Disaster Response

Responding to extreme weather events

Assignments

Keep working on your projects!

Discussion question:

“What do you think of NYU's 2040now campaign?”
https://www.nyu.edu/about/university-initiatives/2040-now.html

Due Friday by midnight

Climate change in the news

Climate change in the news

UN seeks court opinion on climate in win for island states

By ISABELLA O'MALLEY and DANA BELTAJI March 29, 2023

The countries of the United Nations led by the island state of Vanuatu adopted what they called a historic resolution Wednesday calling for the U.N.'s highest court to strengthen countries' obligations to curb warming and protect communities from climate disaster.

Like many Pacific Island nations Vanuatu is at risk of rising seas engulfing swathes of the islands. Scientists say both extreme weather and sea levels have worsened because of climate change caused by the burning of fossil fuels. The resolution asks the court to pay particular attention to the harm endured by small island states.

Saudi Arabia and Iraq sought to soften the resolution, which was co-sponsored by some 132 countries, saying it would increase the workload of the international court.

While the opinion from the International court of justice would not be binding, it would encourage states "to actually go back and look at what they haven't been doing and what they need to do" to address the climate emergency, said Nilufer Oral, director at the Center for International Law at the University of Singapore.

Recap

Mitigation versus Adaptation

Extreme weather events

Climate change has already caused

-more heat waves

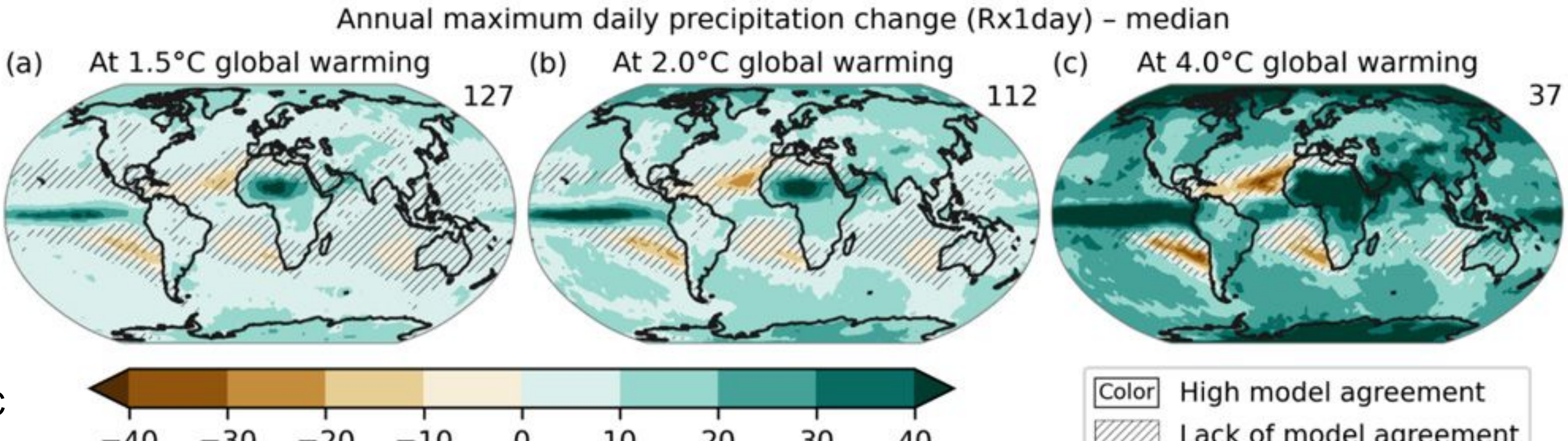
IPCC

Extreme weather events

Climate change has already caused

-more heat waves

-changes in rainfall



IPCC

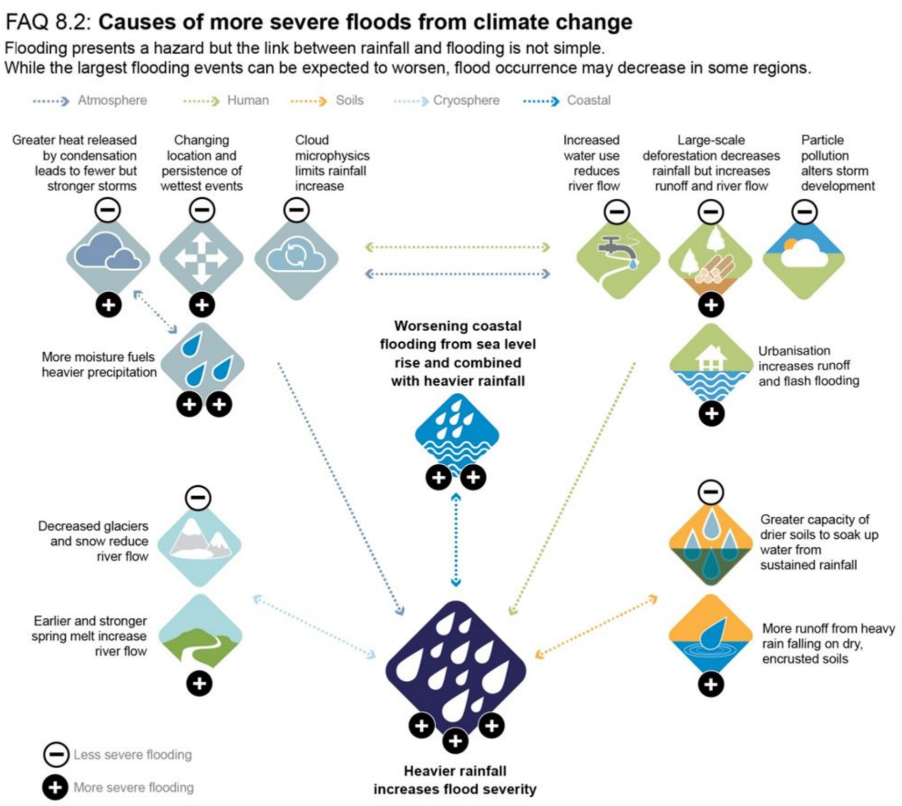
Extreme weather events

Climate change has already caused

-more heat waves

-changes in rainfall

-increased floods in some regions



IPCC

Extreme weather events

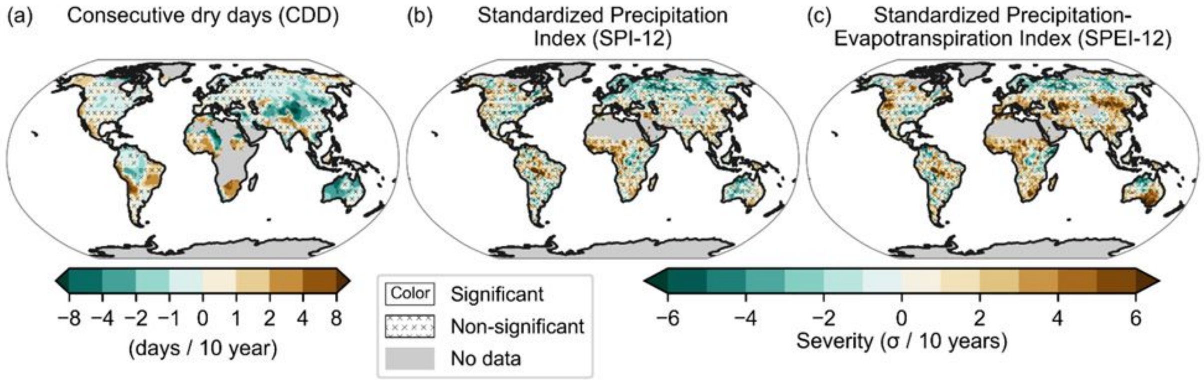
Climate change has already caused

-more heat waves

-changes in rainfall

-increased floods in some regions

-increased drought



IPCC

Extreme weather events

Climate change has already caused

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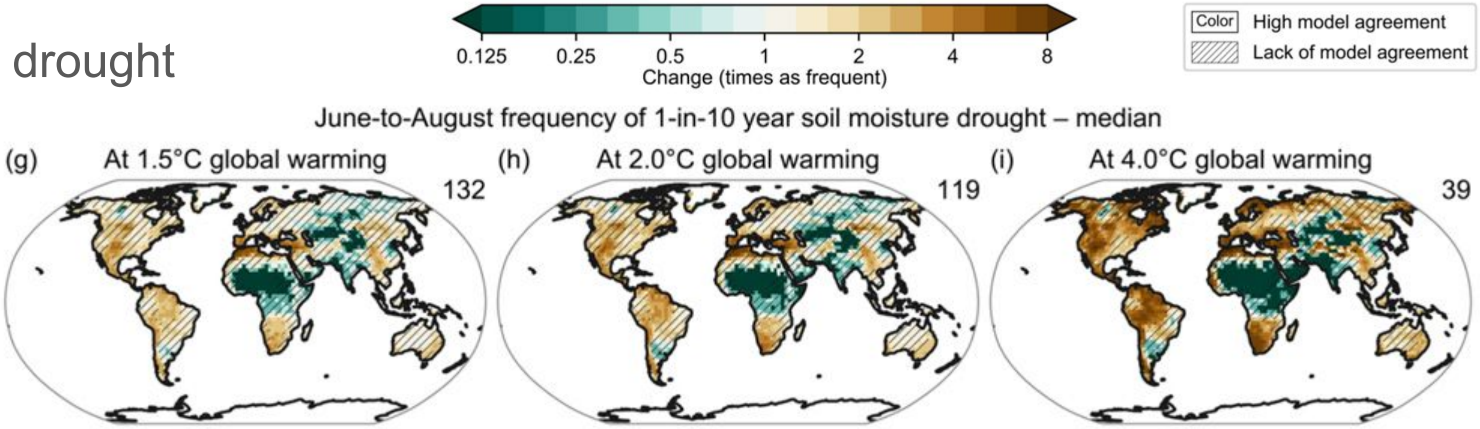


IPCC

Extreme weather events

Climate change has already caused

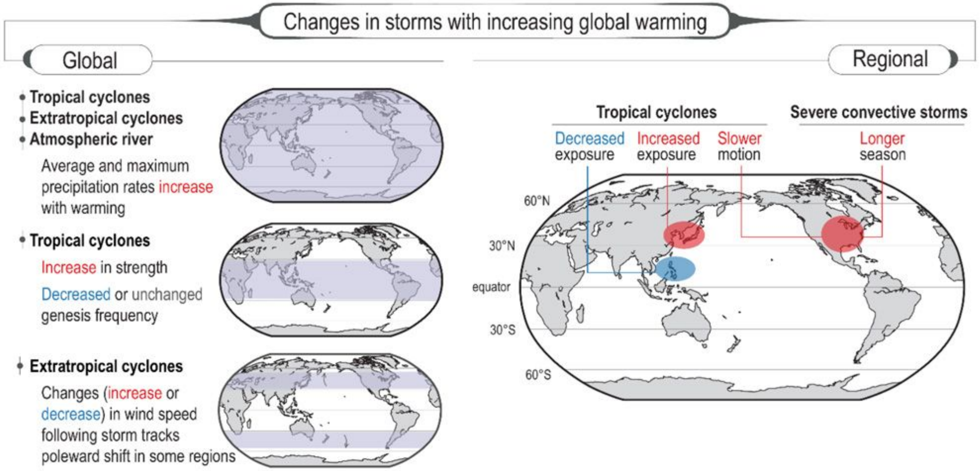
-more heat waves

-changes in rainfall

-increased floods in some regions

-increased drought

-changes in tropical storms



IPCC

Disaster Response and Recovery

Response: the use of resources (including personnel, supplies and equipment) to help restore personal and environmental safety, as well as to minimize the risk of any additional property damage after the disaster

Recovery: involves stabilizing the area and restoring all essential community functions. Recovery requires prioritization: first, essential services like food, clean water, utilities, transportation and healthcare will be restored, with less-essential services being prioritized later. This can take years or decades

https://www.ucf.edu/online/leadership-management/news/the-disaster-management-cycle/

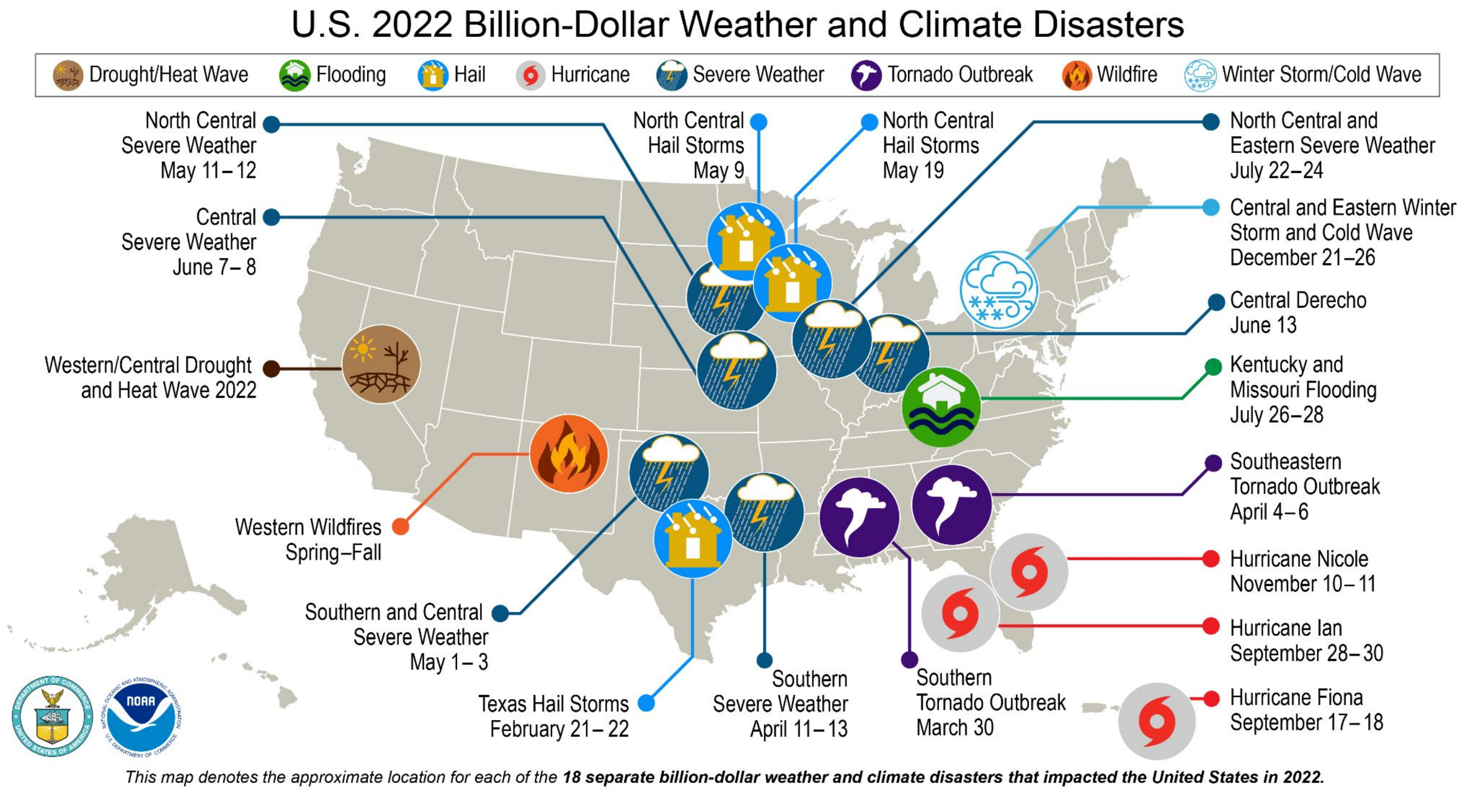
Disaster Response and Recovery

Governments and non-profits are primarily responsible for disaster response.

American Red Cross

https://www.ucf.edu/online/leadership-management/news/the-disaster-management-cycle/

Costs of disaster response



Disaster Response

Wildfire response

Paper Deep Dive

Unsupervised Wildfire Change Detection based on Contrastive Learning

Beichen Zhang[1], Huiqi Wang[2], Amani Alabri[3], Karol Bot[4], Cole McCall[5], Dale Hamilton[5]*, Vít Růžička[6]
[1]University of Nebraska-Lincoln, [2]University of California, Berkeley, [3]Boston University, [4]Lisbon University, [5]Northwest Nazarene University, [6]University of Oxford

https://arxiv.org/pdf/2211.14654.pdf

Background

Identifying where wildfires have occurred is important for

- assessing damage and planning evacuation
- responding to problems and planning ecological restoration
- predicting future wildfire events

The goal

Build a system that can detect where wildfires have occurred using satellite imagery *without previous examples*

- may not have previous examples in many locations
- features of wildfires may differ across locations

Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

How would you measure success?

What difficulties might you face?

The data

Two image sources:

Sentinel-2 satellite imagery (10m resolution, 5 day revisit time, 13-->4 spectral bands)

PlanetScope satellite imagery (3.7m resolution, daily revisit, 4 spectral bands)

The data

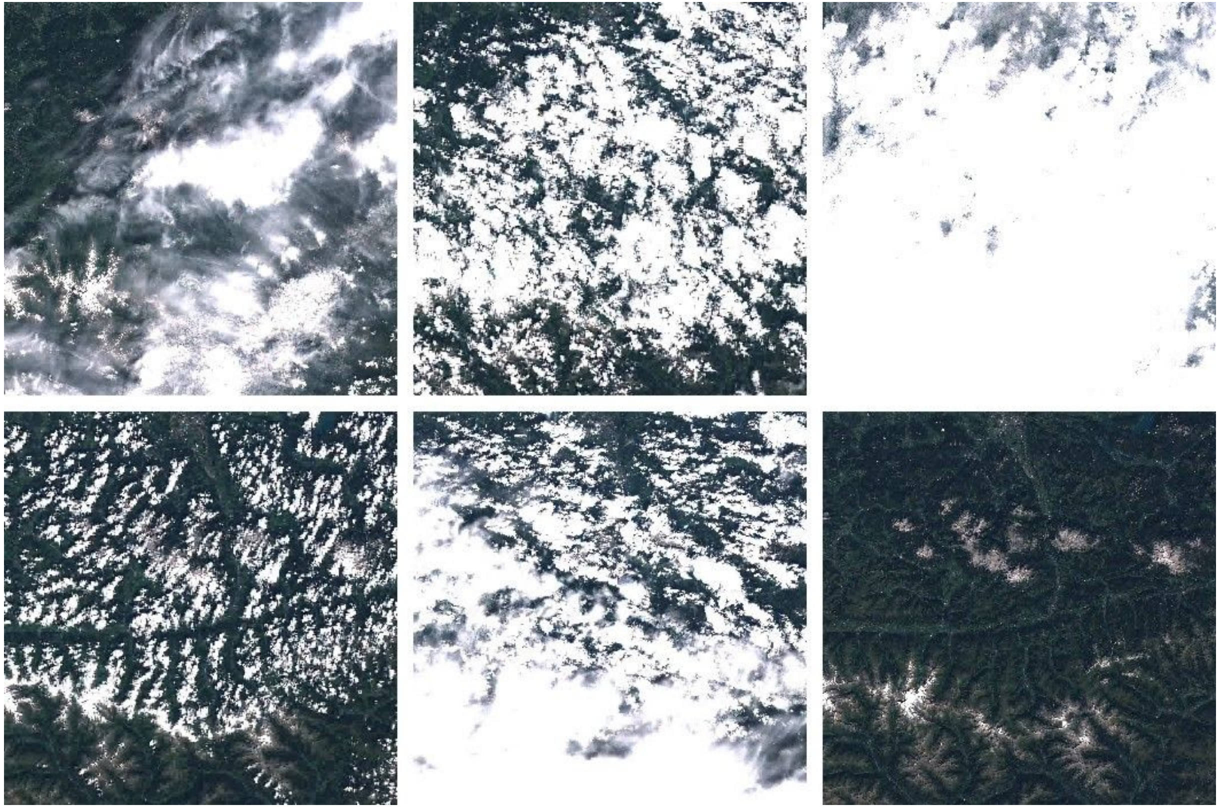
3 different study areas in Western United States:

Table 1: Description of Wildfires used in this Research.

Area of Interest	Fire Start Date	Containment Date	Time of Interest	Size (Hectares)
Mesa Fire	7/26/2018	9/25/2018	7/1/2018 to 10/1/2018	14,050
East Troublesome	10/14/2020	11/30/2020	10/1/2020 to 12/1/2020	78,432
McFarland Fire	7/29/2021	9/16/2021	7/1/2021 to 10/1/2021	49,635

As long as the imagery covered enough of the study area (>50%) and did not have significant cloud cover, each PlanetScope and Sentinel-2 image was added to the dataset and could be considered either pre-fire, active fire, or post-fire imagery.

The data (preprocessing)



Clouds are a problem in satellite imagery.

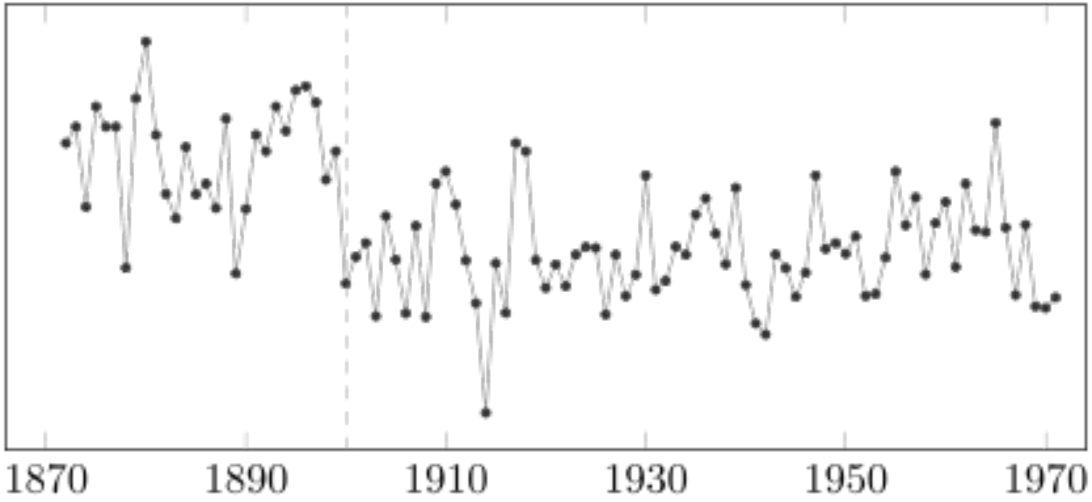
The data (preprocessing)

“The data is normalised using the statistics from the training set, these parameters are saved and later reused for the rest of the data”

```python
def __data_generation(self, list_IDs_temp):
    'Generates data containing batch_size samples' # X : (n_samples, *dim, n_channels)
    # Initialization
    X = np.zeros((self.batch_size,)+self.imsize)
    y = np.zeros((self.batch_size), dtype=int)

    noise = np.random.randn(X.shape[0],X.shape[1],X.shape[2],X.shape[3])*self.noise_std
    noise[np.random.choice(self.batch_size,size=(int(self.batch_size*.45)),replace=False),:,:,:] = 0

    #training set mean and std
    r = [0.33066305322913947, 0.1417965275302205]
    g = [0.3291309715529797, 0.11527820030273506]
    b = [0.280864934417904, 0.0973566175910353]
    ir = [0.45477920985106823, 0.13050297084409782]


    # Generate data
    for i, ID in enumerate(list_IDs_temp):
        # Store sample
        im = np.load(self.im_path + 'im' + "%05d" % ID + '_l'+str(self.labels[ID]) + '.npy')
        X[i,] = im[:self.imsize[0],:self.imsize[1],:self.imsize[2]]/255. #basic crop because some have extra pixels
        X[i,:,:,0] = (X[i,:,:,0]-r[0])/r[1]
        X[i,:,:,1] = (X[i,:,:,1]-g[0])/g[1]
        X[i,:,:,2] = (X[i,:,:,2]-b[0])/b[1]
        X[i,:,:,3] = (X[i,:,:,3]-ir[0])/ir[1]

        # Store class
        y[i] = self.label_convert(self.labels[ID])

    X += noise
    return X, y
```

The method

"***Change detection*** is defined as identifying differences in a site's state or phenomenon by observing it at different times."



The method

“***Change detection*** is defined as identifying differences in a site’s state or phenomenon by observing it at different times.”

“In this context, our work aims to employ *unsupervised machine learning* methods associated with multispectral satellite images to assess the change detection of burned areas”

The method

“SimCLR”

A Simple Framework for Contrastive Learning of Visual Representations

Ting Chen[1] Simon Kornblith[1] Mohammad Norouzi[1] Geoffrey Hinton[1]

https://arxiv.org/pdf/2002.05709.pdf

Contrastive Learning

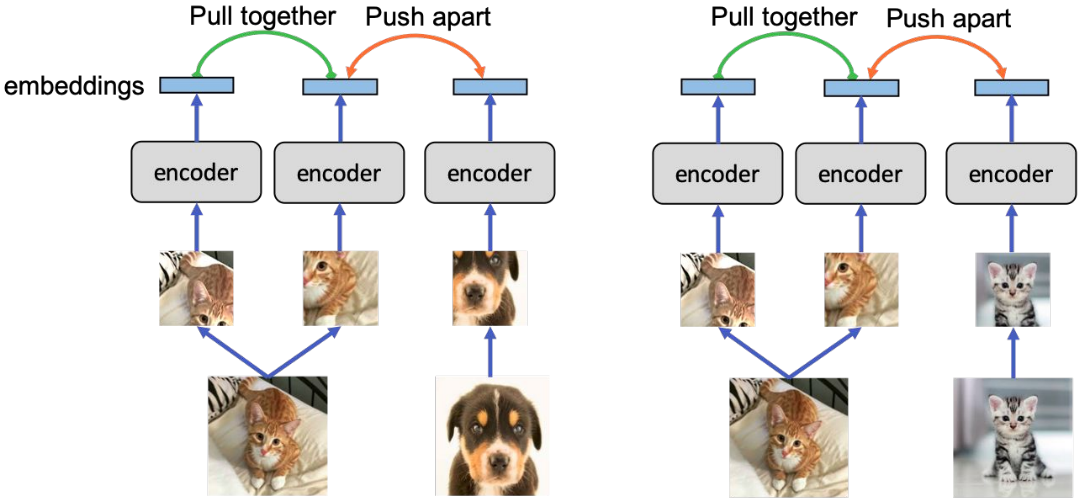
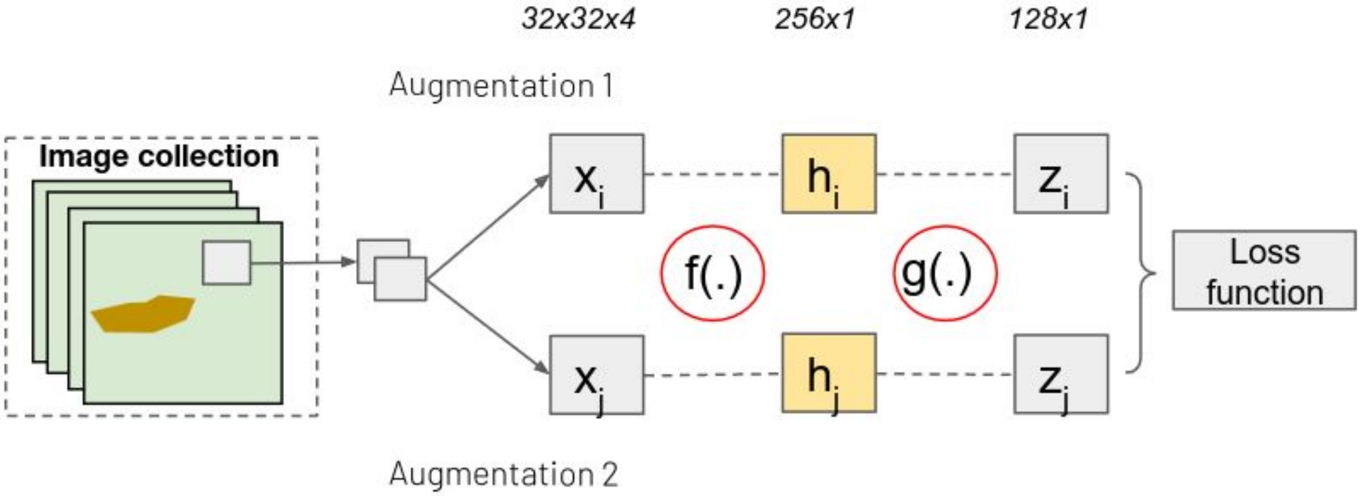


Figure 1 (a) (b)

The goal of contrastive learning is to build a model that will represent similar images similarly, and dissimilar images dissimilarly. It does this through "self-supervised" learning with augmented images

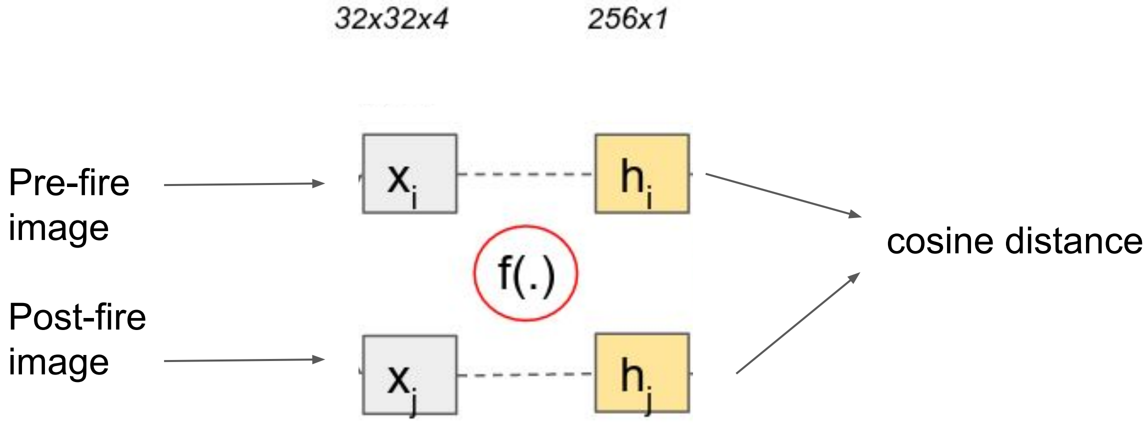
https://blog.salesforceairesearch.com/prototypical-contrastive-learning-pushing-the-frontiers-of-unsupervised-learning/

The method



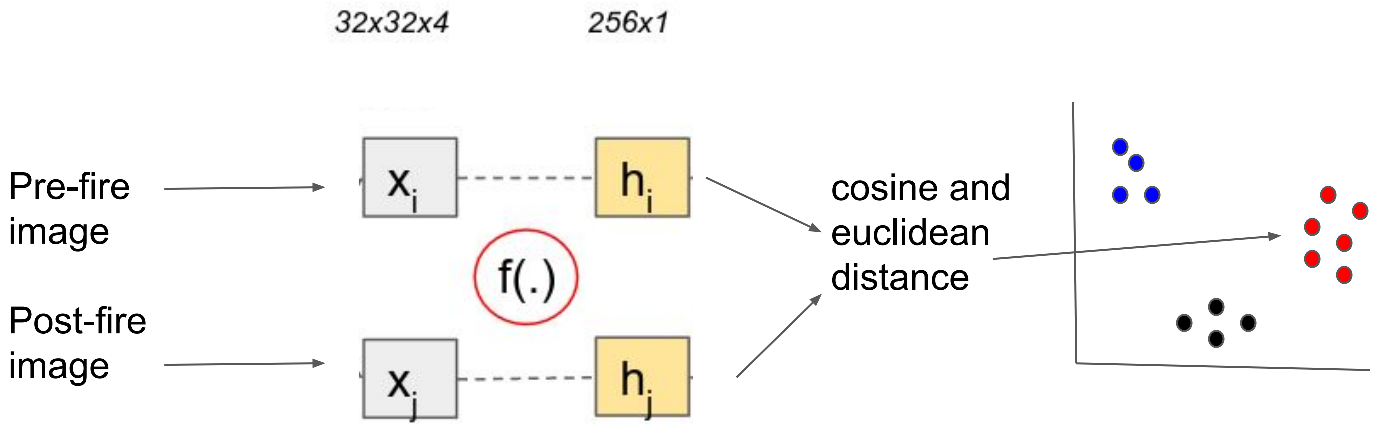
“FireCLR” based on SimCLR. Training: “Data augmentation for image tiles includes: random crop, gaussian blur, random flip and fixed rotation. Importantly, we excluded any augmentation process which would change the color of the images since the changes caused by fires are sensitive to the reflectance.”

The method



“FireCLR” based on SimCLR. To detect changes, the hidden layer representations are compared for two images via cosine distance. This is used to identify if a change due to wildfire has occurred.

The method



“FireCLR” based on SimCLR. To access fire severity, the change in hidden layer representations are entered into a clustering algorithm, and clusters are then related to different levels of burn severity.

The method

Two models trained in order to test two different approaches:

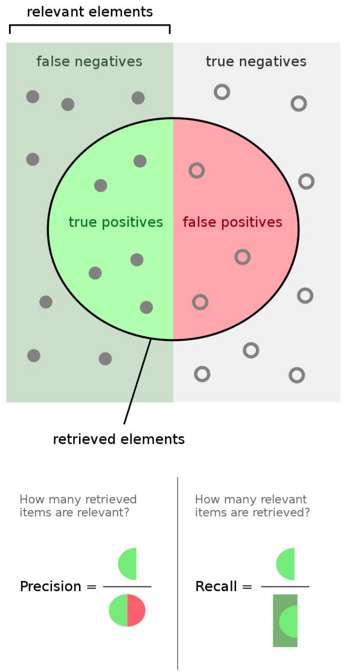
Local model: Trained on same geographical location tested on. Uses Sentinel-2 data

Global model: Trained on other two locations and tested on remaining one. Uses PlanetScope data.

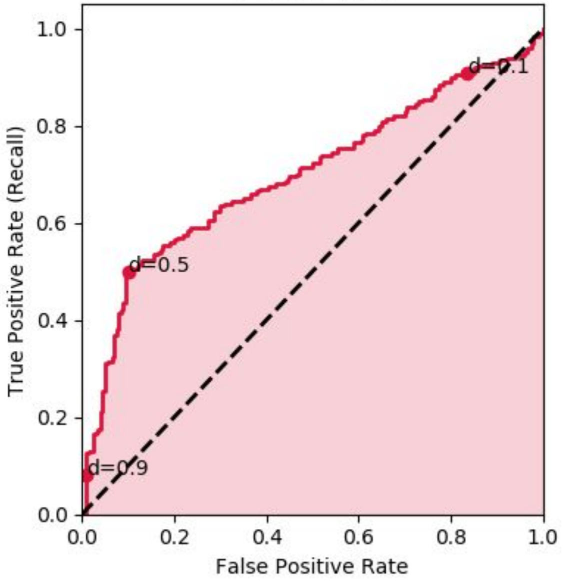
Evaluation

Evaluation

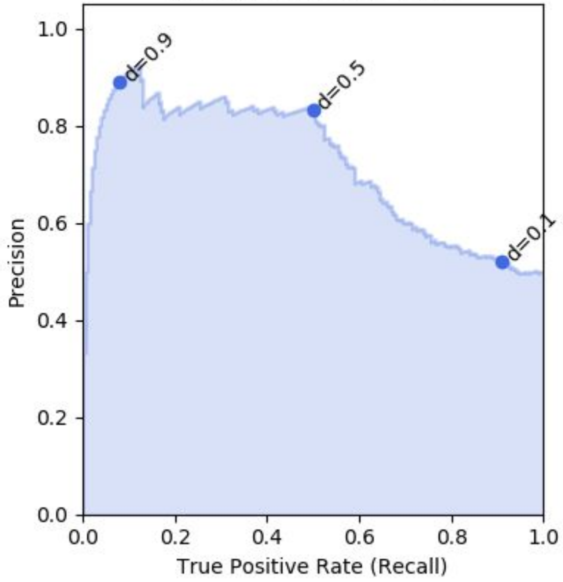
auPRC (precision recall curve)



ROC

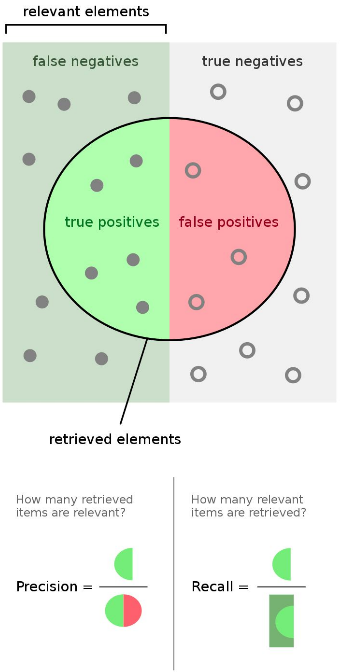


PRC

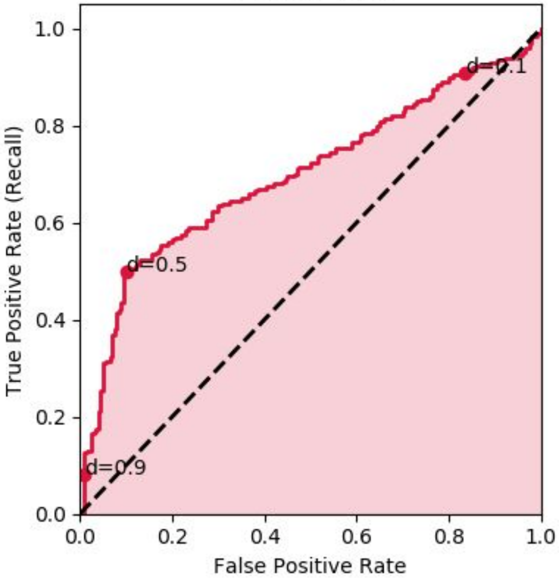


Evaluation

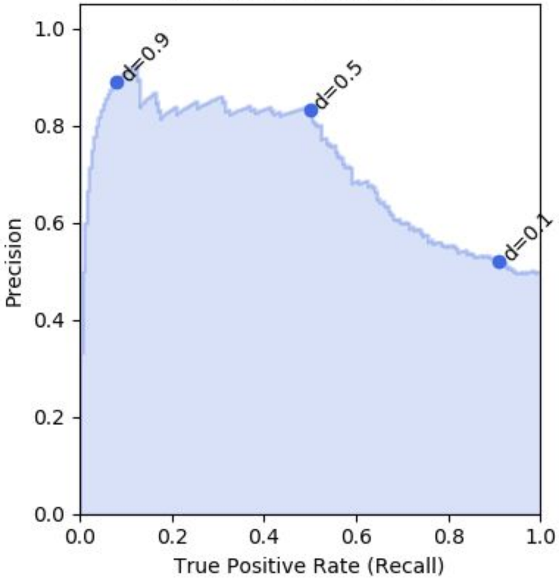
auPRC



ROC



PRC



Evaluation on fire severity: per class F1 score

Evaluation

Comparison to (untrained) baseline methods for change detection:

Change in Normalized Difference Vegetation Index (NDVI) - based on red and near infrared channels available in PlanetScope data

Change in Normalized Burn Ratio (NBR) - based on near infrared and shortwave infrared which is only available in Sentinel-2

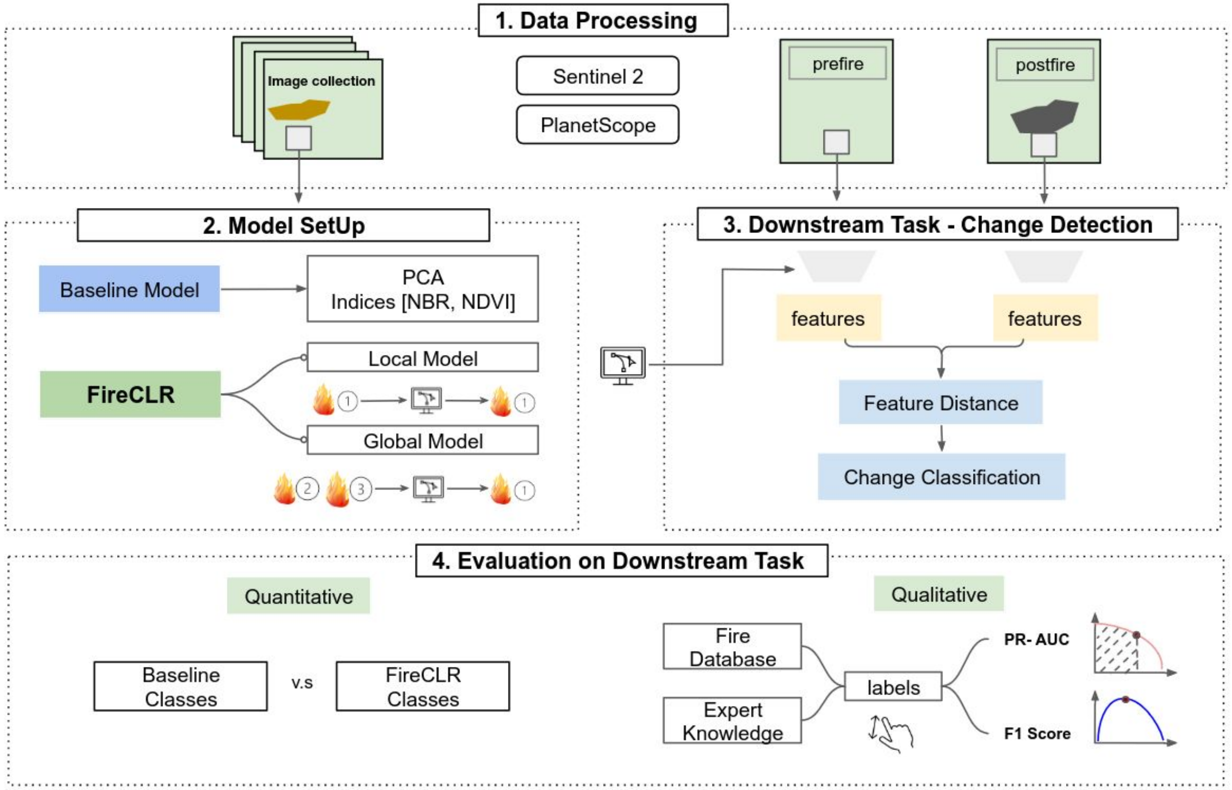
Evaluation

Comparison to (untrained) baseline methods for burn severity:

Change in Normalized Burn Ratio (NBR) + clustering

Principal Components Analysis (PCA) on remote sensing data + clustering

Summary of methods



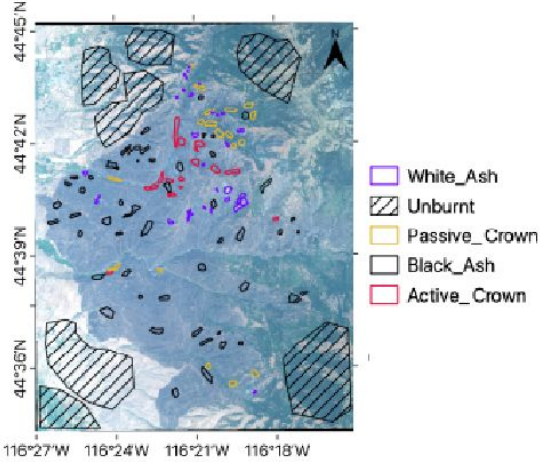
Results

Results

Change detection with Sentinel-2 data

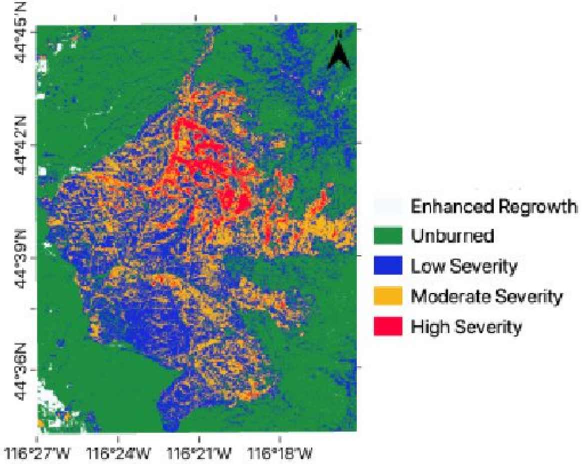
dNDVI
AUPRC: 0.76

Ground Truth



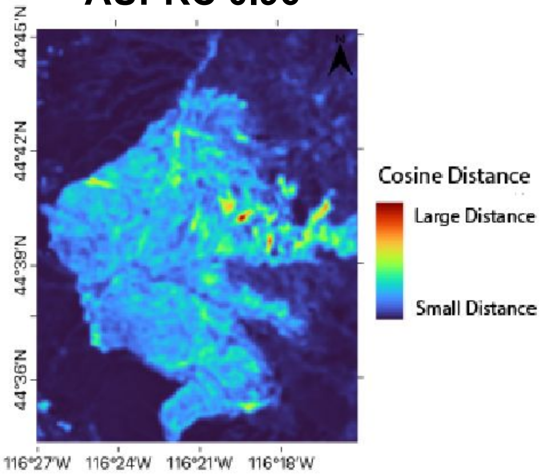
dNBR

AUPRC: 0.95



Local FireCLR

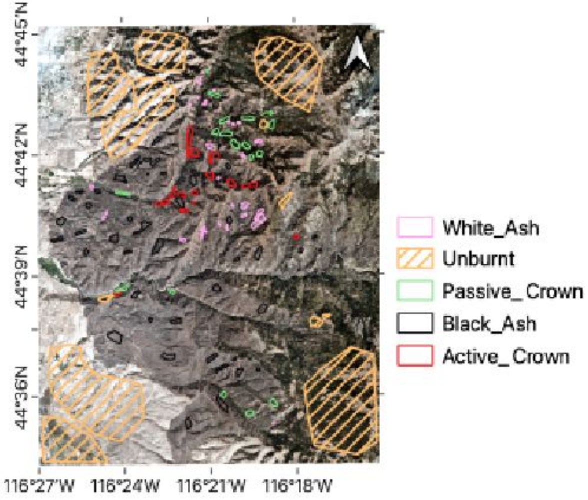
AUPRC 0.96



Results

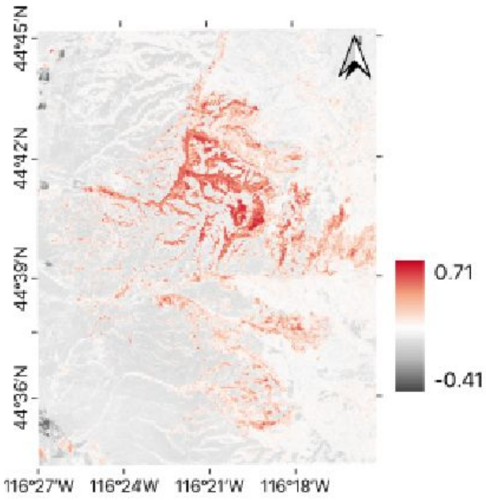
Change detection with PlanetScope data

Ground Truth



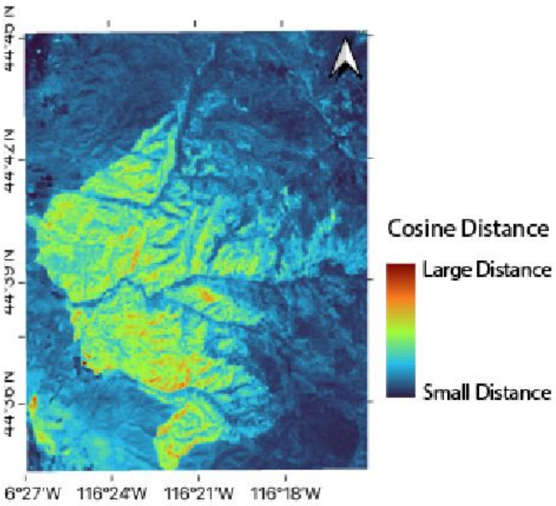
dNDVI

AUPRC: 0.67



Global FireCLR

AUPRC 0.8



Results

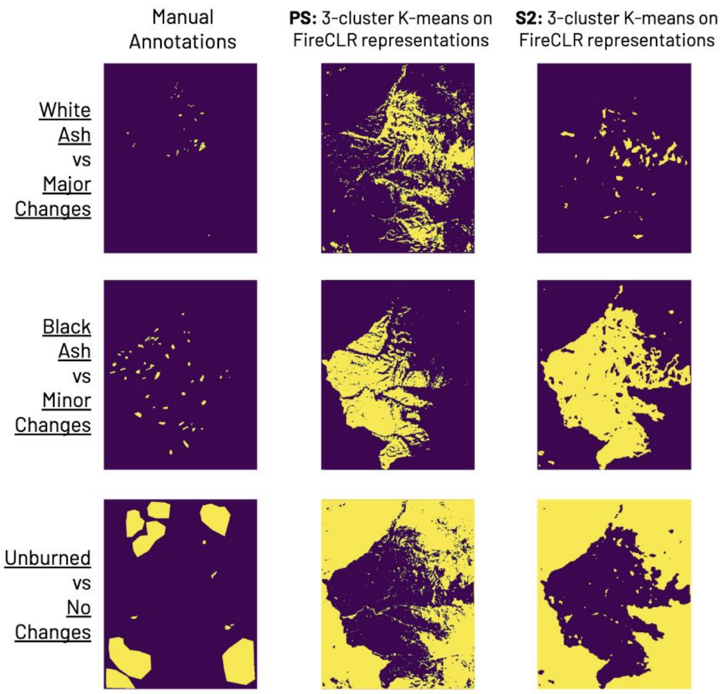
Fire severity

Table 2: F1-scores of the models trained in local mode (the same location for the training and evaluation set, using different times) with Sentinel-2 data on the downstream task of unsupervised cluster classification.

Method	Bands	Effective res.	White Ash	Black Ash	Unburned
PCA + K-means	S2 RGB+NIR	10m	0.59	**0.86**	0.6
dNBR + K-means	S2 RGB+SWIR	10m	**0.93**	0.78	0.76
FireCLR + K-means	S2 RGB+NIR	80m	0.51	0.82	**0.79**

Table 3: F1-scores of the models trained in global mode (different location and timeframes for the training and evaluation sets) with PlanetScope data on the downstream task of unsupervised cluster classification.

Method	Bands	Effective res.	White Ash	Black Ash	Unburned
PCA + K-means	PS RGB+NIR	3m	**0.9**	**0.86**	0.76
FireCLR + K-means	PS RGB+NIR	24m	**0.9**	**0.86**	**0.78**



Conclusions

“In conclusion, the proposed FireCLR model outperforms the baseline methods in both Sentinel-2 and PlanetScope datasets based on the AUPRC score, and shows mixed, but comparable results on downstream validation tasks.

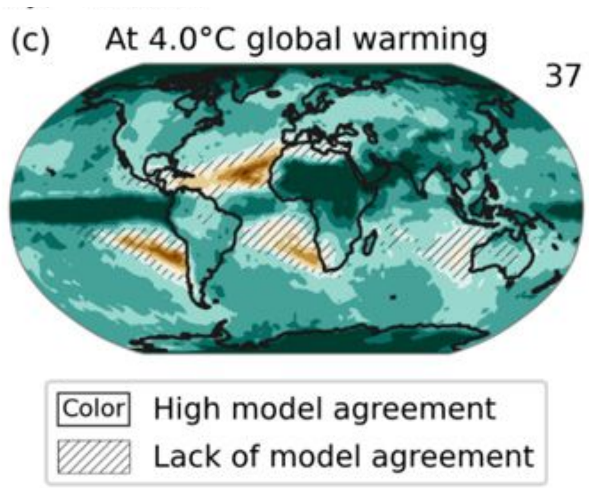
We note that this work should serve as an **initial exploration** of this approach. In future research, we would like to run more experiments to closely compare the performance of using sensor data of different resolutions”

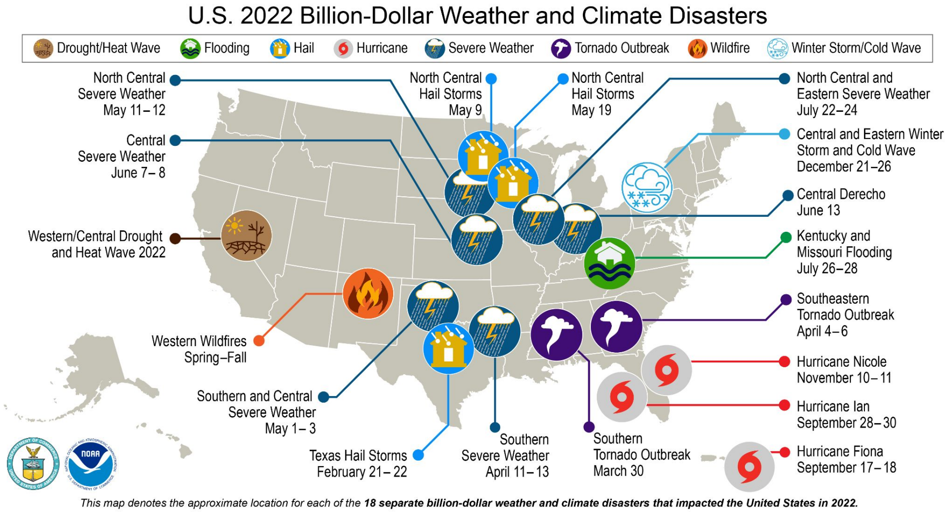
Further resources

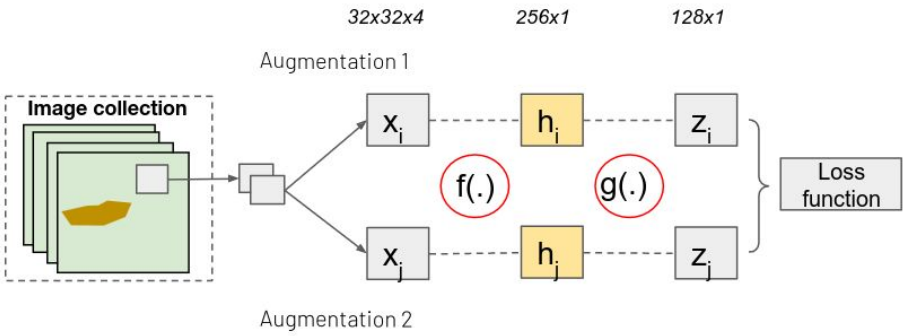
Artificial Intelligence for Humanitarian Assistance and Disaster Response Workshop

https://www.hadr.ai/

Summary


(c) At 4.0°C global warming
37
Color High model agreement
Lack of model agreement


U.S. 2022 Billion-Dollar Weather and Climate Disasters
Drought/Heat Wave
Flooding
Hail
Hurricane
Severe Weather
Tornado Outbreak
Wildfire
Winter Storm/Cold Wave
North Central Severe Weather May 11–12
Central Severe Weather June 7–8
Western/Central Drought and Heat Wave 2022
Western Wildfires Spring–Fall
Southern and Central Severe Weather May 1–3
Texas Hail Storms February 21–22
Southern Severe Weather April 11–13
Southern Tornado Outbreak March 30
North Central Hail Storms May 9
North Central Hail Storms May 19
North Central and Eastern Severe Weather July 22–24
Central and Eastern Winter Storm and Cold Wave December 21–26
Central Derecho June 13
Kentucky and Missouri Flooding July 26–28
Southeastern Tornado Outbreak April 4–6
Hurricane Nicole November 10–11
Hurricane Ian September 28–30
Hurricane Fiona September 17–18
This map denotes the approximate location for each of the 18 separate billion-dollar weather and climate disasters that impacted the United States in 2022.


32x32x4
256x1
128x1
Augmentation 1
Image collection
x_i
h_i
z_i
f(.)
g(.)
Loss function
x_j
h_j
z_j
Augmentation 2