Image Detection Using a Pre-Trained Model

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NSF National Center for Atmospheric Research

ML Bootcamp
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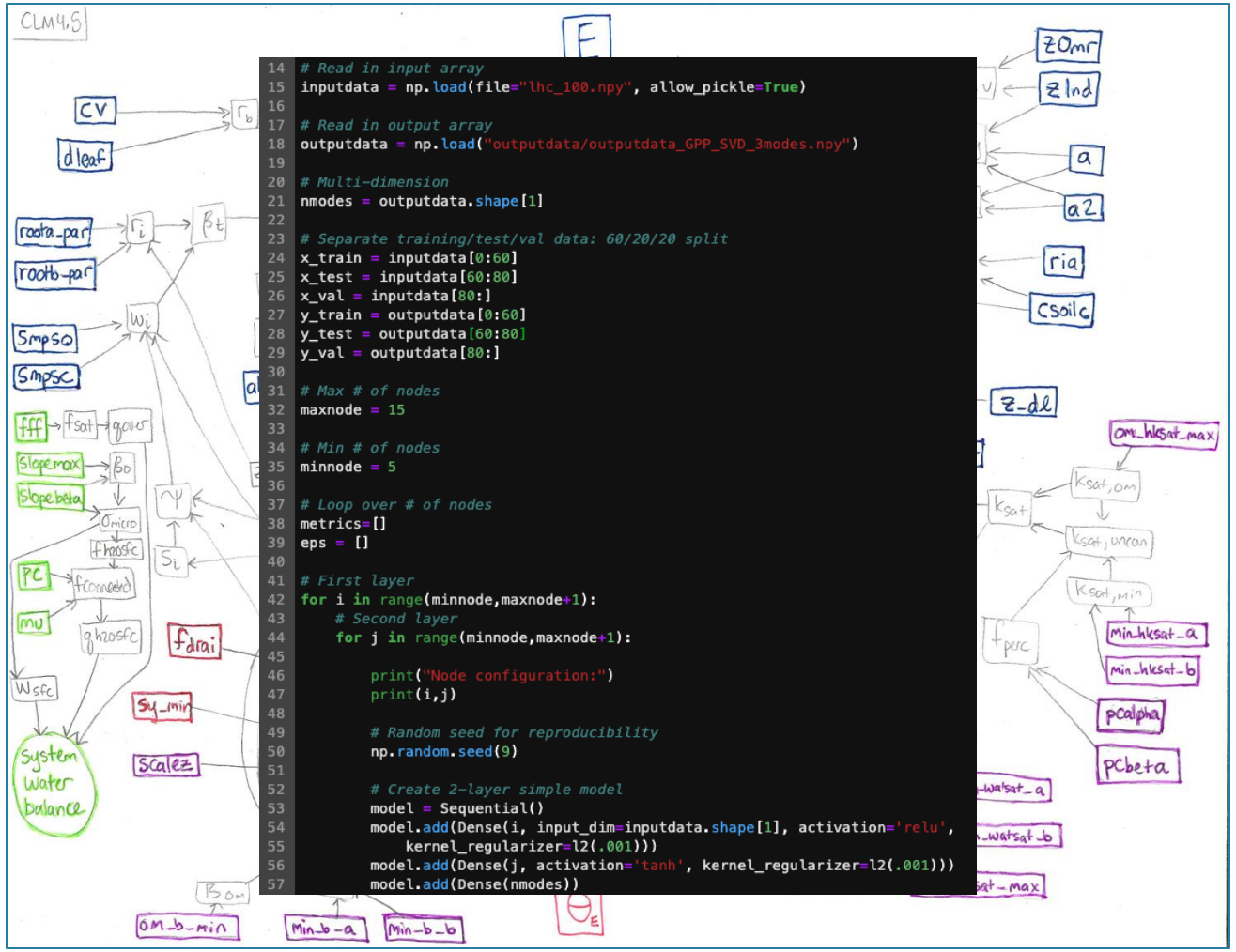
How did I get here?

Exploring land model parameter uncertainty

- How do we fully explore the parameter space of the model without running 1000s of simulations?
- Train ML emulators to map the parameter response space!
- Creating an emulator meant learning some sort of neural network tool…which meant learning Python and Keras

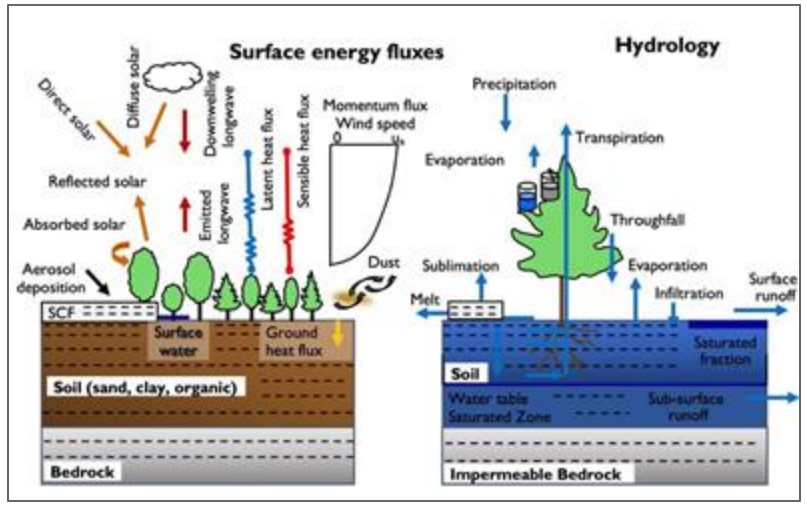



```python
# Read in input array
inputdata = np.load(file="lhc_100.npy", allow_pickle=True)

# Read in output array
outputdata = np.load("outputdata/outputdata_GPP_SVD_3modes.npy")

# Multi-dimension
nmodes = outputdata.shape[1]

# Separate training/test/val data: 60/20/20 split
x_train = inputdata[0:60]
x_test = inputdata[60:80]
x_val = inputdata[80:]
y_train = outputdata[0:60]
y_test = outputdata[60:80]
y_val = outputdata[80:]

# Max # of nodes
maxnode = 15

# Min # of nodes
minnode = 5

# Loop over # of nodes
metrics=[]
eps = []

# First layer
for i in range(minnode,maxnode+1):
    # Second layer
    for j in range(minnode,maxnode+1):

        print("Node configuration:")
        print(i,j)

        # Random seed for reproducibility
        np.random.seed(9)

        # Create 2-layer simple model
        model = Sequential()
        model.add(Dense(i, input_dim=inputdata.shape[1], activation='relu',
            kernel_regularizer=l2(.001)))
        model.add(Dense(j, activation='tanh', kernel_regularizer=l2(.001)))
        model.add(Dense(nmodes))
```

https://github.com/katiedagon/CLM5_ParameterUncertainty

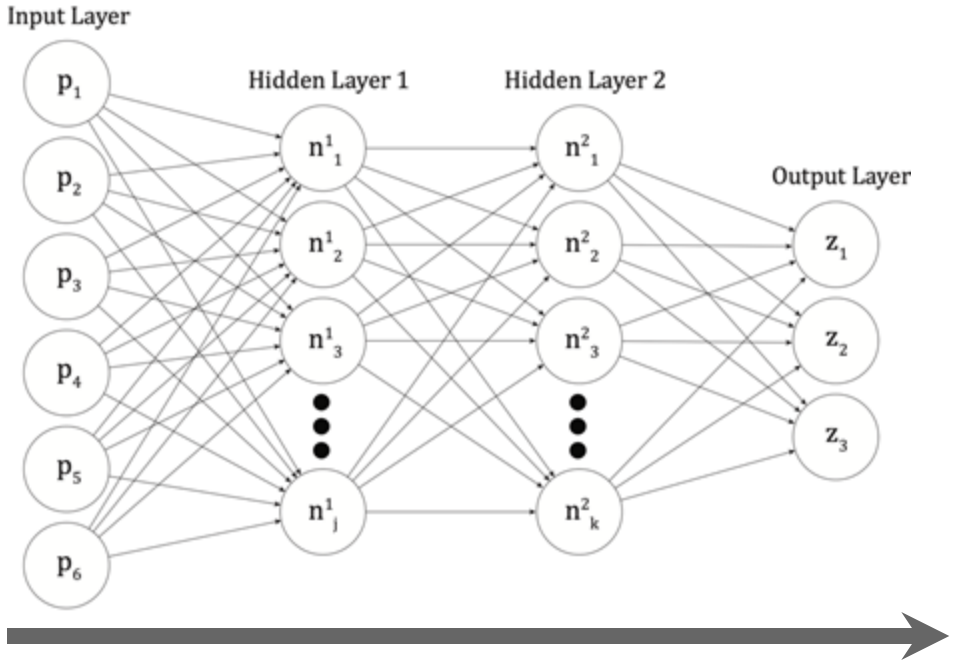
Machine Learning for Land Model Emulation

Input: land model parameter values



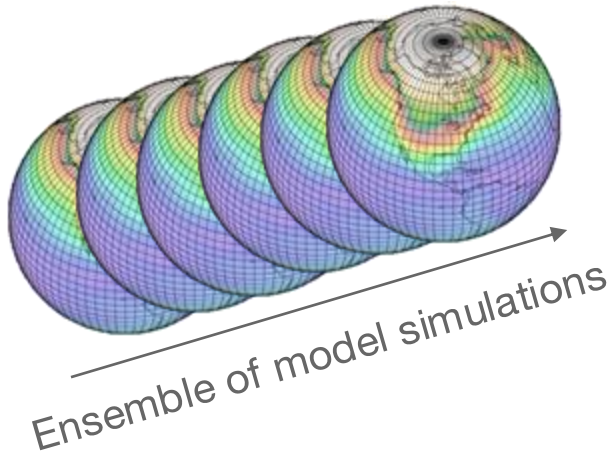
Community Land Model (CLM)

Neural network emulator: ANN with 2 layers



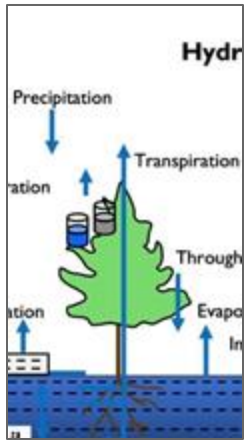
Learning the parameter response functions

Output: land model quantities from a perturbed parameter ensemble (PPE)



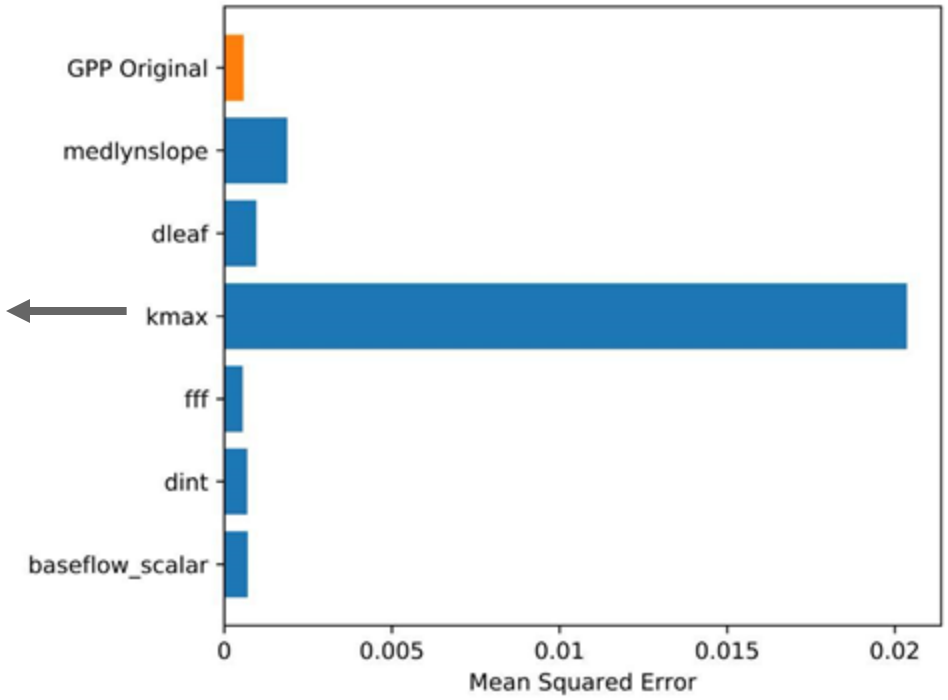
Dagon et al. (2020)

Interpretability Sheds Light on Physics

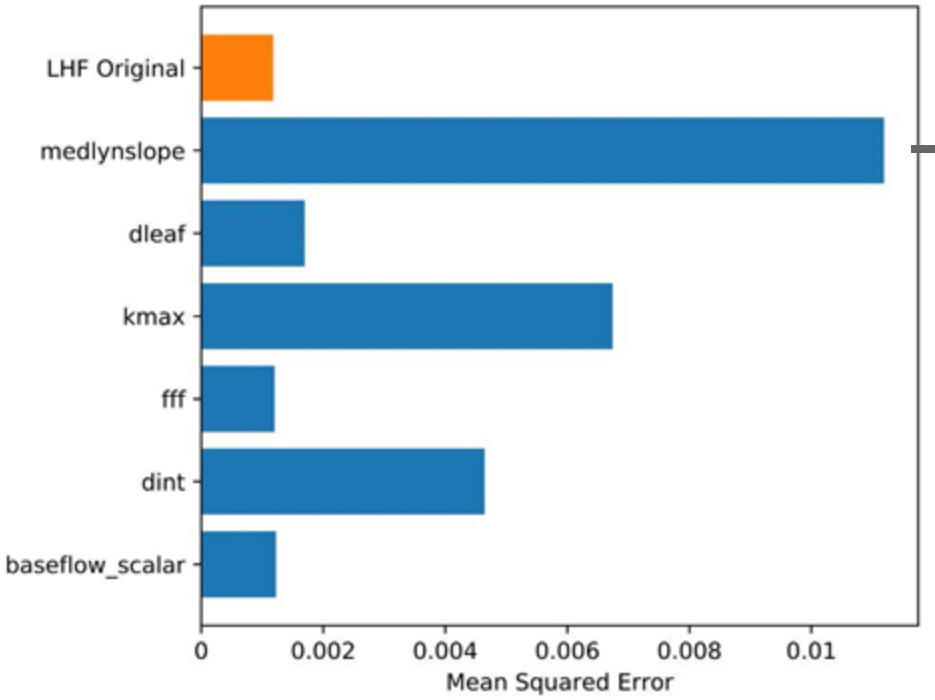


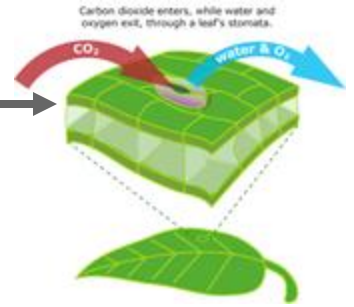
Kennedy et al. (2019)

Carbon Flux Variability



Water Flux Variability





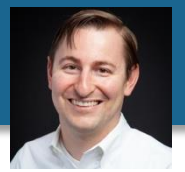
Medlyn et al. (2011)

Variable Importance

- Randomly shuffle values of one parameter (preserving others) and **test performance of emulator**.
- Skill metric is mean squared error between predictions and actual values.
- Larger bar means the parameter is **more important to the predictive skill** of the emulator.

Dagon et al. (2020)

Not Reinventing the Wheel



Model Interpretation

One of the common critiques of machine learning models is that many appear to be a "black box", in which predictions are made without associated reasoning why they were made. However, there are ways to interrogate machine learning models to extract information about how the model weights each input and how the model encodes information internally.

Permutation variable importance is a model-agnostic way of estimating how much each input affects the prediction values on average. In permutation variable importance, a metric is calculated on the model predictions of the validation data. Then each validation set input is permuted, or shuffled, among the examples, and the metric is recalculated. A large change in the metric value corresponds with higher importance for that input.

In [24]:

```
def variable_importance(model, data, labels, input_vars, score_func, num_iters=10):
    preds = model.predict(data)[:, 0]
    score_val = score_func(labels, preds)
    indices = np.arange(data.shape[0])
    imp_scores = np.zeros((len(input_vars), num_iters))
    shuf_data = np.copy(data)
    for n in range(num_iters):
        print(n)
        np.random.shuffle(indices)
        for v, var in enumerate(input_vars):
            print(var)
            shuf_data[:, :, :, v] = shuf_data[indices, :, :, v]
            shuf_preds = model.predict(shuf_data)[:, 0]
            imp_scores[v, n] = score_func(labels, shuf_preds)
            shuf_data[:, :, :, v] = data[:, :, :, v]
    return score_val - imp_scores
```

Code from DJ Gagne (CISL):
https://github.com/djgagne/swirlnet/blob/master/notebooks/deep_swirl_tutorial.ipynb

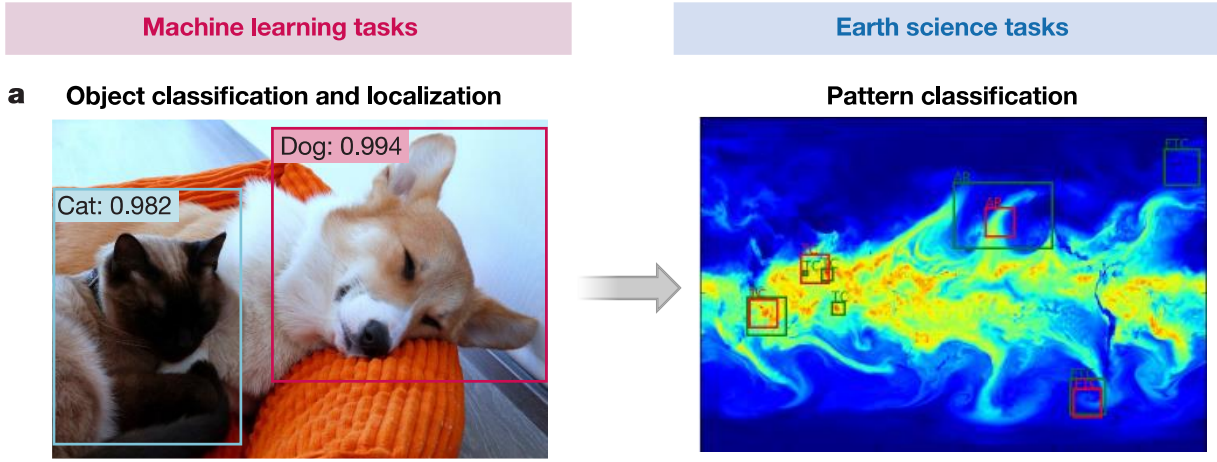
```
# Define function for feature importance
def permutation_feature_importance(input_data, output_data, model,
        score=mse_preds):
    model_preds = model.predict(input_data)
    original_error = score(output_data, model_preds)
    permuted_scores = np.zeros(input_data.shape[1])
    permuted_data = np.copy(input_data)
    permuted_indices = np.arange(input_data.shape[0])
    for c in range(input_data.shape[1]):
        np.random.shuffle(permuted_indices)
        permuted_data[:, c] = input_data[permuted_indices, c]
        permuted_preds = model.predict(permuted_data)
        permuted_scores[c] = score(output_data,permuted_preds)
        permuted_data[:, c] = input_data[:, c]
    return original_error, permuted_scores

# Calculate feature importance
gpp_original, gpp_permuted = permutation_feature_importance(inputdata,
        outputdata_GPP, model_GPP)
lhf_original, lhf_permuted = permutation_feature_importance(inputdata,
        outputdata_LHF, model_LHF)

# Plot importance
# smaller bar is more important
plt.figure(figsize=(12, 5))
plt.subplots_adjust(wspace=0.4)
plt.subplot(1, 2, 1)
plt.barh(np.arange(gpp_permuted.size), gpp_permuted)
plt.barh(gpp_permuted.size, gpp_original)
plt.yticks(np.arange(gpp_permuted.size + 1),
        in_vars + ["GPP Original"])
plt.title("GPP Importances")
plt.subplot(1, 2, 2)
plt.barh(np.arange(lhf_permuted.size), lhf_permuted)
plt.barh(lhf_permuted.size, lhf_original)
plt.yticks(np.arange(lhf_permuted.size + 1),
        in_vars + ["LHF Original"])
plt.title("LHF Importances")
plt.show()
```

https://github.com/katiedagon/CLM5_ParameterUncertainty

Image Detection for Weather Features

Extreme precipitation has significant impacts, and originates from many different sources.

We can leverage machine learning for automated feature detection.



Reichstein et al. (2019)

- Apply **machine learning-based detection algorithm** to automate the classification of weather features such as **fronts** and **atmospheric rivers (ARs)**.
- Study the **causes of extreme precipitation** by associating features with extreme precipitation events.

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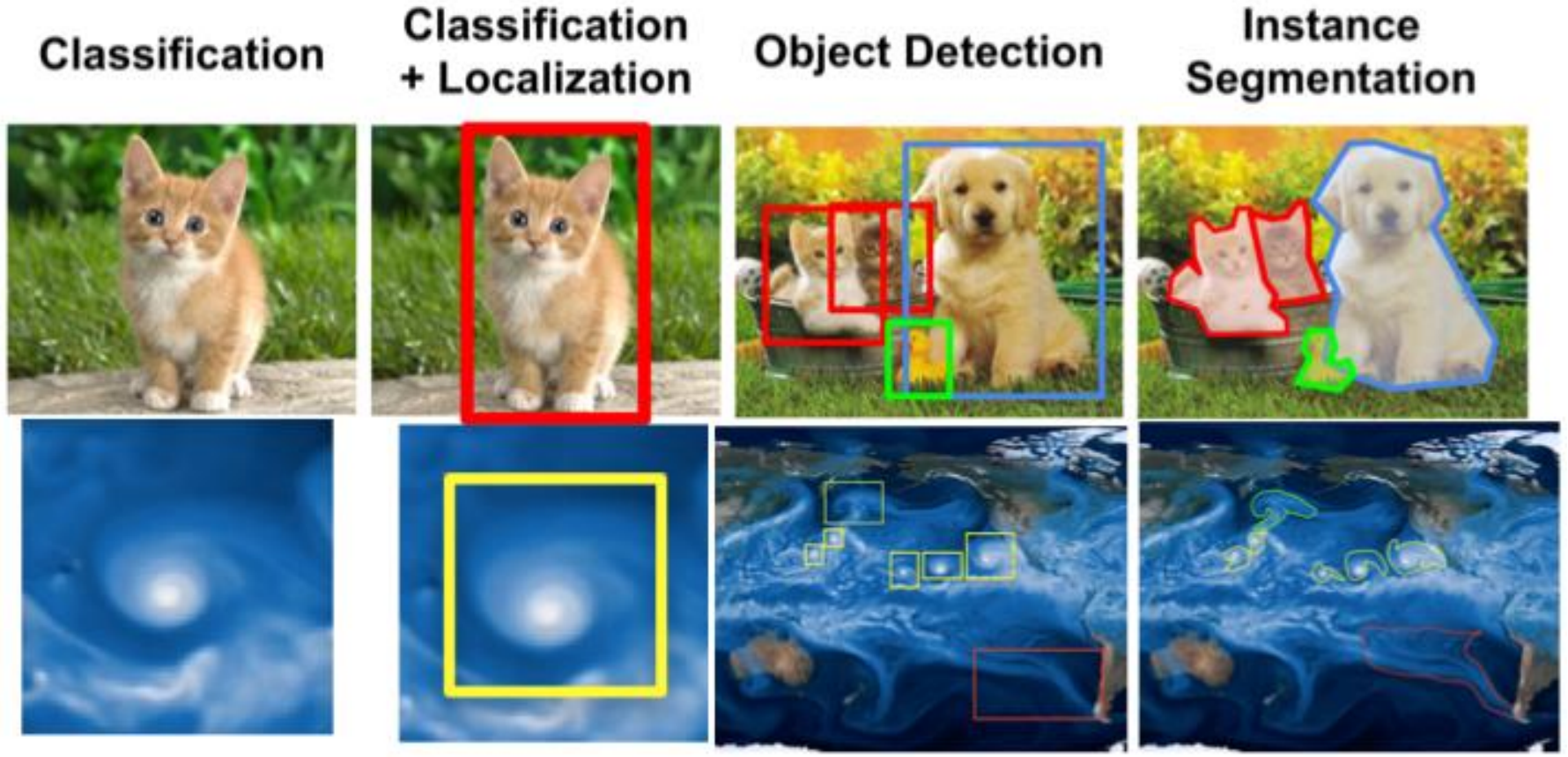
catalyst

Computer Vision <> Climate Science



Key Differences: Multi-variate; Different & multiple spatio-temporal scales; Double precision floating point; Underlying statistics are different.

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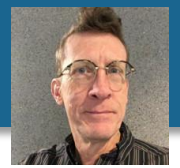
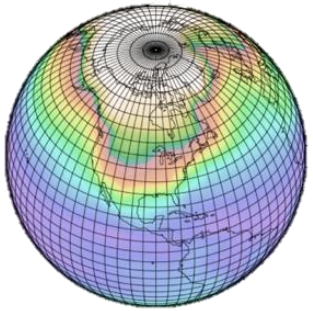
Slide from Karthik Kashinath

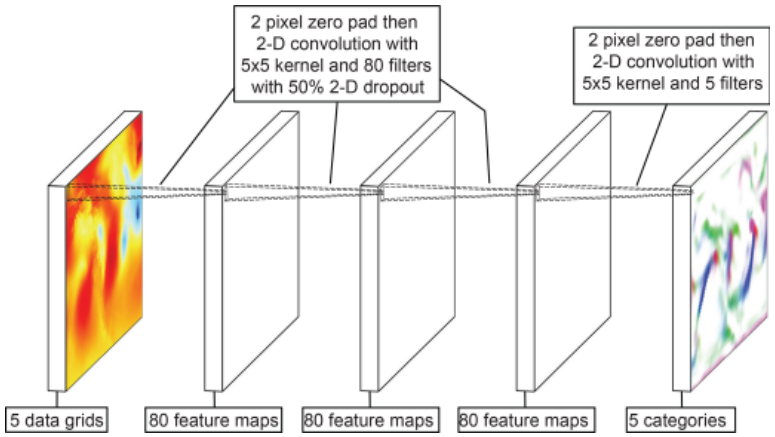
Machine Learning for Detection of Fronts



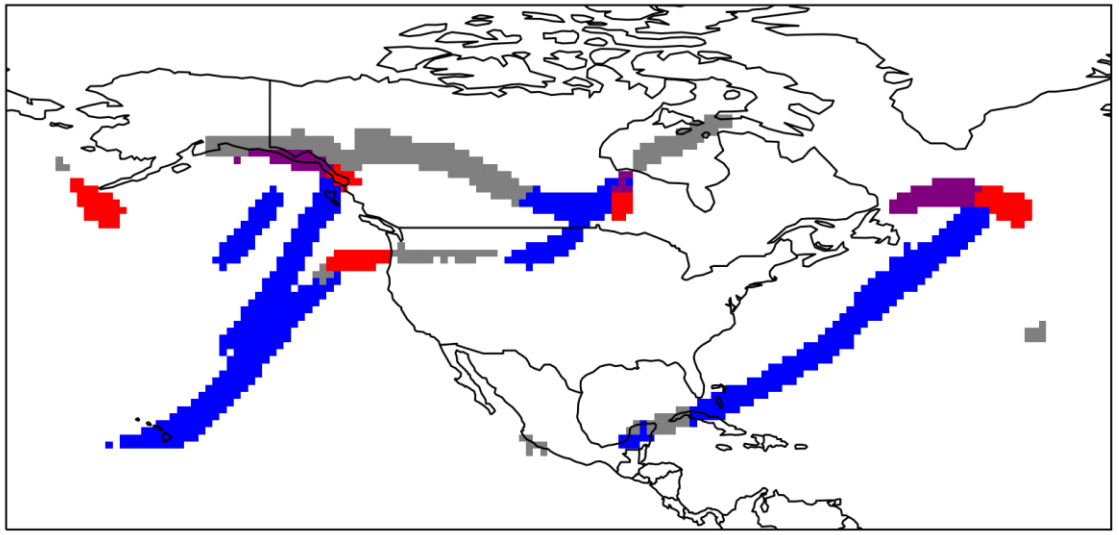

Using the pretrained DL-FRONT algorithm applied to climate model output to detect weather fronts



Specifically, fully coupled Community Earth System Model (CESM) simulations at high spatial and temporal resolution.



For details on DL-FRONT, see: Biard and Kunkel (2019)



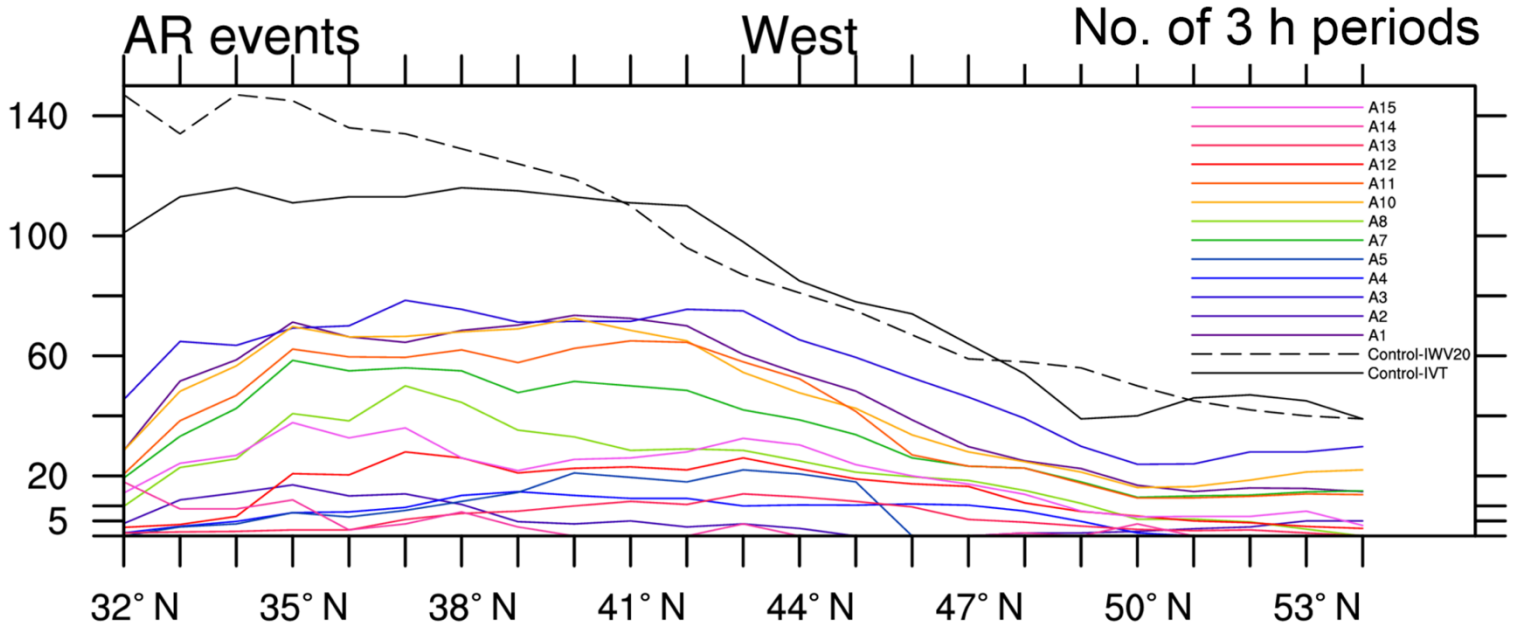
Input fields: surface temperature, sea level pressure, specific humidity and u/v winds
Output fields: 4 frontal categories (cold, warm, occluded, stationary) and none type
Simulation years: Historical climate simulation, 2000-2015
Animation shows 3hrly, 1deg output; Jan 2000.

With: John Truesdale (NCAR), ***Jim Biard (ClimateAI), Ken Kunkel (NC State)****, Jerry Meehl (NCAR), Maria Molina (NCAR/UMD)*

Dagon et al. (2022)

ML vs. Traditional Detection

- Traditional detection methods use specific thresholds of physical quantities (e.g., “heuristics”)
- For ARs specifically, there is a lot of uncertainty across detection methods (see ARTMIP papers)
- Using ML allows for threshold-free detection, which can aid in the objectivity and computational expense of these algorithms
- We can also test on different data sources and climate states



ATMOSPHERIC RIVER TRACKING METHOD INTERCOMPARISON PROJECT (ARTMIP)

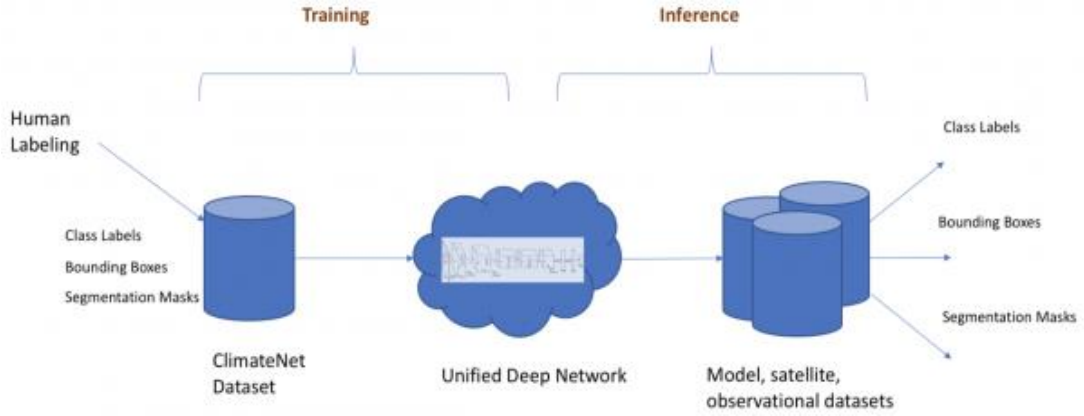
Shields et al. (2018)
https://ncar.github.io/ARTMIP/algorithms.html

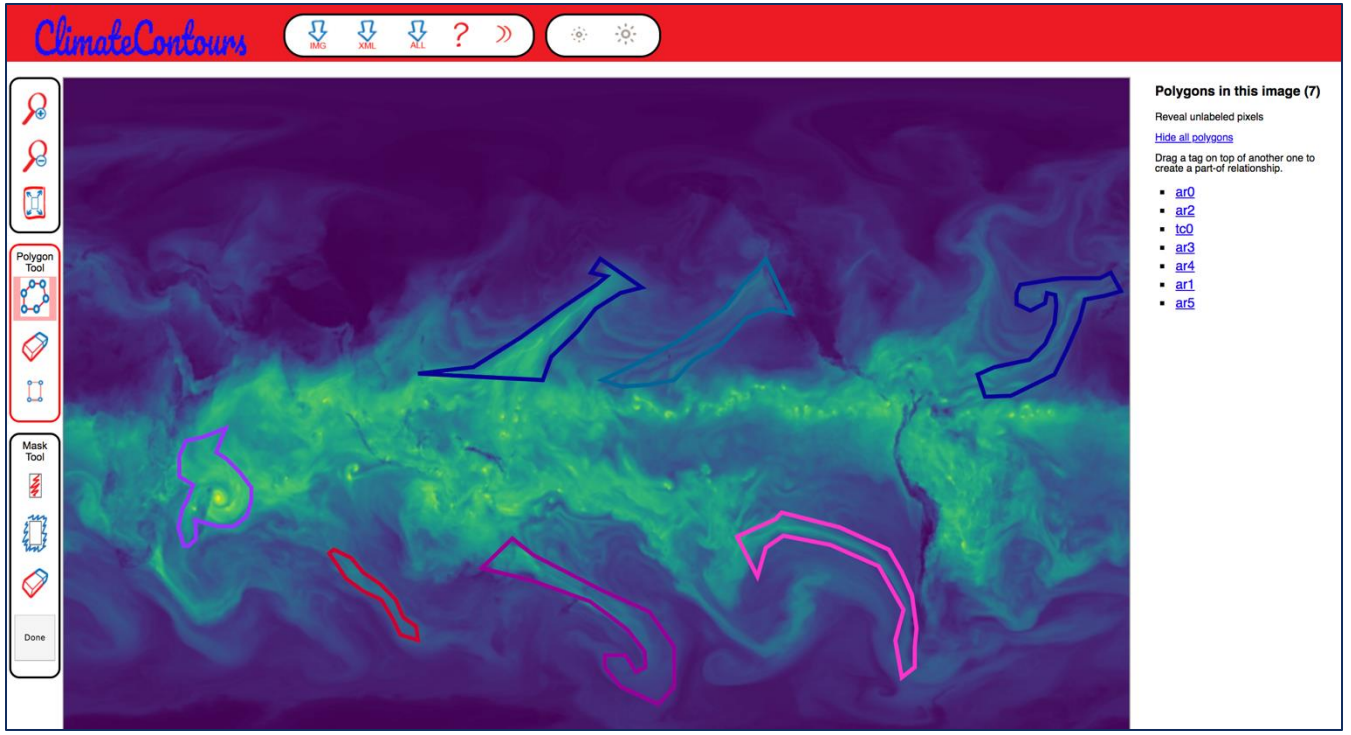
➢ But where do we get the **training data** for this supervised learning application?

Machine Learning for Detection of ARs and TCs

ClimateNet: a community-sourced expert-labeled dataset to improve and accelerate machine learning applications in weather and climate

- *Focus on detecting atmospheric rivers (ARs) and tropical cyclones (TCs).*





For details on ClimateNet, see:
Prabhat et al. (2021)

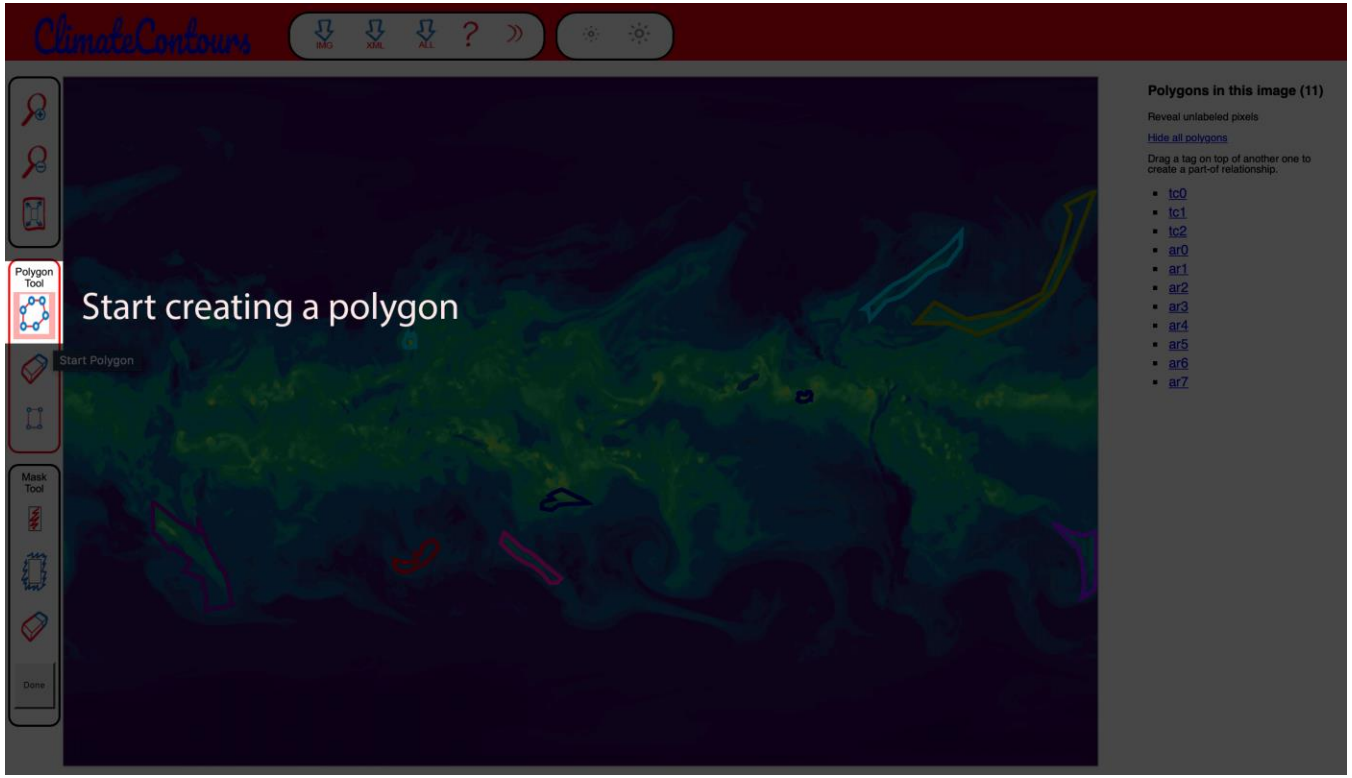
Online Labeling Tool

Tool samples a **random time point** from climate model output.

User **toggles between output fields** (e.g., water vapor, pressure, winds) to categorize events.

User draws boundaries around **atmospheric rivers** or **tropical cyclones**, repeats for all events in the image.

User submits responses with **confidence level** for each event (low, medium, high).

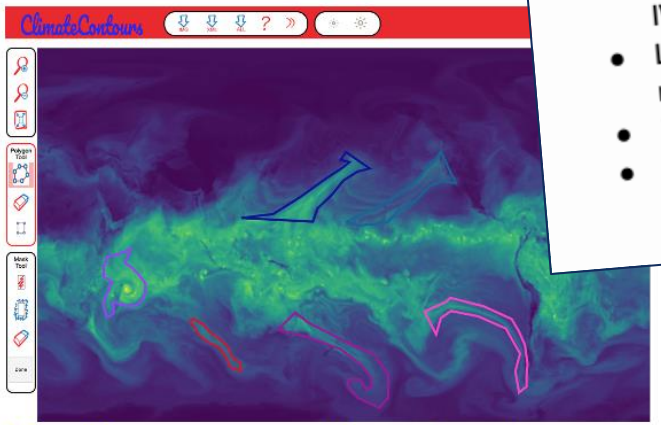


Labeling Campaigns

ClimateNet: a community-sourced expert-labeled dataset to improve and accelerate Machine Learning applications in weather and climate

Pattern recognition using Machine Learning is data hungry and needs plenty of reliable *labeled* data. Climate science is data rich but reliable labeled data is sparse!

Come join us in a community effort to provide high quality labeled data for a range of important event detection and tracking problems, such as tropical cyclones and atmospheric rivers



https://www.nersc.gov/research-and-development/data-analytics/big-data-center/climatenet

When: Nov 20, 10am-12pm MT
Where: Damon Room at NCAR
Remote access: https://lbnl.zoom.us/j/5104862667
RSVP: Christine Shields <shields@ucar.edu>, Katie Dagon <kdagon@ucar.edu>, Karthik Kashinath <kkashinath@lbl.gov>

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DO's

- Look for **long, narrow** columns transporting water from the equator to the mid-latitudes
- A good *guide* (not set in stone at all)/ rule of thumb is areas of high IVT (~750 kg/m/s) or IWV (20-25 mm)
- Longer than it is wide: ~1500 km long, less than 1000 km wide. There should be a roughly 2:1 ratio (at least).
- I usually find it useful to check both IWV and IVT when labelling atmospheric rivers
- At any given time, there can be anywhere from ~6-~12 (loose numbers) atmospheric rivers in the world

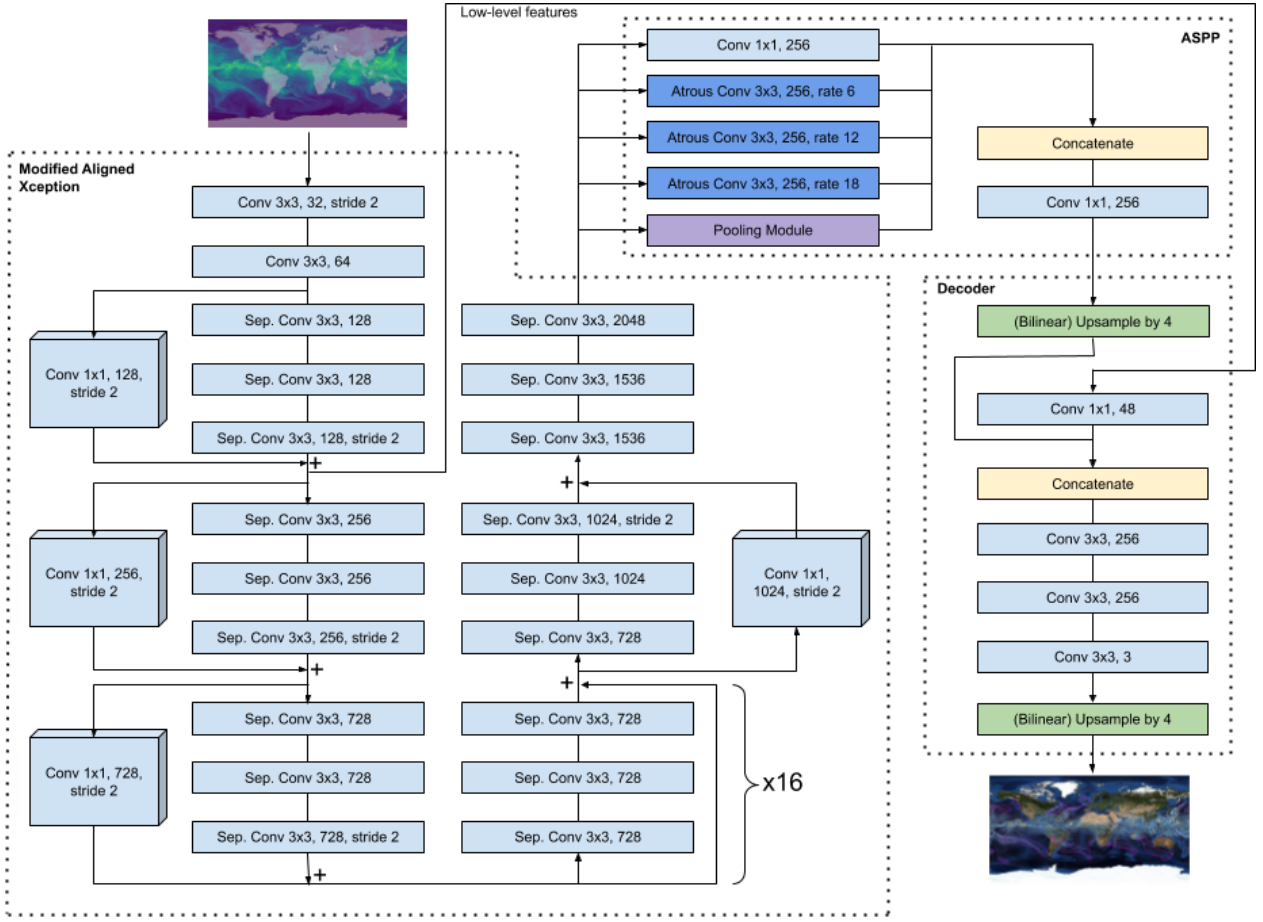
DON'Ts

- Use vorticity in AR detection/ identification
- Label areas near the equator as areas with high IVT
- Label small blobs as atmospheric rivers

After **multiple labeling campaigns** (LBNL, UC Berkeley, NCAR, Scripps/UCSD, 2019 ARTMIP Workshop, 2019 Climate Informatics) with **~80 experts participating, quality control process**, **459 images were finalized for training.**

Trained Models: ClimateNet and CGNet

ClimateNet: based on DeepLabv3+ network architecture



Prabhat et al. (2021), Chen et al. (2018)

CGNet: a light-weight "context-guided" network for image segmentation

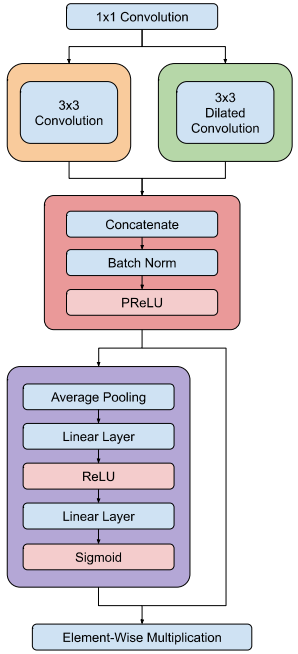


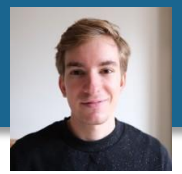
Figure 1: A CGBlock integrates local features and surrounding features into a joint feature. It then refines the representation using global context.

- Fast and scalable
- Fewer trainable parameters
- Introduces spatio-temporal tracking

https://github.com/andregraubner/ClimateNet

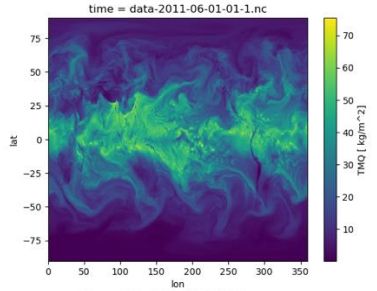
Kapp-Schwoerer et al. (2020), Wu et al. (2019)

Training CGNet

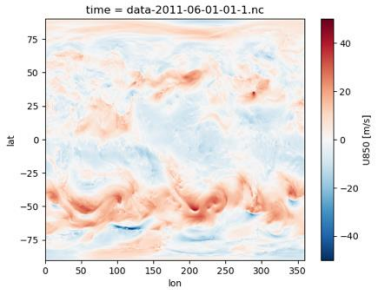



Input: maps of climate variables

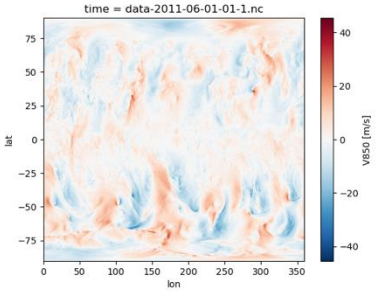
Total column water vapor



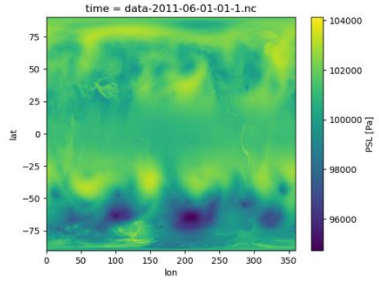
850 hPa zonal wind



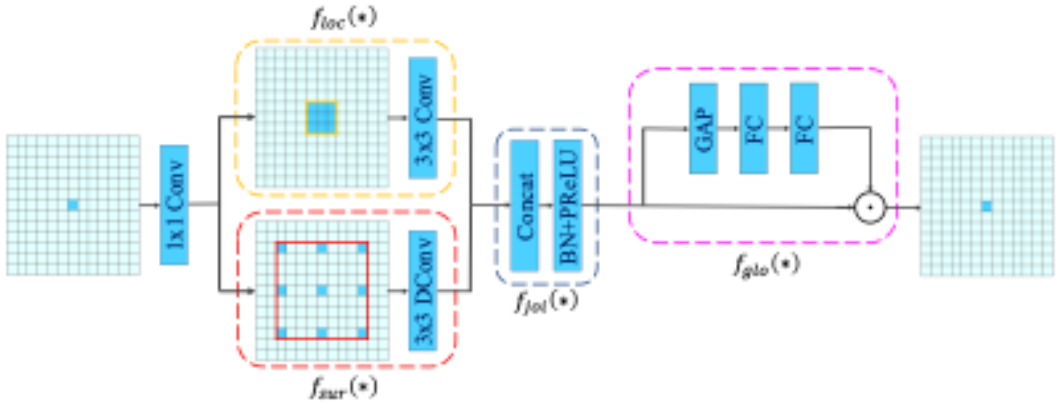
850 hPa meridional wind



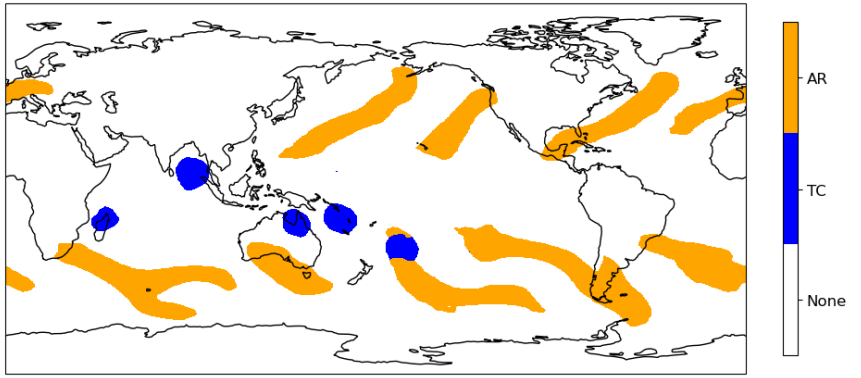
Sea level pressure



CNN (CGNet)



Output: human labels of ARs and TCs



Learning the mapping from climate state to detected feature

With: Lukas Kapp-Schwoerer (Google), Andre Graubner, Sol Kim (Univ. Chicago), Karthik Kashinath (NVIDIA)

Not Reinventing the Wheel

andregraubner / ClimateNet

Code | Issues 4 | Pull requests 2 | Actions | Projects | Security | Insights

Files

main

Go to file t

- climatenet
- LICENSE
- README.md
- conda_env.yml
- config.json
- example.py

ClimateNet / example.py

andregraubner Updated example.py to move epochs to config

Code | Blame | 31 lines (23 loc) · 1022 Bytes

```python
from climatenet.utils.data import ClimateDatasetLabeled, ClimateDataset
from climatenet.models import CGNet
from climatenet.utils.utils import Config
from climatenet.track_events import track_events
from climatenet.analyze_events import analyze_events
from climatenet.visualize_events import visualize_events

from os import path

config = Config('config.json')
cgnet = CGNet(config)

train_path = 'PATH_TO_TRAINING_SET'
inference_path = 'PATH_TO_INFERENCE_SET'

train = ClimateDatasetLabeled(path.join(train_path, 'train'), config)
test = ClimateDatasetLabeled(path.join(train_path, 'test'), config)
inference = ClimateDataset(inference_path, config)

cgnet.train(train)
cgnet.evaluate(test)

cgnet.save_model('trained_cgnet')
# use a saved model with
# cgnet.load_model('trained_cgnet')

class_masks = cgnet.predict(inference) # masks with 1==TC, 2==AR
event_masks = track_events(class_masks) # masks with event IDs

analyze_events(event_masks, class_masks, 'results/')
visualize_events(event_masks, inference, 'pngs/')
```

https://github.com/andregraubner/ClimateNet

Training CGNet

Purpose:

The purpose of this notebook is to train CGnet for machine learning detection of atmospheric rivers and tropical cyclones.
See ClimateNet repo here: https://github.com/andregraubner/ClimateNet

Authors/Contributors:

- Teagan King
- John Truesdale
- Katie Dagon

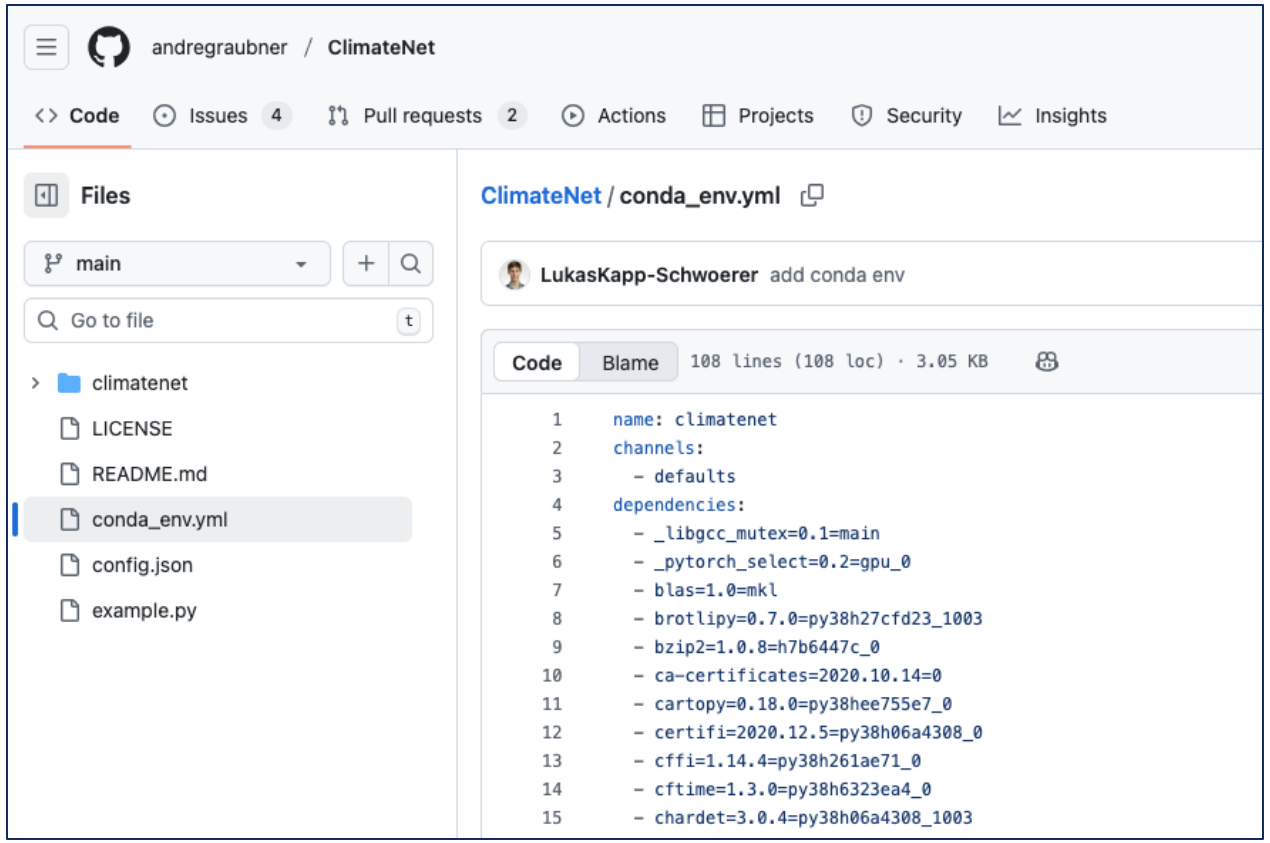
Import libraries

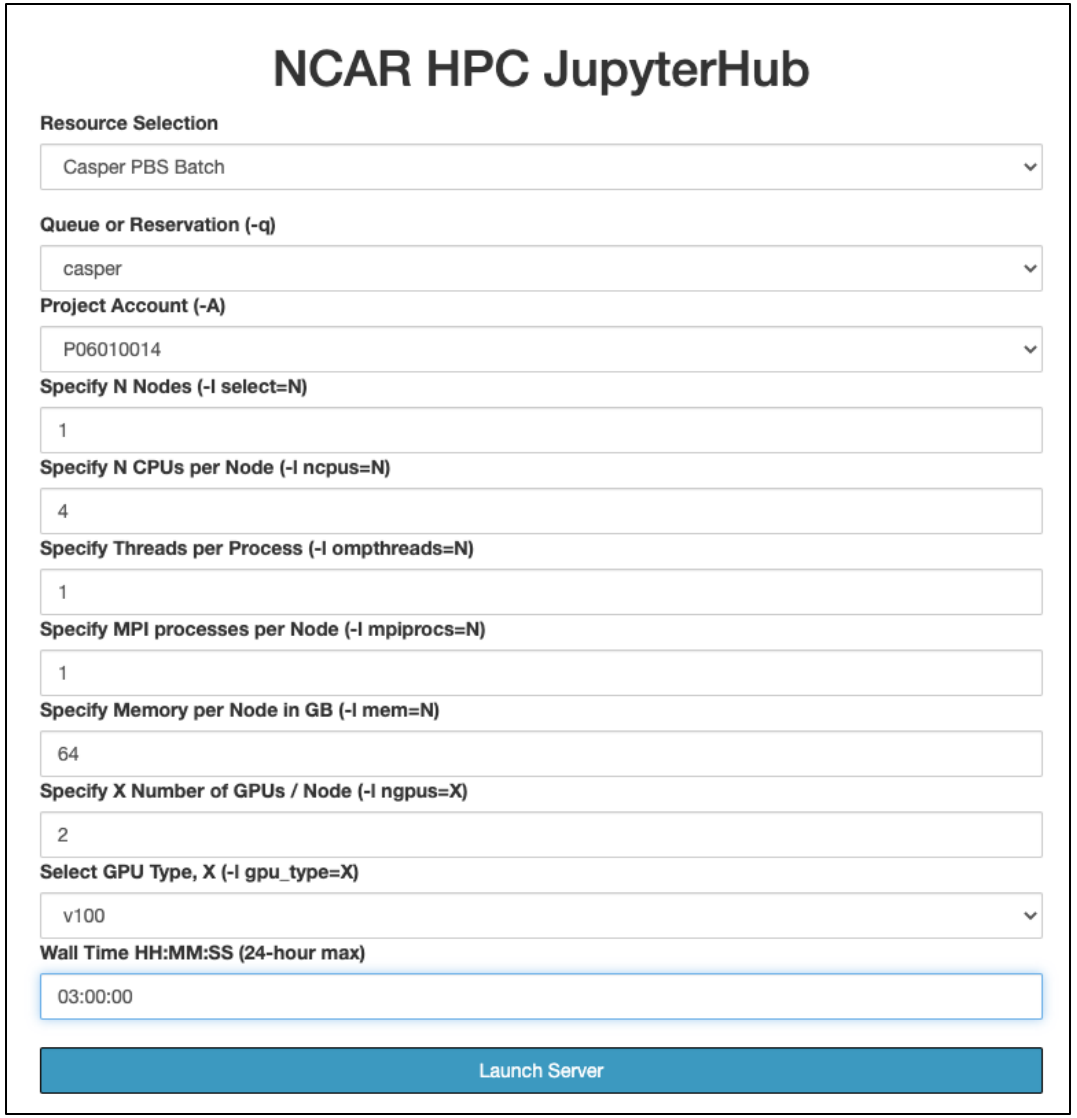
[1]:

```python
import os
import sys
import json
import numpy as np
import matplotlib.pyplot as plt

sys.path.append("/glade/work/kdagon/ClimateNet") # append path to ClimateNet repo
from climatenet.utils.data import ClimateDatasetLabeled, ClimateDataset
from climatenet.models import CGNet
from climatenet.utils.utils import Config
from climatenet.track_events import track_events
from climatenet.analyze_events import analyze_events
from climatenet.visualize_events import visualize_events

from os import path
```

https://github.com/katiedagon/ML-extremes

Environment & Resources



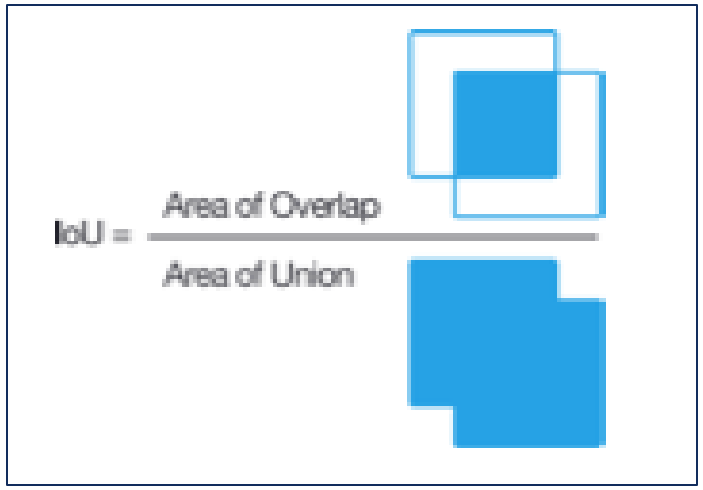


- Some customization to adapt the climatenet conda env to work for our team
- Only works with v100 GPUs (?)

Loss Function & Metrics

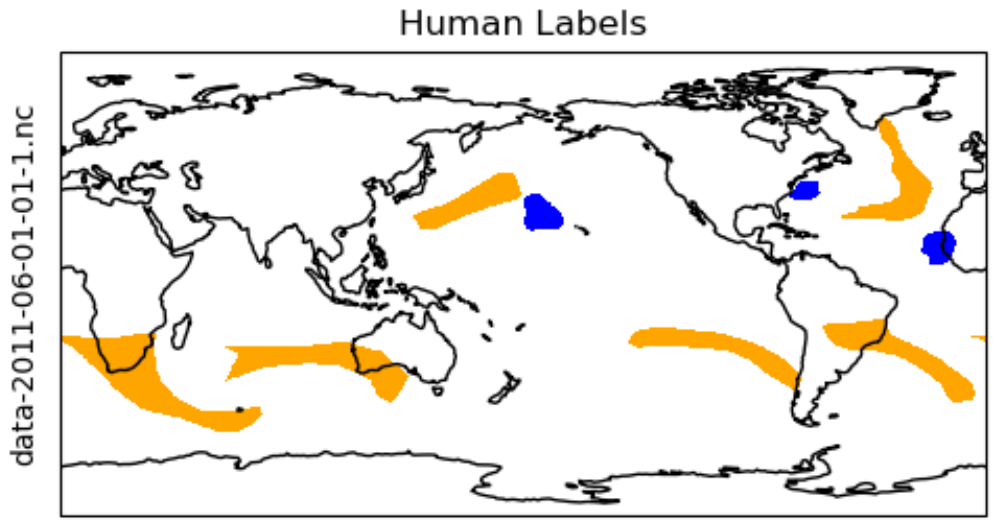
Segmentation problems like these often have an issue called **“class imbalance”** where one of the categories dominates the input data. In this case, it is the “background” class (94% of pixels in ClimateNet).

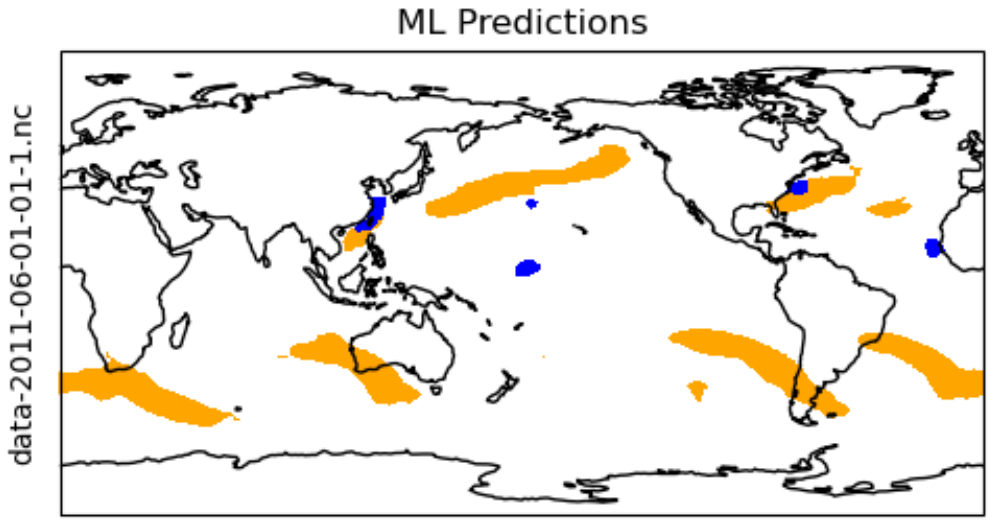
- One approach is to leverage different loss functions (e.g., weighted cross-entropy, Jaccard loss).



Prabhat et al. (2021)

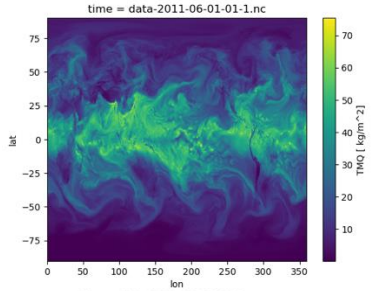
Intersection over Union (IoU) is used to quantify model performance – that is, **how well do the ML generated labels line up with the human labels?**





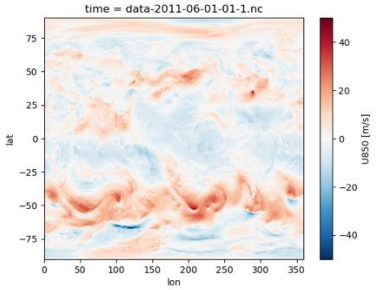
Normalizing the Inputs

Total column water vapor



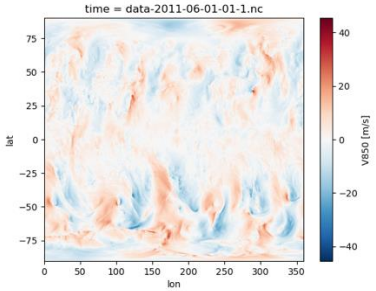
Mean = 19.2 kg/m2

850 hPa zonal wind



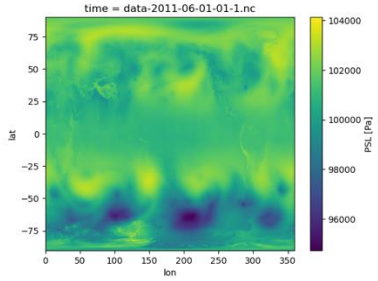
Mean = 1.5 m/s

850 hPa meridional wind



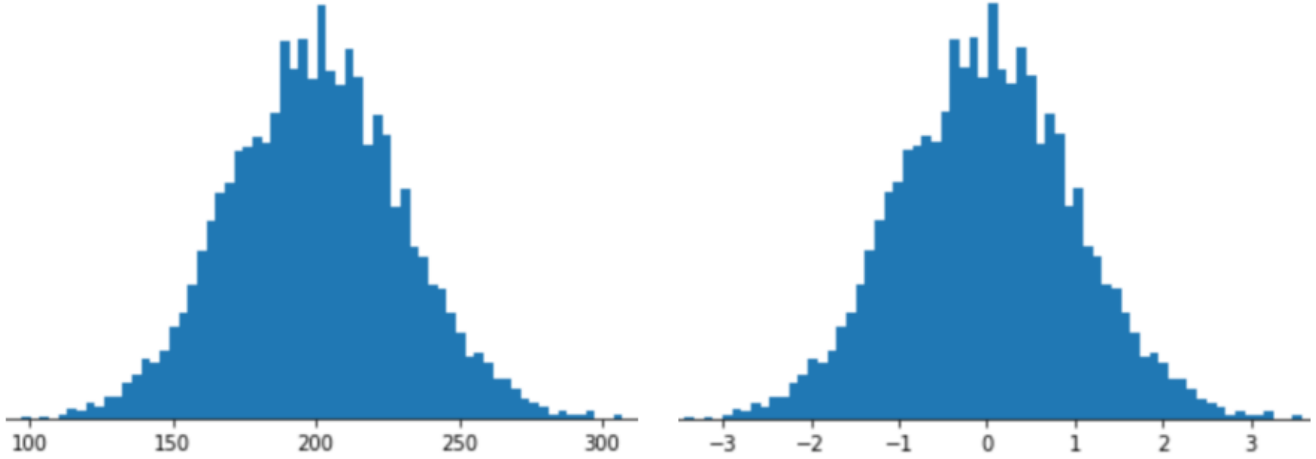
Mean = 0.25 m/s

Sea level pressure



Mean = 100814 Pa

Z-score scaling



raw

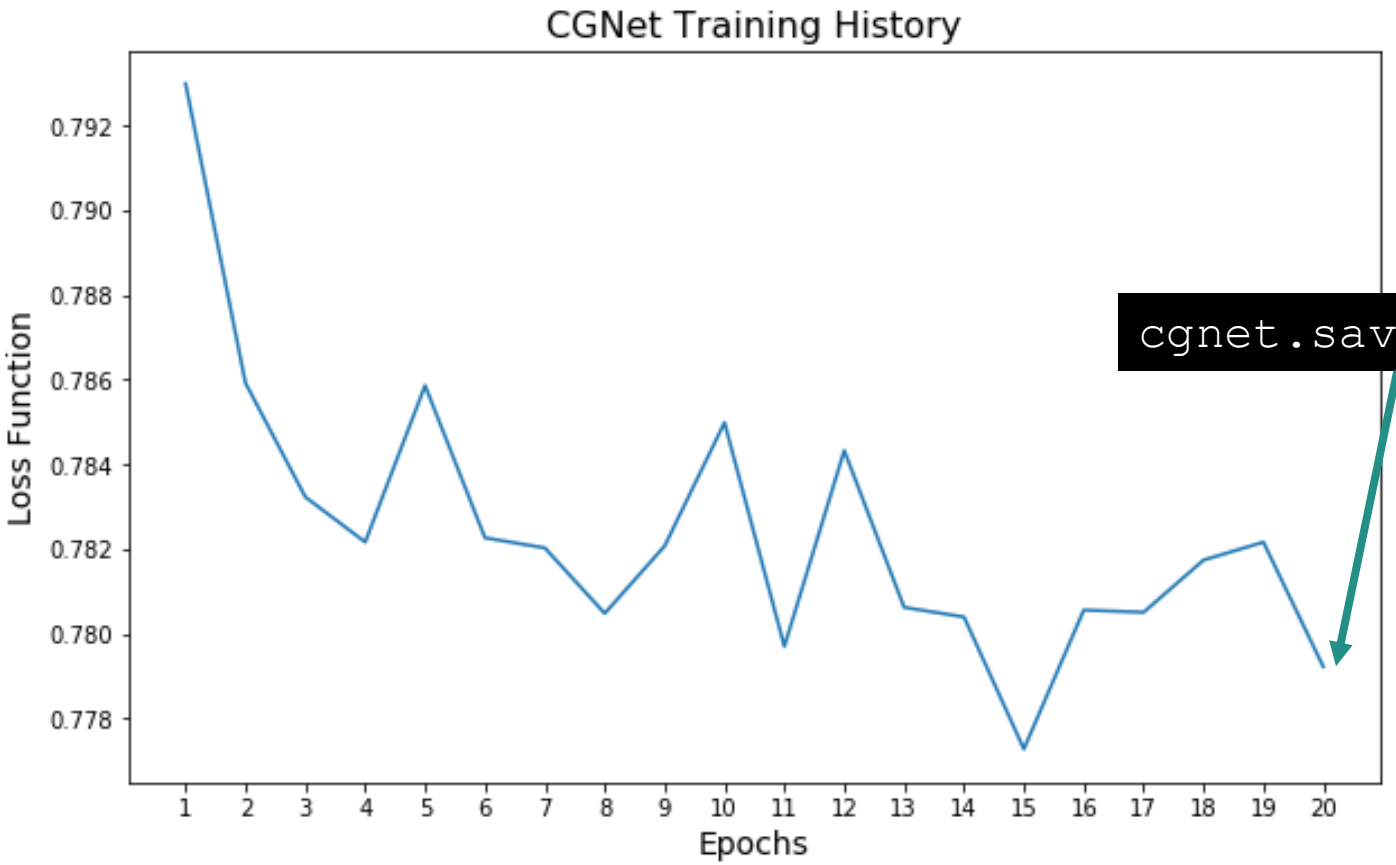
scaled

$$x' = (x - \mu)/\sigma$$

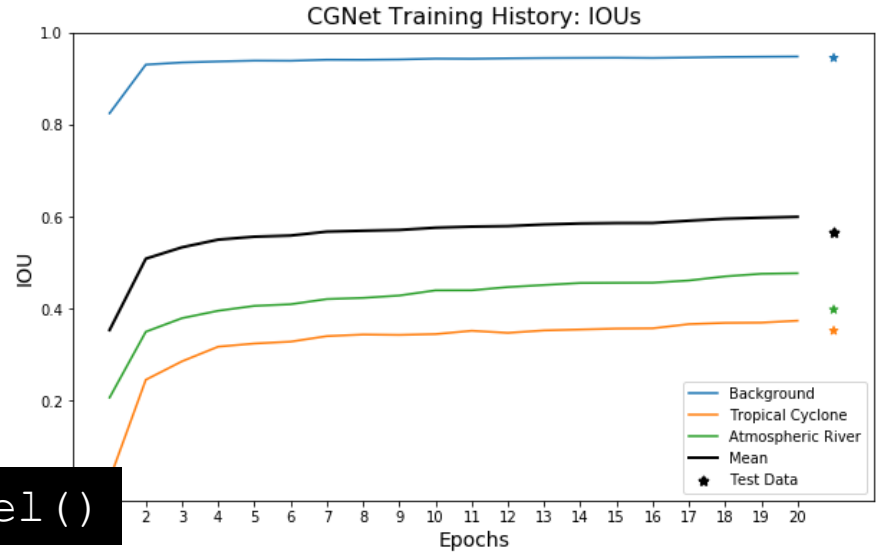
Z-score image from: https://developers.google.com/machine-learning/crash-course/numerical-data/normalization

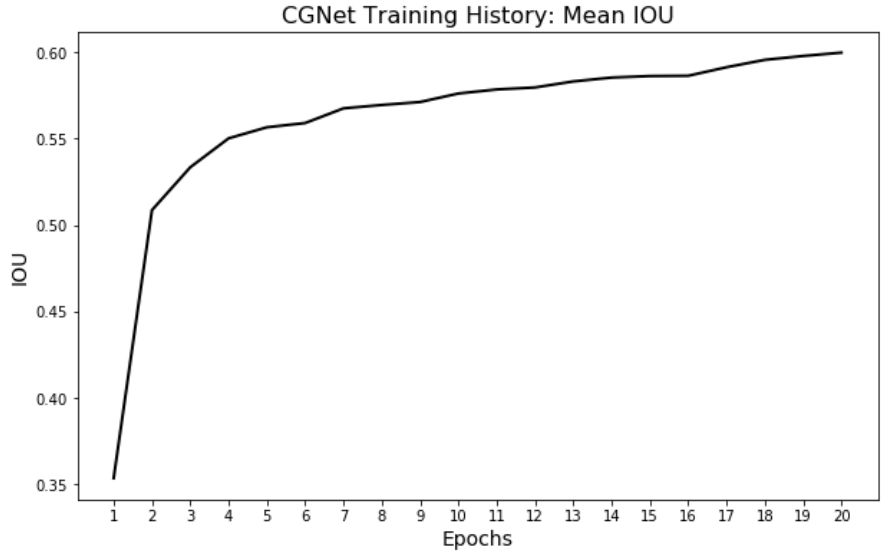
CGNet Training Statistics

Of the 459 samples, 398 used for training (87%; years 1996-2010) and 61 for testing (13%; years 2011-2013).




```
cgnet.save_model()
```





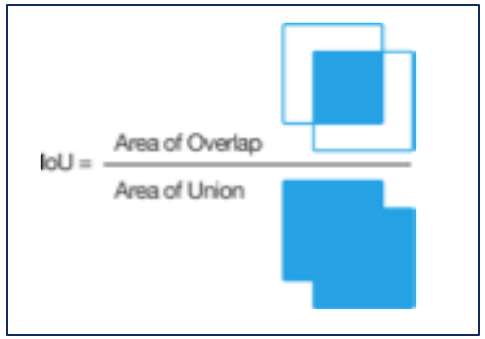
Training takes about 1 min per epoch on 2 casper V100 GPUs

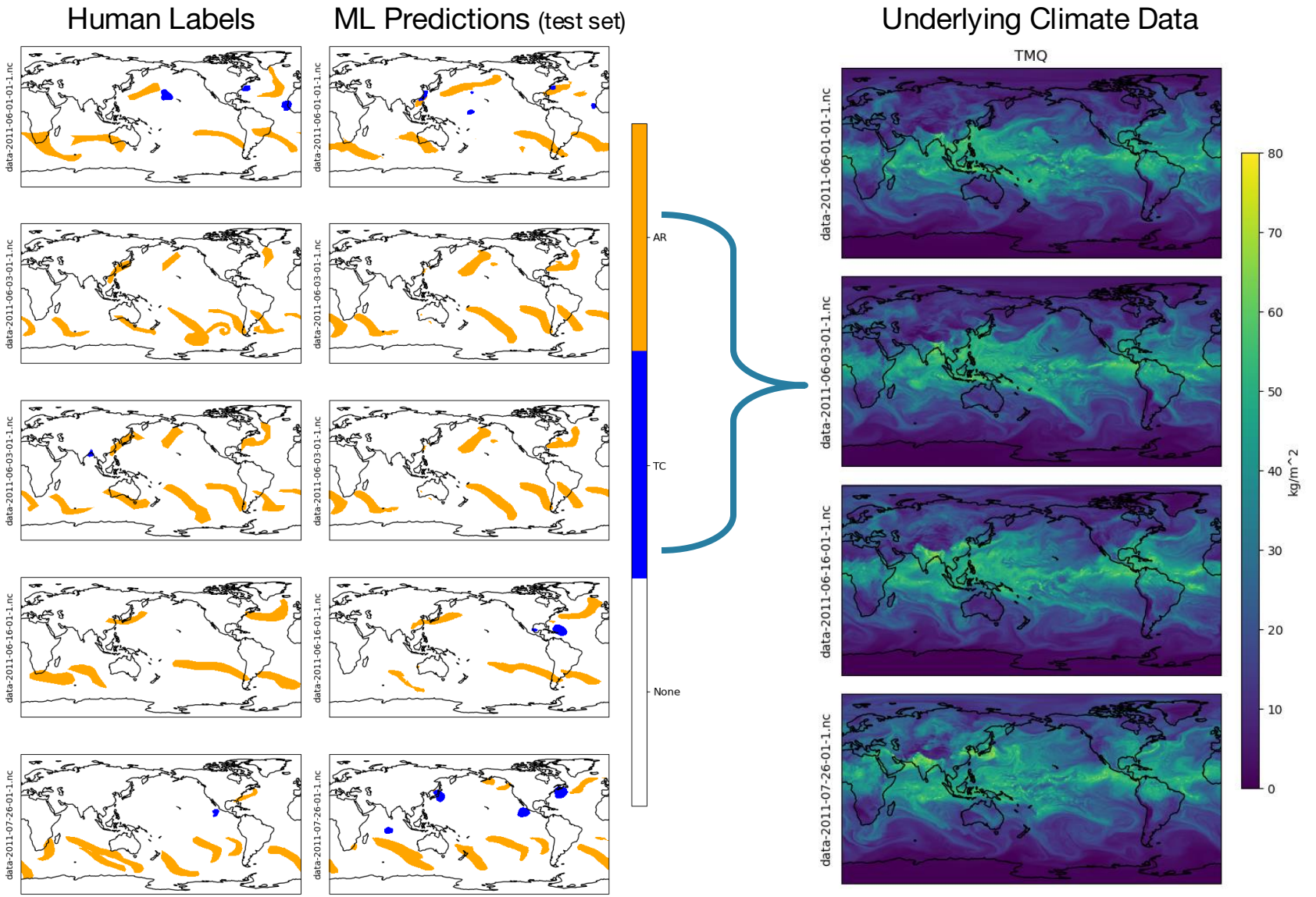
Evaluating CGNet Results: Labels vs. Predictions

How do we evaluate the climate model results?

Different expert-labeled maps; different timepoints*

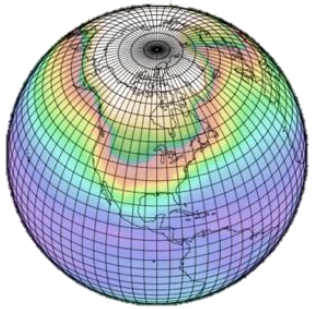
**sometimes two experts label the same timepoint!*





Applying the Trained Model to CESM

Use the retrained CGNet algorithm applied to climate model output to detect ARs and TCs

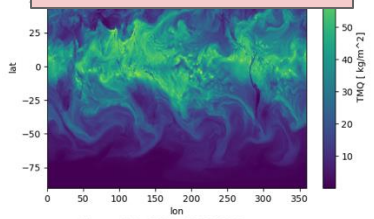


Specifically, fully coupled CESM1.3 simulations at high spatial (0.25deg) and temporal (3hrly) resolution.

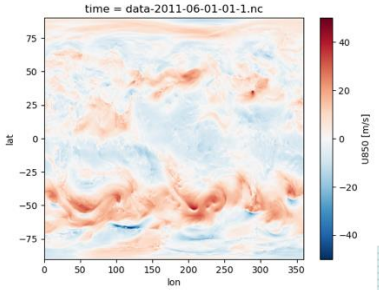
Lots of data processing steps went into this work!

CESM maps

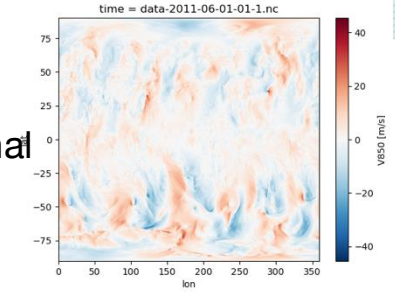
Total column water vapor



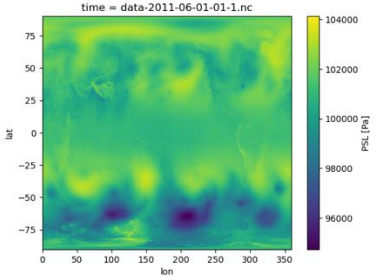
850 hPa zonal wind



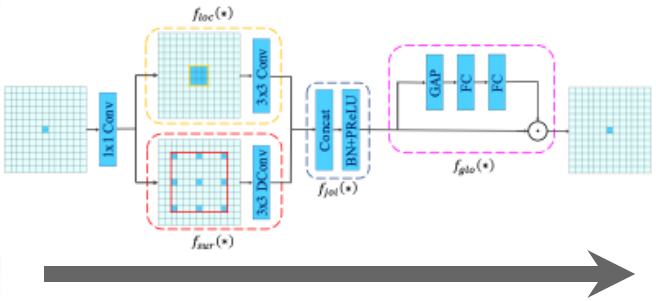
850 hPa meridional wind



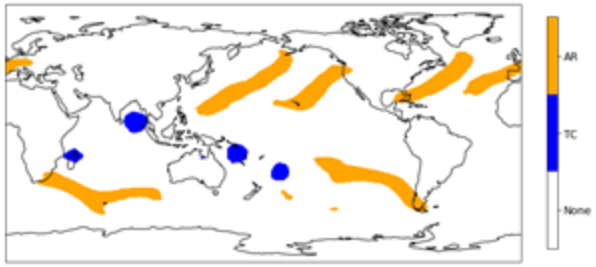
Sea level pressure



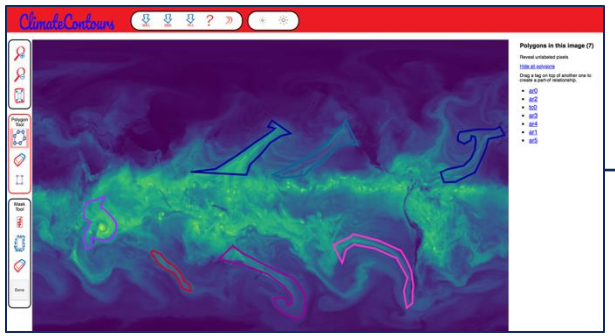
CNN (CGNet)



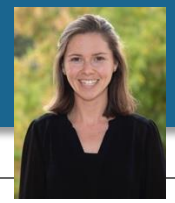
Labels of ARs and TCs in CESM



Data Processing Workflow



QA/QC human labels



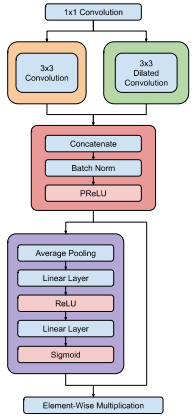
Processed data from labeling campaigns (masks & underlying fields)
Training data: labeled timepoints, 1996-2010
Test data: labeled timepoints, 2011-2013
Calculate means/std for normalization

Train CGNet
1 input: TMQ
2 inputs: TMQ, V850
4 inputs: TMQ, V850, U850, PSL

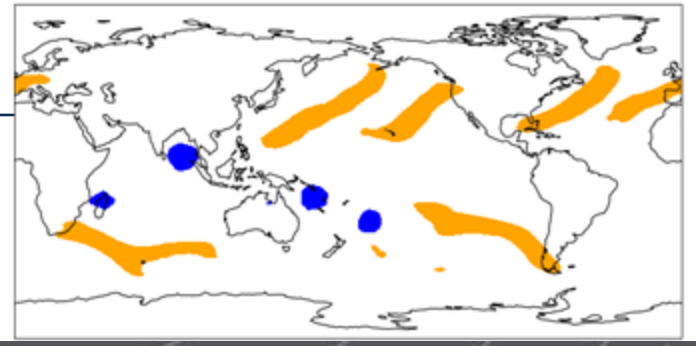
Climate data & HighRes simulations
e.g., for CESM1.3:
Historical 2000-2005
RCP2.6: 2006-2015
RCP8.5: 2086-2100

Processing input fields
- Variable-specific processing, e.g., for CESM1.3:
  - PSL: direct CESM output
  - TMQ: calculate from Q and P
  - U850/V850: interpolate to 850hPa pressure level using PS/U/V, extrapolate high elevation regions
- Remap unstructured mesh to lat/lon grid
- Separate into 3-hourly files

Run processed data through CGNet



Generate AR/TC results



Cool Science!

NCAR/UCAR Earth System Data Science (ESDS)

UX

PROJECT raijin

Analyzing and visualizing CAM-SE output in Python

Overview

We demonstrate a variety of options for analyzing and visualizing output from the Community Atmosphere Model (CAM) with the spectral element (SE) grid in Python. This notebook was developed for the ESDS Collaborative Work Time on Unstructured Grids, which took place on April 17, 2023. A recap of the related CAM-SE discussion can be found here.

https://ncar.github.io/esds/posts/2023/cam-se-analysis/

*Thanks to **Teagan King** and **John Truesdale** (CGD) for their work on this data processing pipeline*

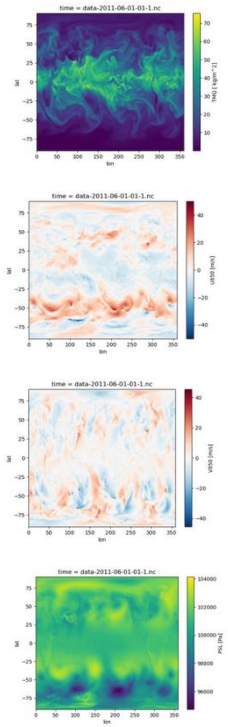
Data Processing Reality

https://docs.dask.org/en/latest/dashboard.html

Applying the Trained Model to CESM

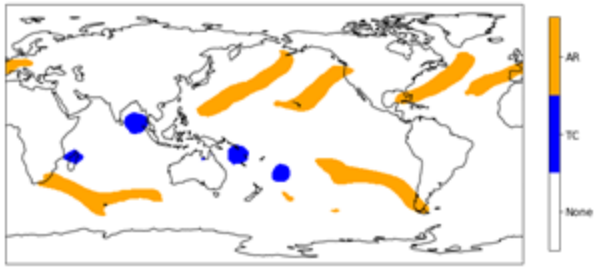
For the CESM historical simulation, 15 years of 3 hourly output translates to **43,800 samples.**

CESM maps



Saved CNN

Labels of ARs and TCs in CESM



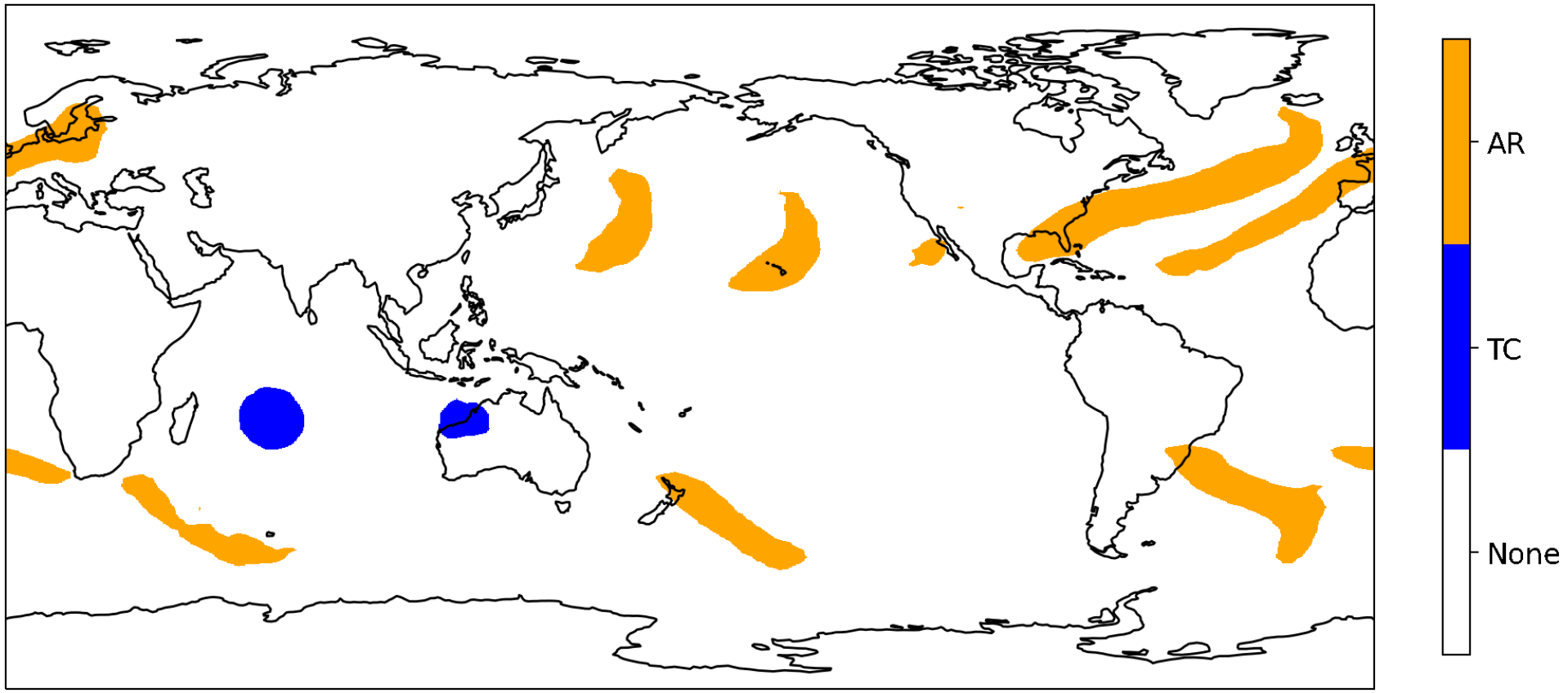
Function for creating TC/AR masks using pre-trained model

```
[3]: def cgnet_load_create_masks(model_path, inference_path, save_dir, analyze=False, visualize=False):
        """Use a pre-trained model to create masks of tropical cyclones (mask value = 1)
        and atmospheric rivers (mask value = 2)

        Function will create NetCDF mask files and save them in the save_directory.

        Parameters:
        -----------
        model_path: str
            filepath to pre-trained CGnet model
        inference_path: str
            filepath to inference data
        save_dir: str
            filepath to where the masks will be saved as .nc files
        analyze: bool (optional)
            default is False; if True, will save plots for analyzing events using climatenet.analyze_events().
            Note that this can significantly increase the time to run.
        visualize : bool (optional)
            default is False; if True, will save plots for visualizing events using climatenet.visualize_events().
            Note that this can significantly increase the time to run.

        """
        # instantiate CGNet with pre-trained model
        cgnet = CGNet(model_path=model_path)

        # inference using the pre-trained config file
        inference = ClimateDataset(inference_path, cgnet.config)
        class_masks = cgnet.predict(inference) # masks with 1==TC, 2==AR

        # create save dir, if needed
        if not os.path.isdir(save_dir):
            os.makedirs(save_dir)
        else:
            print("Warning: might overwrite {}".format(save_dir))

        # save out class masks
        class_masks.name = 'masks'
        class_masks.to_netcdf(save_dir+"/class_masks.nc")
        print("Saved class masks to {}".format(save_dir))
```

Inference takes about 5 min per year on 2 casper V100 GPUs

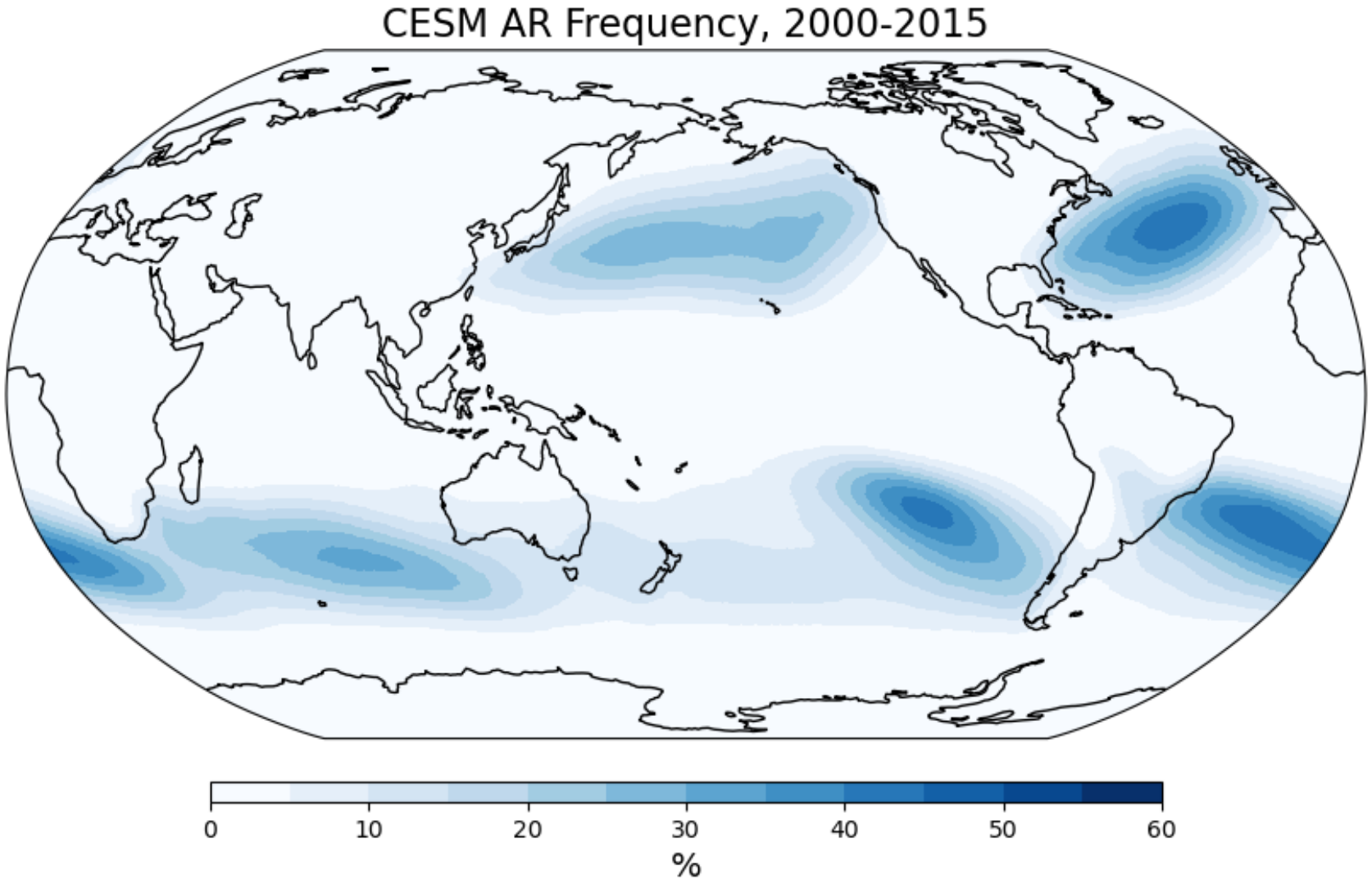
https://github.com/katiedagon/ML-extremes

Applying the Trained Model to CESM



Input fields: TMQ, U850, V850, PSL
Output fields: AR, TC, and none
Simulation years: CESM1.3 Historical climate simulation, 2000-2015
Animation shows 3hrly, 0.25 deg output; Jan-Feb 2000.

Applying the Trained Model to CESM



Dagon et al. *in prep*

Sensitivity to Input Fields

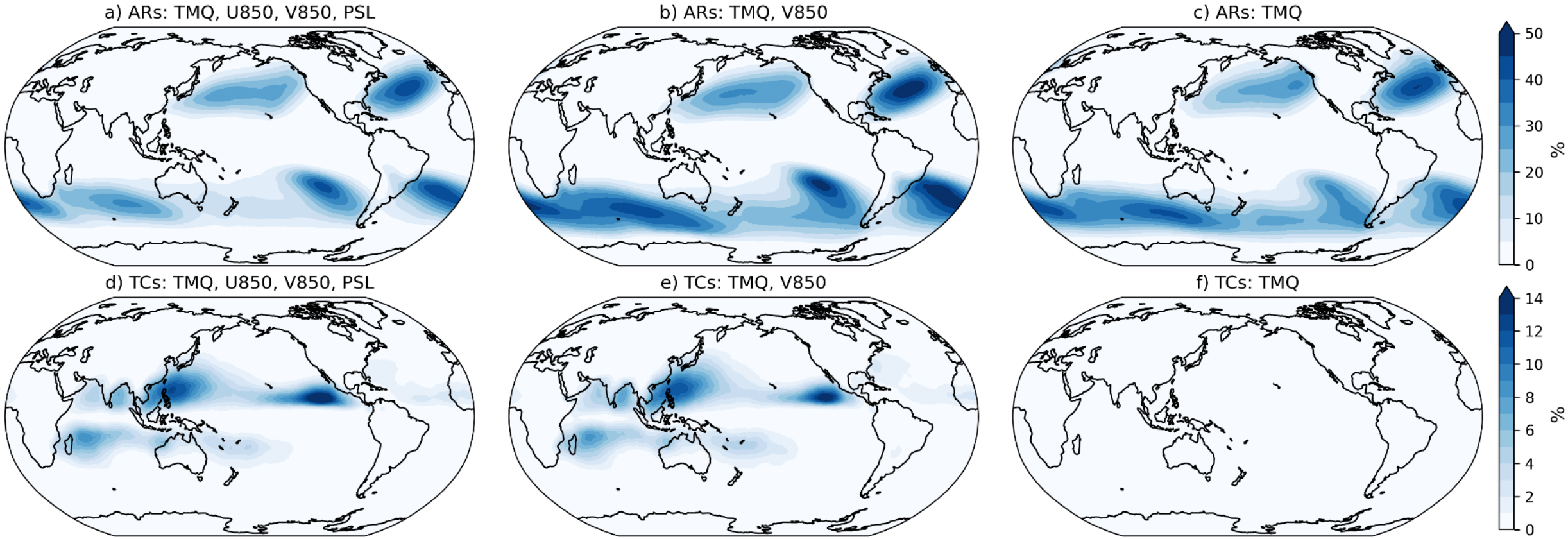
CGNet trained on TMQ, U850, V850, PSL

CGNet trained on TMQ, V850

CGNet trained on TMQ

ARs

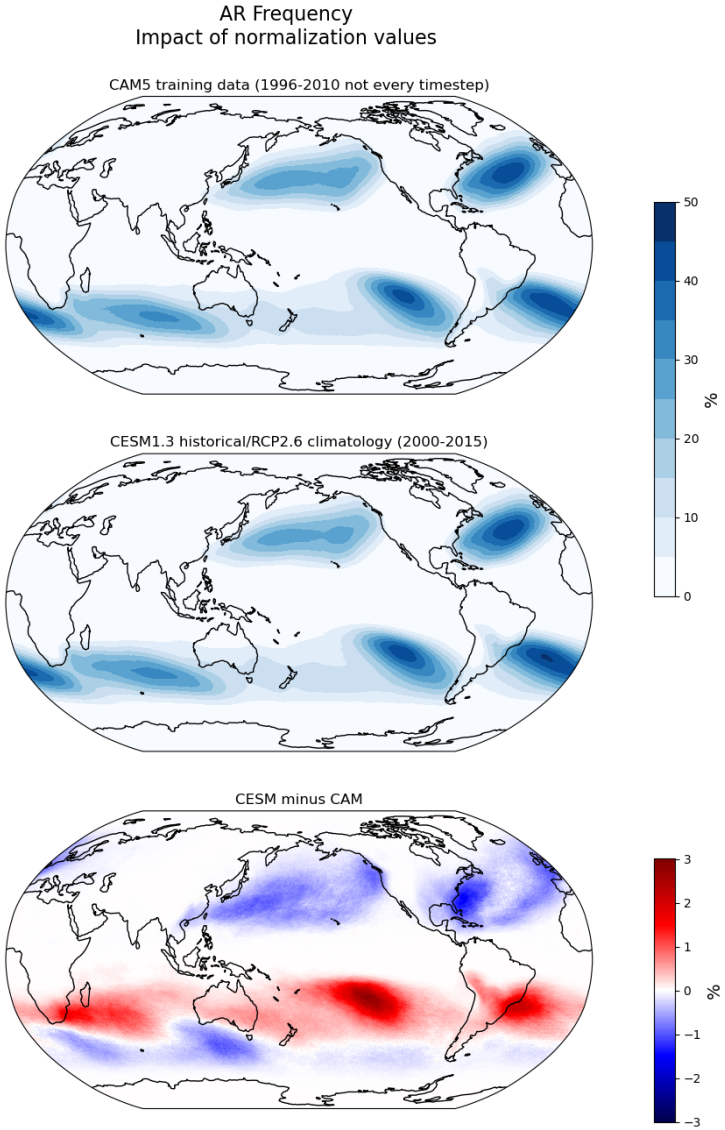
TCs

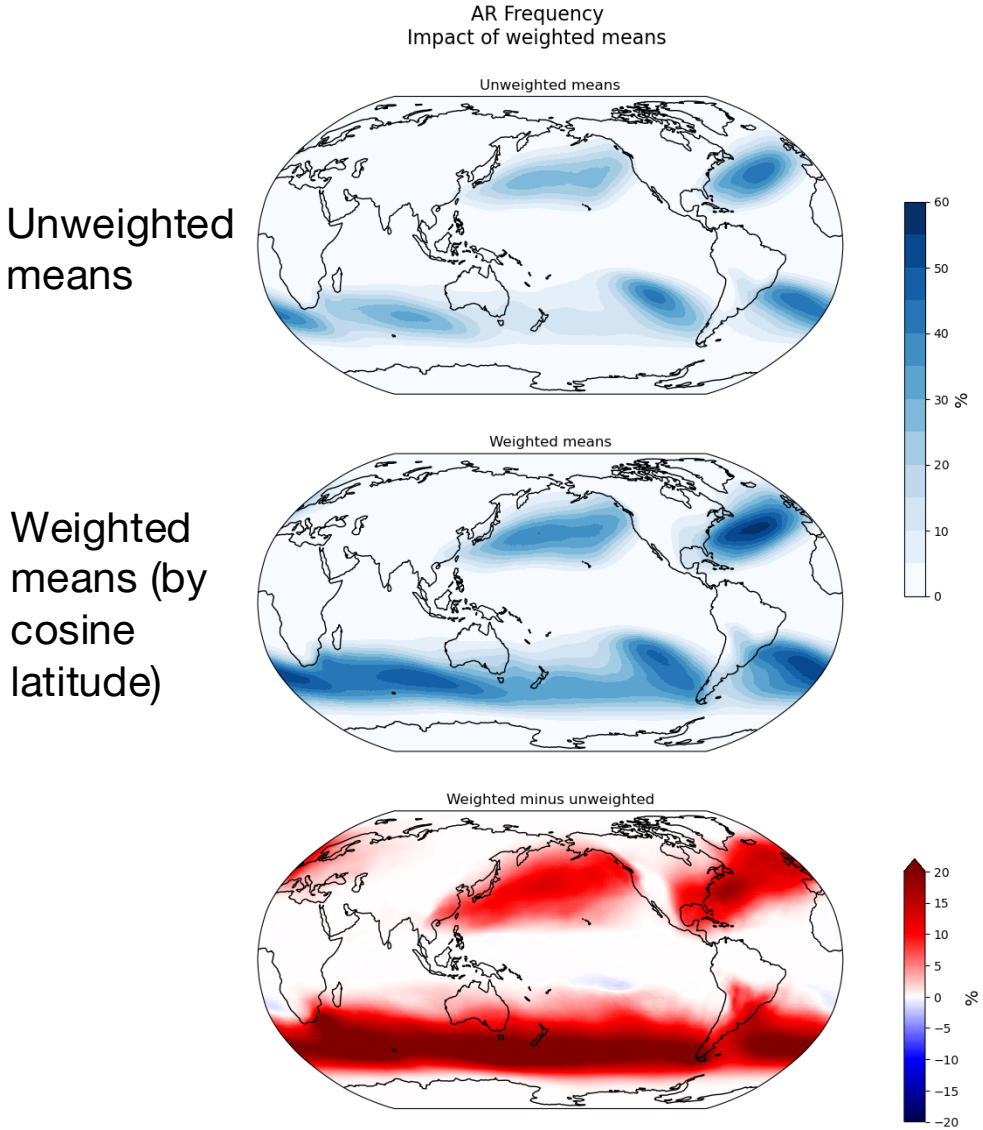


Sensitivity to Normalization

Calculate means/std from the training data (CAM)

Calculate means/std from the inference data (CESM)





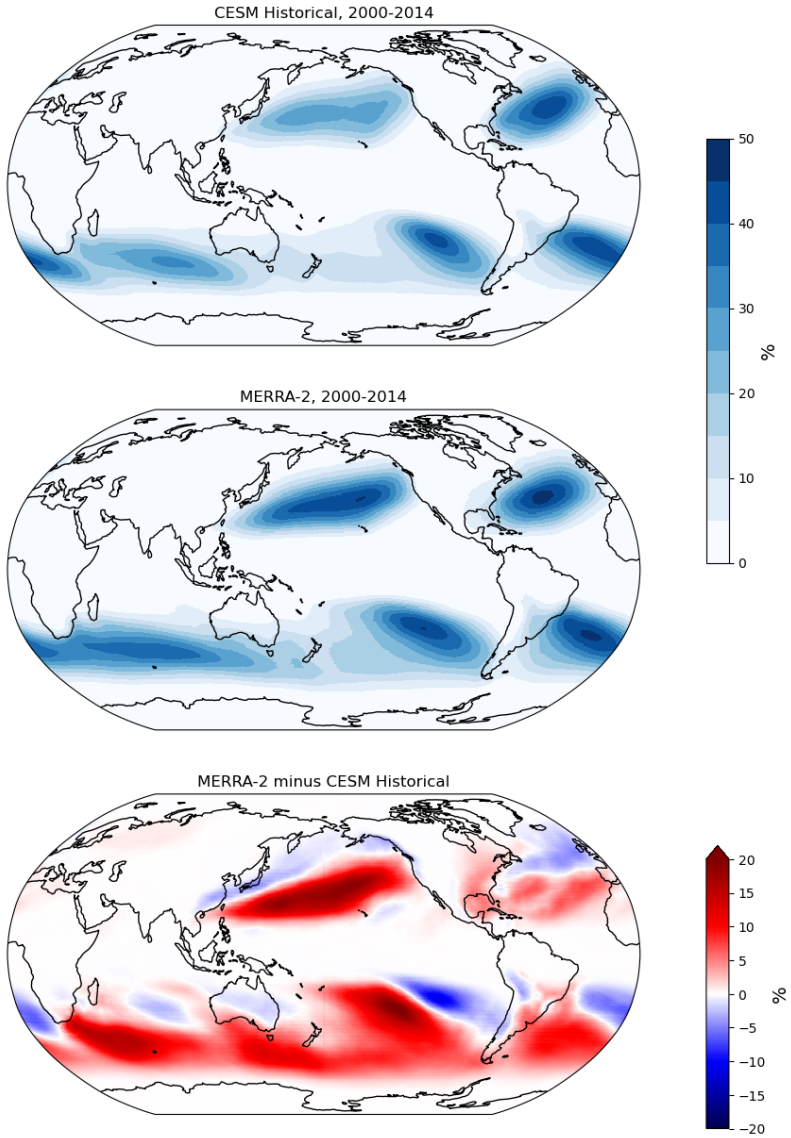
Unweighted means

Weighted means (by cosine latitude)

Evaluating CGNet Results: CESM vs. MERRA-2

CESM1.3 with
ne120 grid
(0.25deg resolution)

MERRA-2 native grid
(0.5deg resolution)



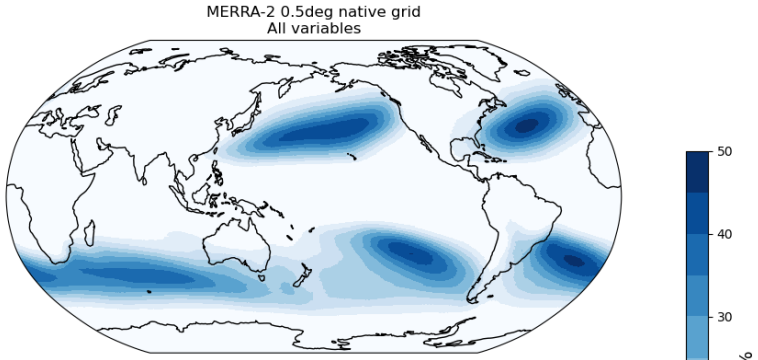
Comparing CESM results to ARs detected with CGNet in reanalysis (MERRA-2).

Why are there (predominantly) more ARs in MERRA-2 than CESM? Differences between climate model and reanalysis? What is the impact of spatial resolution?

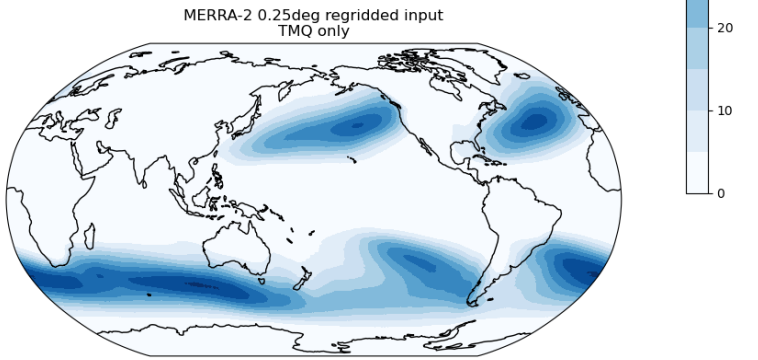
Dagon et al. *in prep*

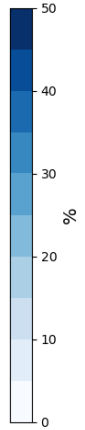
Sensitivity to Spatial Resolution

MERRA-2 native grid
(0.5deg resolution)
All input variables

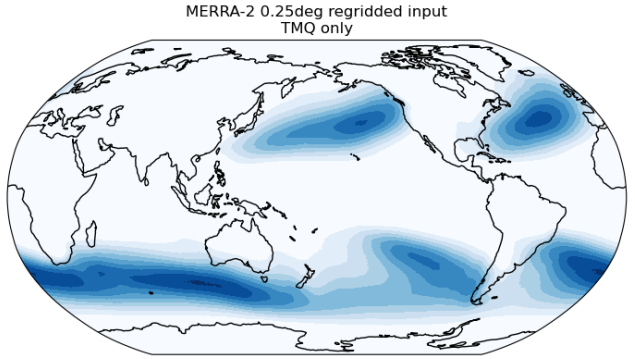


MERRA-2 regridded
(0.25deg resolution)
***Water vapor only**

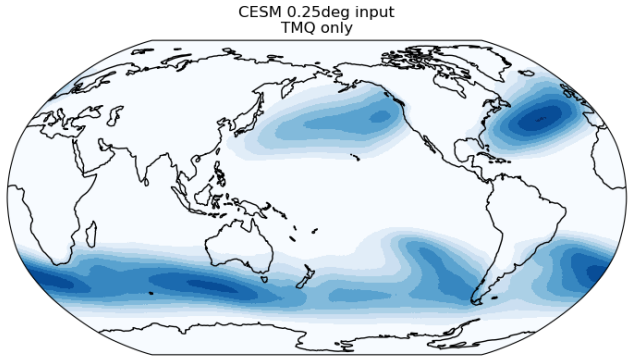


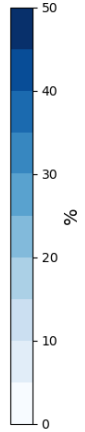


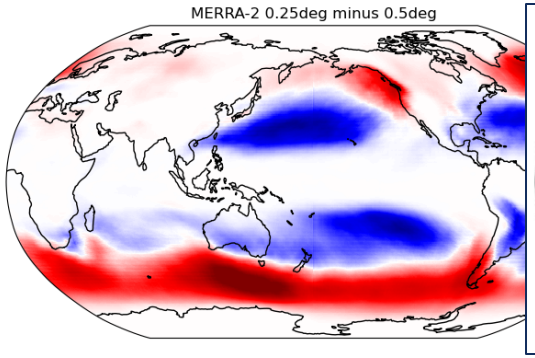
MERRA-2 regridded
(0.25deg resolution)
Water vapor only

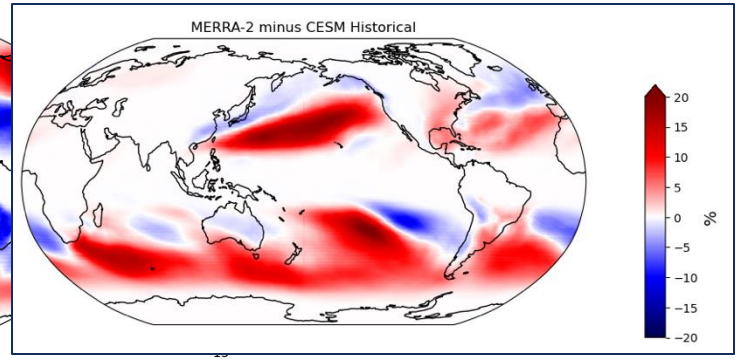


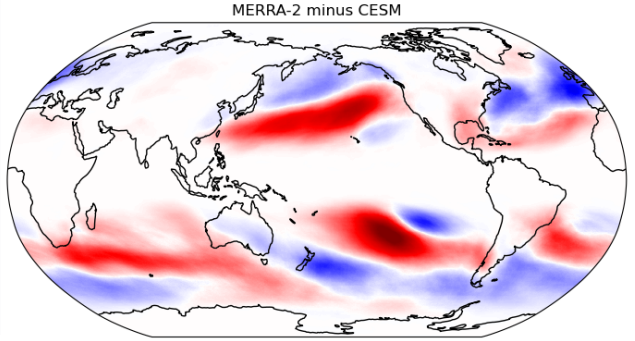
CESM native grid
(0.25deg resolution)
Water vapor only

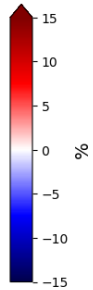








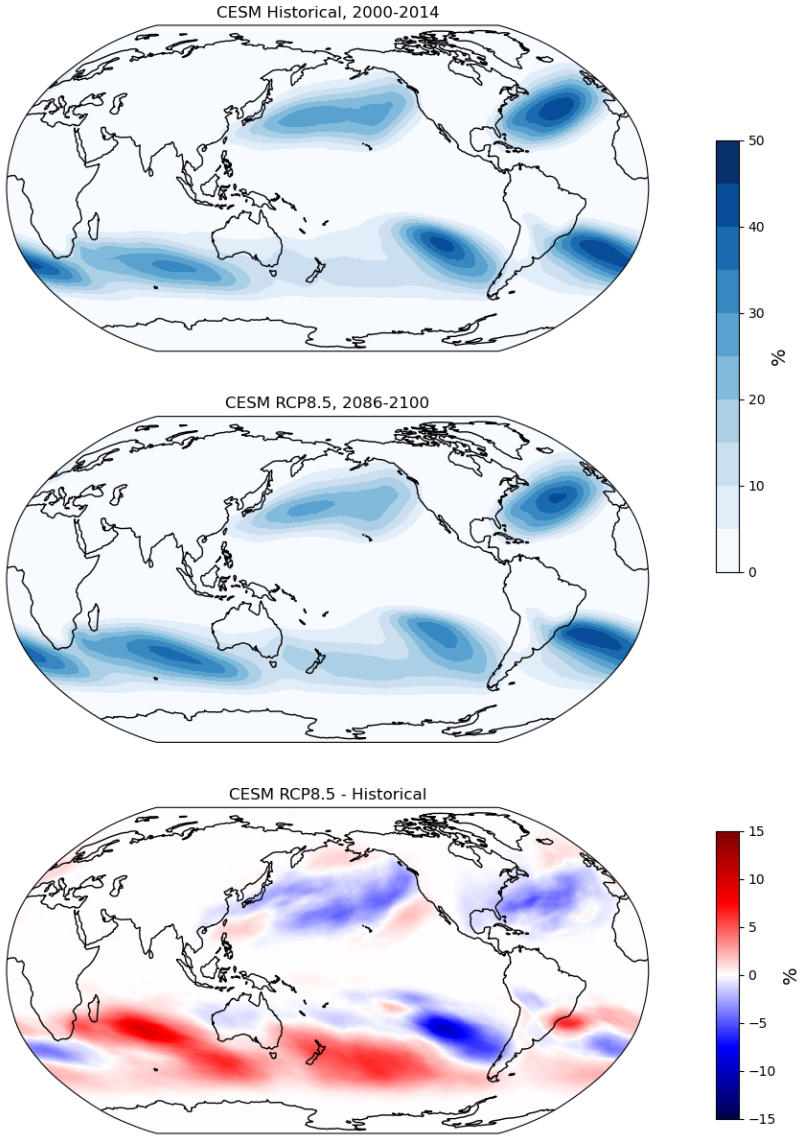




AR Frequency Response to Climate Change

CESM historical, 2000-2014

CESM RCP8.5, 2086-2100



Comparing CESM results across climate states.

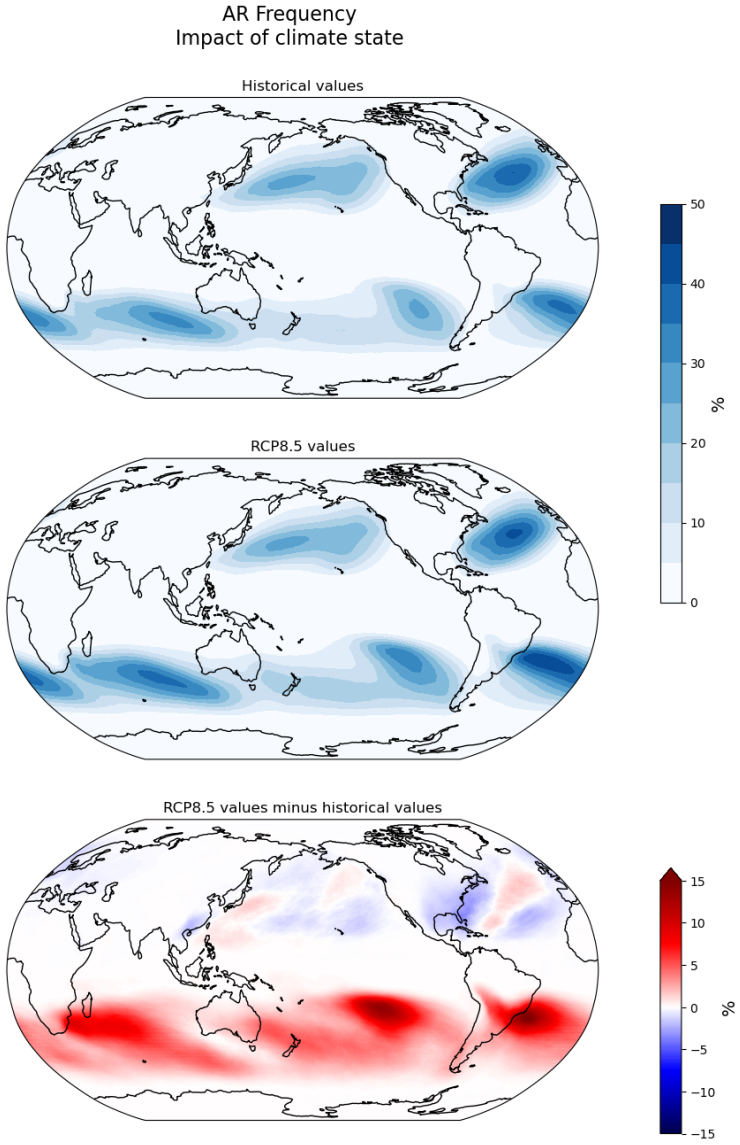
What about the normalization here?

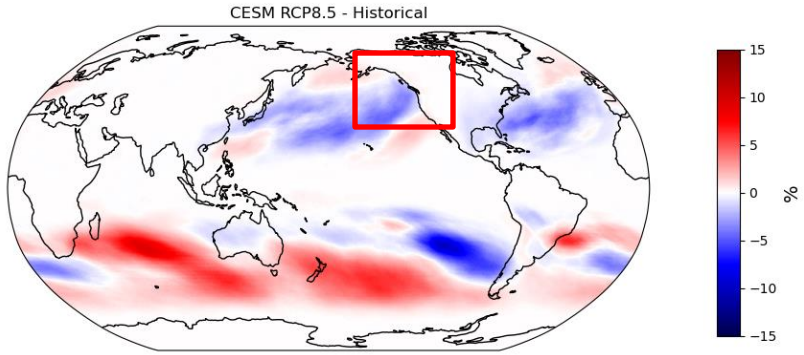
Dagon et al. *in prep*

Sensitivity to Normalization

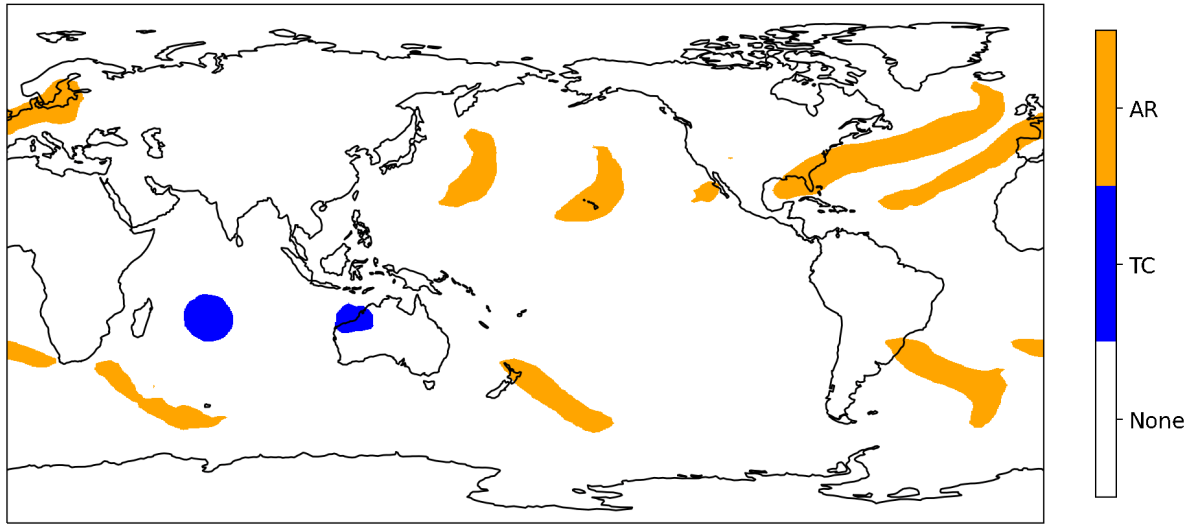
Calculate means/std from the training data (CAM)

Calculate means/std from the inference data (CESM RCP8.5)





Spatiotemporal Event Tracking



andregraubner / ClimateNet

Code | Issues 4 | Pull requests 2 | Actions | Projects | Security | Insights

Files

main

Go to file t

- climatenet
  - bluemarble
  - utils
  - __init__.py
  - analyze_events.py
  - models.py
  - modules.py
  - track_events.py
  - visualize_events.py
- LICENSE
- README.md
- conda_env.yml

ClimateNet / climatenet / track_events.py

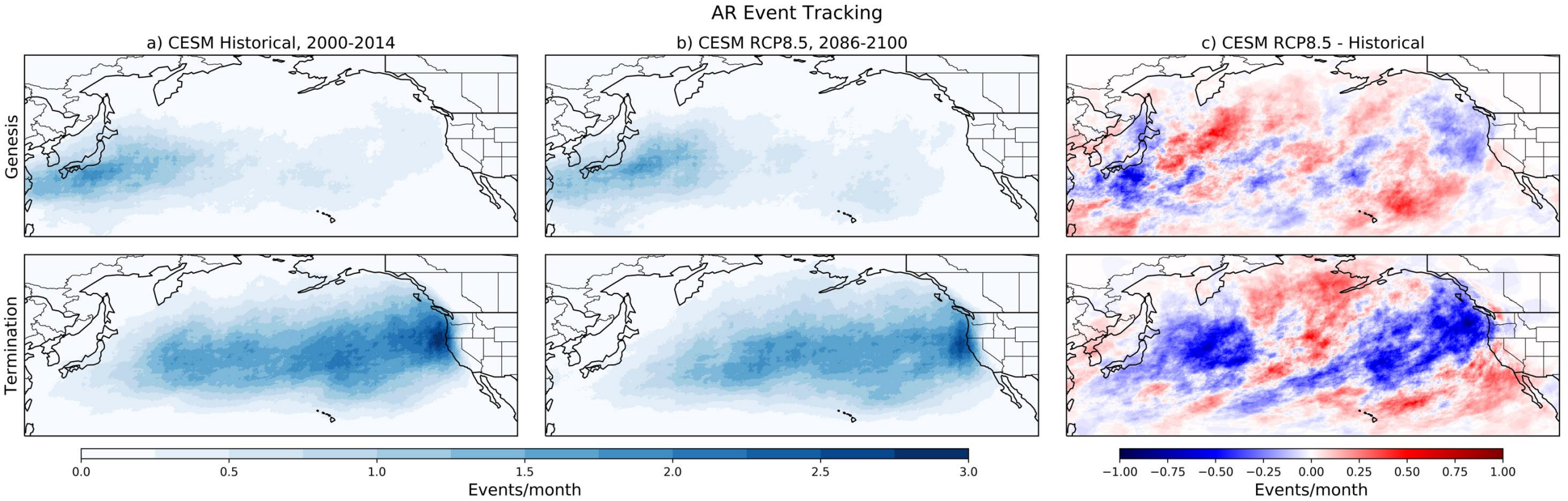
LukasKapp-Schwoerer add event tracking, analyzing, visualizing

Code | Blame | 214 lines (192 loc) · 10.2 KB

```
1   import psutil
2   from multiprocessing import Pool
3   from tqdm import tqdm
4   import numpy as np
5   import xarray as xr
6
7   def track_events(class_masks_xarray, minimum_time_length=5,
8                    tc_drop_threshold=250, ar_drop_threshold=250,
9                    future_lookup_range=1):
10      """track AR and TC events across time
11
12      Keyword arguments:
13      class_masks_xarray -- the class masks as xarray, 0==Background, 1==TC, 2 ==AR
14      minimum_time_length -- the minimum number of time stamps an event ought to persist to be considered
15      tc_dop_threshold -- the pixel threshold below which TCs are droped
16      ar_dop_threshold -- the pixel threshold below which ARs are droped
17      future_lookup_range -- across how many time stamps events get stitched together
18      """
```

- Post-detection script iterates through samples in time and checks for connected components
- Assigns unique IDs to each event
- Omits components smaller than 250 pixels and events lasting less than 12 hours
- Very computationally intensive, so we adapted script to run for specific region (North Pacific basin)

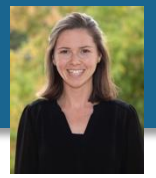
Spatiotemporal Event Tracking



Peak genesis shifts northeastward in RCP8.5 relative to the historical simulation, while termination shifts southeastward along the California coast.

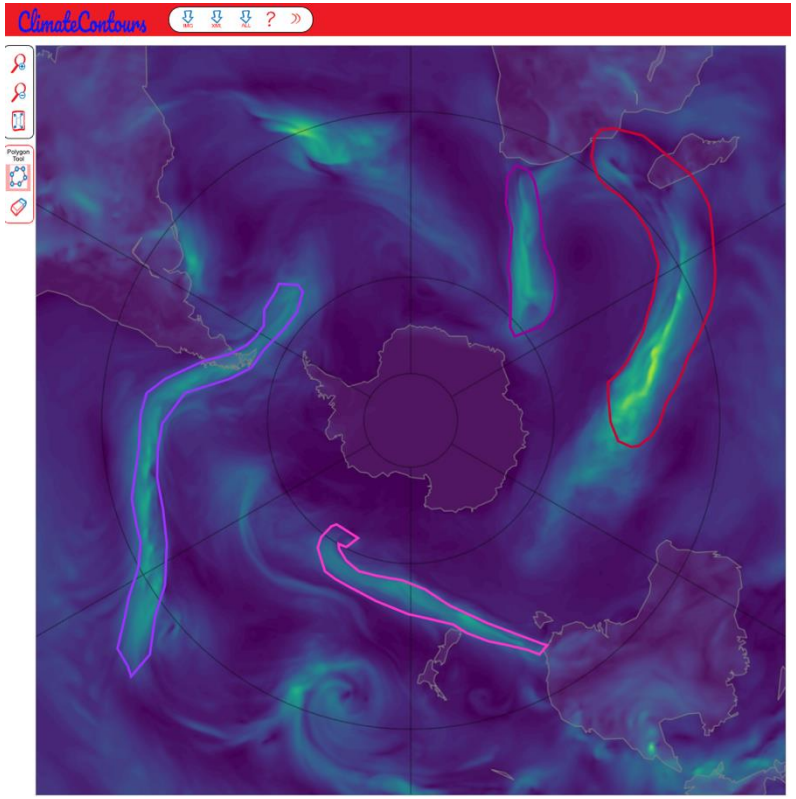
Dagon et al. *in prep*

Future Work: Machine Learning for Detection of Polar ARs

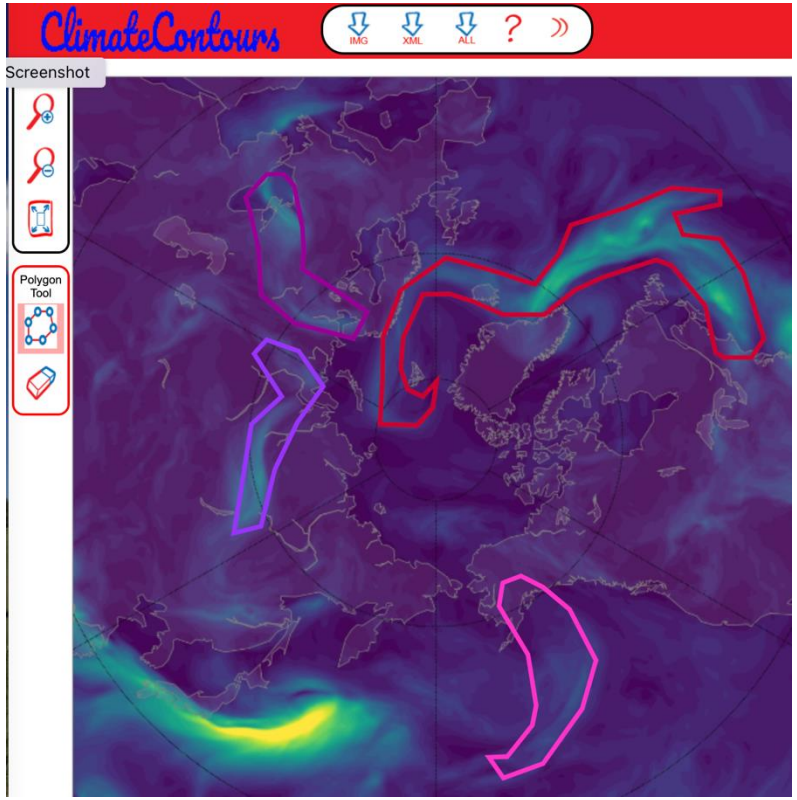



In development…polar AR algorithms for detecting Antarctic and Arctic atmospheric rivers

Antarctic Labeling Tool
~500 labels

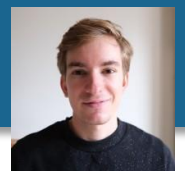


Arctic Labeling Tool
~350 labels (so far)



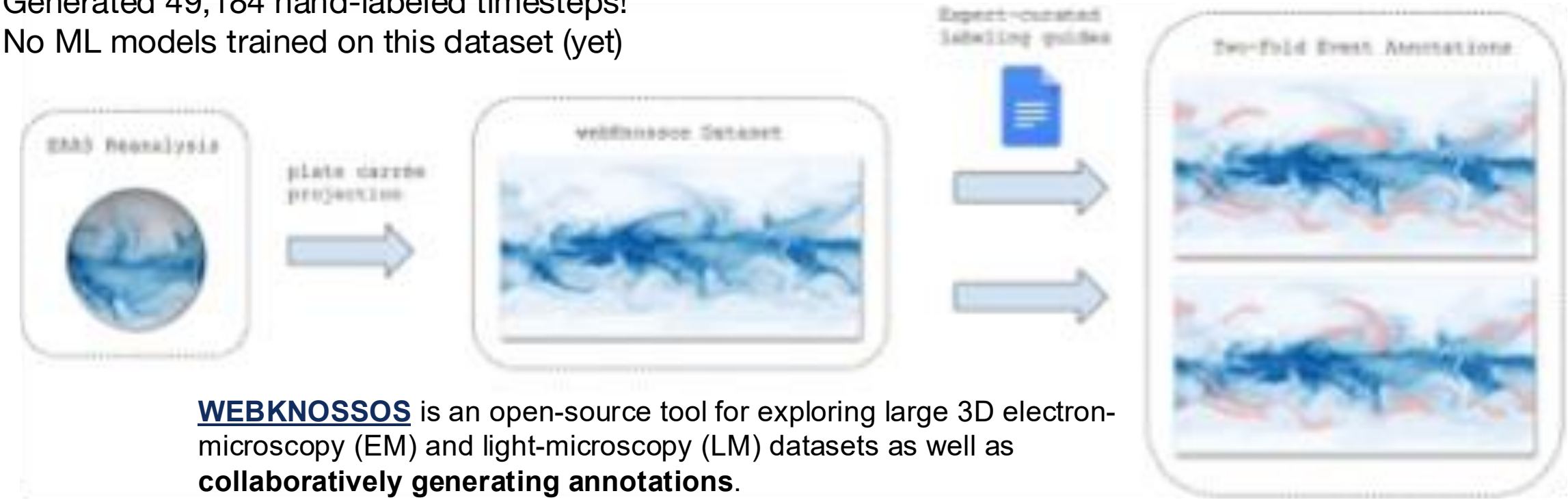
With: ***Christine Shields, Teagan King****, John Truesdale (NCAR CGD); Annette Greiner (LBNL), Sol Kim (Univ. Chicago)*

Future Work: Generating Large Amounts of Training Data



ClimateNetLarge

- Professional crowd-labeling ($$$)
- ARs, TC, and blocking events
- Generated 49,184 hand-labeled timesteps!
- No ML models trained on this dataset (yet)



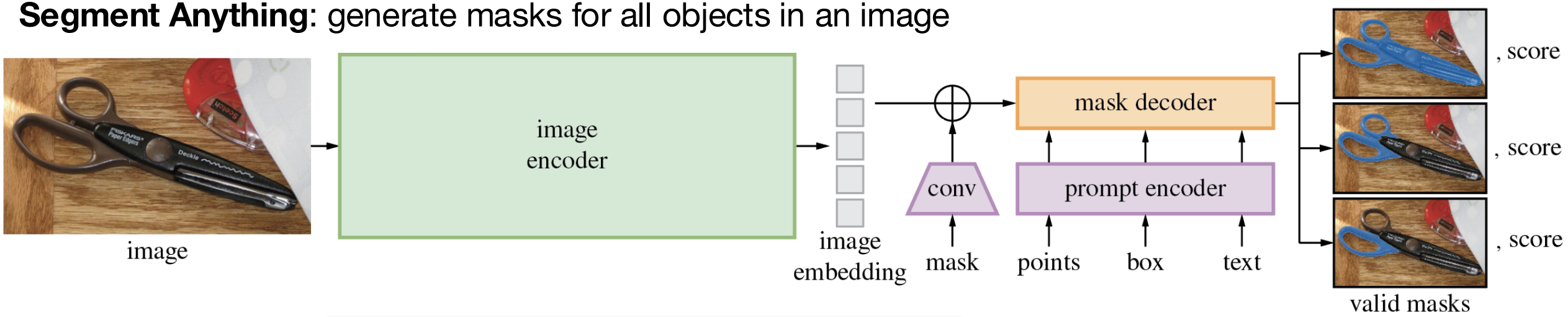
WEBKNOSSOS is an open-source tool for exploring large 3D electron-microscopy (EM) and light-microscopy (LM) datasets as well as **collaboratively generating annotations**.

Also includes a Python API for working with datasets and annotations:
https://docs.webknossos.org/webknossos-py/

Kim et al. 2025

Future Work: Automated Segmentation Tools

Segment Anything: generate masks for all objects in an image



https://github.com/facebookresearch/segment-anything

Label Studio: open source data labeling platform

https://labelstud.io/

Summary

- **Machine learning image detection** applied to atmospheric rivers, tropical cyclones, and weather fronts in climate model simulations.
- Even with a pre-trained model, you still have to do **a lot of data processing!**
- **Leverage existing open-source code** and packages whenever possible.
- **Sensitivity tests** across inputs, resolutions, normalization, etc. are useful to understand the ML results.
- **Collaborations across Earth science and ML** made this work possible!

Thanks!
Questions?

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@katiedagon