# Capstone: Predicting a Climate Refugee Crisis

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# Roadmap

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03 Data and Modeling

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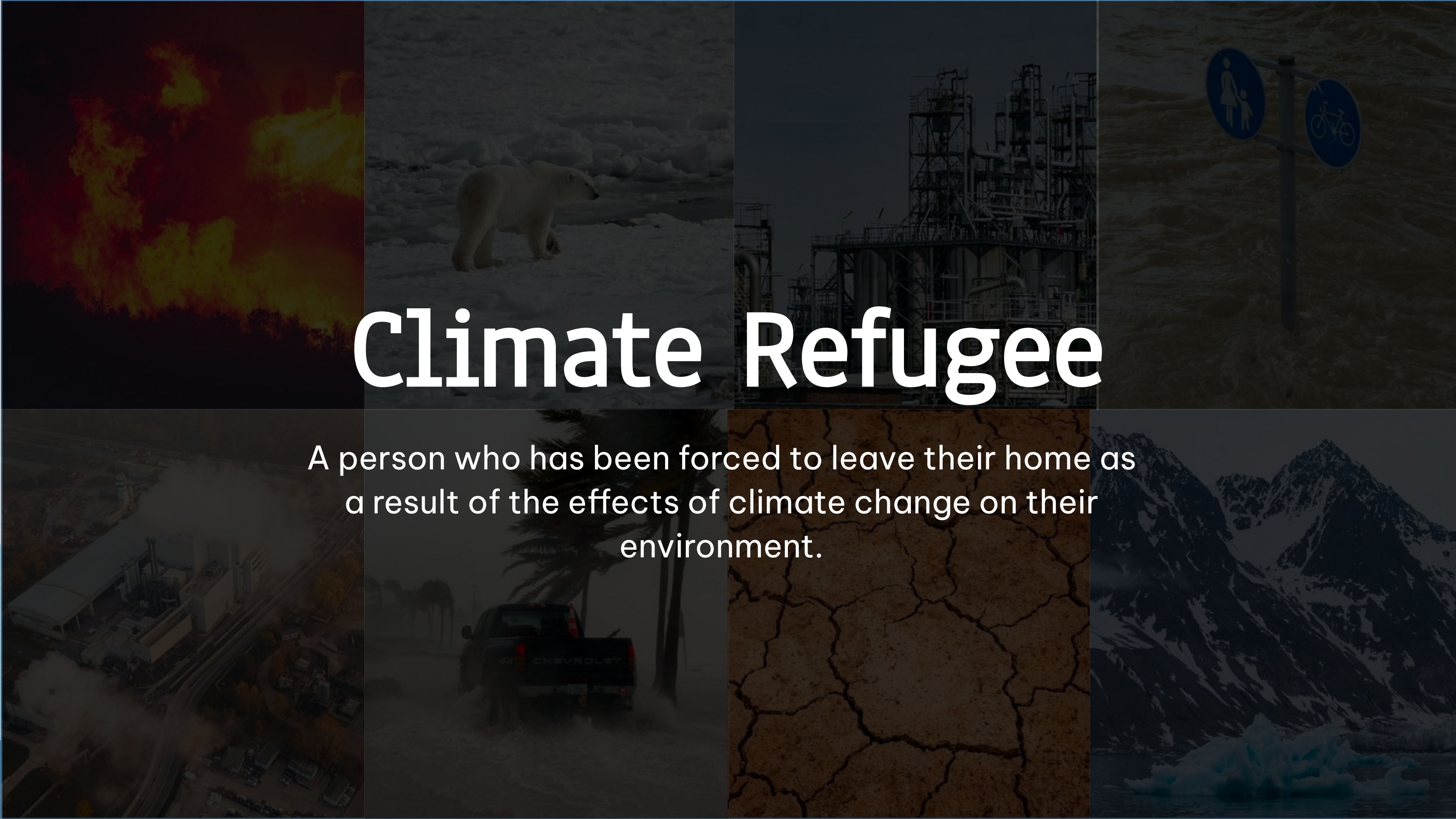
CHEVROLET



# Climate Refugee

A person who has been forced to leave their home as a result of the effects of climate change on their environment.

# Internally Displaced Person (IDP)

Persons who have been forced to leave their homes as a result of natural or human-made disasters, and who have not crossed an internationally recognized state border.

# The Problem

## 31.8 Million

people were internally displaced within the borders of their country due to weather-related hazards in 2022

## 60%

of the 31.8 million displacements were a result of floods in 2022

## 1.2 Billion

people are predicted to be displaced globally by 2050 due to climate change and natural disasters. This is about 15% of the current world poplation.

Yet, no predictive technologies exist to help mitigate a climate refugee crisis.

# The Mission

Bring awareness to the neglect that the data in this field is experiencing and show the potential life-changing impact of complete, quality data.

# Our Model

A model that **predicts the relative level of internally displaced individuals** in a specific region *if a flood were to take place.*


# MVP Demo

https://www.figma.com/proto/7XYiW1g9OGeivnKblfI3pY/Diving-Landing-Page?type=design&node-id=67-25&t=zTs43Q4hjzlEi1gQ-0&scaling=min-zoom&page-id=0%3A1&starting-point-node-id=67%3A25

# Who Are We Targeting?

- Climate/Disaster Researchers
- Policy Influencers

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Climate/Disaster Researchers

Policy Influencers

Humanitarian Agencies

# Data and Modeling

# Solution

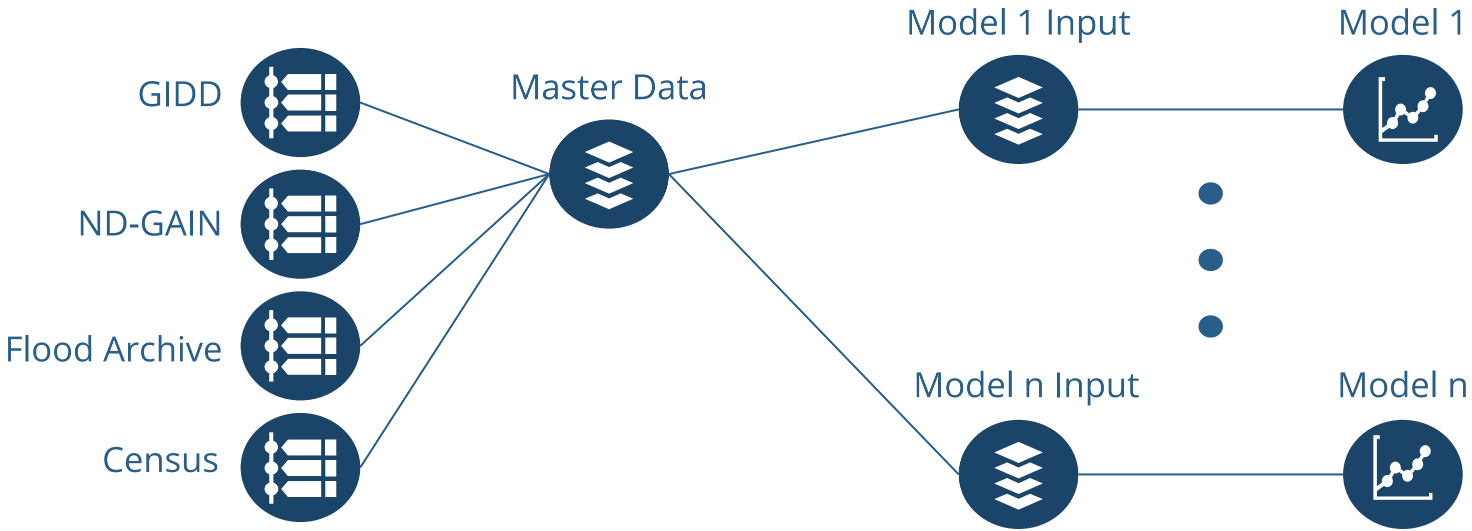
## The Model

- **Random Forest model** predicting a “low”, “medium”, or “high” level of displacement (relative to global events) with an accuracy of ~52%. This model outputs the most **impactful features** in creating accurate predictions.
- **Support Vector Machine** predicts the raw number of IDPs. This is within 3000 IDPs 70% of the time

## The Data

- Currently, data in the wild is decentralized and unorganized.
- We have **specific recommendations** to address these issues in data collection
- Our data **combines four datasets** into one that encodes, for each event, the time/place, magnitude, causes, and features of the country such as population measures and various factors related to preparedness for natural disasters

# Data Pipeline



# Raw Data Sources

## GIDD

| | ISO3 | Country / Territory | Year | Event Name | Date of Event (start) | Disaster Internal Displacements | Disaster Internal Displacements (Raw) | Hazard Category | Hazard Type | Hazard Sub Type |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | TLS | Timor-Leste | 2013 | Babulu gale | 2013-01-17 | 5 | 5 | Weather related | Storm | Storm |

## ND-GAIN

| | ISO3 | Name | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | ... | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | AFG | Afghanistan | 0.496497 | 0.496497 | 0.496497 | 0.496497 | 0.496497 | 0.496497 | 0.496497 | 0.496497 | ... | 0.175065 | 0.178628 | 0.201495 | 0.200231 | 0.261156 | 0.238742 | 0.21024 | 0.224049 | 0.213706 |

## Flood Archive

| | Country | Area | Began | Ended | MainCause | Severity | ISO3 | Year Month |
|---|---|---|---|---|---|---|---|---|
| 0 | Indonesia | 2178.65 | 2008-01-02 | 2008-01-06 | Heavy rain | 1.0 | IDN | 2008-01 |

## Census

| | Name | Region | GENC | Year | Population | Population Density (People per Sq. Km.) | Net international migrants, both sexes | ISO3 |
|---|---|---|---|---|---|---|---|---|
| 0 | Afghanistan | 2008,Afghanistan | AF | 2008 | 27,703,539 | 42.5 | 222,570 | AFG |

# Master Data

| | IDPs from Event | Economics | Governance | Social | Capacity | Ecosystem | Exposure | Food | Habitat |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 270 | 0.178628 | 0.172592 | 0.335777 | 0.757451 | 0.507907 | 0.480512 | 0.580916 | 0.537736 |
| 1 | 740 | 0.201495 | 0.193780 | 0.341216 | 0.732208 | 0.503280 | 0.480512 | 0.576083 | 0.539343 |
| 2 | 244 | 0.201495 | 0.193780 | 0.341216 | 0.732208 | 0.503280 | 0.480512 | 0.576083 | 0.539343 |

| | Health | Infrastructure | Sensitivity | Area | Began | Ended | MainCause | Severity | Duration | Magnitude |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.832165 | NaN | 0.437181 | 14653.47 | 2013-04-23 | 2013-04-29 | Torrential Rain | 1.0 | 6.0 | 11.384192 |
| 1 | 0.828587 | NaN | 0.436659 | 83722.34 | 2014-04-20 | 2014-05-16 | Torrential Rain | 1.5 | 26.0 | 14.998823 |
| 2 | 0.828587 | NaN | 0.436659 | 83722.34 | 2014-04-20 | 2014-05-16 | Torrential Rain | 1.5 | 26.0 | 14.998823 |

| | Population | Population Density (People per Sq. Km.) | Net international migrants, both sexes | Scaled_IDP |
|---|---|---|---|---|
| 0 | 31,098,161 | 47.7 | -67,219 | 270 |
| 1 | 31,809,829 | 48.8 | -58,115 | 740 |
| 2 | 31,809,829 | 48.8 | -58,115 | 245 |

# Modeling Approach

## Feature Engineering

Combined a few features (i.e. duration, severity, and area)

## Skewed Data

Performed logarithmic transformation on IDP counts for flood events. Normalized all inputs

## Data Binning

Binned IDP counts two or three quantiles. Our problem then becomes a multiclass classification task.

# Model Selection

| | |
|---|---|
| **Neural Network** | • Able to capture nonlinear complex patterns<br>• High accuracy on categorical models |
| **Support Vector Machine** | • Performs well in high dimensional spaces<br>• High accuracy for regression model |
| **Random Forest** | • Good accuracy and robustness to overfitting<br>• Provides a measure of feature importances for interpretability |

# Model Results Summary

| Model Type | Output | Recall | Precision | Test Accuracy |
|---|---|---|---|---|
| **NN** | 3 Classes | **H** 0% \| **M** 0% \| **L** 100% | **H** 0% \| **M** 0% \| **L** 32% | 33.90% |
| **NN** [Log + Norm] | 3 Classes | **H** 60% \| **M** 8% \| **L** 76% | **H** 53% \| **M** 38% \| **L** 43% | 47.20% |
| **RF** [Log] | 3 Classes | **H** 50% \| **M** 43% \| **L** 62% | **H** 61% \| **M** 42% \| **L** 54% | 52.00% |
| **SVM** [Norm] | 3 Classes | **H** 38% \| **M** 30% \| **L** 53% | **H** 48% \| **M** 34% \| **L** 40% | 40.59% |
| **NN** [Log + Norm] | 2 Classes | **H** 56% \| **L** 67% | **H** 67% \| **L** 68% | 66.30% |
| **NN** [Log + Norm] | Continuous | - | - | **RMSE** 167168 |
| **SVM** [Log + Norm] | Continuous | - | - | **RMSE** 225414 |
| **RF** [Log] | Continuous | - | - | **RMSE** 258013 |

*Norm = Normalized variables*
*Log = Log-transformed variable(s)*

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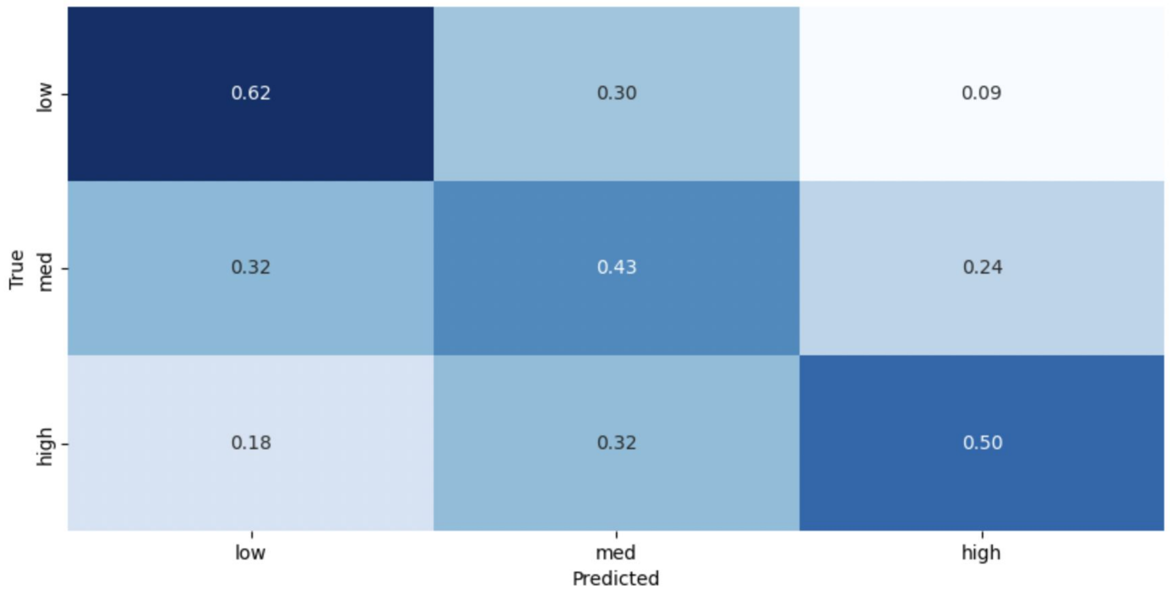
# Main Models

# Random Forest Classification




## Findings

- Achieved overall test accuracy of ~52%
- Top features included magnitude and other ND GAIN indicators (i.e. infrastructure, social, economic, etc)
- Confusion matrix and class recall scores showed model did best among all models for ‘Medium’ class

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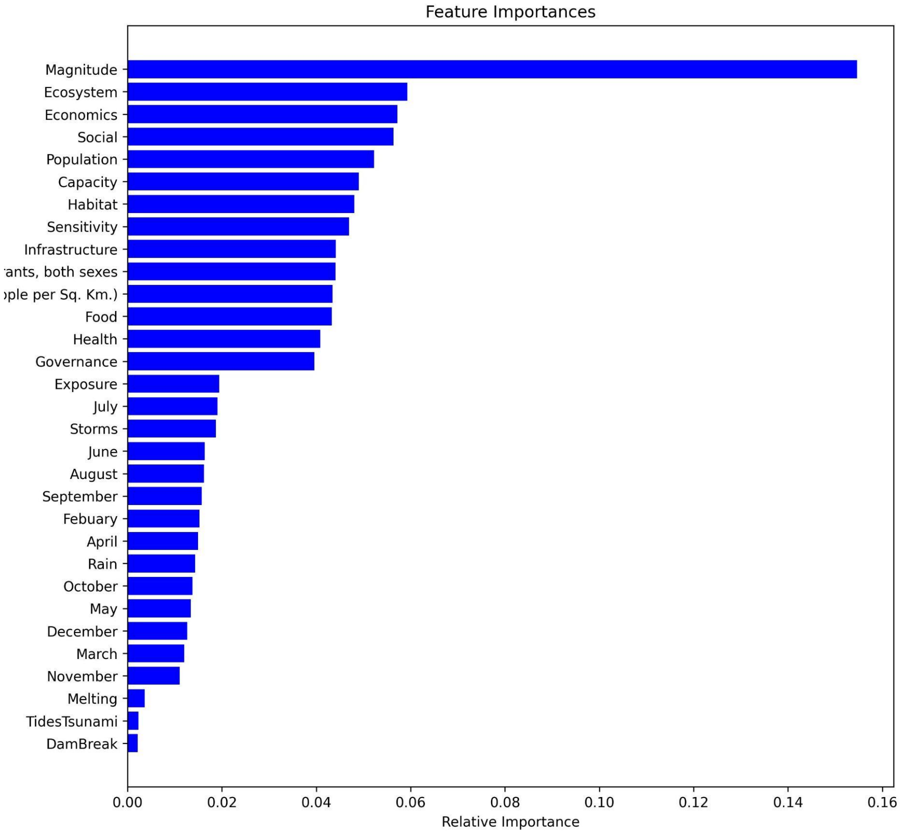


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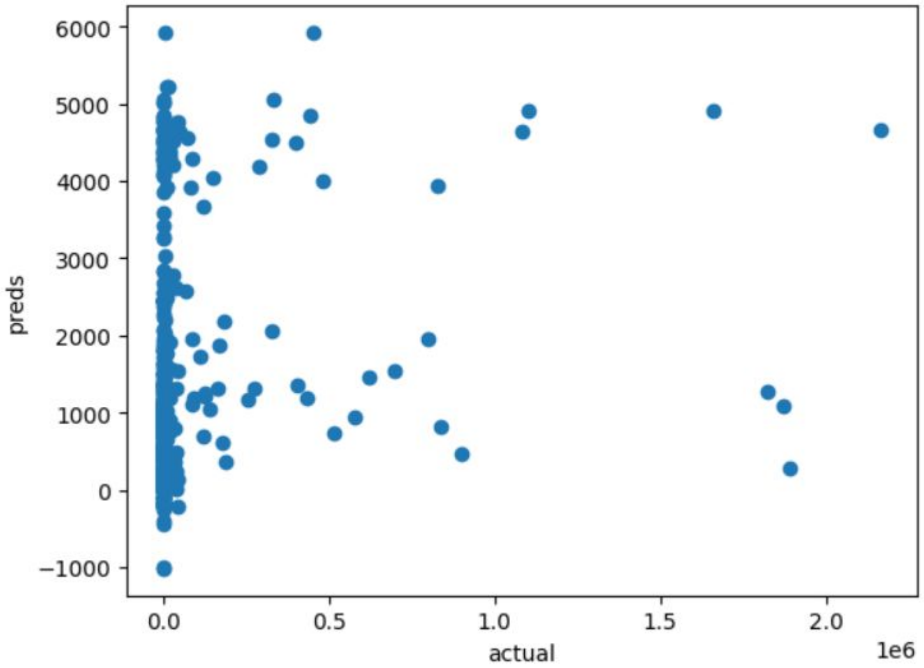
# SVM Regression




### Findings

- SVM with PCA IDP predictions were within 3000 IDP counts of true value ~72% of the time
- RMSE was fairly high (above 200,000)
- Group up data to find patterns and also sensitive to outliers or large events

# Wrap-Up

# Challenges

## Data Availability

- Data access
- Lack of observations
- Lack of spatial information
- Limits of coverage and sharing

## Event Definition

- Neglected field
- Varying definitions of what counts as a distinct flood event

# Our Contribution

## Current Industry Steps

- Reactive: only makes short term predictions after the event has occurred to allocate resources
- Have monitoring stations to predict IDP counts at those regions only

## Our Improvements

- Takes other factors into account (environment, economic, social, and population density) in predicting IDP counts
- Makes IDP count predictions in the event of a flood, meaning one would only have to look at flood data
- Focuses on root causes

# Next Steps

Use a unified global system better assess the impacts of climate change on flood displacement risk

Create a publicly available, up to date, centralized database where all the scattered information can come together

# Final Note

## 13 Weeks

Using data science to help predict a climate refugee crisis

## Limited Results

**By 2050 15% of the world's population will experience displacement**

## Continue with Trends

Where the most vulnerable will be most neglected

## Act Now

Help humanitarian agencies/governments prepare for the future

# Thank you for listening!

Any questions?

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