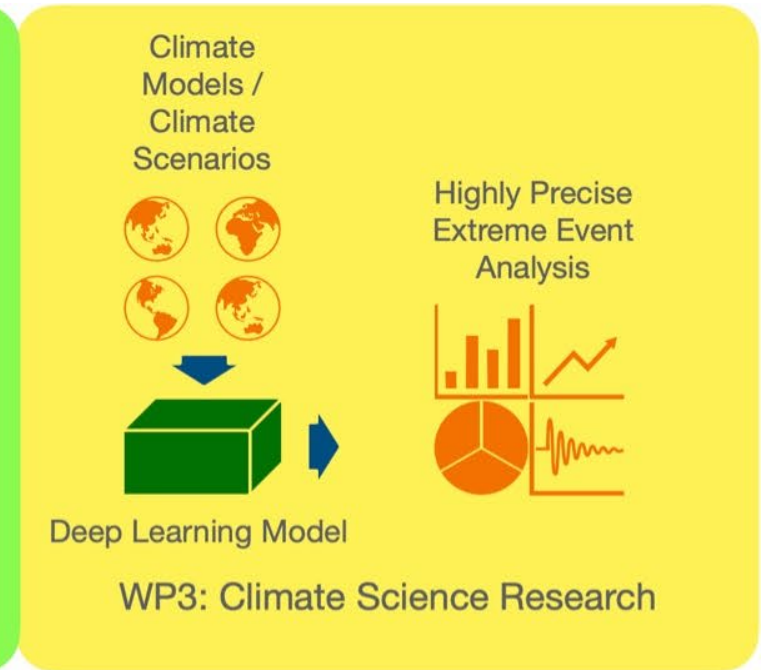
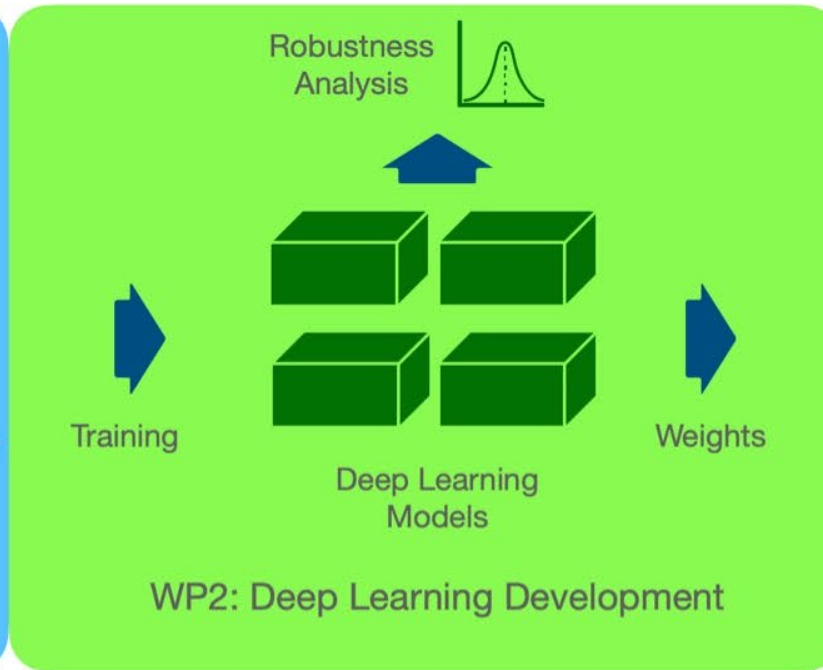
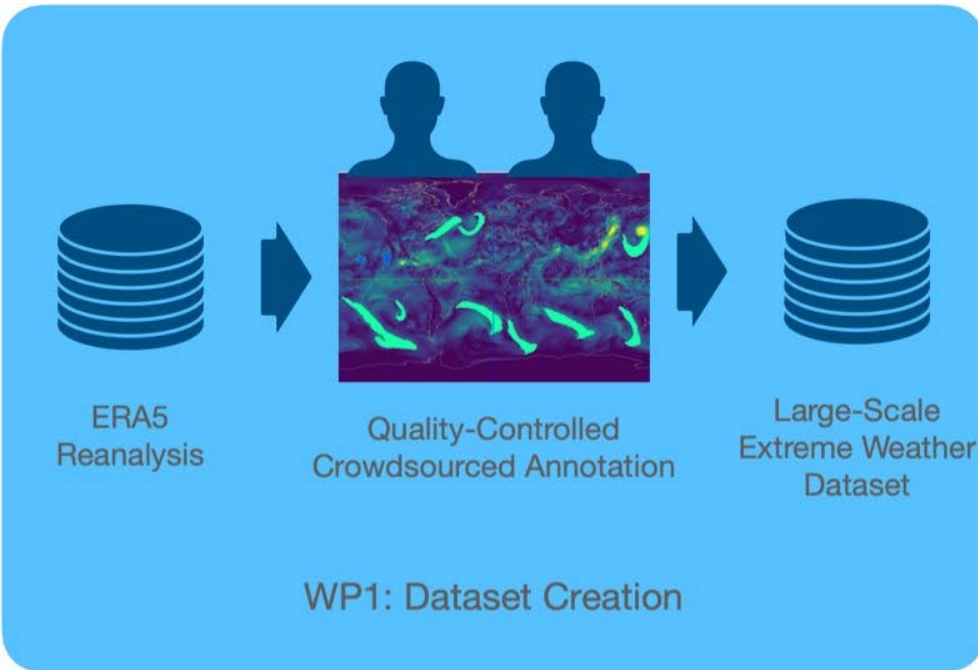


Advancing the Study of Extreme Weather Events with Data, Deep Learning Methods and Climate Analysis

ESA Artificial Intelligence for EO:
AO/1-10468/20/I-FvO

Sol Kim, Lukas Kapp-Schwoerer, Andre Graubner, Karthik Kashinath, Konrad Schindler

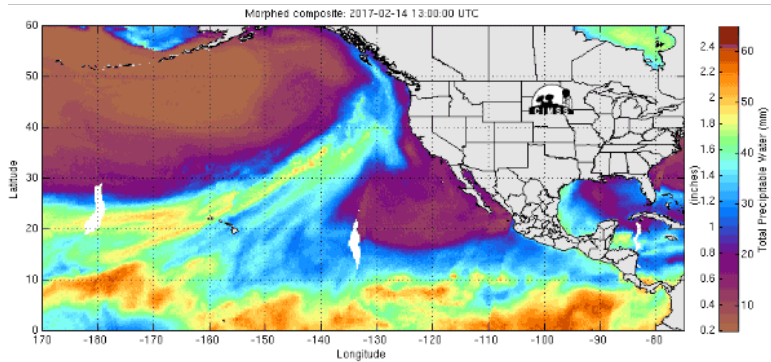


LARGE-SCALE DATASET

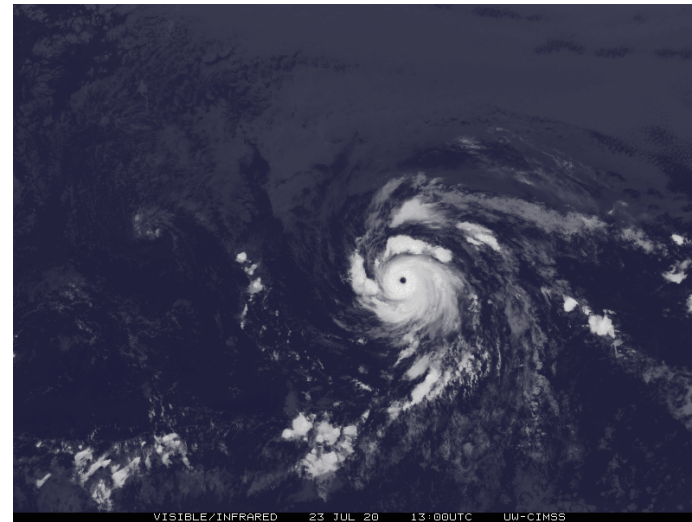
DEEP LEARNING

CLIMATE SCIENCE

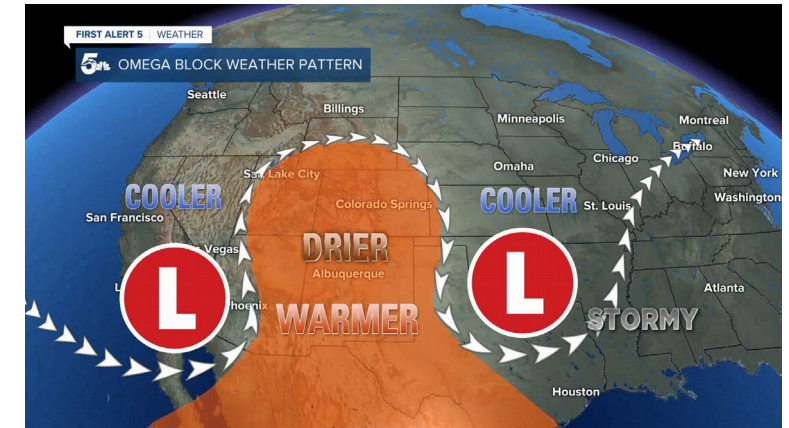
Dataset Creation – Types of Events



Atmospheric Rivers



Tropical Cyclones



Blocking Events

Dataset Creation - Source of Data

- ERA5 data by the European Centre for Medium-Range Weather Forecasts (ECMWF)
- Sampled uniformly at random from 1980-2022
-> covers different years, seasons and hours
- Used different data channels per event, e.g. TCWV & IVT for Atmospheric Rivers, computed Z500 anomalies for Blocking events
- For blocking events: Sampled intervals of 10 days to capture the temporal nature of blocking events



Dataset Creation – Annotation Guides

- In order to guide crowd workers, experts have created annotation guides
- Based on reviewing annotations and feedback by the annotators we have iteratively improved the guides
- The guides provide an overview of the extreme weather event, how to label it in the context of the annotation tool, as well as concrete examples & counter-examples

Atmospheric River (AR) Labeling Guide ClimateNet Team

What is an atmospheric river?

Atmospheric rivers are long, flowing regions of the atmosphere that carry water vapor through the sky. Much like a river is water moving over land, an atmospheric river is a stream of water vapor moving in the sky. Below is a satellite image of an AR on the west coast of the U.S.



Tropical Cyclone (TC) Labeling Guide ClimateNet Team

What is a tropical cyclone?

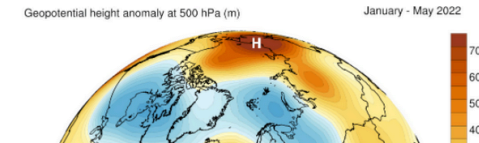
A tropical cyclone (or also known as a hurricane or typhoon) is a rotating, organized system of clouds and thunderstorms that originates over tropical or subtropical waters and has a closed low-level circulation (ci



Blocking Event (BE) Labeling Guide ClimateNet Team

What is a blocking event?

Atmospheric blocking events (BEs) are large-scale, mostly-stationary, high pressure (anticyclonic) weather systems that block the west-to-east winds and deflect weather systems in the midlatitudes. They are correlated with extreme weather such as heat waves, cold spells, and floods. Below are examples of a blocking event characterized by persistent positive geopotential height anomalies. Geopotential height at 500 hPa = how high up in the atmosphere do you need to go to reach a pressure of 500 hPa. Lower heights = low pressure, higher heights = high pressure.



Dataset Creation – Total Number of Annotations

Summary: We've created the largest hand-annotated dataset of extreme weather events

Atmospheric Rivers and Tropical Cyclones:

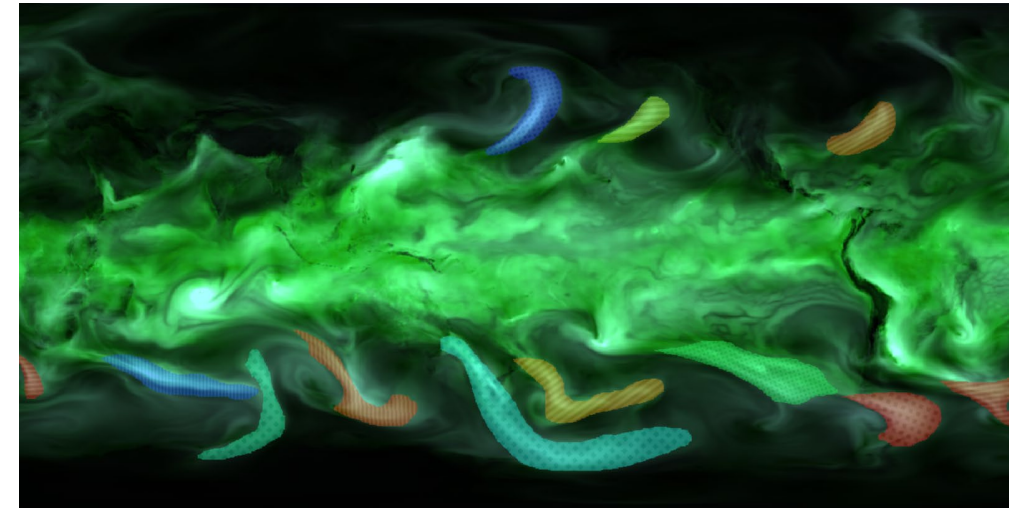
- **10,000** timesteps for ARs
- **10,000** timesteps for TCs

Blocking Events:

- **5,000** timesteps, clustered in intervals of 10 timestamps

Each timestep was separately annotated by 2 annotators, resulting in a total of

- **50,000** individual annotations



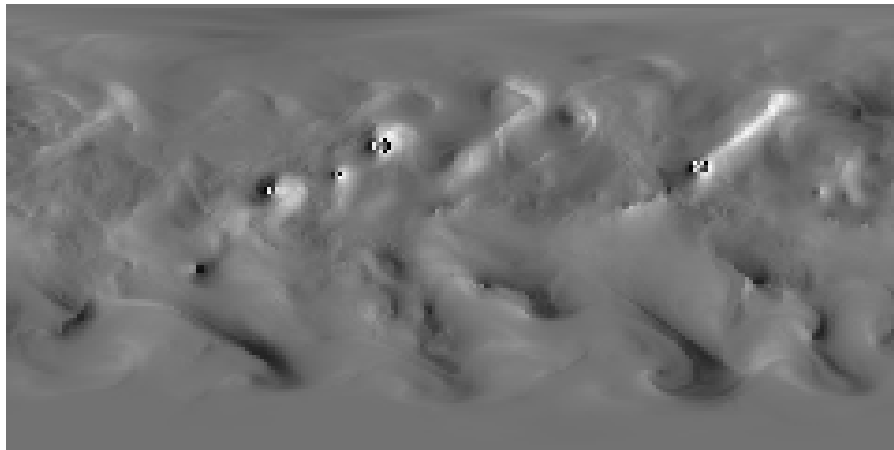
An example annotation of atmospheric rivers. The green background indicates the underlying data channel (total column water vapor)

Detecting Extreme Events with Deep Learning

How can we use this new dataset?

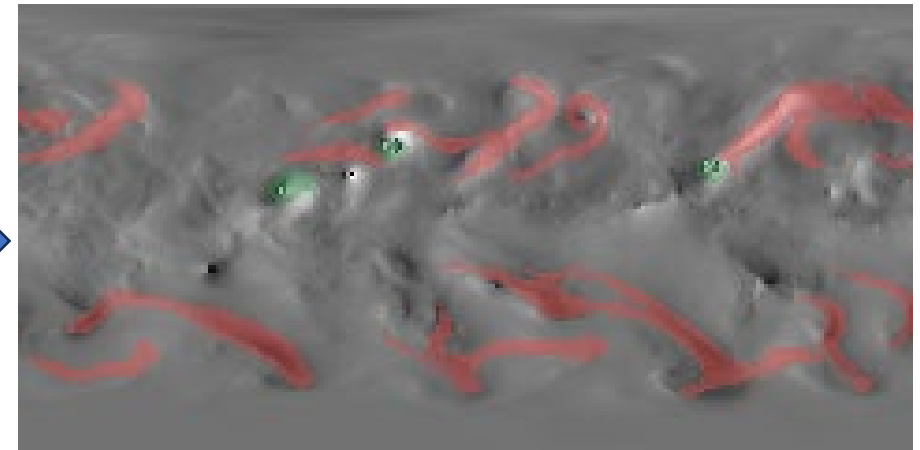
- Train machine learning models on it!

Atmospheric State



DEEP
LEARNING
MODEL

Extreme Event Detection



Semantic Segmentation

How can we leverage progress in computer vision for this problem?

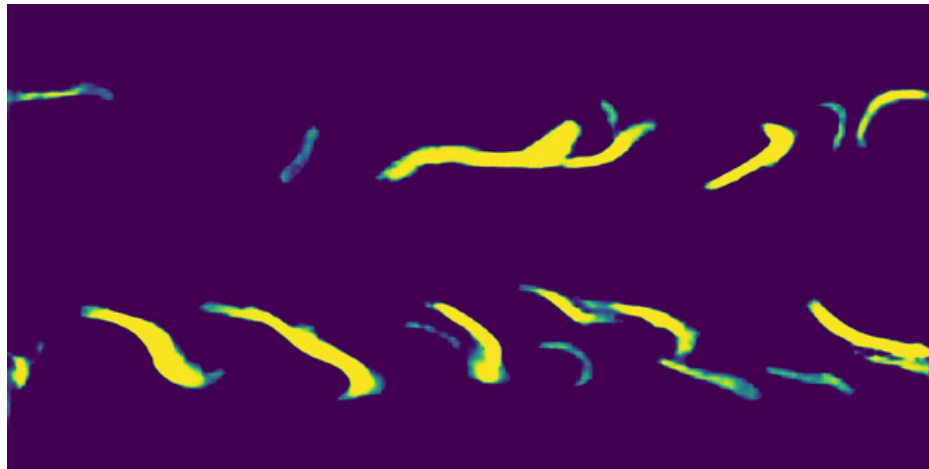
- Understand extreme event detection as a semantic segmentation problem!



Source: [ICNet, Zhao et al. 2017](#)

Probabilistic Segmentation

Use deep learning architectures to predict event probability at each pixel



Probabilistic AR Segmentation using CGNet



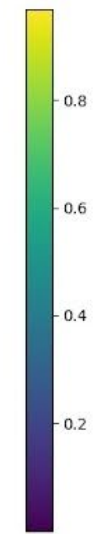
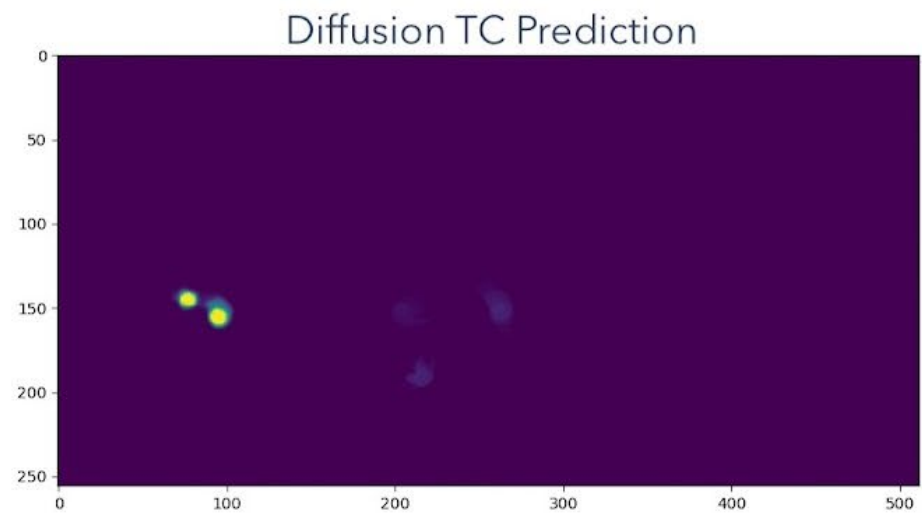
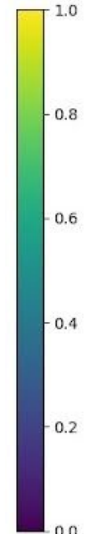
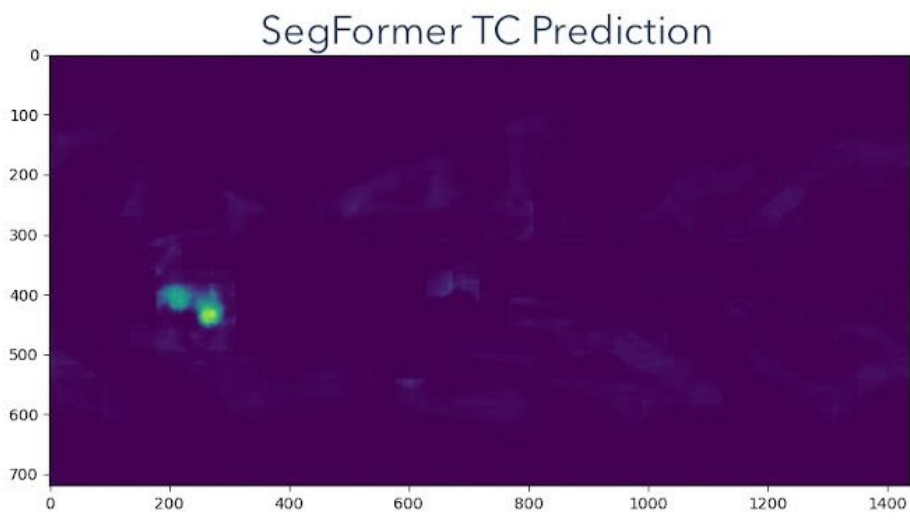
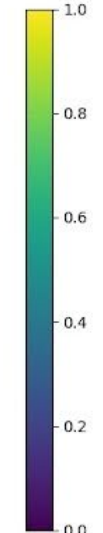
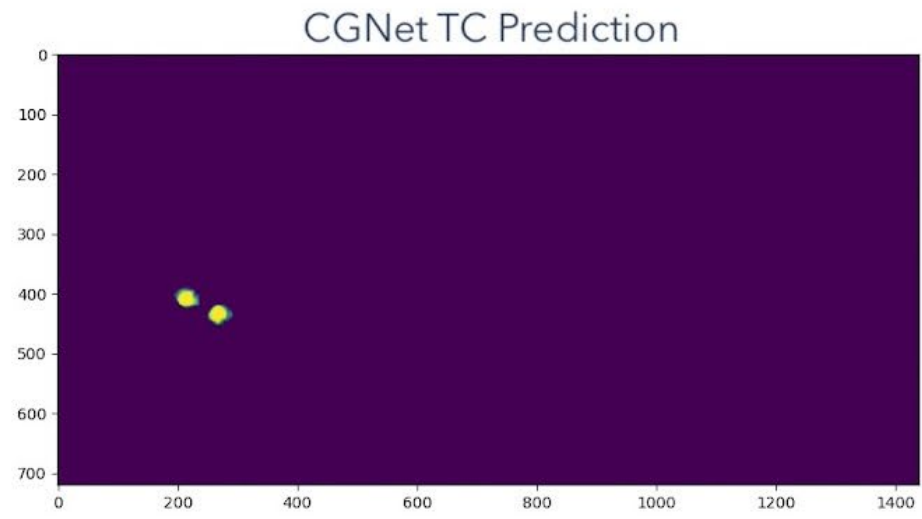
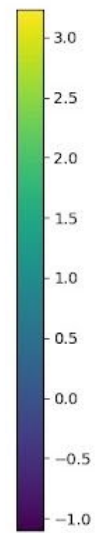
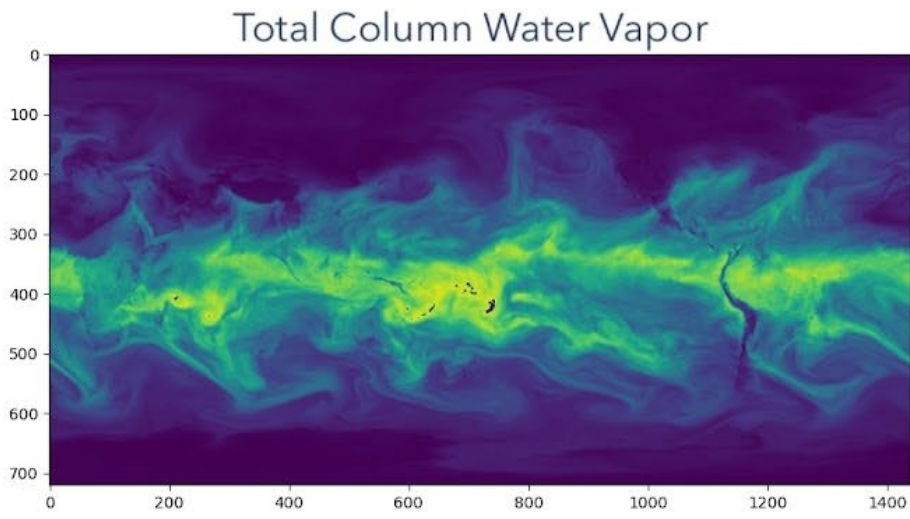
Probabilistic AR Segmentation using Diffusion Model



0

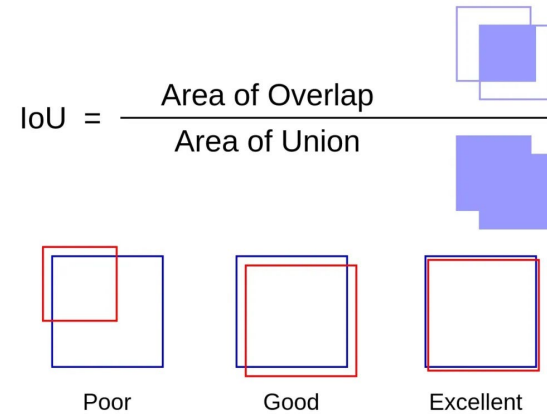
1

Comparing individual TC predictions made by the different models

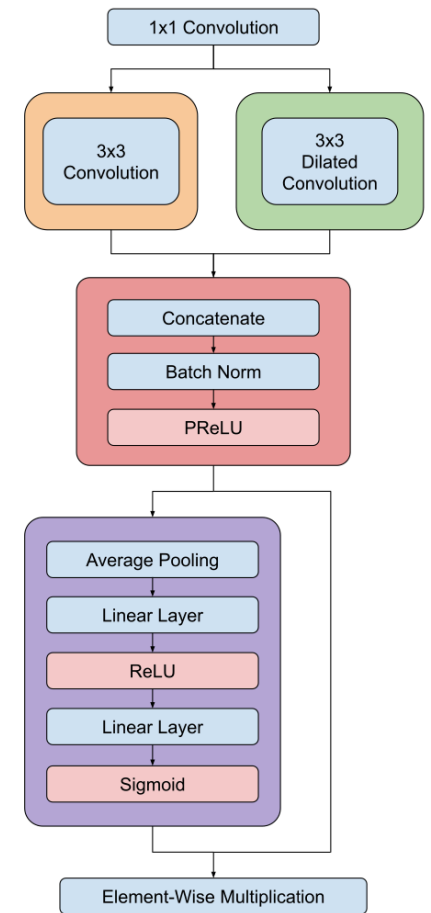
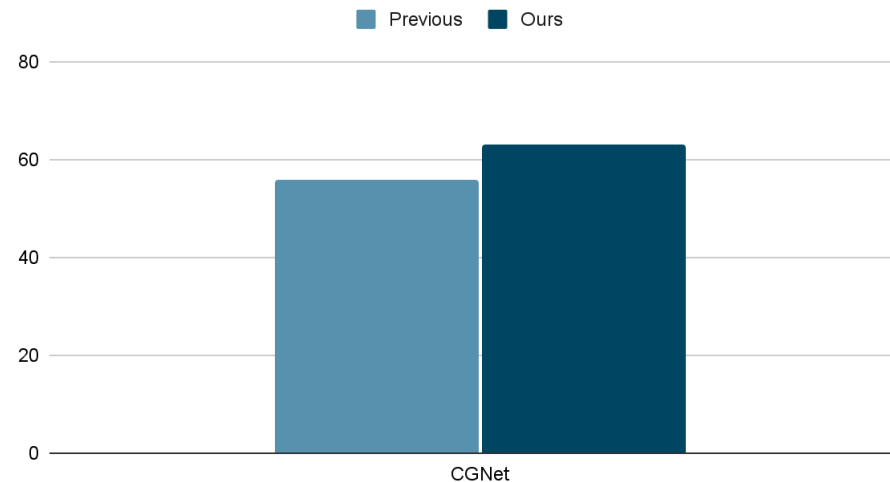


CGNET

- Efficient and strong baseline for extreme weather segmentation (cheap to train and run)
- Can achieve reasonable performance using previous (much smaller datasets)

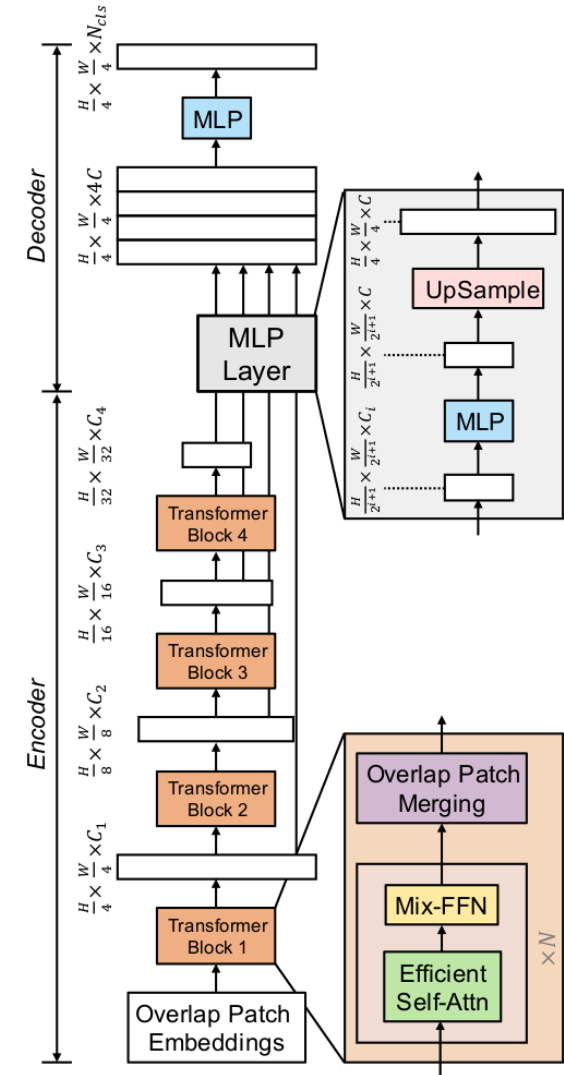
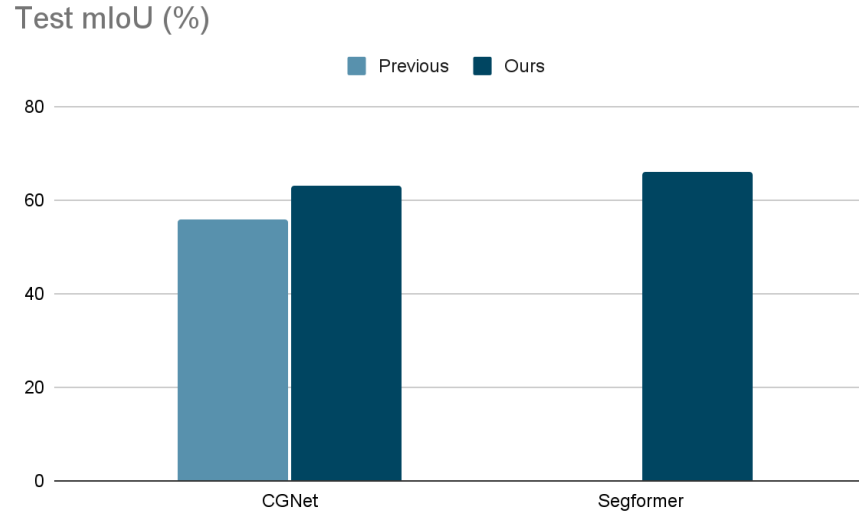


Test mIoU (%)



Segformer

- Vision Transformers are strong models but require more data to train...
- Our new dataset makes it possible to train this type of model!



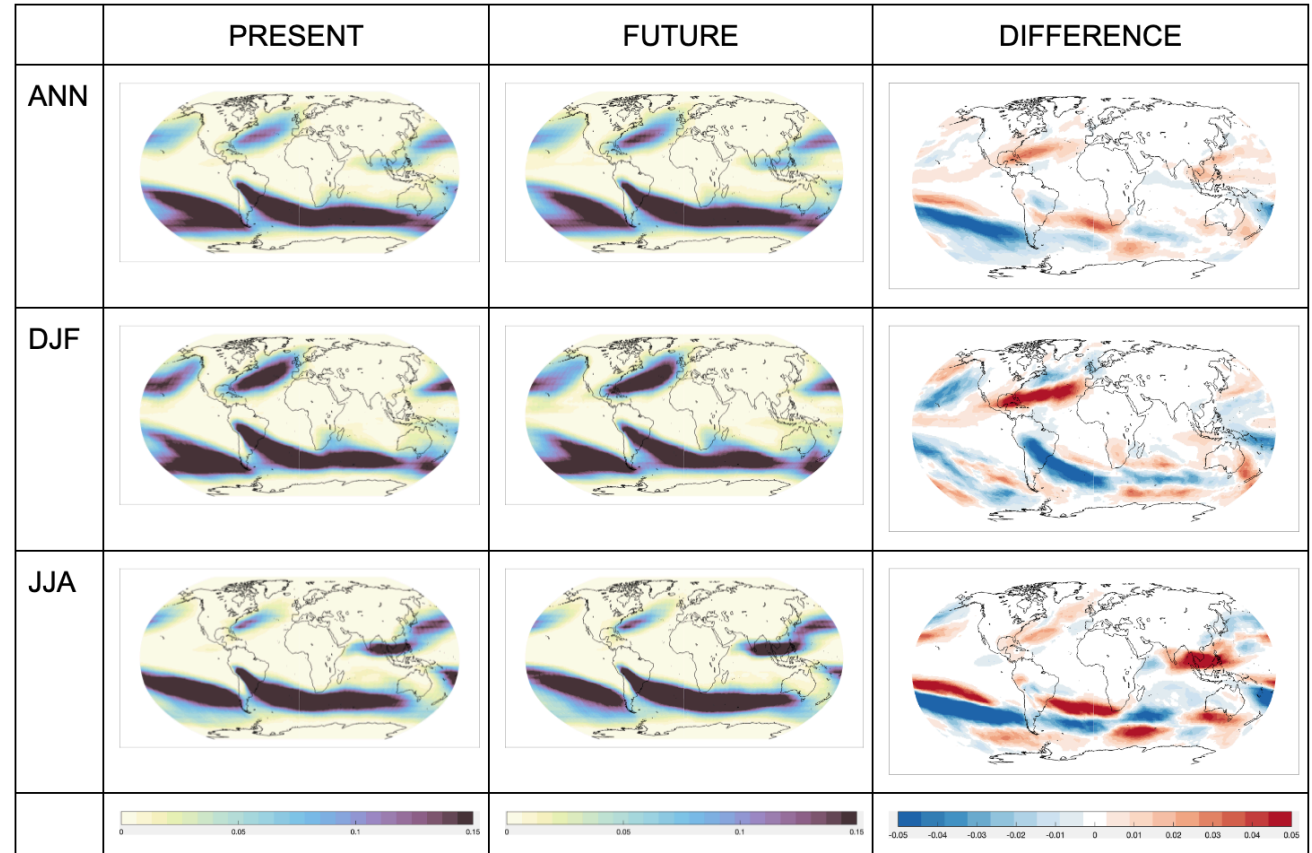
Climate science targets were to use:

1. HighResMIP: Present simulations compared with near-future/short-term projections using EC-EARTH3P-HR
2. ScenarioMIP: Near-future/short-term projections for low, medium, and high emission scenarios (SSP126, SSP245, and SSP585) using CNRM-CM6-1

Additionally, the model selections allowed us to test the DL models on different resolutions

Climate Science - near-future projections

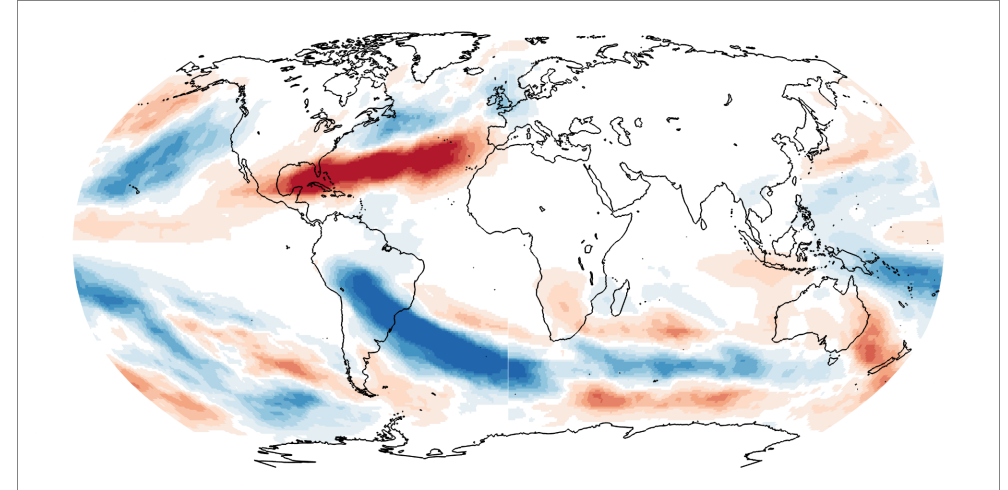
- Comparing AR frequencies in the present (2000-2014) and the near future under SSP585 (2025-2050)
- Generally, the DL model frequencies are in agreement with other AR detection methods in terms of magnitude and distribution
- In the near future, AR frequency changes are strongly impacted by an equatorward shift in the wintertime subtropical jet



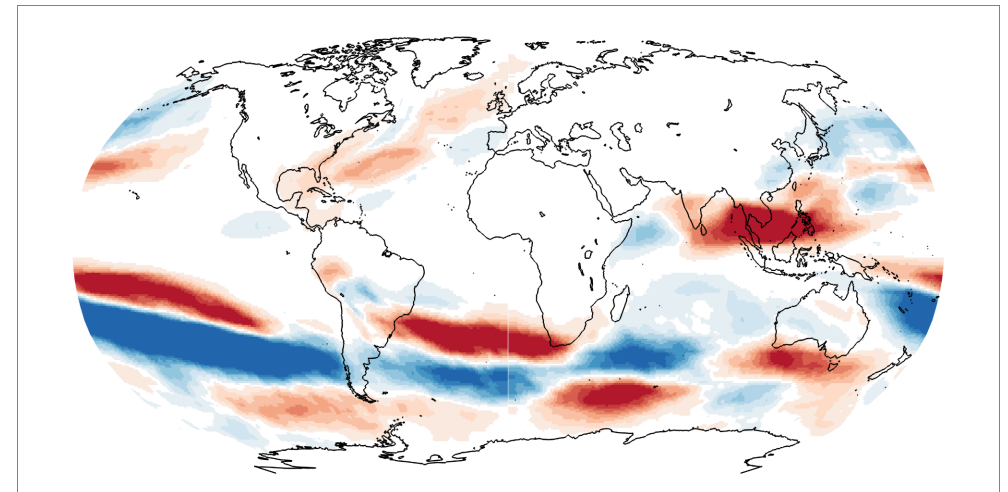
Blue = LESS ARs in the near-future
Red = MORE ARs in the near-future

- For the European continent, the seasonal differences show more ARs for Portugal and Spain during the northern hemisphere winter and less for the rest of western Europe
- During northern hemisphere summer, less ARs for Portugal and Spain while more ARs occur over the UK
- ARs in the higher latitudes in the warmer seasons have been known to bring significant heat energy into the Arctic which may have implications for the arctic climate e.g. sea ice minimums

EU Winter



EU Summer



Blue = LESS ARs in the near-future
Red = MORE ARs in the near-future

Climate Science - regional, country, and city scale analysis

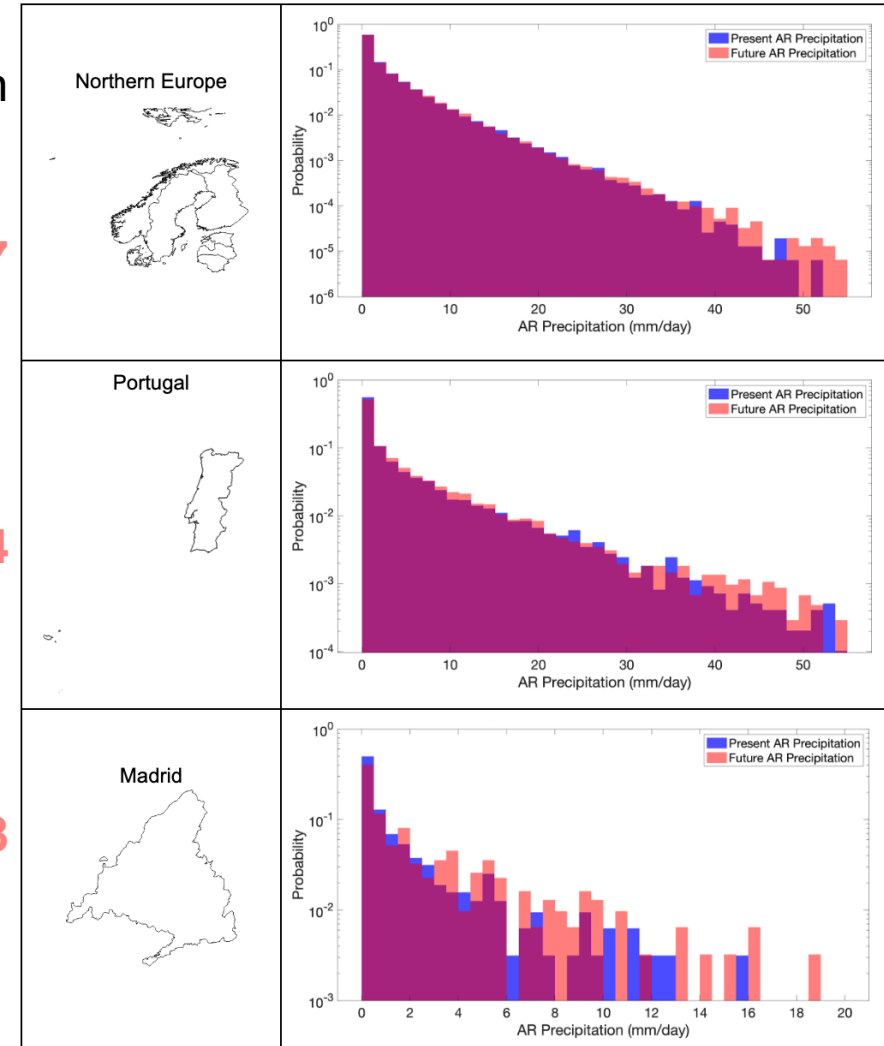
- Our climate analysis can ingest shapefiles of any boundary or gridded masks of various resolutions.
- Here we examine precipitation from AR events over the Northern Europe region, Portugal, and Madrid using a 10 year sample from the present and near-future simulations (2000-2009 & 2025-2034)
- At all places/scales, AR precipitation intensity increases (especially at the extremes) in the near future despite slightly lower frequencies of AR events

Mean AR precipitation

2.44 to 2.47
mm/day

4.17 to 4.64
mm/day

2.04 to 2.48
mm/day



Climate Science - regional, country, and city scale analysis

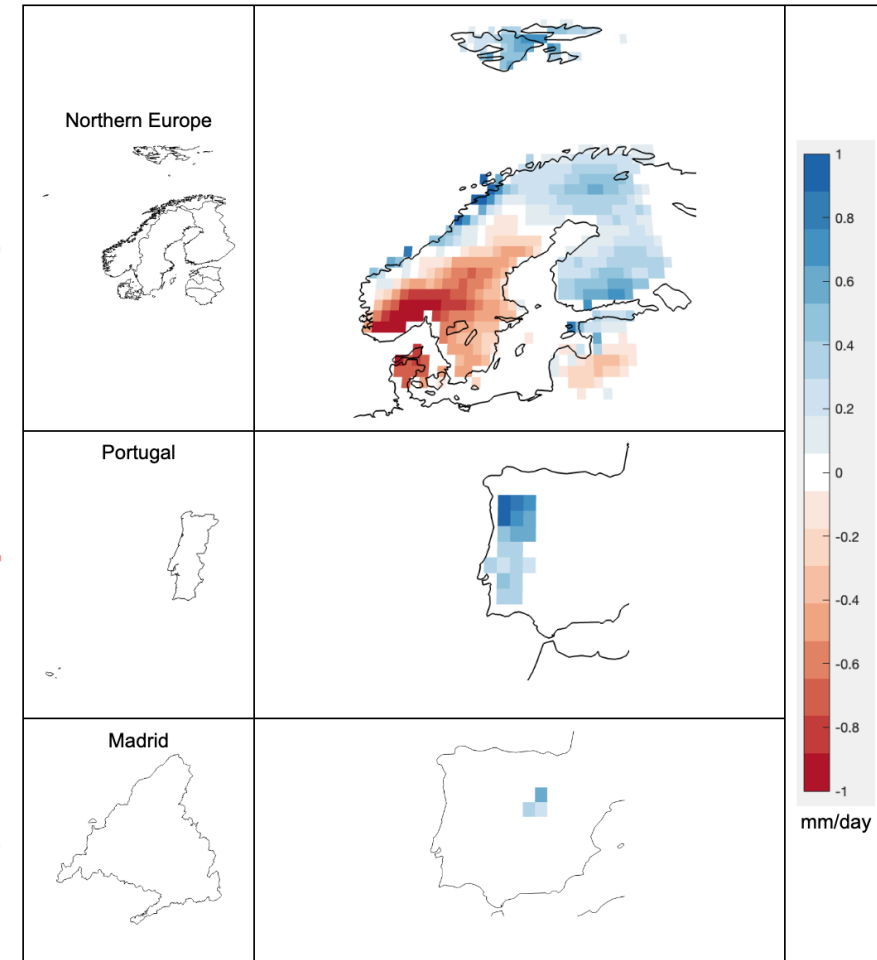
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2.04 to 2.48
mm/day



Blue = MORE AR precipitation in the near-future
Red = LESS AR precipitation in the near-future

Open Sourcing

We've open sourced data, models and code.

The project website is here:

<https://andregr.com/extremes>

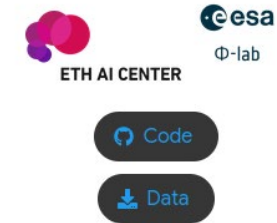
The GitHub repository is here:

https://github.com/andregraubner/extreme_weather

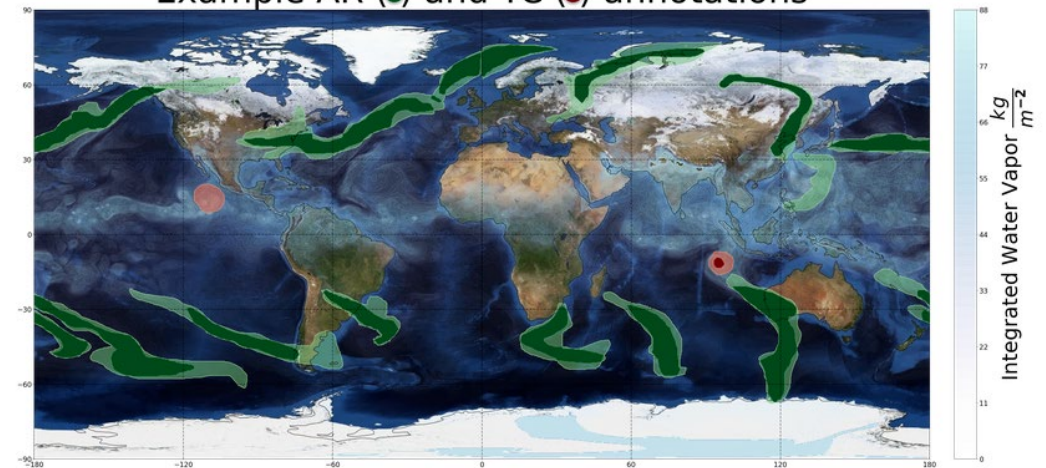
The data and machine learning models are here:

<https://polybox.ethz.ch/index.php/s/nBr0t1cuZM6SrgM>

Advancing the Study of Extreme Weather Events with Data, Deep Learning Methods and Climate Analysis



Example AR (●) and TC (●) annotations



We present ClimateNetV2, a large-scale human-annotated dataset of extreme weather events. The supported event types are atmospheric rivers, tropical cyclones and blocking events.

Community Outreach

- We already presented some of this work at AGU23 in a poster session
- Planning to publish a complete journal article
- We have also had multiple knowledge exchange sessions with scientists from the National Center for Atmospheric Research (NCAR) to assist on the CATALYST (Cooperative Agreement to AnaLyze variability, change and predictability in the earth SysTem) project, as well as Lacombe et al.
- Plan to use the DL model and climate science pipelines to characterize changes to extreme events for various Climate Rights initiatives in collaboration with NTNU (Norwegian University of Science and Technology)



Published as a workshop paper at "Tackling Climate Change with Machine Learning", ICLR 2023

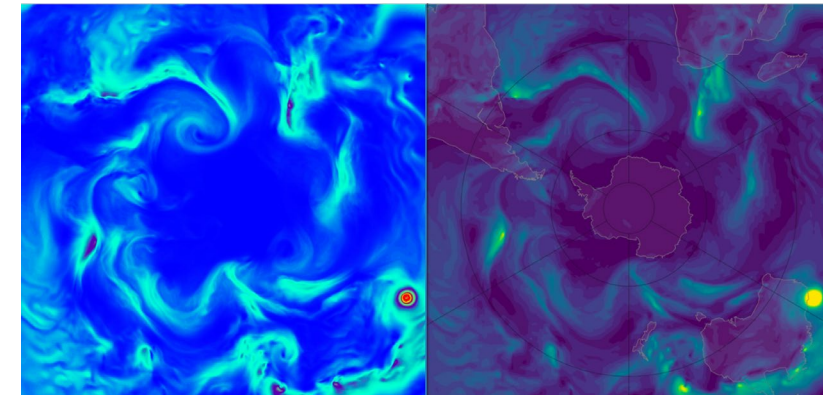
IMPROVING EXTREME WEATHER EVENTS DETECTION WITH LIGHT-WEIGHT NEURAL NETWORKS

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Climate Rights:
Designing Evidence for Climate Justice

Thank you

Contact: solkim@uchicago.edu