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UCLA

ClimateLearn: Machine Learning for Predicting Weather and Climate

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Rapid increase in the extreme weather events globally

Thousands of Migrant Workers Died in Qatar's Extreme Heat. The World Cup Forced a Reckoning

Droughts Take Widening Toll On World's Largest Economies

E&E NEWS

CLIMATE CHANGE

Report on California Climate Impacts 'Paints a Pretty Grim Picture'

Devastating floods in Pakistan

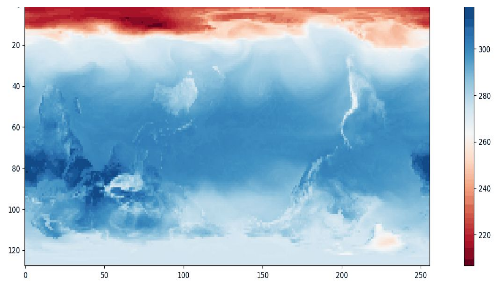
UNICEF is on the ground working with partners to help children and families.

Climate Modeling

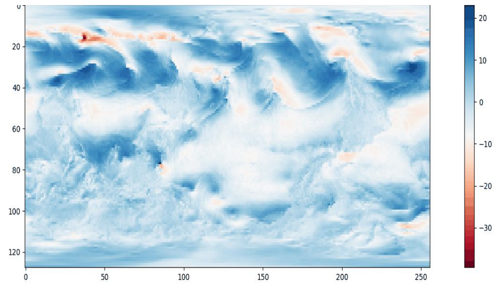
- ❖ Climate modeling is fundamental in understanding atmospheric, oceanic, and surface processes.

- ❖ Climate models can be used for short-term weather forecasts or long-term climate projections.
  - ➢ Short-term forecasts: Predicting weather 3 days ahead from the current weather conditions.
  - ➢ Long-term forecasts: Understanding average condition changes in a region over years or decades.

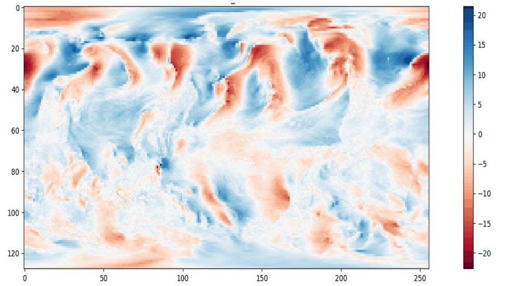
Temperature



U-component of wind



V-component of wind



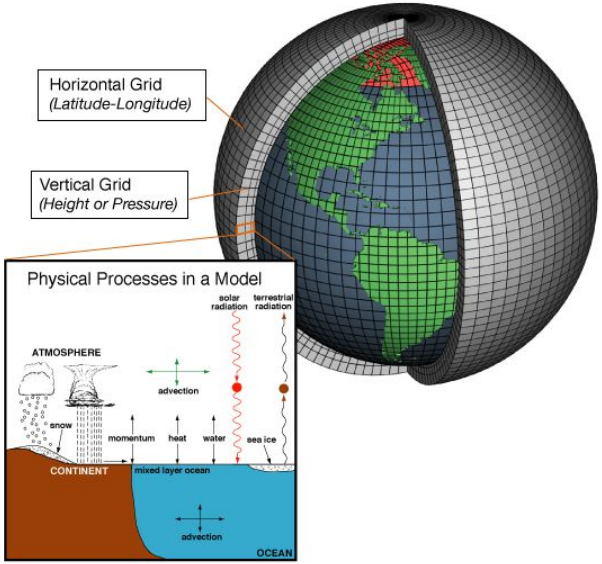
Grover 2022: Rethinking Machine Learning for Climate Science: A Dataset Perspective

Traditional Climate Modeling Through Physics-based models

- ❖ System of differential equations based on the laws of physics, fluid motion, and chemistry.
  - ➢ Numerical Weather Prediction (NWP),
  - ➢ Global Climate Models (GCMs)

PROS

- ❖ Reasonably accurate
- ❖ White box



CONS

- ❖ Slow and computationally expensive
- ❖ Difficult to improve given more data

Image credits: https://celebrating200years.noaa.gov/breakthroughs/climate_model/

Data-driven Approach for Spatiotemporal Modeling of Climate

- We aim to address two fundamental tasks:
  - Temporal Forecasting
  - Spatial Downscaling

Machine Learning for Weather Forecasting

- ❖ Train a neural network from historical weather data to predict future scenarios.
- ❖ Similar to image-to-image translation.

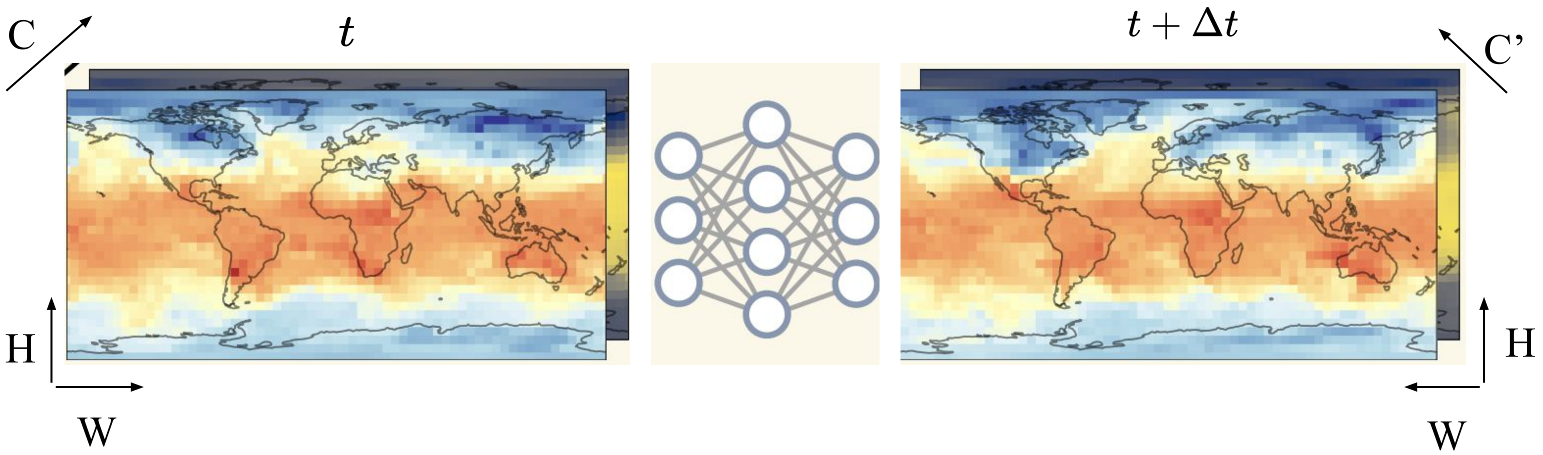
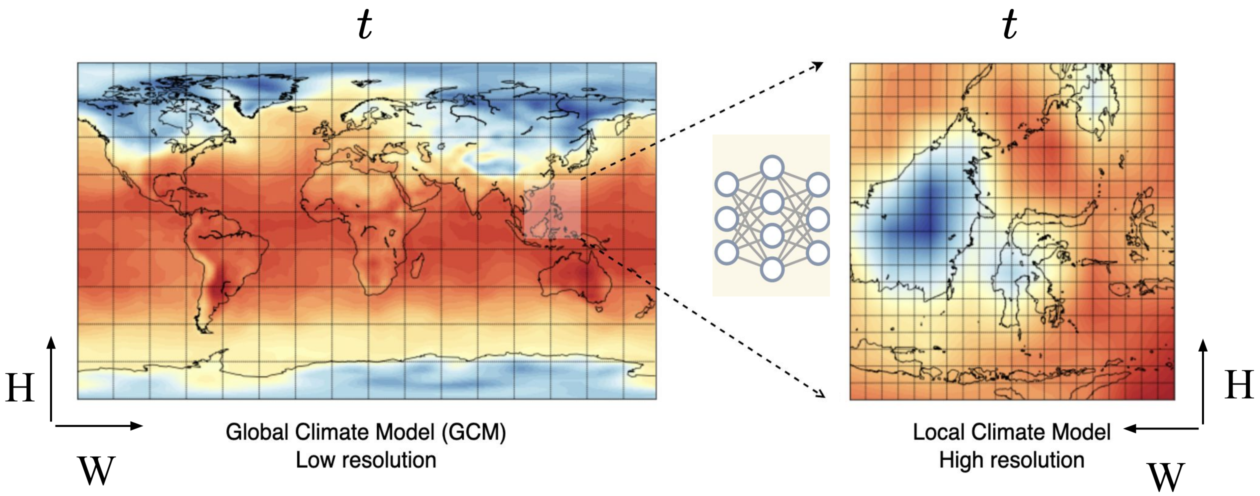


Illustration of Machine Learning
for Weather Forecasting

Image credits: Rasp, Stephan, et al. "WeatherBench: a benchmark data set for data driven weather forecasting." Journal of Advances in Modeling Earth Systems 12.11 (2020): e2020MS002203.

Machine Learning for Spatial Downscaling

- Train a neural network model from historical weather data to predict high resolution values of a variable from the low resolution variable grid.
- This task is similar to super-resolution for images.



Introduction to **ClimateLearn** Package

Datasets

Models

Metrics

Visualization

Tasks

Overview

Datasets

ERA5
WeatherBench

Models

Convolutional Neural Network,
Vision Transformers

Metrics

Latitude-Weighted RMSE
Bias

Visualization

Snapshot-based
Period of time

Tasks

Temporal Forecasting
Spatial Downscaling

ERA5 Dataset

- ❖ The ERA5 dataset that provides an hourly estimate of a large number of atmospheric, land and oceanic climate variables from 1959 to present.
- ❖ It contains historical observations that are combined with global estimates using advanced modelling and data assimilation systems.

Long name	Short name	Description	Unit	Levels
geopotential	z	Proportional to the height of a pressure level	$[m^2 s^{-2}]$	13 levels
temperature	t	Temperature	[K]	13 levels
specific_humidity	q	Mixing ratio of water vapor	$[kg\ kg^{-1}]$	13 levels
relative_humidity	r	Humidity relative to saturation	[%]	13 levels
u_component_of_wind	u	Wind in x/longitude-direction	$[m\ s^{-1}]$	13 levels
v_component_of_wind	v	Wind in y/latitude direction	$[m\ s^{-1}]$	13 levels

Example of climate variables in ERA5 dataset

Downloading ERA5

The ERA5 dataset is made available via two sources:

- ❖ Copernicus
  - ➢ Official EU's Earth observation programme
  - ➢ Climate Data Store (CDS) that hosts ERA5 data
  - ➢ Freely accessible - Need API key

- ❖ Weatherbench
  - ➢ Pre-downloaded/processed data from Copernicus
  - ➢ Selected variables

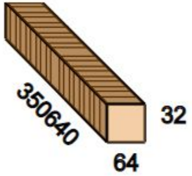
Snippet

❖ The data is stored in the [NetCDF]() files with ***.nc*** extension. One of the distinct features of this format is the **named** specification to the coordinates and the data variables.

```python
from climate_learn.utils.data import load_dataset, view

dataset = load_dataset("data/weatherbench/era5/5.625/2m_temperature")
view(dataset)
```

xarray.DataArray 't2m' (**time**: 350640, **lat**: 32, **lon**: 64)

	Array	Chunk
Bytes	2.68 GiB	68.62 MiB
Shape	(350640, 32, 64)	(8784, 32, 64)
Count	120 Tasks	40 Chunks
Type	float32	numpy.ndarray



▾ Coordinates:

lon	(lon)	float64	0.0 5.625 11.25 ... 348.8 354.4
lat	(lat)	float64	-87.19 -81.56 ... 81.56 87.19
time	(time)	datetime64[ns]	1979-01-01 ... 2018-12-31T23:00:00

▾ Attributes:

units : K
long_name : 2 metre temperature

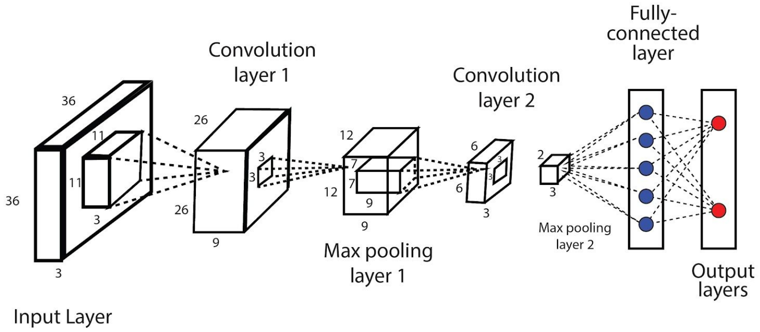
Dataloading

- ❖ Package is built over PyTorch framework.
- ❖ Example dataloader for weather forecasting

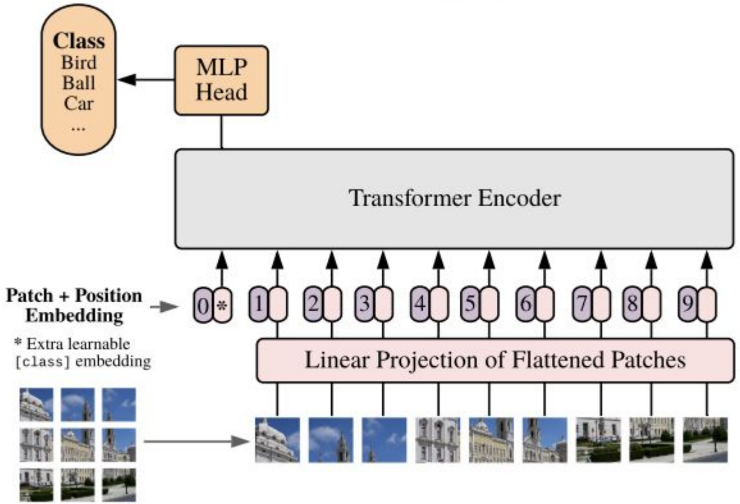
```python
from climate_learn.utils.datetime import Year, Days, Hours
from climate_learn.data import DataModule

data_module = DataModule(
    dataset = "ERA5",
    task = "forecasting",
    root_dir = "data/weatherbench/era5/5.625/",
    in_vars = ["2m_temperature"],
    out_vars = ["2m_temperature"],
    train_start_year = Year(1979),
    val_start_year = Year(2015),
    test_start_year = Year(2017),
    end_year = Year(2018),
    pred_range = Days(3),
    subsample = Hours(6),
    batch_size = 128,
    num_workers = 1
)
```

Models

- ❖ Convolutional Neural Network (CNN)

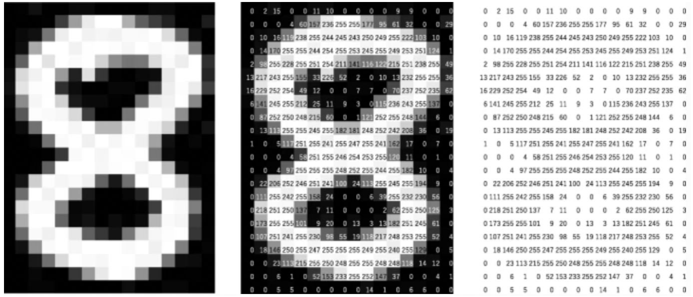


- ❖ Vision Transformer (ViT)

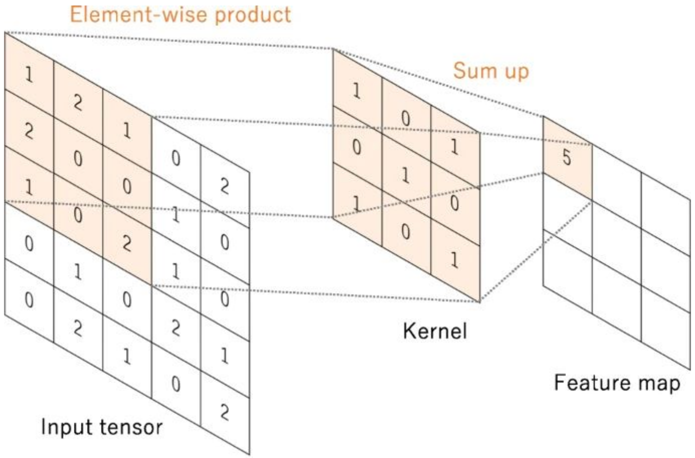


Convolutional Neural Network (CNN)

- ❖ Deep Learning model for processing gridded data.
  - ➢ Like RGB/Grayscale images

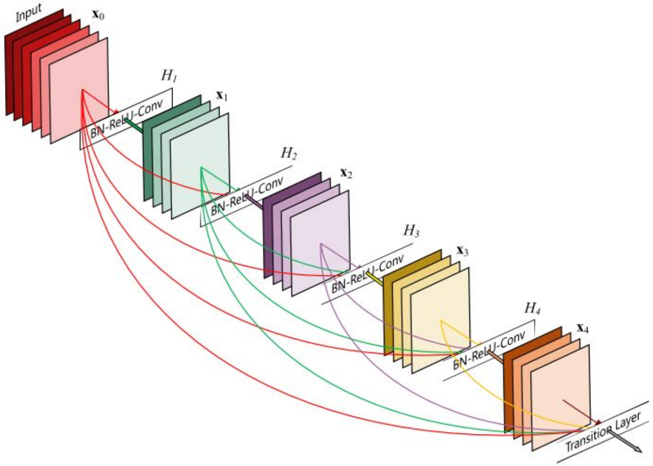


- ❖ Designed to learn spatial features from lower to higher resolution.
  - ➢ Many layers of transformations, including convolutions, to extract information.

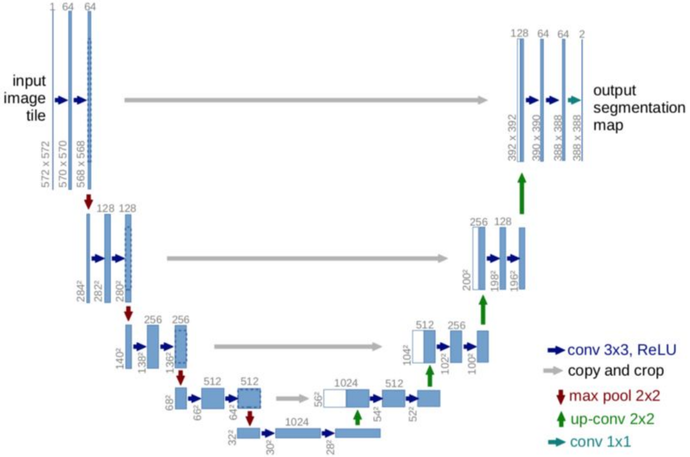


CNN variants

ResNet



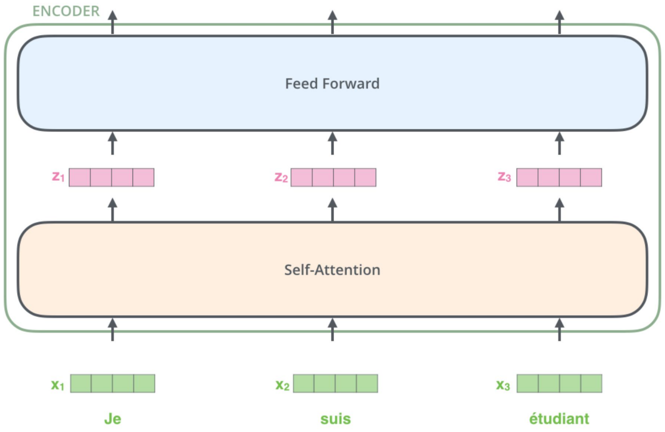
U-Net



Vision Transformer (ViT)

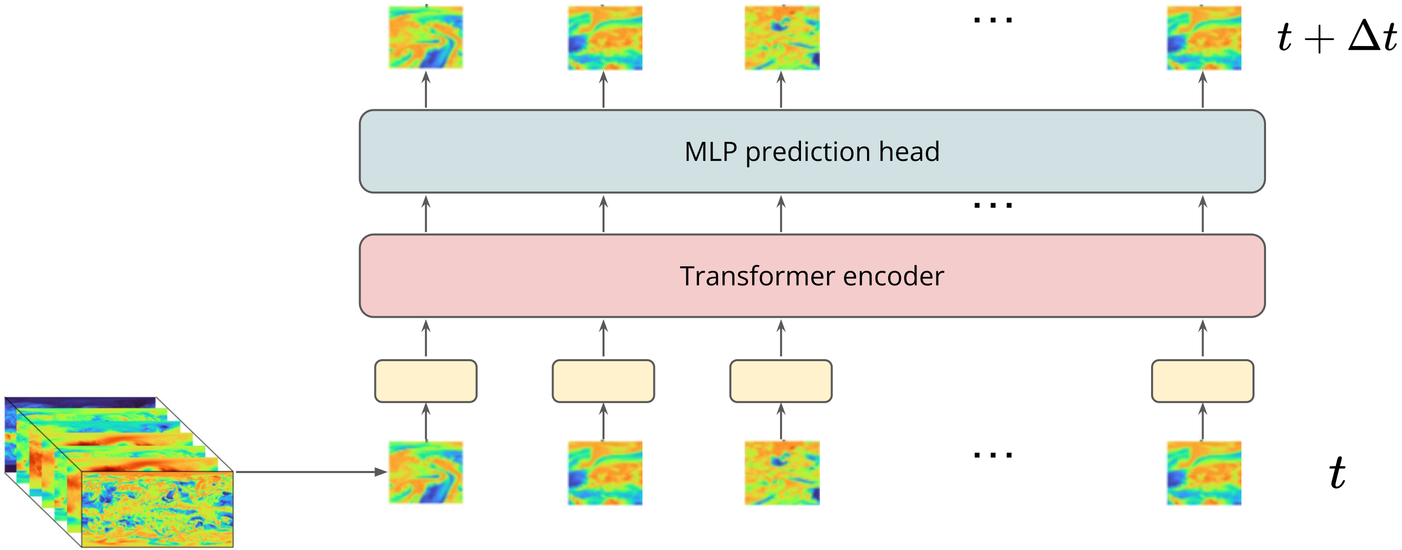
- ❖ Transformer
  - ➢ Deep learning model that is suitable for processing sequential data like natural language.
  - ➢ The model uses stack of multi-headed attention layers.

$N\,x$



ViT for Forecasting

❖ Simply attach an MLP prediction head on top of the transformer encoder

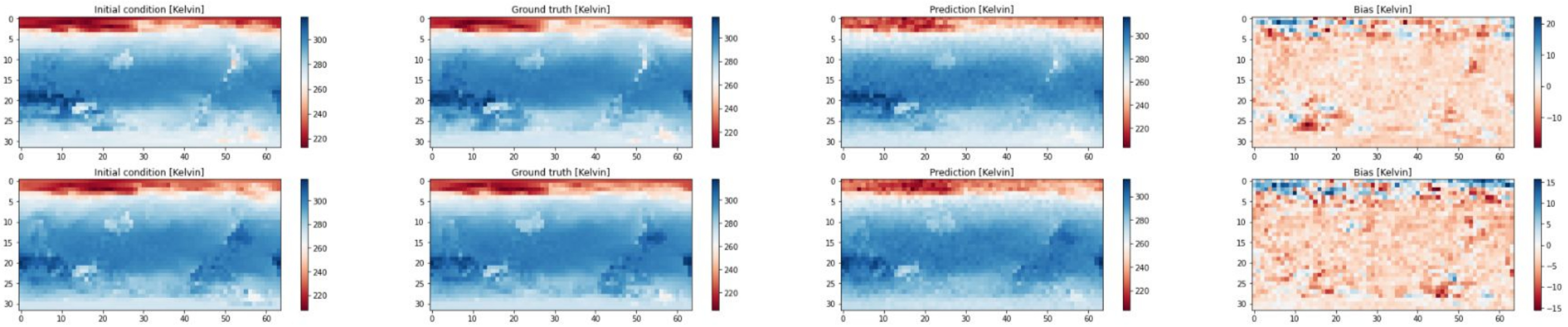


Metrics

Metric	Description	Formulation
RMSE	Root Mean Square Loss	$\sqrt{\frac{1}{N_{lat}N_{lon}}\sum_{N_{lat}}\sum_{N_{lon}}(prediction - truth)^2}$
Latitude-weighted RMSE	Pixels near the equator are given more weight because the earth is curved leading to less area towards the pole.	$\sqrt{\frac{1}{N_{lat}N_{lon}}\sum_{N_{lat}}\sum_{N_{lon}}w_{lat}(prediction - truth)^2}$
Bias	Absolute difference between spatial mean of predictions and observations.	$\sqrt{\frac{1}{N_{lat}N_{lon}}\sum_{N_{lat}}\sum_{N_{lon}}\lvert prediction - truth\rvert}$

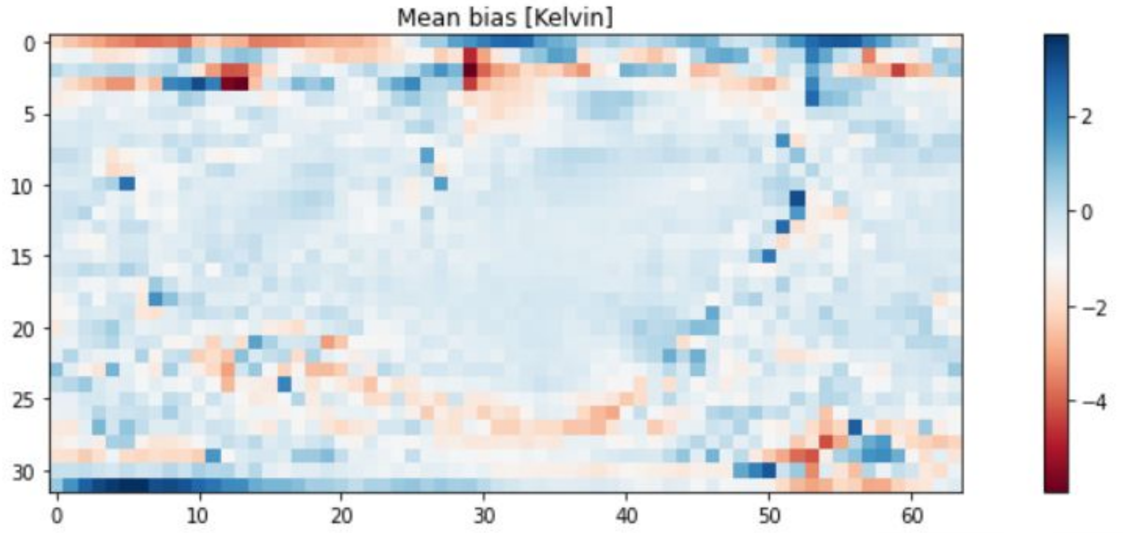
Visualizing a Snapshot

```
visualize(model_module, data_module, samples = ["2017-06-01:12", "2017-08-01:18"])
```



Visualizing the model outputs for two sample timestamps (rows)

Visualizing over a period of time



Calculated over all days in 2017 - 2018

More Advancements in the ClimateLearn Package

Datasets

ERA5
WeatherBench
<u>CMIP6</u>
<u>ClimateBench</u>

Models

Convolutional Neural Network
Vision Transformers
<u>Diffusion Models</u>

Metrics

Lat-Weighted RMSE
Bias
<u>Anomaly Correlation Coefficient</u>
<u>Pearson's Correlation</u>

Tasks

Temporal Forecasting
Spatial Downscaling
<u>Uncertainty Prediction</u>

Resources

- Colab: https://colab.research.google.com/drive/1GMT_CnxL1o4Za1Uc3Gf7u_tm_M5ECoZo?usp=sharing

- Github: https://github.com/tung-nd/climate_learn

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