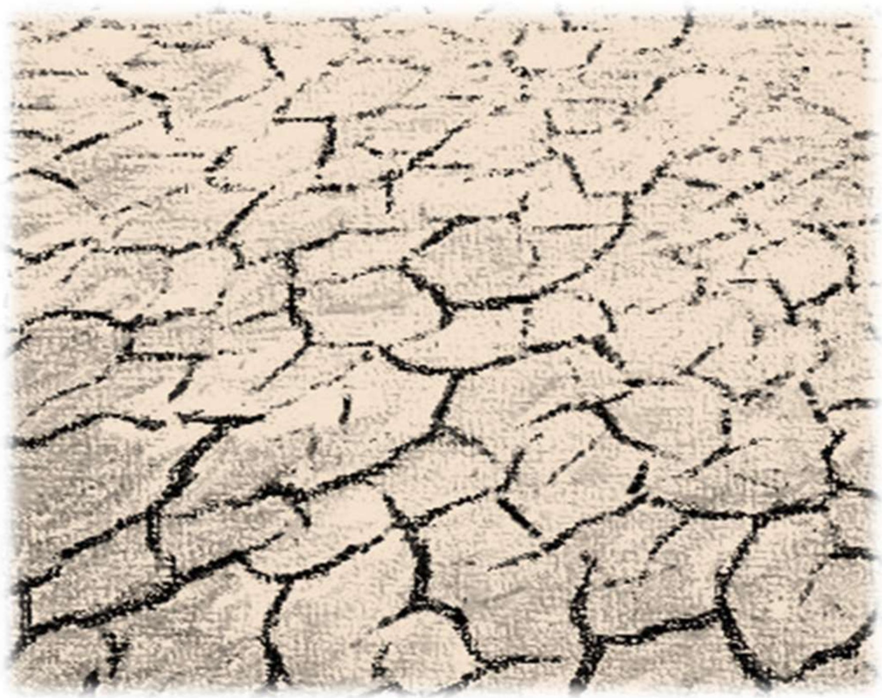
FORECAST-BASED FINANCING FOR FOOD SECURITY (F4S)

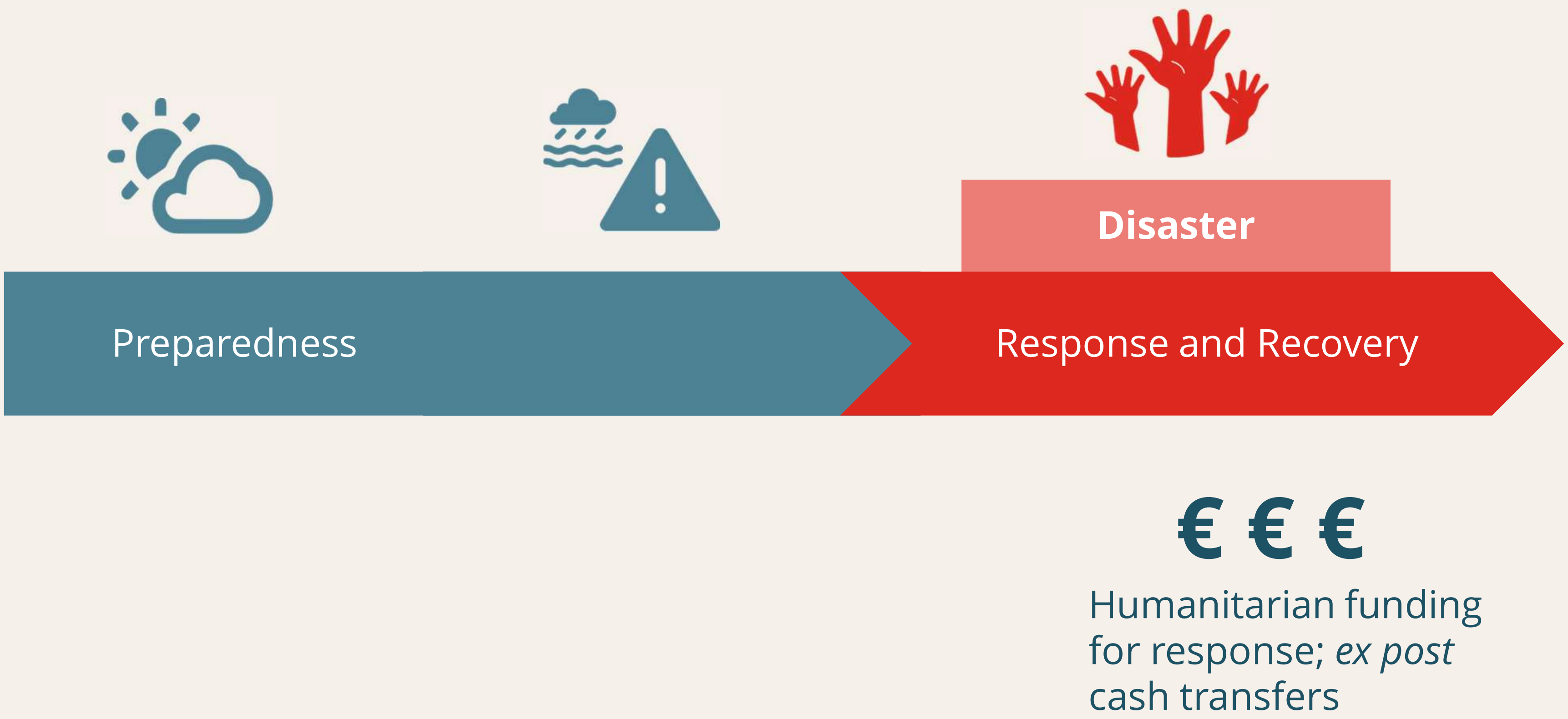


IVM Institute for Environmental Studies | VU | 510 AN INITIATIVE OF THE NETHERLANDS RED CROSS | Climate Hazards Center UC Santa Barbara | ICHA International Center for Humanitarian Affairs

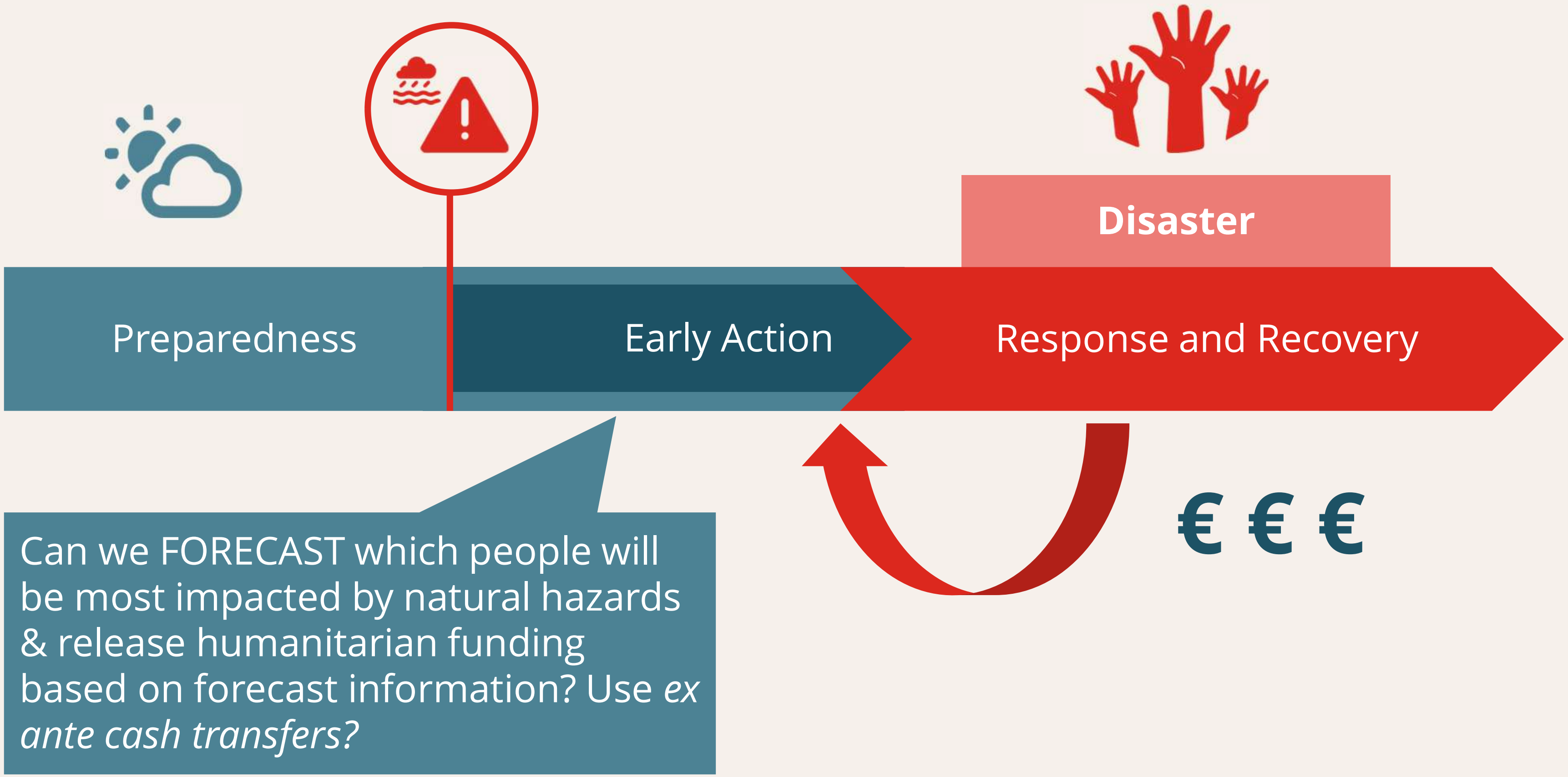
Funded by: GFDRR Global Facility for Disaster Reduction and Recovery

Marc van den Homberg
mvandenhomberg@redcross.nl

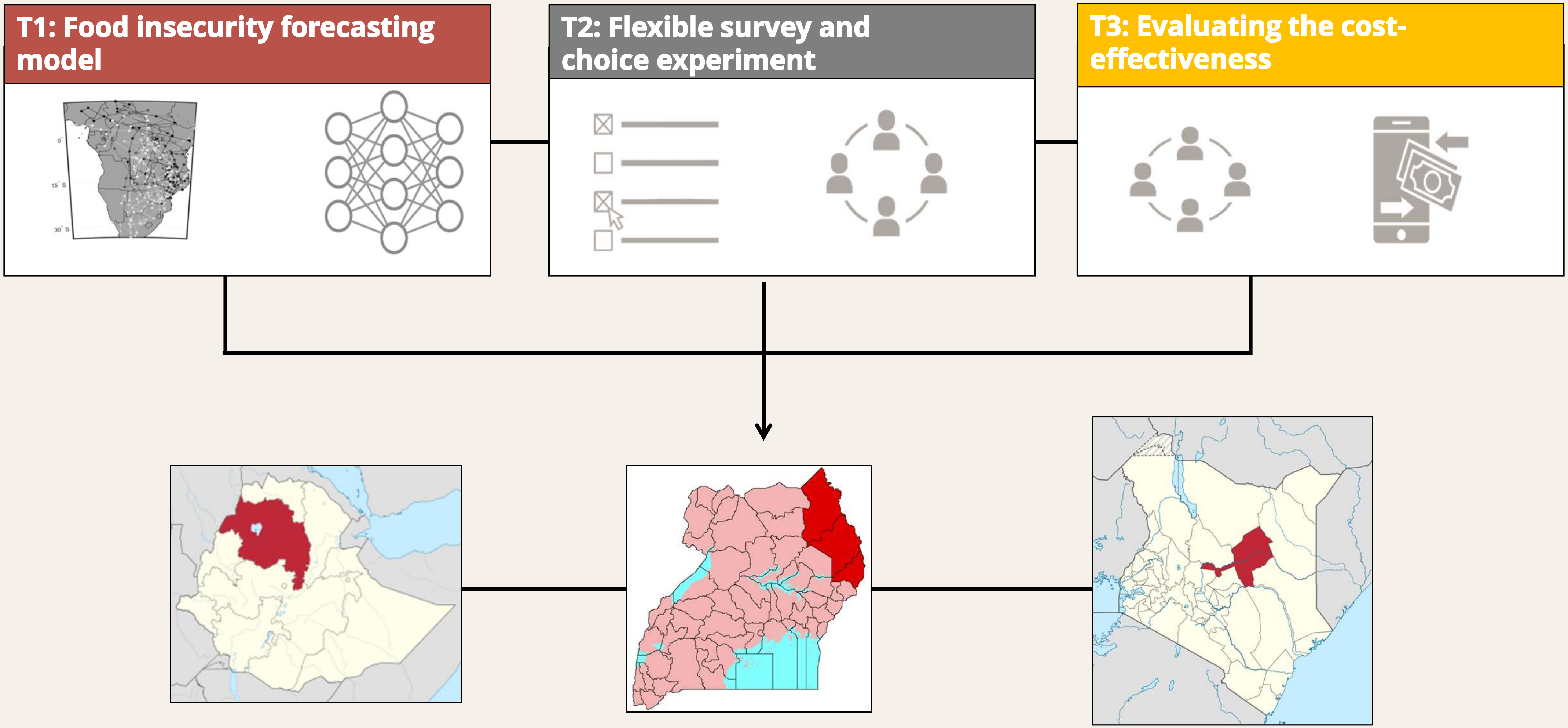
CURRENT SITUATION



FORECAST-BASED FINANCING: EARLY WARNING, EARLY ACTION



FLOWCHART OF THE PROJECT



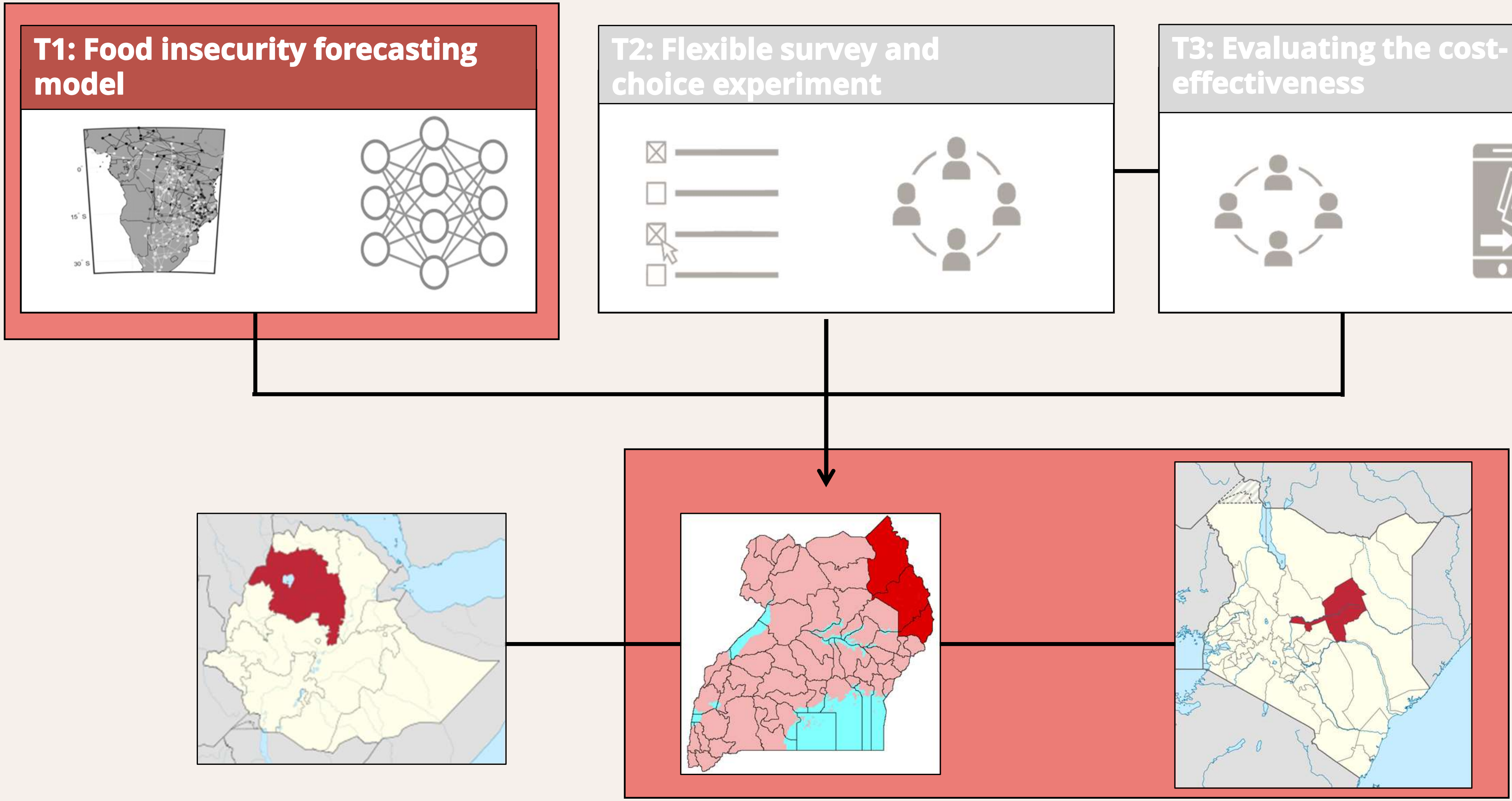
REVIEW OF EXISTING CASH PROGRAMS: KENYA, ETHIOPIA AND UGANDA

- We carried out a feasibility study to assess the extent to which the contexts in Kenya, Ethiopia and Uganda, and the capacities of KRCS, ERCS and URCS and other relevant stakeholders, are favorable to the implementation of cash and voucher assistance (CVA) to support to the most vulnerable people

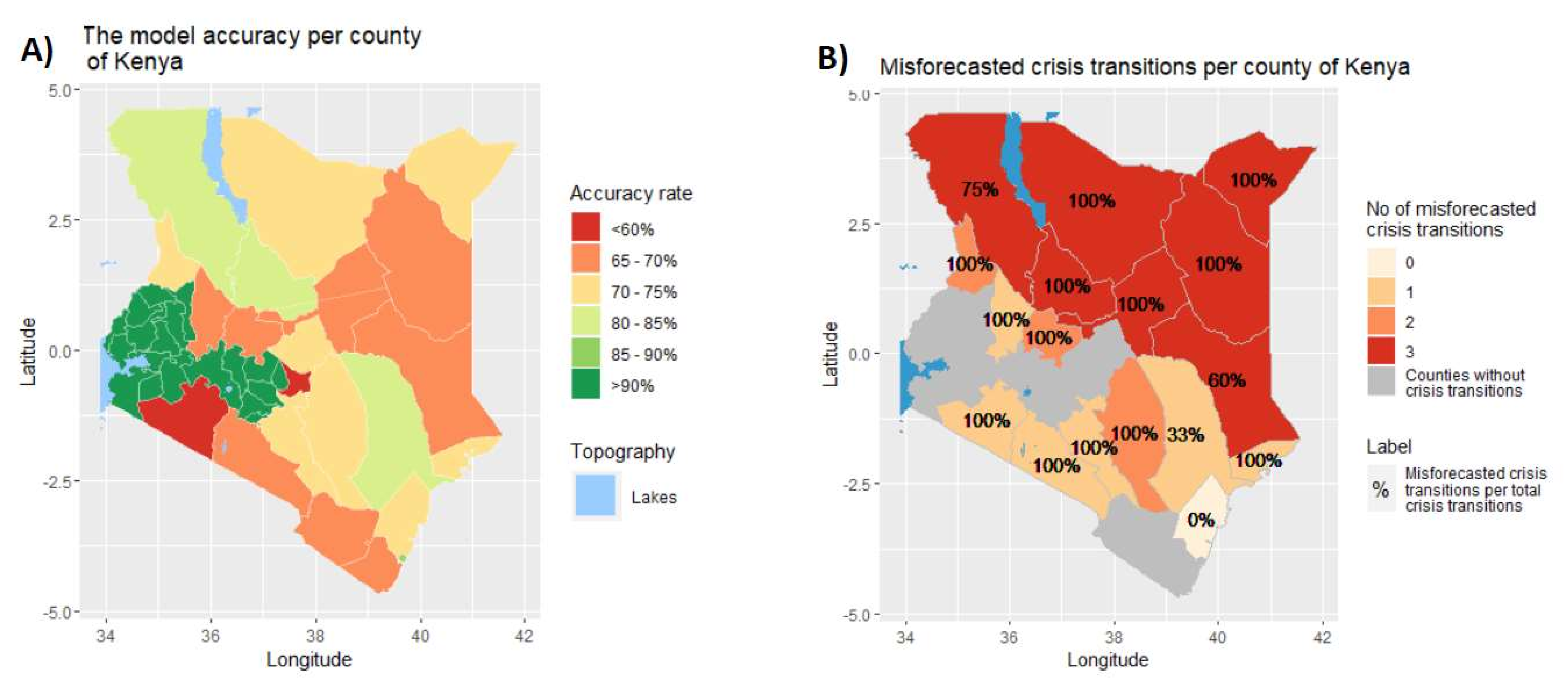
  - In the three countries covered by the F4S project, cash intervention is a feasible measure that can be explored to meet the dietary needs of the affected population, thus minimizing the levels of food insecurity.
  - The current environment is conducive as the government continues to support the CVA interventions.

Early Action = **Modelling** + **Local knowledge** + **Beneficiaries' preference** + **Cost-effectiveness**

T1: FOOD INSECURITY FORECASTING MODEL | KENYA & UGANDA

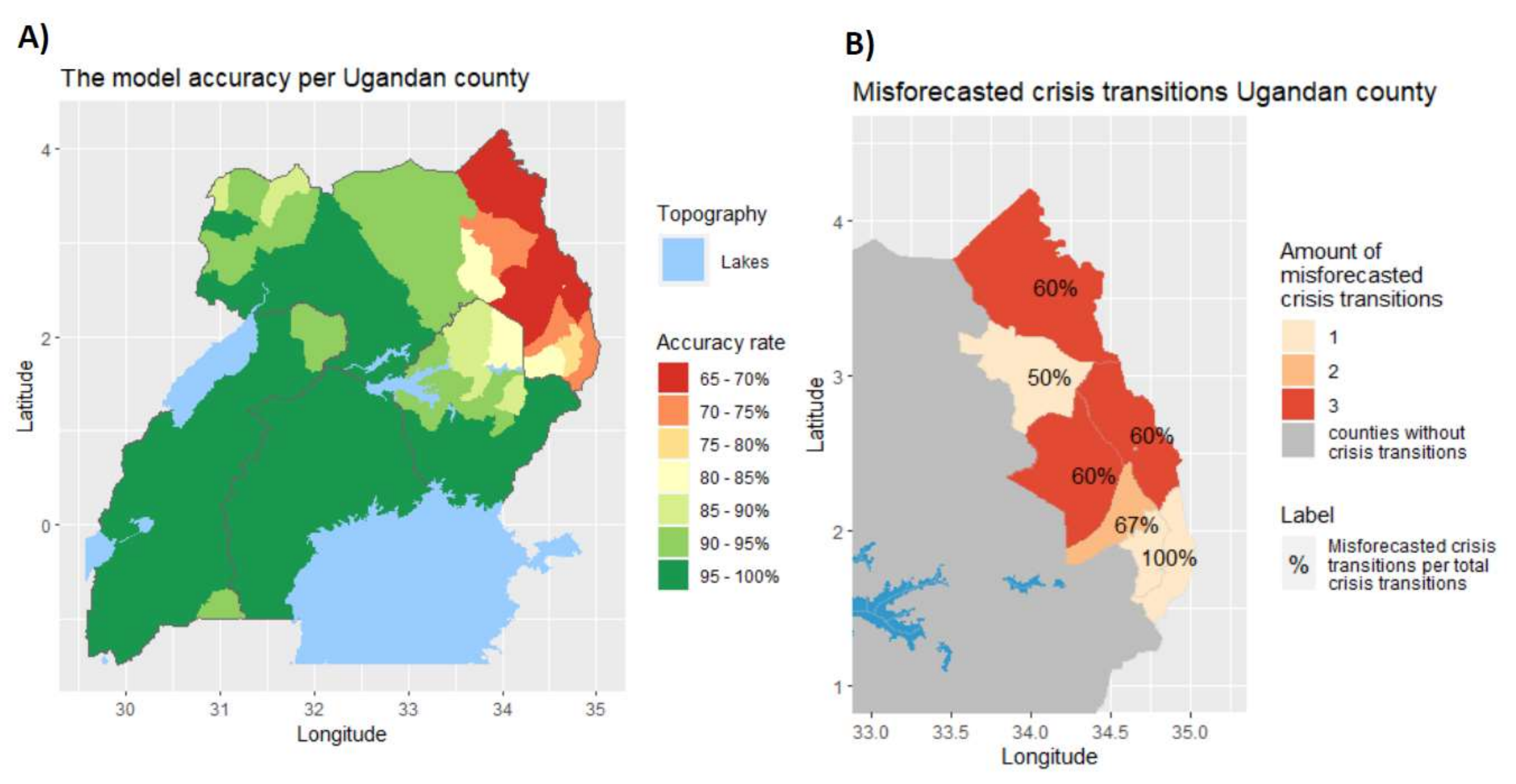


T1: ACCURACY OF FEWSNET IPC CLASSIFICATION - KENYA



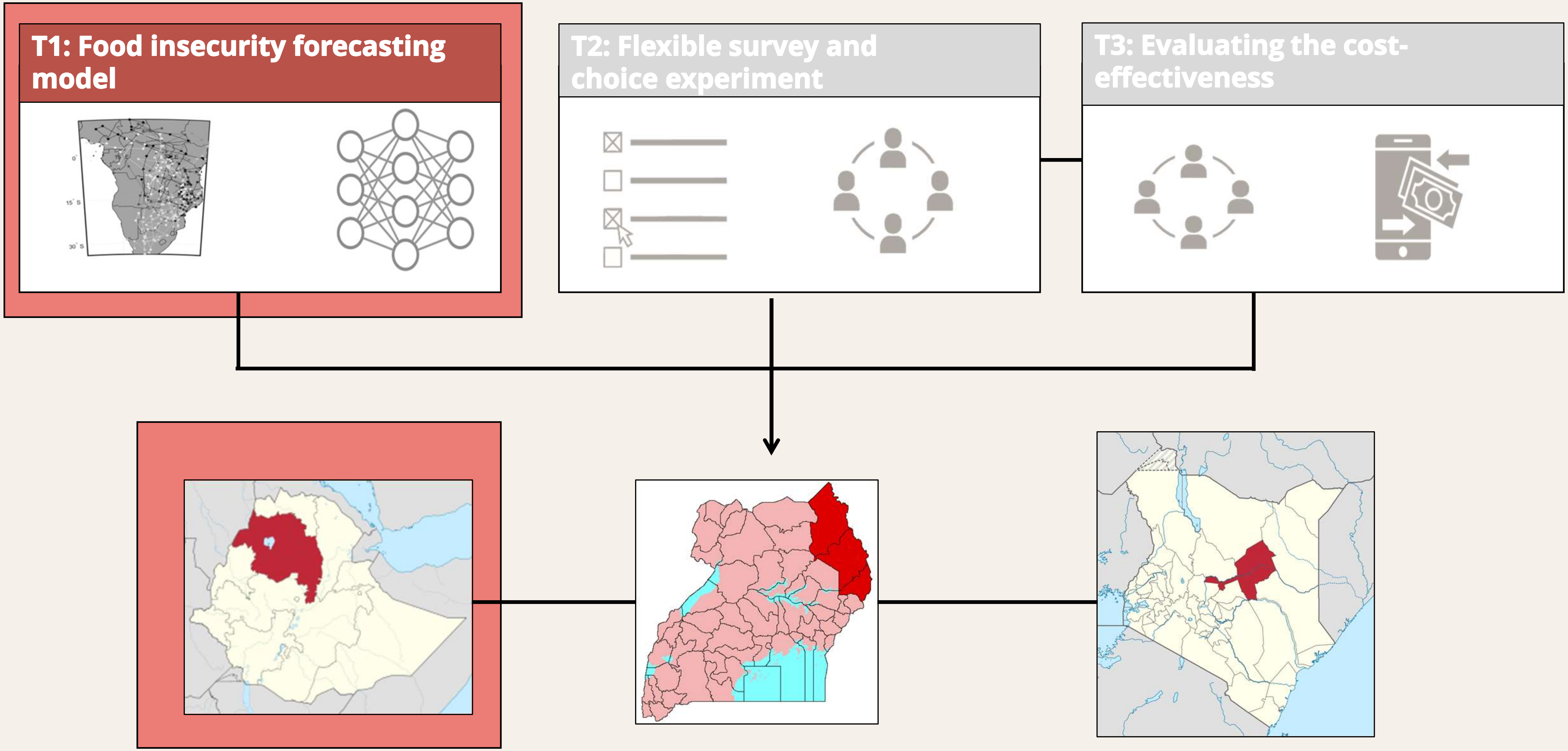
Source: Mathijs van Eeuwijk. “How accurate is food security early warning? Evaluation of Famine early warning systems accuracy in Kenya and Uganda”. *In preparation.*

T1: ACCURACY OF FEWSNET IPC CLASSIFICATION - UGANDA



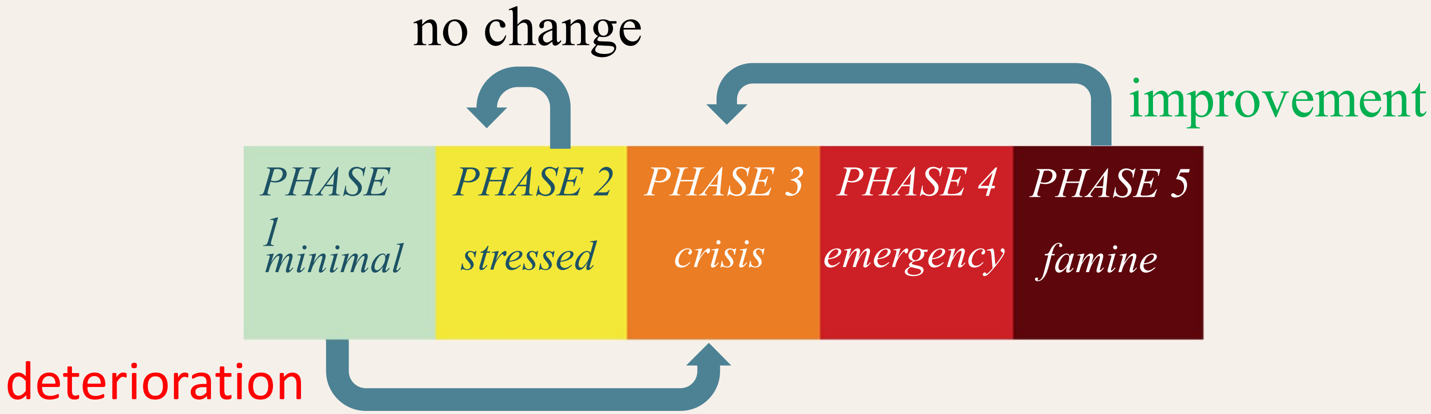
Source: Mathijs van Eeuwijk. "How accurate is food security early warning? Evaluation of Famine early warning systems accuracy in Kenya and Uganda". *In preparation.*

T1: FOOD INSECURITY FORECASTING MODEL | ETHIOPIA



T1: NOVEL APPROACHES - MODELLING FOOD INSECURITY

- Big, preferably open-source, data in combination with data-driven Machine Learning could enable an improvement in the monitoring and prediction of food security risks
  - We built a model that can predict the transitions in food security (IPC) in Ethiopia
  - We test this approach on a case study of Ethiopia, focusing on livelihoods zones.

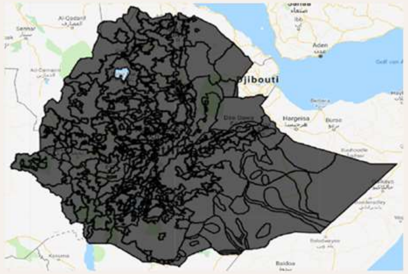


Source: Joris Westerveld et al. "Modelling Food Insecurity in Ethiopia: Towards a machine learning model that predicts the transitions in food security using scalable features." *In preparation.*

T1: MODELLING FOOD INSECURITY IN ETHIOPIA

Create XGBoost Model

Predict transitions (+4) per livelihoodzone



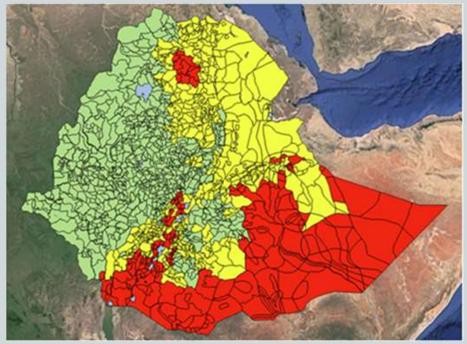
Collect scalable data, based on lterature review

Baselines Benchmark

RESULTS

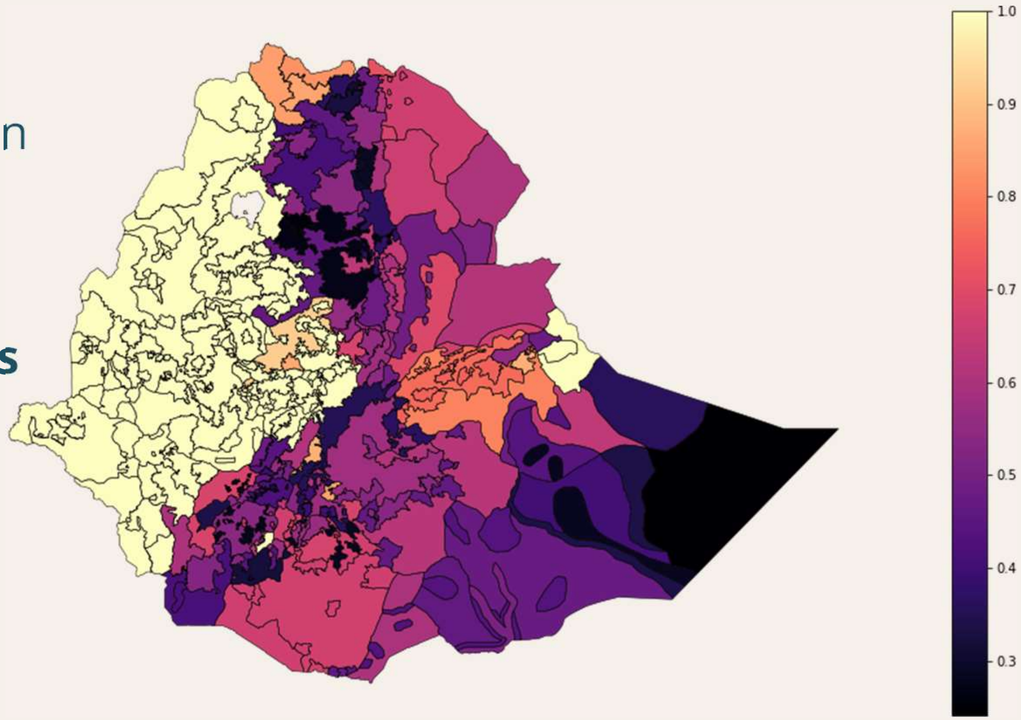
Source: Joris Westerveld et al. “Modelling Food Insecurity in Ethiopia: Towards a machine learning model that predicts the transitions in food security using scalable features.” *In preparation.*

T1: MODELLING FOOD INSECURITY IN ETHIOPIA - BUILDING RELEVANT DATABASE

PREDICTORS	PREDICTAND
Biophysical	 Integrated Food Security Phase Classfication IPC or indicators linked to IPC
Rainfall, temperature, Normalized Difference Vegetation Index (NDVI), Oceanic Nino Index (ONI), soil moisture, ….	
Socio-economic	
Staple food prices, poverty, infrastructure, societal unrest, conflicts	

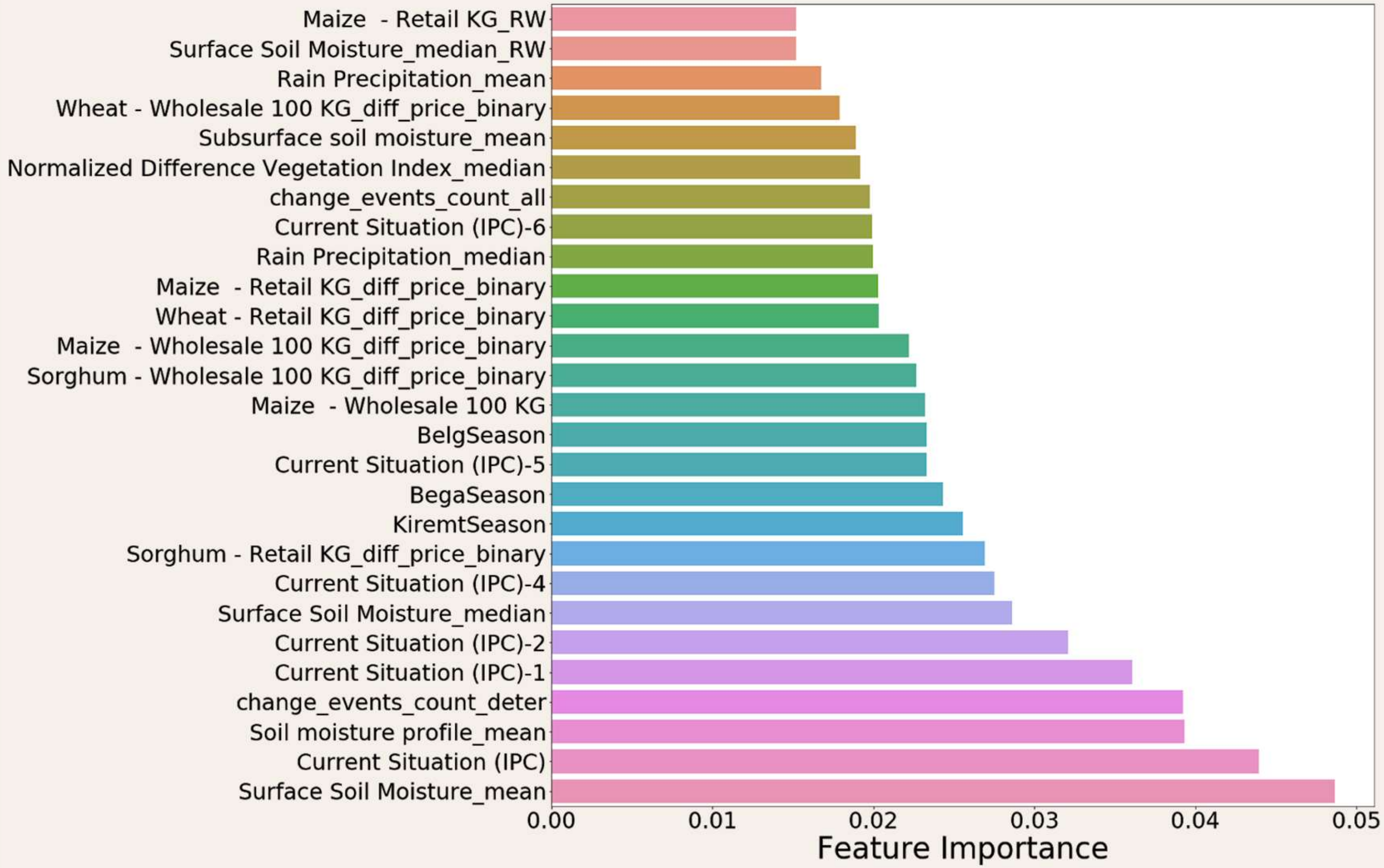
T1: RESULTS

1. Model identify **improvement** and **deterioration** in food security more **effective** than the **baselines**
2. Model even identifies **improvements better** than our **benchmark**
3. Model has **more trouble** in identifying **transitions** in the **south east** of Ethiopia compared to other regions
4. Model performs **better** for **longer prediction** intervals



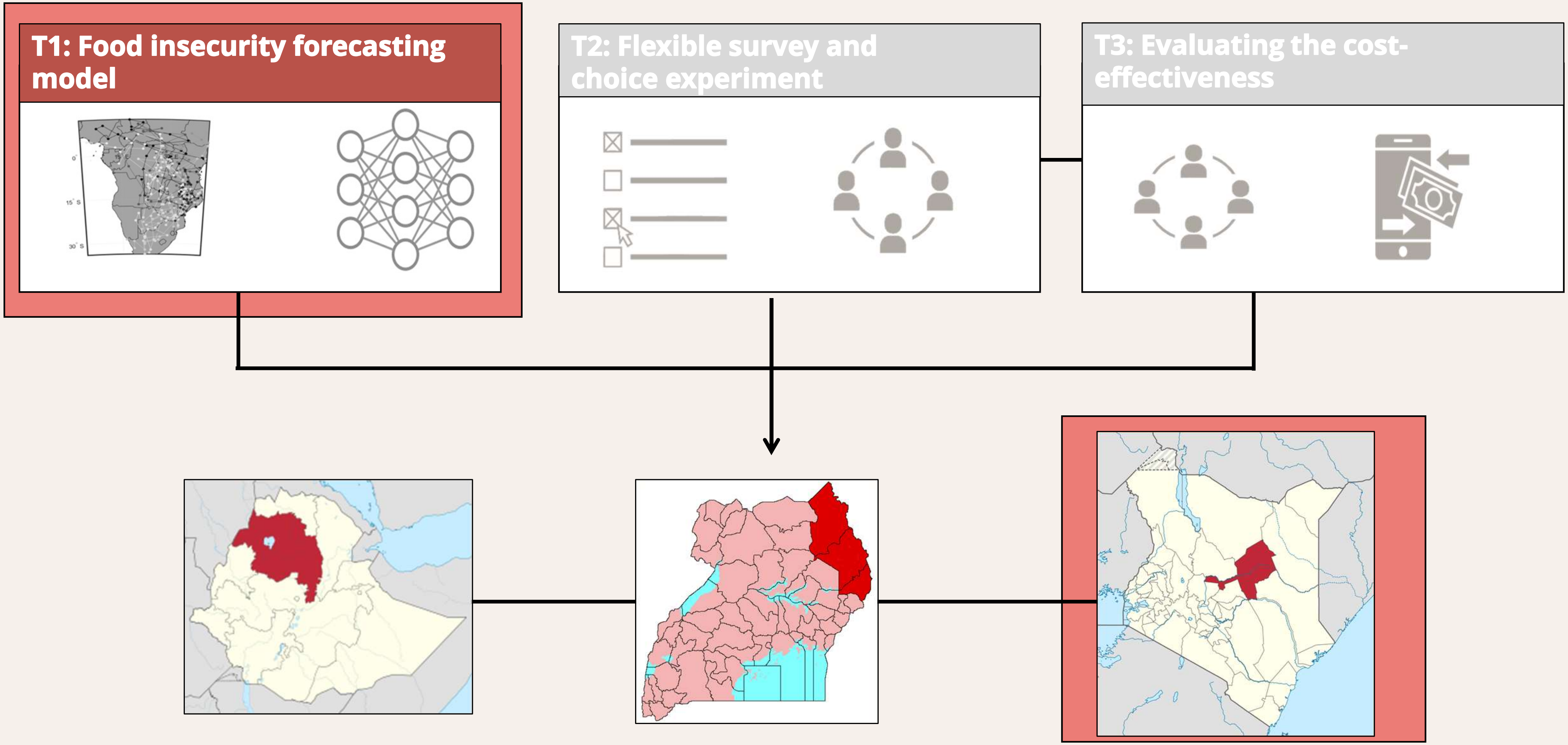
Source: Joris Westerveld et al. "Modelling Food Insecurity in Ethiopia: Towards a machine learning model that predicts the transitions in food security using scalable features." *In preparation.*

T1: FEATURE IMPORTANCE



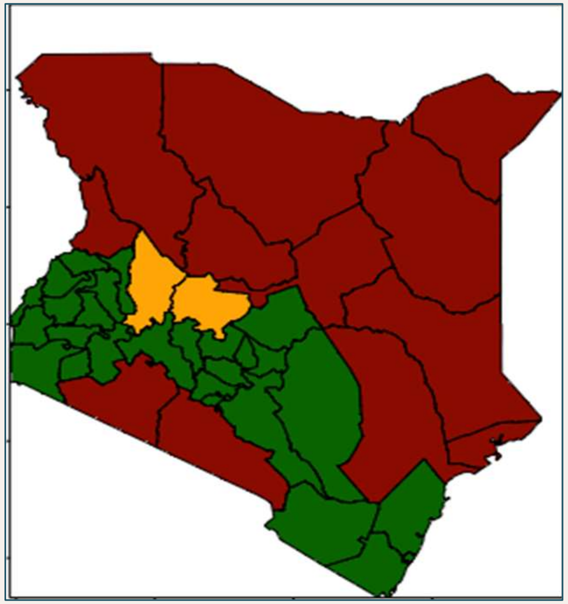
Source: Joris Westerveld et al. “Modelling Food Insecurity in Ethiopia: Towards a machine learning model that predicts the transitions in food security using scalable features.” *In preparation.*

T1: FOOD INSECURITY FORECASTING MODEL | KENYA



T1: MODELLING DRIVERS OF FOOD INSECURITY | KENYA

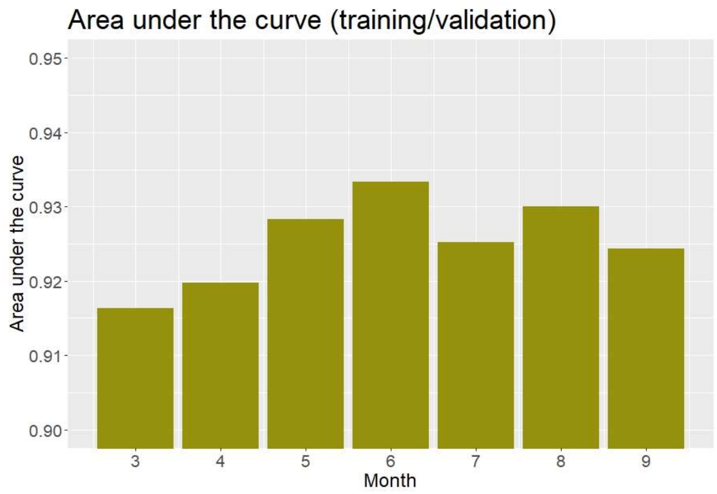
- First extract a number of monthly indicators to be used as predictors in the Machine Learning Model, and annual indicators of “shortages in the availability of maize calories” to be used as predictands.
- Second, we apply the Random Forest algorithm to predict high/low shortages in the availability of maize calories events for each month within the growing season of the maize.
- Third, we assess the accuracy metrics of each model, and their ability to predict future events.



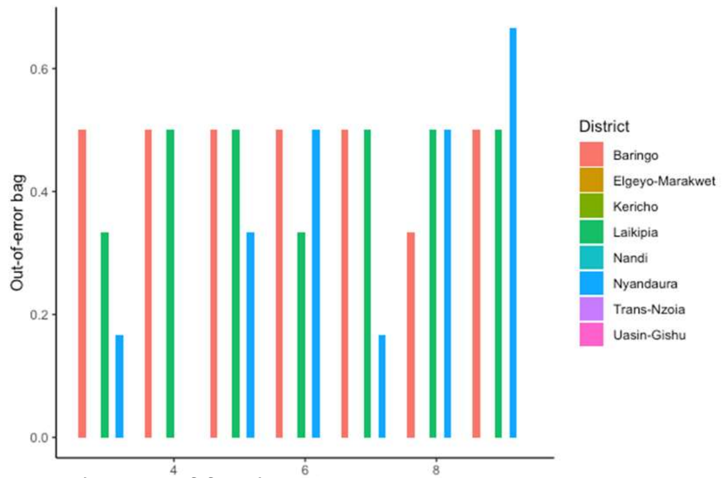
Source: Willemijn van Vuure. “.” *In preparation.*

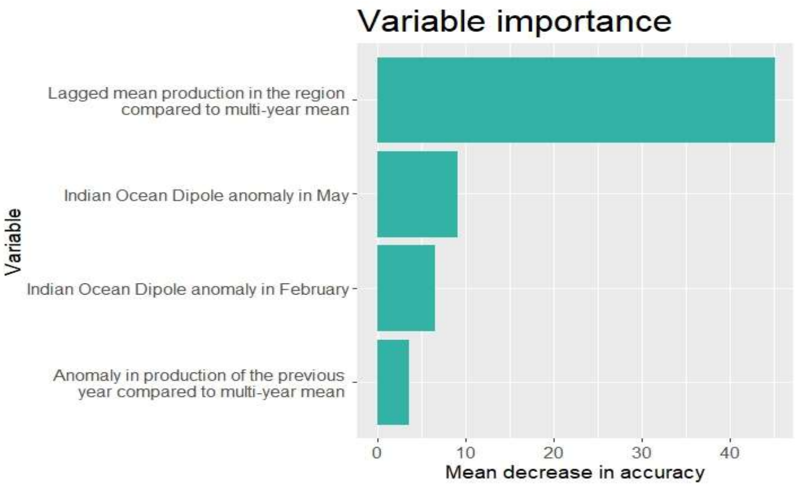
T1: MODELLING PERFORMANCE | KENYA

Past events



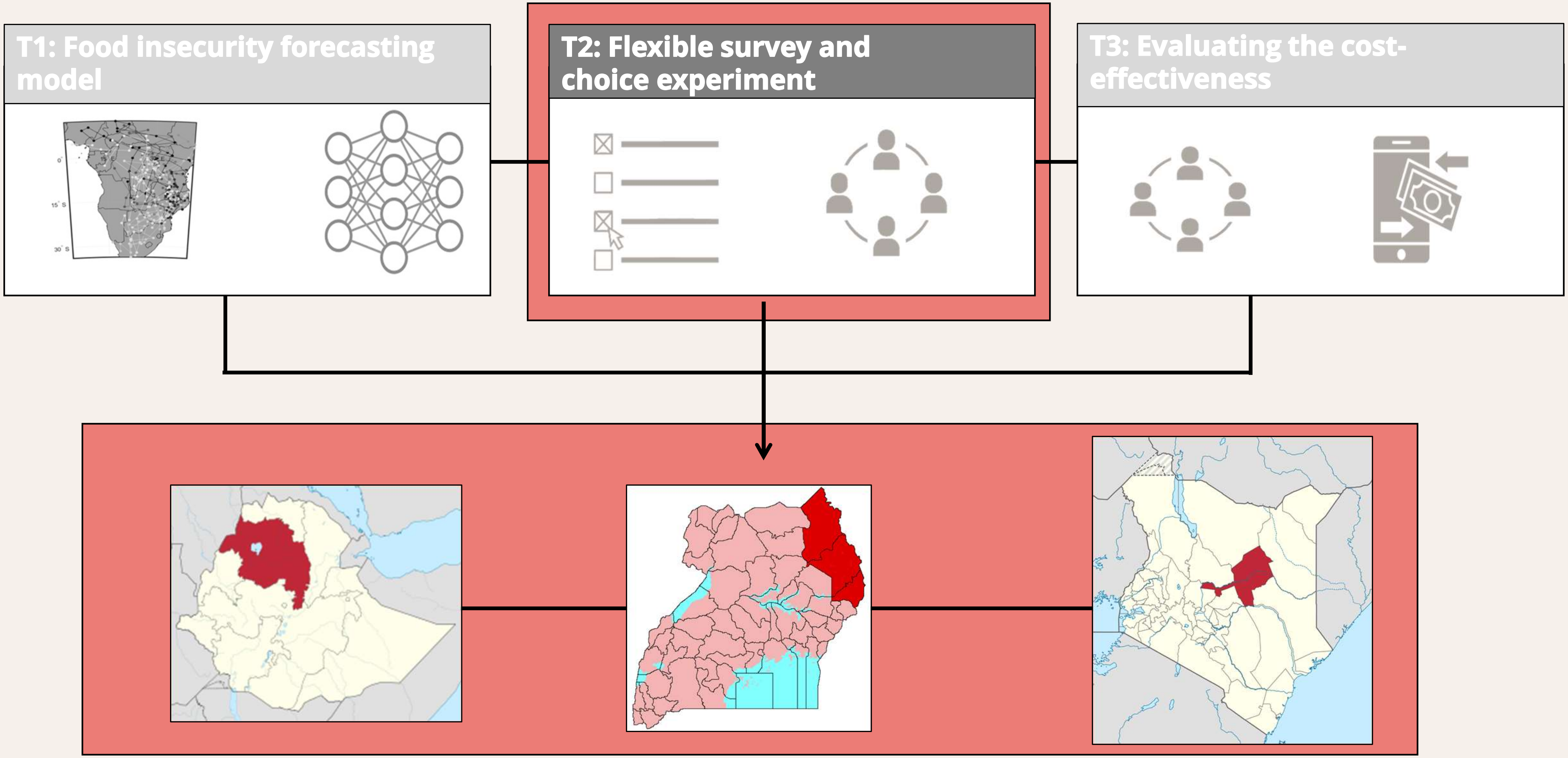
"Future" events



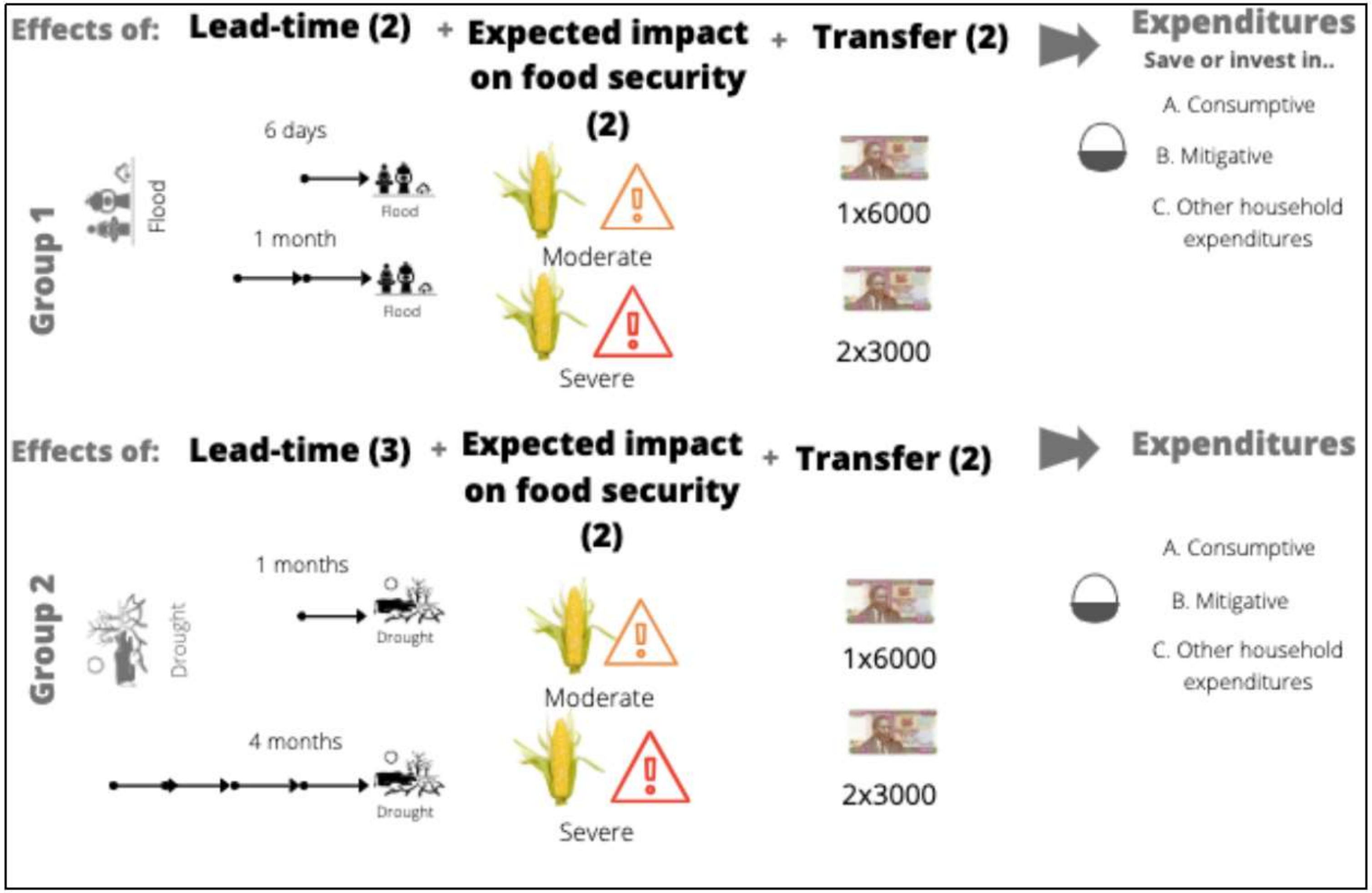


Source: Willemijn van Vuure. "Predicting drivers of food insecurity in Kenya" *In preparation.*

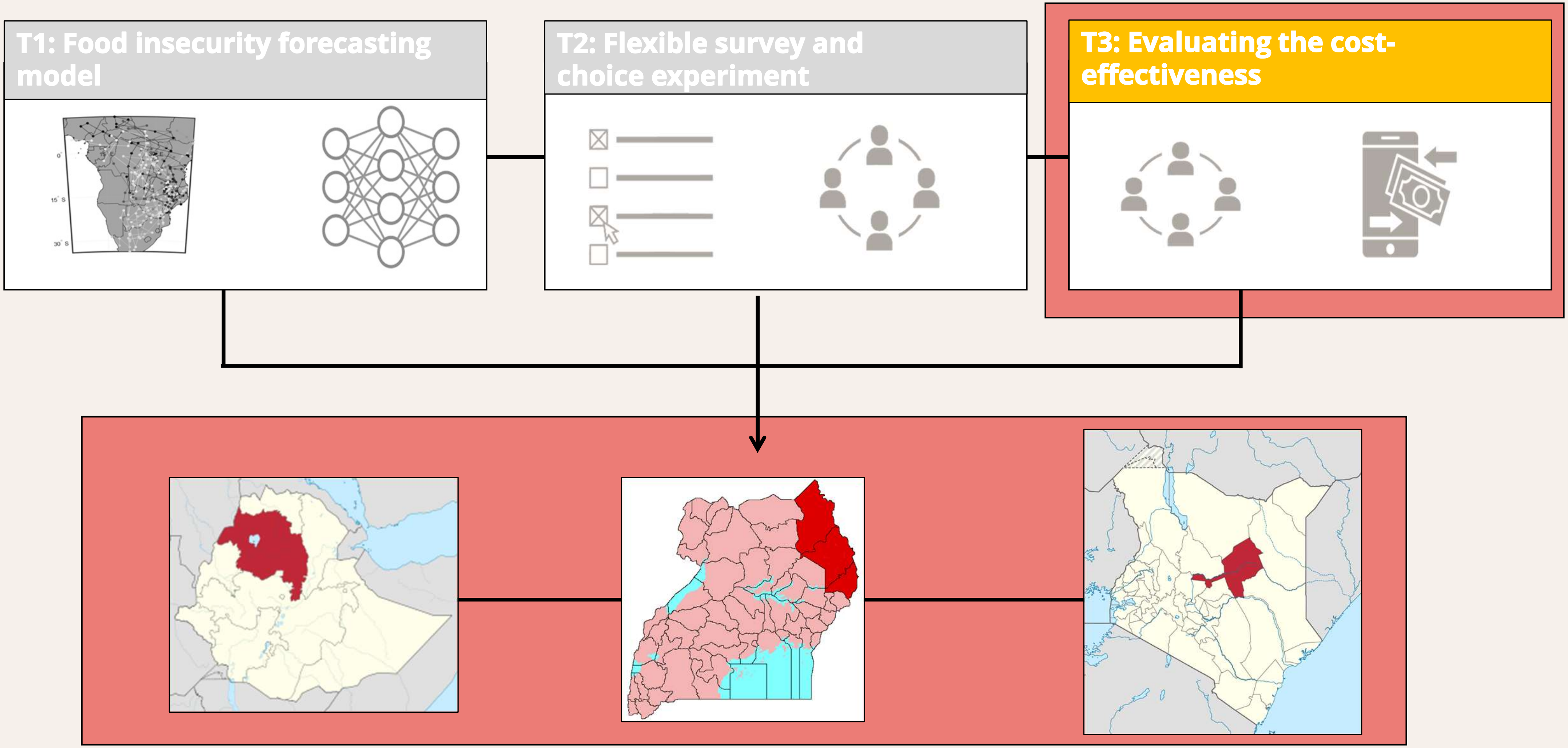
T2: SURVEY AND CHOICE EXPERIMENT



T2: CHOICE EXPERIMENTS



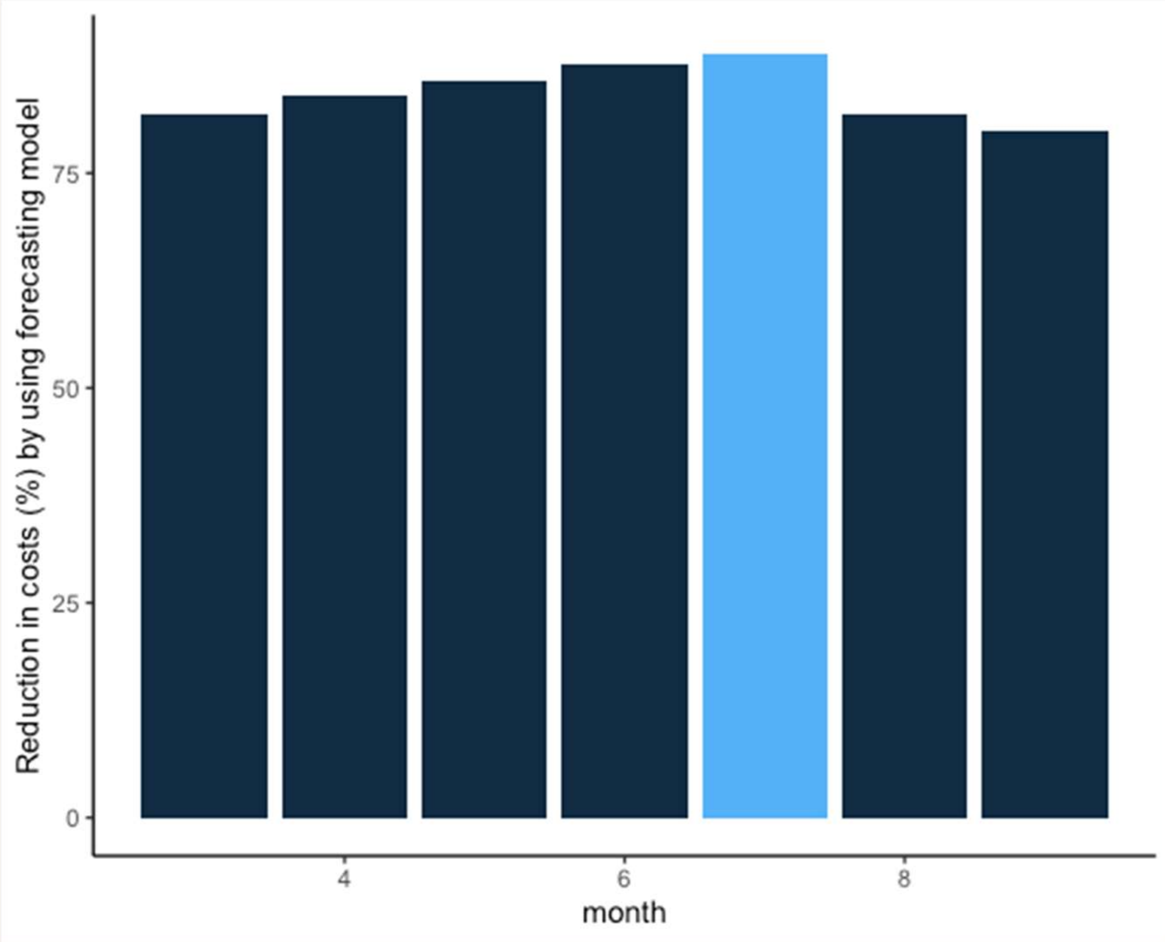
T3: COST-EFFECTIVENESS



T3: PRELIMINARY: COST-EFFECTIVENESS - KENYA

How much reduction in costs a cash transfer programs can potentially achieve by using a forecasting model?

- Based on outputs of the Random Forest (Kenya) we compare two scenarios in which cash transfer payments are triggered by a forecast model vs. a scenario without forecasting



Marc van den Homberg, Gabriela Guimarães Nobre, Ted Bolton

Thank you!

Mvandenhomberg@redcross
g.guimaraesnobre@vu.nl

AN INITIATIVE OF THE NETHERLANDS RED CROSS