OCHA

Carnegie Mellon University

Predicting Food Insecurity

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Structure

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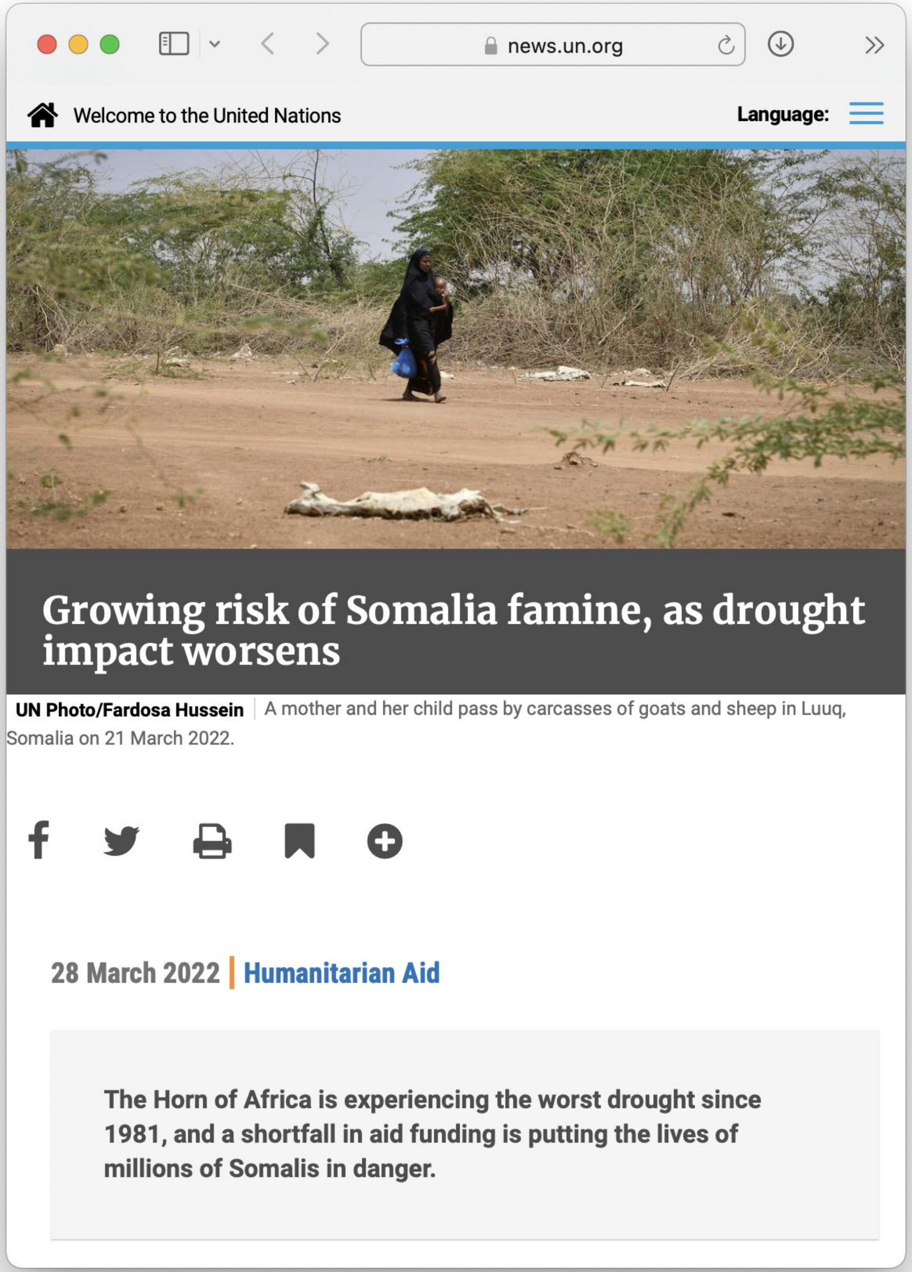
Target Problem

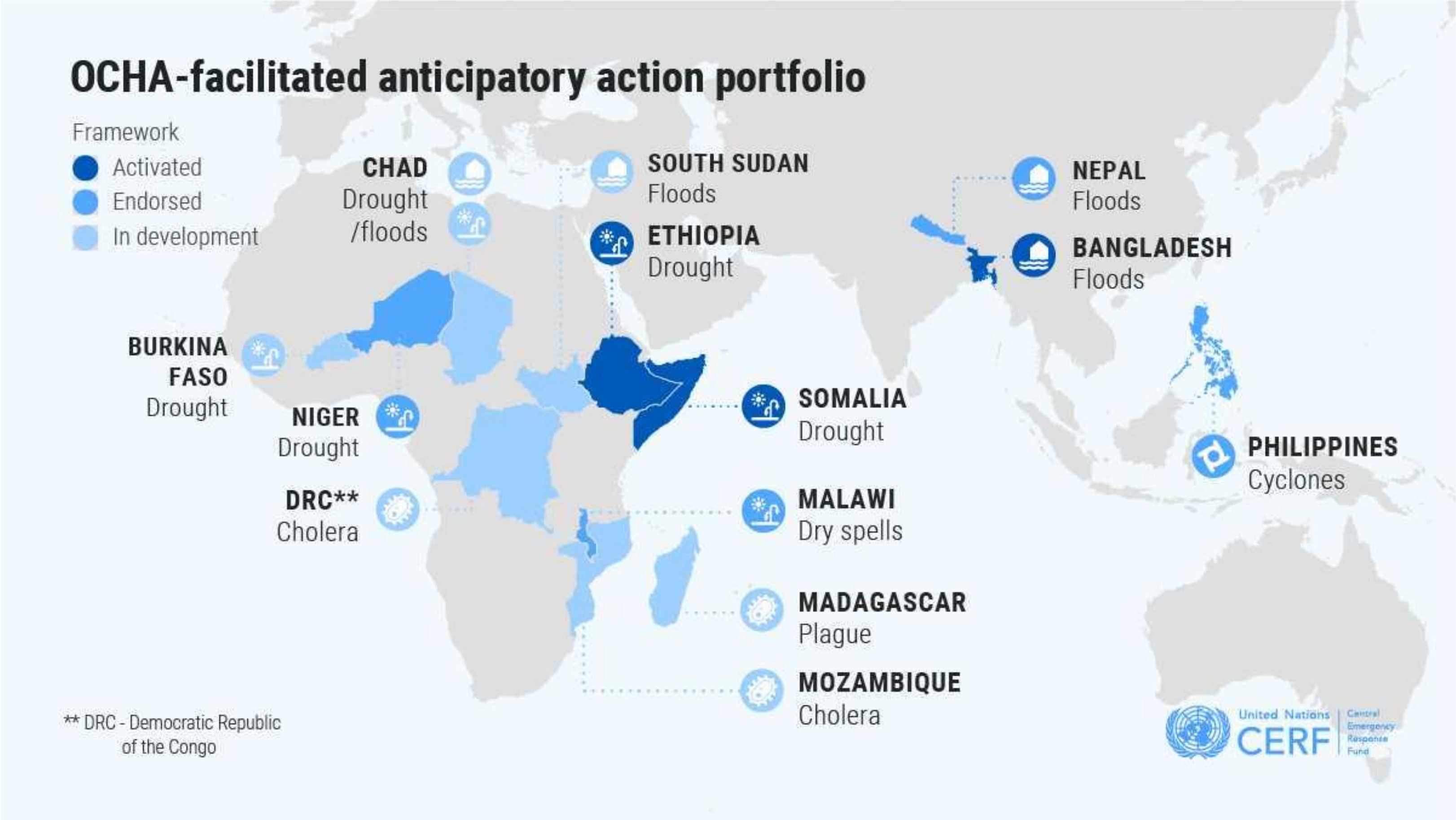
Food insecurity

- 20 million people facing food insecurity in the Horn of Africa
- Worst drought in 40 years



Sources: https://news.un.org/en/story/2022/04/1116442, https://news.un.org/en/story/2022/03/1114902

OCHA Food Insecurity Triggers
(United Nations Office for the Coordination of Humanitarian Affairs)



Source: https://www.unocha.org/our-work/humanitarian-financing/anticipatory-action

IPC levels

1 Generally food secure

More than 80% of households can meet basic food needs without atypical coping strategies

2 Moderately food insecure

For at least 20 percent of households, food consumption is reduced but minimally adequate without having to engage in irreversible coping strategies. These households cannot fully meet livelihoods protection needs.

3 Acute food and livelihood crisis

At least 20 percent of households have significant food consumption gaps OR are marginally able to meet minimum food needs only with irreversible coping strategies such as liquidating livelihood assets.

4 Humanitarian Emergency

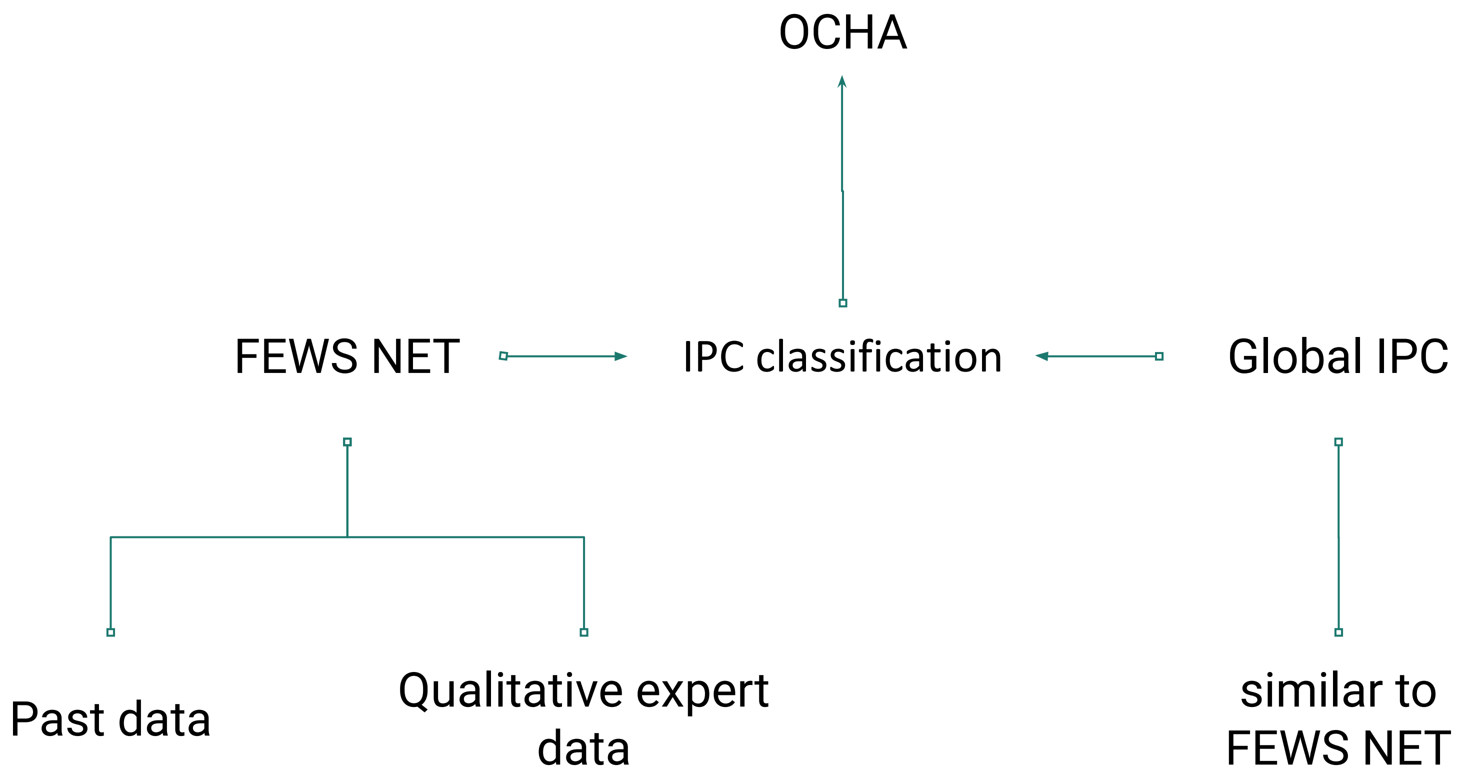
At least 20 percent of households face extreme food consumption gaps, resulting in very high levels of acute malnutrition and excess mortality.

5 Famine/Humanitarian Catastrophe

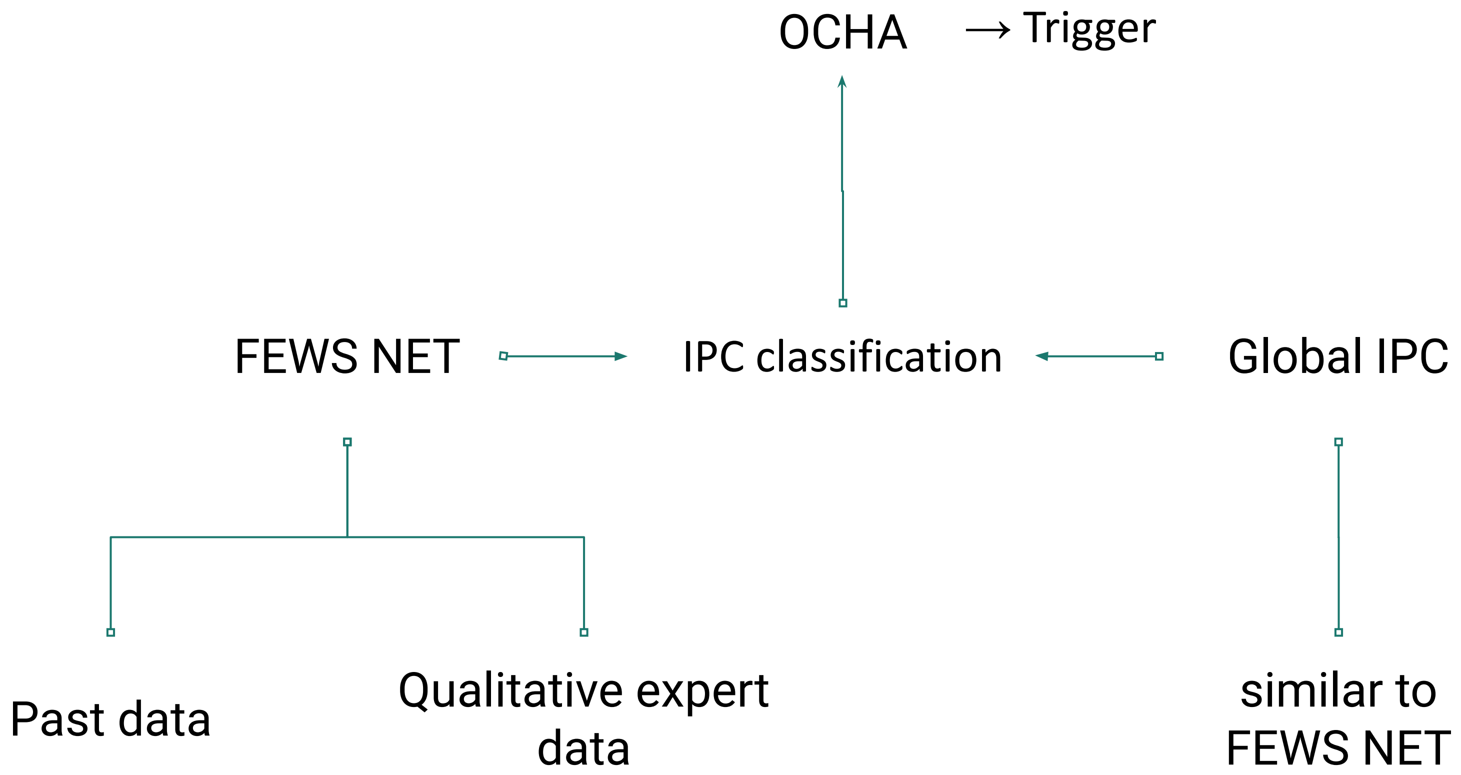
At least 20 percent of households face a complete lack of food and/or other basic needs and starvation, death, and destitution are evident; and acute malnutrition prevalence exceeds 30%; and mortality rates exceed 2 per 10,000 per day

Source: IPC Global Partners. 2008. **Integrated Food Security Phase Classification** Technical Manual. Version 1.1. FAO. Rome. ISBN: 978-92-5-106027-8

Current pipeline



Current pipeline



“Prediction” of food insecurity

```python
def define_trigger_percentage(row, period, level, perc):
    """Return 1 if percentage of population in row for period in level "level"
    or higher, equals or larger than perc."""
    # range till 6 cause 5 is max level
    cols = [f"{period}_{lev}" for lev in range(level, 6)]
    if np.isnan(row[f"pop_{period}"]):
        return np.nan
    if round(row[cols].sum() / row[f"pop_{period}"] * 100) >= perc:
        return 1
    else:
        return 0
```

Sources: https://github.com/OCHA-DAP/pa-anticipatory-action/blob/develop/src/indicators/food_insecurity/ipc_definemetrics.py and https://github.com/OCHA-DAP/pa-anticipatory-action/blob/develop/analyses/eth/notebooks/eth_ipc_trigger_analysis.ipynb

Problems with the status quo

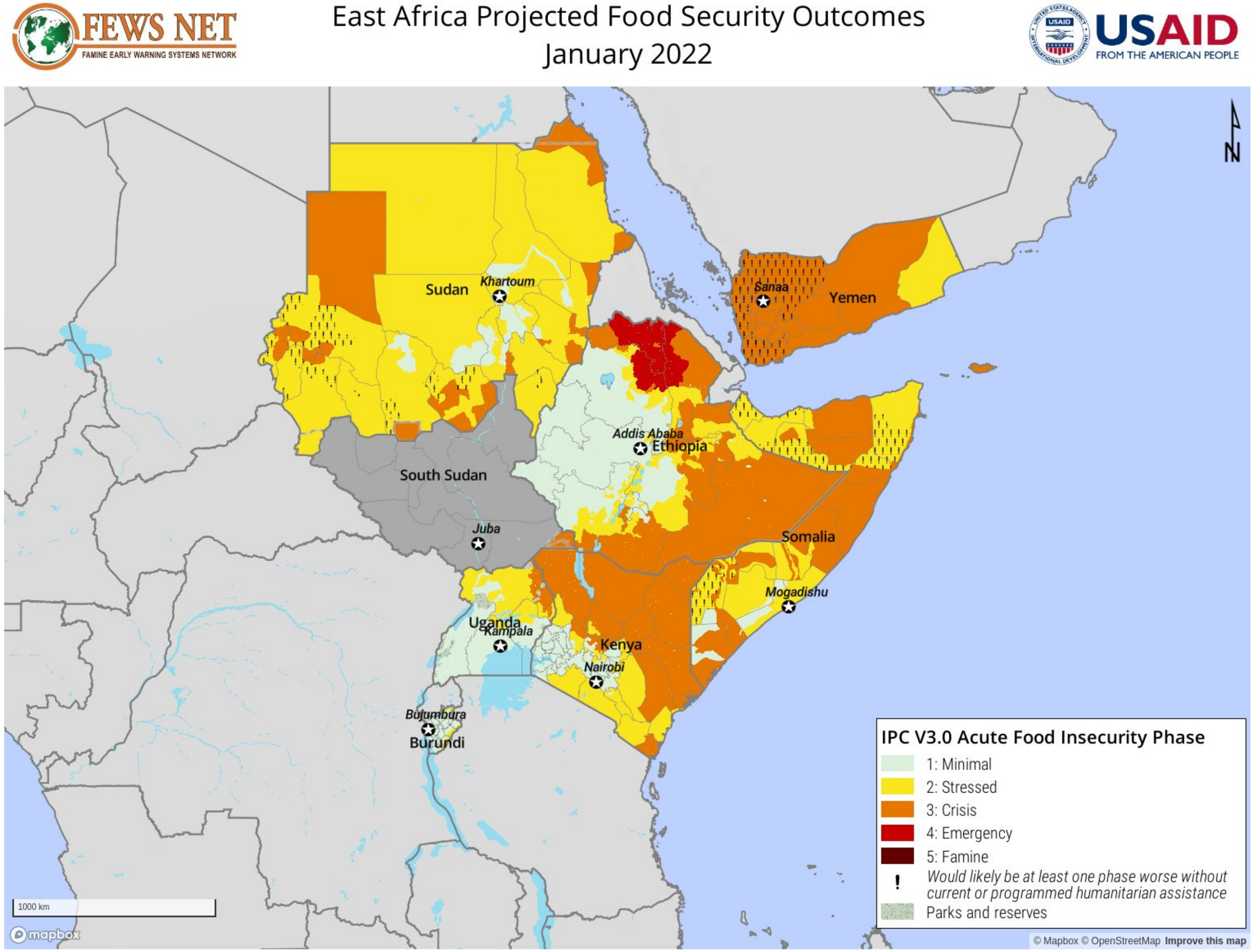
- IPC classification only every 3-6 months
- Decisions manually determined – susceptible to biases
- Accuracy of predictions only 70% (in Somalia)

Impact

- Proof of concept for ML
- Better predictive analysis can optimise humanitarian aid by OCHA
  - Increasing frequency of predictions
  - Reducing human bias
  - Improving accuracy

Data Used

FEWS NET



FEWS NET classification is IPC-compatible. IPC-compatible analysis follows key IPC protocols, but does not necessarily reflect the consensus of national food security partners.

FEWS NET is a USAID-funded activity. The content of this graphic does not necessarily reflect the view of the United States Agency for International Development or the United States Government.

Data

Variables	**d**	**Region-varying**	**Description**	**Source**
IPC level	1	yes	Dependent variable; post facto IPC classification by FEWS NET	FEWS NET 2021; pre-processed by OCHA AA Team.
Dummies	89	yes	Two one-hot vectors of 18 regions and 73 subregions of Somalia	Generated
Temporal trends	1	no	Time variable, one observation per 3-5 quarters	Generated
Spatial Trends	2	yes	Latitude and longitude of region	United Nations
Population	1	yes	Population of region	OCHA

Data

Variables	**d**	**Region-varying**	**Description**	**Source**
Last IPC	1	yes	The last observed IPC value for the subregion	Fewsnet, OCHA
Weather	5	yes	Precipitation data: absolute and relative to season; mean, maximum and minimum	OCHA
Economic	8	no	Unemployment rates (male and female), child labour (male and female), exports, urban growth, rural water access, public debt; all variables are yearly	World Bank
Food prices	1	yes	Average price of corn at the two closest recorded markets (in Somali Shilling)	WFP
Exchange rate	5	no	Exchange rate of Somali Shilling to US Dollar; absolute and change, quarterly maximum and minimum	Investing 2022
Conflict data	8	yes	Fatalities in conflict, battles, explosions, protests, riots, strategic developments, violence against civilians; per capita	ACLED

Related Work

Related Work

- **Wang, D., Andree, B.P.J., Chamorro, A.F. and Girouard Spencer, P., 2020. Stochastic modeling of food insecurity.**
    - Autocorrelation (similar to RNN without nonlinear activation)
    - Country-level results of population breakdown in each IPC class

- **Andree, B.P.J., Chamorro, A., Kraay, A., Spencer, P. and Wang, D., 2020. Predicting food crises.**
    - Random Forests (no time-varying component; predict next 3 months or 6 months)
    - Region-level and country-level results
    - Binarize labels to predict transition from food secure to insecure and vice-versa

Related Work

Zhou, Y., Lentz, E., Michelson, H., Kim, C. and Baylis, K., 2021.
Machine learning for food security: Principles for transparency and usability.
Applied Economic Perspectives and Policy.

Westerveld, J.J., van den Homberg, M.J., Nobre, G.G., van den Berg, D.L., Teklesadik, A.D. and Stuit, S.M., 2021. **Forecasting transitions in the state of food security with machine learning using transferable features**. *Science of the Total Environment*, 786, p.147366.

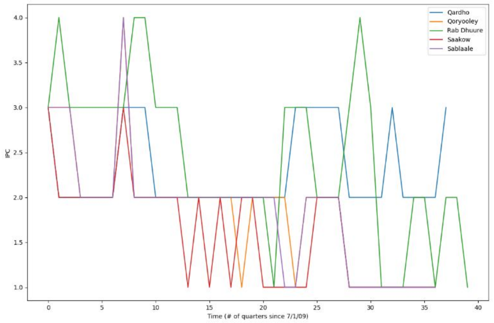
Our Contributions

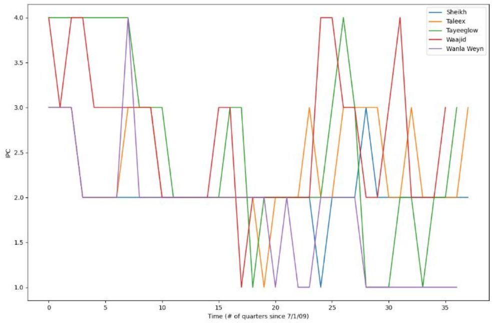
- Automate prediction of food insecurity levels in the case of Somalia
    - Input: range of data sources (described previously)
    - Target: IPC three months ahead at region level
    - Work with extreme class imbalance via upsampling and sample weighting
- Models used
    - Random Forests
    - Gradient-Boosted Trees
    - SVMs (+ radial basis kernel)
    - Shallow NNs
    - Gaussian Processes
- Reproduce results of Andree et. al. 2020 with multiclass IPC targets

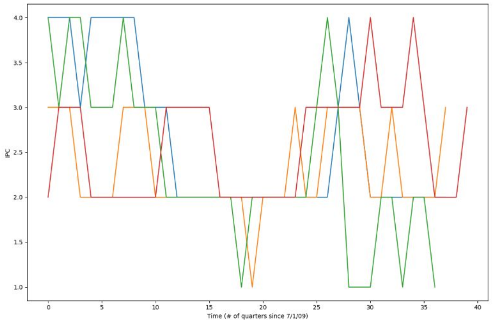
Methodology

Methodology

- **Phase 1**: Use time series modeling with RNNs after LASSO feature extraction
  - Inspired by autocorrelation in Wang et. al. 2020
- Results: …not great
- Hypotheses:
  - Limited data
  - No seasonality in IPC
  - Constant features cannot help predict time-varying values







Methodology

- **Phase 2**: Predict IPC in 3 months given features describing current status
- Inspired by Andree et. al. 2020
- Differences
    - Granular IPC prediction (multiclass classification)
    - Focused on Somalia (smaller amounts of data)
    - Considered alternative statistical modeling techniques
    - Use current IPC as input to model
        - Idea: when covariates are not predictive of IPC, rely on previous IPC

Methodology

- All models except shallow NN
  - 5 trials of temporal holdout validation -> out-of-sample test evaluation
  - Validation
    - Tune hyperparameters based on performance on data 3 months later
  - Test
    - Evaluate best model on unseen future test data

Methodology

- Shallow NN
    - One network: feedforward with [64, 32, 16, 4] neurons, ReLU and softmax activation (only 4 IPC classes seen)
    - Still run 5 trials to test effects of randomness

Takeaways

Results

Model / Average Accuracy	Test Accuracy on Aug 2020 data of best model	Test Accuracy on Oct 2020 data of best model
Random Forests Baseline (with RandomOverSampling)	0.973	0.561
Shallow NN	0.812	**0.582**
XGBoost (with sample weighting)	**0.985**	0.522
SVM	0.731	0.552
Random Forests with last IPC	0.579	0.516
Majority Class Baseline	0.687	0.575
Gaussian Process	0.970	0.552
Human Predictions by FEWS NET	0.919*	0.541**

* = short-term prediction in June 2020
** = medium-term prediction in June 2020

Results

Model	Confusion Matrix Aug 2020				Confusion Matrix Oct 2020			
Shallow NN	6.8	0.8	0	0.4	12.6	2.4	0	0
	0	46.6	0.4	1	2.2	23.8	4.4	0.6
	0	8.2	0.8	0	1	19.8	0.2	0
	0	0	0	0	0	0	0	0
XGBoost (with sample weighting)	10	0	0	0	10	4	1	0
	0	47	1	0	0	24	7	0
	0	0	9	0	0	20	1	0
	0	0	0	0	0	0	0	0

Discussion

- “Predictions are difficult, especially about the future”
  - Drop in performance across all models from Aug 2020 to Oct 2020 suggests temporal domain shift
  - Prediction with limited data a challenge
  - Classes are imbalanced

Discussion

- GPs and NNs better model uncertainty in predictions than tree-based approaches
  - Output probability distributions instead of fractions of classes at leaf nodes
  - Kernel crafting and GP prior configuration could be tuned via expert input, similarly to Wang et. al. 2020
  - Could also aid prescription and decision-making
- Consider ethical and real-world implications of this work
  - Could affect livelihood of millions of people
  - Effects of prediction errors and/or bias
  - Should leave room for “safety switch” if stakeholders are wary of approach

Future Work

- Gather more data
  - Potentially even help organizations digitize old archives for this process
  - Utilize data from other countries
- Develop aid allocation strategies based on predictions alongside NGOs
- Ensure deployment is in line with human values