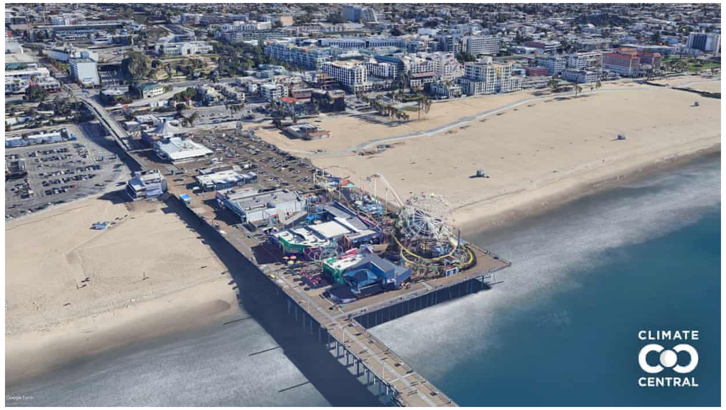
SIMONS FOUNDATION

NYU

Relating **coastal sea level** to its drivers in the **ocean interior**

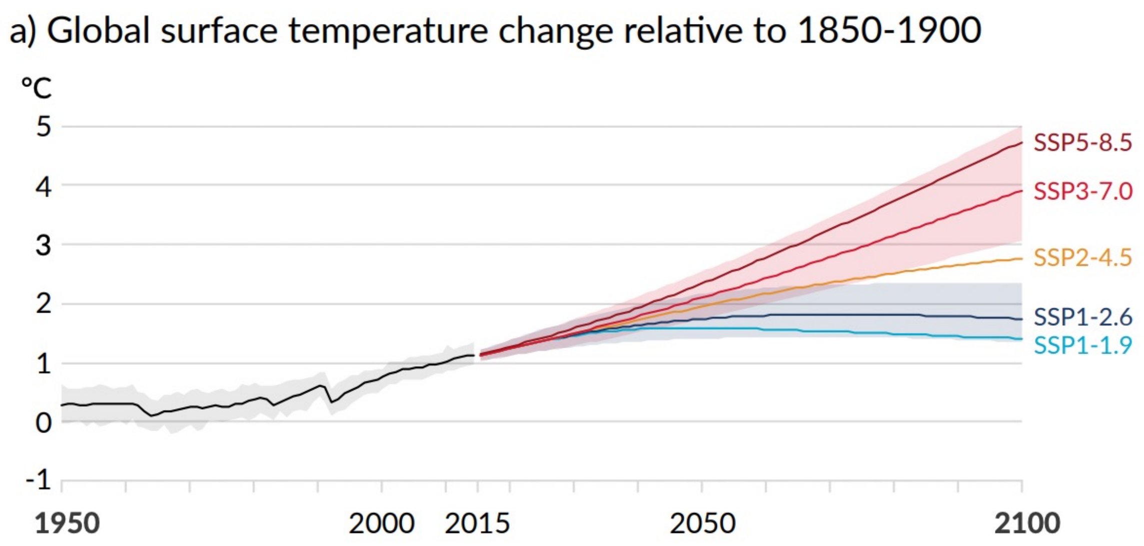
Abigail Bodner
CAOS, NYU

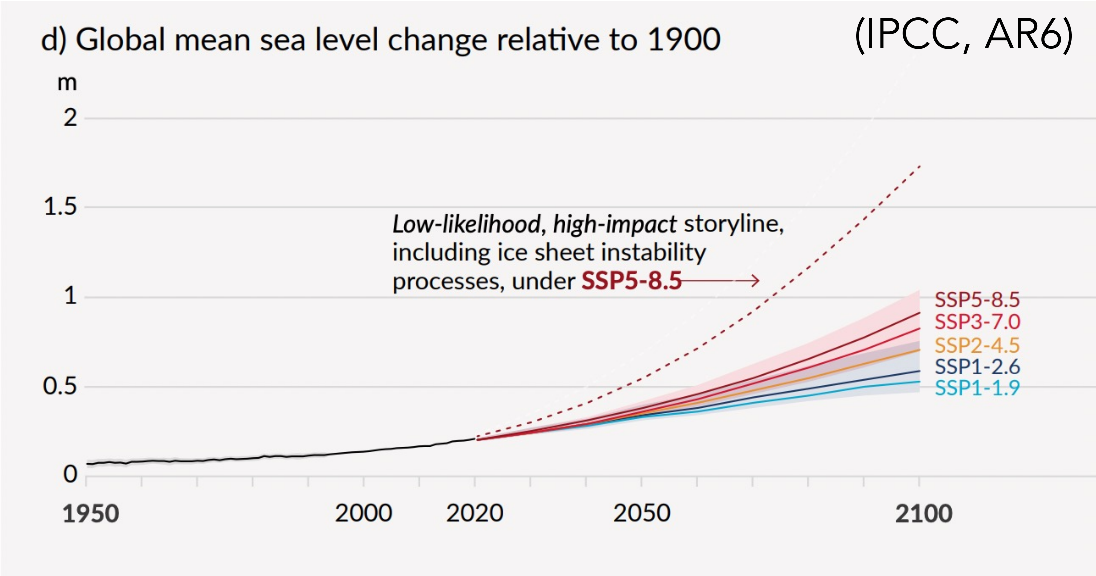
Santa Monica Pier, present day



Santa Monica Pier, +1.5C^{o}

Santa Monica Pier, +3C^{o}





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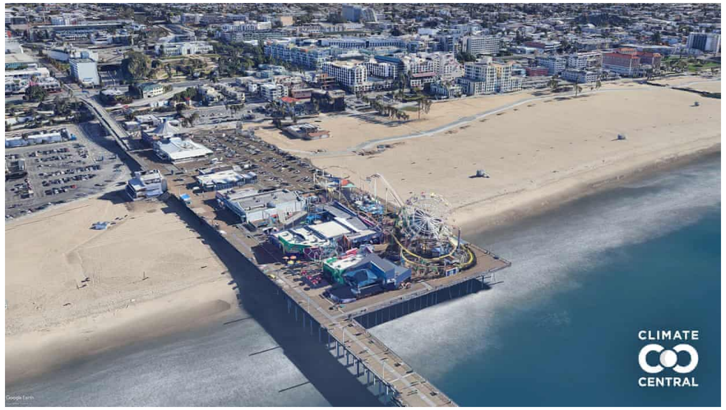

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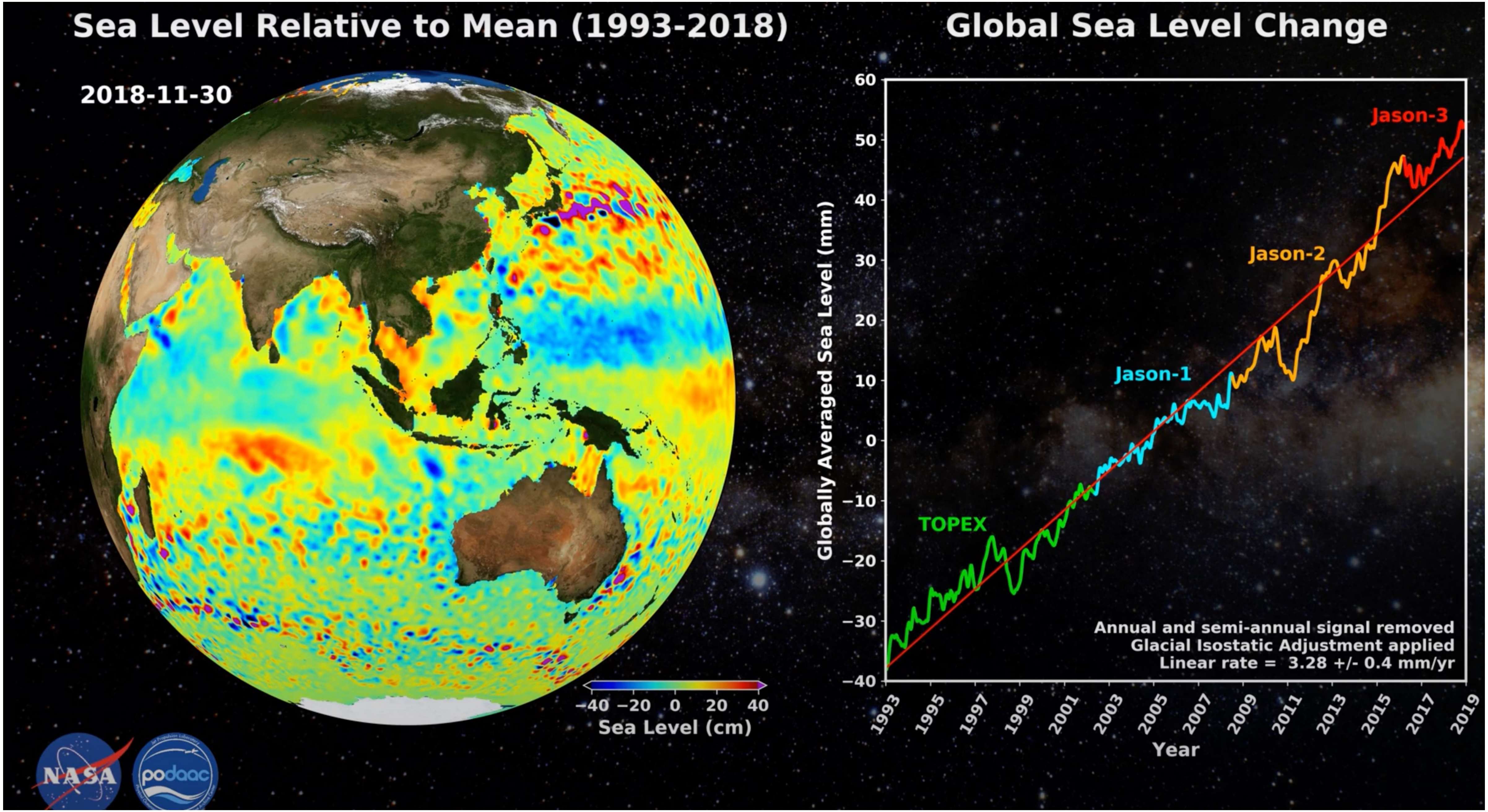
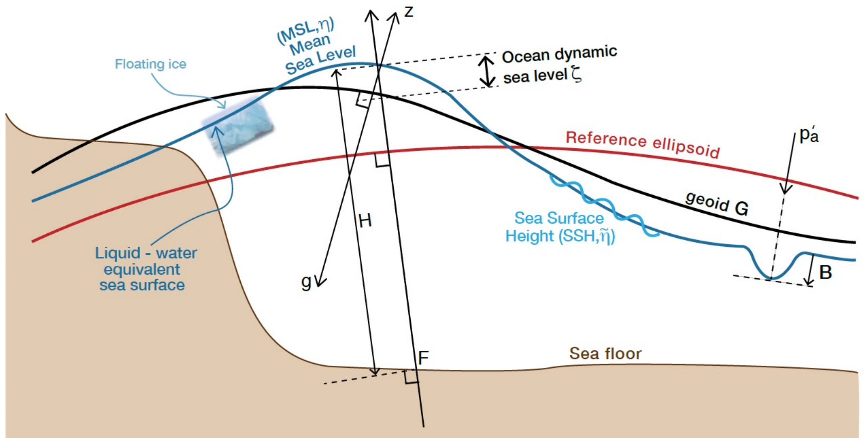


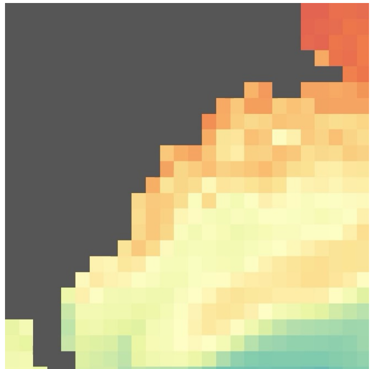
Sea Level Relative to Mean (1993-2018)
2018-11-30
−40 −20 0 20 40
Sea Level (cm)
NASA
podaac
Global Sea Level Change
Globally Averaged Sea Level (mm)
60
50
40
30
20
10
0
−10
−20
−30
−40
TOPEX
Jason-1
Jason-2
Jason-3
Annual and semi-annual signal removed
Glacial Isostatic Adjustment applied
Linear rate = 3.28 +/- 0.4 mm/yr
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013
2015
2017
2019
Year

Sea Level

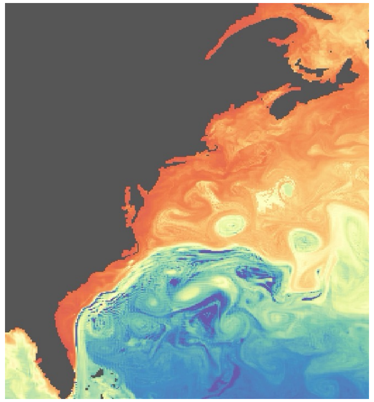
- Global-- driven by thermal expansion and ice melt
- Regional– determined by atmospheric forcing, bathymetry, water density, and turbulent flows
- Wide range of scales.
- Model and resolution dependent !!

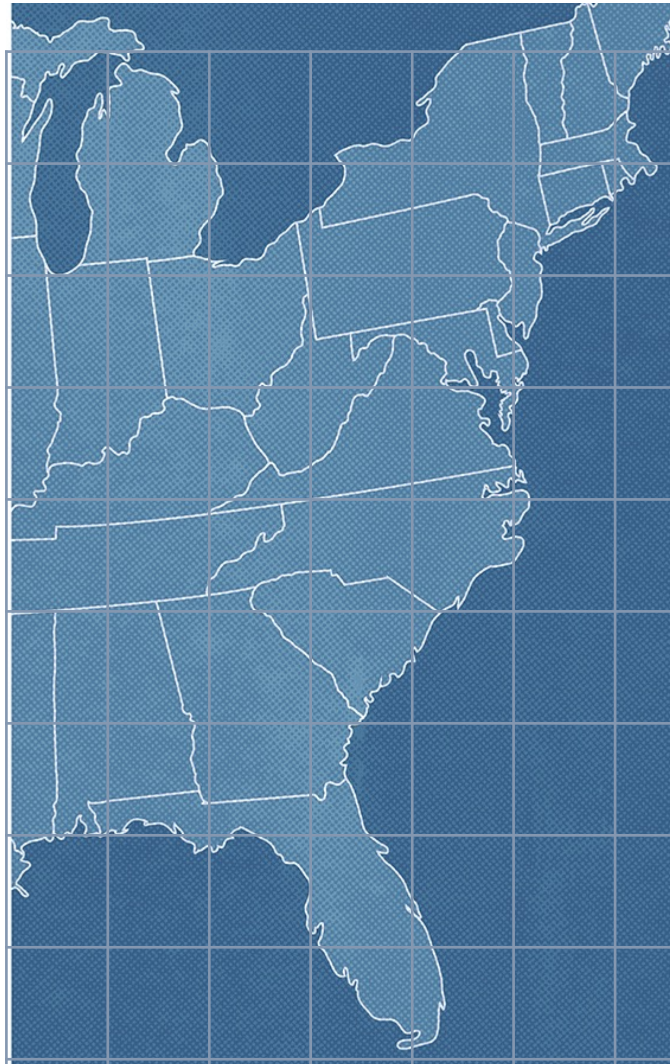


Gregory et. Al. (2019)



Courtesy of Julius Busecke





Motivation

- There is a relationship to be learned between coastal sea level and its drivers in the ocean interior
- Multiscale problem, too wide a range to simulate on scales relevant for coastal sea level
- If traditional climate simulations cannot resolve, perhaps a machine/deep learning approach is possible?
- What data can we trust and how to meaningfully use it?

SIMONS FOUNDATION

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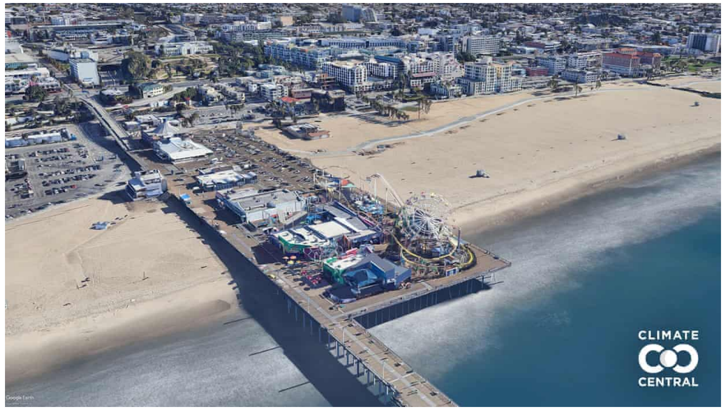
Relating **coastal sea level** to its drivers in the **ocean interior**

a machine learning approach

Abigail Bodner
CAOS, NYU

Santa Monica Pier, present day



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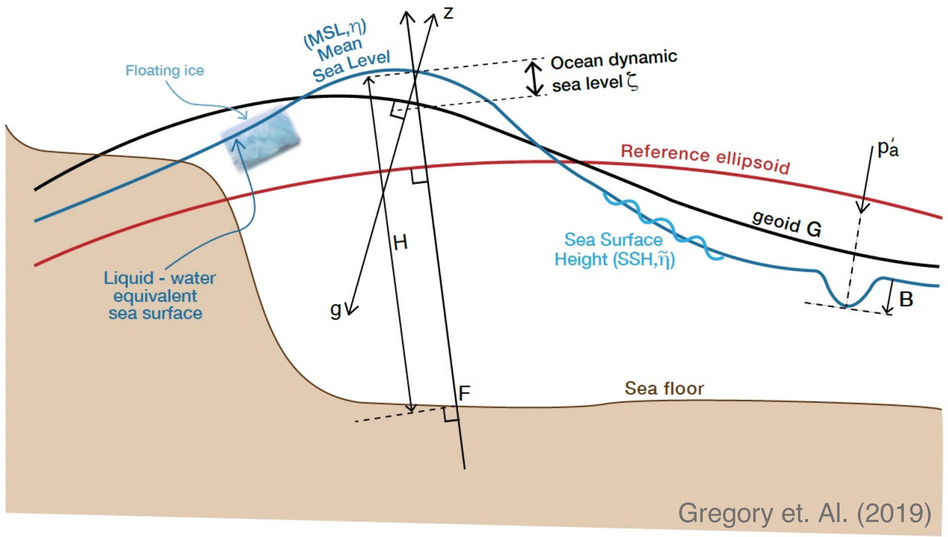
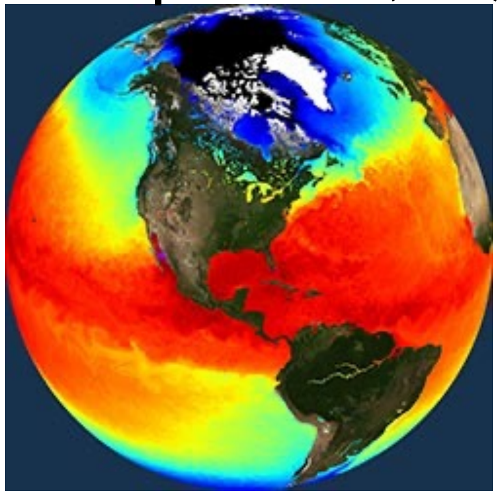
Input:
Satellite data

- Surface measurements reflect flow properties in ocean interior
- Related to dynamic sea level components
- Issues: coastal measurements are very poor

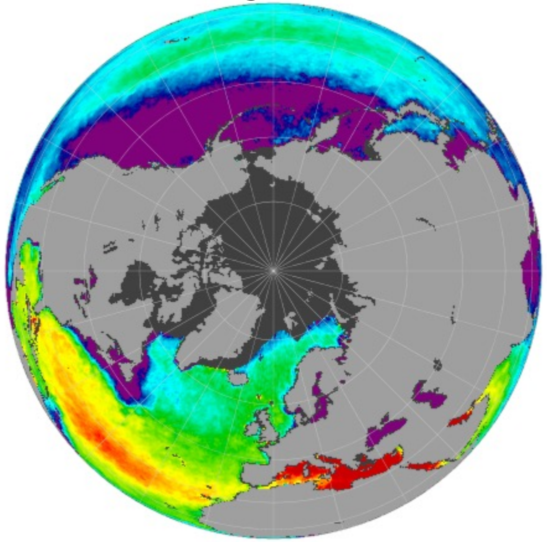


Gregory et. Al. (2019)

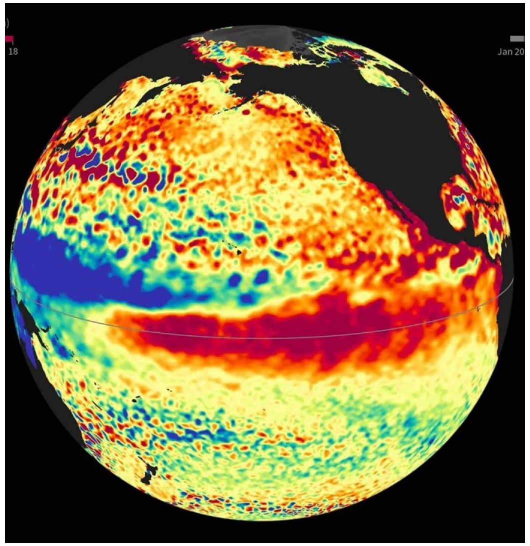
Sea surface temperature (SST)



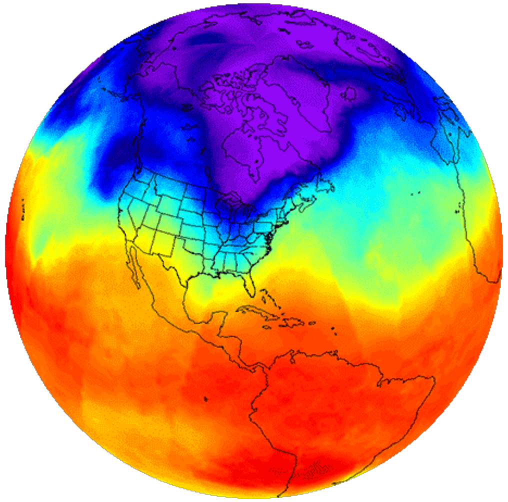
Sea surface salinity (SSS)



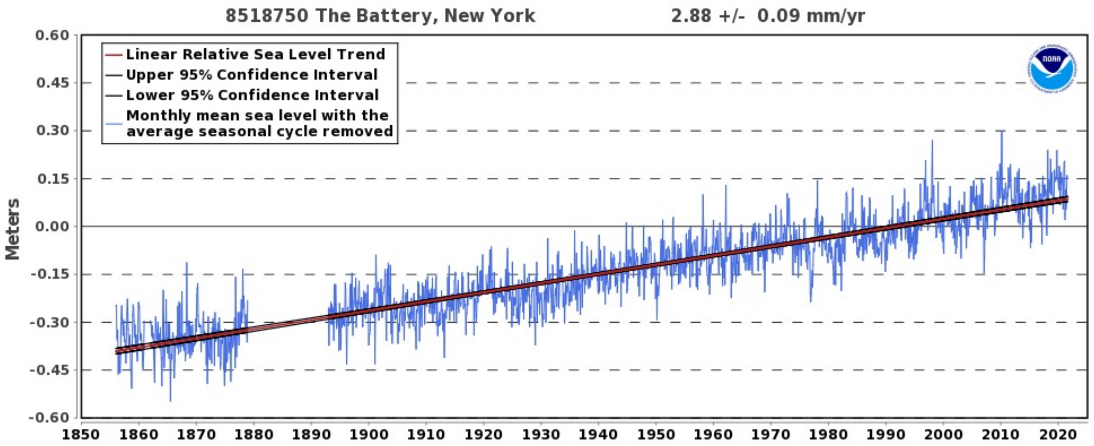
Altimetry, sea surface height (SSH)



Surface pressure (Pa)



<u>Target</u>:
Tide gauge data



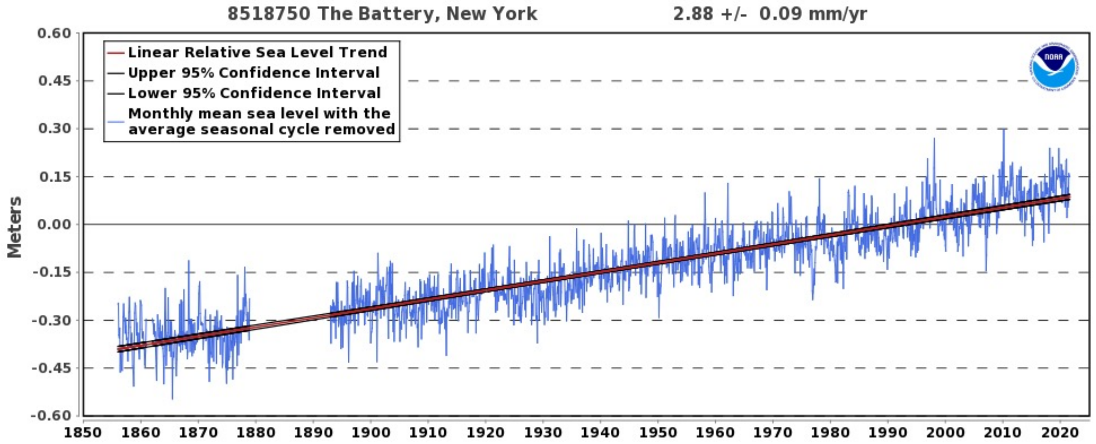
- Effective sea level at coastal locations
- Global distribution
- Issues: noisy, gaps in data, not consistent among all locations

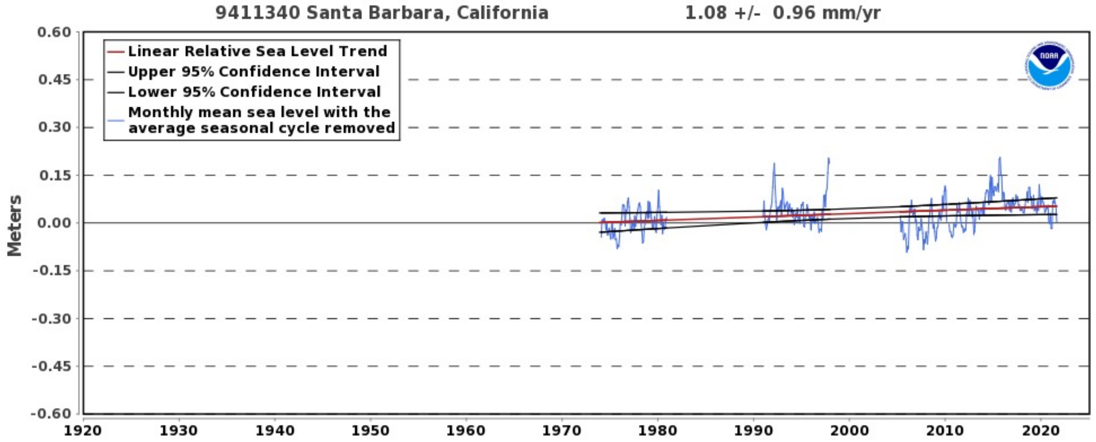
Global tide gauge locations

<u>Target</u>:
Tide gauge data

- Effective sea level at coastal locations
- Global distribution
- Issues: noisy, gaps in data, not consistent among all locations

Global tide gauge locations





Objective

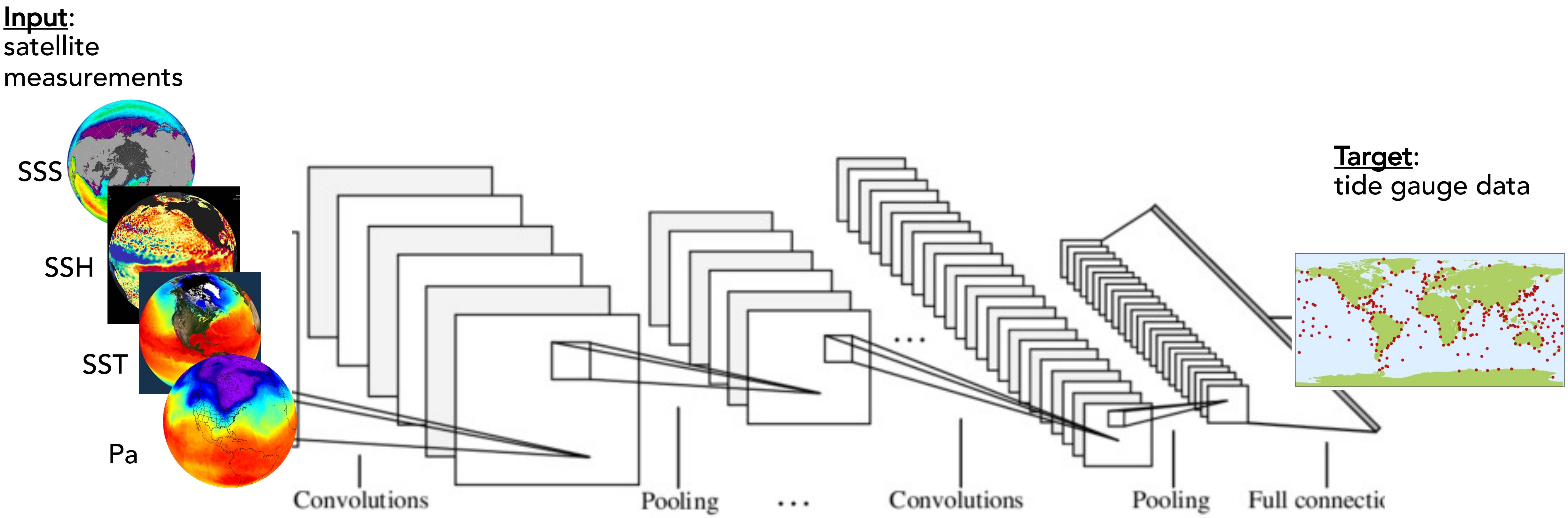
- Satellite surface measurements reflect interior properties important for sea level

- Tide gauge data reflects effective sea level at coastal locations

- Use machine learning to link between satellite measurements (input) and tide gauge data (target)

Objective:

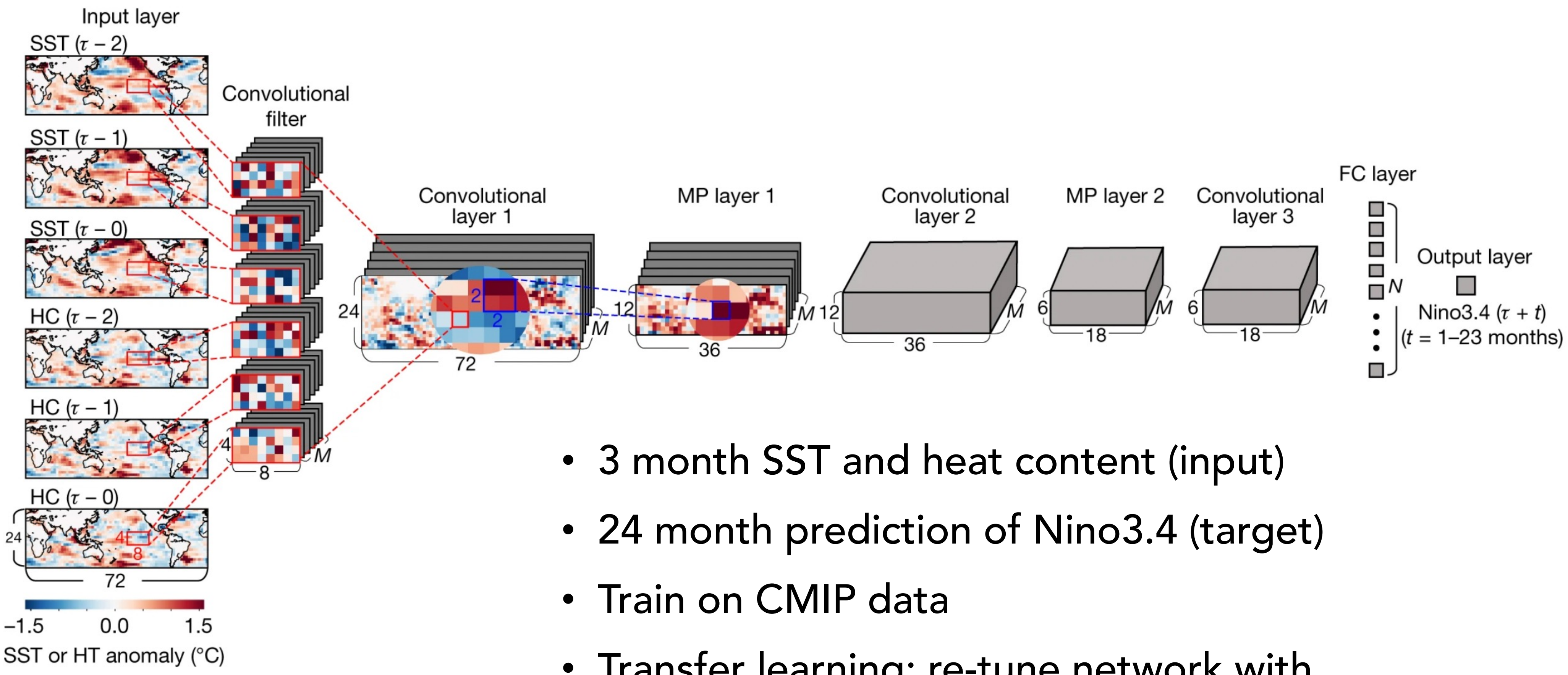
Machine learning to link between satellite measurements (input) and tide gauge data (target)



Convolutional Neural Network (CNN)

Inspiration: Deep learning for multi-year ENSO forecasts

Yoo-Geun Ham, Jeong-Hwan Kim & Jing-Jia Luo

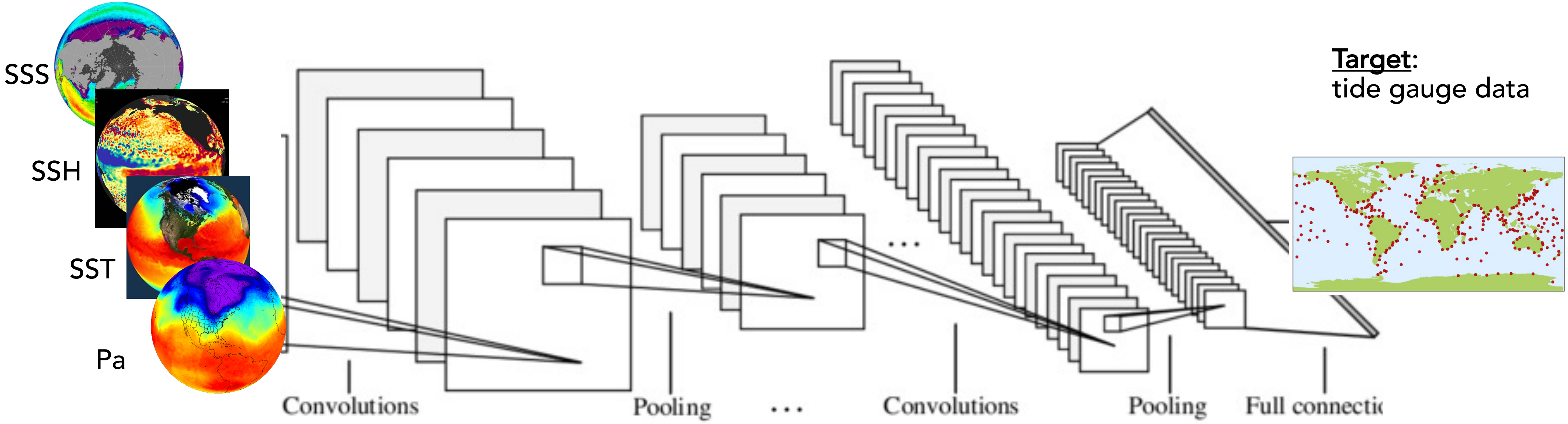


- 3 month SST and heat content (input)
- 24 month prediction of Nino3.4 (target)
- Train on CMIP data
- Transfer learning: re-tune network with reanalysis data

Objective:

Machine learning to link between satellite measurements (input) and tide gauge data (target)

Input: satellite measurements



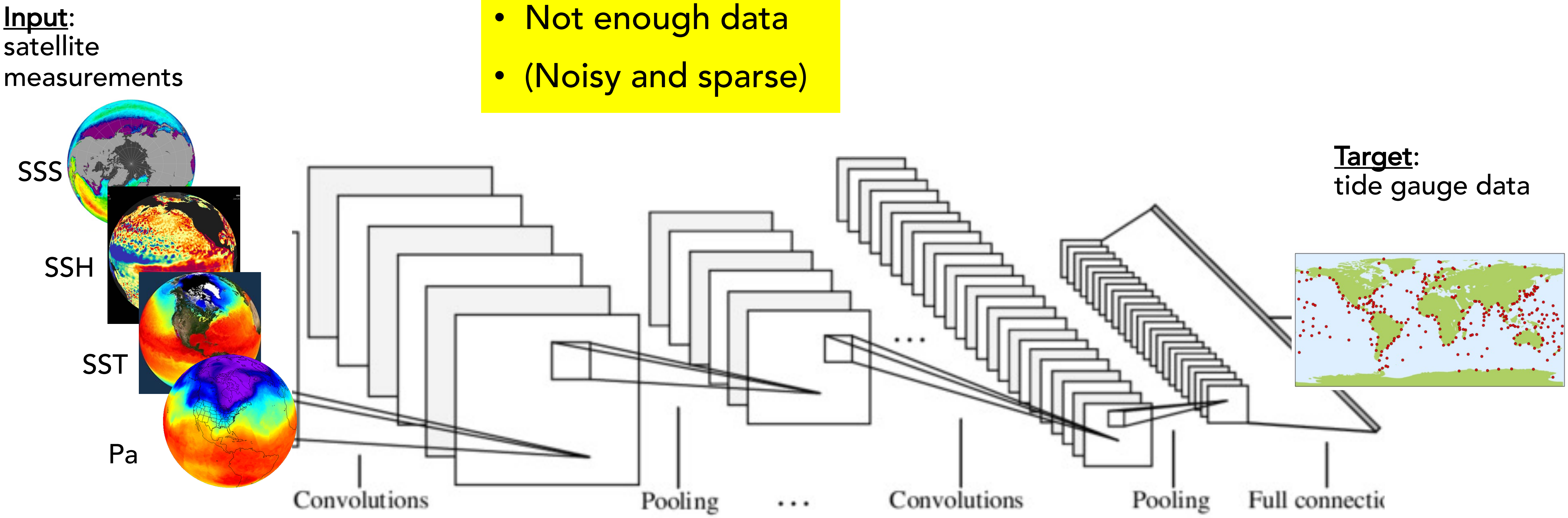
Target: tide gauge data

Convolutional Neural Network (CNN)

Objective:

Machine learning to link between satellite measurements (input) and tide gauge data (target)

- Not enough data
- (Noisy and sparse)



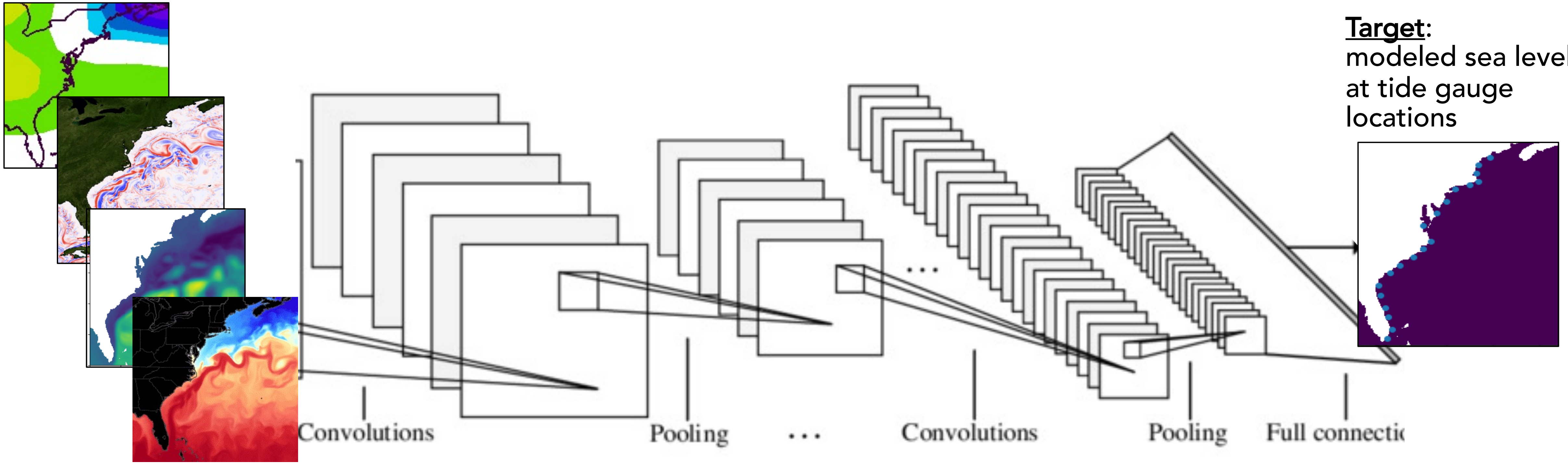
Convolutional Neural Network (CNN)

Transfer Learning

Pre-train network on model data for physical relationships

Input:
modeled surface data

Target:
modeled sea level at tide gauge locations

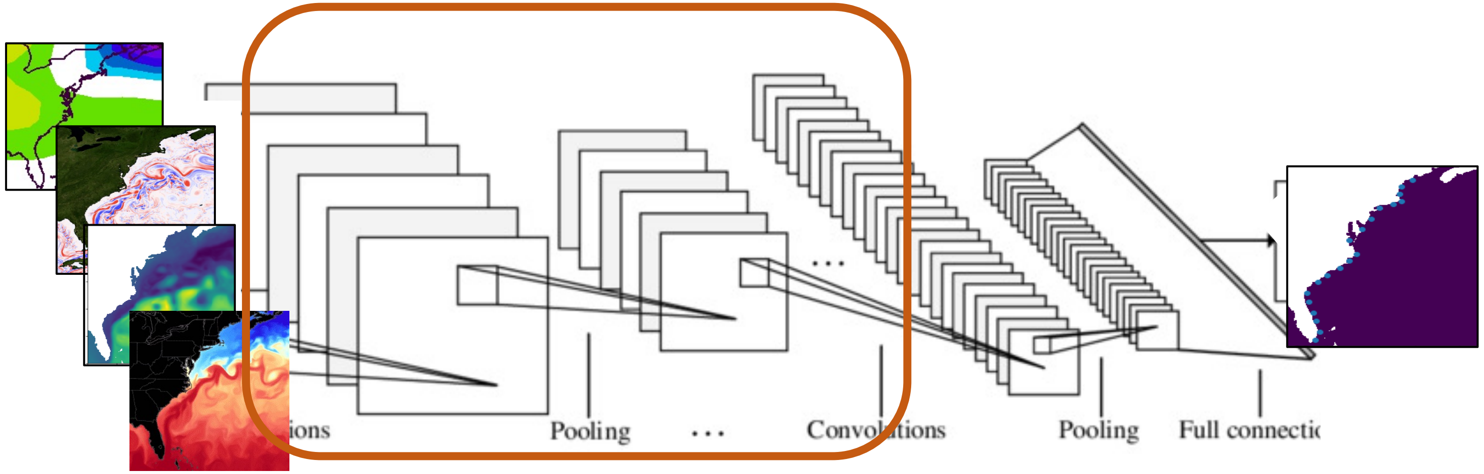


Convolutional Neural Network (CNN)

Transfer Learning

Pre-train network on model data

- Train network on model data: picontrol simulation for general physical relationships

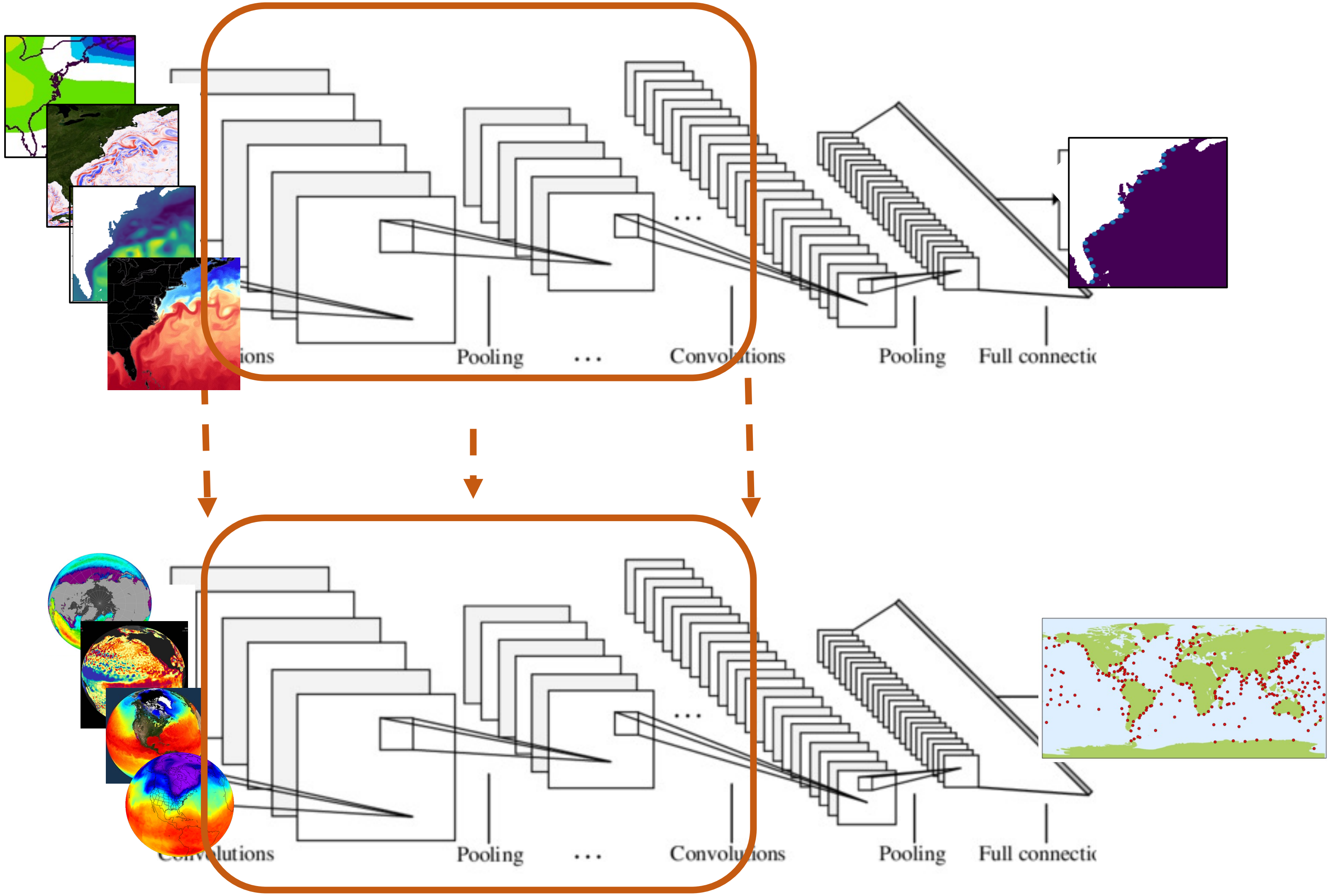


Transfer Learning

Pre-train network on model data

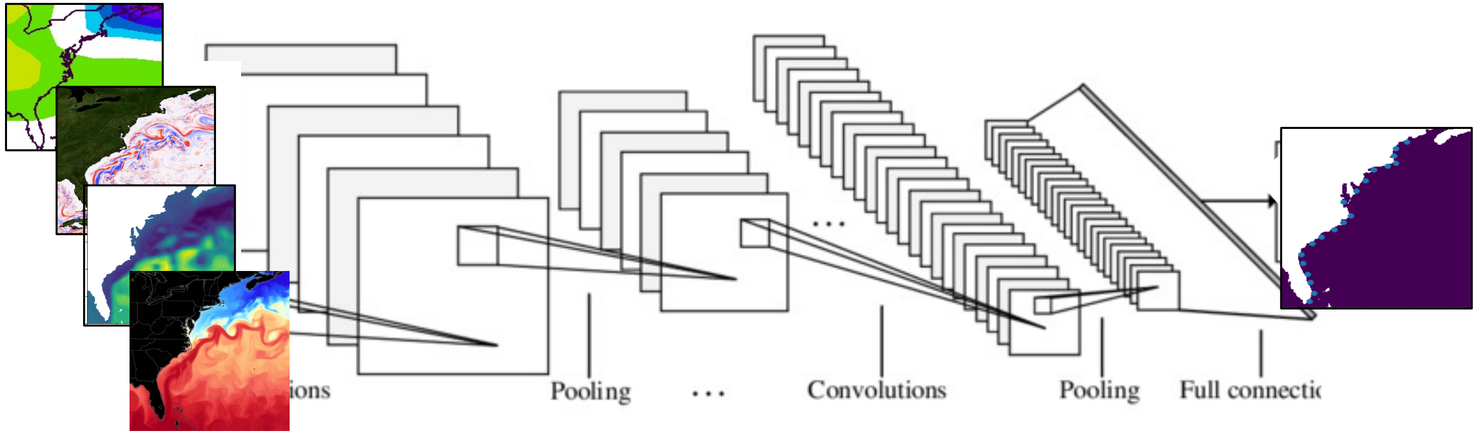
- Train network on model data: picontrol simulation for general physical relationships

- Transfer pre-trained network and re-tune deep layers with observations



Very preliminary work...

- MOM6 CM2.6 in North Atlantic
- Input: surface velocities and temperature (masked coast)
- Target: hand selected locations of coastal sea level
- Generic convolutional neural network
- Each input-target is a single time step



Very preliminary work…

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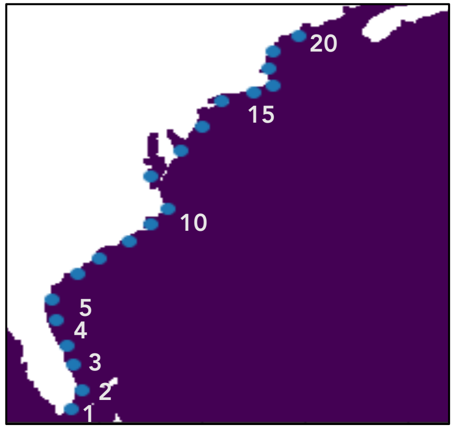
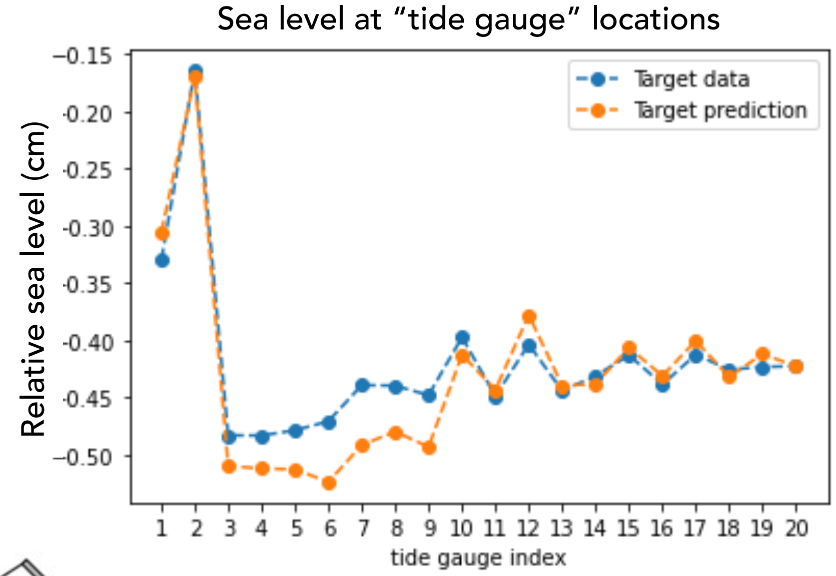
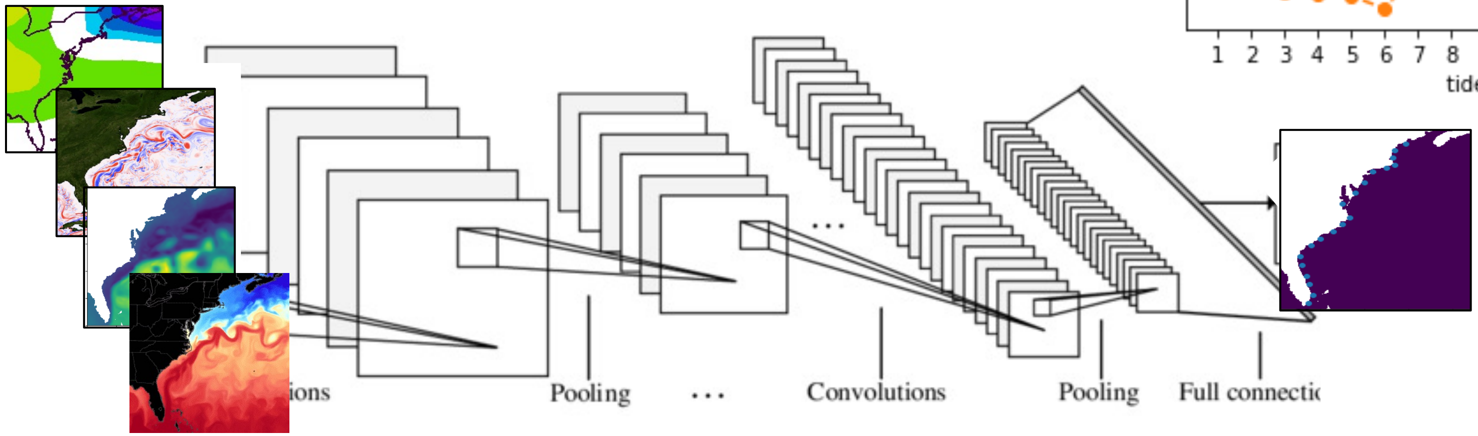
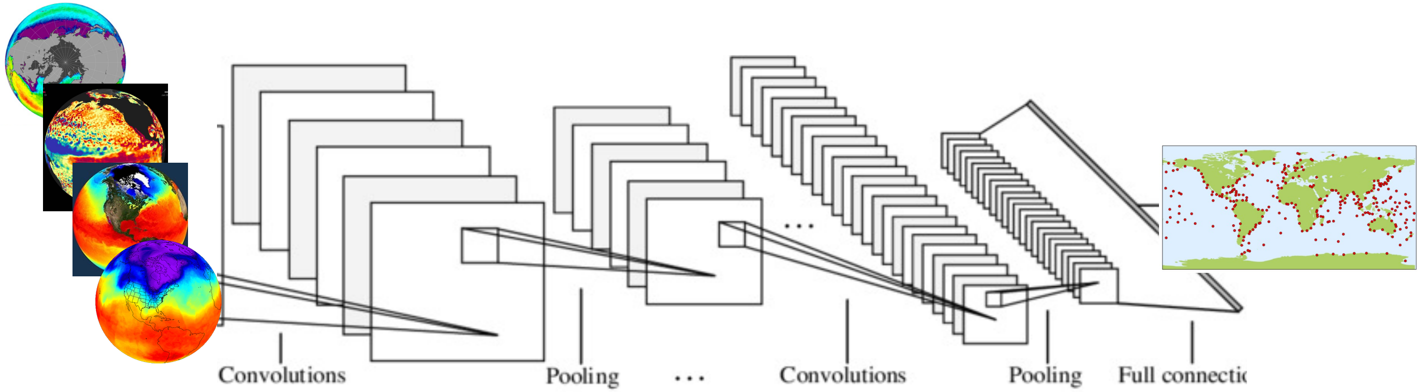




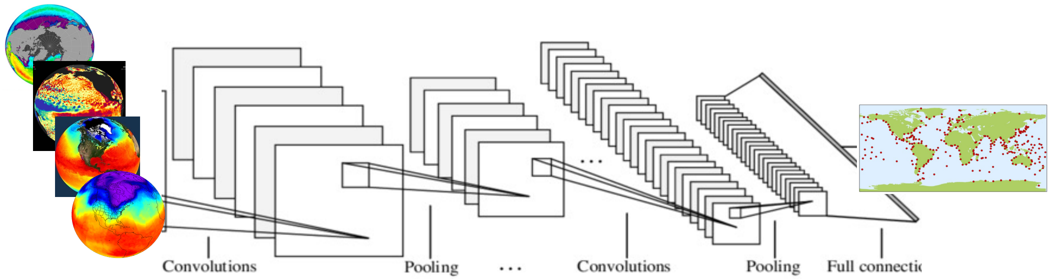


Summary

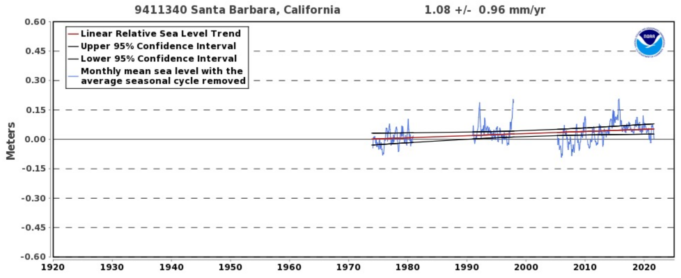
- Relate costal sea level to its drivers in the ocean interior
- Use machine learning to link between satellite measurements (input) and tide gauge data (target)
- A transfer learning method trained on modeled and observed sea surface data to predict coastal sea level at tide gauge locations
- Gain new insights on this multiscale problem where traditional simulations fail



Smaller questions

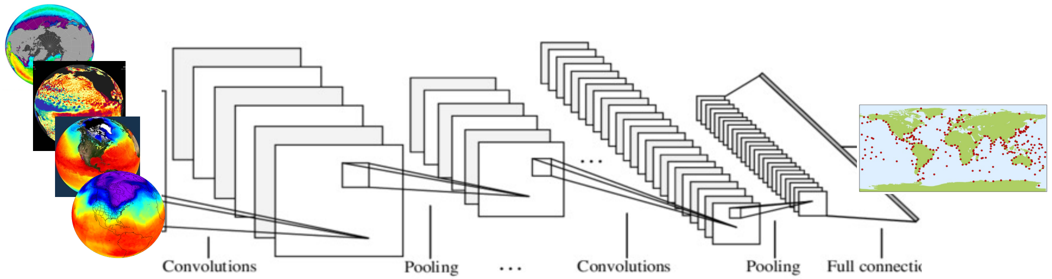


- Network architecture?
- Input format? gridded vs along track, model resolution?
- Output format? Moments?
- How to match consistently input and target data?



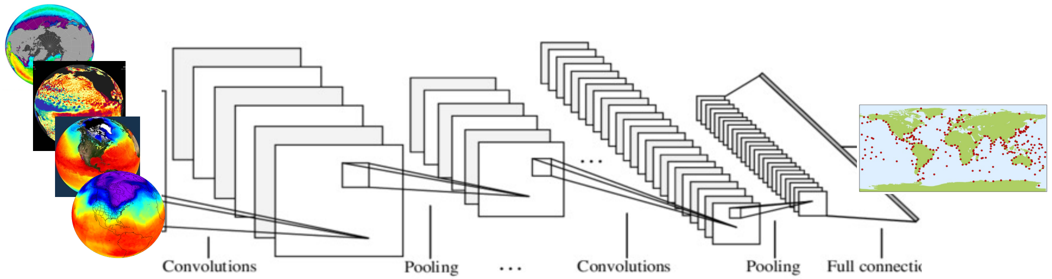
- How to treat gaps in (observational) data?
- Is geographical bias an issue?
- Account for lag between interior and coast? Include more input channels (e.g. more time steps)?

Medium questions



- How does this method hold for different regions? Seasonality?
- Are some properties more important than others? (e.g. sst, sss, ssh, Pa).
  Remove some data from training and evaluate
- Explore future coastal predictions given modeled surface conditions?

Bigger questions



- What else can we learn from the learning process?
- Causality vs correlation?
- Generalizable to other climate problems?

Smaller questions	Medium questions	Bigger questions
Network architecture? Input format? gridded vs along track, model resolution? Output format? Moments? How to match consistently input and target data? How to treat gaps in (observational) data? Is geographical bias an issue? Account for lag between interior and coast? Include more input channels (e.g. more time steps)?	How does this method hold for different regions? Seasonality? Are some properties more important than others? (e.g. sst, sss, ssh, Pa). Remove some data from training and evaluate Explore future coastal predictions given modeled surface conditions?	What else can we learn from the learning process? Causality vs correlation? Generalizable to other climate problems?