



# INTRODUCING THE US CLIVAR DATA SCIENCES WORKING GROUP

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For scientifically focused discussion on emerging  
tools

Mike Pritchard  
Associate Professor  
University of California, Irvine

# Road map: The Data Science WG

## I. Motivation.

Who we are, context, the goal.

## II. Three themes.

1. How should we change modeling practices?

2. What is potential for data-driven discovery (patterns, predictability)?

3. Learn & talk - which methods are achieving breakthrough potential?

## III. Objectives, timeline, upcoming events.

Webinars, collecting tools & data, how to get involved.

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# Co-conspirators.

**Amy Braverman**



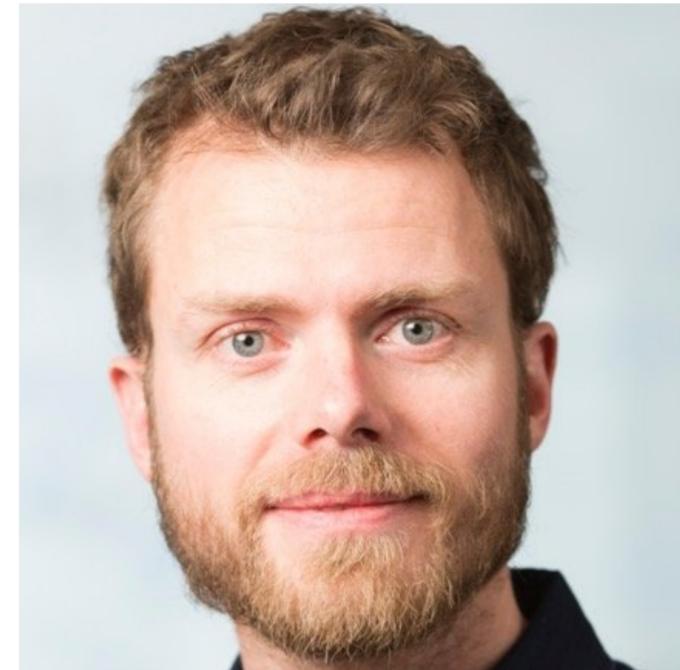
Principal Statistician  
NASA / JPL

**Elizabeth Barnes**



Associate Professor  
Colorado State U.

**Pierre Gentine**



Associate Professor  
Columbia U.



# CLIVAR RESEARCH

How does climate vary and  
change on multiple timescales?

Analysis of observations

Modeling of observations

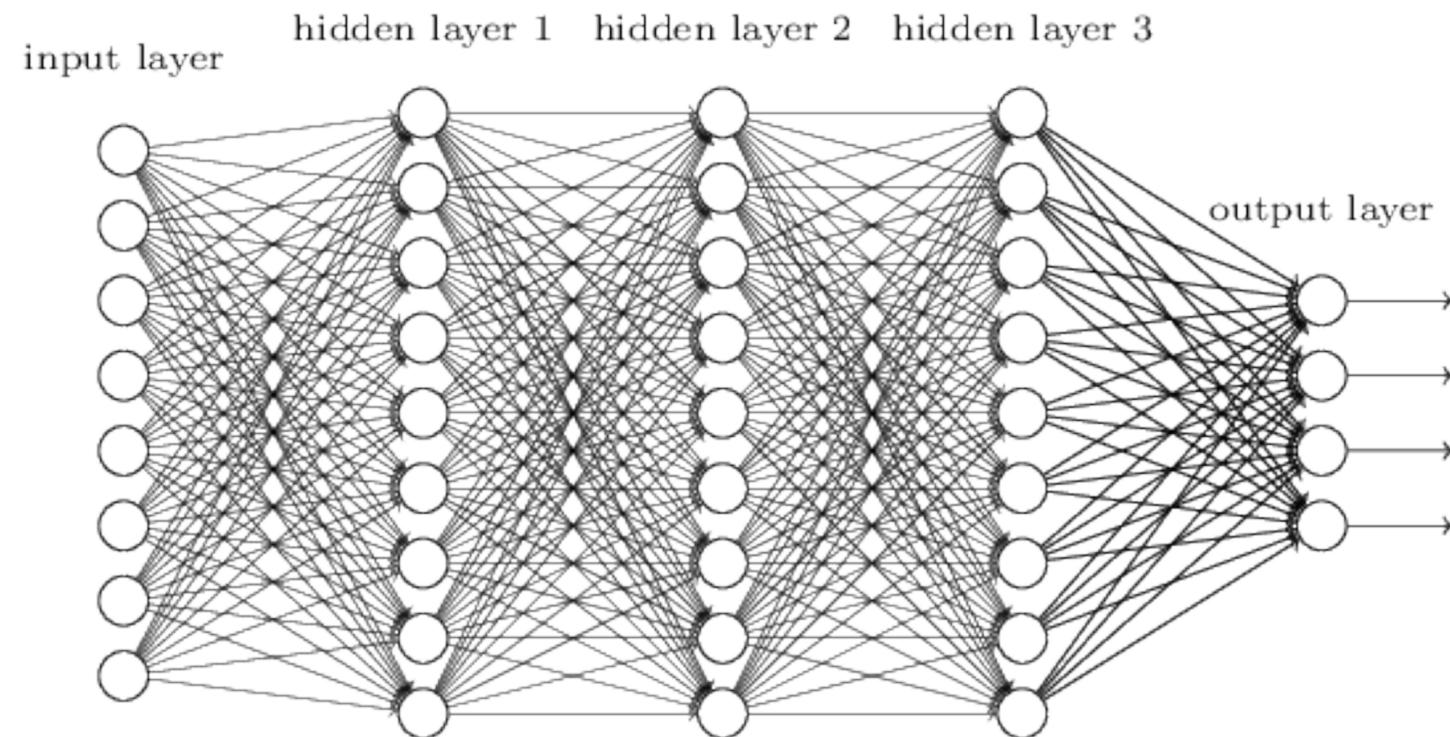
# Exploding information.



Analysis of observations

Modeling of observations

# New computational tools to meet the challenge.



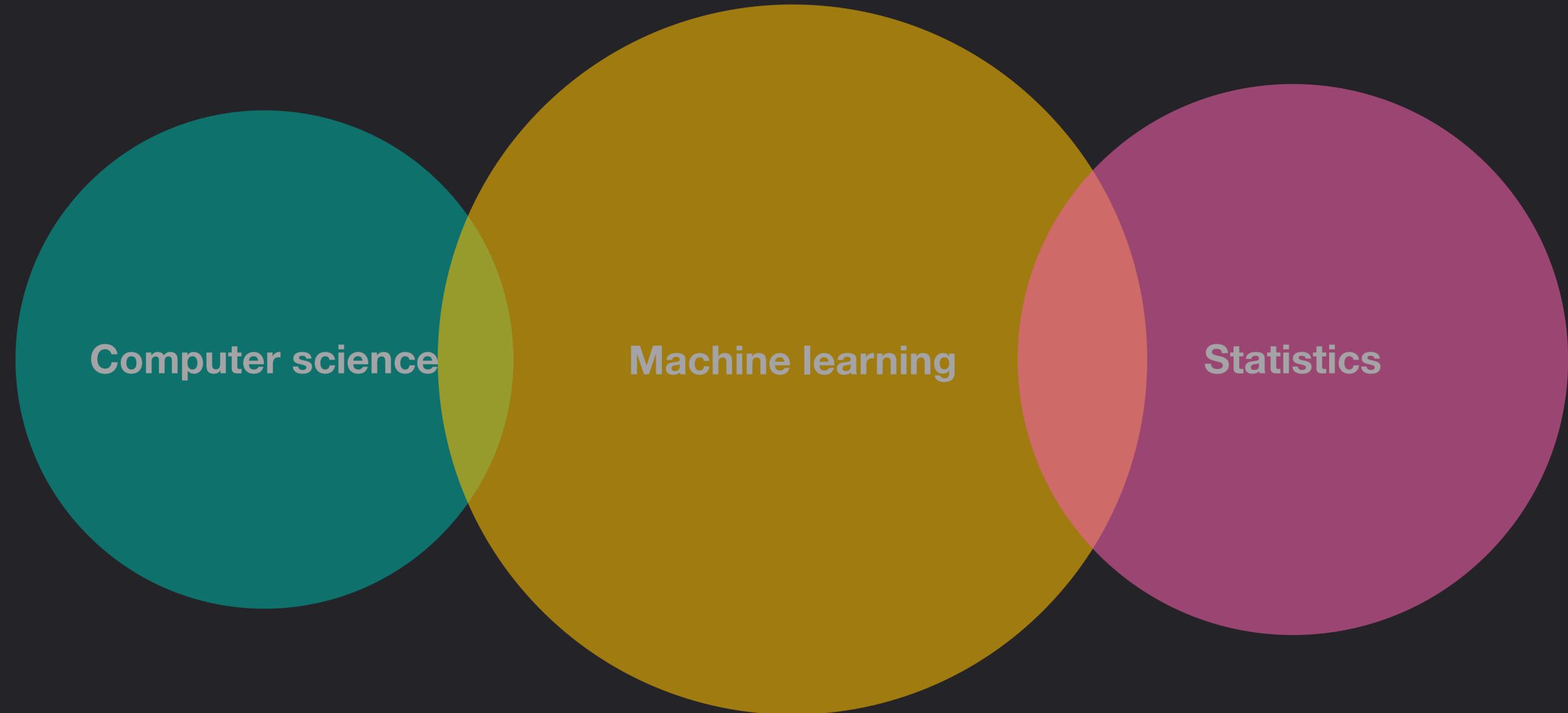
**Example:** “Deep Neural Networks” — powerful emulators of high-dimensional nonlinear functions disrupting industry and science.

# Evidence that data sciences are transforming engineering, science & the economy.

- Near-human-level image classification
- Near-human-level speech recognition
- Near-human-level handwriting transcription
- Improved machine translation
- Improved text-to-speech conversion
- Digital assistants such as Google Now and Amazon Alexa
- Near-human-level autonomous driving
- Improved ad targeting, as used by Google, Baidu, and Bing
- Improved search results on the web
- Ability to answer natural-language questions
- Superhuman Go playing

Example: Deep Neural Networks have driven “breakthroughs .. in historically difficult areas of machine learning”

Behind the tools are new methodologies & algorithms.



This is what our team means by “data science”



# NEW TOOLS, NEW SCIENCE?

Discovery of relationships and processes in large datasets that may have gone unnoticed?

Computationally efficient emulation of physical models?

# MAIN GOAL

To foster...

Understanding

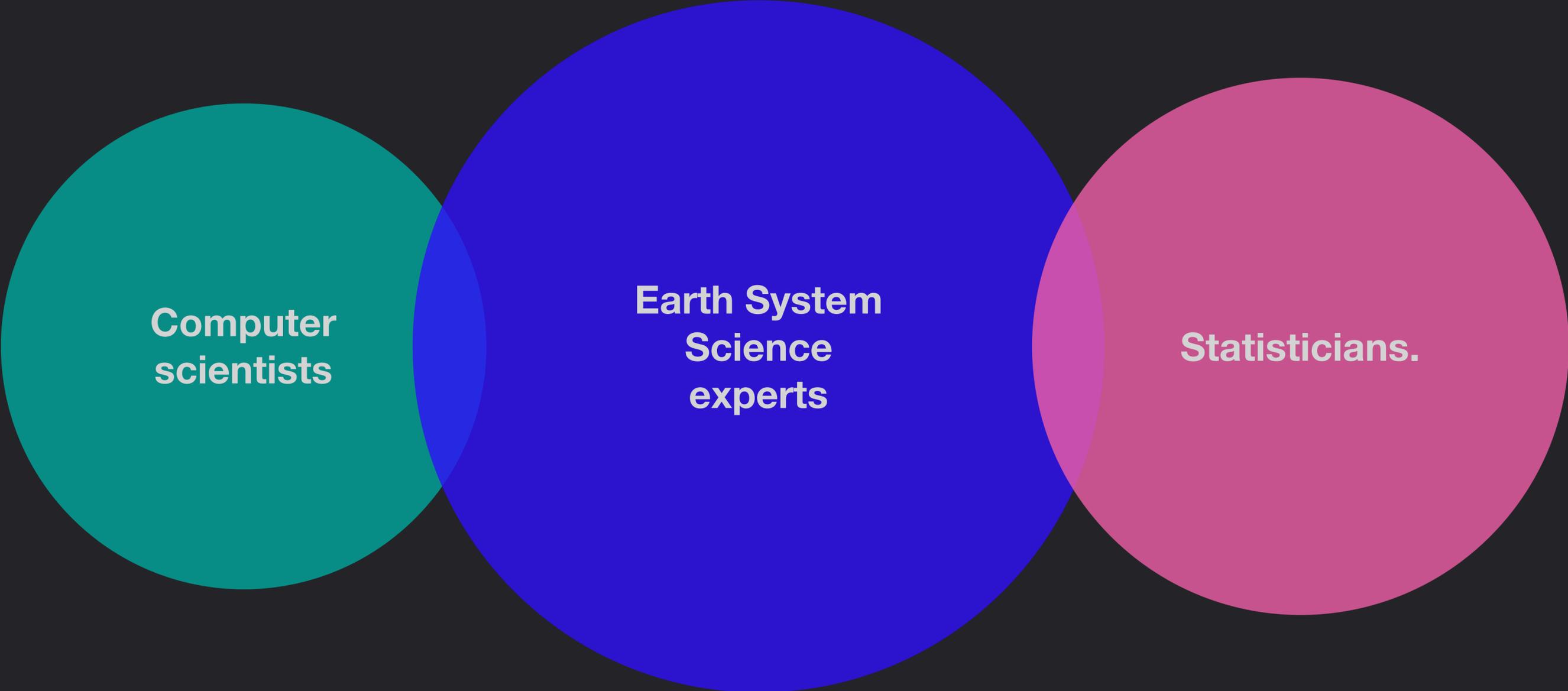
Adoption

Development

Of modern data science tools

in ways that advance CLIVAR science.

The WG will try to unite:



Computer  
scientists

Earth System  
Science  
experts

Statisticians.

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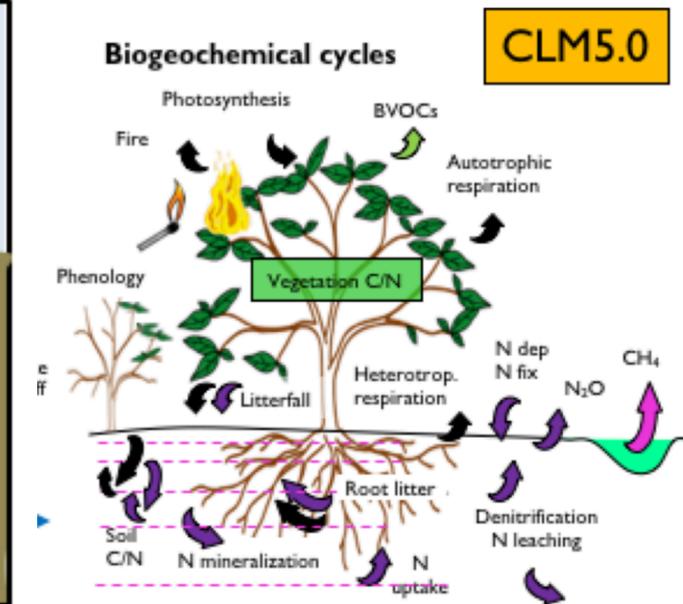
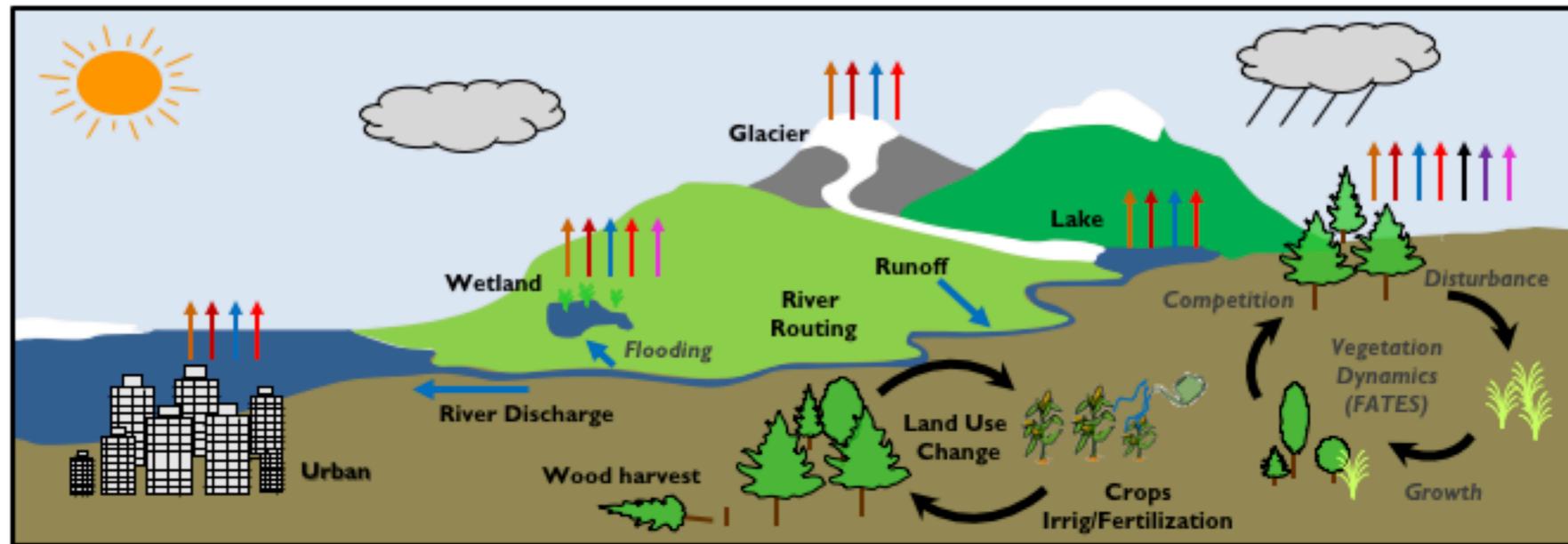
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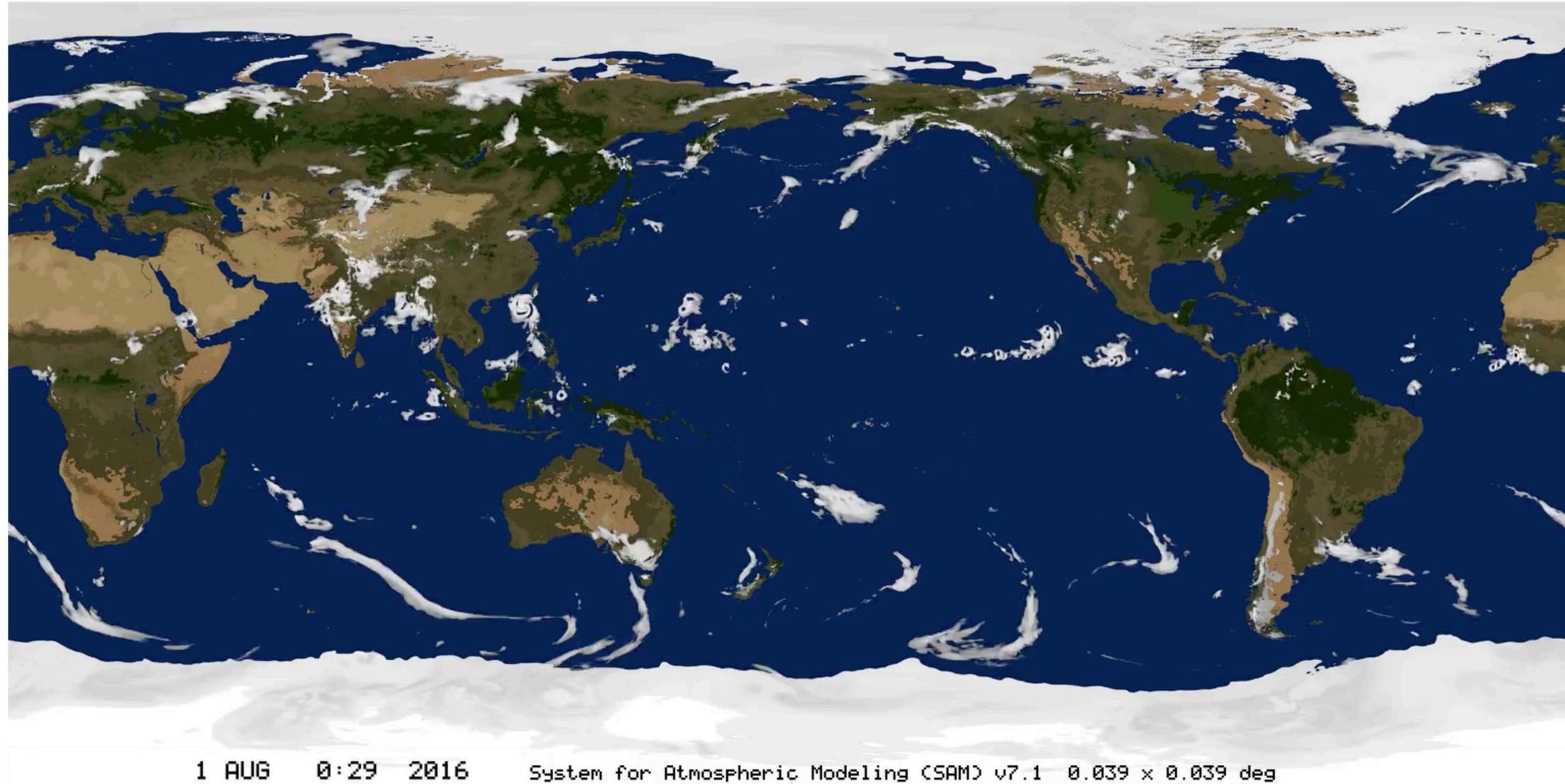
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Some areas of the climate system have weak physical constraints but rich data constraints.



Example: Terrestrial or oceanic biosphere modeling

Other areas are becoming rich in quality synthetic data.

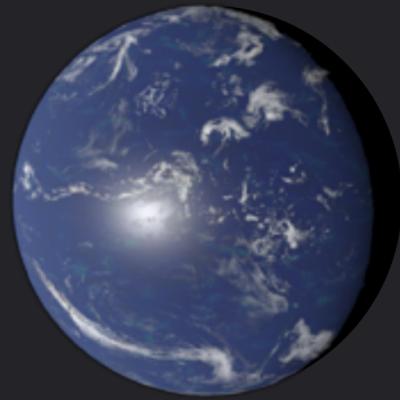


Example: Global Cloud-Resolving model output.

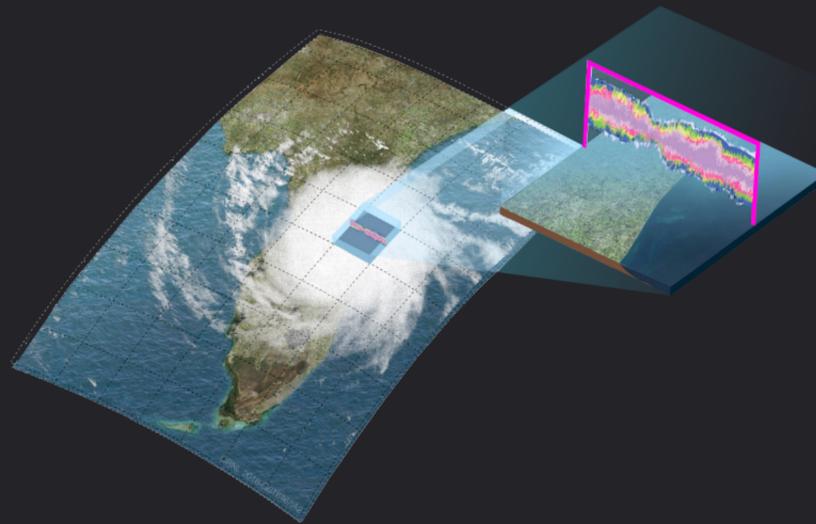
Animation by Marat Khairoutdinov, Stony Brook U. (System for Atmospheric Modeling v7.1)  
1 sim-day integrates in 4 hours using ~ 4,000 NCAR processors.

# Example: Neural networks for emulating superparameterization?

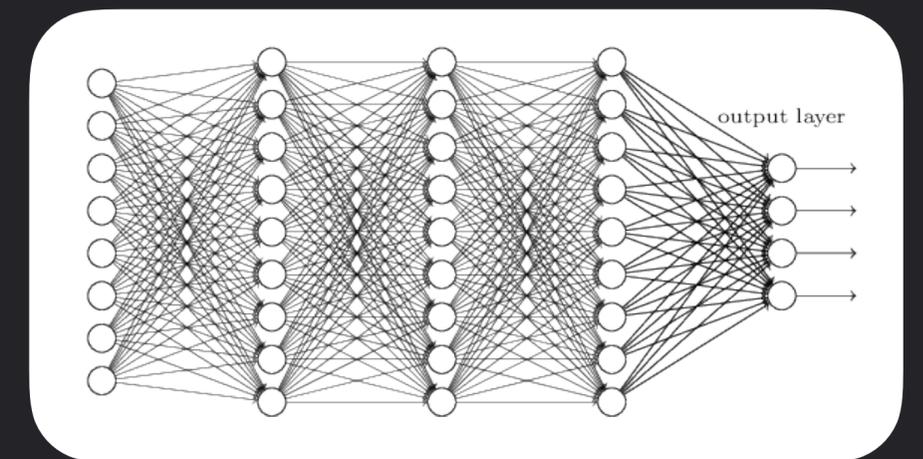
Global aquaplanet testbed



Can 140,000,000 outputs from 1 year of ~ 10,000 cloud-resolving models...



Be fit by a deep neural network?



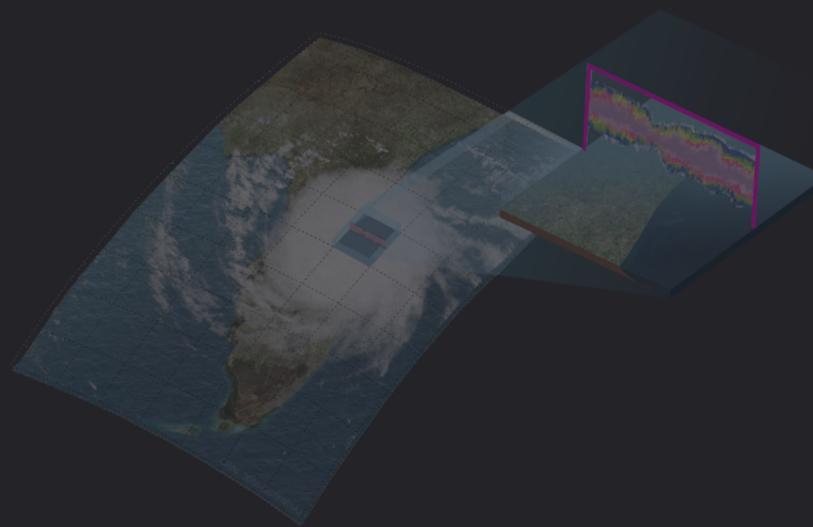
# Is deep learning viable for emulating superparameterization?

Quite possibly!

Global aquaplanet testbed

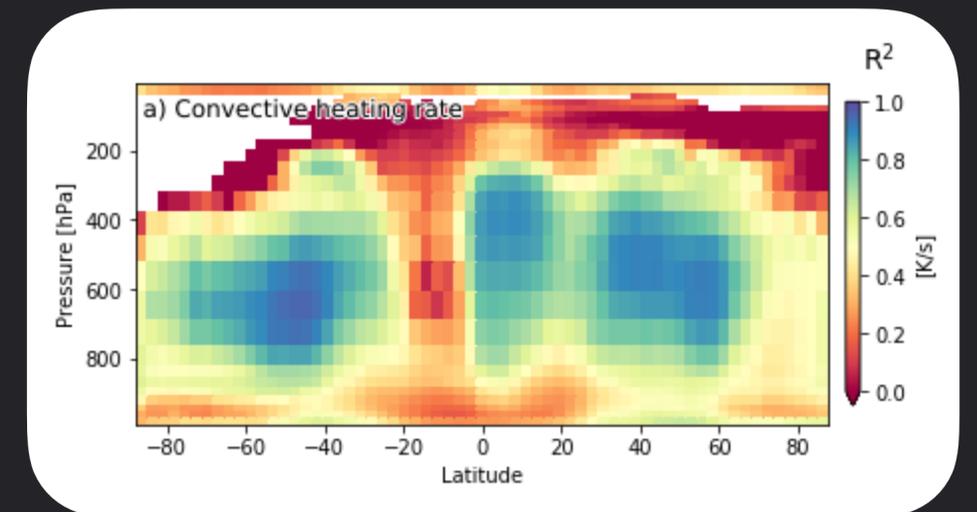


Can 140,000,000 outputs from 1 year of ~ 10,000 cloud-resolving models...



The "Cloud Brain"

Be fit by a deep neural network?



...right? ...forming tropospheric heating by convection and radiation.

# WHAT IS THE OUTLOOK?

For replacing process  
parameterization with data-  
driven machine learning  
emulators?

Glimmer of recent success  
in cloud physics

But many outstanding  
issues challenges:

Interpretability?

Generalizability?

Stability?

Physical constraints?

How should uncertainties  
be incorporated?

What are the philosophical  
trade-offs?

Our community has  
only scratched the surface.

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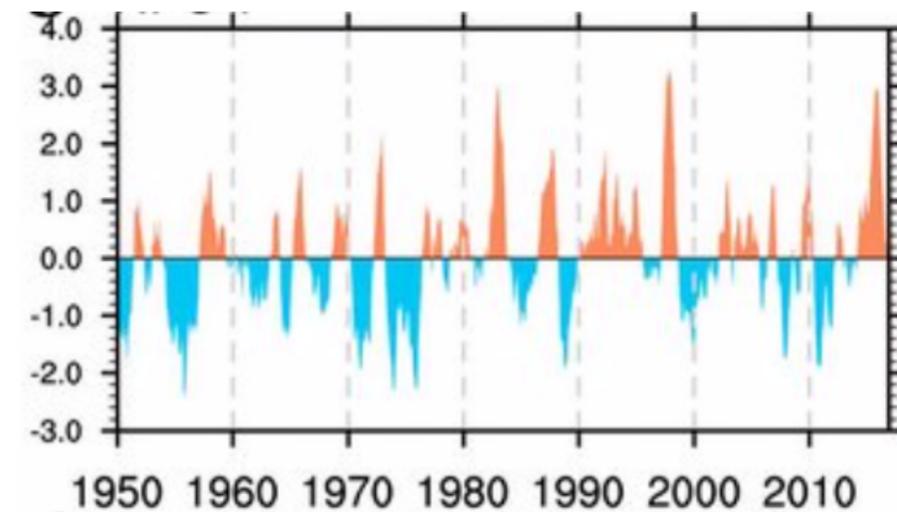
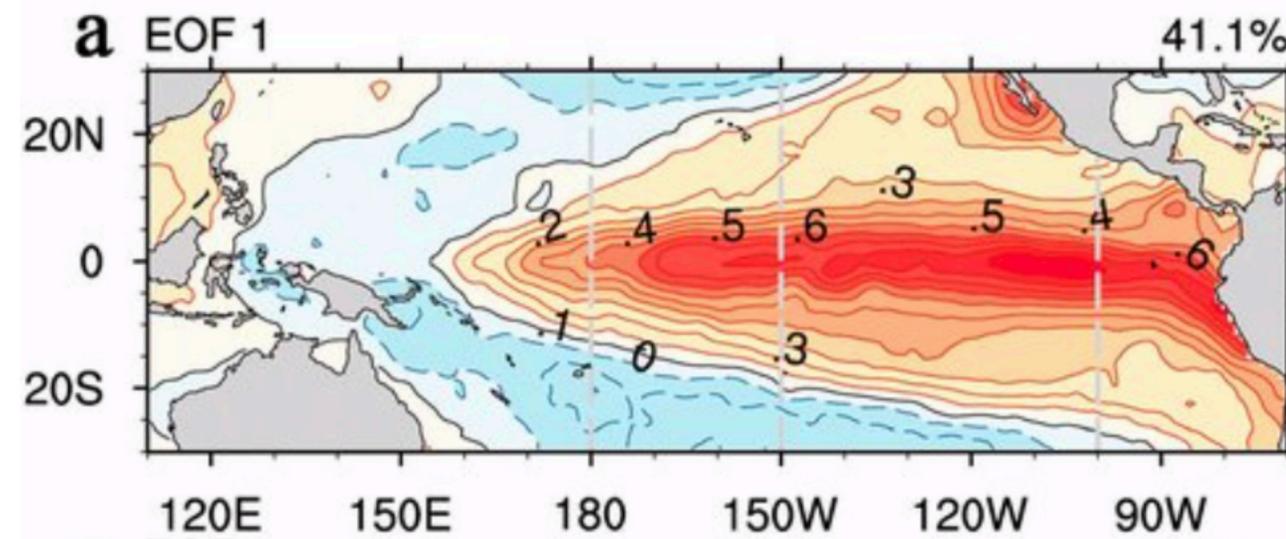
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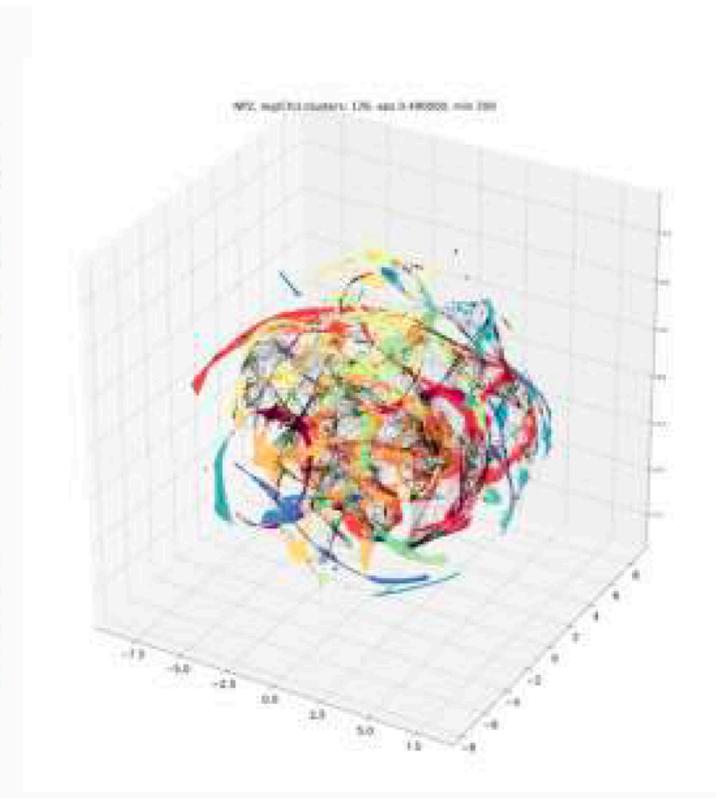
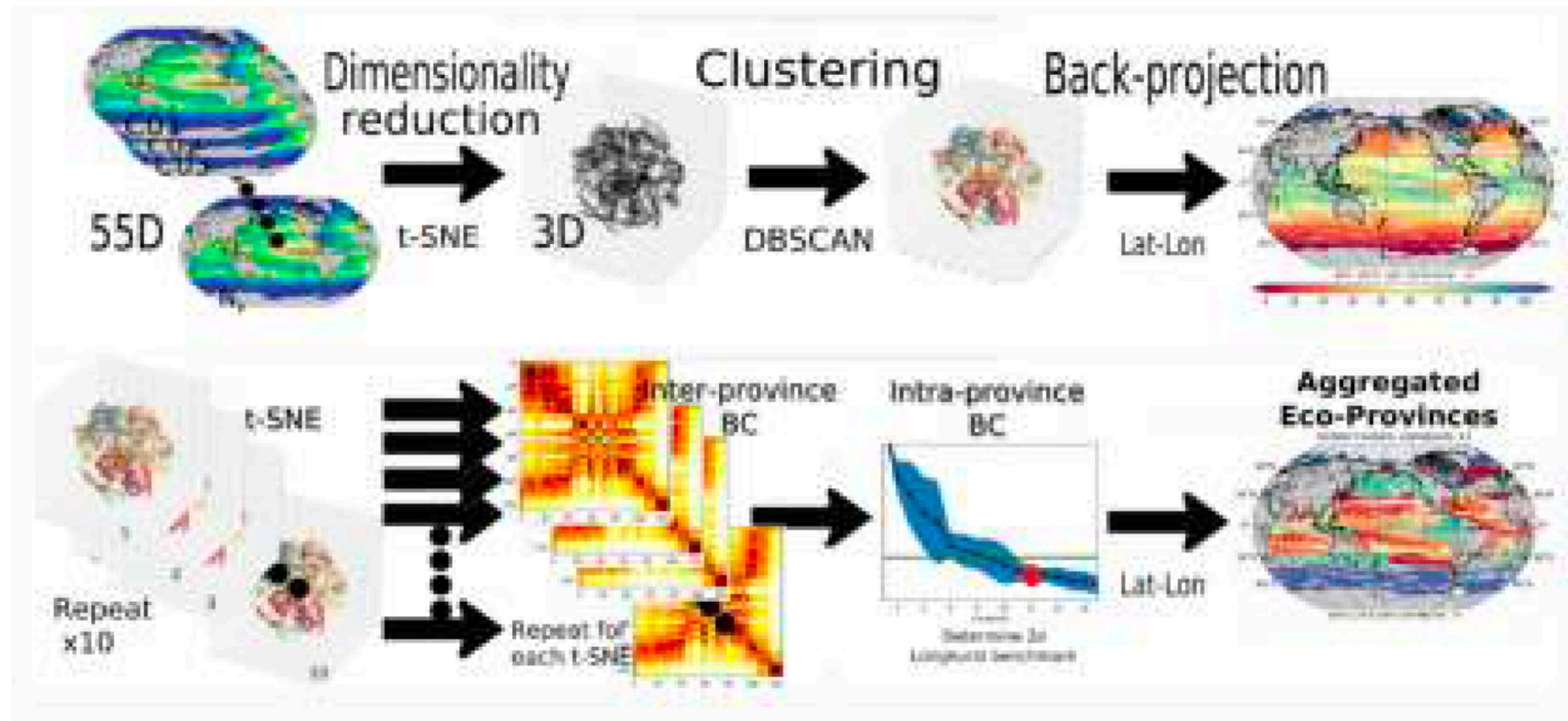
Webinars, collecting tools & data, how to get involved.

# Data-driven ways to identify correlations and relevant patterns.



**EOFS: We've been making good use of them for decades**

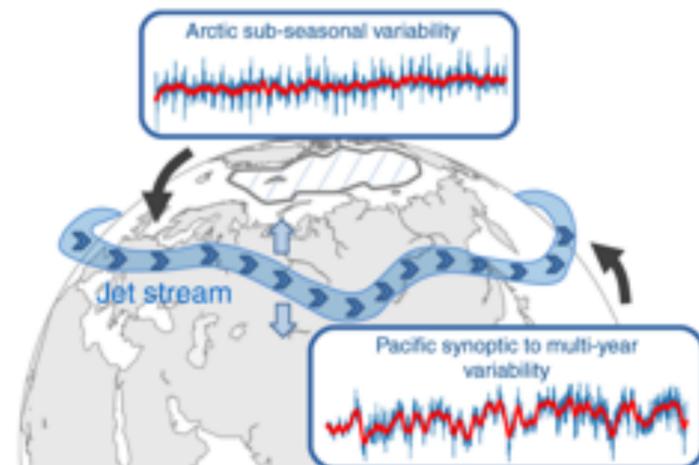
# New methods from data sciences have potential to help.



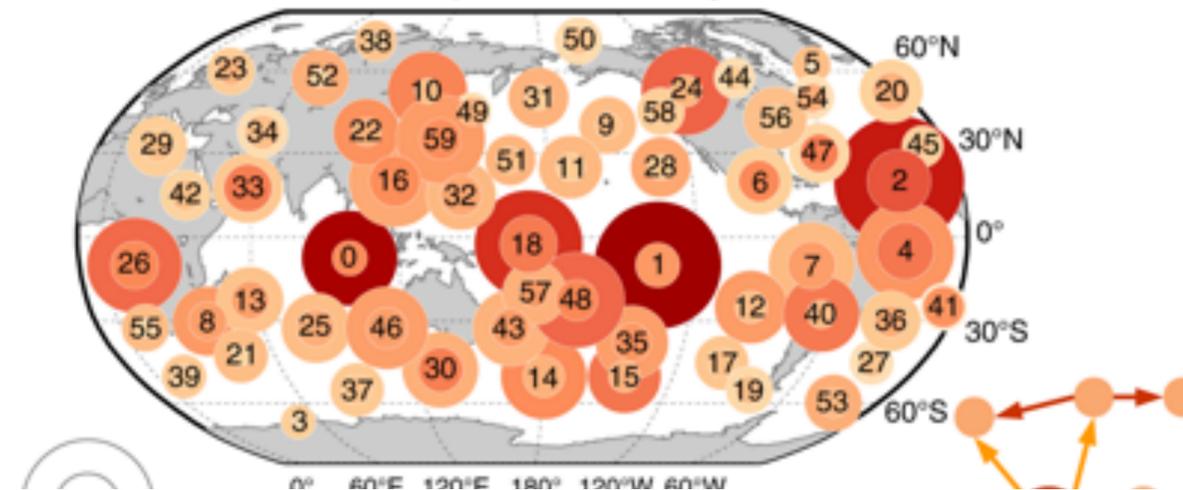
## More “tools for the toolbox”

# Example: Causal inference theory for studying teleconnections

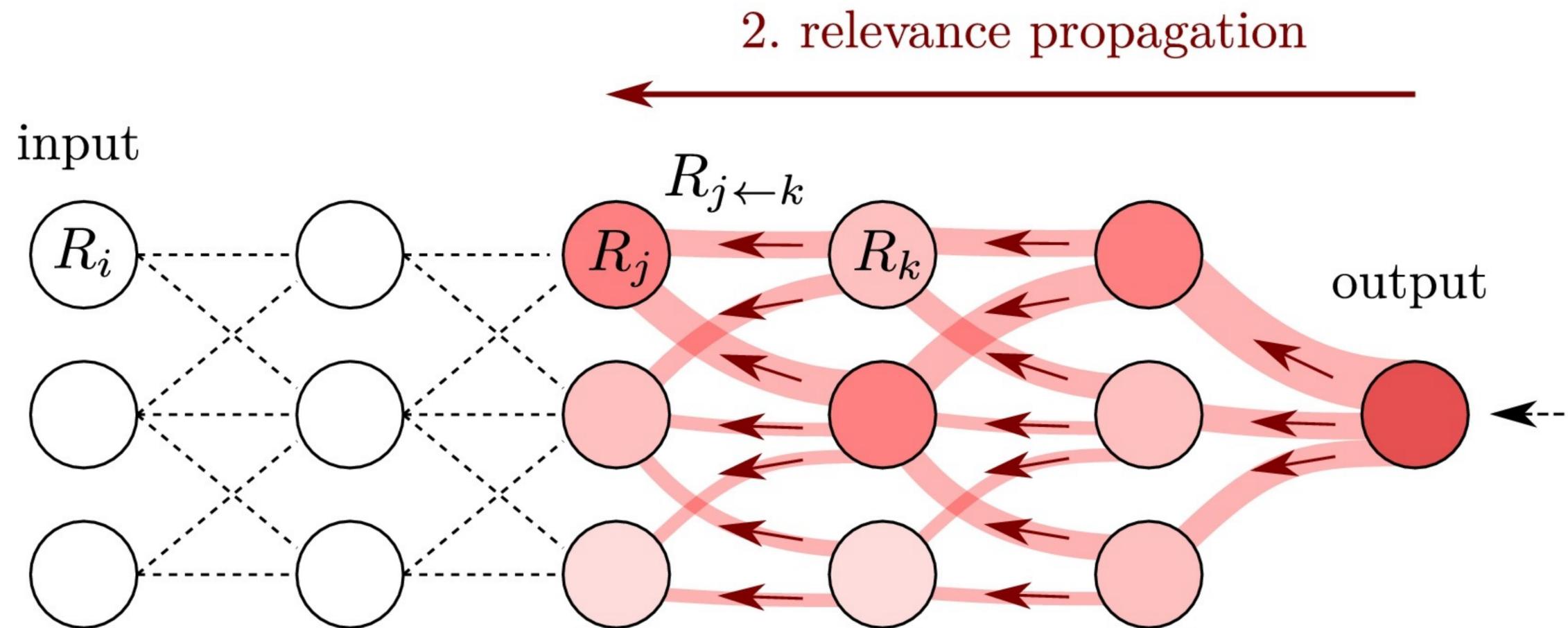
**a** Causal hypothesis testing



**b** Causal complex network analysis



# Example: Machine learning is beginning to be interpretable.



# OPPORTUNITIES.

Developing machine learning  
interpretability methods for climate  
applications.

How to leverage data-hungry  
methods when samples  
infrequent (e.g. extreme events)

Promising avenues

Optimal input analysis?

Layer-wise relevance propagation?

How should  
uncertainties be  
incorporated?

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We are in the infancy of  
adopting emerging data science  
tools.

Some are tinkering but  
scattered across disciplines

Which specific tools  
are:

reproducibly helpful?

statistically  
novel?

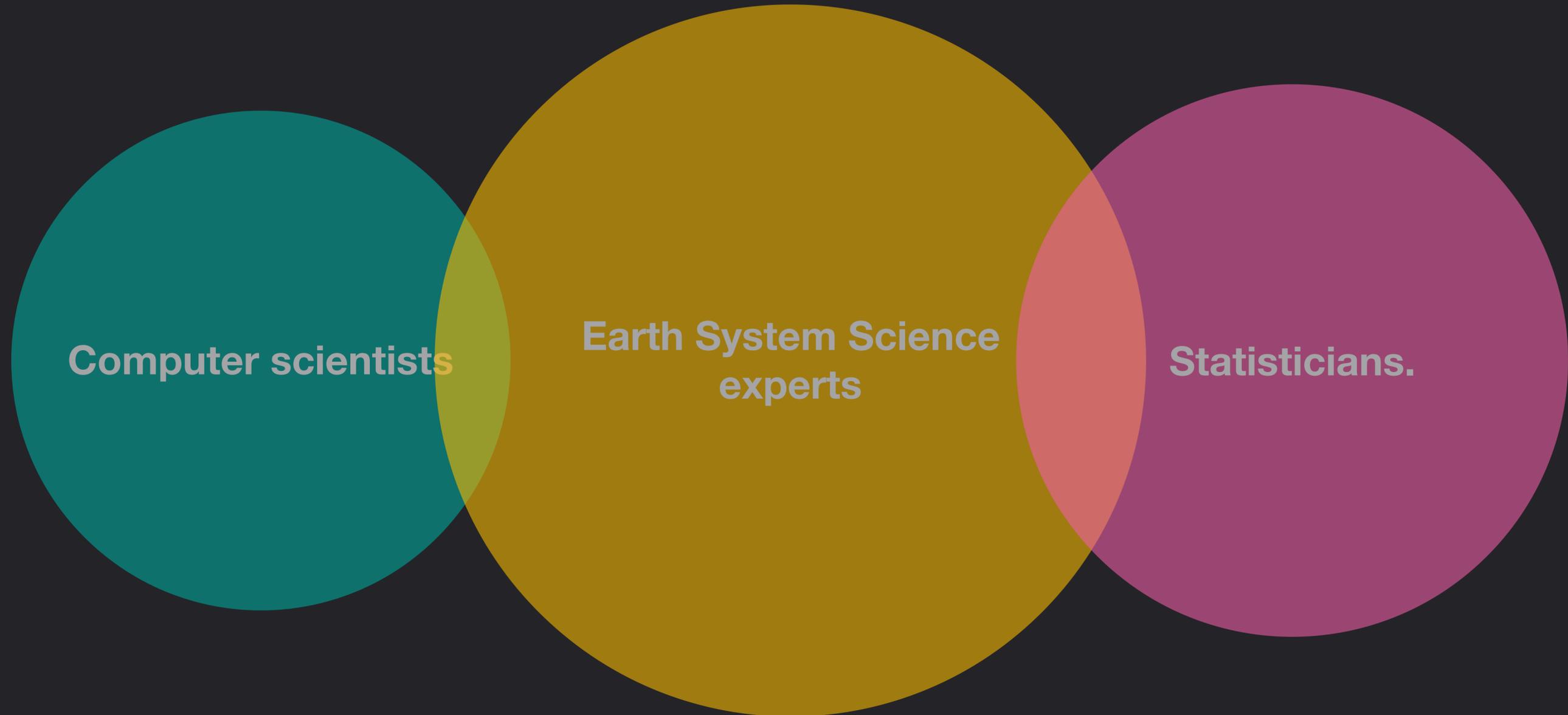
technically approachable?

gaining consensus?

How should the  
community organize  
itself?

(including this working group)

# CONVERSATIONS NEEDED.



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WHAT'S NEXT?





# WHAT'S NEXT?

Working group invitations  
are out (yesterday)

Bi-monthly webinars  
begin this fall.

WG  
discussions  
with community

Curated  
experiences

Curated tools  
(& how-to  
guides)

Online  
presence

Working group  
discussions with each other  
(years 2 & 3)

Publications:  
Years 1 & 3.





THANKS

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