

# Predicting Food Insecurity

A deep dive into nowcasting, forecasting,  
and demystification

2022 May



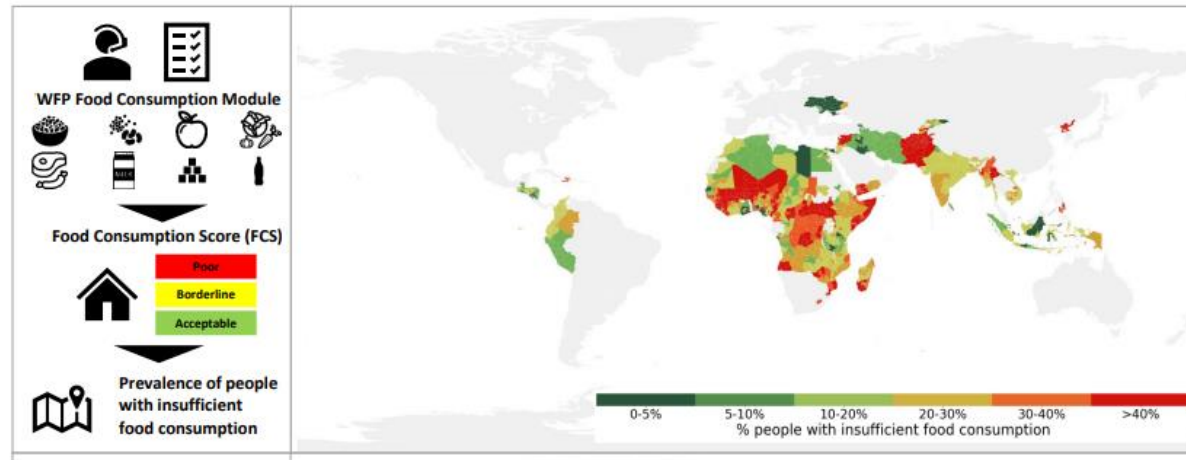
World Food  
Programme

SAVING  
LIVES  
CHANGING  
LIVES

# MODELLING KEY FOOD SECURITY INDICATORS:

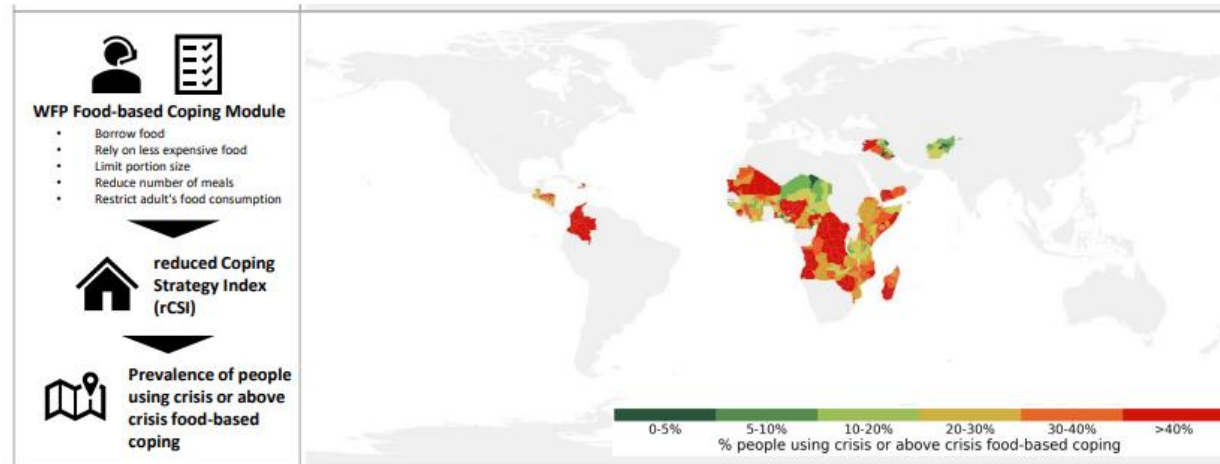
Our predictive model aims to provide daily estimates of the two main food security indicators:

- Prevalence of insufficient food consumption
  - Indicator: Food Consumption Score (FCS)



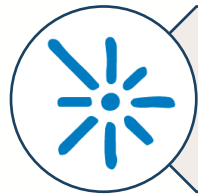
# MODELLING KEY FOOD SECURITY INDICATORS:

- Prevalence of above crisis food-based coping
  - Indicator : Reduced Coping Strategy Score (rCSI)



# MODELLING KEY FOOD SECURITY INDICATORS

We found open Datasets that relate to these 3 key drivers of food insecurity:



Conflict



Economic Shocks



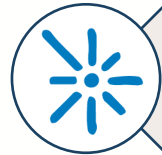
Extreme Weather Events

# OPEN DATASETS – INPUT DATA

Data is automatically pulled from a variety of sources:



- Prevalence of Undernourishment – FAOSTAT
- FCS and rCSI Indicators – WFP food security surveys



- Number of Conflict Related Fatalities - ACLED Data



- Alert Price Spike (ALPS) - WFP Economic Explorer
- GDP, Food and Headline Inflation, Currency Exchange - Trading Economics



- Vegetation Index (NDVI) and Rainfall Data – WFP Seasonal Explorer (CHIRPS & MODIS Data)

# OPEN DATASETS – INPUT DATA

## Food Security Data

- FCS and rCSI Indicators – WFP food security surveys
  - We use data coming from face-to-face or mobile phone assessment.
  - Historical values used to predict current estimates in real time.
  - The values are updated periodically as more data becomes available
- Prevalence of Undernourishment – FAOSTAT
  - This is a national yearly indicator publicly available in FAOSTAT.
  - Available for most countries.



# OPEN DATASETS – INPUT DATA

## Economic Shocks

- Alert Price Spike (ALPS) - WFP Economic Explorer
  - Comparing Long-term seasonal price trend of a commodity's price with the last observed price.
  - The higher the difference, the more severe the alert.
- GDP, Currency Exchange, Food and Headline Inflation - Trading Economics
  - 4 macro-economics features are considered
    1. Most recent available annual GDP;
    2. Monthly headline inflation rates;
    3. Monthly food inflation rates;
    4. Percentage variation of currency exchange.



# OPEN DATASETS – INPUT DATA

## Extreme Weather Events

- NDVI and Rainfall – WFP Seasonal Explorer (CHIRPS & MODIS Data)
  - We take the average rainfall and NDVI and their anomalies with respect to historical averages.





# OPEN DATASETS – INPUT DATA

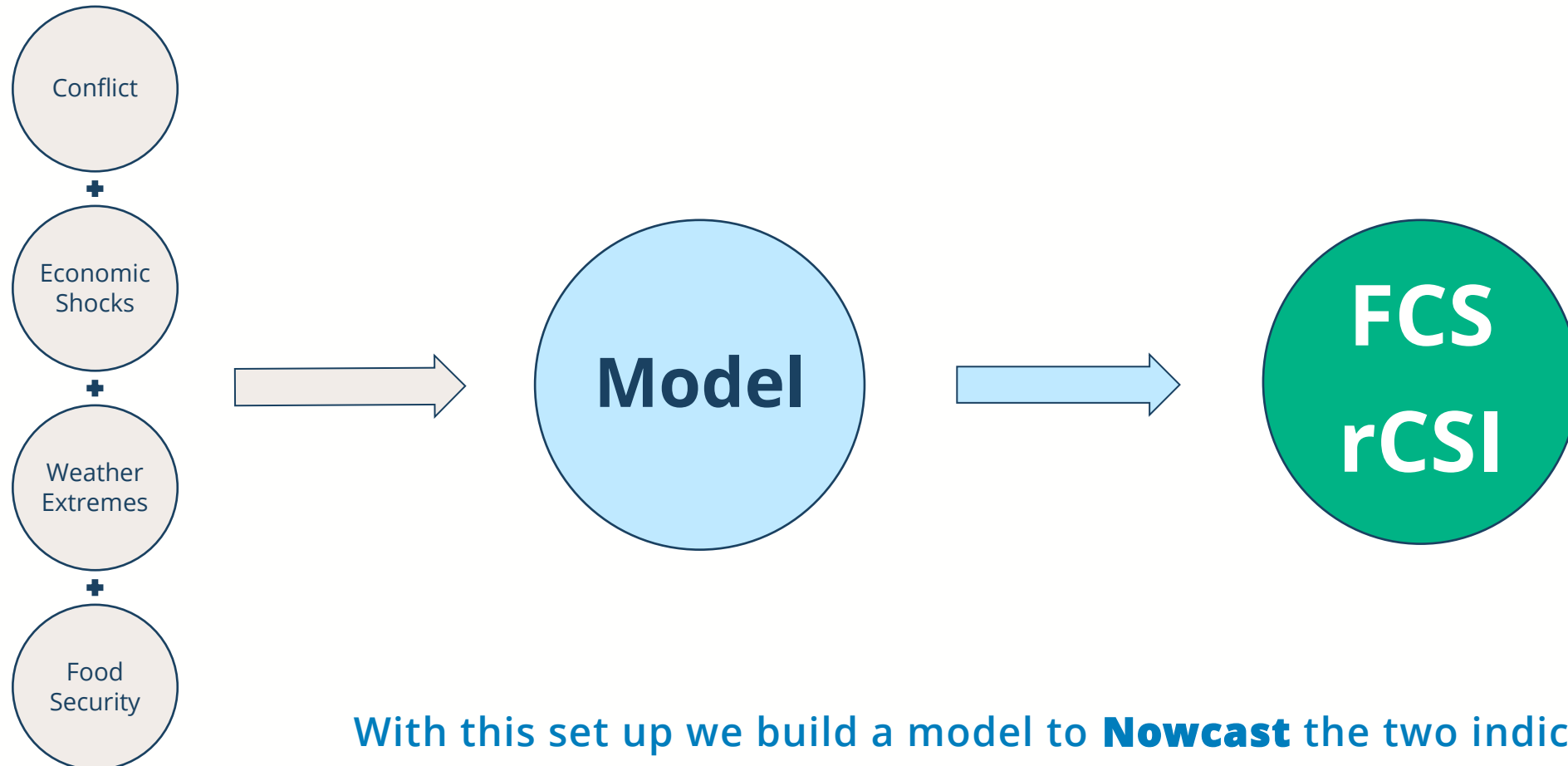
## Conflict

- Number of Conflict Related Fatalities - ACLED Data
  - A publicly available repository of reported conflict events and related fatalities across most areas of the world.
  - The date, longitude and latitude of each event is reported.



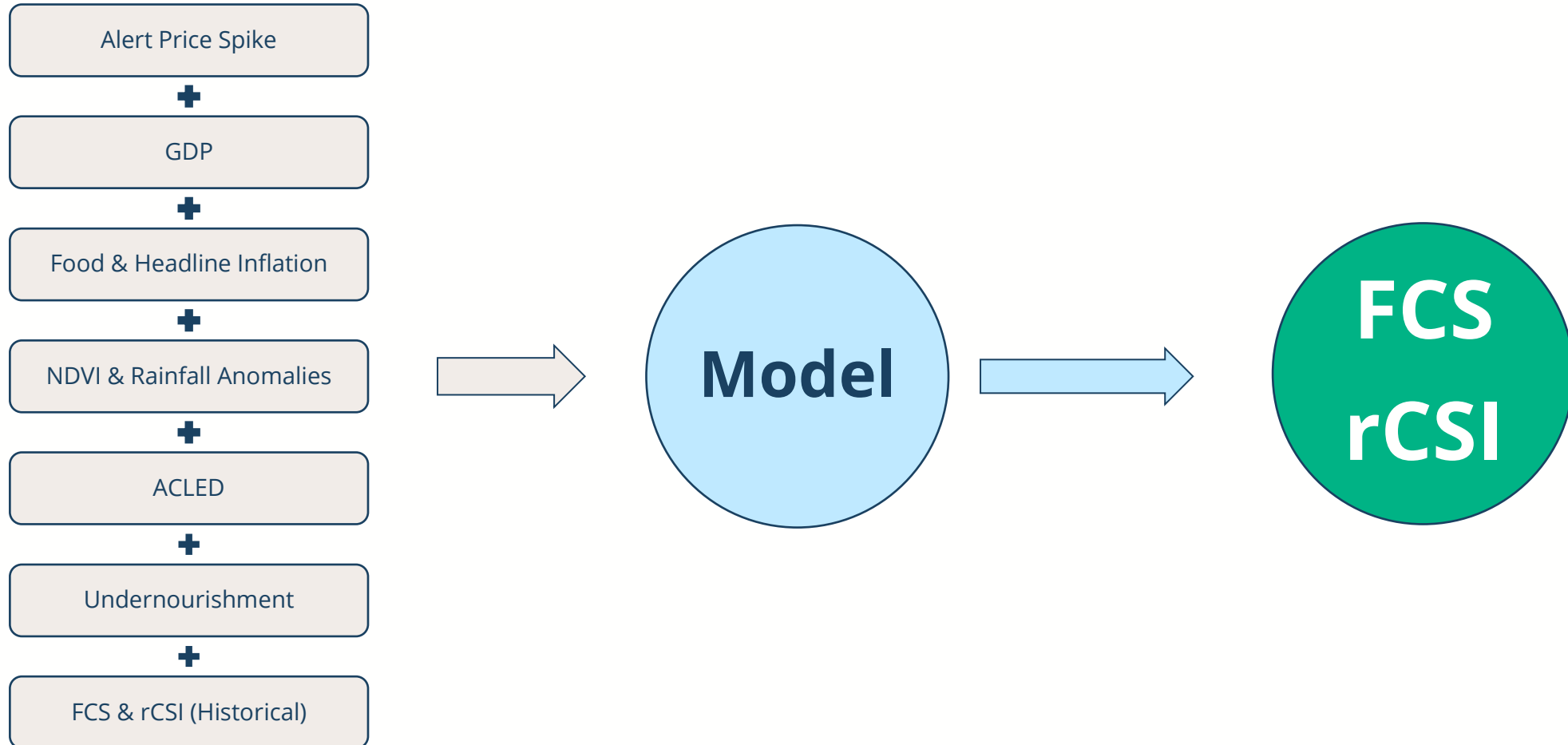
# MACHINE LEARNING MODELLING

Our goal is to train a Machine Learning model to infer the FCS and rCSI from the input data.



With this set up we build a model to **Nowcast** the two indicators on countries with no real time food security monitoring.

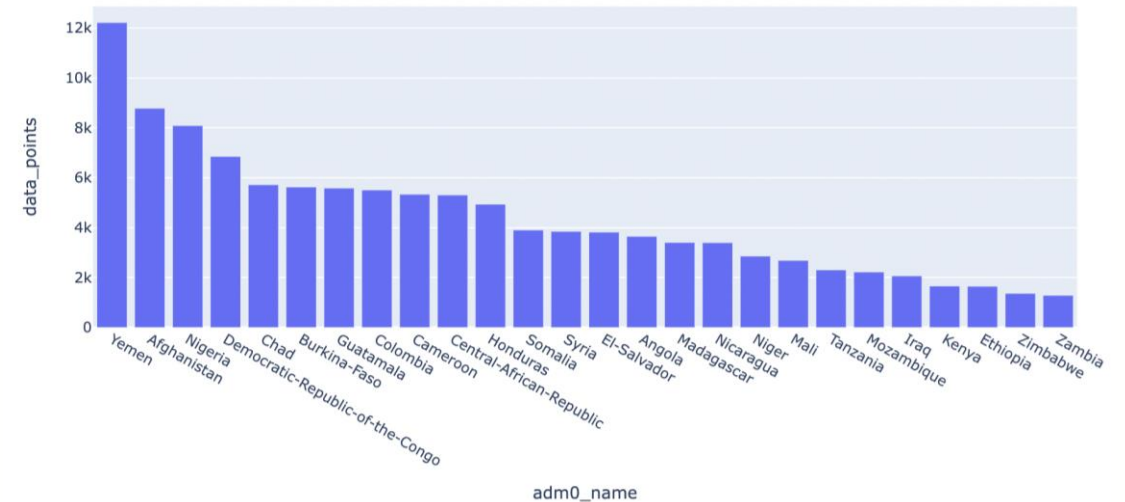
# MACHINE LEARNING MODELLING



# NOWCASTING – TRAINING

- The model was trained on a very large dataset spanning 50+ countries.
- Several input features were built starting from the datasets we have seen.
- We used an XGBoost regressor, retrained regularly on the new data stream
- We have used a bootstrap approach and repeated the training 100 times, to calculate the confidence interval of the predictions.

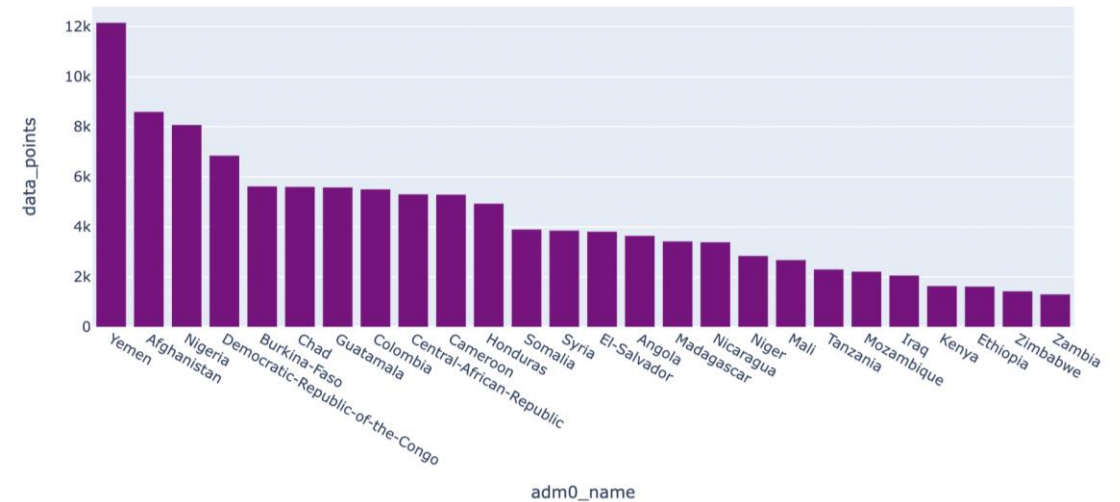
*FCS data per country:*



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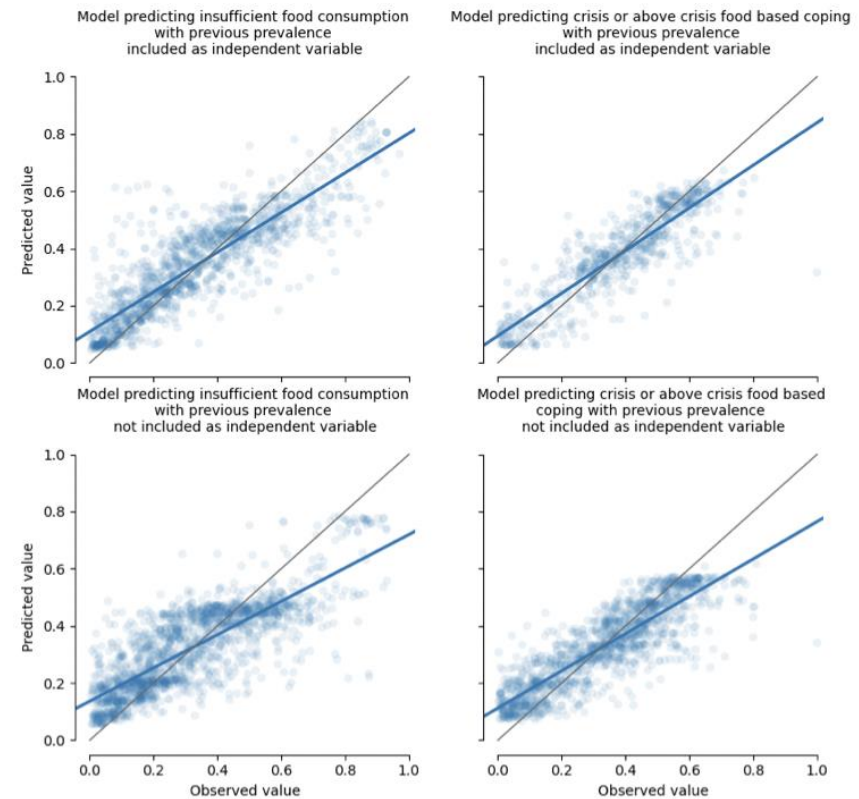
*rCSI data per country:*



# NOWCASTING – PERFORMANCE

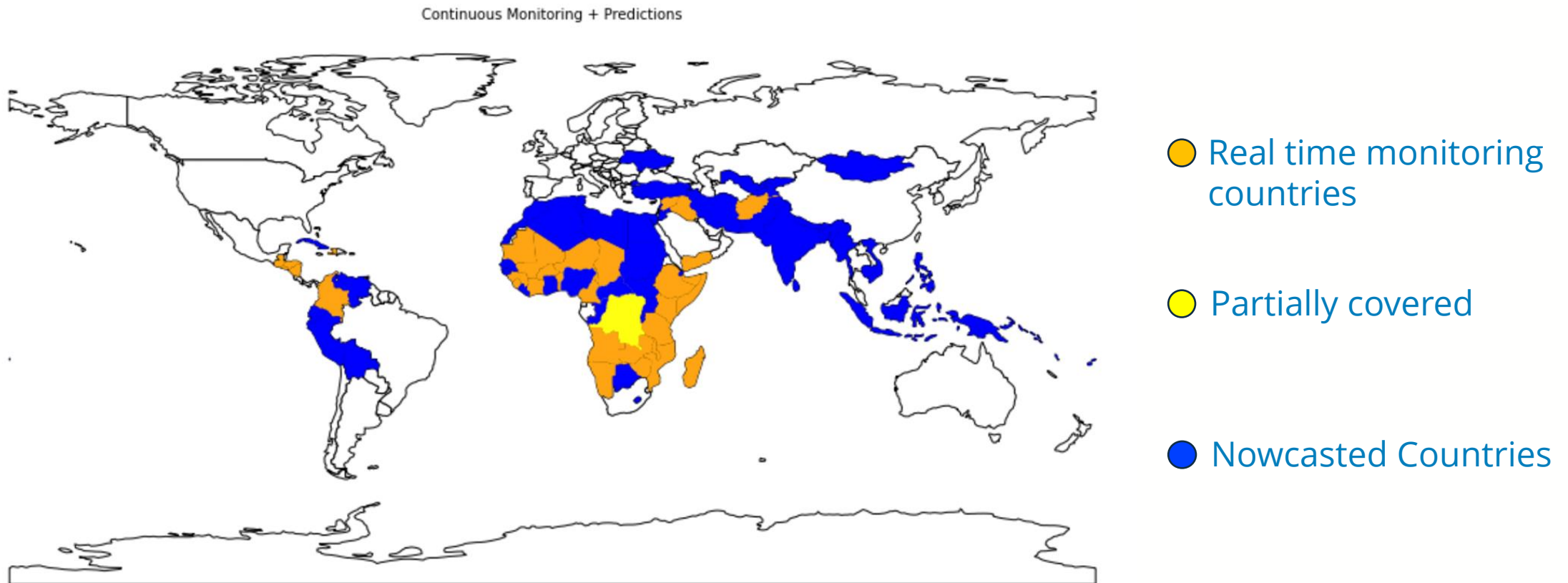
How does it perform?

		$R^2$	MAE
Food consumption	Prevalence from previous assessment included as independent variable	0.75	0.08
	Prevalence from previous assessment <b>not</b> included as independent variable	0.63	0.09
	Naive model	0.39	0.12
Food-based coping	Prevalence from previous assessment included as independent variable	0.78	0.06
	Prevalence from previous assessment <b>not</b> included as independent variable	0.73	0.07
	Naive model	0.42	0.10



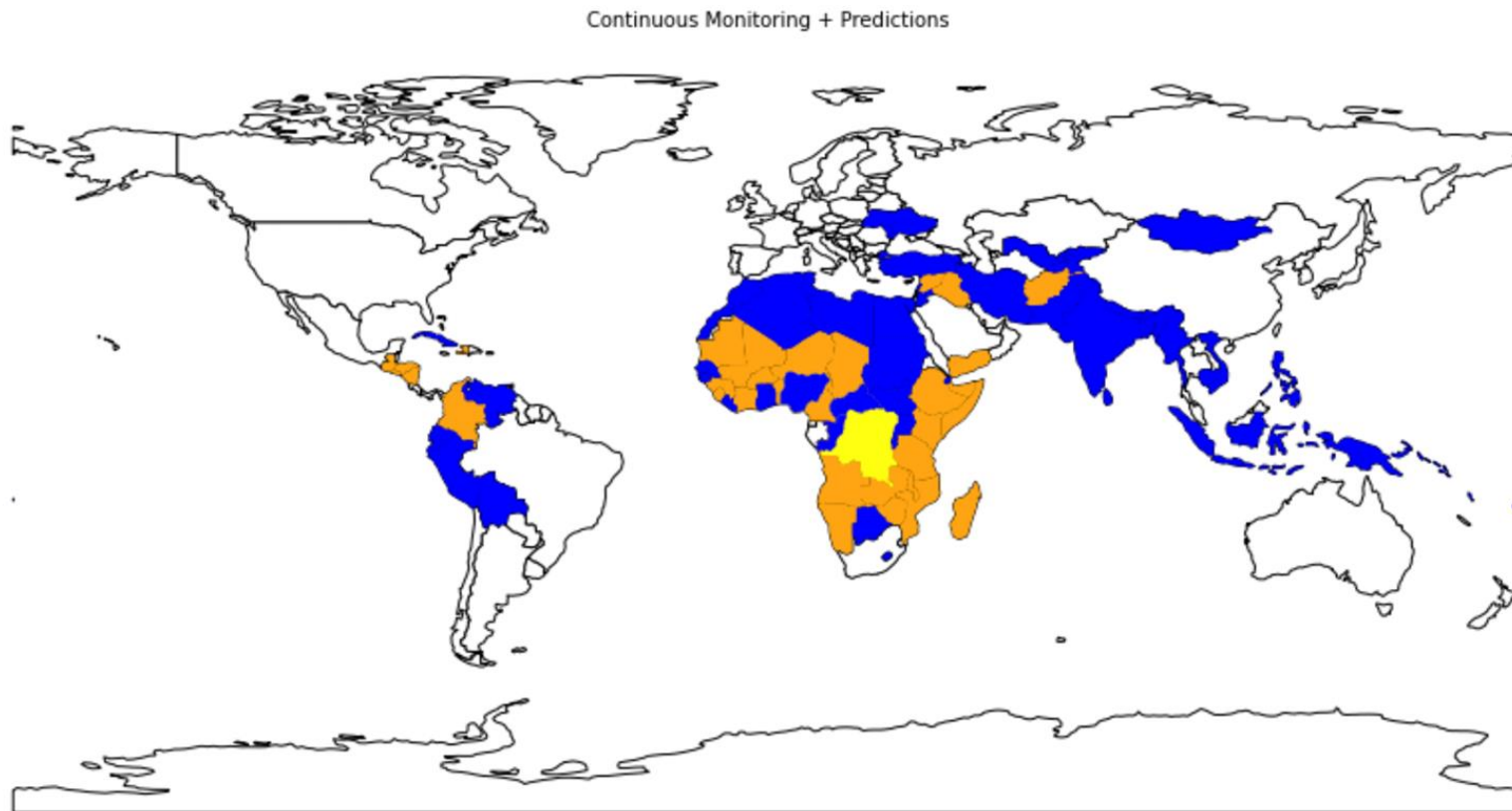
# NOWCASTING

We use the trained model to nowcast the value of the two indicators in 64 countries where the input variables are available, but the indicators are not collected in real time.



# NOWCASTING

Every night we update the input variables for the datasets and nowcast the two indicators in 64 countries.

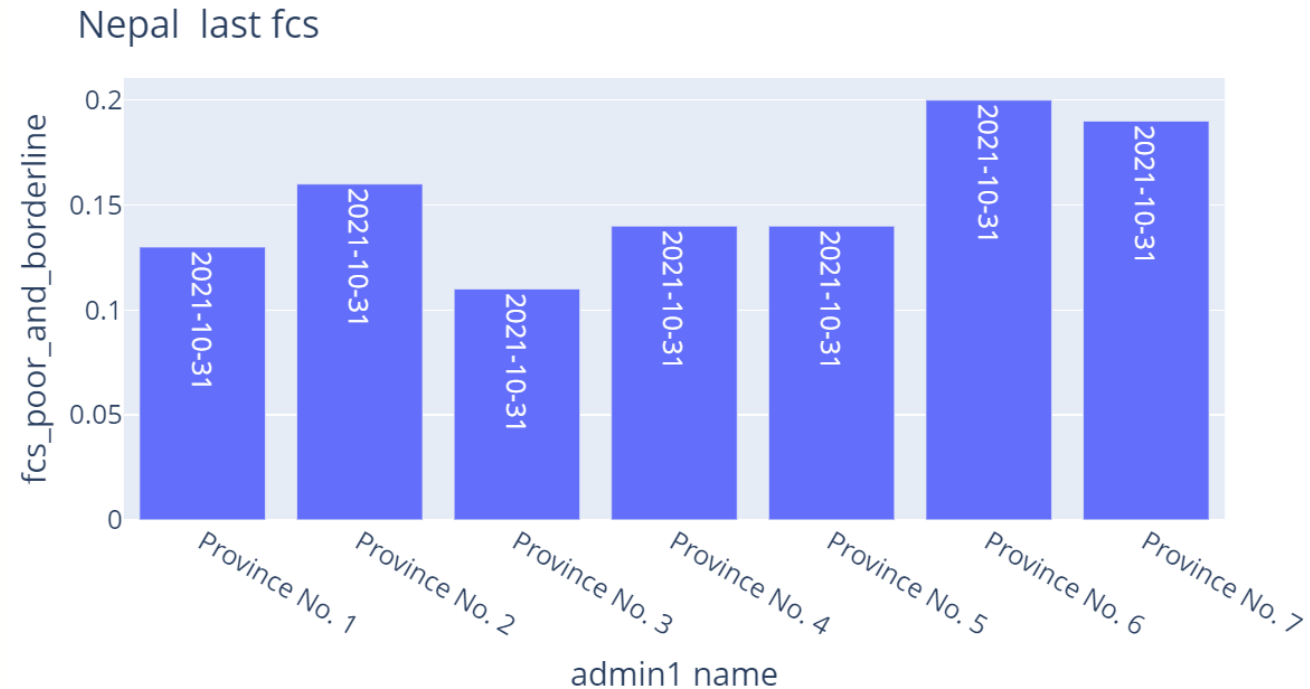


- Real time monitoring countries
- Partially covered
- Nowcasted Countries



# NOWCASTING — NEPAL EXAMPLE

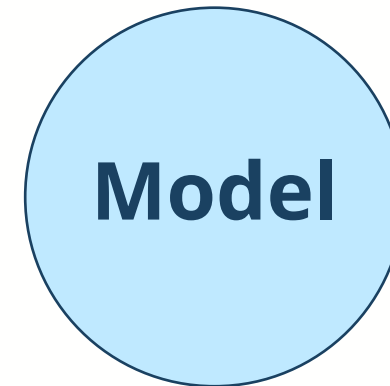
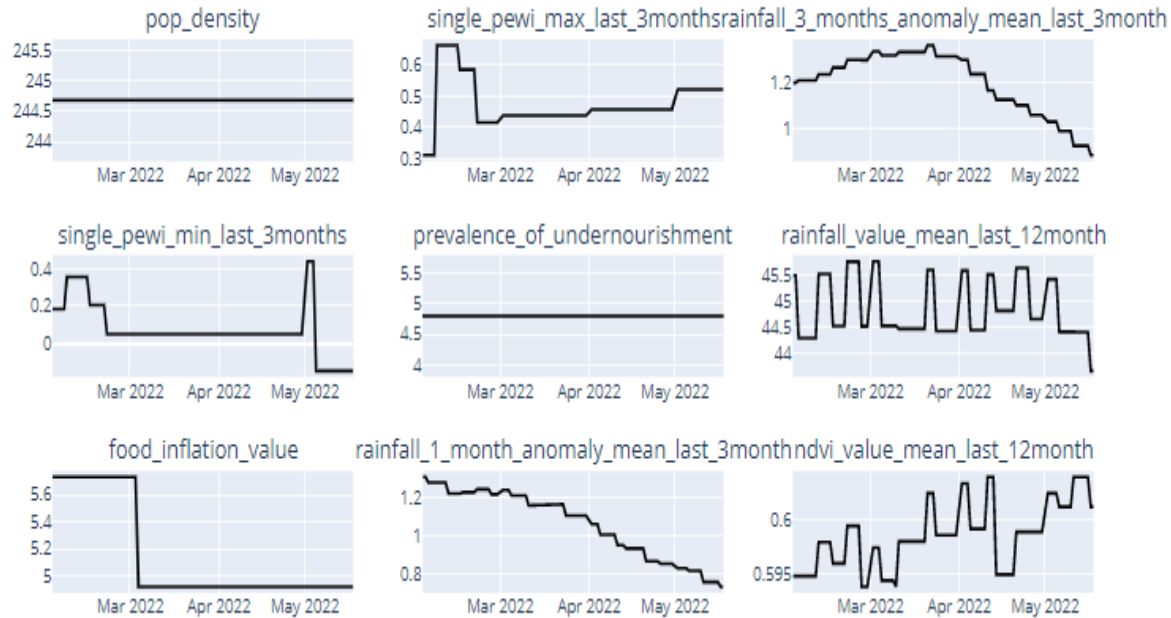
In Nepal the last FCS historical assessment in our database is the 2021-10-31. From then on we don't have any new information



# NOWCASTING – PREDICTIONS

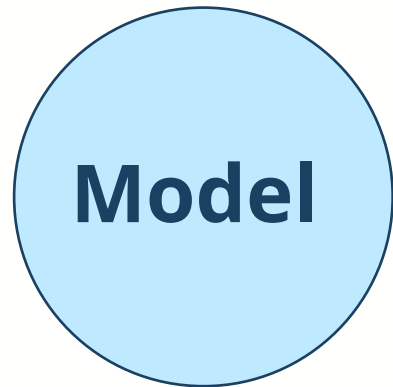
We have access though to the secondary data we have trained our model on. Through our nowcasting procedure we can there give an estimate of the indicator in real time.

Nepal-Province No. 1

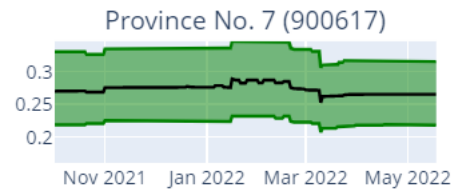
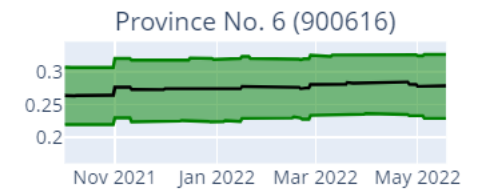
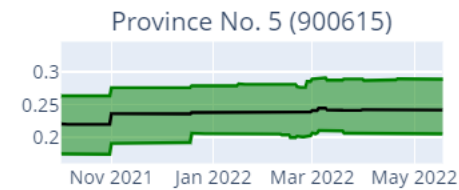
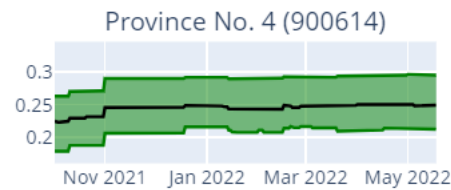
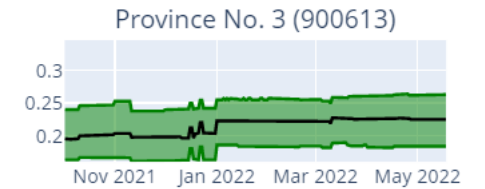
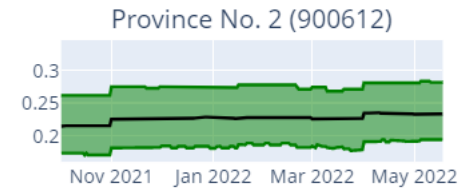
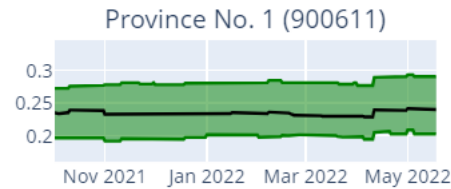


# NOWCASTING – PREDICTIONS

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Nepal-fcs

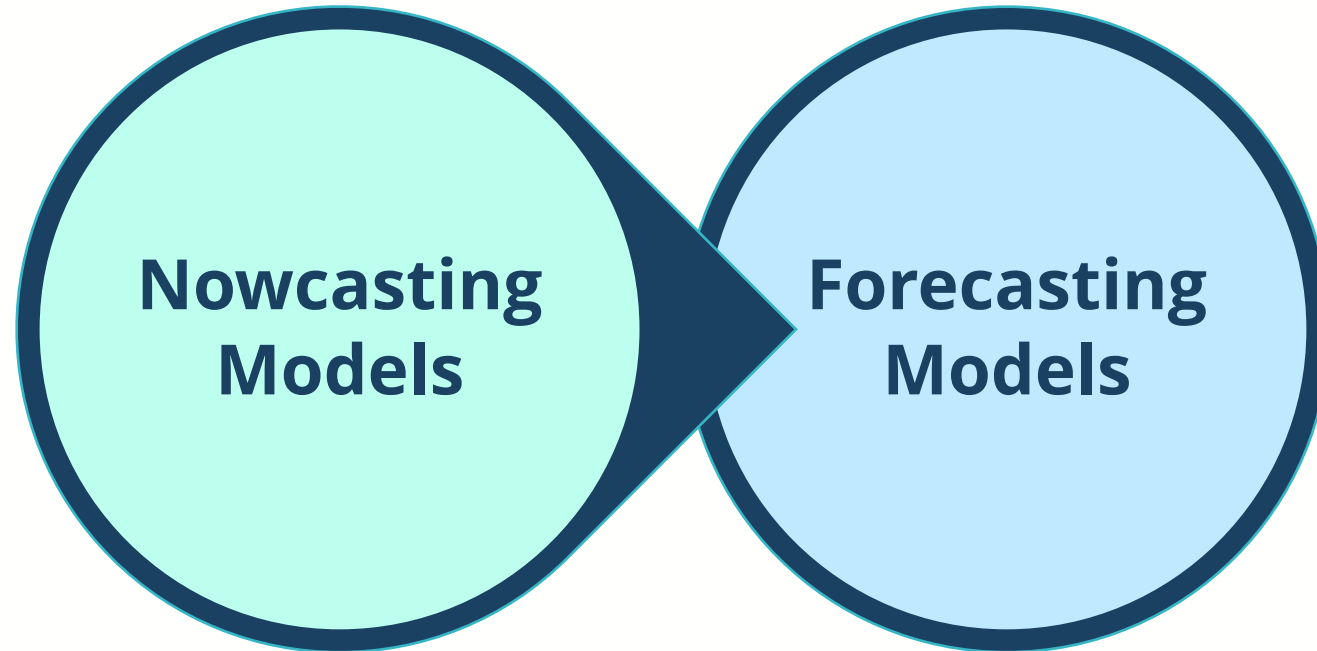


# HUNGERMAPLIVE

The data and the nowcasting prediction are showed in our interactive platform HungerMap<sup>LIVE</sup>



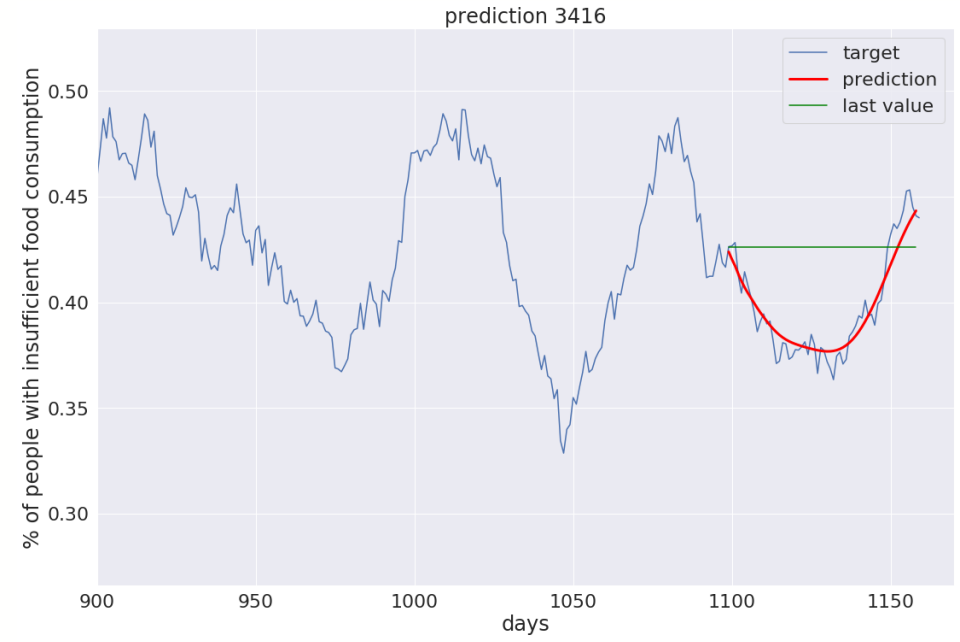
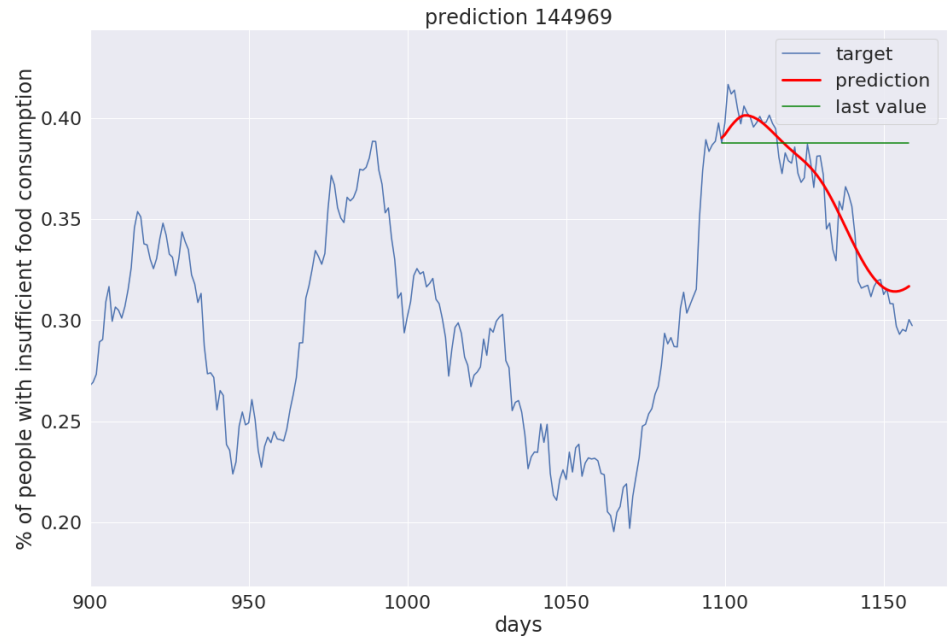
# FROM NOWCASTING TO FORECASTING



- Now in production
- Daily estimates for countries where **there is no** real-time monitoring

- Under development
- Estimates 30 days ahead for countries **where there is** real-time monitoring

# FORECASTING



- For each country a model is needed (lot of data required)
- Approach tested on 6 countries (Syria, Yemen, Mali, Burkina Faso, Nigeria, Cameroon) so far.

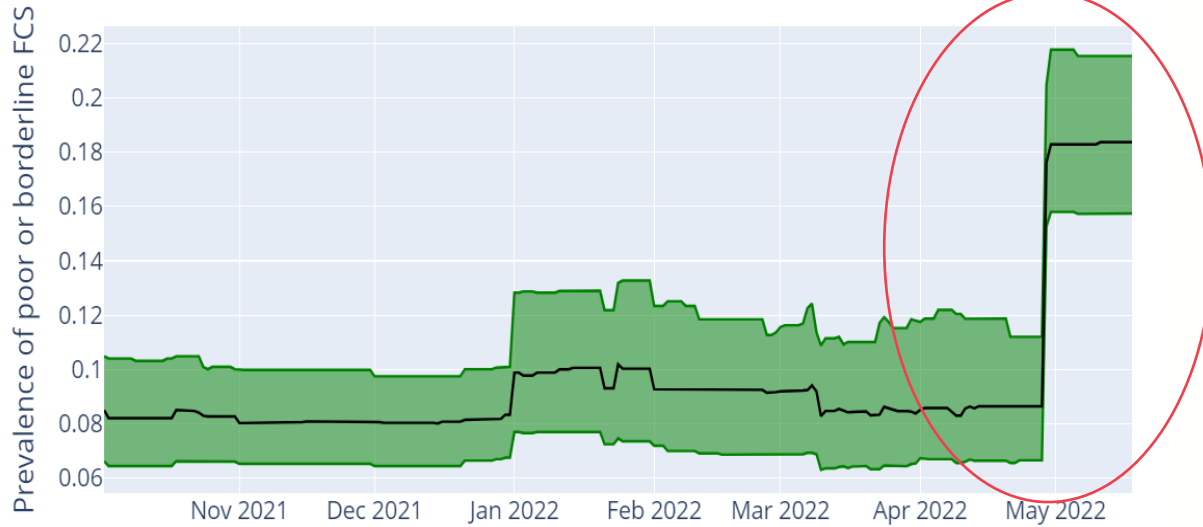


# Demystifying predictions

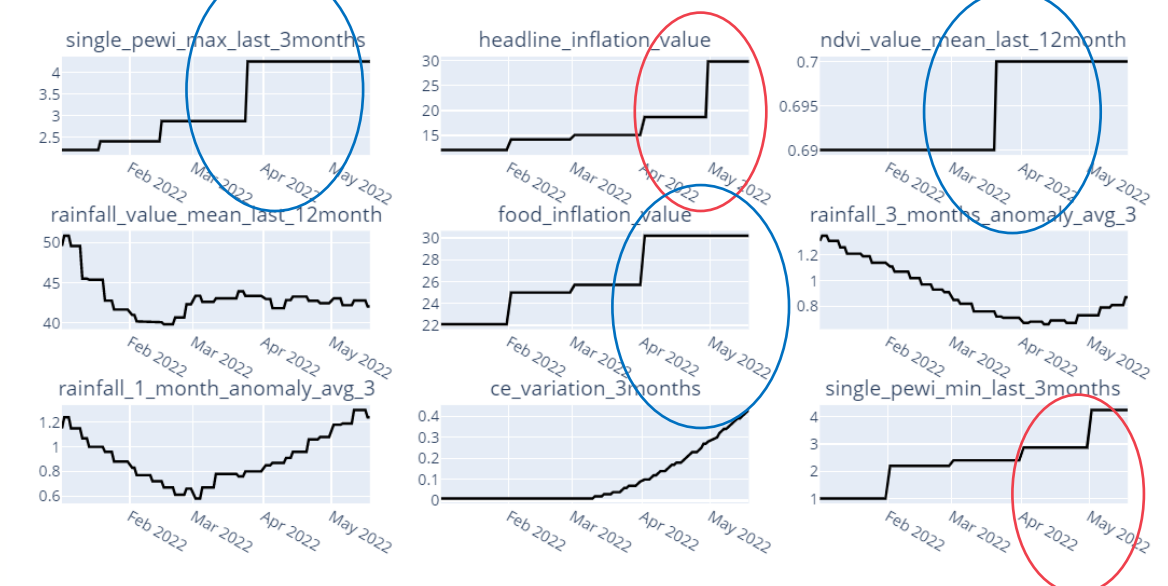
- What caused a change in the prediction?
  - All the input variables change in time
  - Which change in input variable(s) drove the change in the prediction?
  - We have developed a method based of Shap Values to understand the drivers of the prediction.

# NOWCASTING – PREDICTIONS

Sri Lanka-Eastern(2737)



Sri Lanka-Eastern





# For a deeper dive

Nowcasting food insecurity on a global scale

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## On the forecastability of food insecurity

Pietro Foini,  Michele Tizzoni, Daniela Paolotti,  Elisa Omodei

doi: <https://doi.org/10.1101/2021.07.09.21260276>

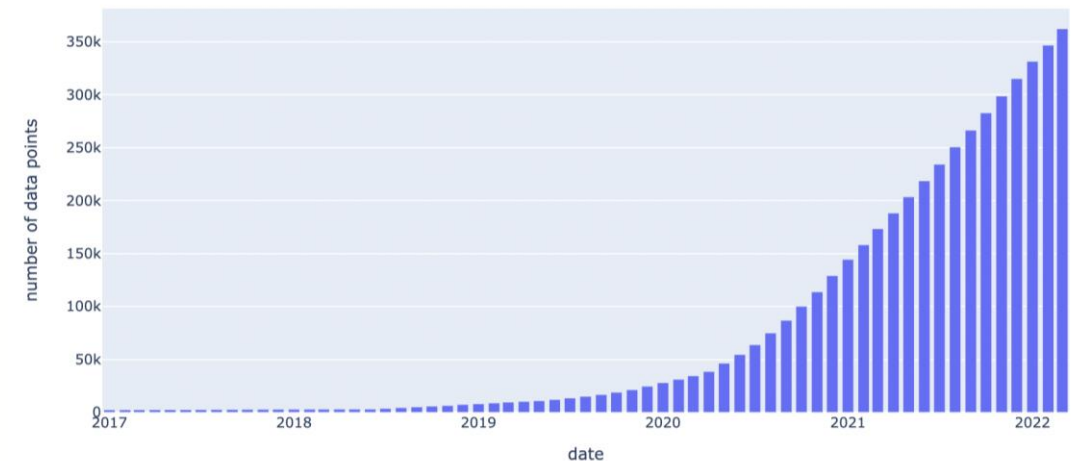
**This article is a preprint and has not been peer-reviewed [what does this mean?]. It reports new medical research that has yet to be evaluated and so should not be used to guide clinical practice.**



# NOWCASTING / FORECASTING WHAT'S NEXT

- Every day our dataset is growing and with it the quality of our models and predictions.
- Larger Datasets allow us to switch to **deep learning** approaches which have outperformed state of the art predictions in many fields.
- Improving and increasing new input datasets will be one of our focus.

*Continuous Monitoring Data Inflow*



# Thank you



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