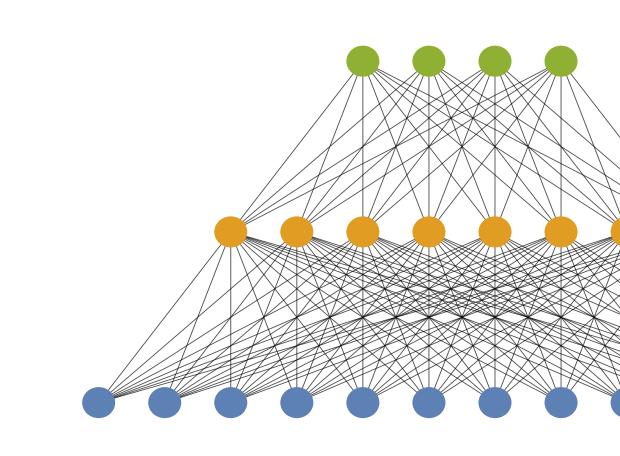


Historic measurements

# AtmoRep Representation learning on atmospheric data to address climate change

Christan Lessig



large scale machine learning

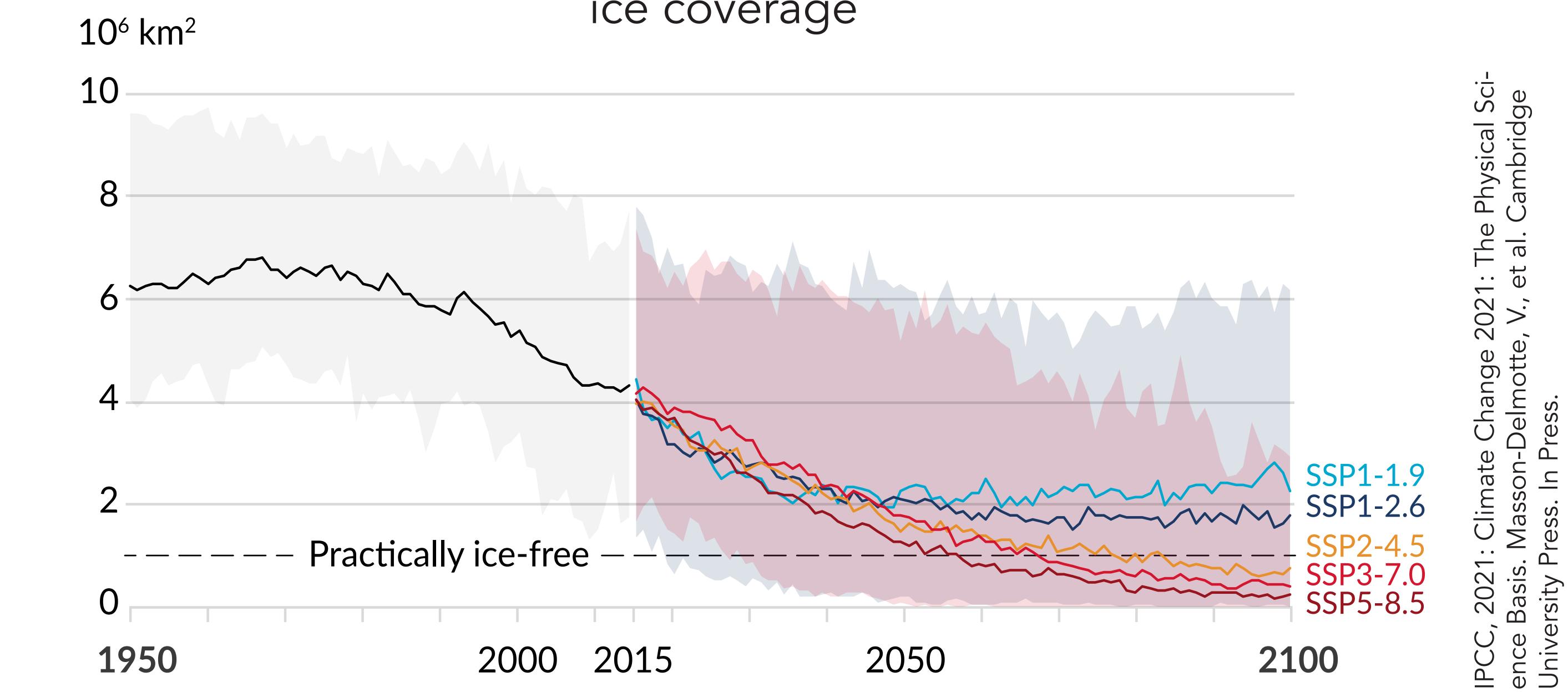
## Ilaria Luise, Maike Sonnewald, Martin Schultz, Annesh Subramanian,

## mitigate climate change obtain scientific insight

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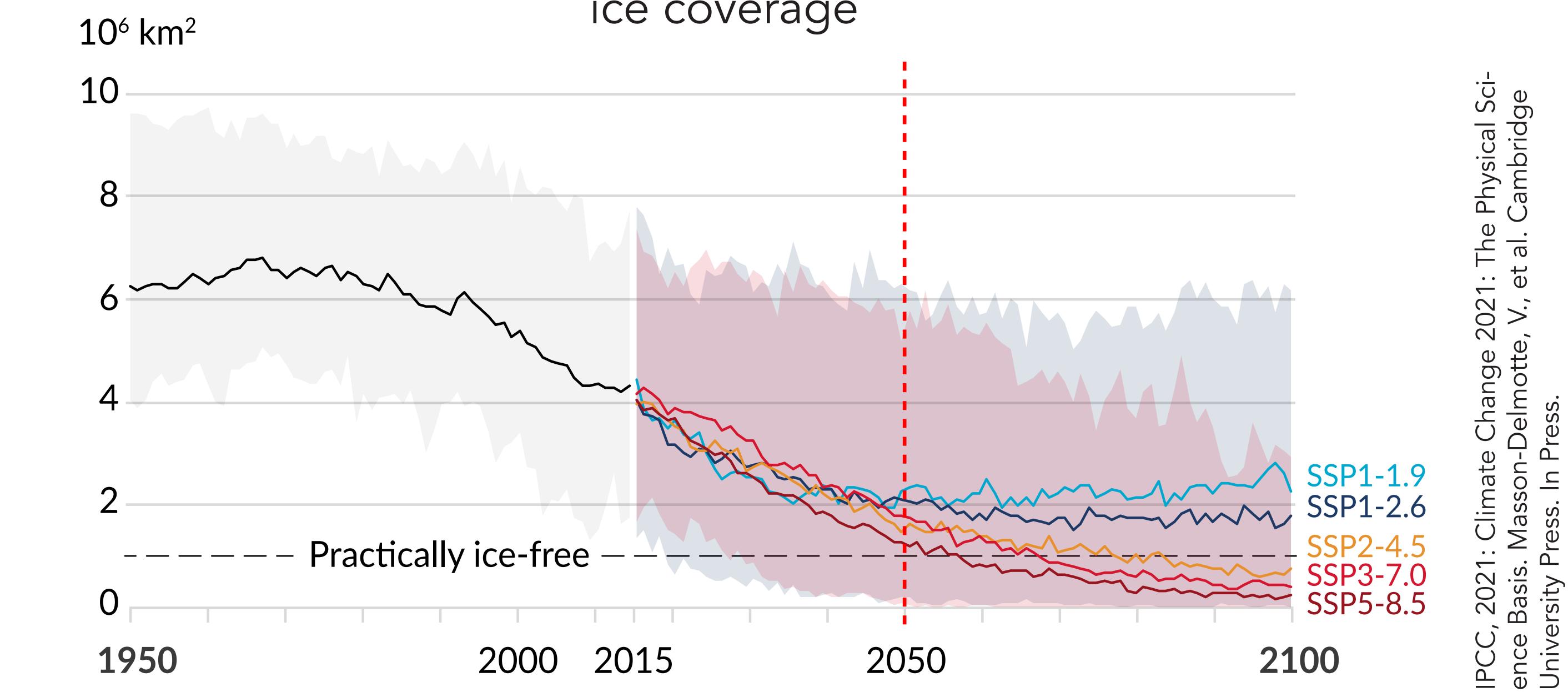
## Climate projections have very significant uncertainties

## Climate projections have very significant uncertainties



ice coverage

## Climate projections have very significant uncertainties



ice coverage

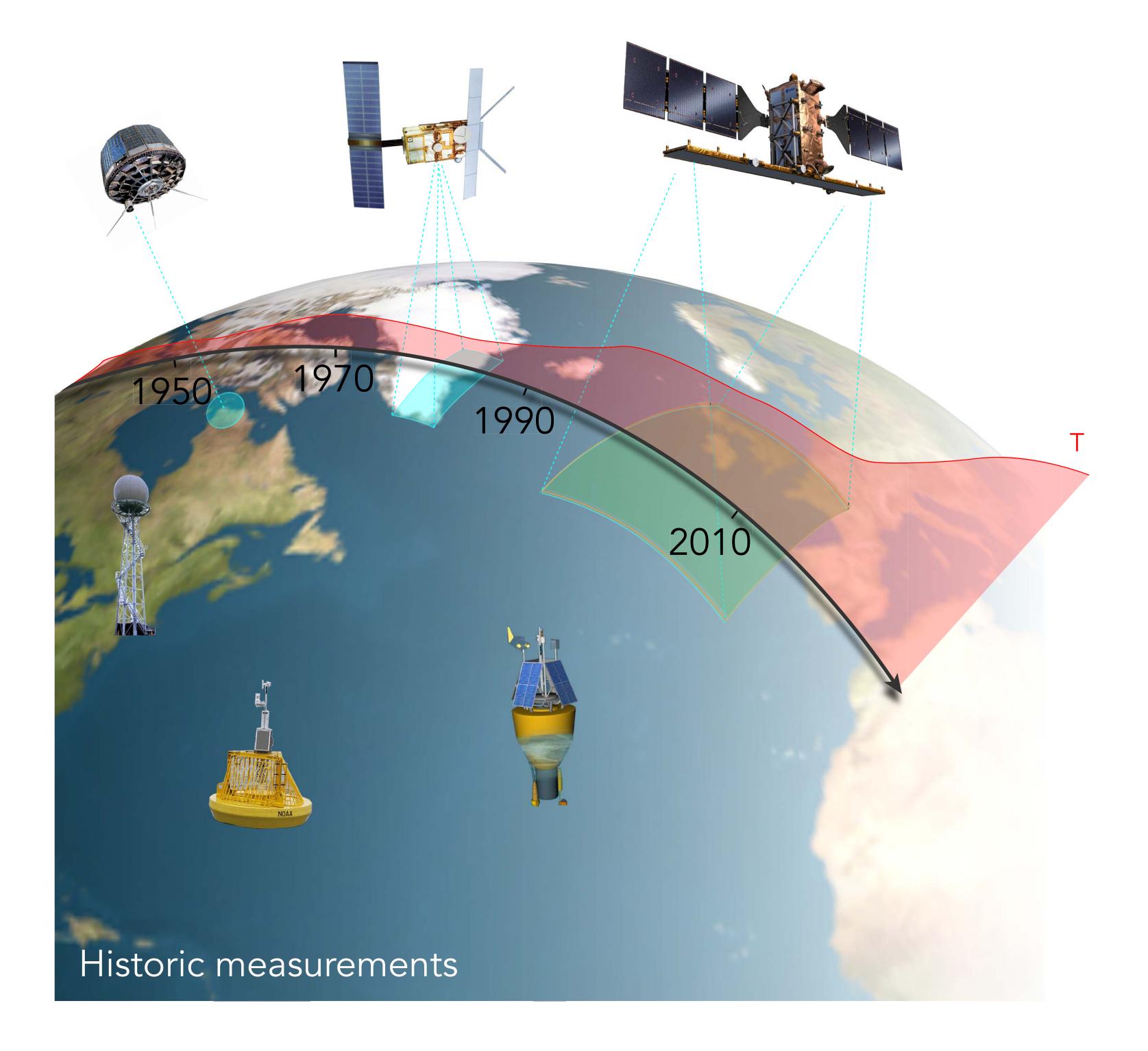
# Motivation

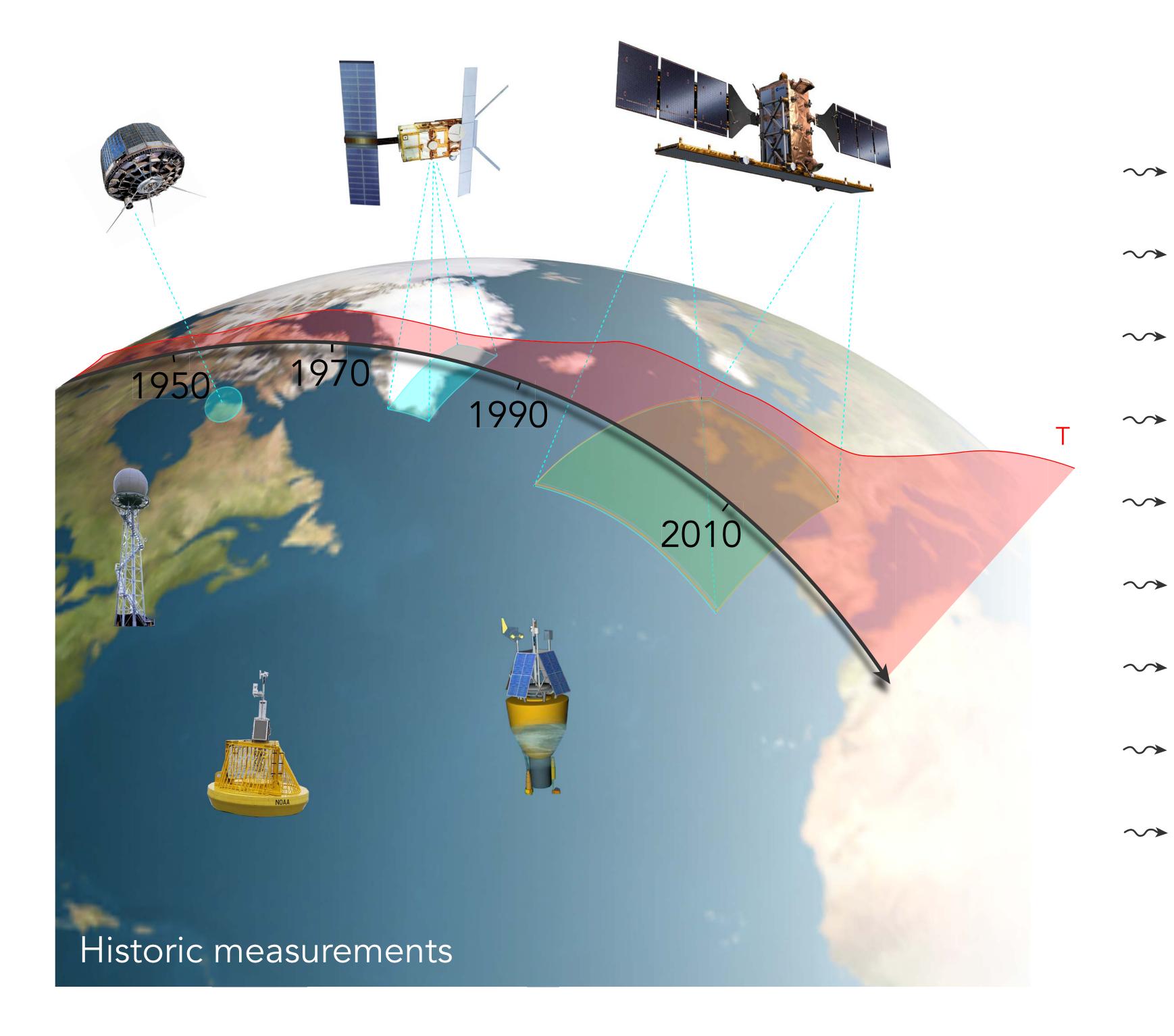
 Climate projections have very significant uncertainties Only incomplete description of physical processes in the atmosphere in current simulations

with biosphere, ... > ...

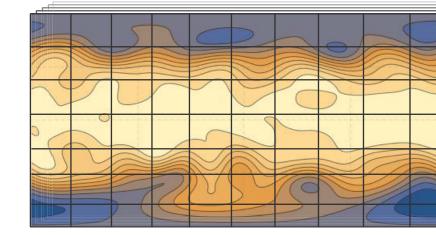
atmosphere in current simulations

- Climate projections have very significant uncertainties Only incomplete description of physical processes in the
  - No (effective) models for cloud formation, interaction
  - Very large number of interacting scales (1 m to 10<sup>7</sup> m)



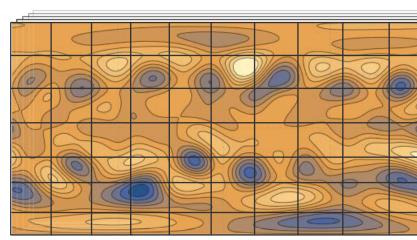


## ERA5 reanalysis



		3		DE
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777		20	5	6		5
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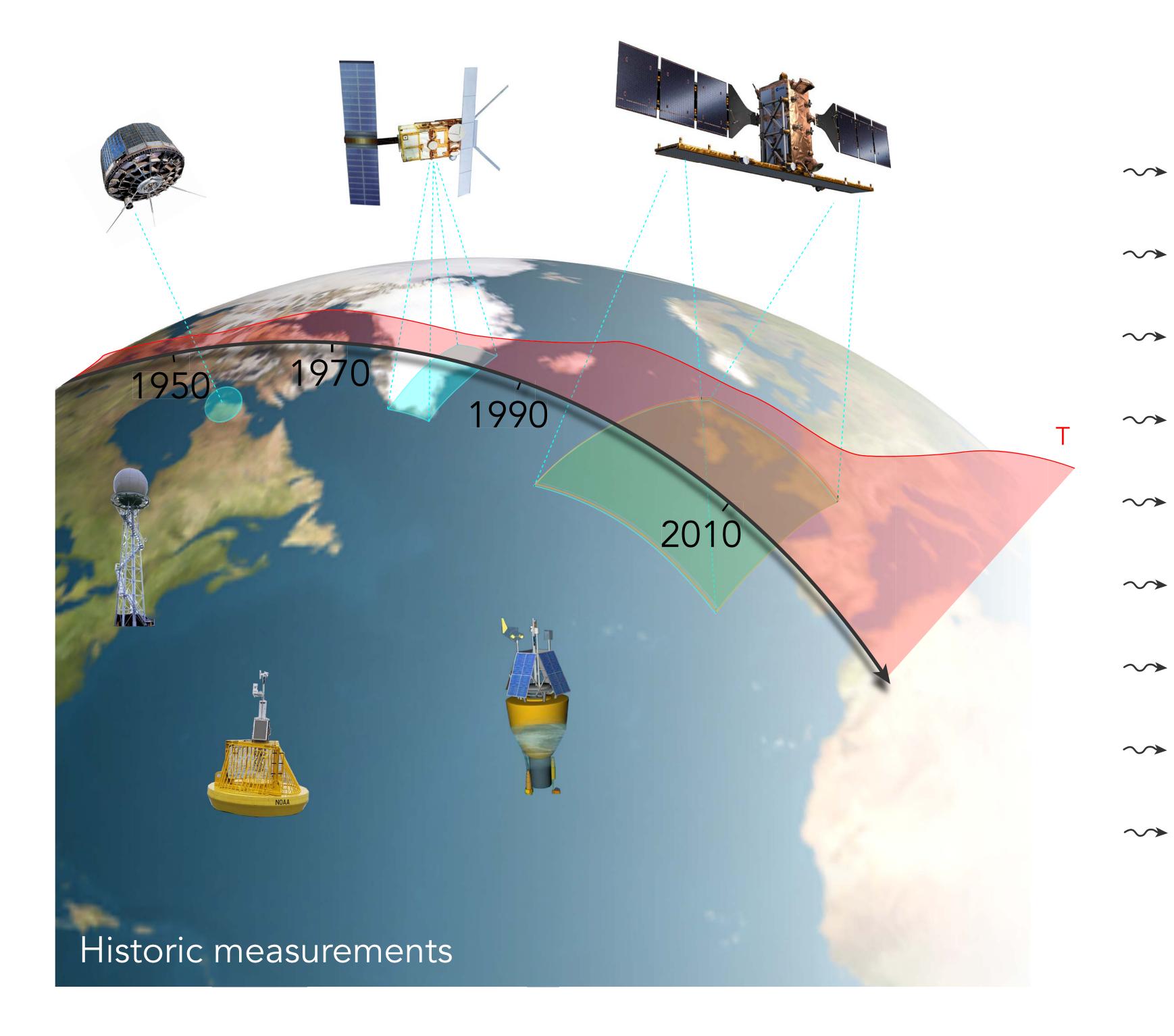


5 petabyte

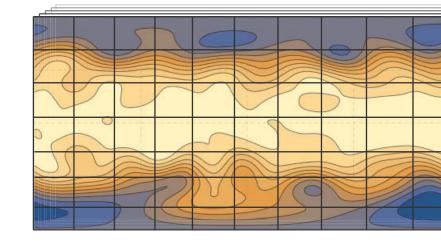






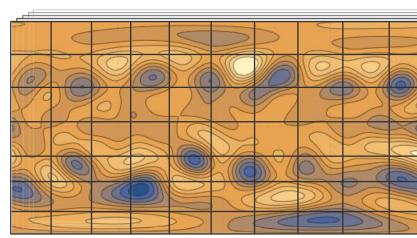


## ERA5 reanalysis



		3		DE
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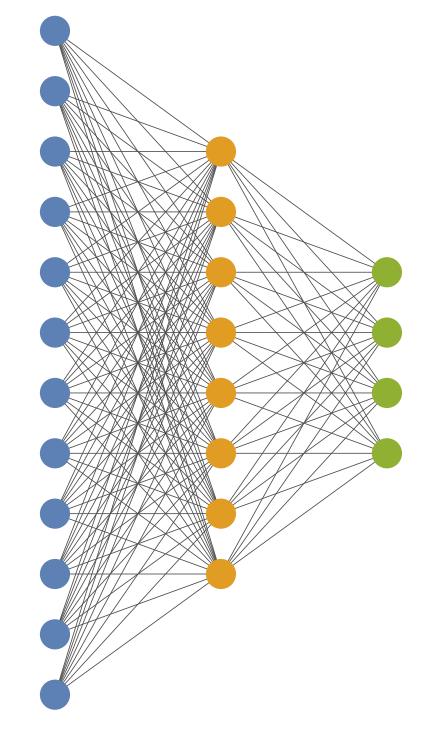


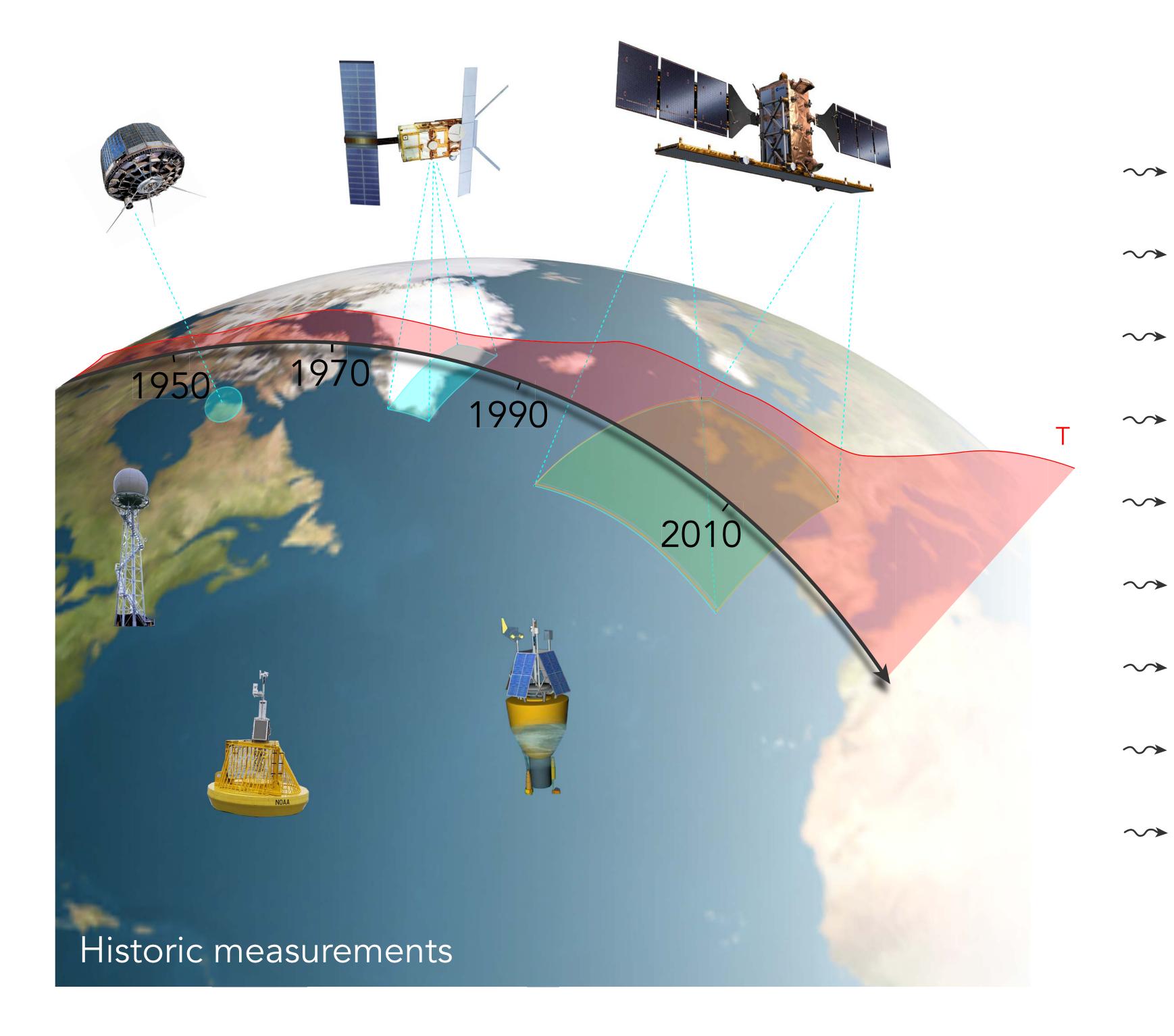




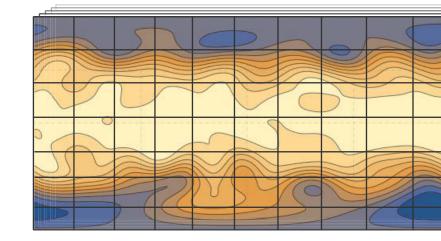






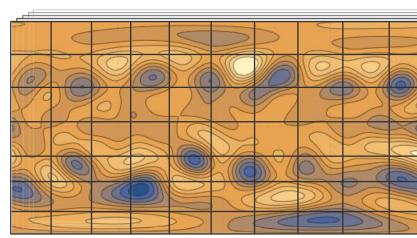


## ERA5 reanalysis



		3		DE
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		11	2	$\leq$ (	F	
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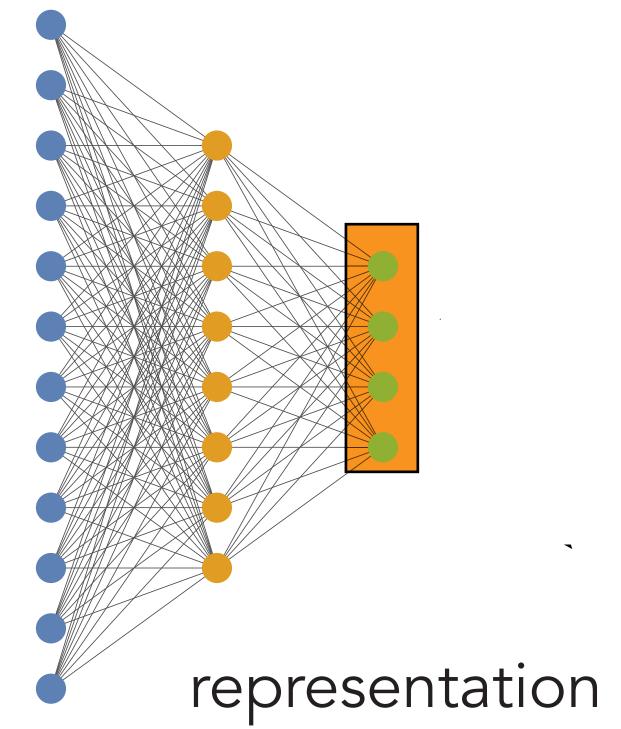


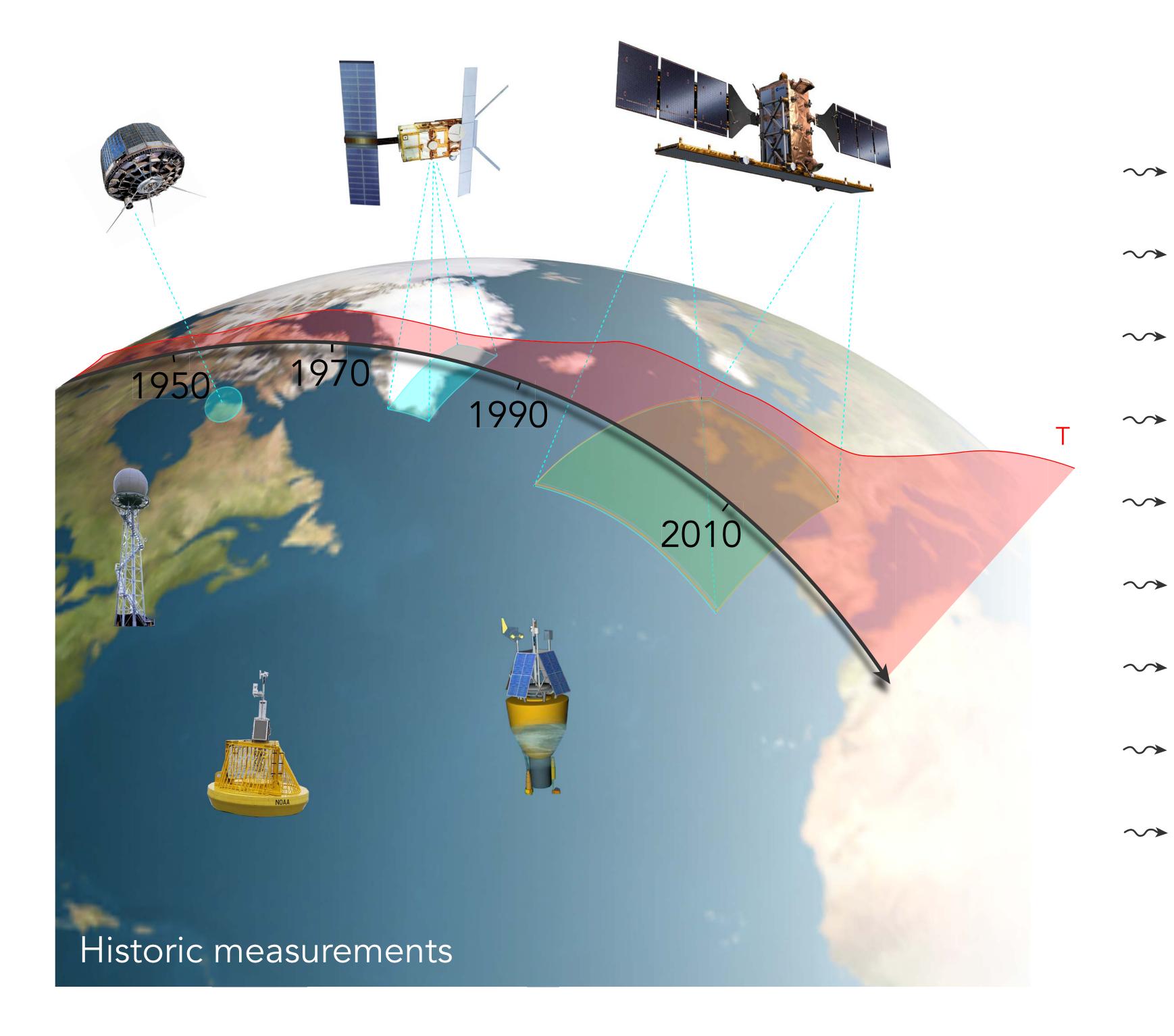




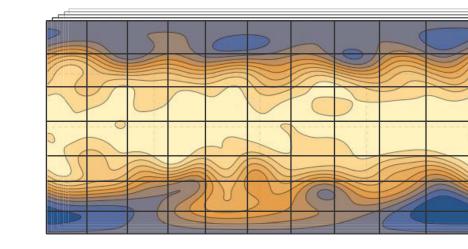






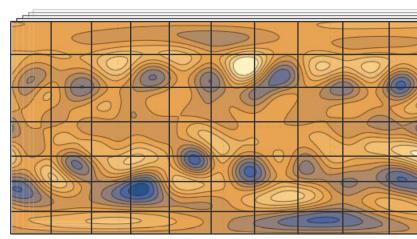


## ERA5 reanalysis



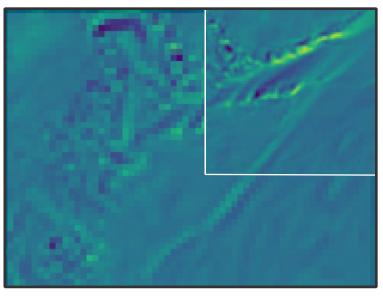
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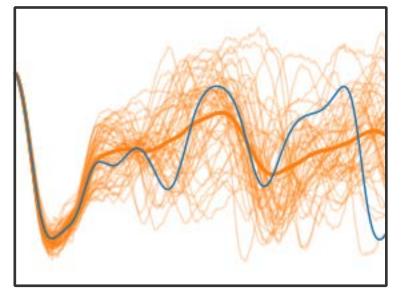


5 petabyte

## address climate change



Downscaling

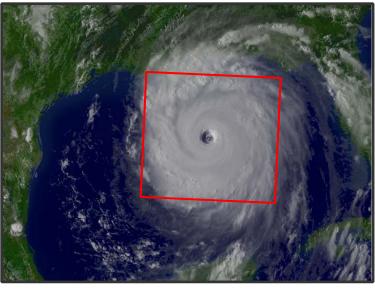


Predictability

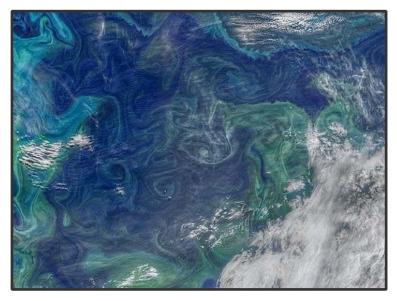
## large scale machine learning

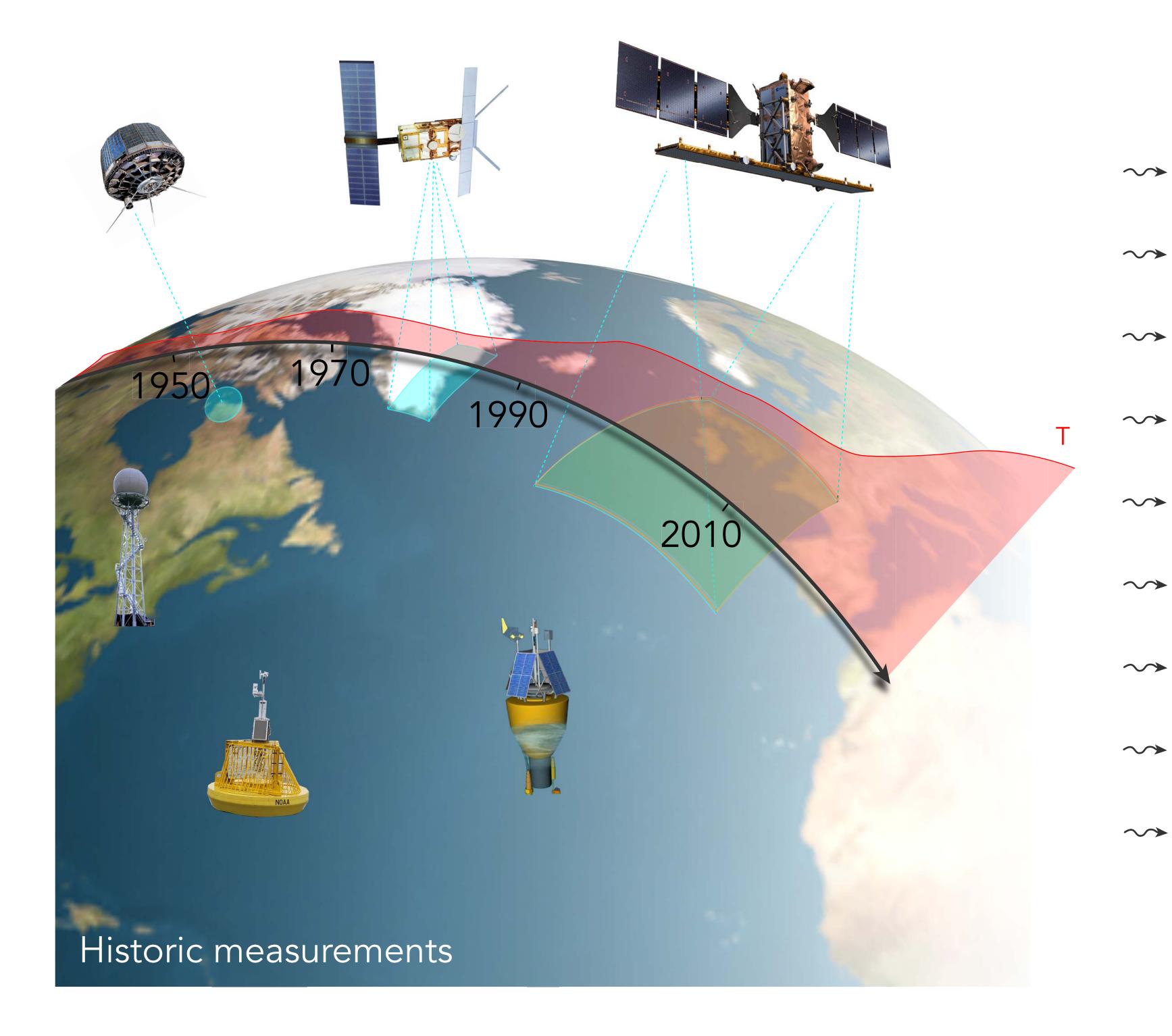




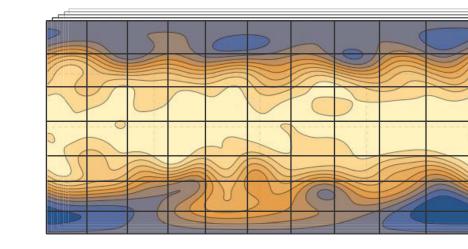


## Classification



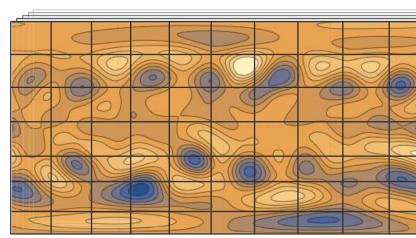


## ERA5 reanalysis



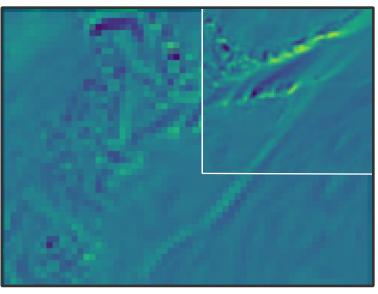
		3		DE
		DOT		
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		11	2	$\leq$ (	F	
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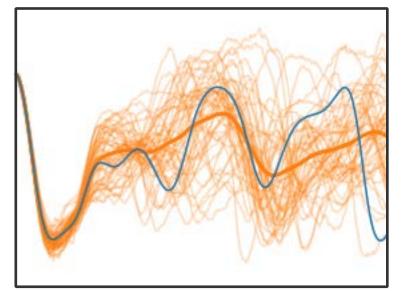


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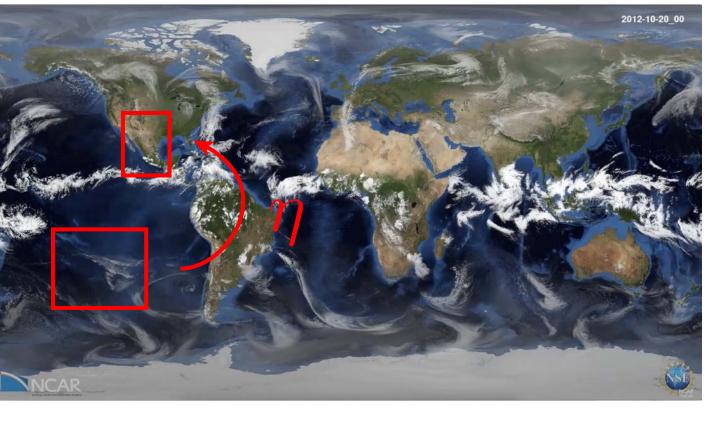
## address climate change



Downscaling

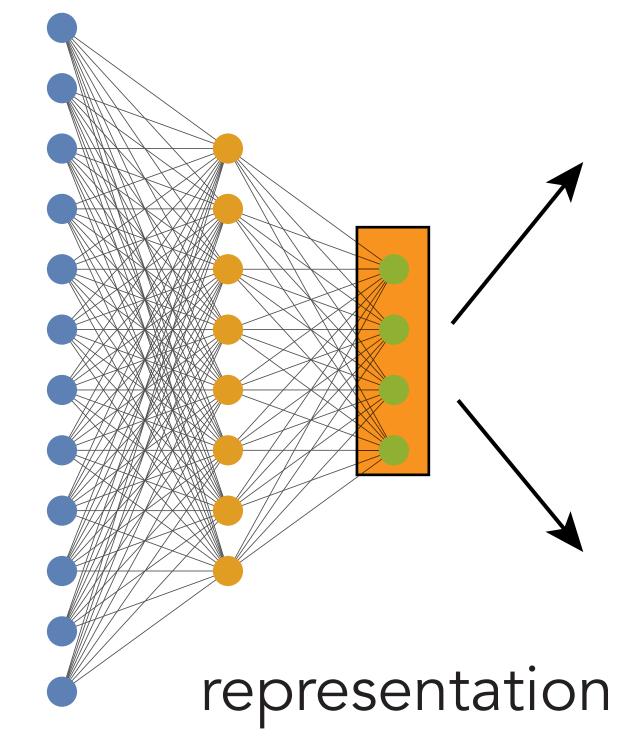


Predictability

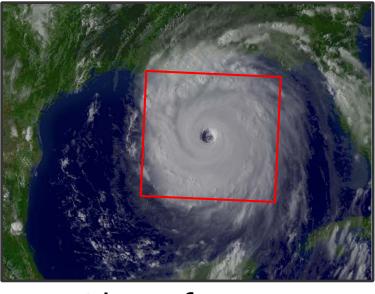


## scientific insight

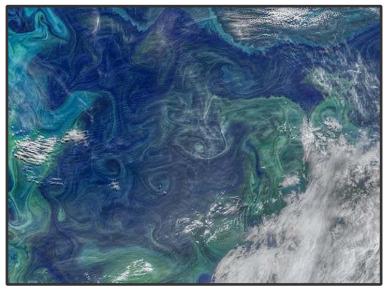
## large scale machine learning

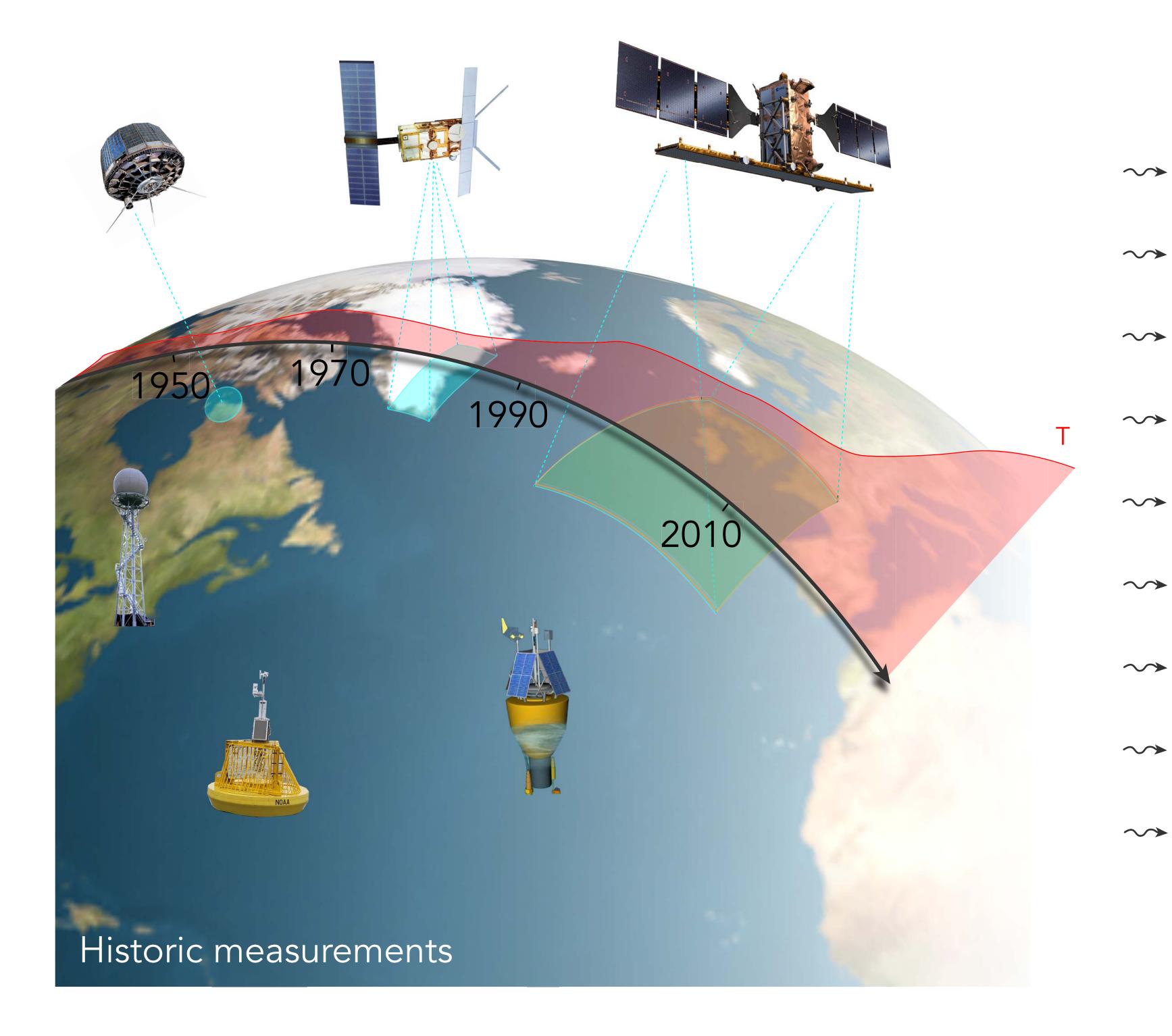




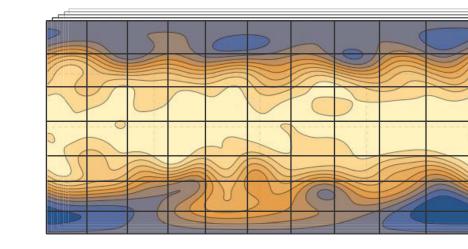


## Classification



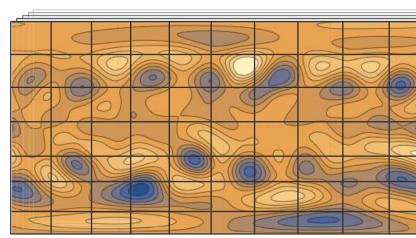


## ERA5 reanalysis



		3		DE
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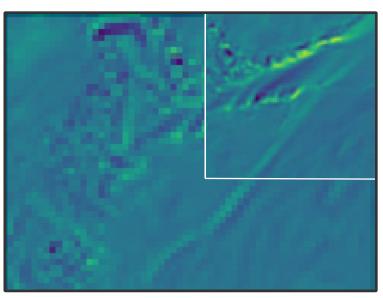
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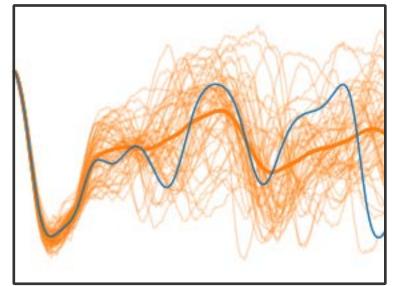
5 petabyte

## AtmoRep

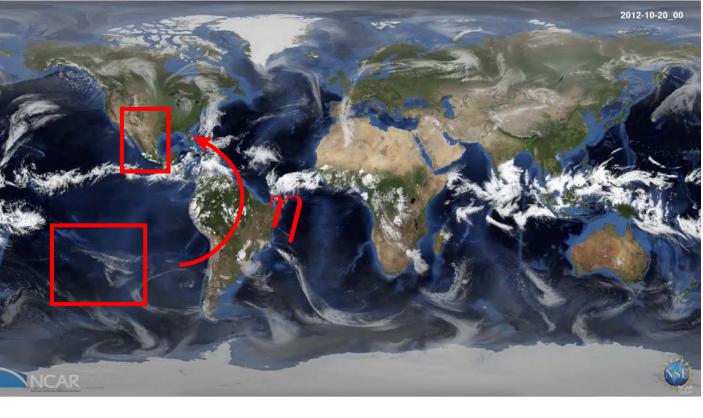
## address climate change



Downscaling

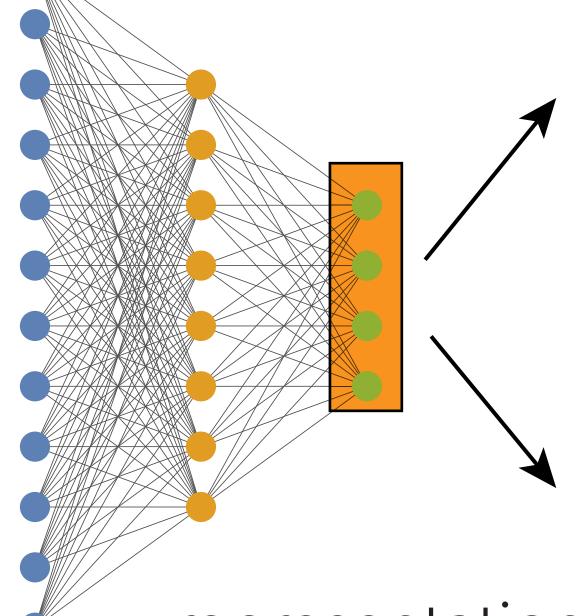


Predictability



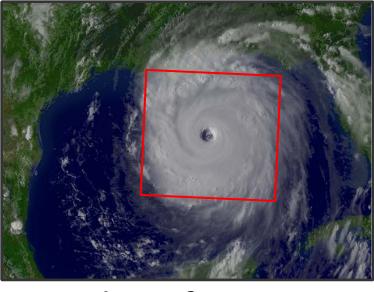
## scientific insight



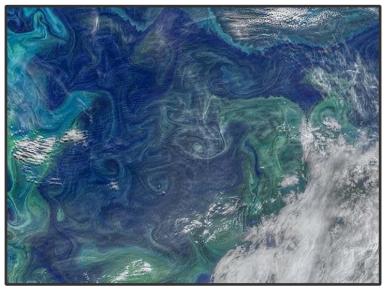


## representation





Classification



# Why machine learning? Incomplete description of physical processes in the

atmosphere

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=> Representation learning on observations

## Large amounts of historical atmospheric observations

# Why machine learning? Incomplete description of physical processes in the

atmosphere

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=> Representation learning on observations

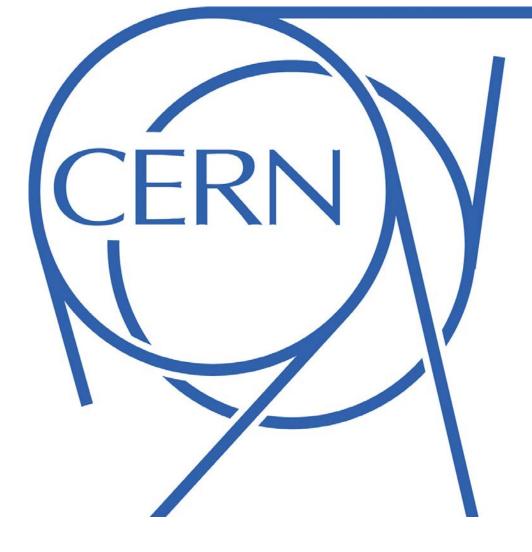
## Large amounts of historical atmospheric observations

# Impact Address climate change Scientific insight

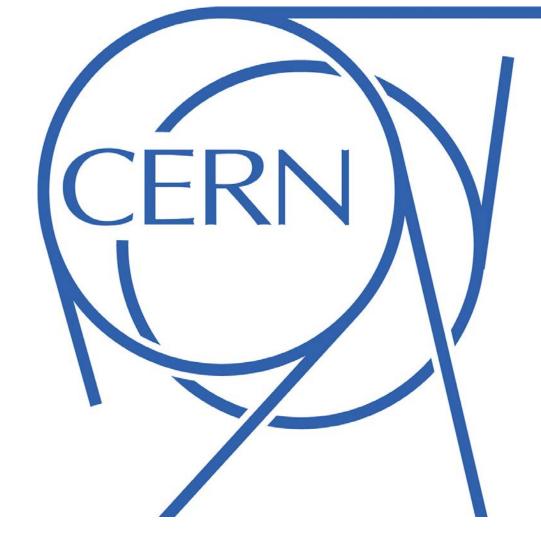
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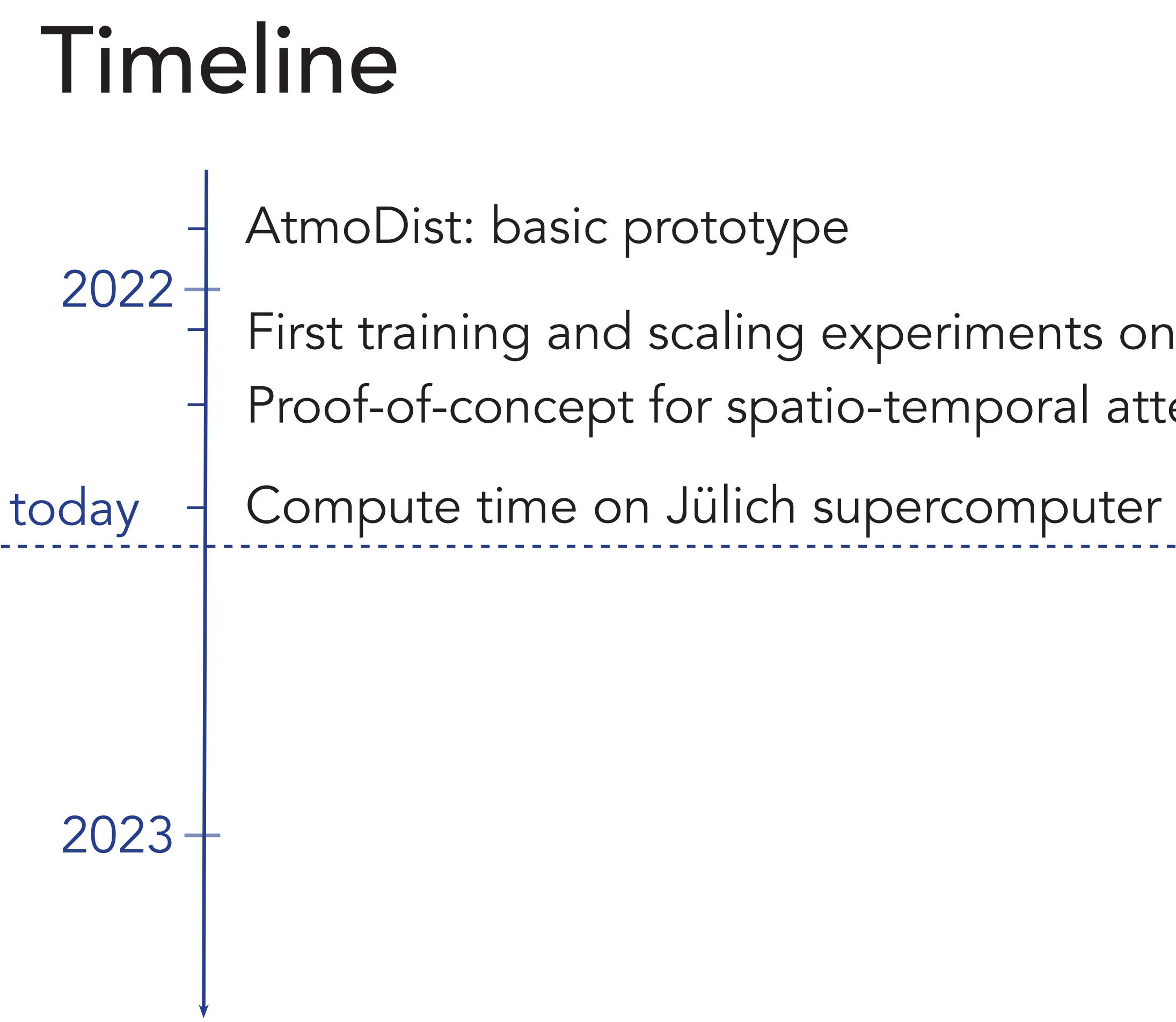
- Super-resolution, classification, predictability, ... Machine-learning corrected climate simulations
- > Finite space-time description of interaction across scales and phenomena in the atmosphere

# AtmoRep@CERN • CERN expertise of relevance: > Handling of large data sets / storage infrastructure Distributed analysis Machine learning Incertainty / error estimation • • •



# AtmoRep@CERN Collaboration with OpenLab (Sofia Vallecorsa) already underway Common interests and directions Information extraction from large amounts of data Incertainty quantification in deep learning Transformer neural networks **>** ...

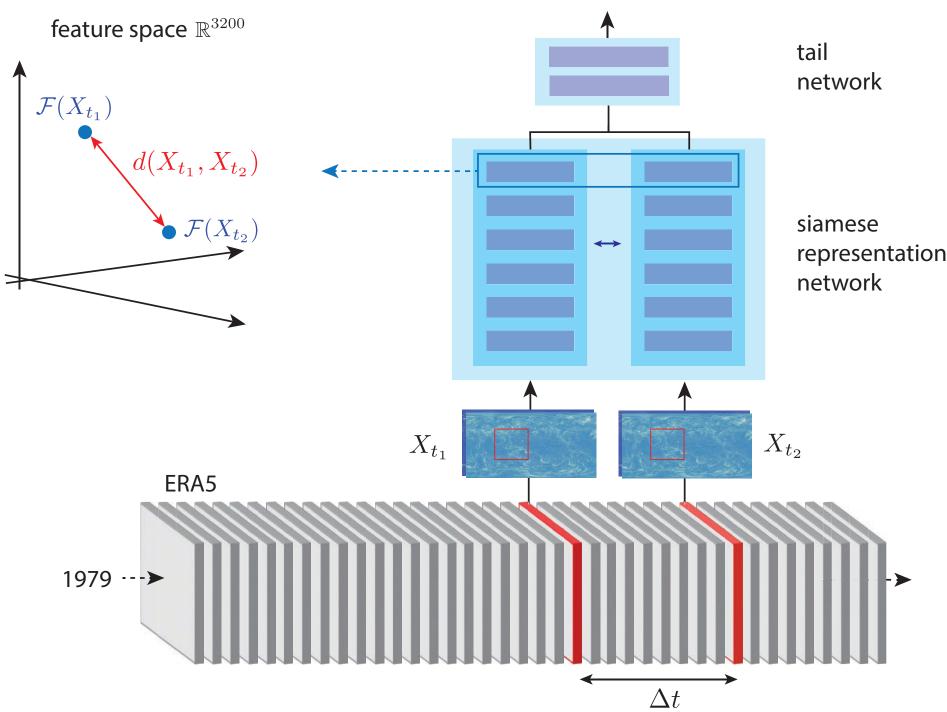


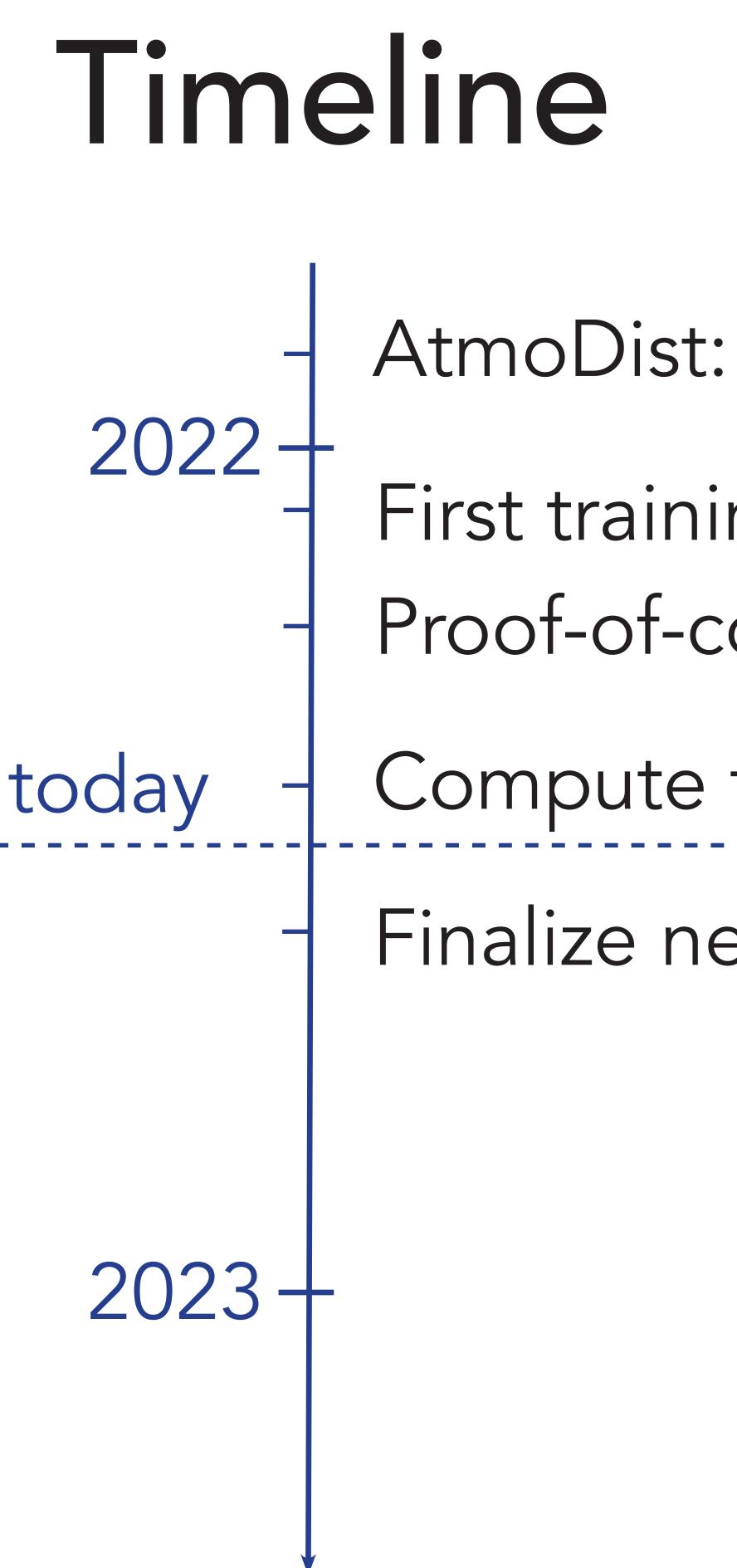


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AtmoDist: basic prototype

First training and scaling experiments on supercomputer Proof-of-concept for spatio-temporal attention maps





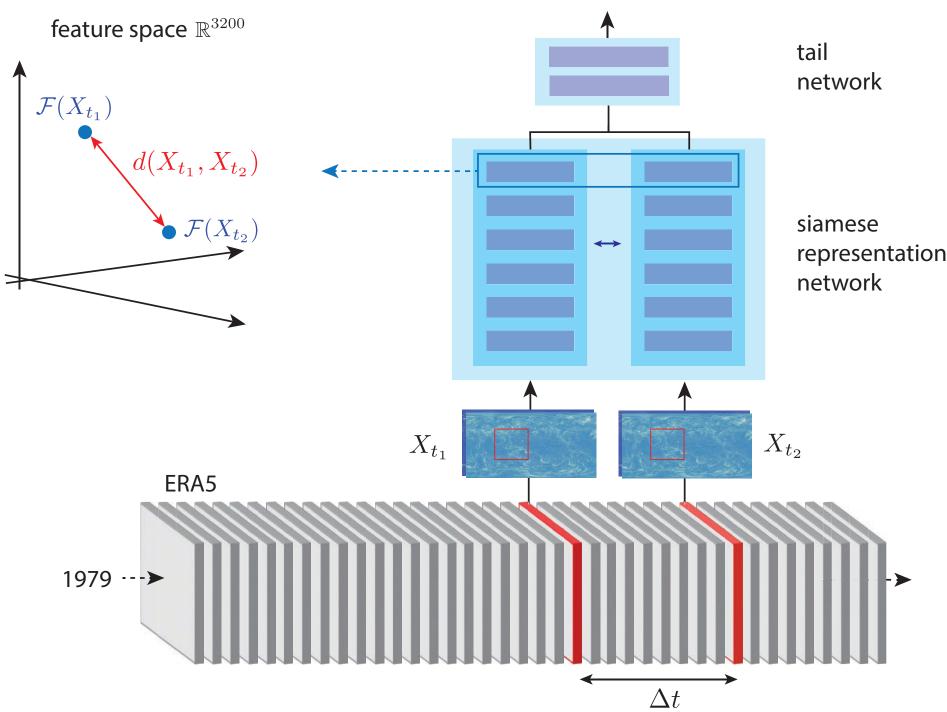
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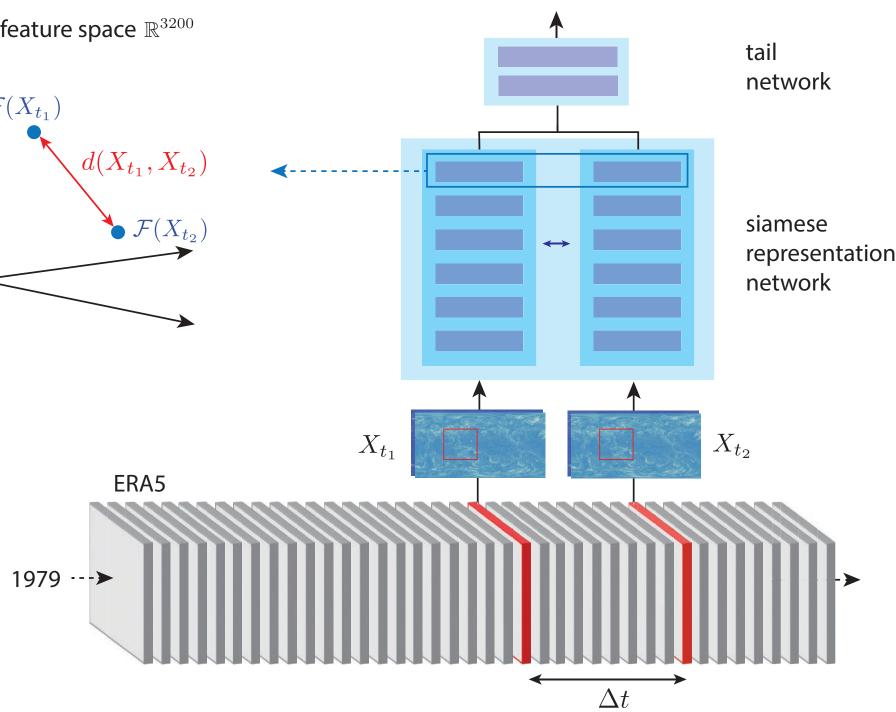
AtmoDist: basic prototype

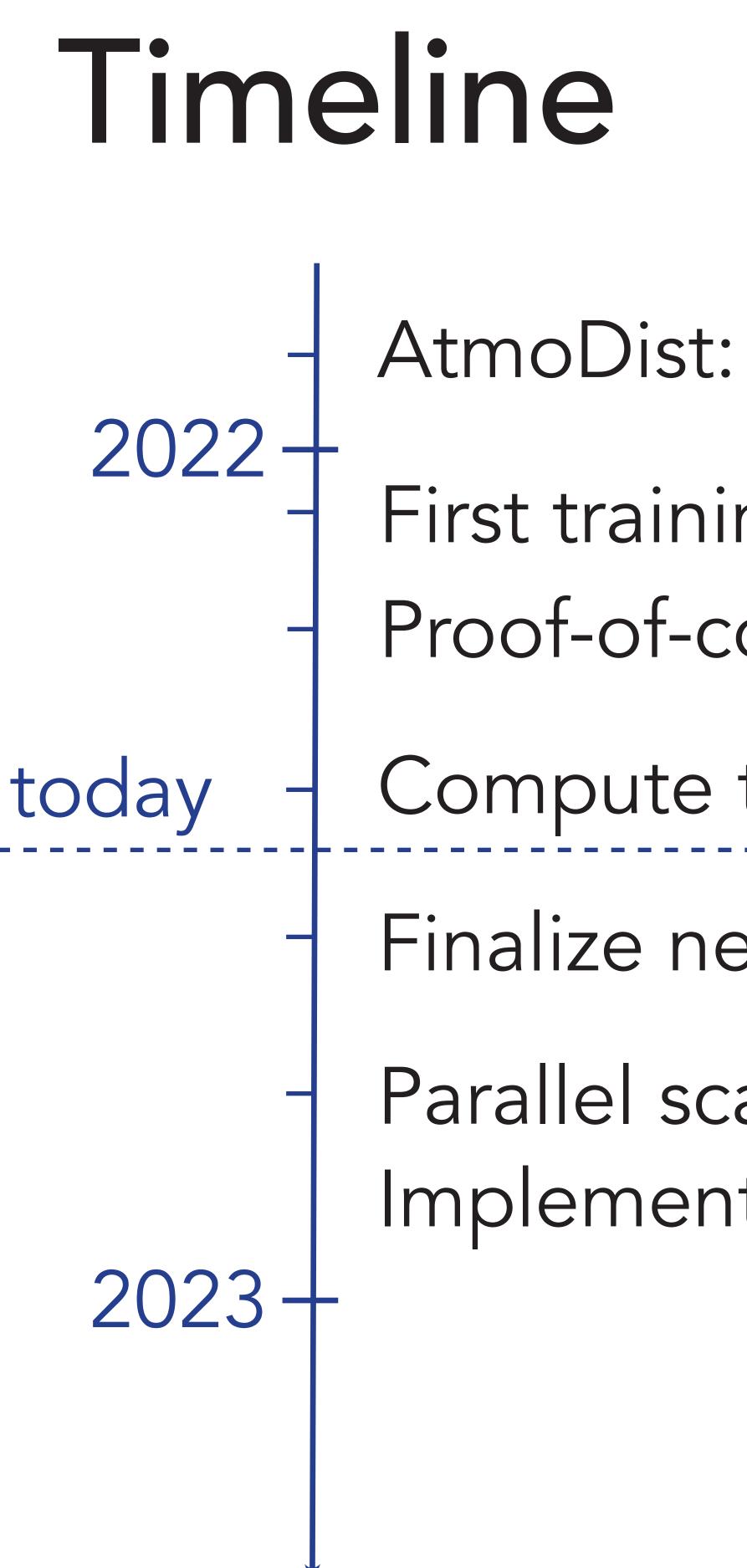
First training and scaling experiments on supercomputer Proof-of-concept for spatio-temporal attention maps

Compute time on Jülich supercomputer

Finalize neural network architecture and training







AtmoDist: basic prototype

First training and scaling experiments on supercomputer Proof-of-concept for spatio-temporal attention maps

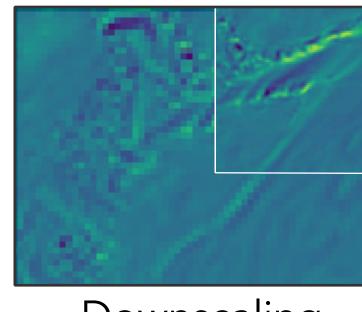
Compute time on Jülich supercomputer

Finalize neural network architecture and training

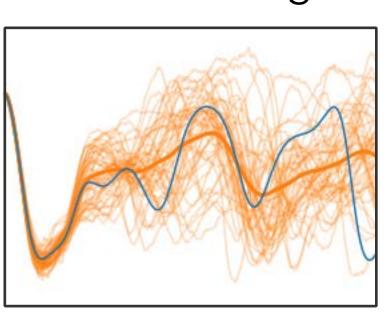
Parallel scaling and training on O(100) TB Implementation of demonstration applications



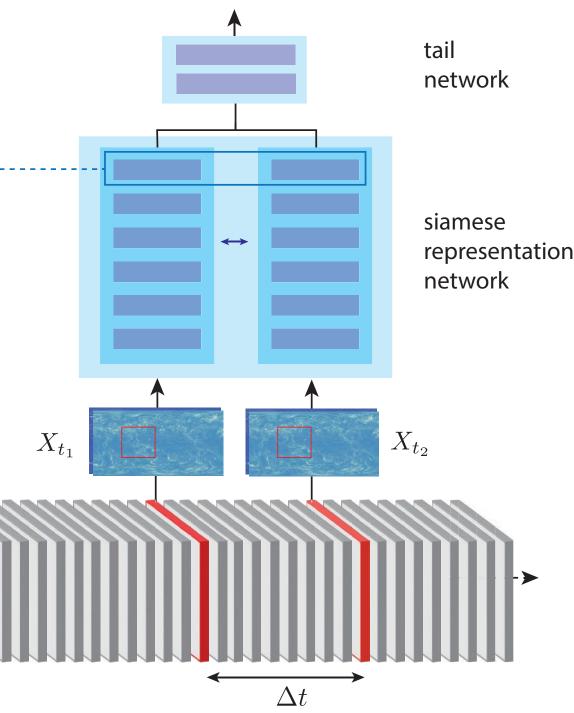
1979 ---▶



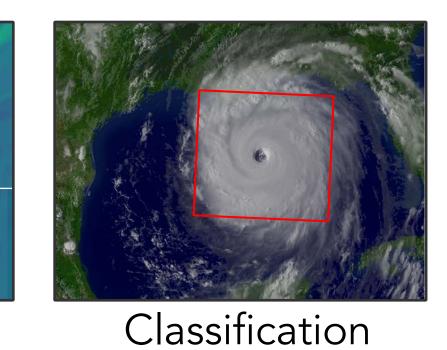
Downscaling

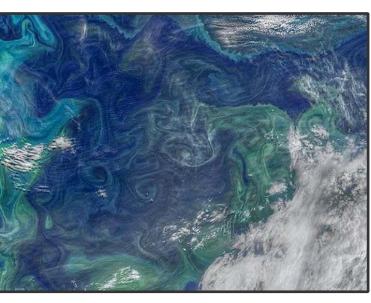


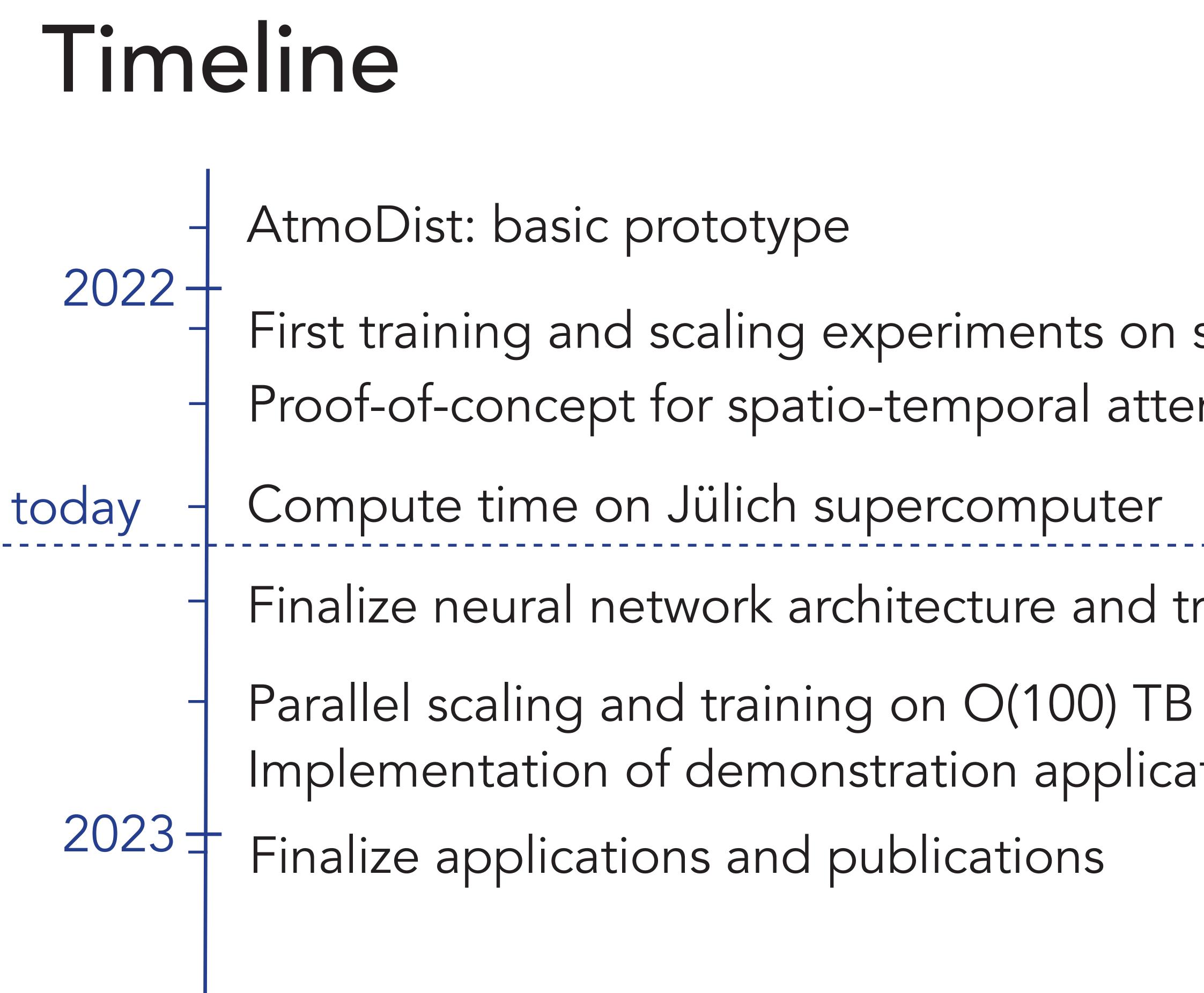
Predictability



## address climate change







Implementation of demonstration applications Finalize applications and publications

Finalize neural network architecture and training

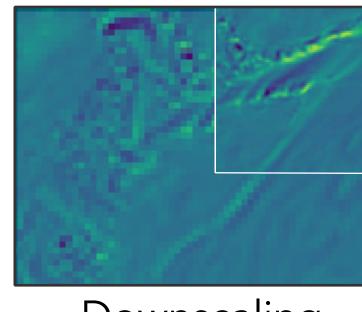
Compute time on Jülich supercomputer

First training and scaling experiments on supercomputer Proof-of-concept for spatio-temporal attention maps

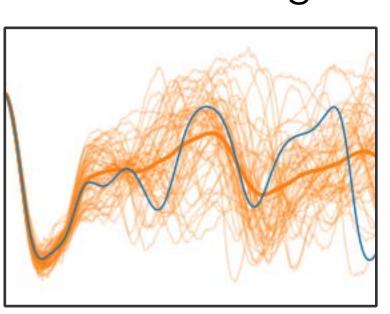
AtmoDist: basic prototype



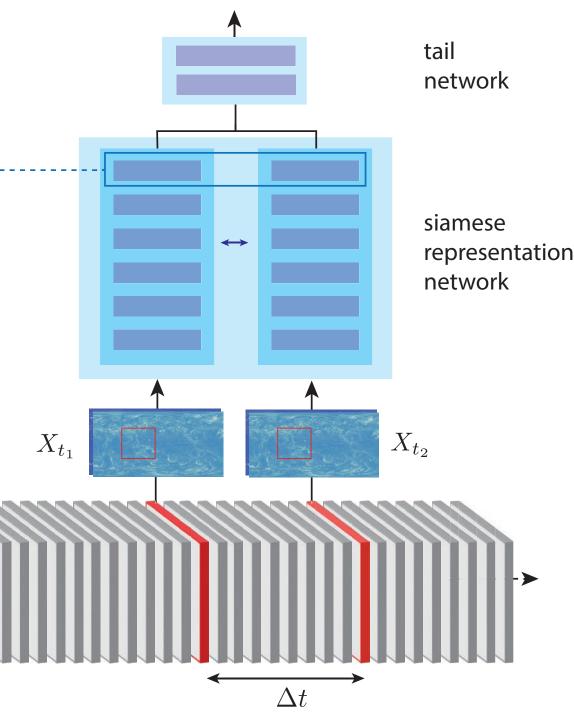
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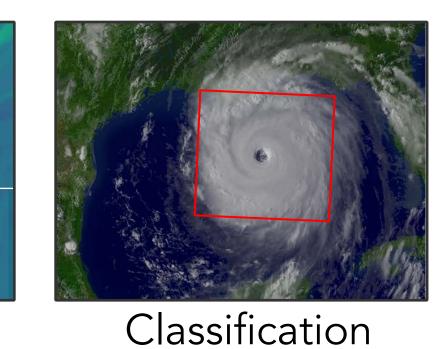
Downscaling

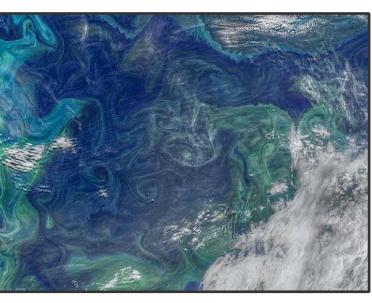


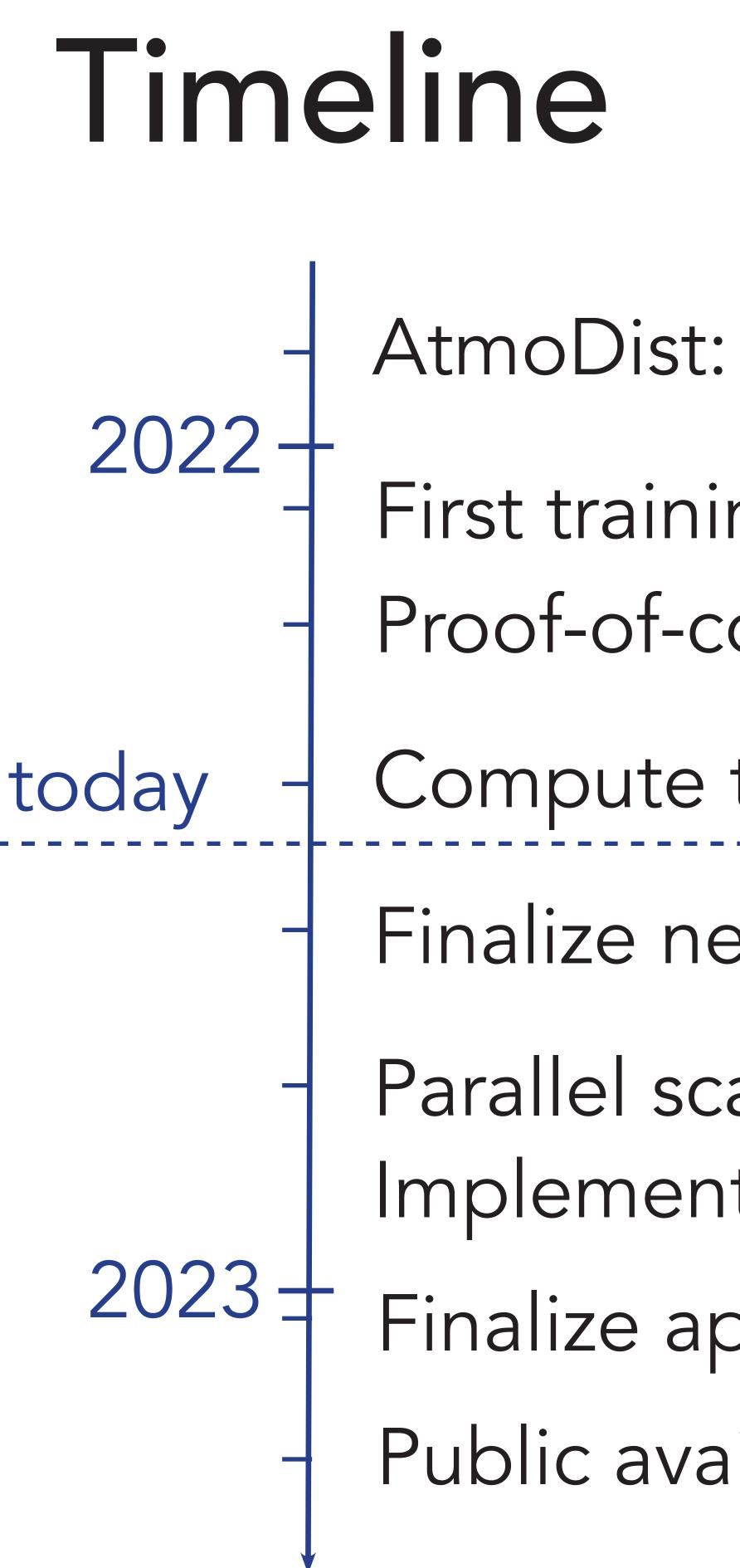
Predictability



## address climate change

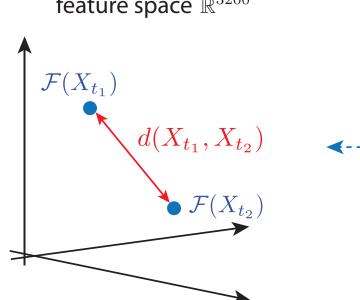


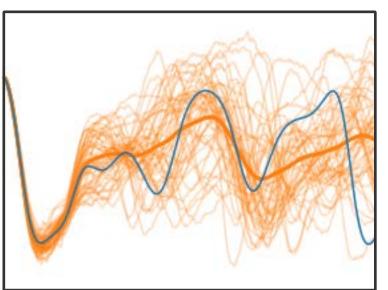




- Parallel scaling and training on O(100) TB Implementation of demonstration applications Finalize applications and publications Public availability of pretrained neural network
- Finalize neural network architecture and training
- Compute time on Jülich supercomputer
- First training and scaling experiments on supercomputer Proof-of-concept for spatio-temporal attention maps
- AtmoDist: basic prototype

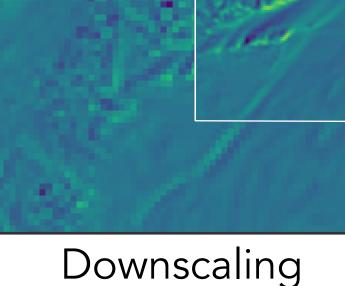
1979 ---▶



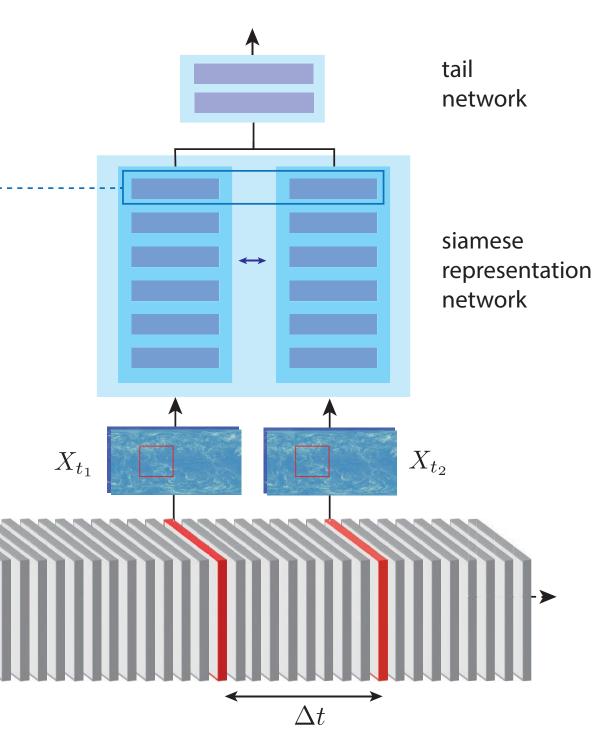


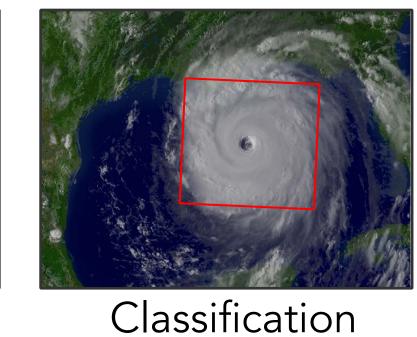
Predictability

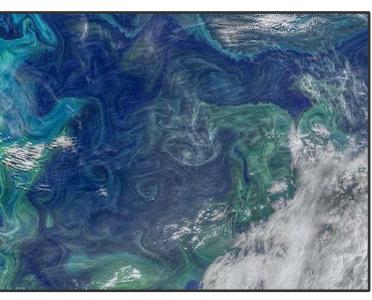
Downscaling



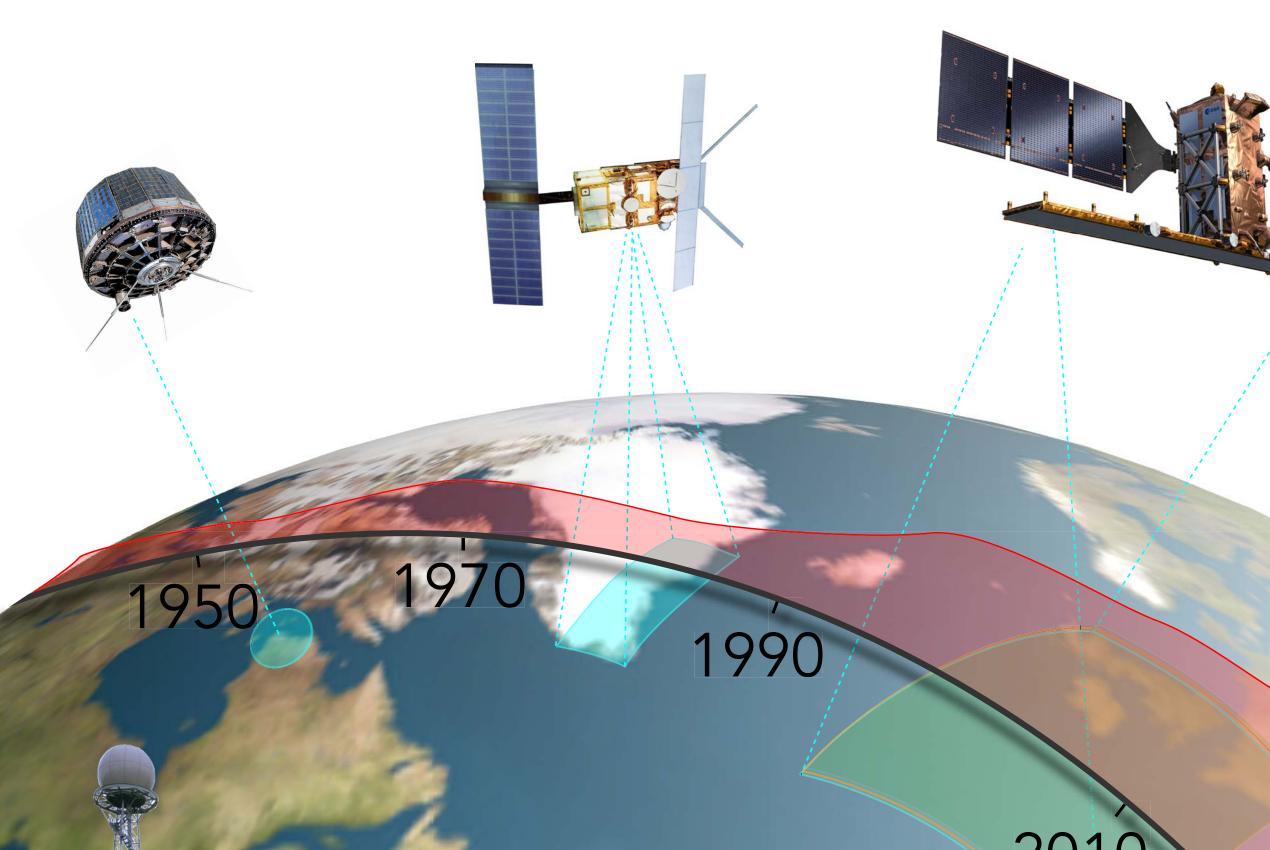
## address climate change





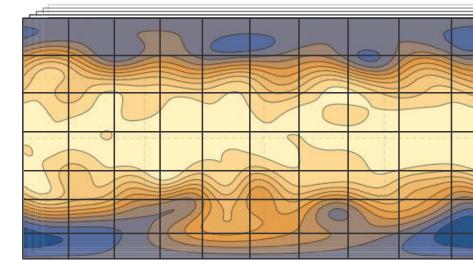


# AtmoRep



# Use large amounts of historical observations to improve climate projections and related applications Significant potential impact through various applications Scientifically interesting and challenging





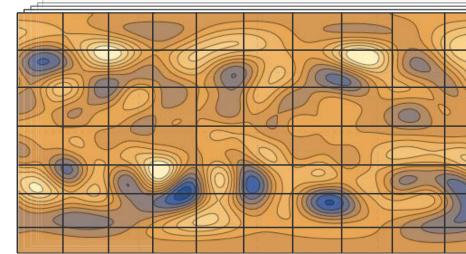
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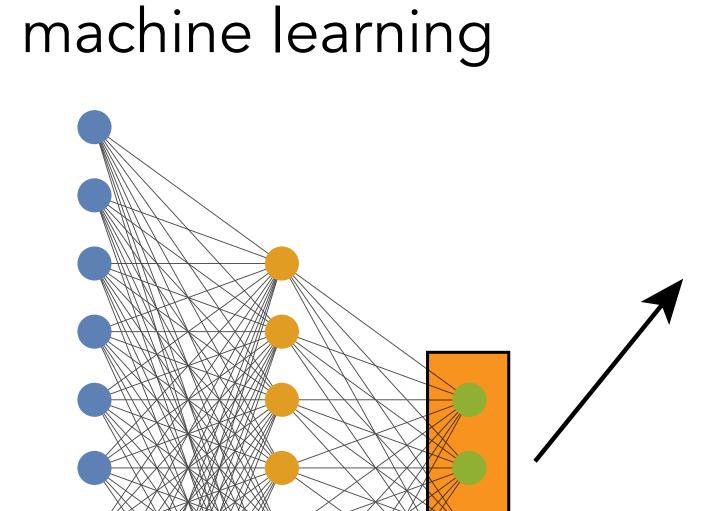
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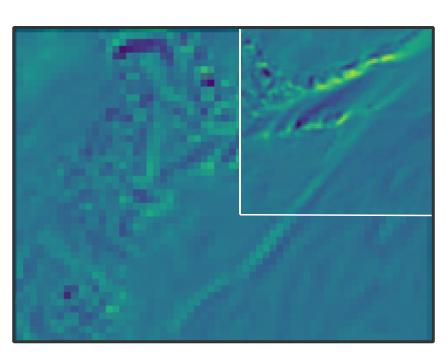




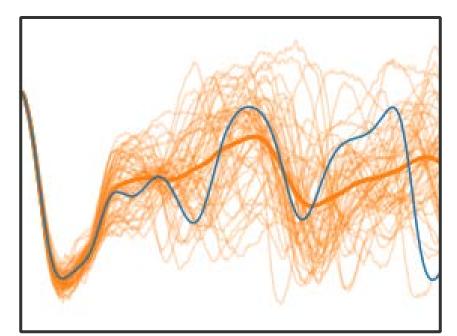




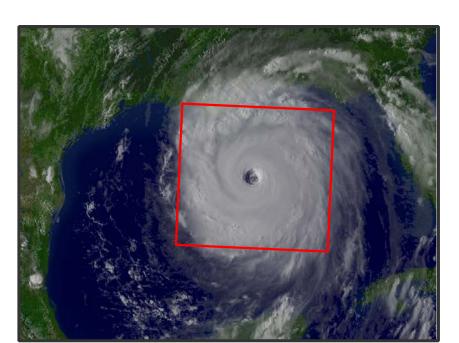
large scale



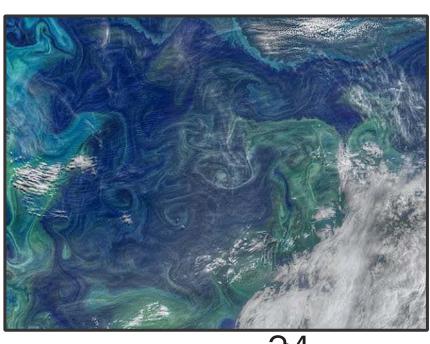
Downscaling



Predictability



Classification



 What is a representation? tor space)

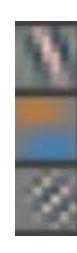
# Representation learning

- > Layers of neural network are nonlinear maps of input data to intermediate representation (elements in a vec-

  - ful for a range of tasks

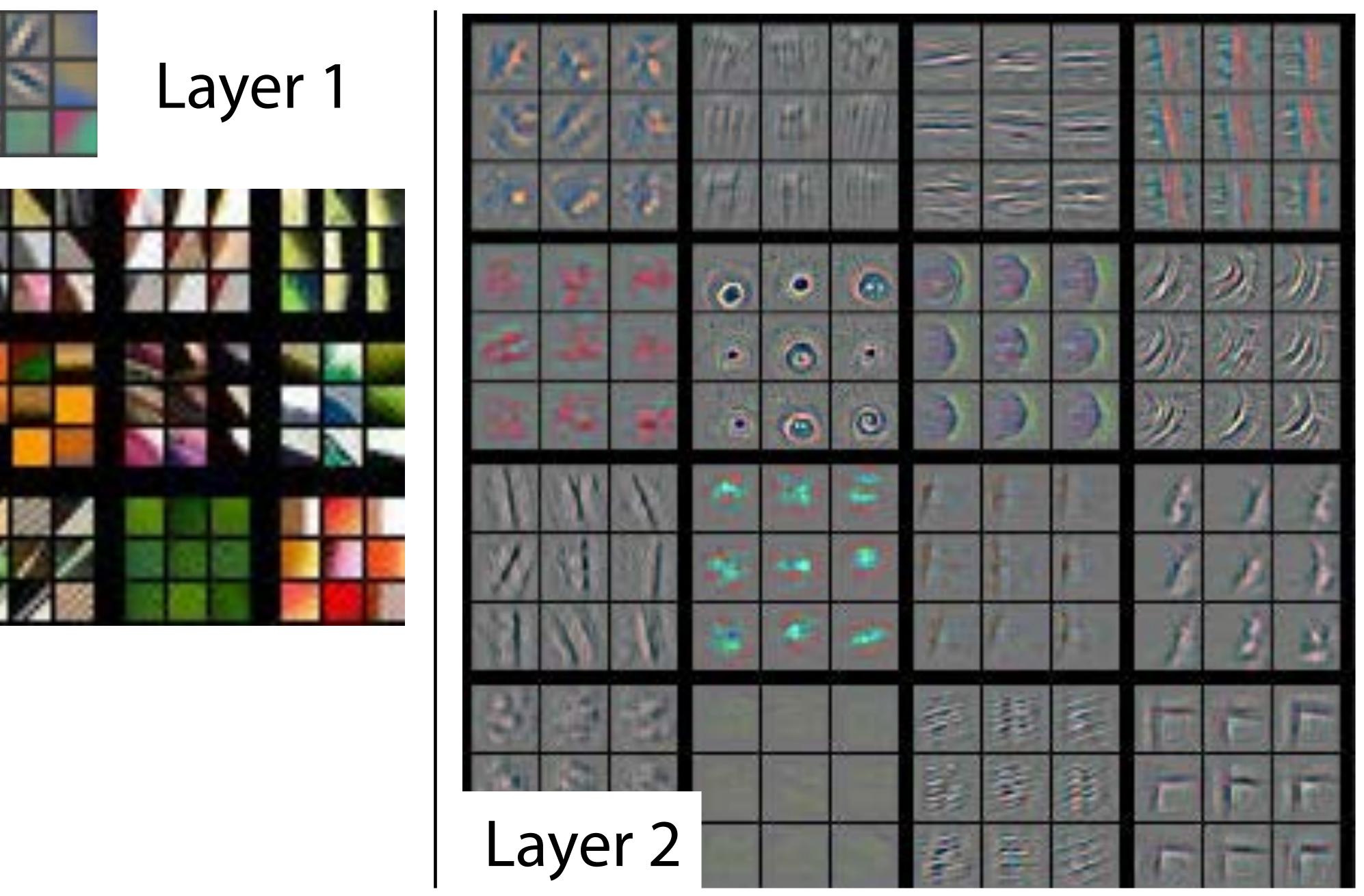
> For a trained neural network the intermediate layers hence provide transformed data adapted to a domain Often the same intermediate representations are use-

# **Representation learning**



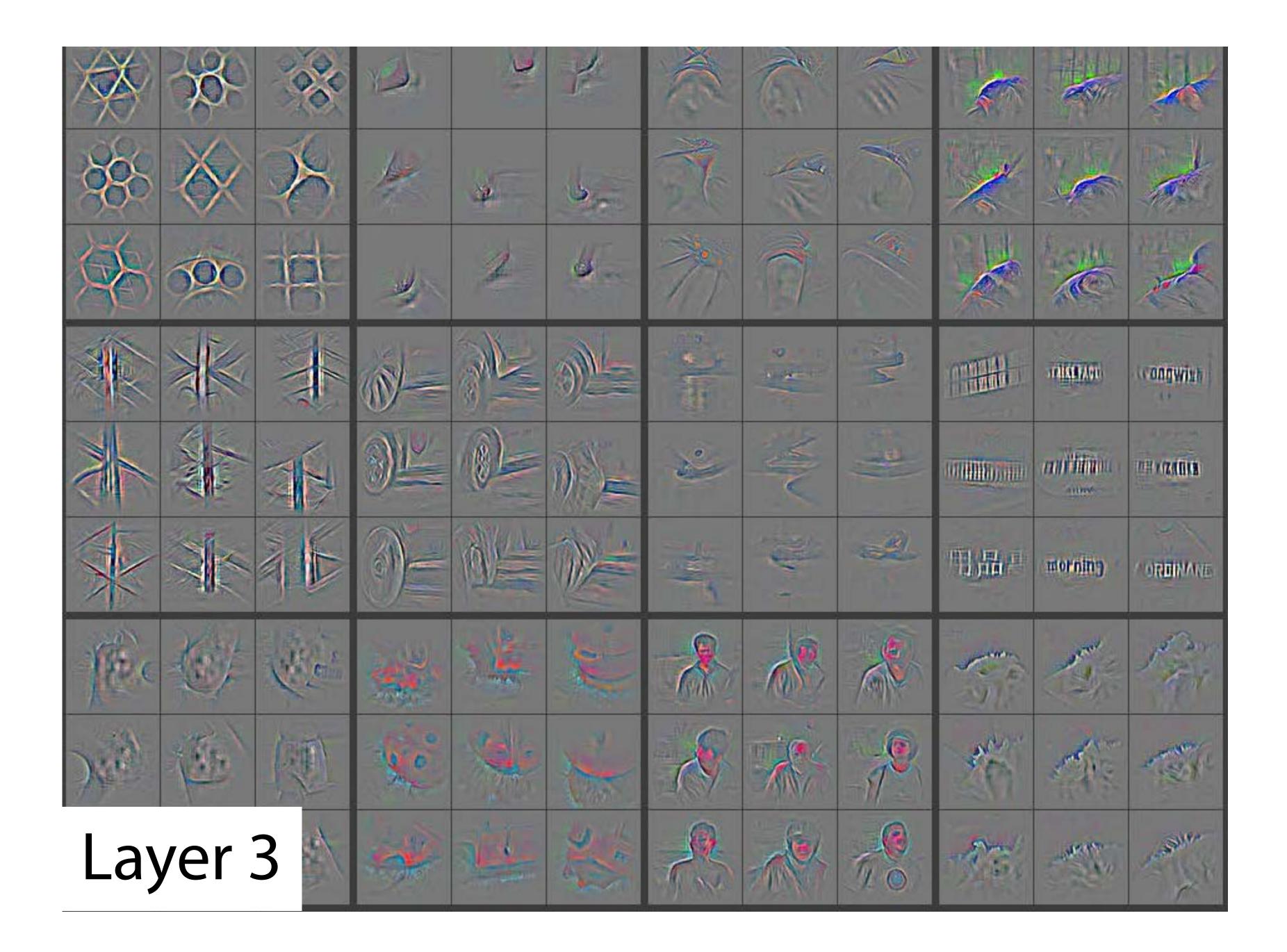


From M. D. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. In D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, editors, Computer Vision – ECCV 2014, pages 818–833, Cham, 2014. Springer International Publishing.



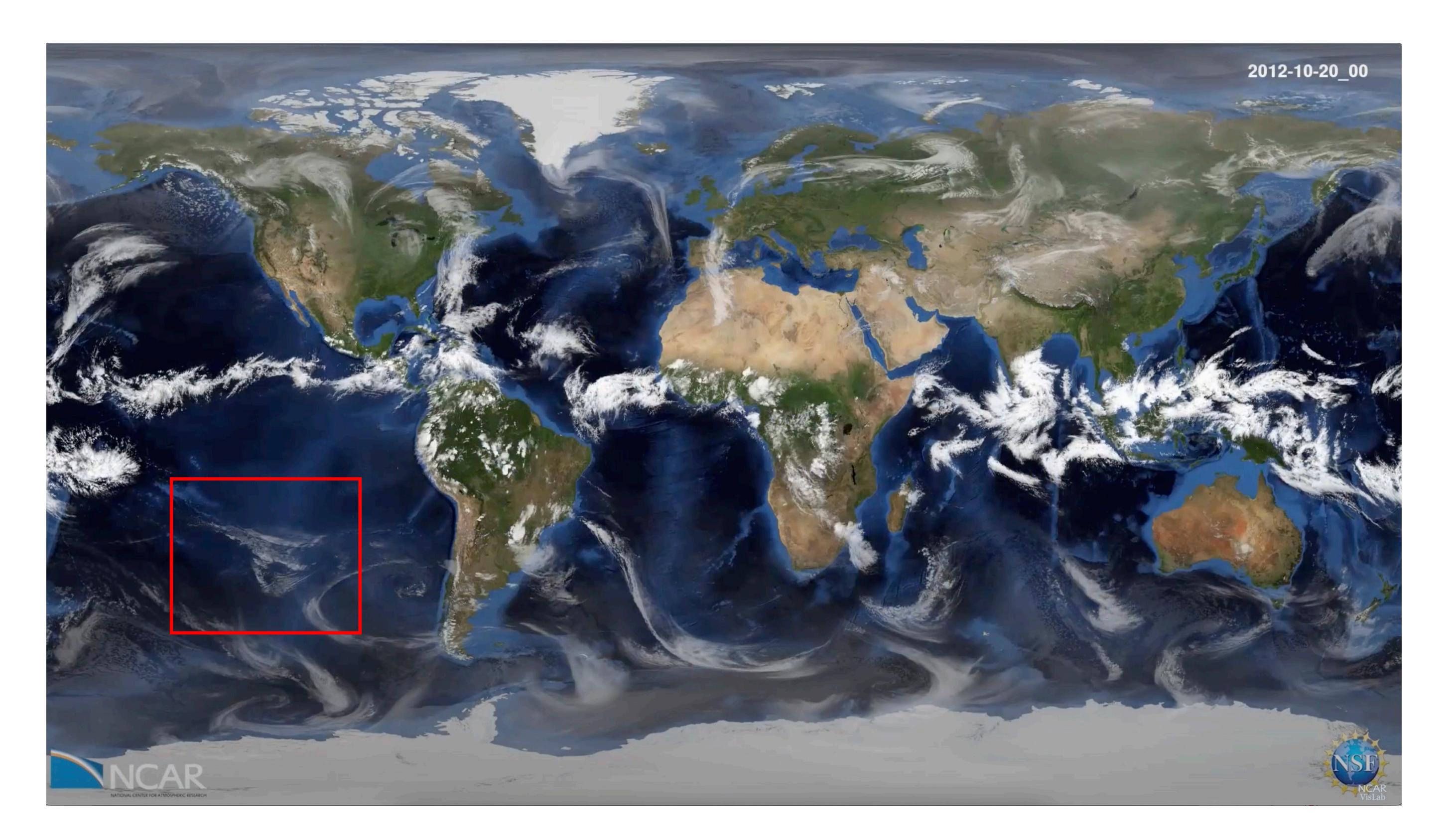
# **Representation learning**

From M. D. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. In D. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, editors, Computer Vision – ECCV 2014, pages 818–833, Cham, 2014. Springer International Publishing.

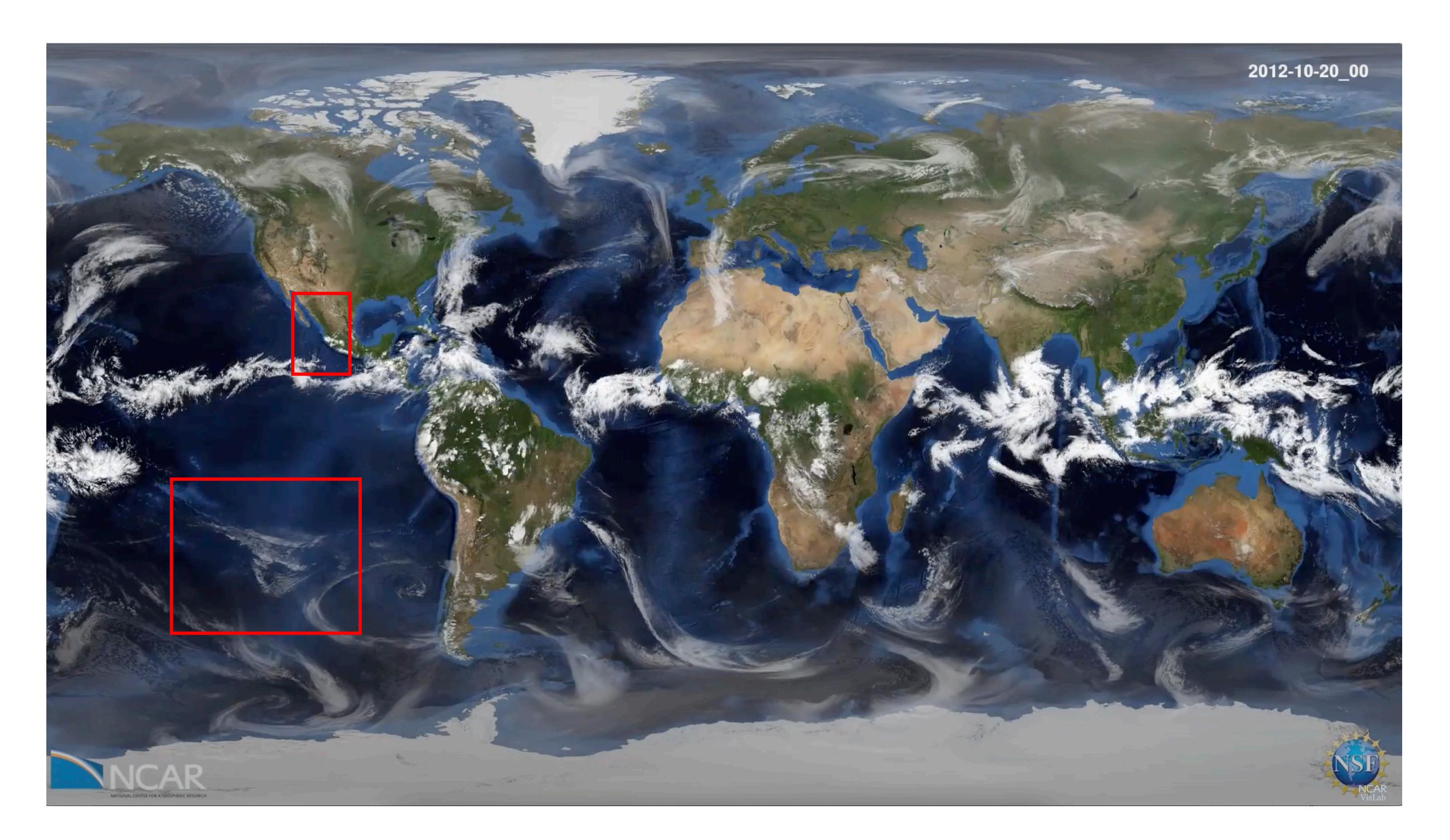


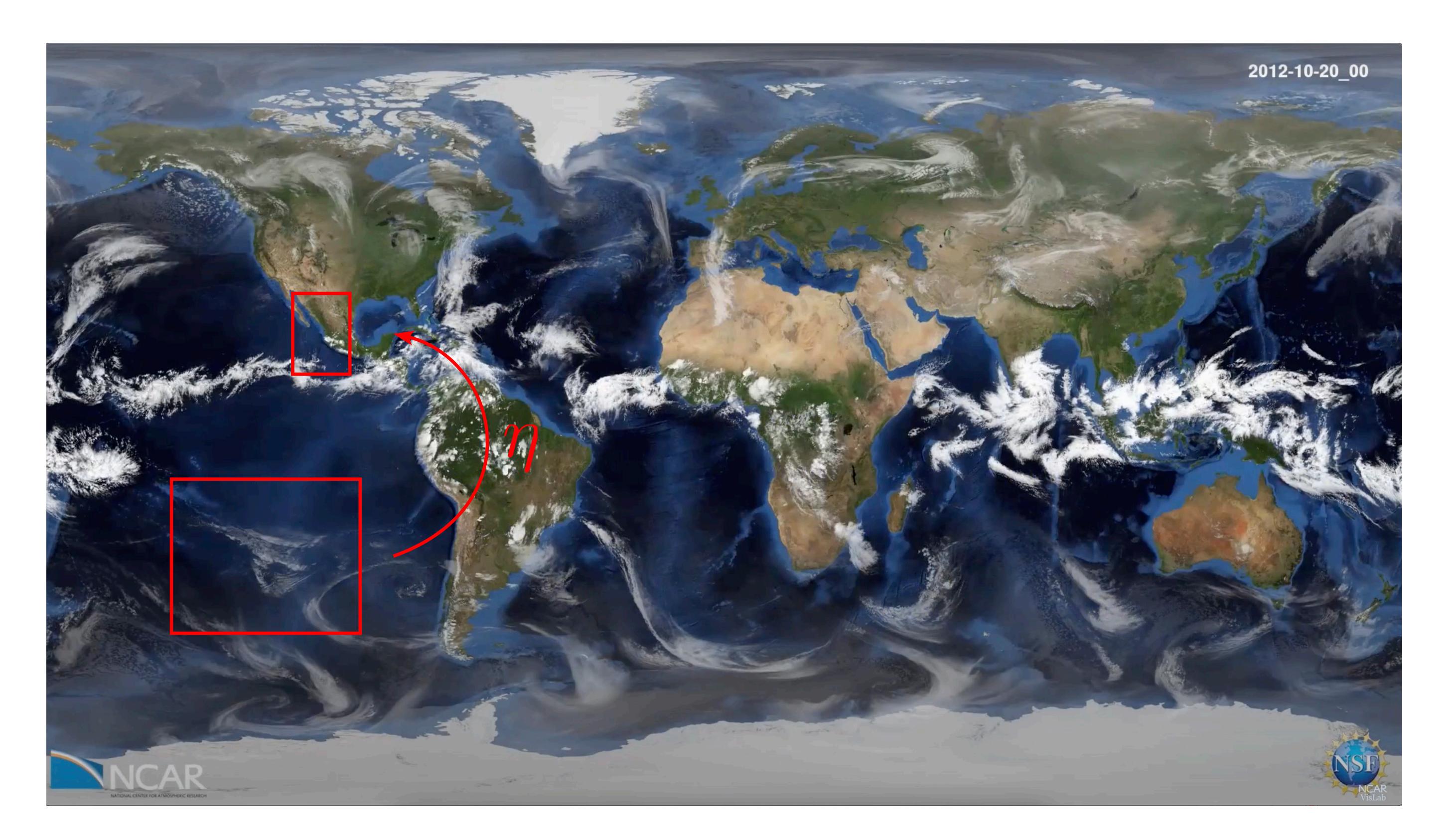
# Scientific insight Spatio-temporal representation learning: Learn representation that describe finite time spatiotemporal interactions across scales

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- Spatio-temporal representation learning:
  - > Learn representation that describe finite time spatiotemporal interactions across scales
  - Capture interactions that are difficult to describe with classical approaches
  - > Transformer neural networks allow for simple interpretability

# Why machine learning? Only incomplete description of physical processes in the atmosphere > No (effective) models for cloud formation, interaction with biosphere, ... Nost models only provide infinitesimal information Very large number of interacting scales (1 m to 10<sup>8</sup> m) => Machine learning based on observations to capture phenomena and interactions not well described so far