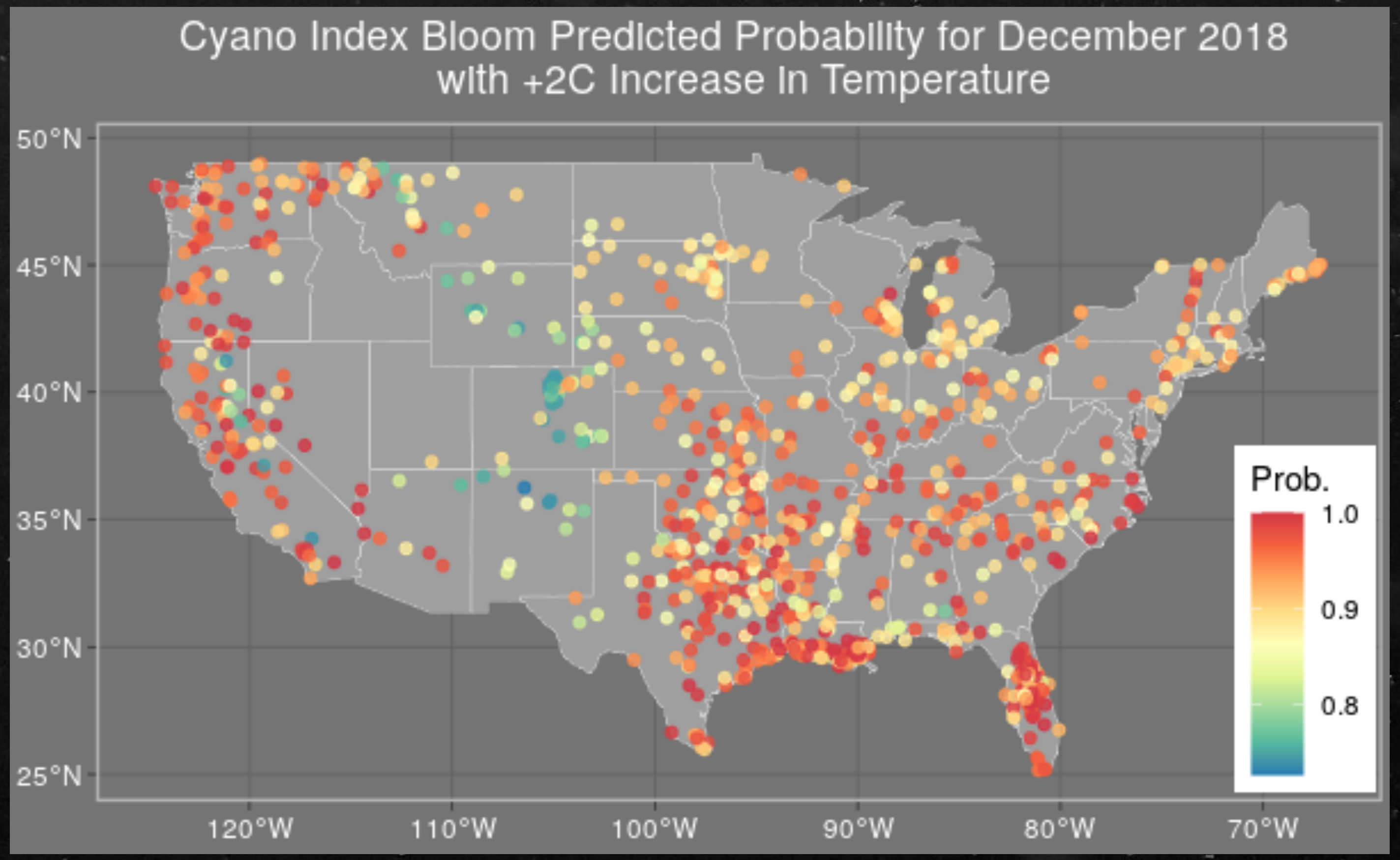

Seasonal and Climate sensitivity (CYAN)

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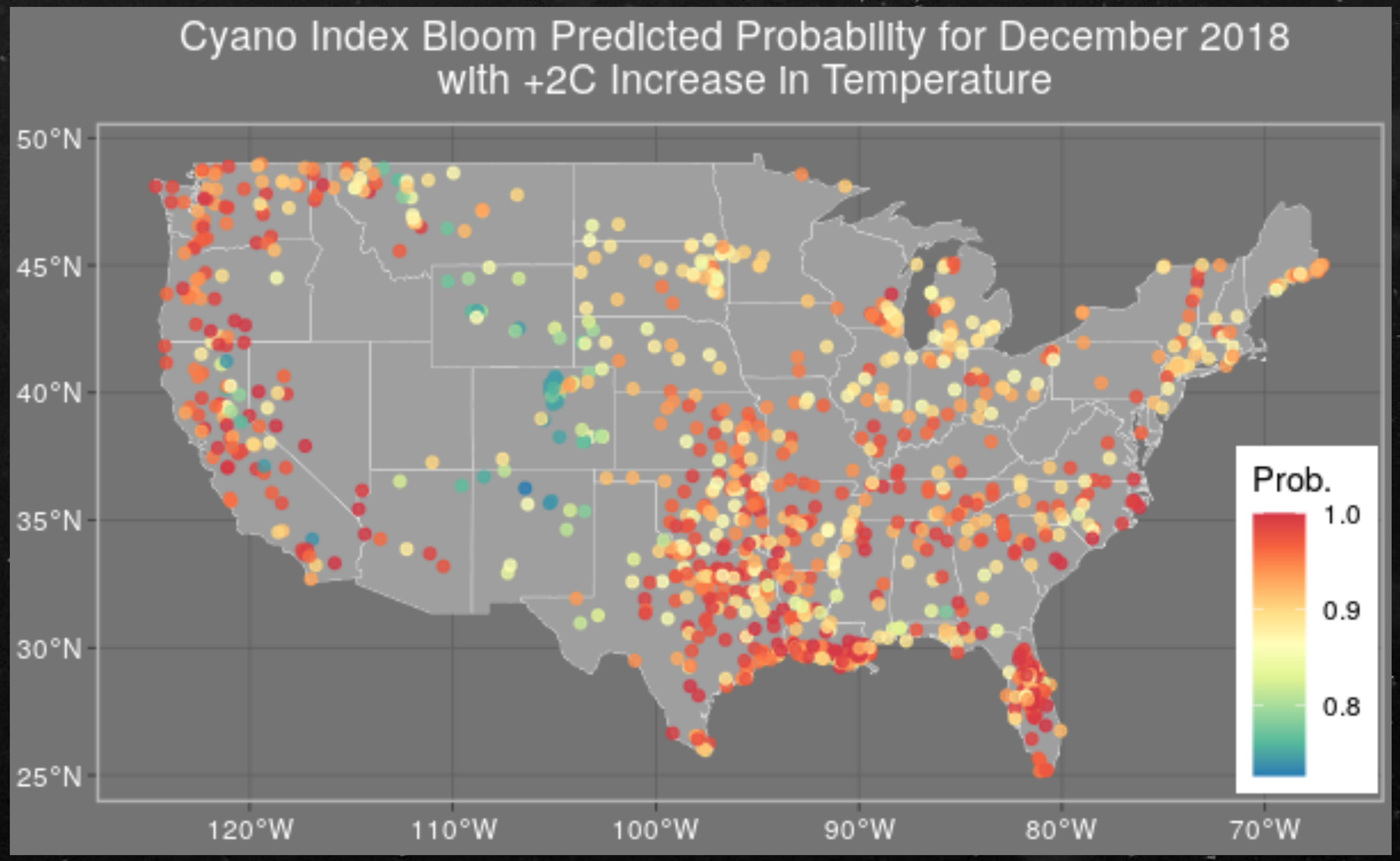

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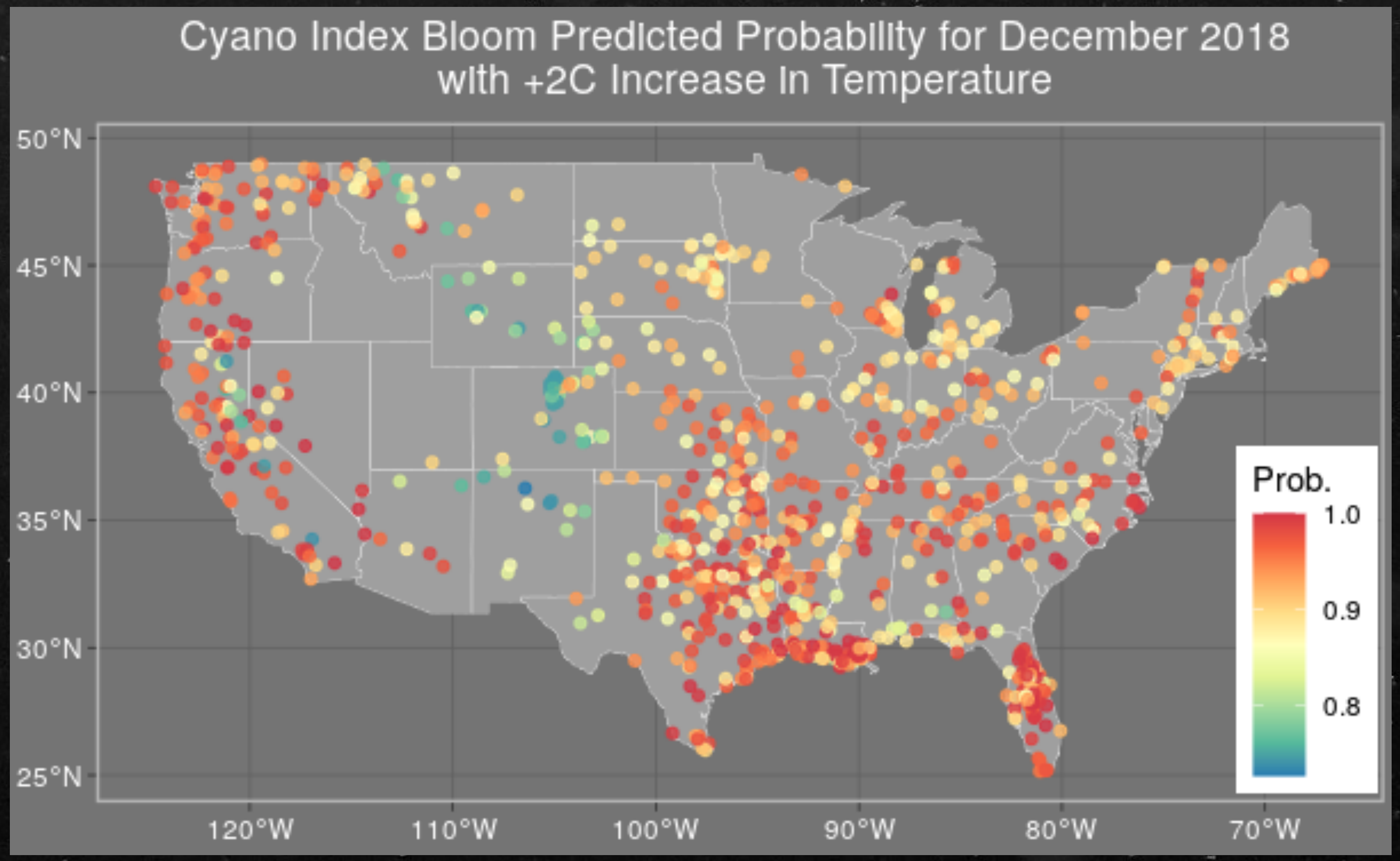

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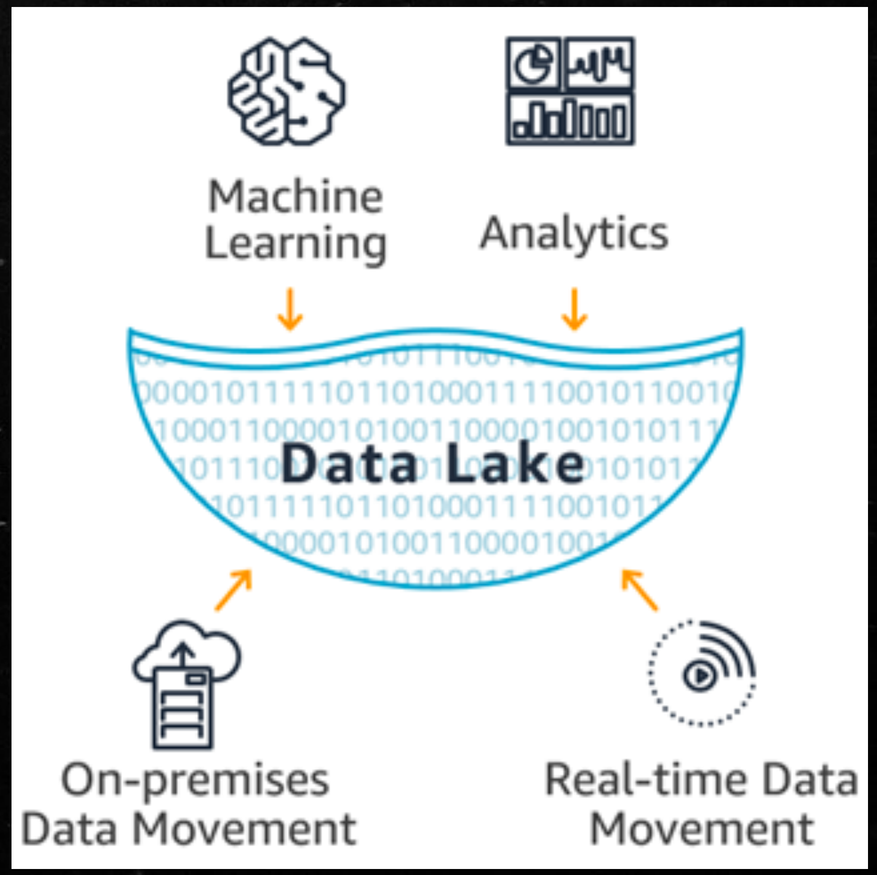

Cloud Infrastructure

Operational Forecasts

Detroit Lake: Bayesian Model Averaging framework applied to the in situ data collected from the lake to provide daily 1-week and 2-week forecasts of cyanobacteria and toxin concentrations

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Bayesian model averaging for harmful algal bloom prediction

Grant Hamilton,[1,4] Ross McVinish,[2] and Kerrie Mengersen[3]

[1]*School of Natural Resource Sciences, Queensland University of Technology, GPO Box 2434, Brisbane, Queensland 4001 Australia*
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We expanded the Bayesian Model Averaging approach to include neural nets in addition to linear and non-linear functions

Based on empirical samples

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Operational Dashboard (Detroit Lake)

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In addition to operational forecasts (1-2 week timescales), we have been developing seasonal (6 month) and decadal forecasts (e.g. 2030, 2050, 2100).

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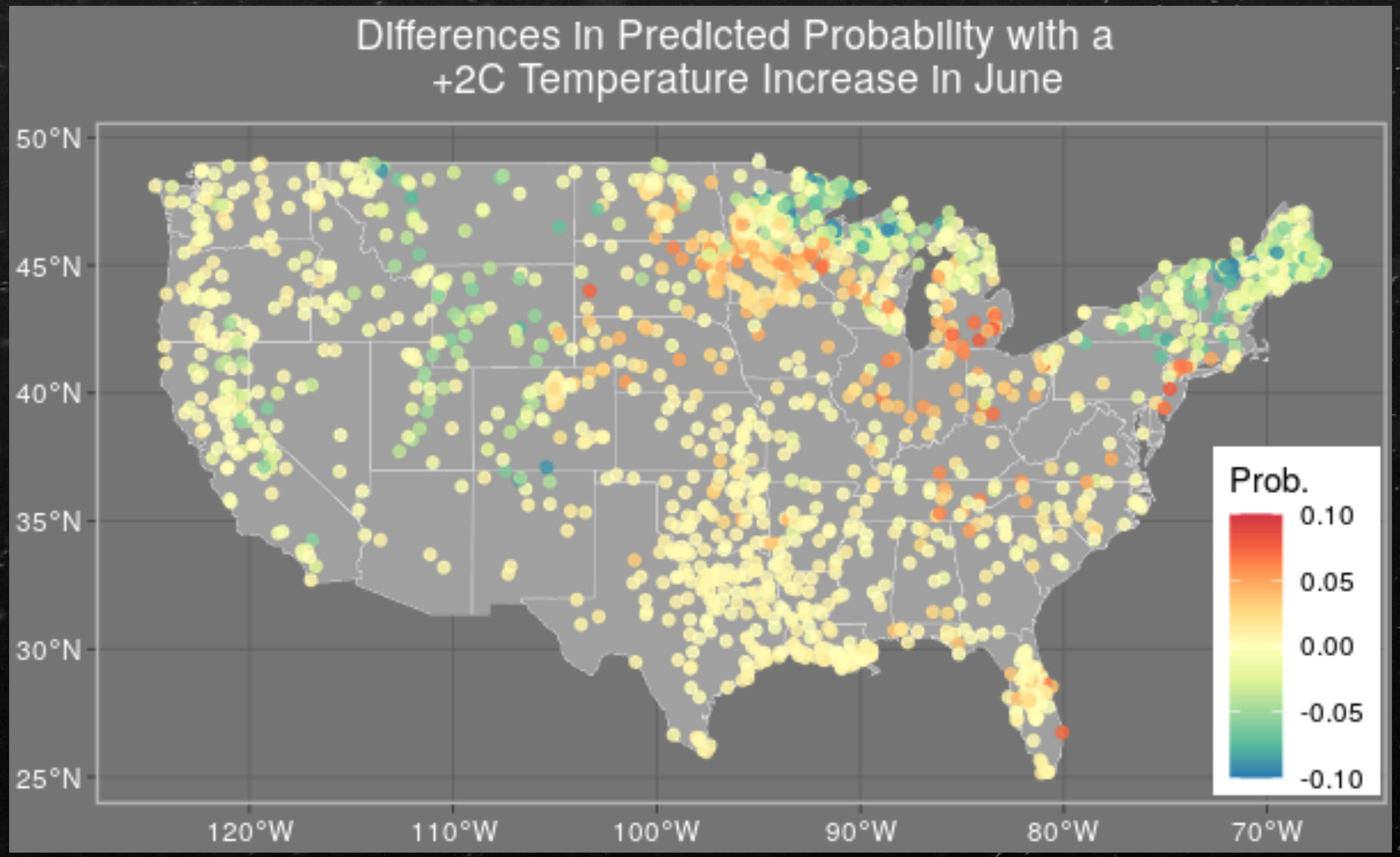

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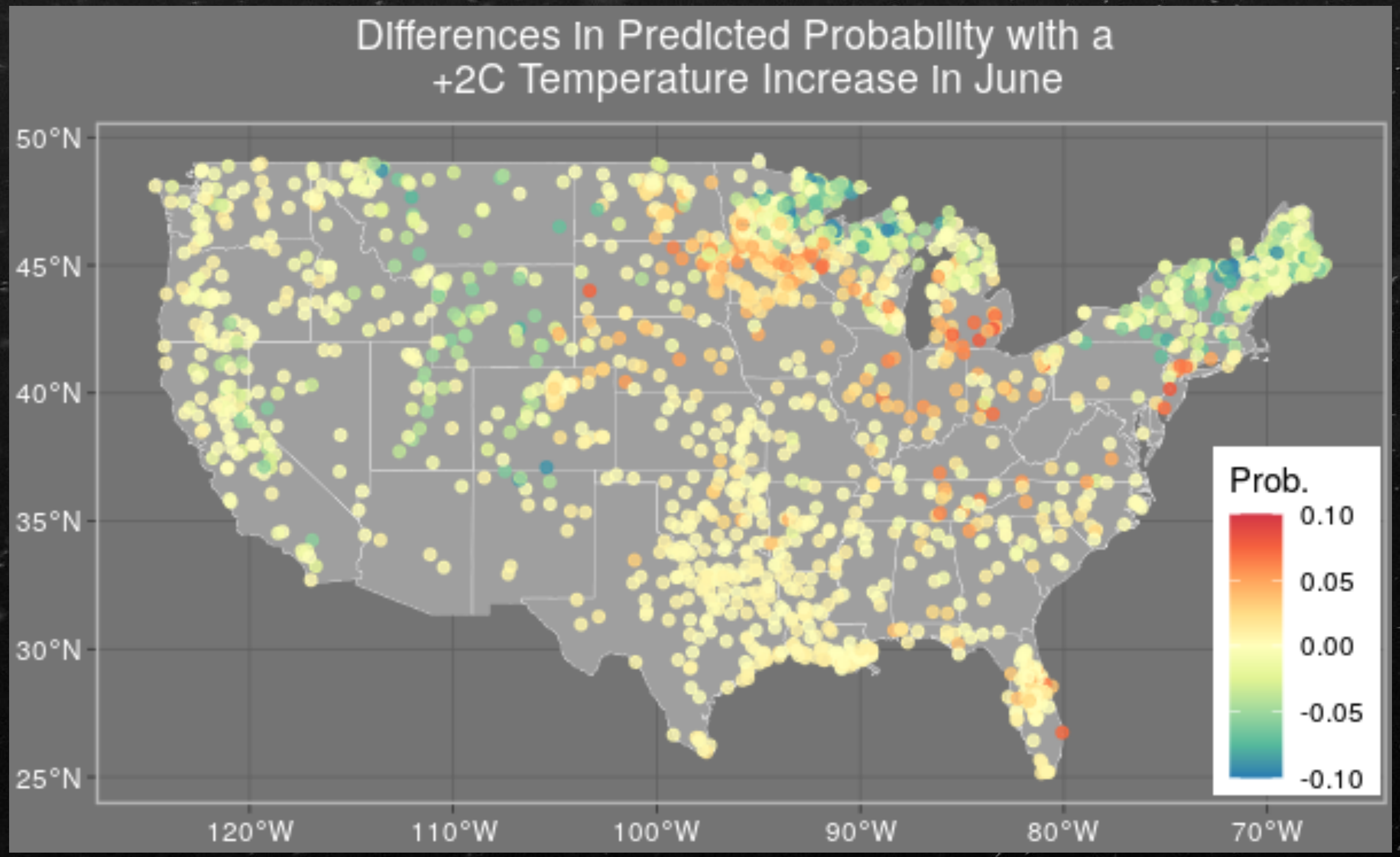

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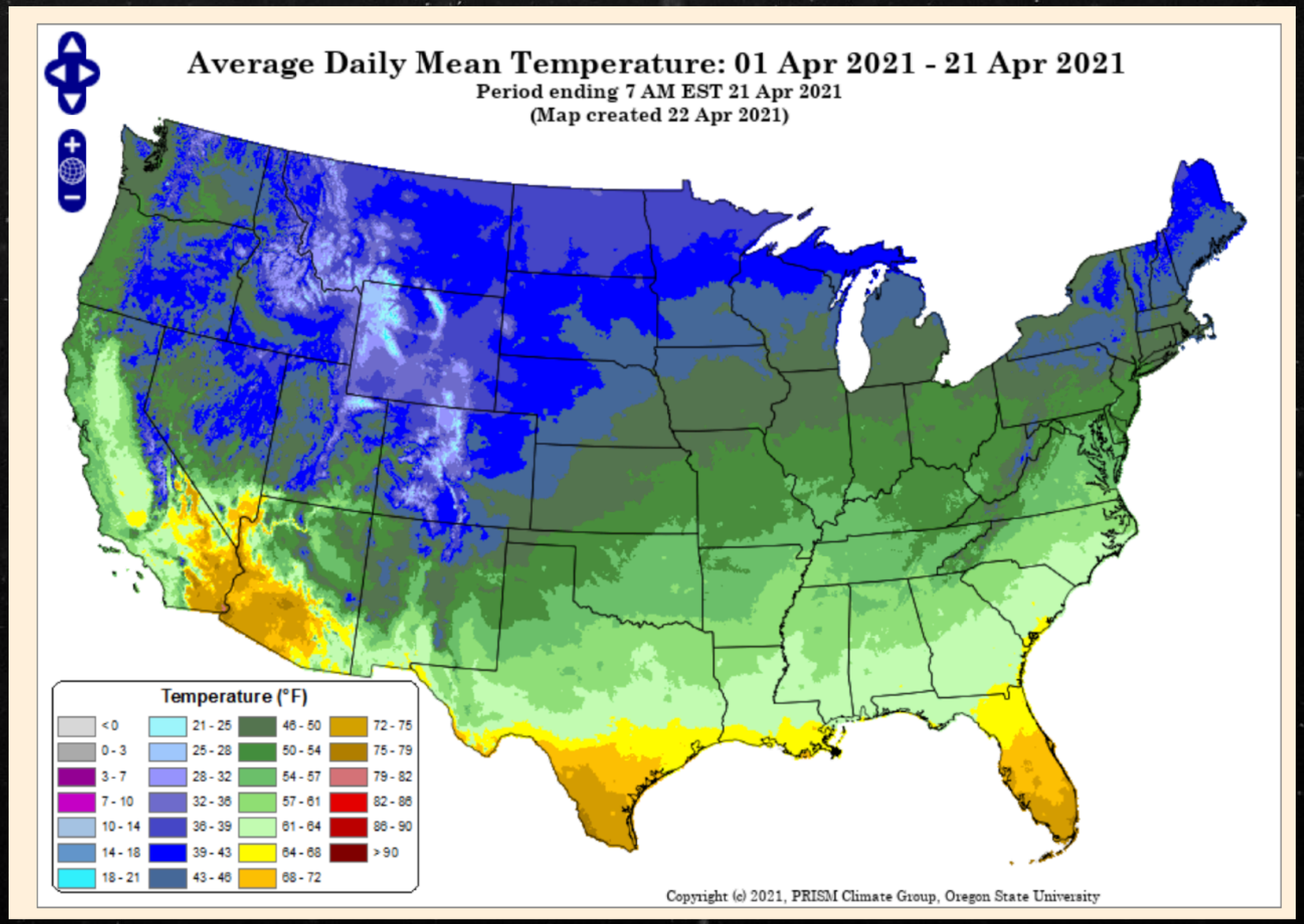

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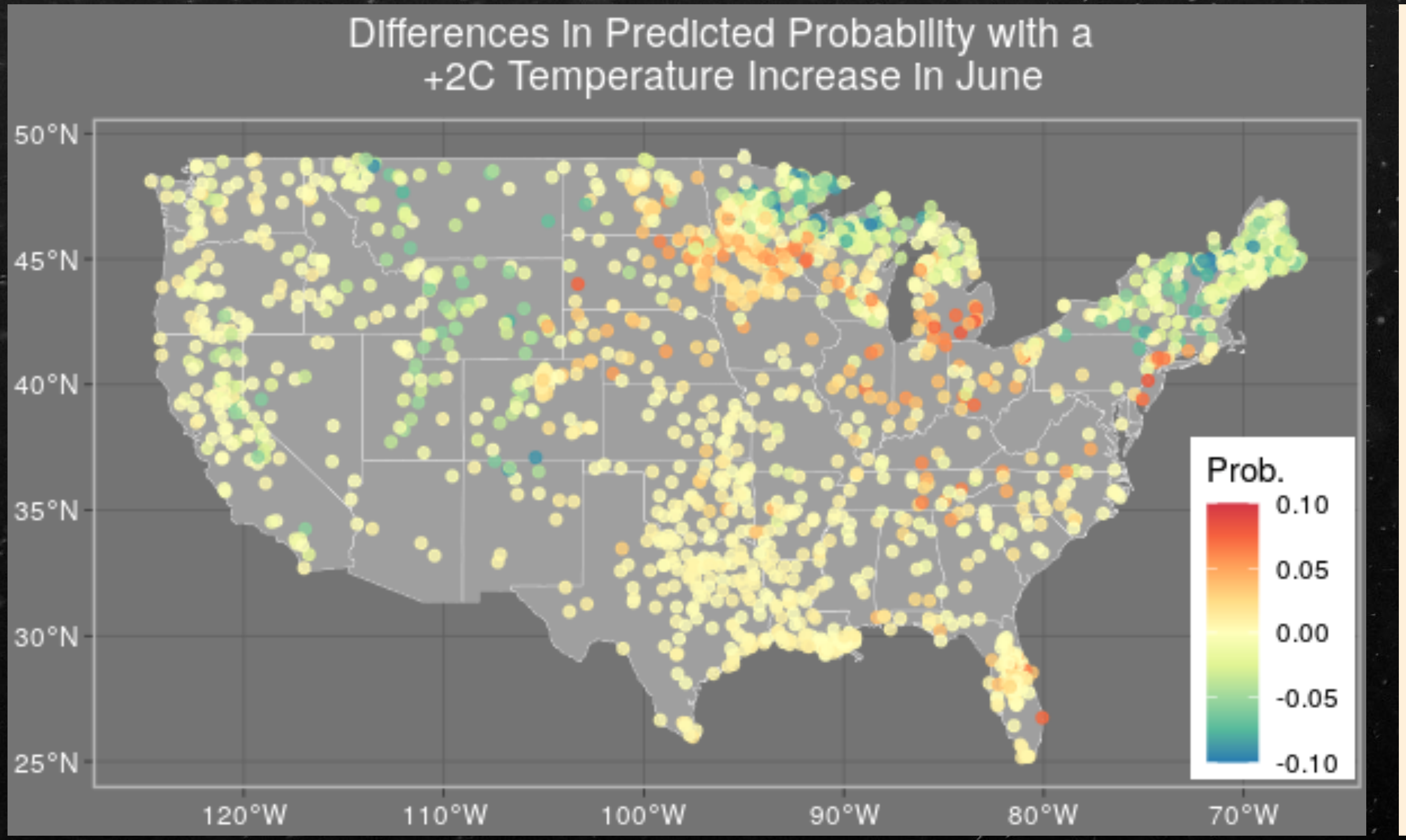

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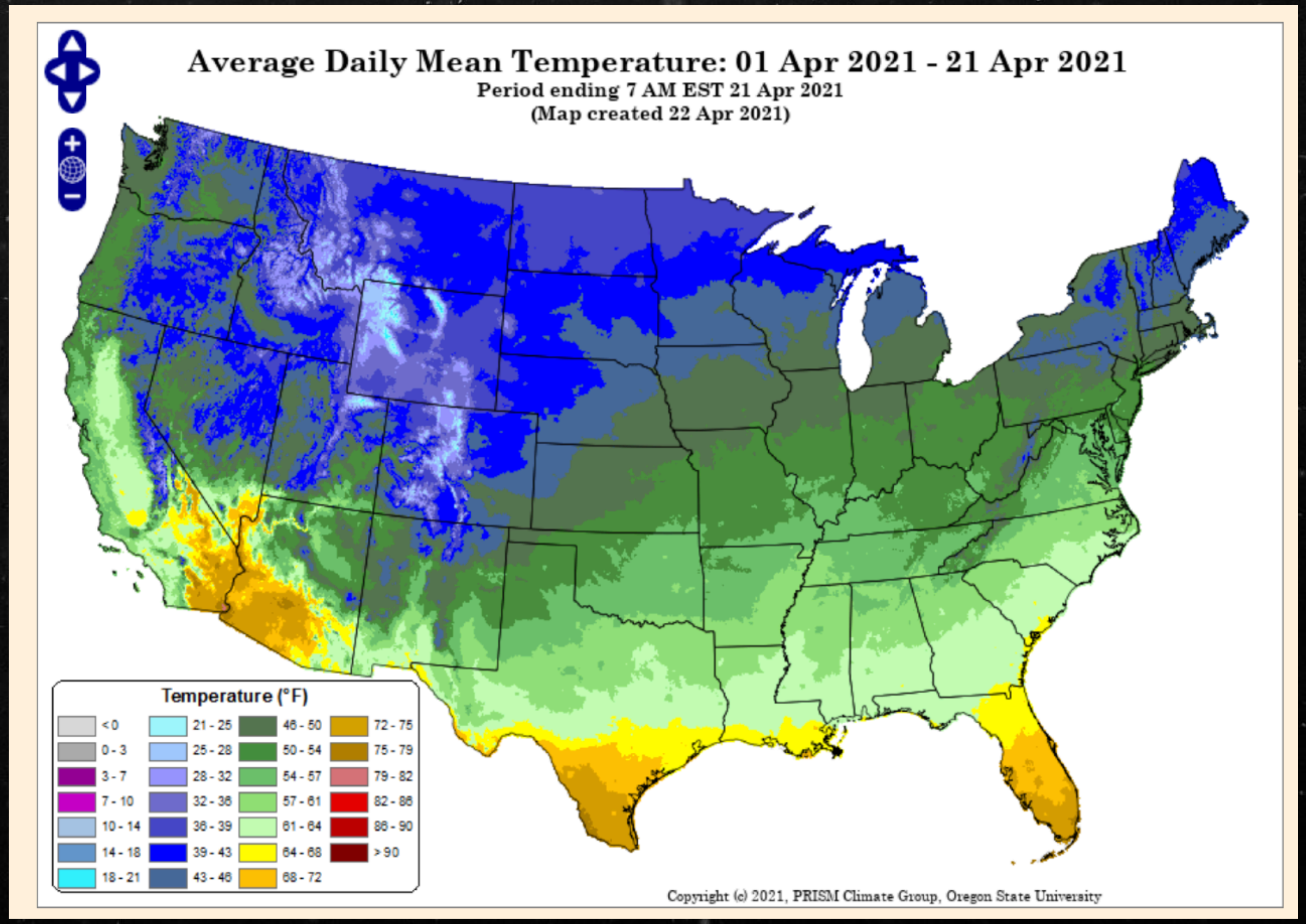

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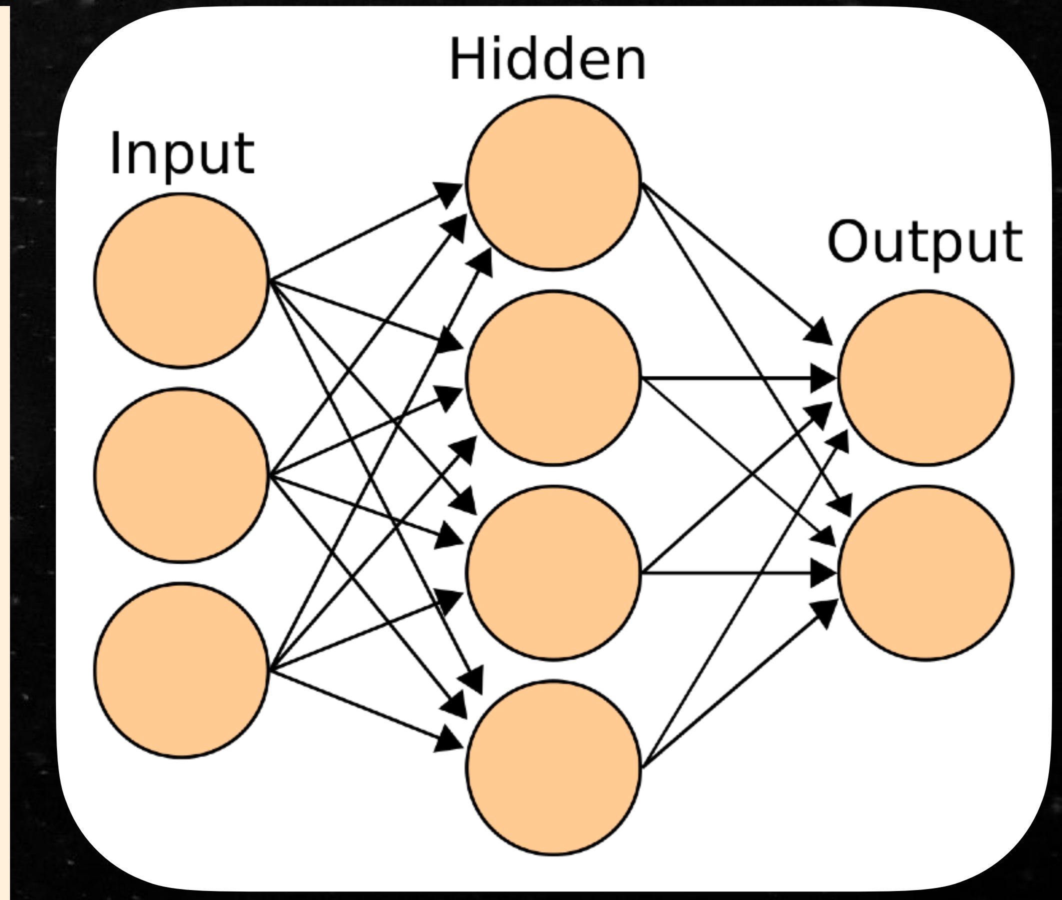

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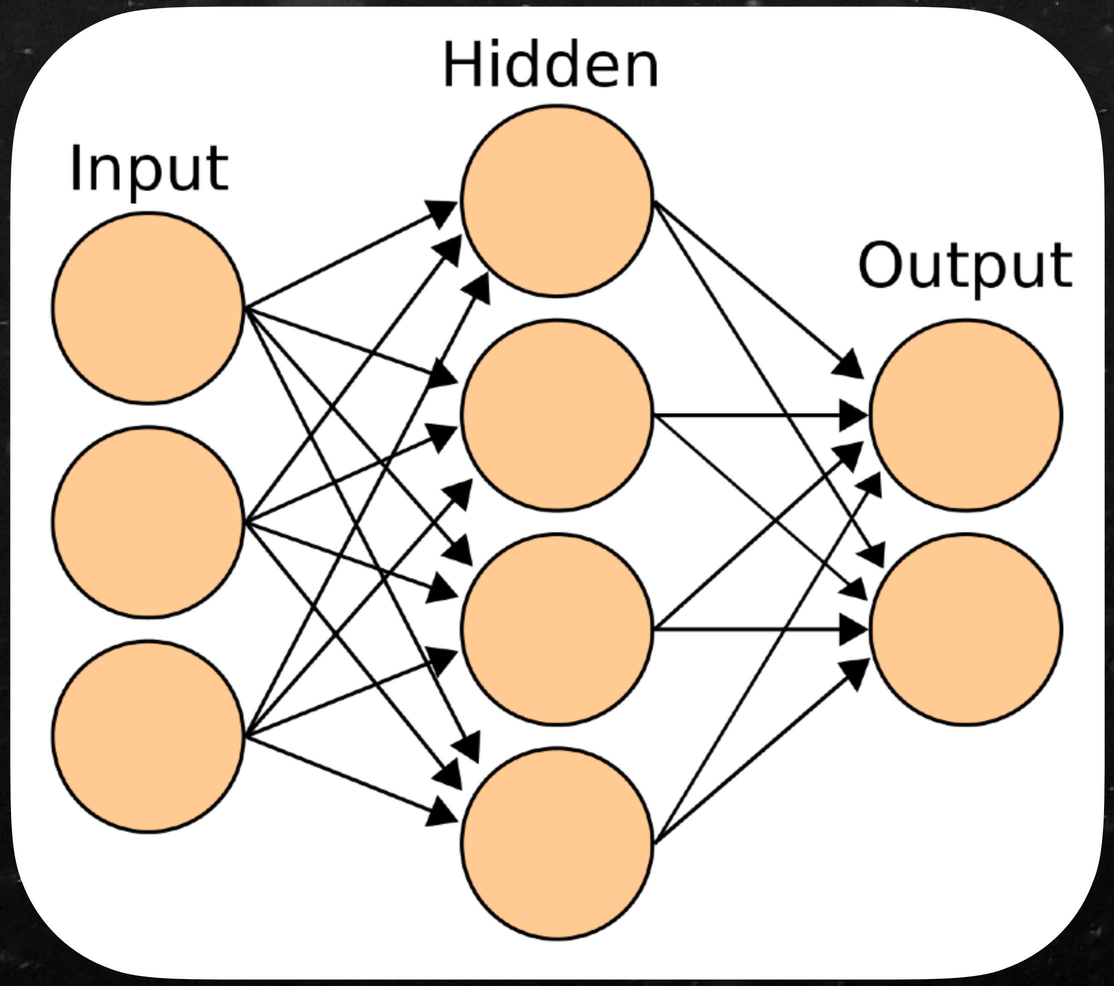

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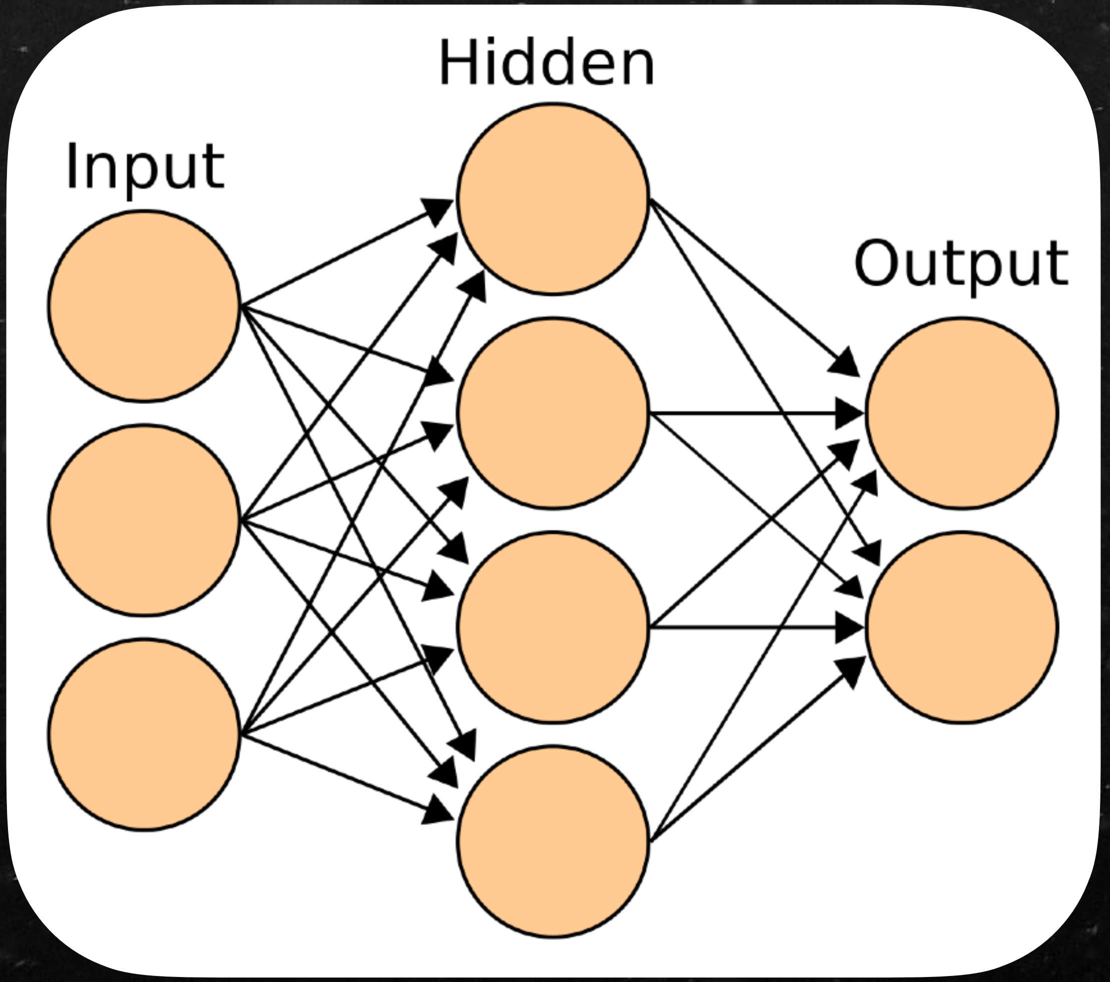

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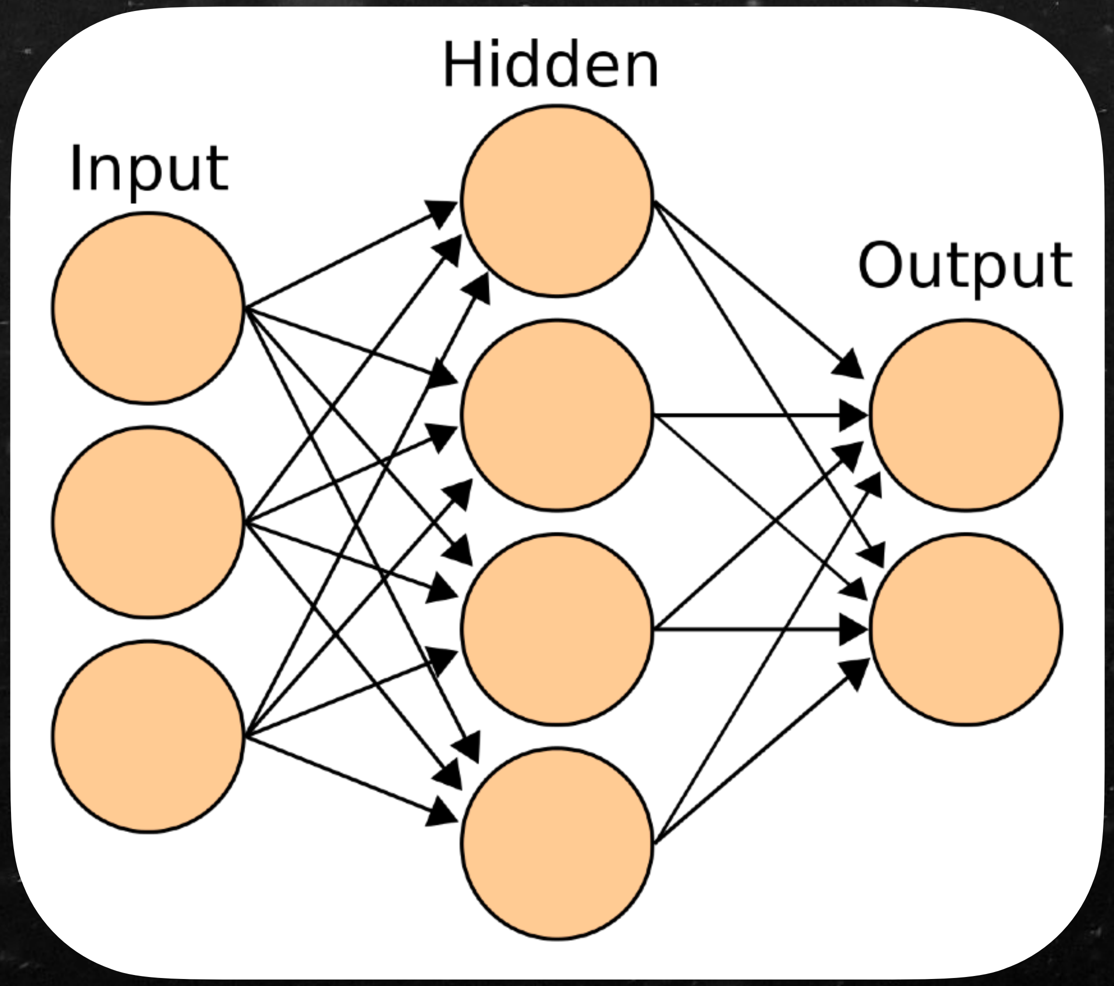

Machine learning modeling

Long-range weather forecasts

CMIP6 Climate Projections

Next Gen: Hybrid Machine Learning

Purely data driven machine learning (e.g. our Bayesian Model Averaging, or Neural Nets, or Random Forests) do not explicitly respect the laws of physics or biology.

But, hybrid machine learning models do. Case study - this year!

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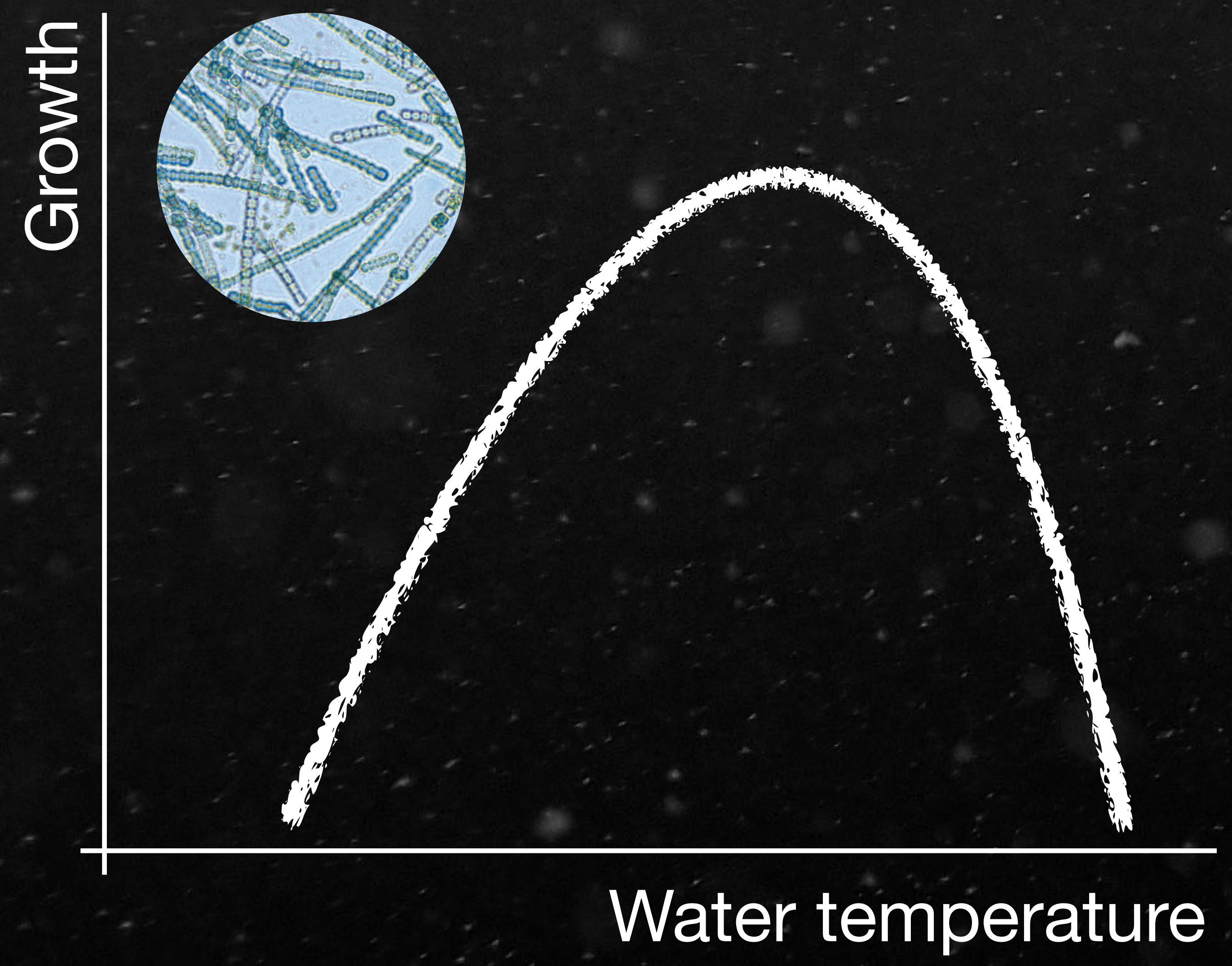

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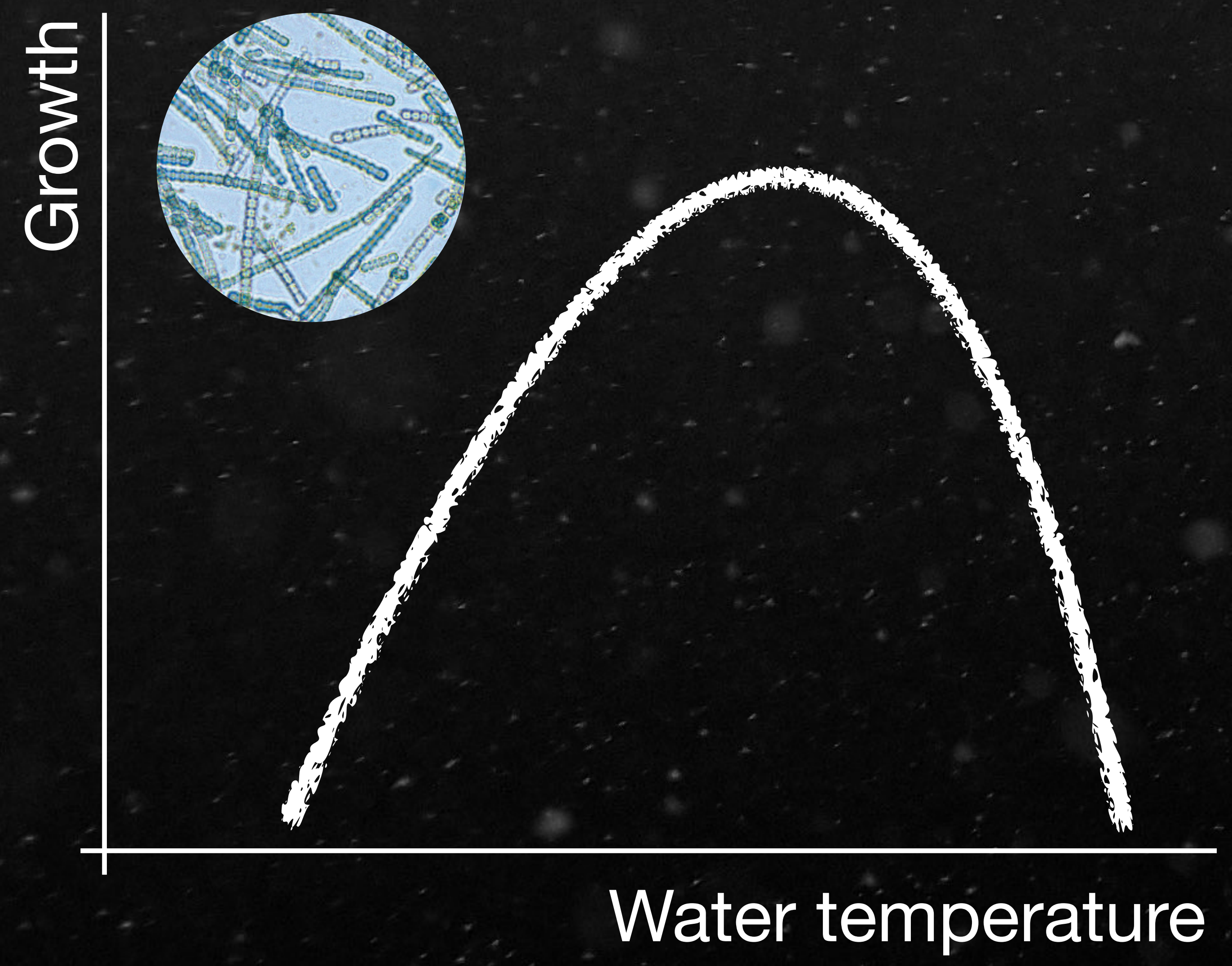

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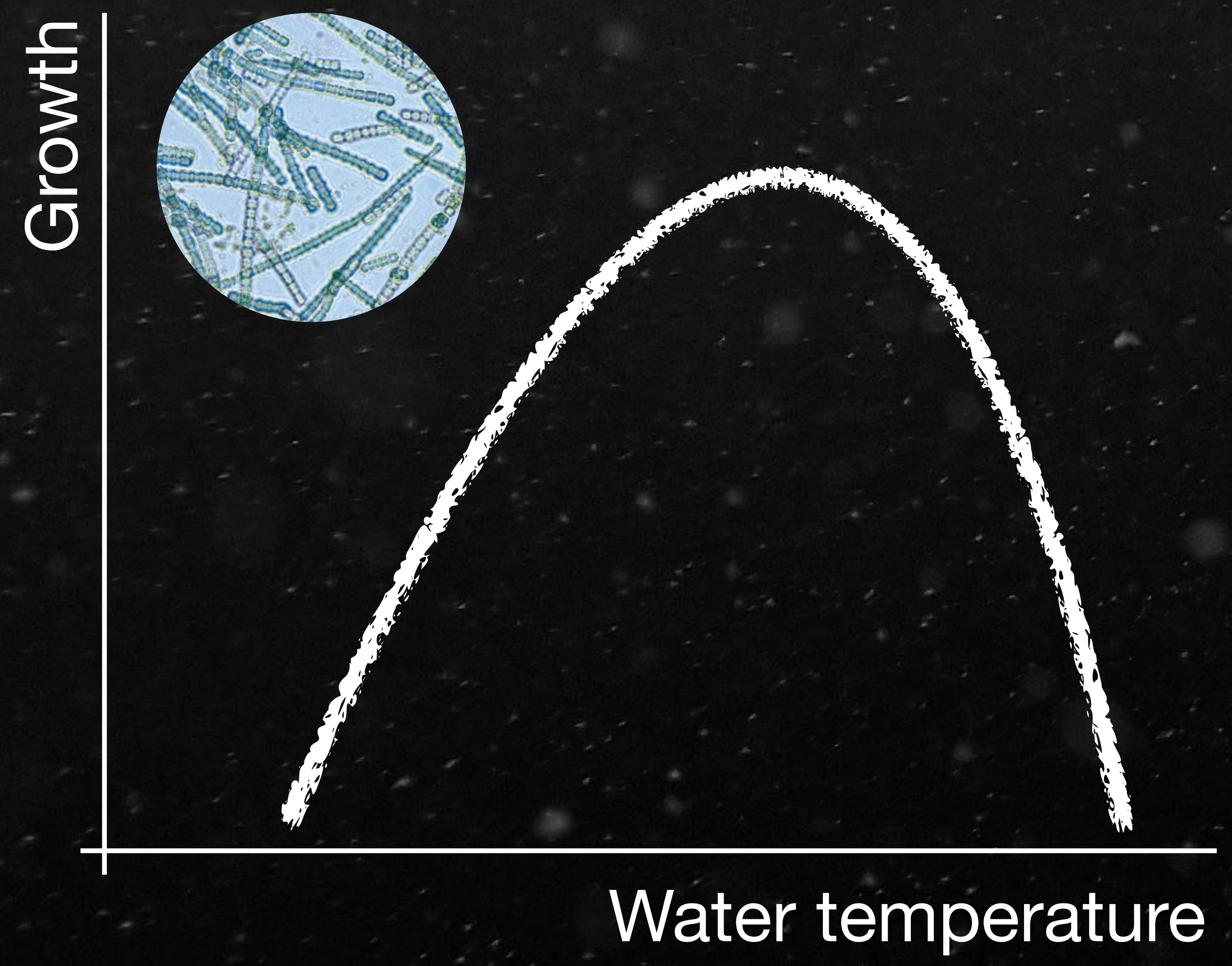

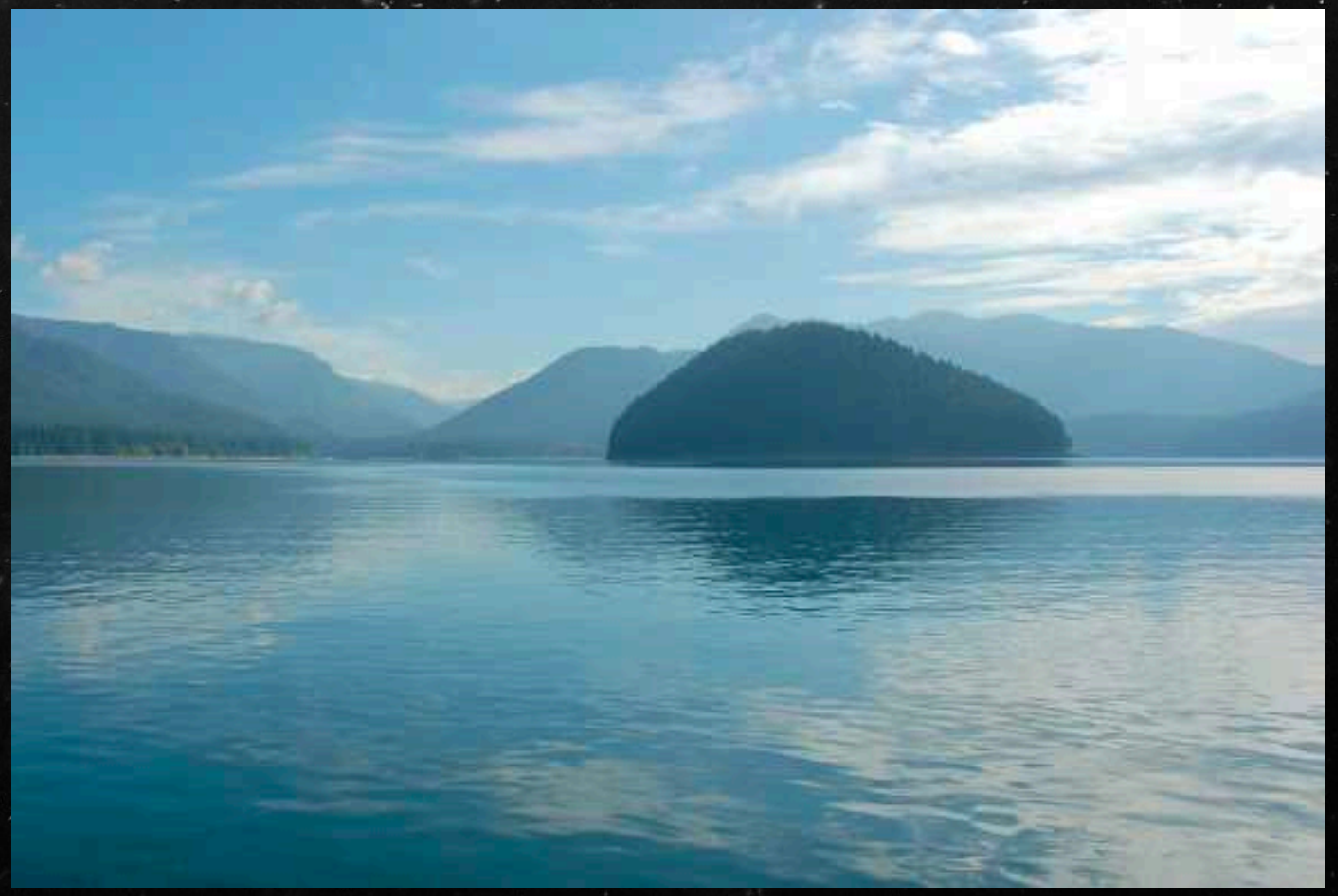

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Next Gen: Interpretable AI

Machine learning (e.g. neural nets) offer accurate predictions, but you don't know what's going on under the hood. Interpretable AI is a class of machine learning that people can understand

The Learning Boundary

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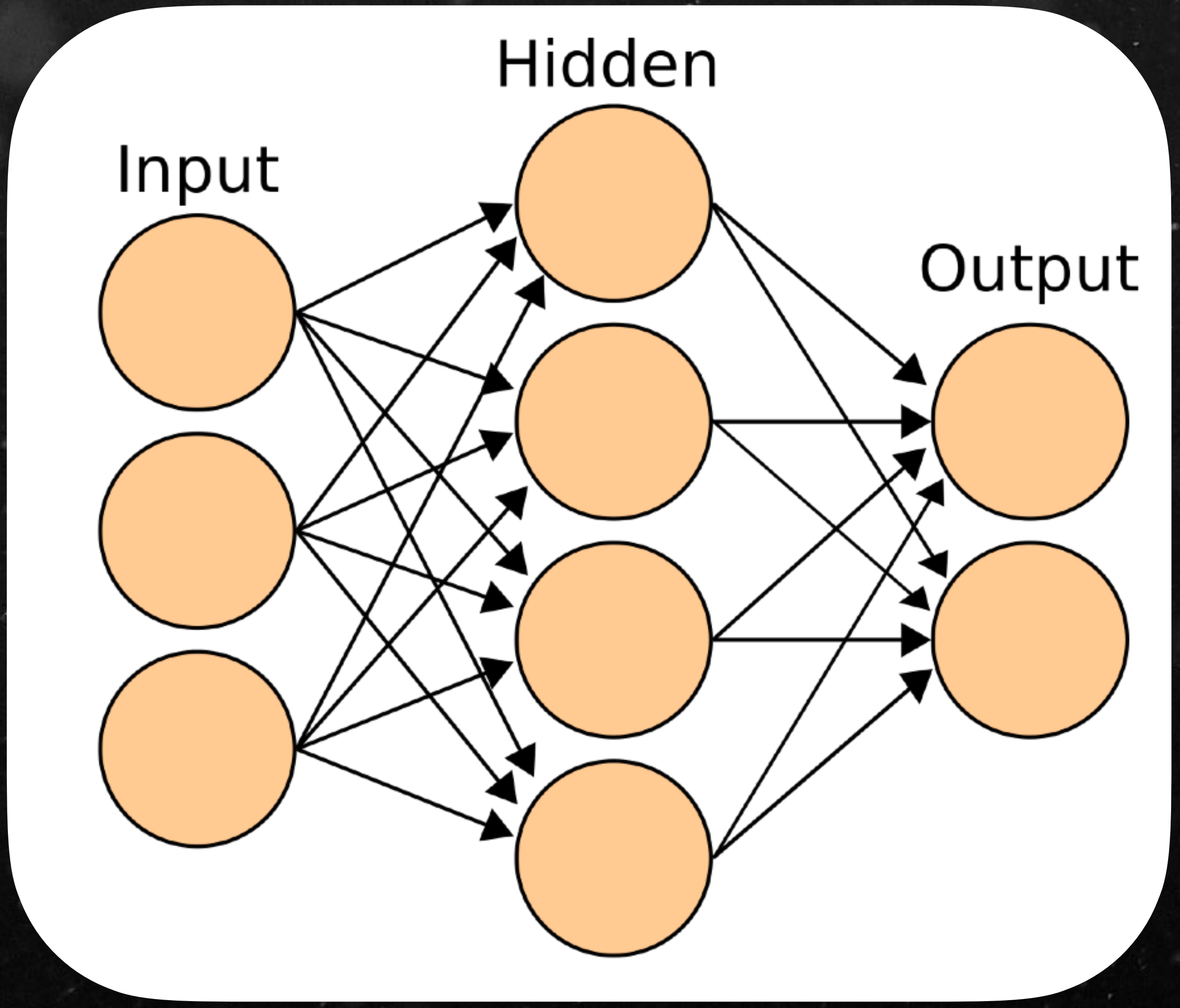
Black box neural network



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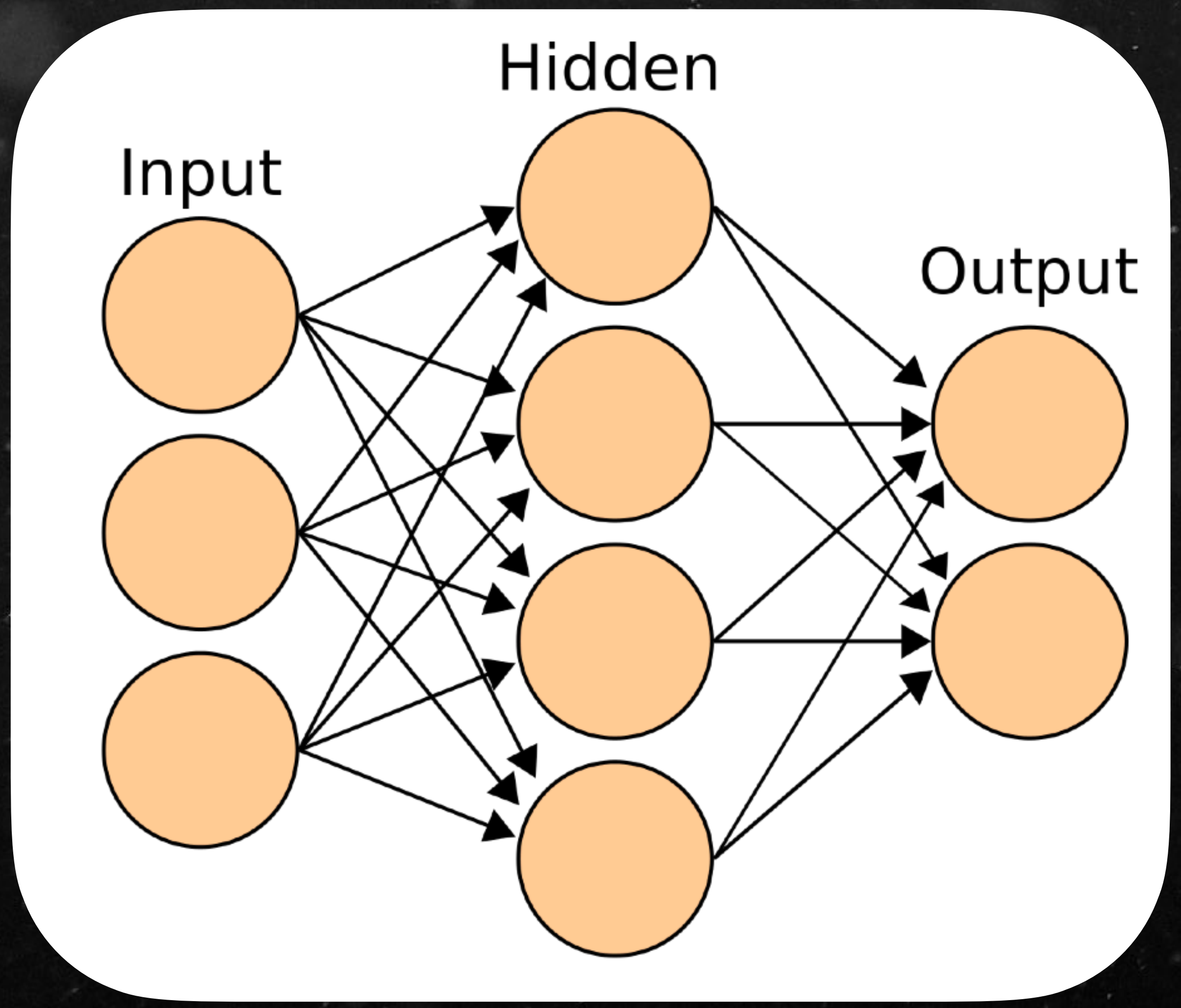
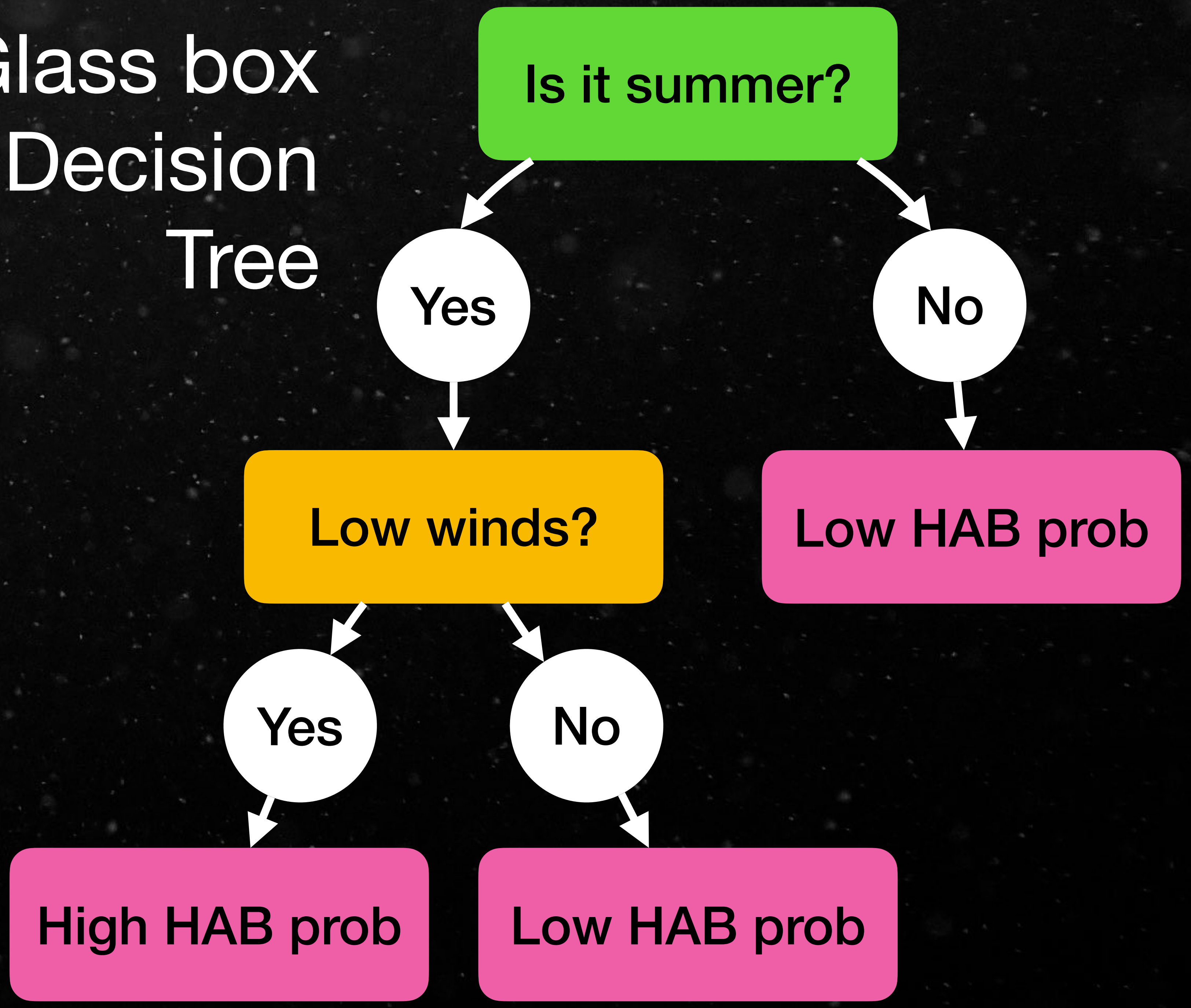


The Learning Boundary

Glass box Decision Tree



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Next Gen: Transfer Learning

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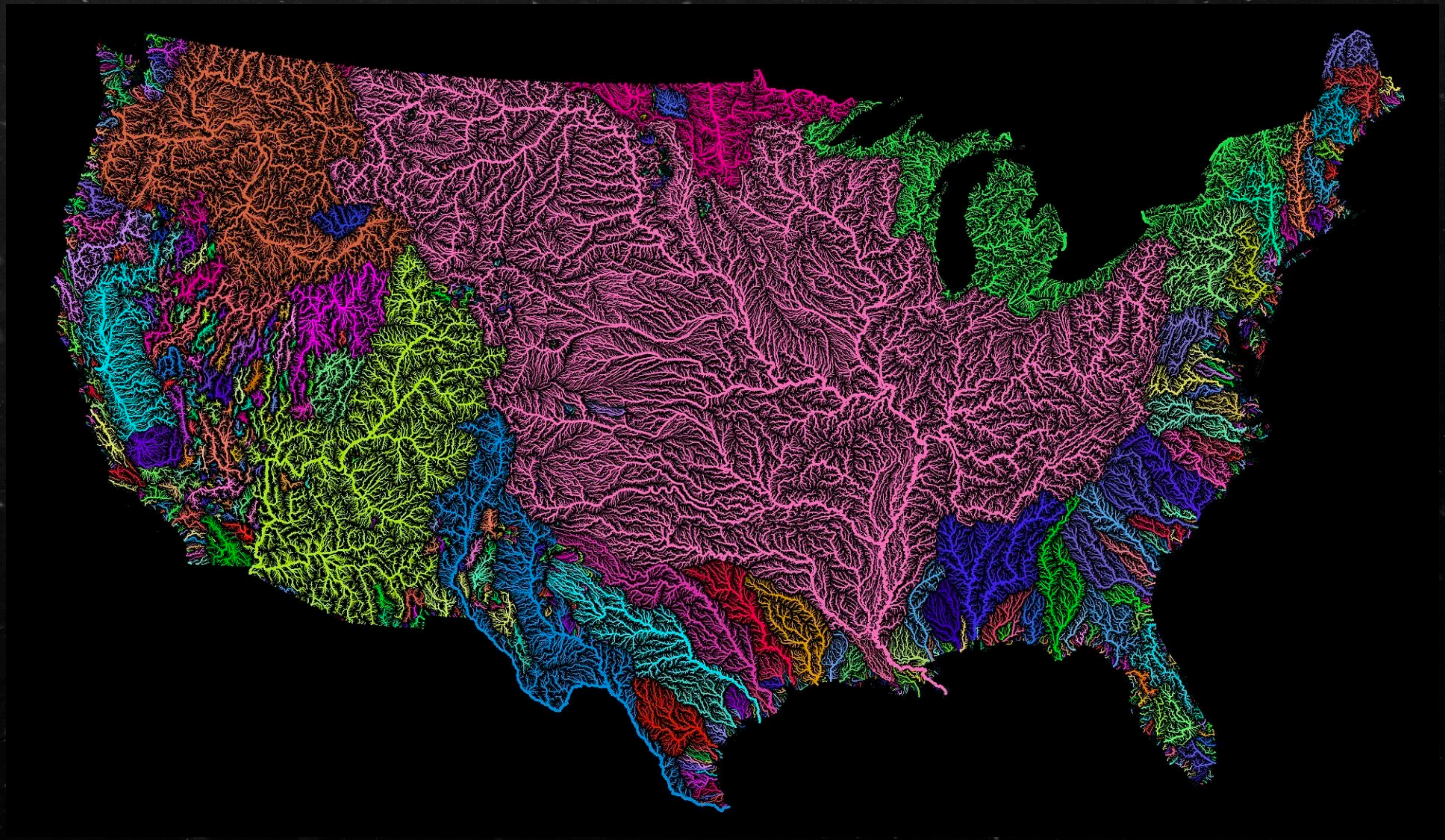

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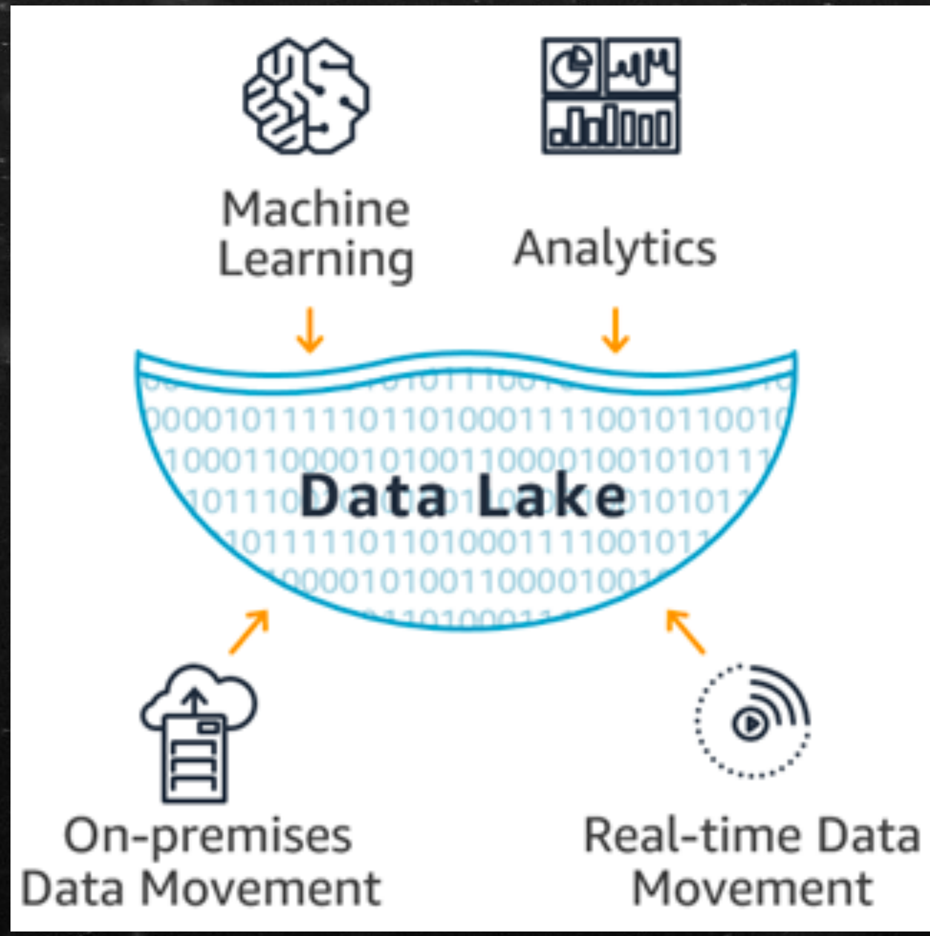
Cloud Data Infrastructure

It's not just about modeling though. We're learning how important it is to have a unified, standardized and accessible (via API) database: AWS Data Lake + database…



Unified, standardized Data Lake and database

Collaborators in a 2021 Water Research Foundation project to develop a national water quality database for application to transfer learning

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Conclusions: Measurable Usefulness

In sum, collectively we are doing really well monitoring and modeling our environments. I think the next steps are:

1) synthesize all available data in a standardized database (Cyan, water samples, qPCR, cubesat imagery, USGS… etc etc)

2) developing metrics by which we can measure the impact of our monitoring efforts and modeling.

LAGOS LAke multi-scaled GeOSpatial and temporal database

Publicly accessible lake water quality and ecological context data for the US

University of Michigan

In Summary:

- Multimodal data synthesis and open access
- Models: interpretable AI and transfer learning
- Predictions: at weekly, monthly and decadal timescales
- Measurable impacts

The Prediction Lab

james@thepredictionlab.com

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