National Aeronautics and Space Administration

Humanitarian Applications Using NASA Earth Observations

Part 4: Assessing Climate Hazards at Refugee Camps

June 23, 2022

Outline

This webinar series is scheduled around **World Refugee Day** on **June 20, 2022**, and includes four parts:

> **Part 1: Monitoring Urban Damage with InSAR (14 June)**
>
> **Part 2: Mapping Refugee Settlement Growth and Population Change (16 June)**
>
> **Part 3: Detecting Agricultural and Vegetation Changes In and Surrounding Refugee Settlements (21 June)**
>
> **Part 4: Assessing Climate Hazards at Refugee Camps (23 June)**

Each part is 2 hours long, including a question-and-answer session at the conclusion.

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Part 4: Assessing Climate Hazards at Refugee Camps

Motivation

- As refugee settlements are established in new regions, novel climate hazards may arise.
- There is ever more data related to climate-driven events and hazards, but the availability of data does not guarantee its appropriate use.
- Satellite data can guide estimates of climate and environmental exposure in support of humanitarian monitoring.

Goals

- Use multi-criteria hazard analysis to estimate climate hazard potential across multiple sites
- Evaluate how different satellite products influence climate hazard assessment
- Compare climate hazard profiles to known hazard events

Homework and Certificate

- **Homework Assignment:**
  - There will be one homework assignment for this webinar series.
  - Answers must be submitted via Google Form found on the training page
  - Due Date: July 7, 2022
- **A certificate of completion will be awarded to those who:**
  - Attend all live webinars
  - Complete the homework assignment by the deadline
  - You will receive a certificate approximately two months after the completion of the course from: marines.martins@ssaihq.com

Meet your presenters!

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Consultant

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Andrew Kruczkiewicz

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Columbia University / Climate School / IRI

Red Cross Red Crescent Climate Centre

University of Twente / ITC

Jamon Van Den Hoek

Associate Professor of Geography

Oregon State University

Previous ARSET trainings

- **SAR for Disasters and Hydrological Applications:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-sar-disasters-and-hydrological-applications
- **Earth Observations for Disaster Risk Assessment & Resilience:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-earth-observations-disaster-risk-assessment-resilience
- **Remote Sensing for Disasters Scenarios:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-remote-sensing-disasters-scenarios

Background:

Mapping Environment and Climate Exposure in Cox’s Bazar, Bangladesh

Refugee camps are exposed to climate hazards such as landslides, flooding, droughts, and heat waves.

Flooding in Cox's Bazar refugee camp in Bangladesh in 2017
(Photo by Reuters/Cathal McNaughton)

- Non-durable dwellings, limited livelihood opportunities, and camps placed in isolated, marginal borderland regions all challenge local climate adaptation.
- Refugees are made doubly vulnerable by restrictive migration and communication policies.

There is little research on environmental and climate hazards at refugee camps.

To date, we have anecdotal evidence of hazards at refugee camps, but there has never been a systematic assessment across multiple refugee sites, for example.

Source: UNHCR (2006)

In 2006, heavy rains flooded Dadaab Refugee Camp Complex in northeastern Kenya.

- 2 people were killed, and homes of nearly 13,000 people were lost.

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In 2017, floods once again affected Dadaab Refugee Camp Complex.

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In 2014, Lietchuor Refugee Camp in Ethiopia was flooded.

- The camp was closed, and 40,000 refugees were relocated.

Flooding at Cox's Bazar has perhaps received the most attention of climate hazards in refugee settings.

Flash flood events have been recorded in Cox's Bazar refugee settings in 1988, 1992, 1998, 2012, 2015, and 2021.

In 2021, floods killed eight and displaced 21,000 refugees in Cox's Bazar. Source: Floodlist (2021)

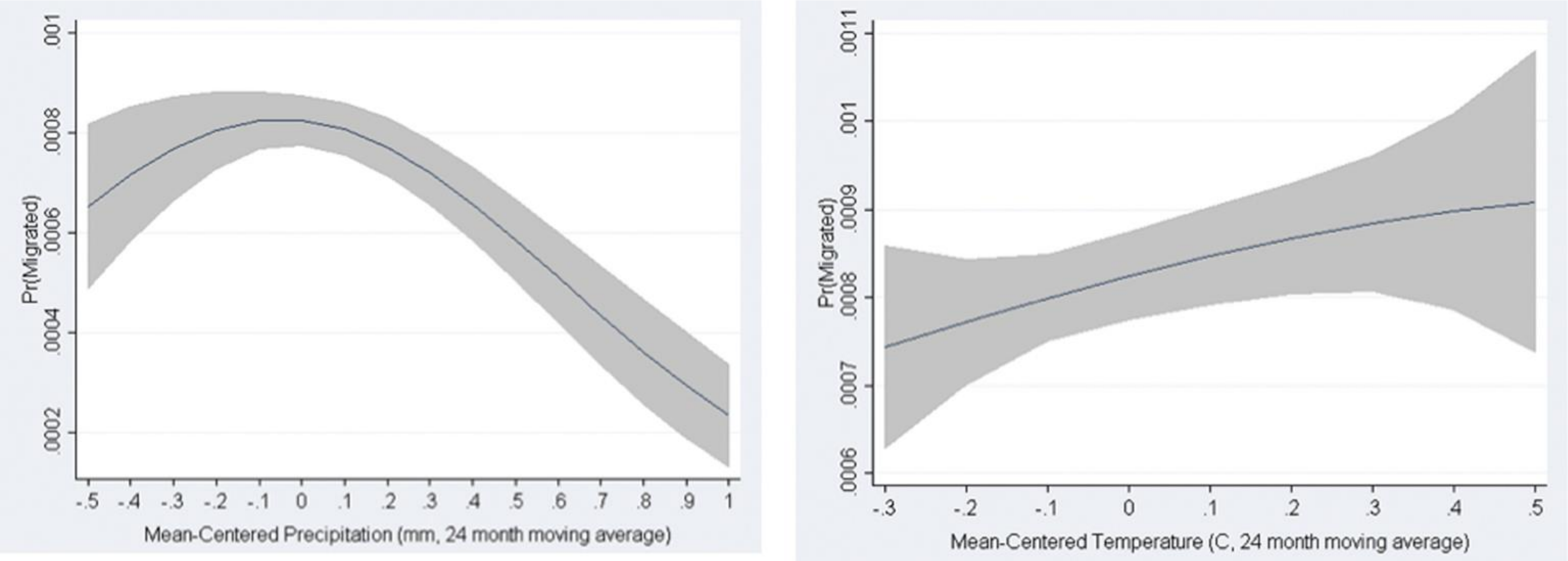
- Floods may bring water 1 to 2 meters high, and waters may linger for several hours or over a day.
- Floods contribute to landslides, which can also be deadly.
- Flooding may also destroy homes, terraces, and crops, leaving long-term consequences for affected households.

Refugees at Cox's Bazar, the world's largest refugee camp, are at high risk for flooding and landslides.

- There are 1.2 million Rohingya refugees living in 34 camps across Cox's Bazar.
- The Rohingya were forcibly displaced from Myanmar and settled in Cox's Bazar as early as the 1970s.
- The arrival of nearly 700,000 refugees in August 2017 contributed to rapid, widespread landscape changes – such as deforestation and terracing – that increase risk of landslide potential.
- Flooding and landslides most commonly follow the approx. 1.6 meters of rain that falls between June and August.

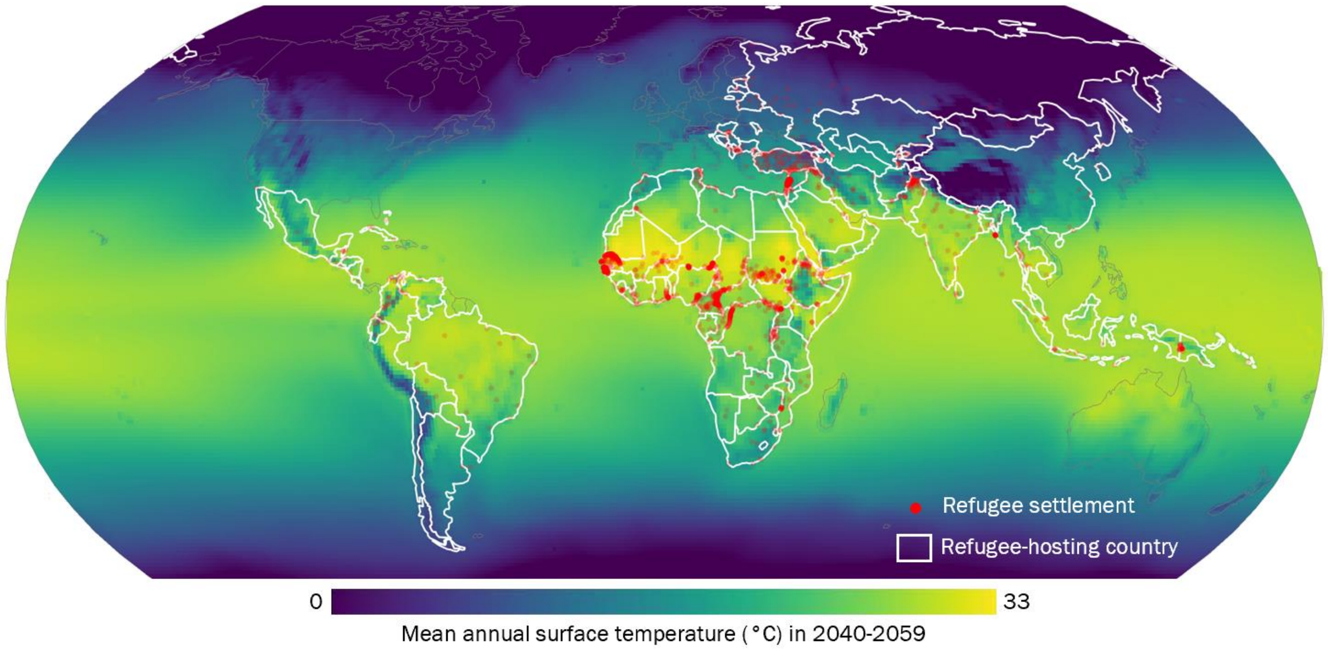
Policies in Bangladesh and other refugee-hosting countries restrict refugees from leaving the camp even during/following extreme climate events.

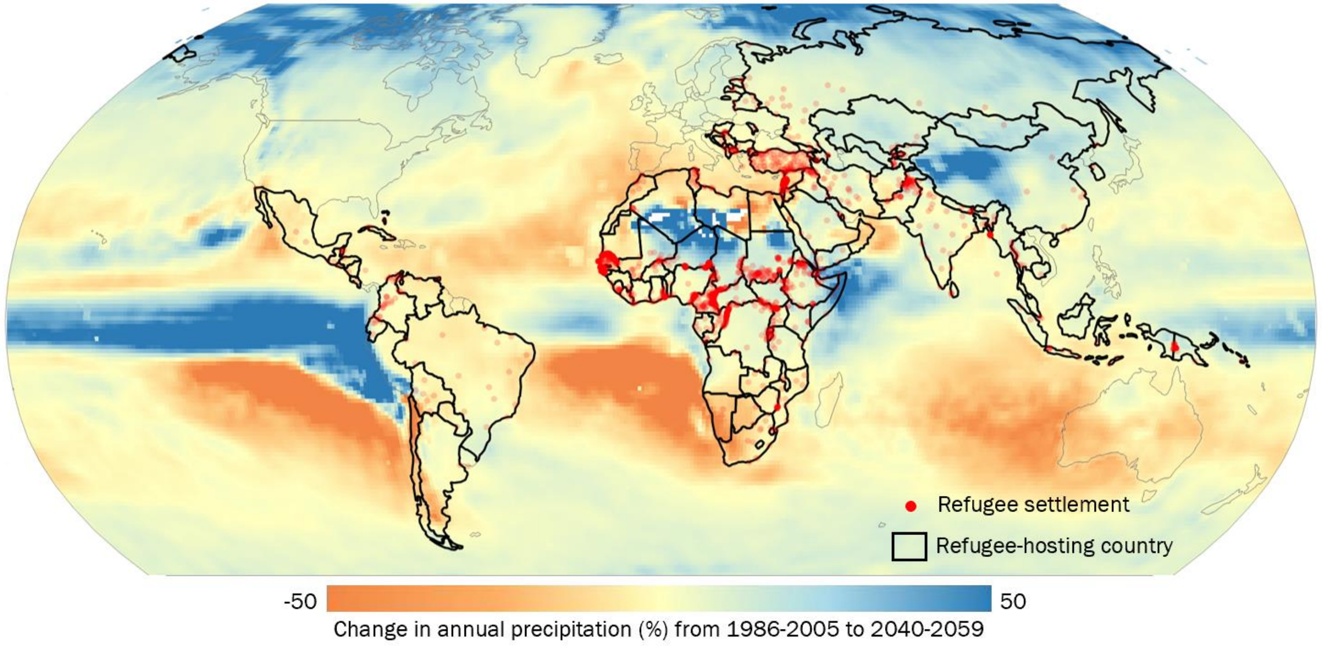
- Voluntary migration is a strategic decision to mitigate climate effects.
- Higher temperatures and rainfall extremes drive out-migration through crop failures and challenges to livelihoods.



Predicted probabilities of migration in Bangladesh as a function of precipitation and temperature

Source: Call et al. (2017)



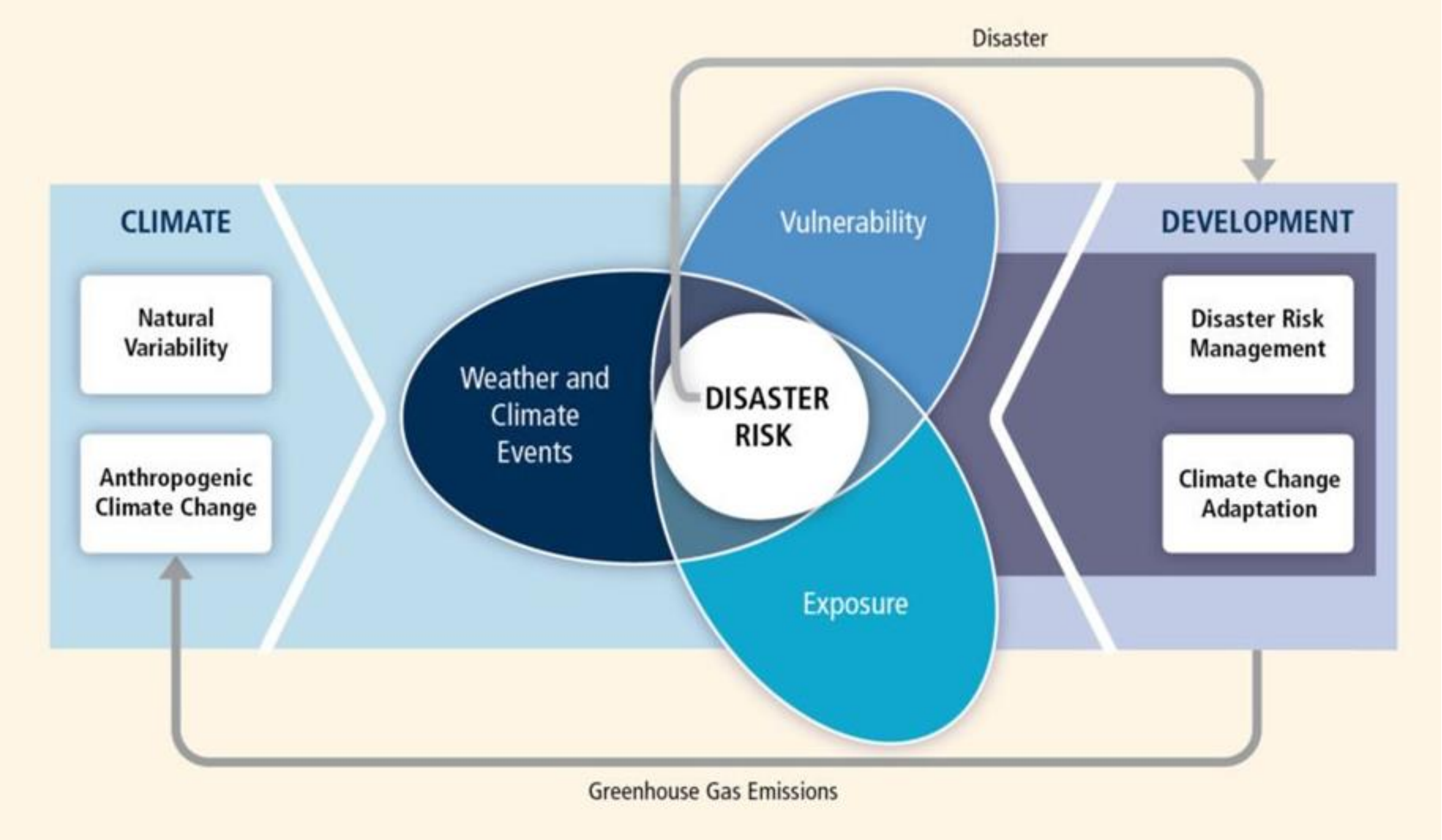


Future climate change effects – notably, **more rainfall and higher temperatures** – in Bangladesh and other refugee-hosting countries are likely to exacerbate current climate hazards.

Source: Peters & Van Den Hoek (2021)

Gauging climate disaster risk in refugee settings means understanding how exposure, social vulnerability, and weather and climate events interact.

- Refugee populations are extremely vulnerable due to societal exclusion and marginalization.
- Refugees also face high disaster risks since they are exposed to climate extremes and have low collective adaptive capacity (i.e., the resources needed to adjust to actual or expected climate effects).



Source: IPCC (2022)

Case Study: Environmental and Climate Exposure at Cox’s Bazar Refugee Camp, Bangladesh

Photos: Melody Braun and Andrew Kruczkiewicz

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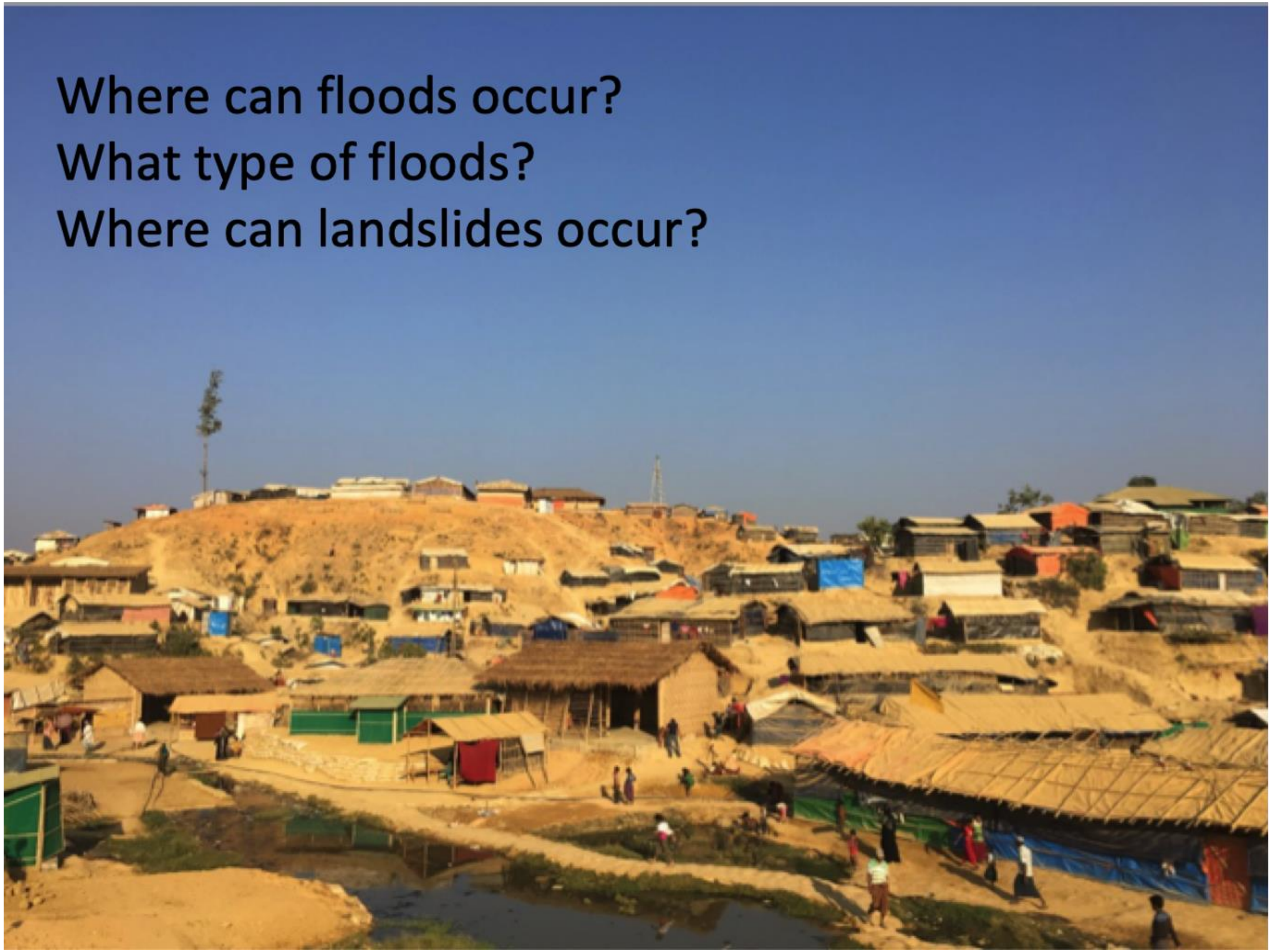
Source: [International Organization for Migration (IOM) and OpenAerialMap (OAM)]

Photos: Melody Braun and Andrew Kruczkiewicz



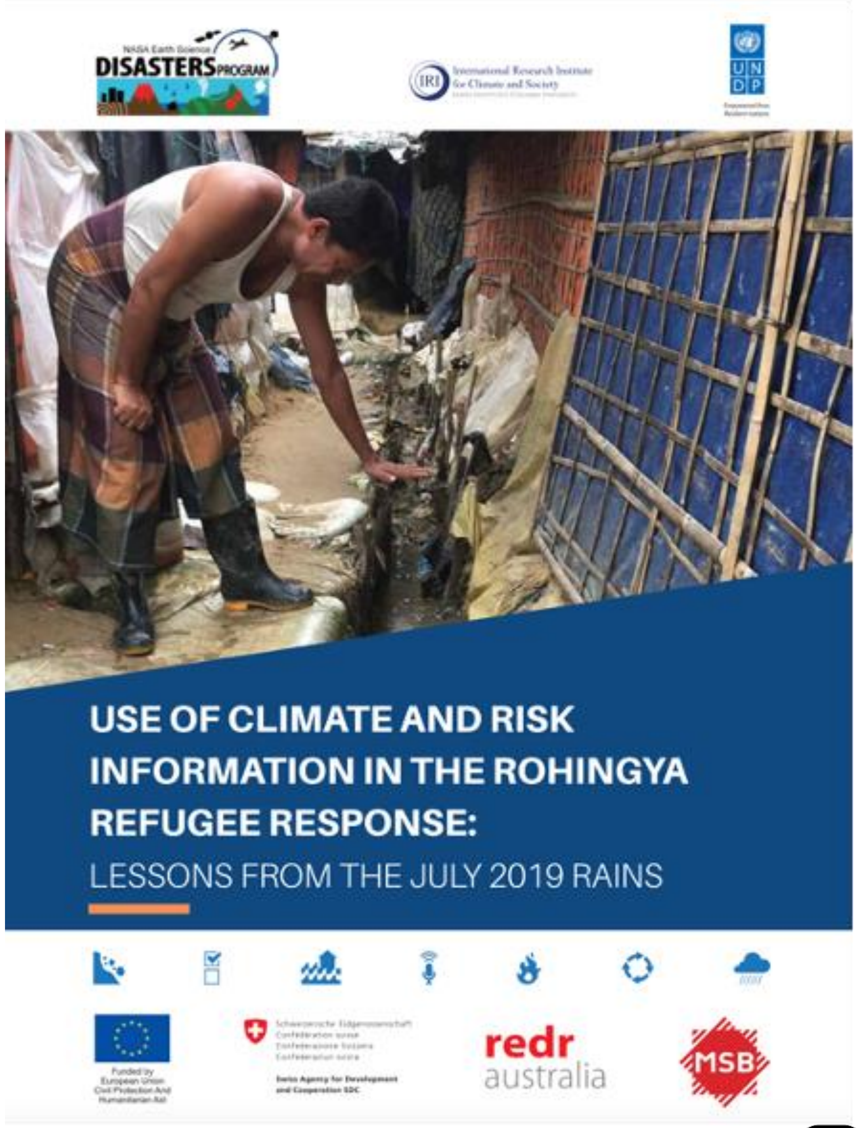
Photos: Melody Braun and Andrew Kruczkiewicz

Cox's Bazar is a climate shock-prone area.

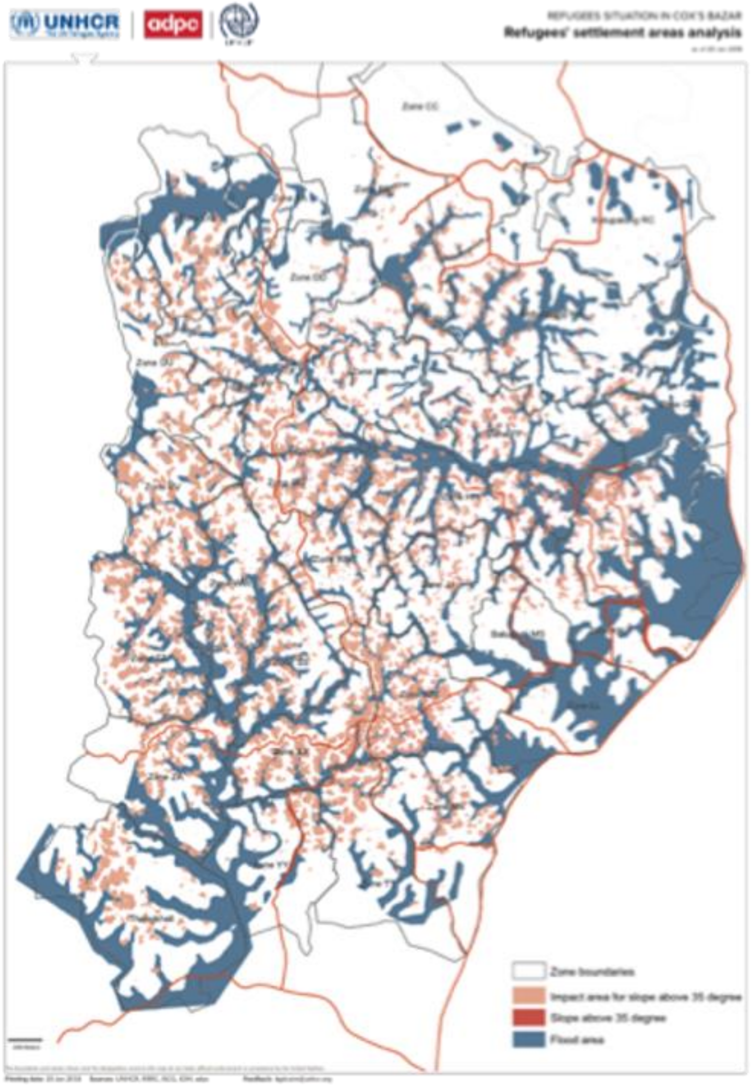
Photos: Washington Post, TRT World and Agencies, Norwegian Refugee Council

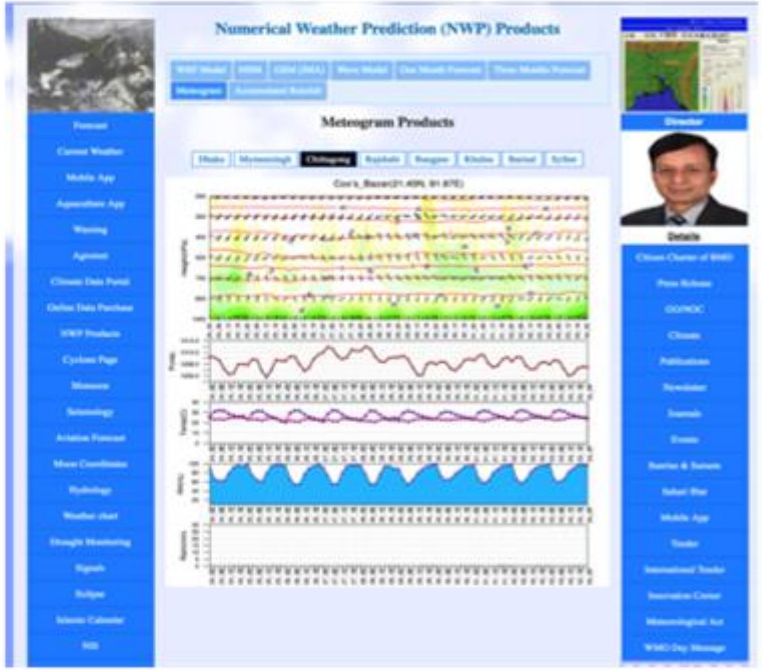
However, action can be taken if risk is understood – and if there are standard operating procedures to act if a shift (increase) of that risk is identified in forecasts.

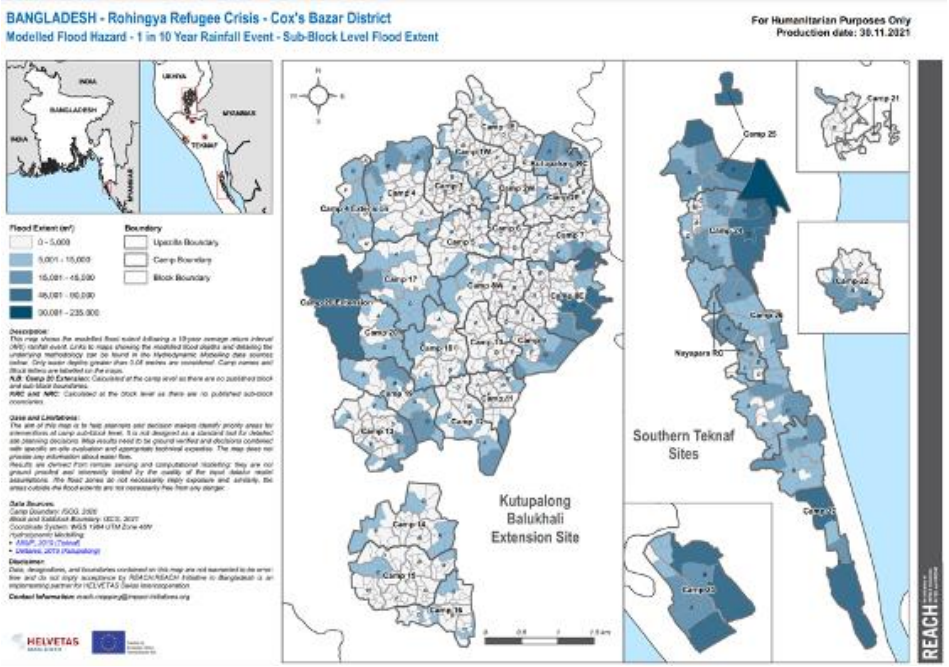
Photo: [Logistics Cluster]



‘Official’ / ‘Authoritative’ data exist….







Source: Bangladesh Met Department, REACH, UNHCR

… but what does that mean when there are so many options?

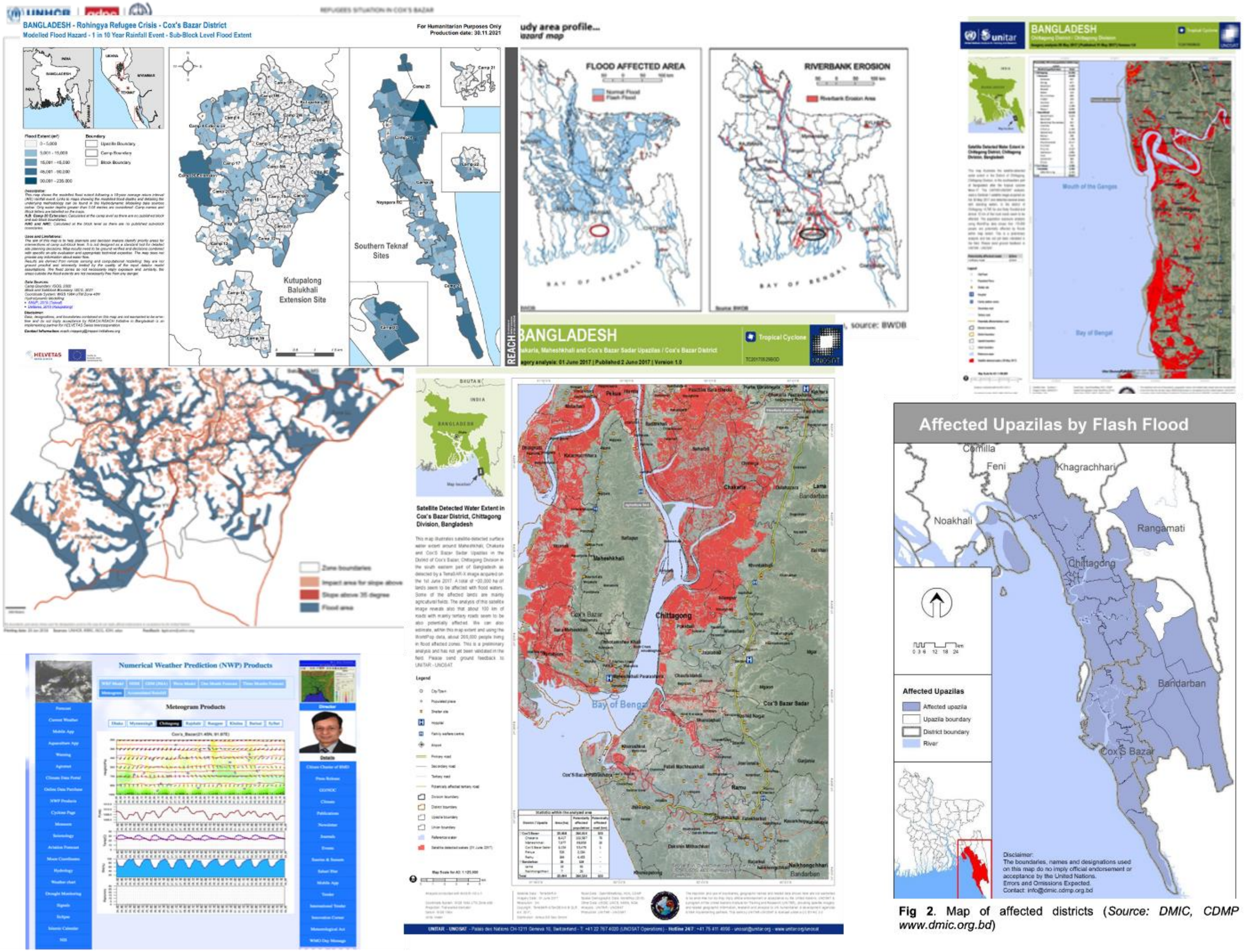


Fig 2. Map of affected districts (*Source: DMIC, CDMP www.dmic.org.bd*)

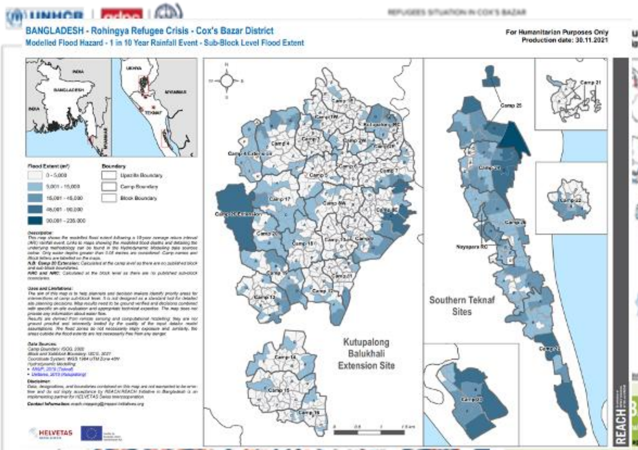
… but what does that mean when there are so many options?

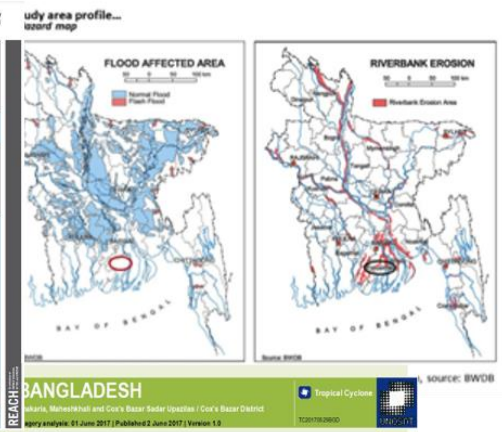
Too much data, not enough time?

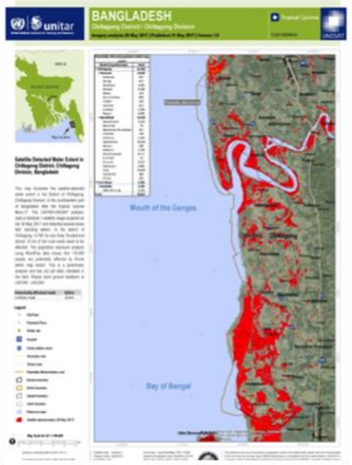
How is one prioritized over another?

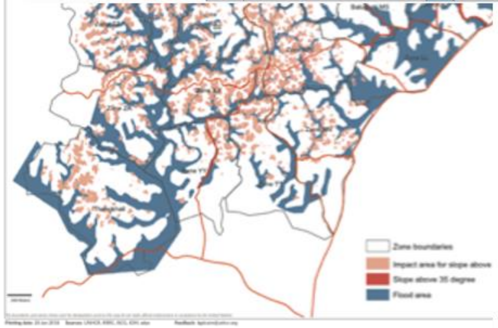
How is one de-prioritized over another?

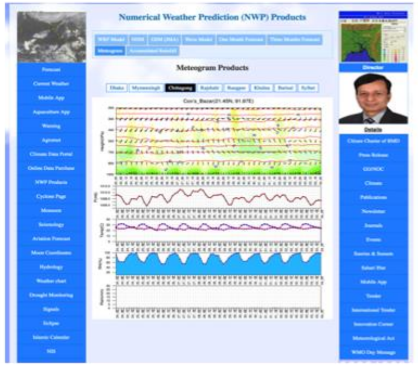
Who is most impacted by this prioritization / de-prioritization?

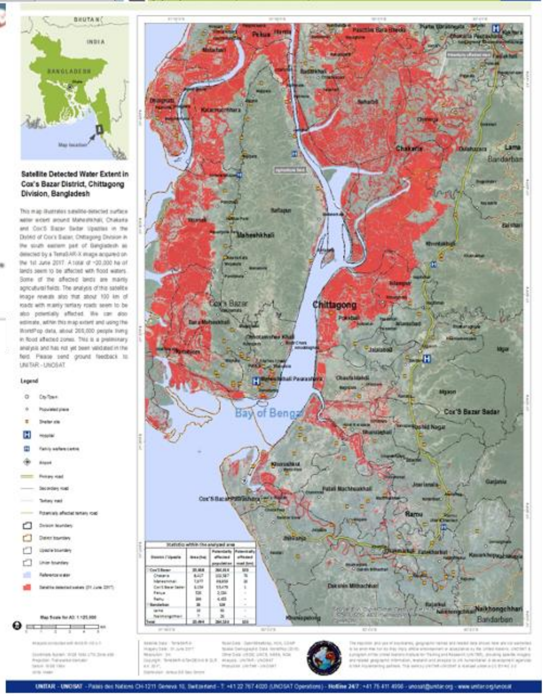












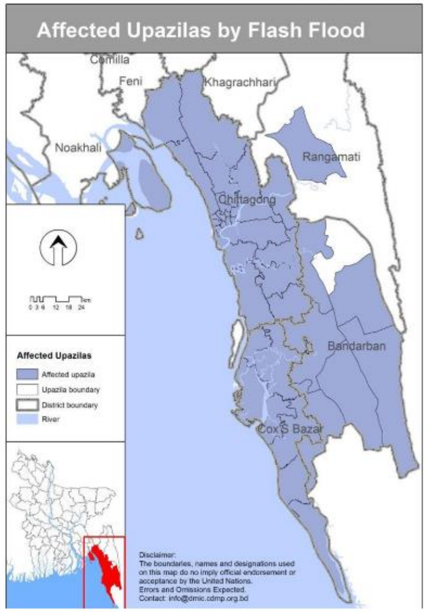
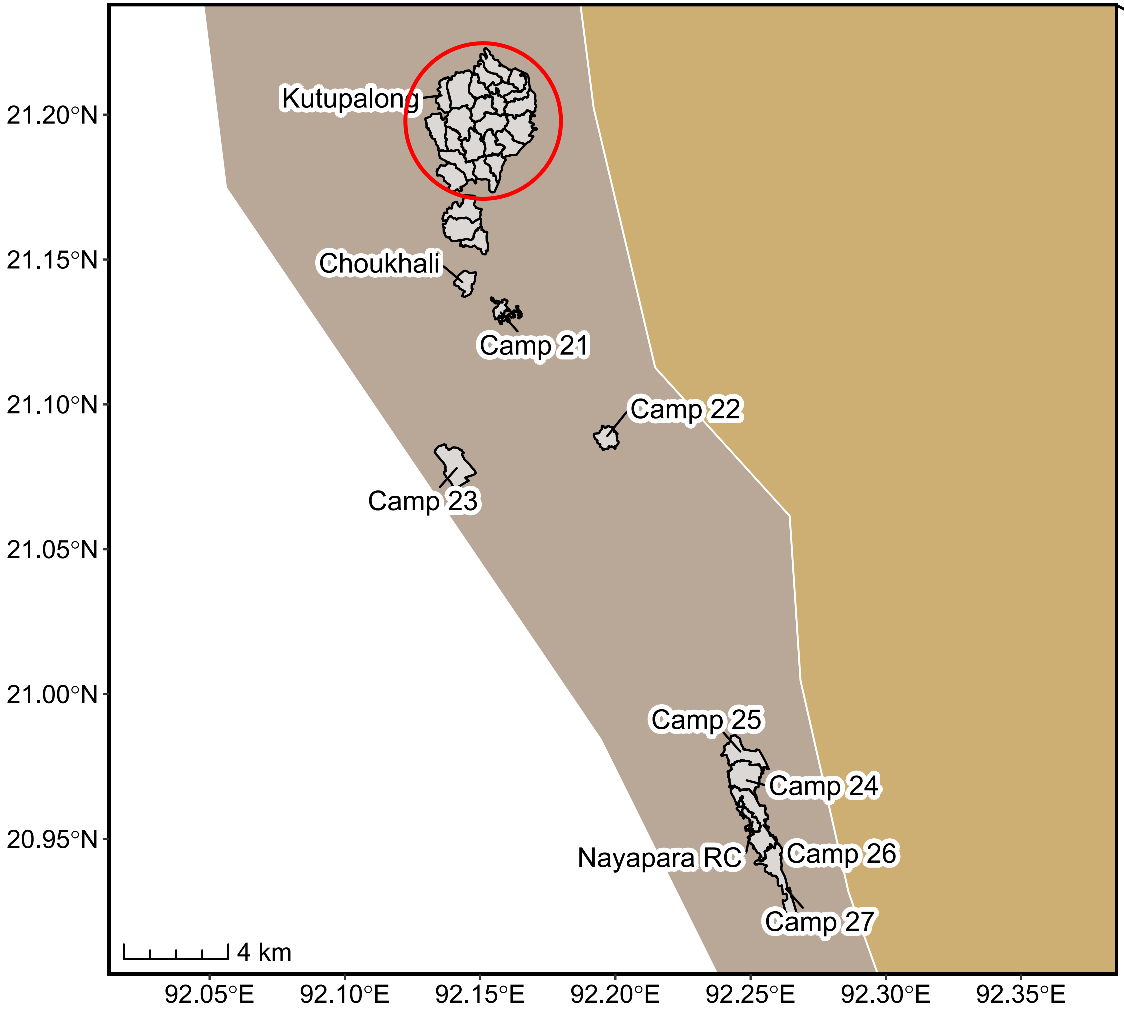
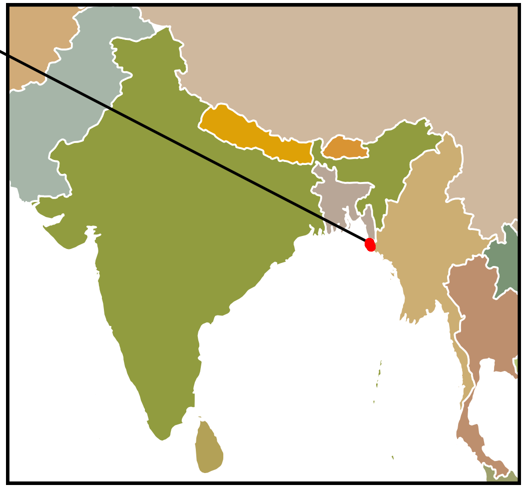


Fig 2. Map of affected districts (*Source: DMIC, CDMP www.dmic.org.bd*)

The variability of climate risks within the Cox's Bazar complex of camps requires localized humanitarian attention.

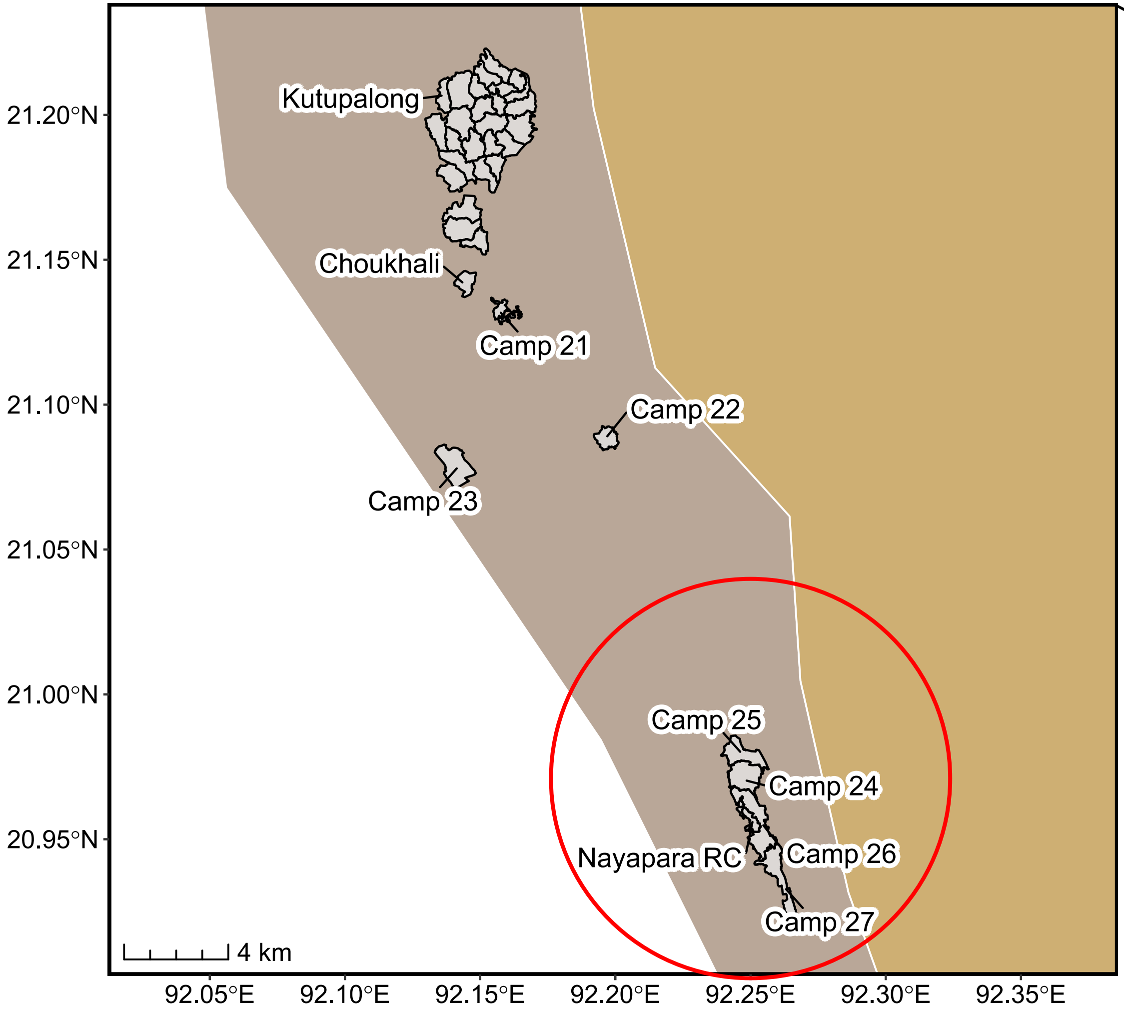
- Kutupalong is subject to riverine and flash floods.

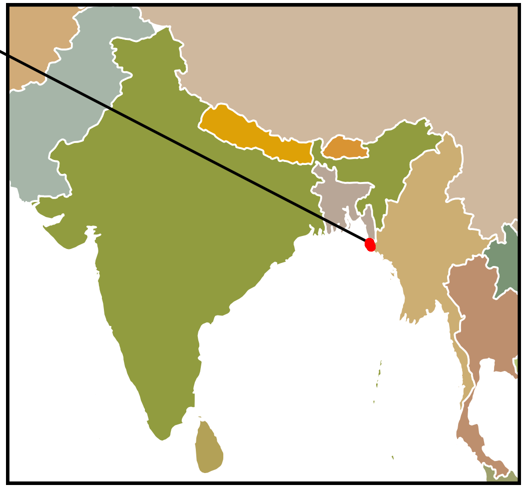




The variability of climate risks within the Cox's Bazar complex of camps requires localized humanitarian attention.

- Kutupalong is subject to riverine and flash floods.
- Nayarpara and surrounding camps are at risk to three types of floods: flash, riverine, and coastal.





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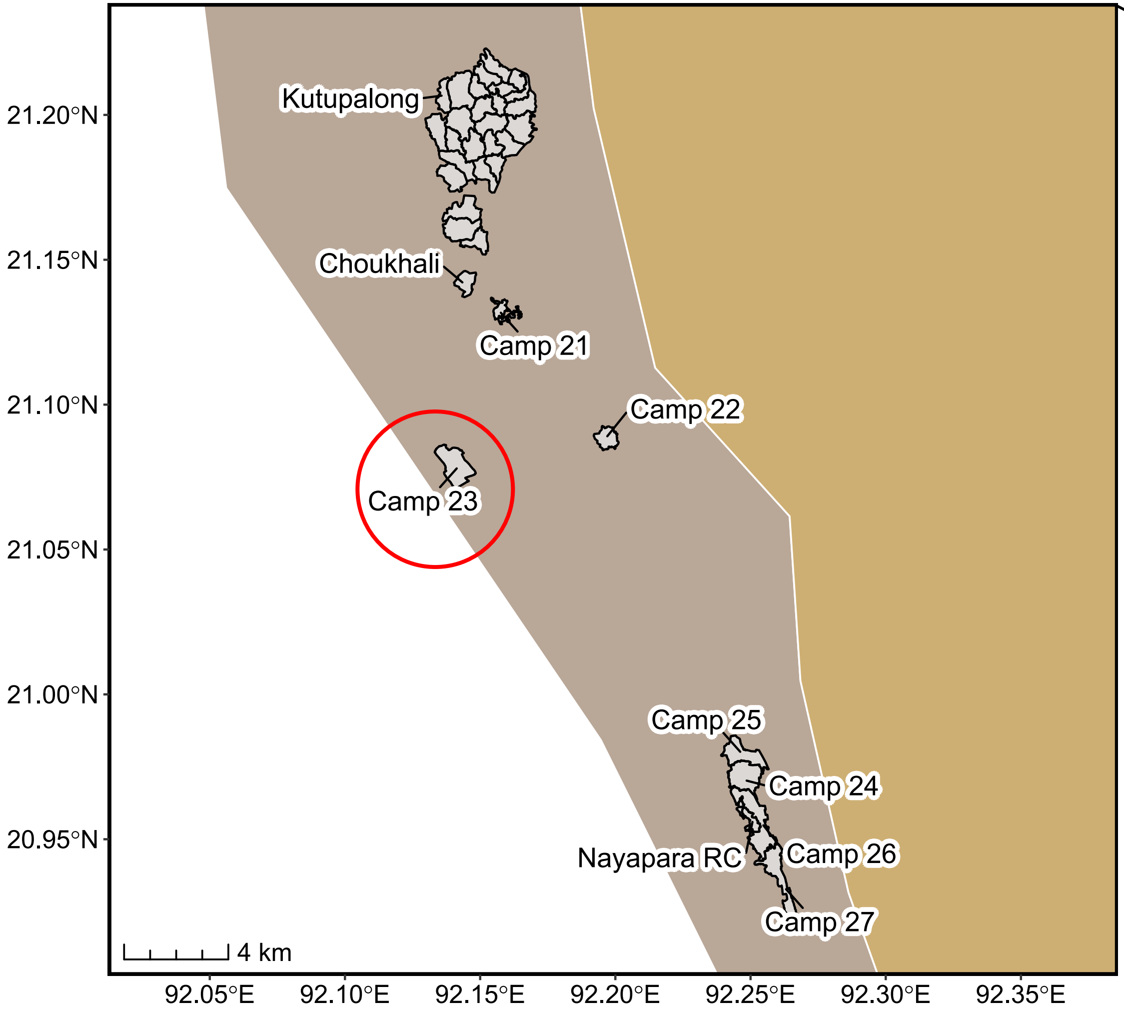
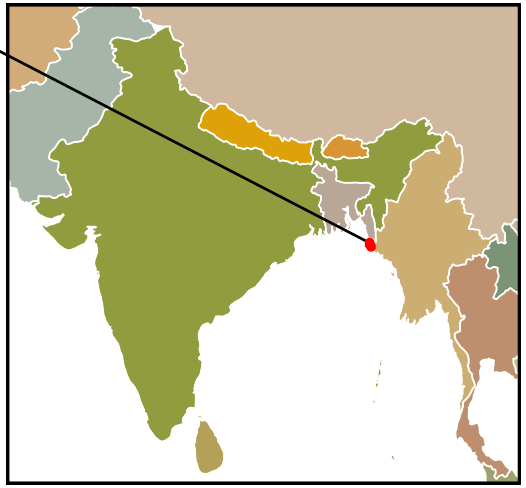
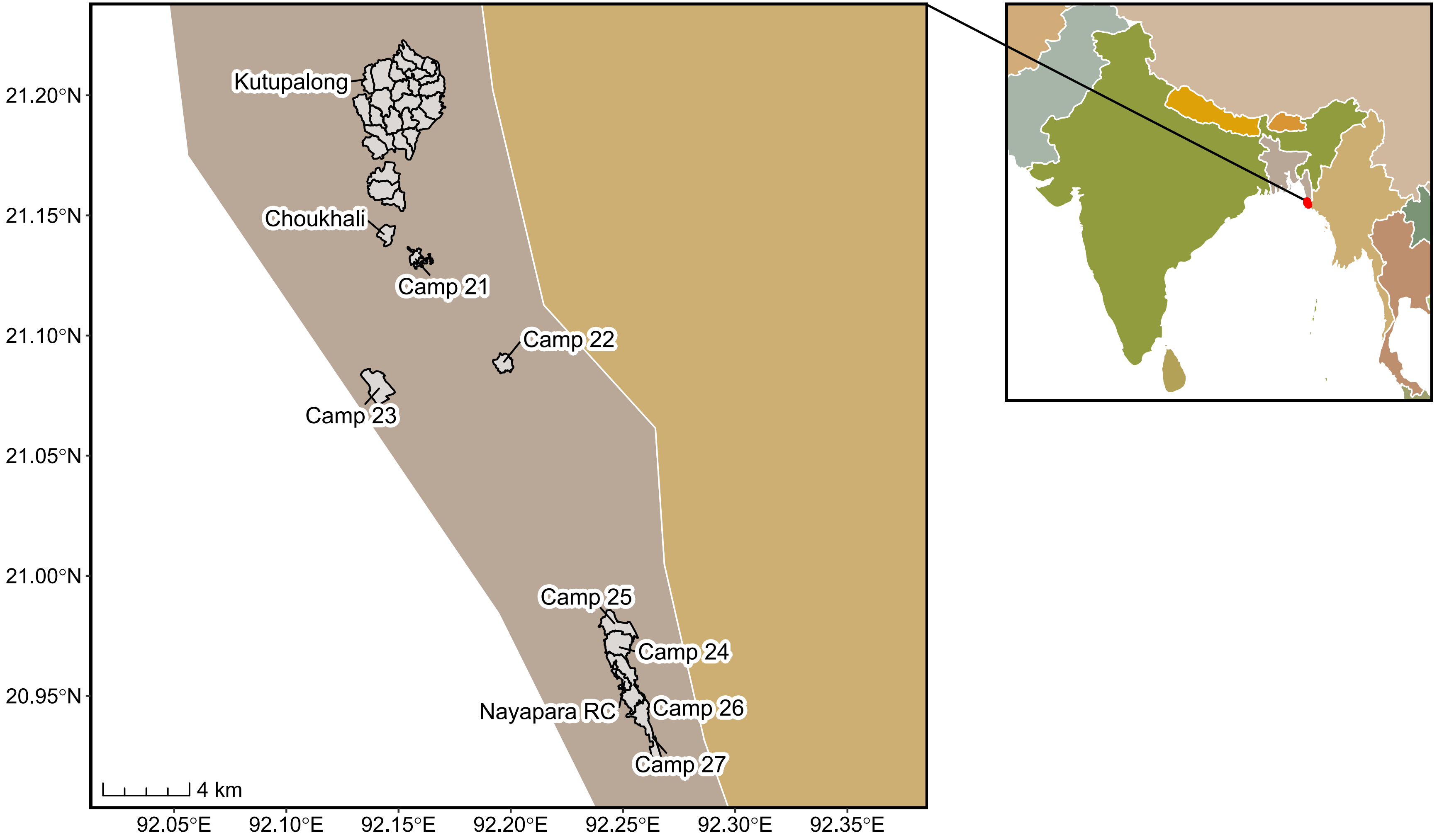
- Nayarpara and surrounding camps are at risk to three types of floods: flash, riverine, and coastal.
- Camp 23 is primarily at risk to coastal flood.





There is also social variability within the Cox's Bazar complex of camps.

- Kutupalong camp is mainly inhabited by new arrivals.
- Other camps are more likely to have long-term refugees, some of whom have lived there for decades, as well as more recent arrivals.



To aid humanitarian decision-making processes related to climate hazards, this part of the training focuses on generating a composite index of environmental and climatic exposure that reflects multiple considerations.

- Since we can't say what the single most important factor may be across Cox's Bazar or necessarily identify what the "best" data are, we compromise and incorporate data that we know are relevant into an index that can be measured across all refugee camps and any other locations of interest.

This tutorial includes:

1) Data Access and Preprocessing
2) Overview of Methodology
3) Variable Selection Approach
4) Variable Selection
5) Study Location
6) Index Calculation
7) Results

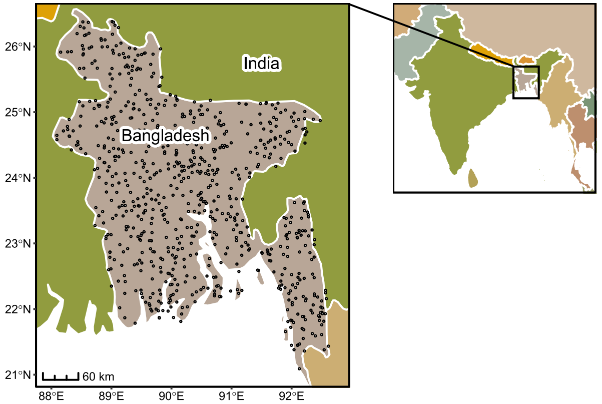
All data access and pre-processing are through Google Earth Engine.

- Our analysis will be performed in Google Colab (Jupyter notebooks)
  - https://colab.research.google.com/drive/1dhk66ZlhoGwtb368tEs5wWzIoE0y4vFd?usp=sharing
- We are using the following supplemental packages:
  - ee (Earth Engine)
  - folium
  - pandas
  - numpy
  - plotly
- The underlying datasets (slide 43) used to construct the index have been preprocessed in Google Earth Engine to speed up the tutorial.

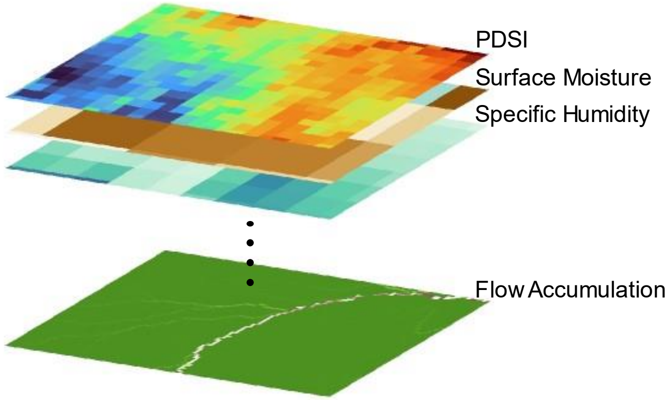
We will measure an index of exposure across study refugee camps relative to other sites in the host country of Bangladesh.

1) Define camp boundaries using greenest pixel composite and UNHCR camp locations

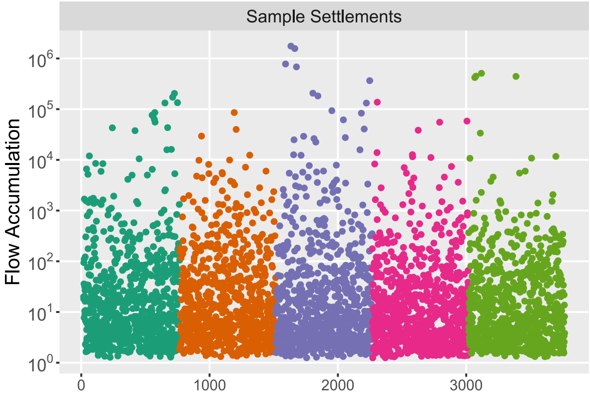
2) Generate 750 1-kilometer "simulated" camps within country border



3) Generate stack of 11 variable rasters, and compute mean of each per camp geometry



4) Review structure of data and impute missing data where necessary



5) Normalize data from 0 – 1, by country depending on variable interpretation

$$Normalized_i = \frac{x - \min(x)}{\max(x) - \min(x)}$$

For reverse scale normalization:

$$Normalized_i = \frac{\max(x) - x}{max(x) - \min(x)}$$

6) Calculate exposure and percentile by country for each camp

$$Exposure = \frac{\sum var\ 1 + var\ 2 \ldots}{11}$$

⋮

$$Percentile = \left(1 - \frac{Exposure\ Rank}{N\ camps/country} \times 100\right)$$

The exposure index is based on multiple input variables.

Variables are selected based on:

1) Availability within Google Earth Engine
2) Relevance to site, climate, and geography (e.g., landslide triggers, seasonal rainfall patterns)
3) Coherence to existing climate vulnerability mapping literature

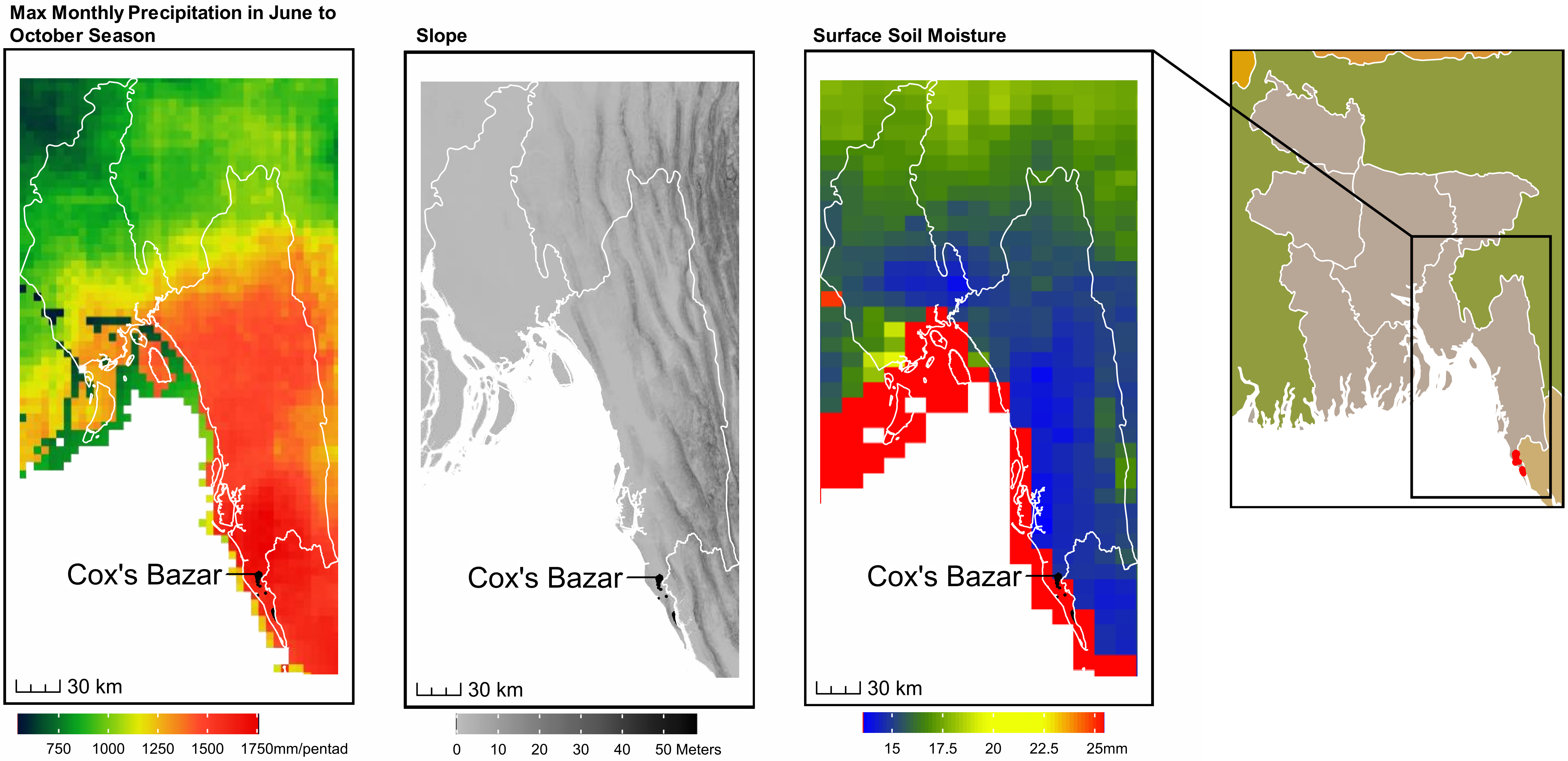
Variables were not included in the index if:

1) They are not observed within study camps over the time series
2) They are highly correlated with another variable, and less representative of the element of exposure that the index is attempting to capture (e.g., subsurface soil moisture was nearly perfectly correlated with surface soil moisture)

Our 11 index variables reflect regionally relevant climate, weather, and geophysical conditions.

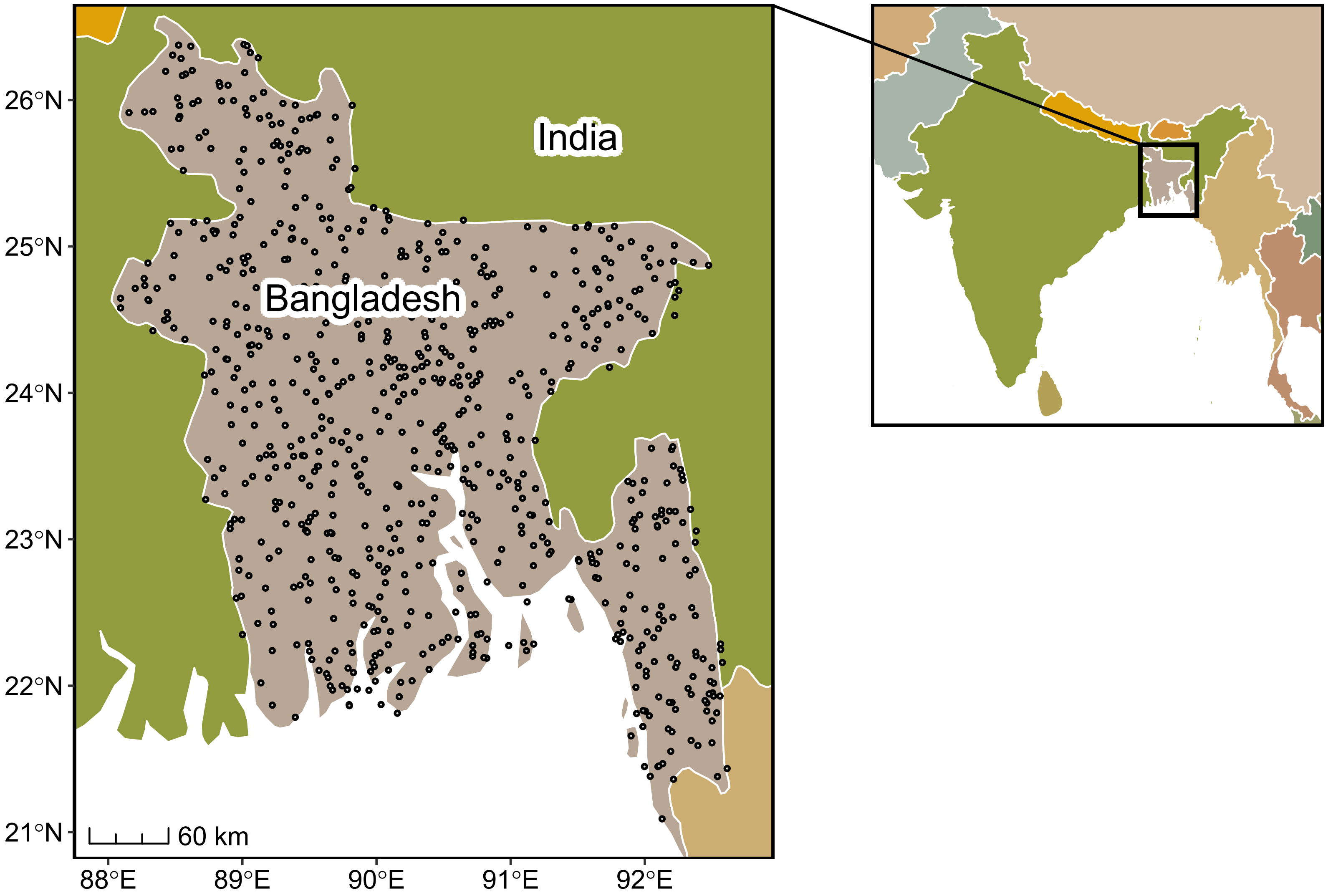
	Variable	Spatial Resolution	Source
Climate and Weather	Maximum Monthly Precipitation in June to October Season	0.05°	UCSB CHIRPS
	PDSI Average	0.04°	TerraClimate Palmer Drought Severity Index
	Temperature Anomaly	2.5°	NCEP/NCAR Reanalysis Data, Surface Temperature
	Annual Daytime Average Surface Temperature	2.5°	CFSV2: NCEP Climate Forecast System Version 2 (6-Hourly Products; Average temperature 2m above ground)
	Specific Humidity	0.1°	FLDAS
	Change in Annual Precipitation Accumulation	0.05°	UCSB CHIRPS Pentad
	Coefficient of Variation of Interannual Precipitation	0.05°	UCSB CHIRPS Pentad
Geophysical	Surface Soil Moisture	0.1°	NASA-USDA Enhanced SMAP Global Soil Moisture
	Slope	0.001°	SRTM Digital Elevation Data Version 4
	Flow Accumulation	0.004°	WWF HydroSHEDS Flow Accumulation
	Friction	0.01°	Oxford Global Friction Surface

All input variables have coverage across the entire country.



We'll simulate a population of potential refugee-hosting sites across the country.

- Our index aims to situate the exposure of refugee camps at Cox's Bazar relative to other sites across Bangladesh.
- In this example, we'll sample from across the country. In other countries, we may instead choose to only sample within border regions that are typically home to refugee camps.



Generating 'Simulated' Camps

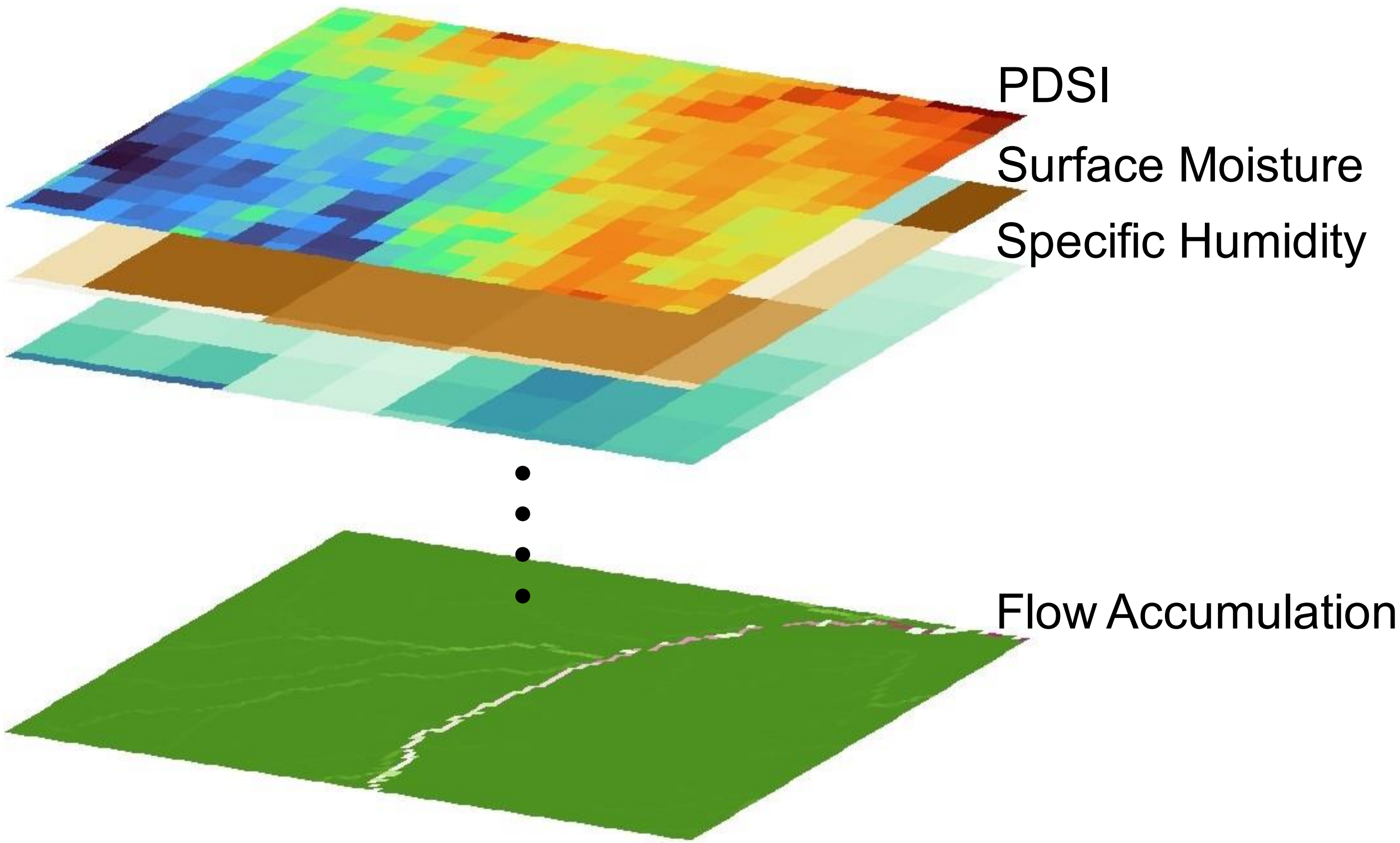
```
def grow_buffers(country):
    country_boundary = ee.Feature(ee.FeatureCollection('USDOS/LSIB_SIMPLE/2017').filterMetadata('country_na',
'equals', country).first())

    seasonality = ee.Image('JRC/GSW1_0/GlobalSurfaceWater').select('seasonality')
    water_mask = seasonality.lte(1).unmask(1);
    permanent_water_masked = water_mask.updateMask(water_mask).eq(1)

    water_out = permanent_water_masked.reduceToVectors(**{
        'geometry': country_boundary.geometry(),
        'scale': 500,
        'geometryType': 'polygon',
    })
    return water_out
```

Generating 'Simulated' Camps

```
def gen_random_points(countries, num_points):
    random_points = []

    for idx, country in enumerate(countries):
        curr_country_geo = grow_buffers(country)

        curr_pts = ee.FeatureCollection.randomPoints(curr_country_geo, num_points, 1)
        curr_pts = curr_pts.map(lambda point: point.set({"country": country}))
        curr_pts = curr_pts.map(lambda point: point.buffer(1000))

        random_points.append(curr_pts)

    sample_camps = ee.FeatureCollection(random_points).flatten()

    task = ee.batch.Export.table.toAsset(**{
        'collection': sample_camps,
        'description':'sample_camps',
        'assetId': 'ASSET_LOCATION'
    })
    task.start()

    return sample_camps
```

With our sites identified, we'll create a single 'stacked' dataset that includes all index variables.

- All data are georeferenced.
- Input layers can be included in a single multi-band image even though spatial resolutions and nominal extent vary.
- We clip the 'stacked' image by feature collection.
- Finally, we calculate the mean value of each variable in our study refugee camps and in the 1-kilometer region surrounding simulated sites.



Creating Raster Stack

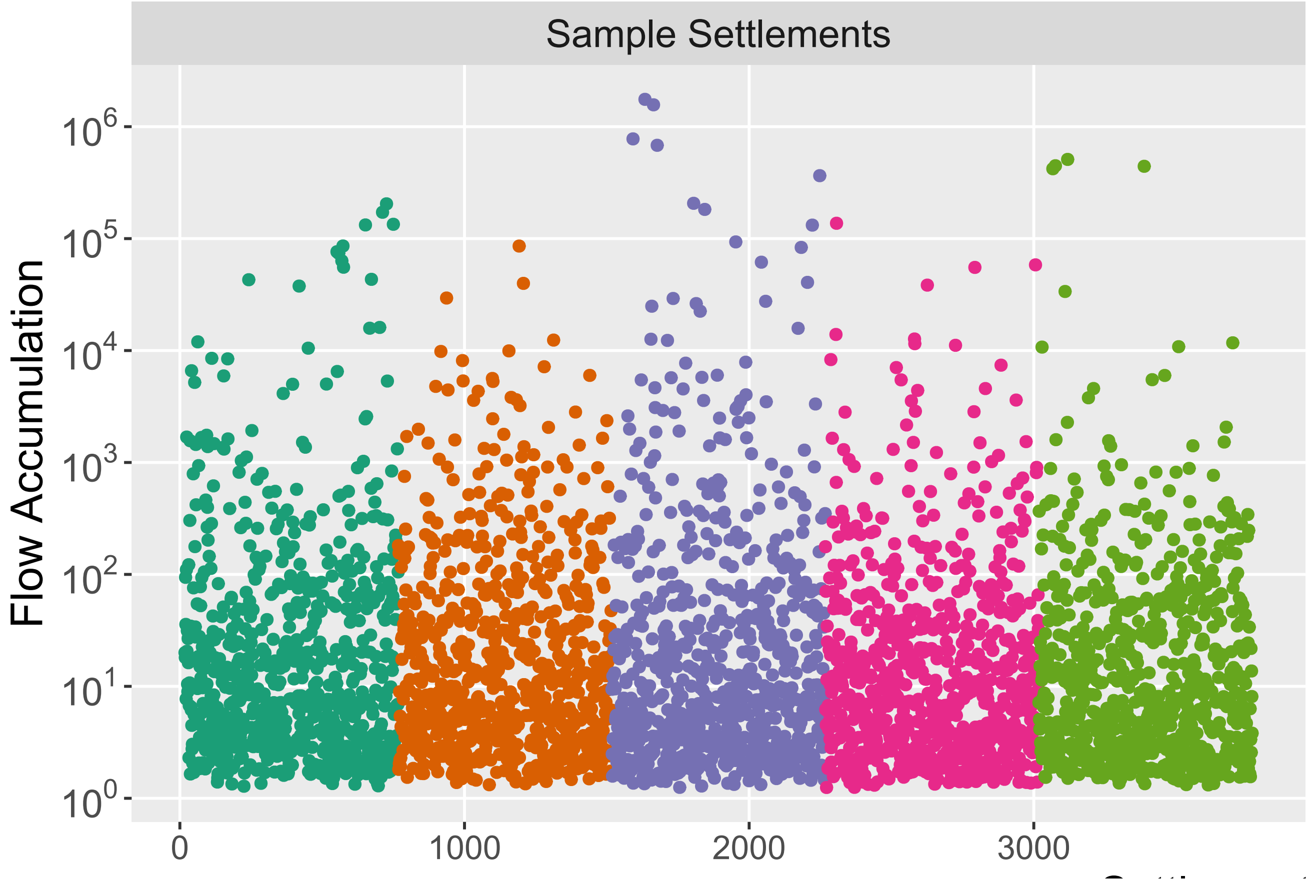
```
def concatenate_all_layers():
    return ee.Image.cat([
                         population_change_per_area(),
                         specific_humidity(),
                         surface_soil_moisture(),
                         subsurface_soil_moisture(),
                         average_annual_precip_change(),
                         evi_change(),
                         flow_accumulation(),
                         slope(),
                         friction(),
                         mean_pdsi(),
                         seasonal_precipitation_max(),
                         coefficient_variation_ndvi(),
                         interannual_coefficient_variation_precipitation(),
                         daytime_maximum_temperature(),
                         temperature_anomaly()
                                ])
```

Processing Individual Layers for Inclusion in the Index

```python
def process_layers(feature_collection, file_name):

    all_layers = concatenate_all_layers().clipToCollection(feature_collection)
    forest_loss_image = forest_loss().clipToCollection(feature_collection)

    feature_collection_data = all_layers.reduceRegions(**{
        'collection': feature_collection,
        'reducer': ee.Reducer.mean(),
        'scale': 30,
        'tileScale': 4
    })
    task = ee.batch.Export.table.toAsset(**{
        'collection': feature_collection_data,
        'description':'{name}'.format(name=file_name),
        'assetId': 'ASSET_LOCATION/{name}'.format(name=file_name)
    })
    task.start()
```

Next, we'll address missing values in the distributions of our variables.

- Since our source data covers nearly all of Bangladesh, we have very few clean-up tasks.
- The distributions of two variables requires **imputation** (replacing missing data with the mean value): *specific humidity* and *surface soil moisture*
- The *flow accumulation* variable and two ancillary variables (forest loss and the coefficient of variation of NDVI) require **winsorization** (outlier removal) at the 99th percentile



With the diverse range of values across input variables, we need to normalize each dataset before calculating the index.

```
def normalize_winsorized_data(dataset, min_max, max_min):
    dataset[min_max] = dataset.groupby('country')[min_max].transform(lambda x: ((x - x.min()) / (x.max() - x.min())))
    dataset[max_min] = dataset.groupby('country')[max_min].transform(lambda x: ((x.max() - x) / (x.max() - x.min())))
    return dataset
```

$$Normalized_i = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Min-Max normalization

$$Normalized_i = \frac{\max(x) - x}{max(x) - \min(x)}$$

Max-Min normalization

- We **normalize** all input data to a single, shared data range of 0-1 before inclusion in the index.
- We apply a Max-Min normalization for all variables, except for *surface soil moisture*.
- For *surface soil moisture*, we use a Max-Min normalization, since reduced surface soil moisture could lead to desertification and lower agricultural yields.

Finally, we calculate the relative exposure of study refugee camps using a uniform weighting scheme.

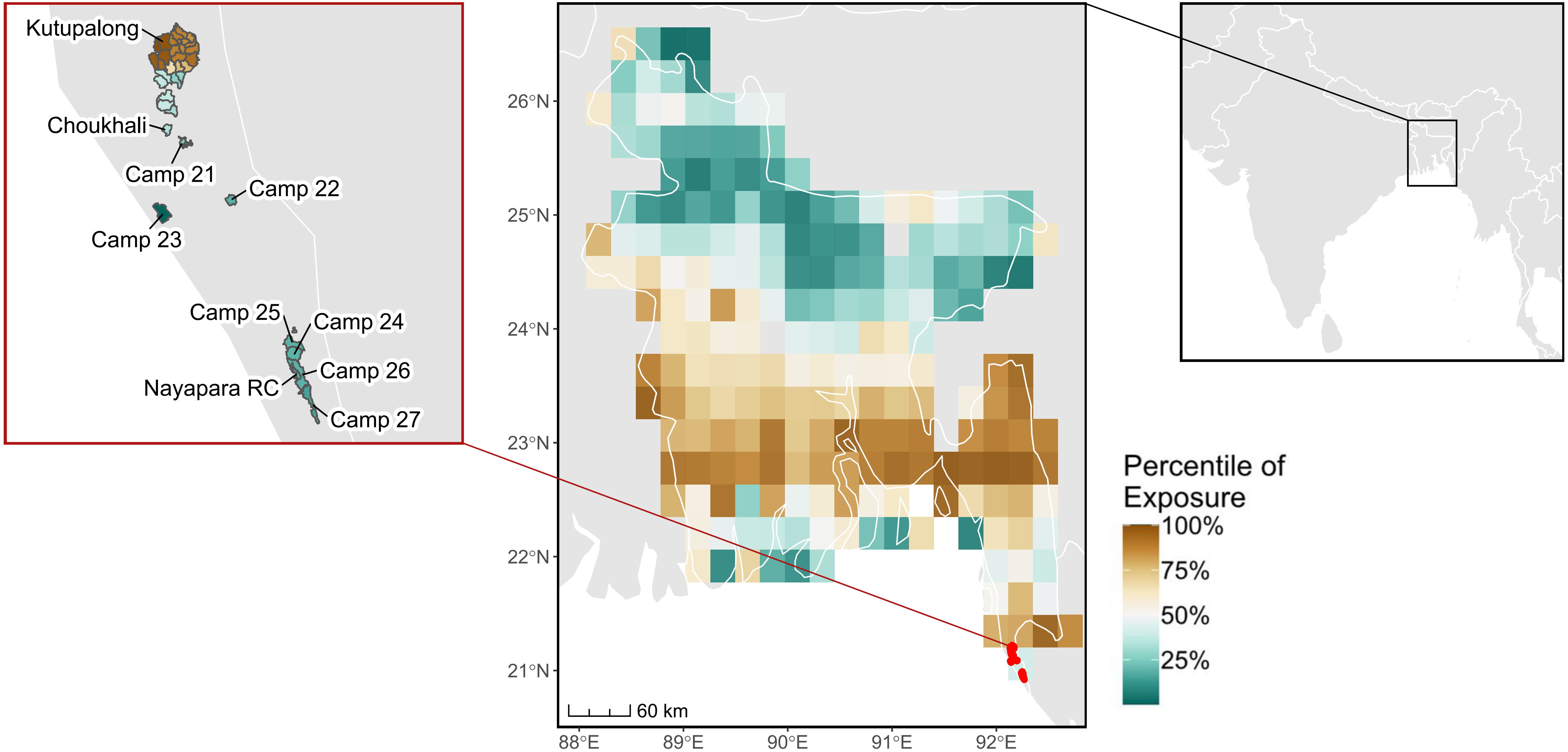
```
def generate_index(index_vars, normalized_dataset):
    normalized_dataset['exposure'] = normalized_dataset.loc[:, index_vars].sum(axis=1)
    normalized_dataset['exposure'] = normalized_dataset['exposure'].div(len(index_vars))
    normalized_dataset['rank'] = normalized_dataset.groupby('country')['exposure'].rank(method="dense",
ascending=False)
    normalized_dataset['percentile'] = normalized_dataset.groupby('country')['exposure'].rank(pct=True)

    return normalized_dataset
```

$$Exposure = \frac{\sum var\ 1 + var\ 2 \ldots}{11}$$

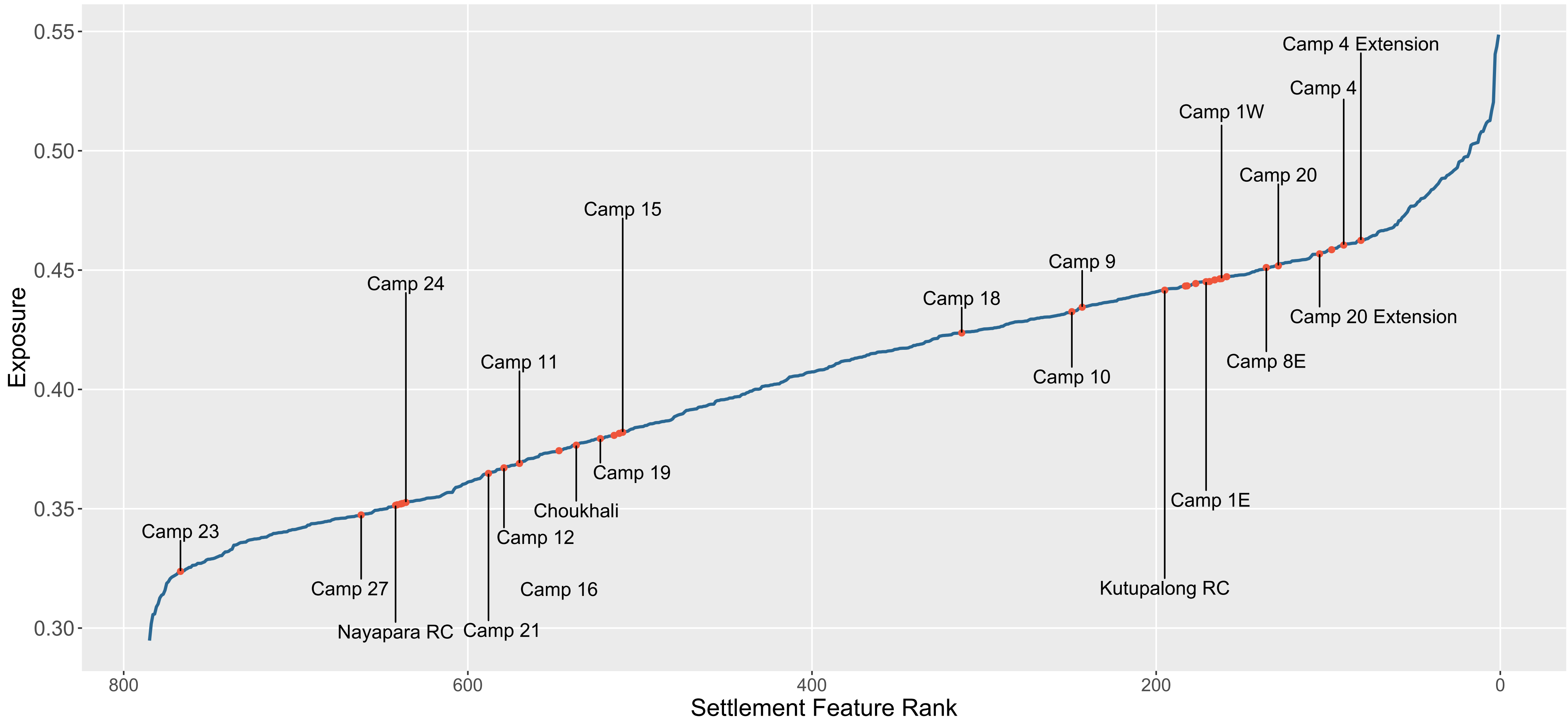
$$\vdots$$

$$Percentile = \left(1 - \frac{Exposure\ Rank}{N\ camps/country} \times 100\right)$$

We see a broad range of exposure across Bangladesh and across our study refugee camps.



We can compare the relative exposure of all refugee camps in Cox's Bazar to each other as well as simulated sites across the country.



Suggestions for Measuring Climate Exposure in Refugee Settings

- There are a variety of modifications to tailor the index to best reflect the geography and regionally relevant hazards and risks, especially those identified by refugees, themselves.
- Results should be validated through conversation with camp managers and refugees and through ground truthing with observed hazard events or other empirical data whenever possible.
- Caution should be taken by applied scientists and camp managers to acknowledge the uncertainties of the input data and exposure index, itself, and consider which thresholds of uncertainty/certainty are sufficient to justify prioritization and de-prioritization actions around climate hazard mitigation or resilience-building.

List of Citations

- *Livelihood Impacts of Flash Floods in Cox's Bazar District, Bangladesh* by Ahmed et al. (2019)
- *Earth Observations for Anticipatory Action: Case Studies in Hydrometeorological Hazards* by Kruczkiewicz et al. (2021)
- *Flood Risk and Monitoring Data for Preparedness and Response: From Availability to Use* by Kruczkiewicz et al. (2021)
- *Charting a justice-based approach to planned climate relocation for the world's refugees* by Peters & Van Den Hoek (2021)
- *Geospatial indicators of exposure, sensitivity, and adaptive capacity to assess neighbourhood variation in vulnerability to climate change-related health hazards* by Yu et al. (2021)

Questions?

- Please enter your questions in the Q&A box. We will answer them in the order they were received.
- We will post the Q&A to the training website following the conclusion of the webinar.

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  - www.conflict-ecology.org
- Training Webpage:
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-humanitarian-applications-using-nasa-earth-observations

Thank you for your attention throughout this training!