Lightweight neural networks for detecting and tracking of Atmospheric rivers and Tropical cyclones

Presented by:

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People paddle and row through the flooded Barlow Market District of Sebastopol, after an atmospheric river dumped inches of rain on the region in February, 2019.
PHOTOGRAPH BY ERIC RISBERG, AP

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'Rivers in the sky' are why California keeps flooding

Problem statement:

Identifying weather patterns that frequently lead to extreme weather events is a crucial first step in understanding how they may vary under different climate change scenarios.

Atmospheric river:

Atmospheric rivers are long, concentrated regions in the atmosphere that transport moist air from the tropics to higher latitudes.

You may have heard of atmospheric rivers in the news lately due to the intense rainfall and flooding along the U.S. West Coast.

Tropical Cyclone:

A **tropical cyclone** is a rapidly rotating storm system characterized by a low-pressure center, a closed low-level atmospheric circulation, strong winds, and a spiral arrangement of thunderstorms that produce heavy rain and squalls.

Depending on its location and strength, a tropical cyclone is referred to by different names, including **hurricane** and **typhoon**

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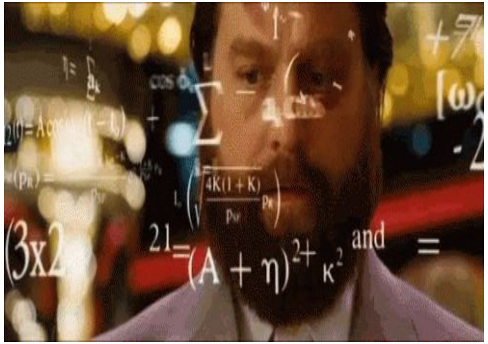
Our Approach:

Spatio-temporal segmentation and tracking of weather patterns with light-weight Neural Networks.

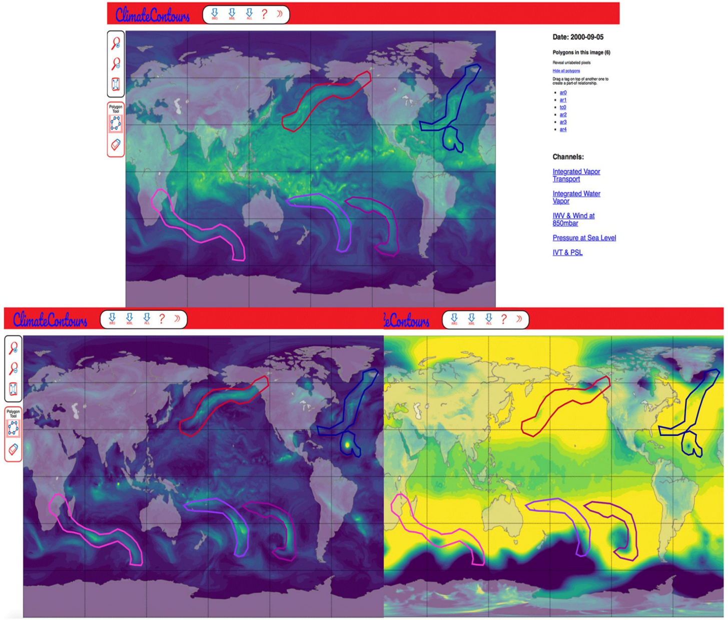
The lightweight neural network event detecting approach suggested here addresses the primary drawbacks of cutting-edge Deep Learning models trained on ClimateNet's expert-labeled, vetted climate data.



Past scenario limitations:

- Required lot of manual training
- Computationally expensive
- They couldn't track individual events over time.

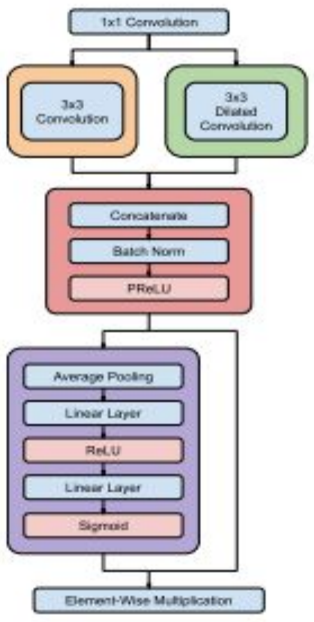
Dataset:



- ClimateNet dataset contains 16-channel 1152x768 pixel image ,that is the output of a historical 25-km CAM5.
- We have selected 4 channels which are related to AR’s.
- Experts labelled 459 samples with AR’s and TC’s

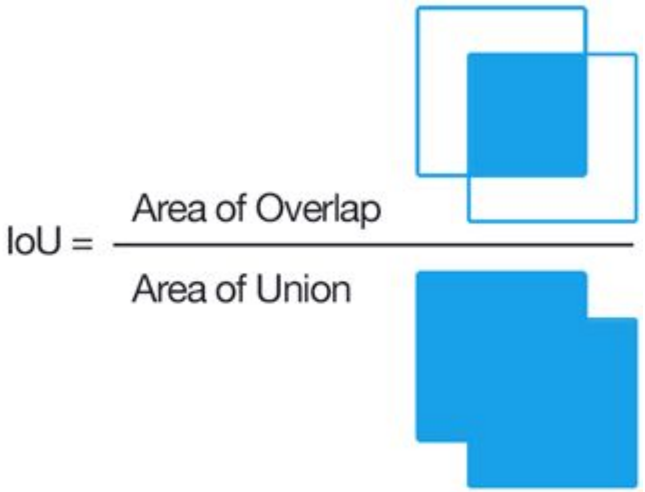
Model Architecture

CGNet



- It is a light-weight network specially tailored for semantic segmentation
- It combines local and surrounding context into a joint feature.
- Refine the joint feature further
- Designed to reduce the number of parameters and save memory footprint

Training



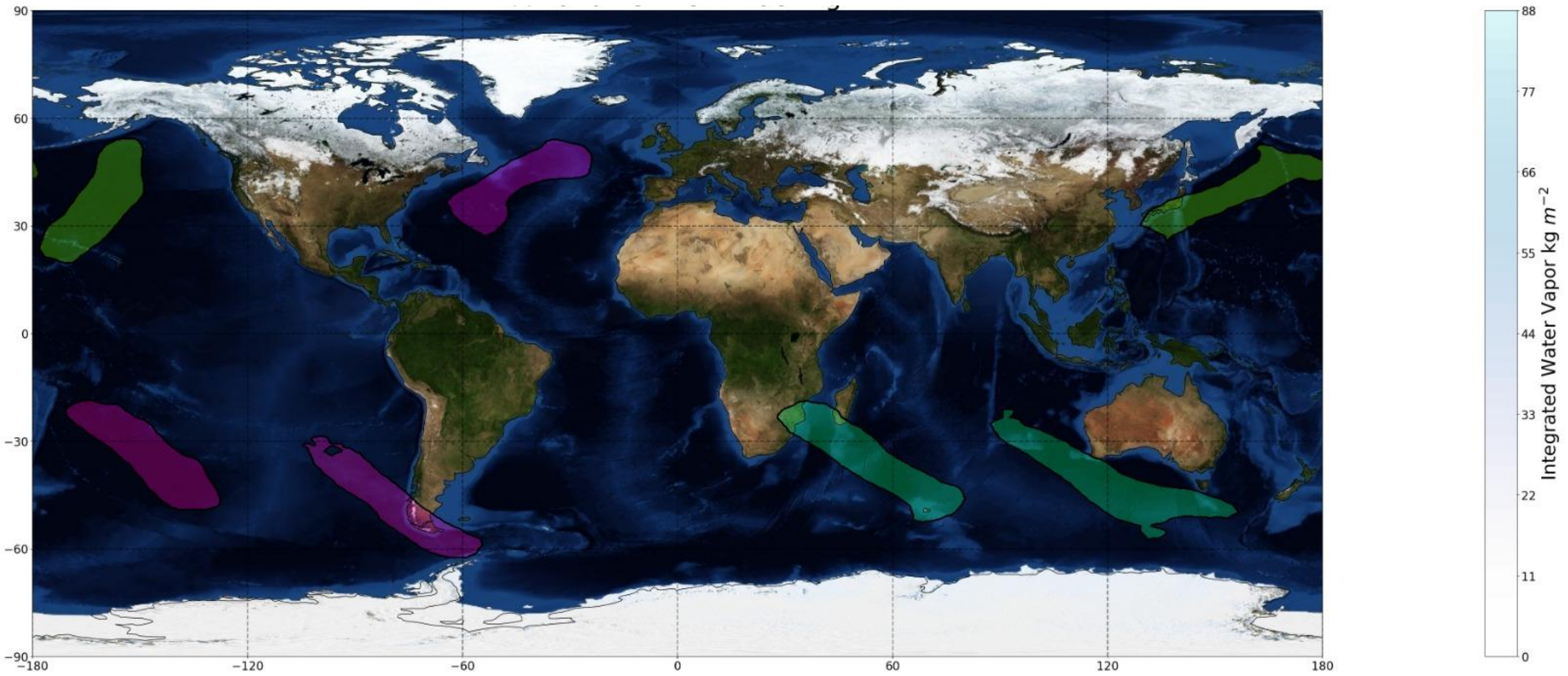
- Can’t use cross entropy
- Jaccard Entropy is used

$$I(X) = \sum_{v \in V} X_v * Y_v \, .$$

$$U(X) = \sum_{v \in V} (X_v + Y_v - X_v * Y_v) \, .$$

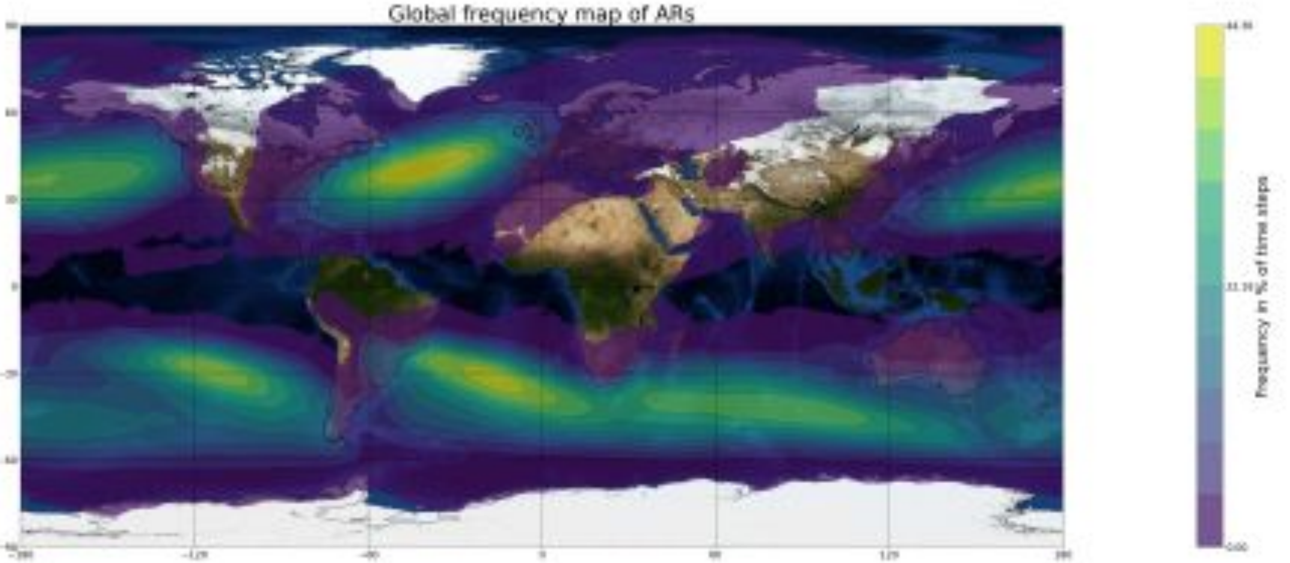
$$L_{IoU} = 1 - IoU = 1 - \frac{I(X)}{U(X)} \, .$$

Results

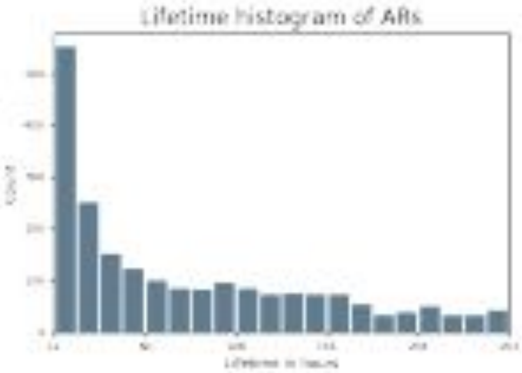


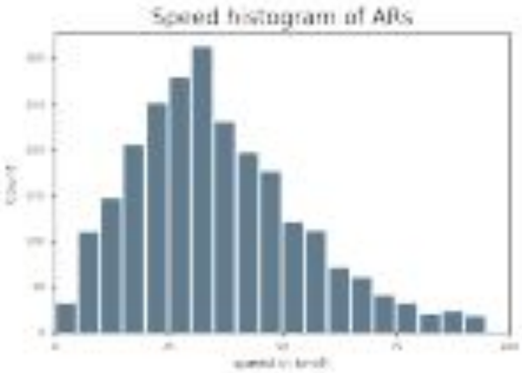
90
60
30
0
−30
−60
−90
−180
−120
−60
0
60
120
180
88
77
66
55
44
33
22
11
0
Integrated Water Vapor kg m^{-2}

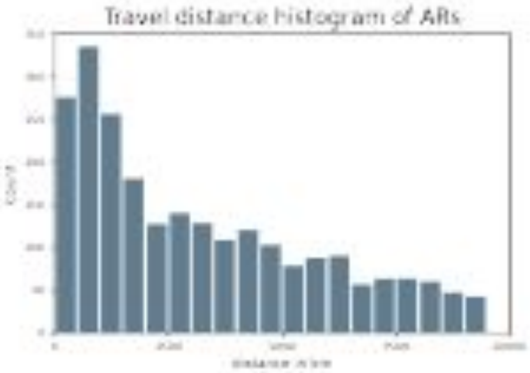
Global Frequency Map of AR's



Histogram of AR Lifecycle







Results so far:

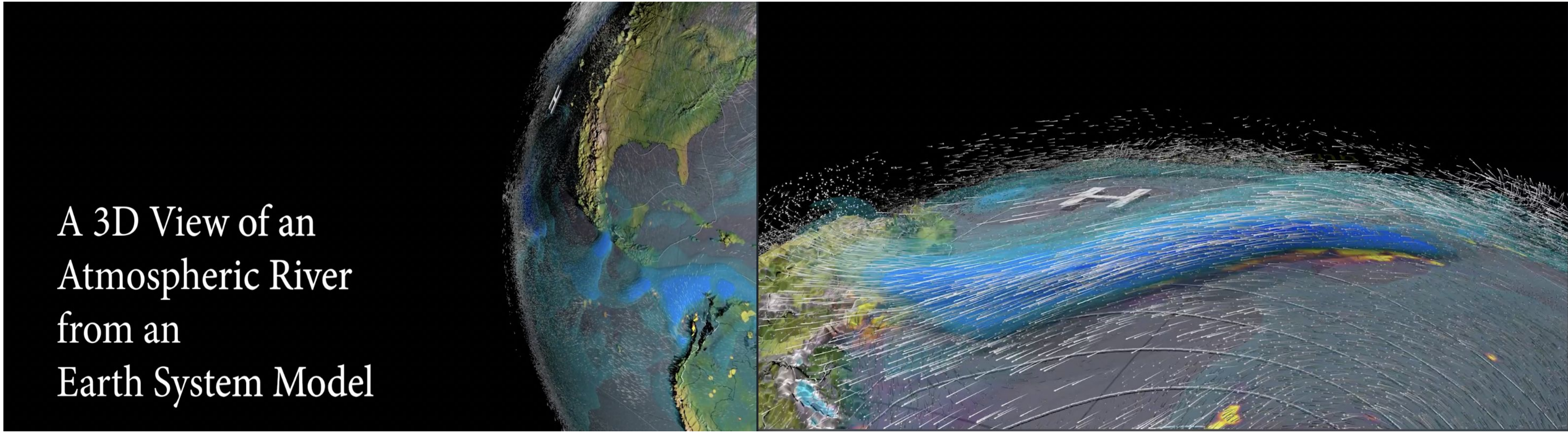
- Human labelers largely exceeded the frequency of AR events compared to a range of heuristics
- This model produces very low frequencies over land and in higher latitudes.
- most ARs having speeds between 20-60 km/hr with a peak at 25-35 km/hr
- AR travel distance peaks at 500-1000km while the GW tracking has distance peak at 0-500km

Results so far:

S.No.	Optimizer	Epochs	Learning Rate	train_batch	pred_batch	Activation Function	Train Accuracy	Test Accuracy
1	Adam	15	0.001	1	8	ReLU	60.91%	55.96%
2	Adam	25	0.001	1	8	ReLU	63.75%	55.83%
3	Adam	15	0.0001	1	8	ReLU	59.30%	55.78%
4	Adam	15	0.01	1	8	ReLU	46.66%	44.38%
5	Adam	15	0.001	2	8	ReLU	60.24%	56.92%
6	Adam	15	0.001	8	4	ReLU	Memory Allocation error	
7	Adam	15	0.001	2	4	ReLU	60.36%	56.78%
8	Adam	15	0.001	1	4	ReLU	61.02%	55.81%
9	Adam	15	0.001	1	2	ReLU	60.92%	56.29%
10	AdamW	15	0.001	1	8	ReLU	61.07%	56.25%
11	AdamW	18	0.001	1	8	ReLU	61.91%	56.19%
12	AdamW	17	0.001	1	8	ReLU	61.52%	56.71%
13	AdamW	17	0.001	1	8	PReLU	61.62%	56.44%
14	AdamW	17	0.001	1	8	ELU	61.72%	56.76%
15	AdamW	17	0.001	1	8	**GELU**	**61.60%**	**57.25%**

Limitations:

- Most current AR detection algorithms are primarily based on 2D features, which is partly due to computational considerations and data availability, but ARs have distinct 3D structure.



Limitations:

- Existing detection and tracking methods do not consider that there might be different “flavors” of ARs : Wet, Windy, Wet and Windy, Neutral

Source: https://eos.org/articles/atmospheric-rivers-have-different-flavors

“

Researchers are realizing that IVT alone is no longer enough to understand the behavior of atmospheric rivers.

“

Individual atmospheric river events are generally characterized using a metric called integrated vapor transport (IVT). But it is not uncommon for storms with similar IVT values to have different impacts on land.

Limitations:

- Limited training data: The quality of our segmentation results is fundamentally limited by access to large amounts of expert-labeled data. Instead of the difficulties of a manual heuristics design, this approach is limited by training data quality and quantity.
- Projecting the data onto a flat sheet is not area-preserving

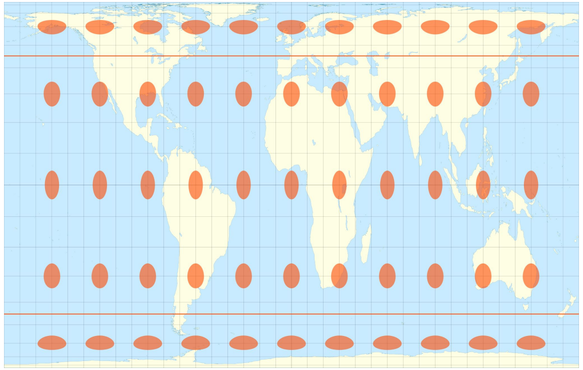


Fig: Gall-Peters projection,
preserves area while distorting shape

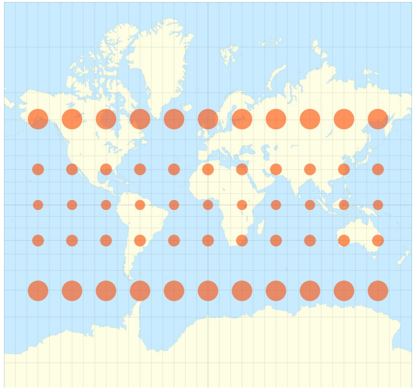


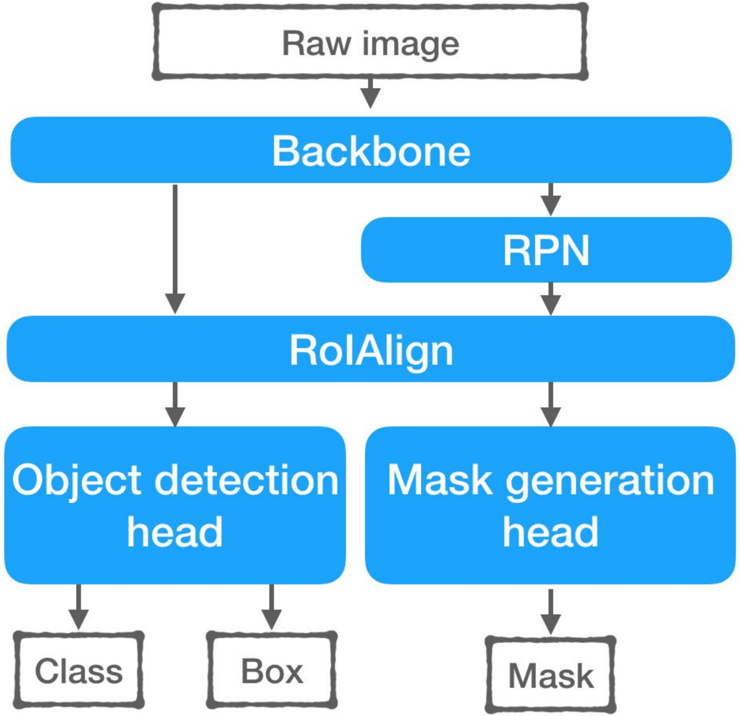
Fig: Mercator projection preserves the shape
of countries while distorting the size.

Future work:

- Research keeping in mind the different flavors of ARs can lead to different classes of detection/tracking algorithms.
- Applicability of curriculum learning: this techniques can be used to increase the performance with limited data.
- Need more training data.
- Apply methods to satellite observations

Future work:

Mask R CNN



- It performs pixel-level segmentation on detected objects.
- Backbone extracts abstract information of an image.
- RPN function is scanning the feature map and proposing regions that may have objects in them
- ROI extracts feature vectors from a feature map based on RoI proposed by RPN
- Mask generation head generates mask for each object

How will our work make an Impact !

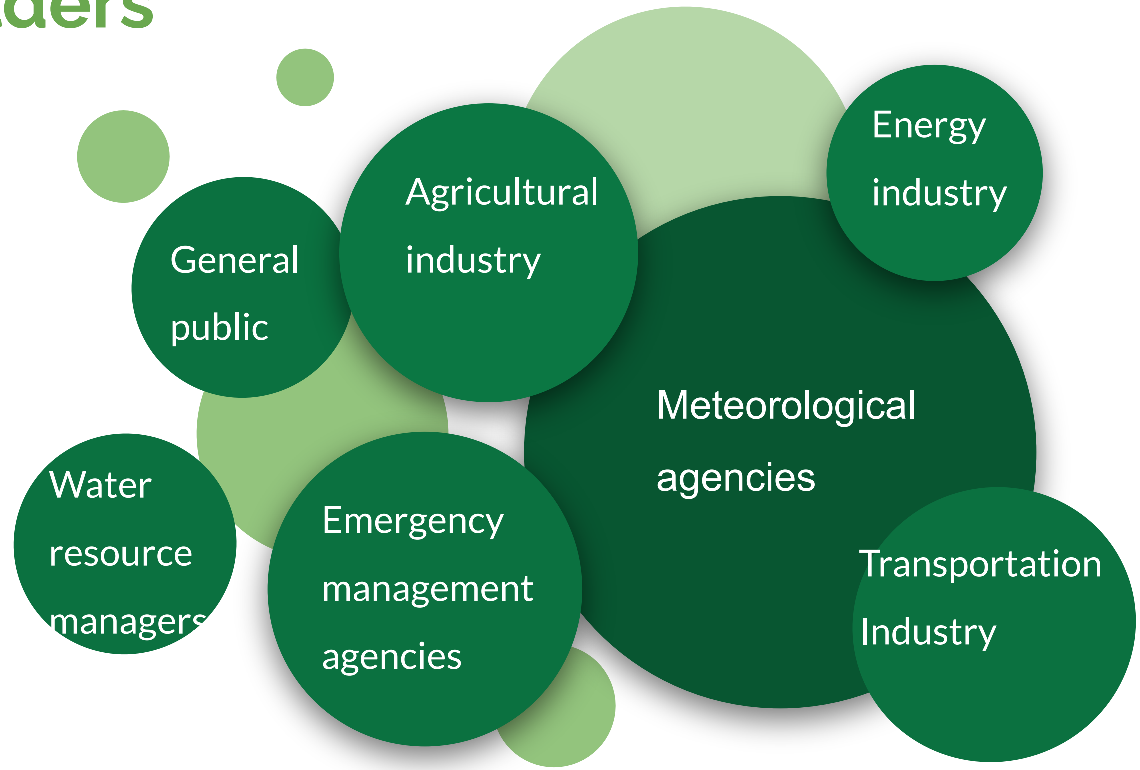
- On average, at least 300 million people around the world are exposed to floods and droughts linked to atmospheric rivers each year

- Annual expected AR-related flood damages in the western United States could increase from $1 billion in the historical period to $2.3 billion in the 2090s.

- Improve energy generation forecasting of hydro-electric power generation companies

- Understanding of the behavior of such extreme weather events can help in policy making
- Can contribute significantly to the research and improvement in Climate modeling

Stakeholders



Questions / Answers