



# Weather shocks and migrations Intension in Western in Africa

John Aoga, Juhee Bae, and Stefanija Veljanoska



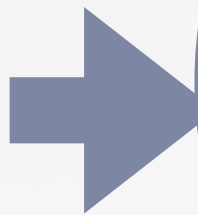
# Our Motivation

Why we are doing this research ?



# OBJECTIVE OF THIS STUDY

What is our goal?



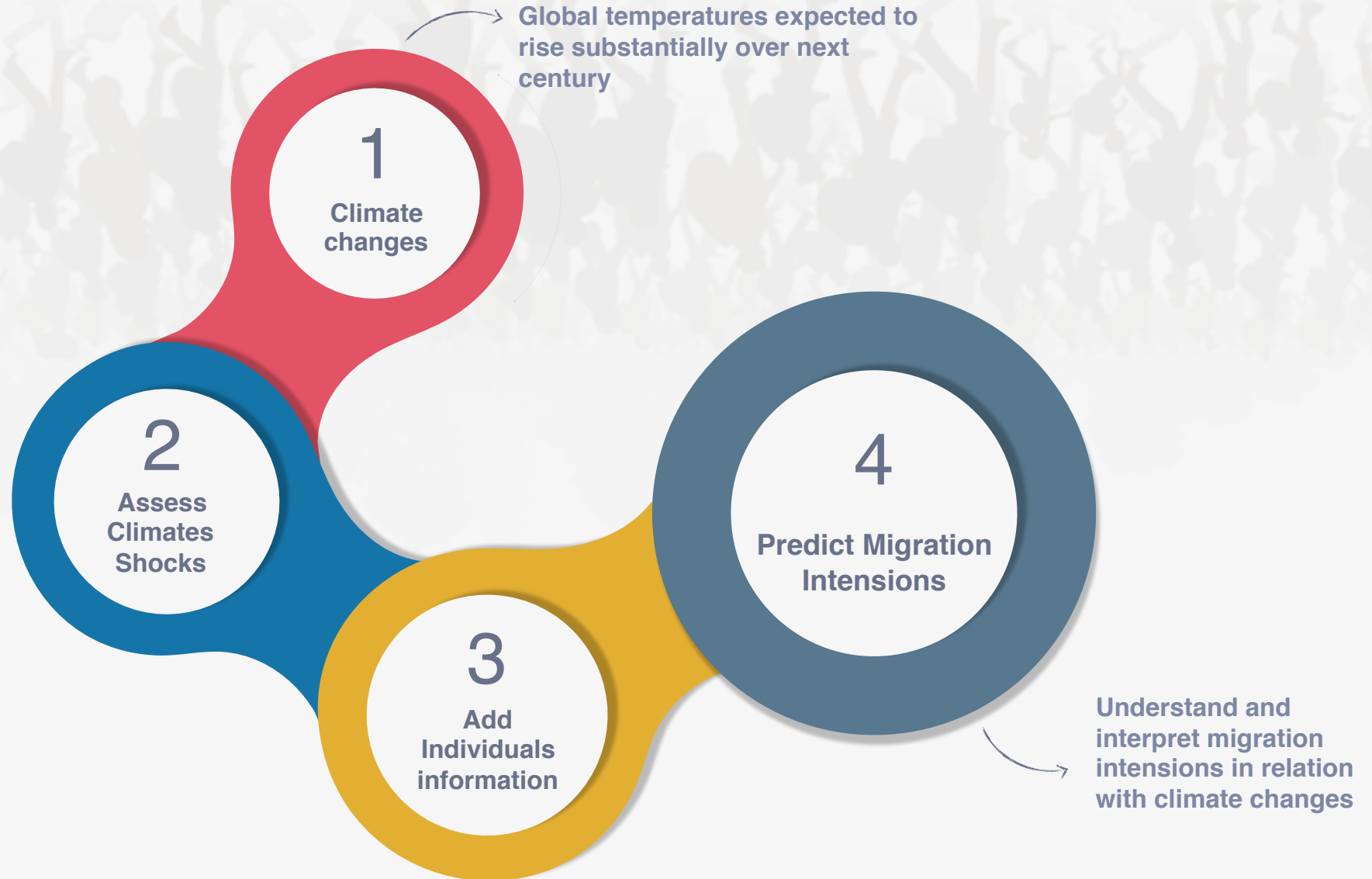
Understand  
and interpret  
migration  
intensions





# HOW?

Weather shocks + individuals information => migration intension





# WHY WEATHER?

Combine Economic and climate shocks variables

- ◆ Changes in weather conditions induce economic, health and welfare effects within a given spatial unit [1,2].
- ◆ Temperature or Rainfall have strong impacts on agriculture-dependent economies (like west-africa countries).
- ◆ Other parameters can also influence economic outcomes => it is **difficult to identify the causative effects of climate shocks.** [1].

Interesting paper

[1] Dell, M., Jones, B. F., & Olken, B. A. (2014). **What do we learn from the weather? The new climate-economy literature.** *Journal of Economic Literature*, 52(3), 740-98.

[2] Rigaud, K., Jones, B., Bergmann, J., Clement, V., Ober, K., Schewe, J., Adamo, S., McCusker, B., Heuser, S., and Midgley, A. (2018). *Groundswell: Preparing for internal climate migration.* Washington, DC: The World Bank.



# HOW?

Answering these research questions

## Research questions

- How can we explain migratory intentions based on climate shocks?
- Which time horizon is mandatory to capture the shocks which impact the decision of people to move?
- Which shocks (variables) most affect people's decisions to move (internally and internationally)?
- Which time horizon is mandatory to capture the shocks which impact the decision of people to move?



## **WEATHER SHOCKS**

Temperature, rainfall, SPEI

Covered in  
a previous  
presentation



# Multilevel approach

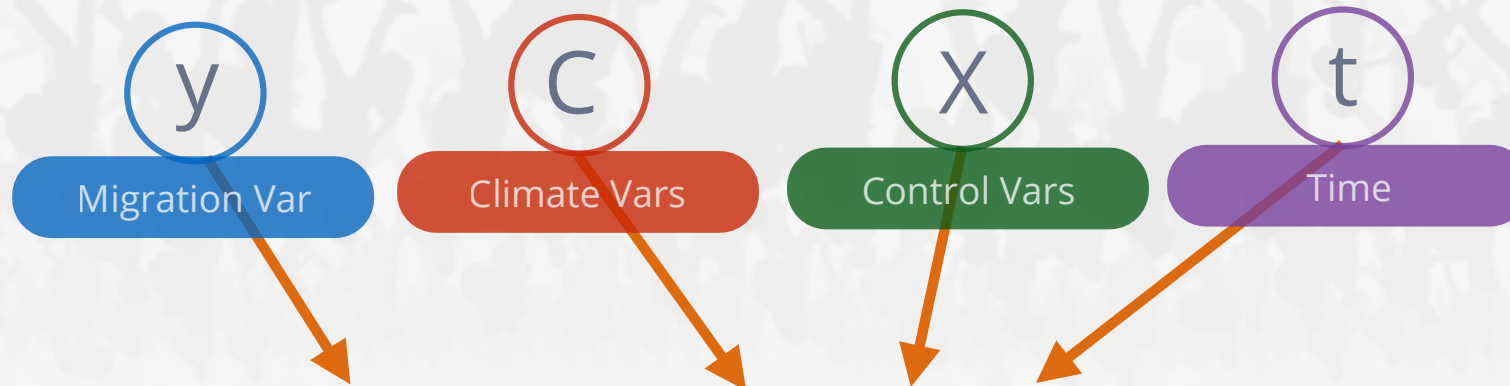
Bertoli, Docquier, Rapoport, and Ruysen





# GENERAL MODEL

What is parameter learning ?



$$y = f(C, X, t)$$

Global Model

WE ARE LOOKING FOR  $f$



[1] Bertoli, S., Docquier, F., Rapoport, H., & Ruysen, I. (2019). Weather shocks and migration intentions in Western Africa: Insights from a multilevel analysis Workshop on Climate change, Inequality and Human Migration, AFD, Oct 2019, Paris, France.



# DATA DESCRIPTION

From the Gallup World Polls data (1,7 millions of obs. x 2,600 of vars.)

- Targeted countries (over 9 years, ~60,000 obs. x 900 vars)
  - Burkina Faso, Ivory Coast, Mali, Mauritania, Niger, and Senegal.
  - The most « at risk » regions of the world in term of environmental balance and associated mobility patterns
- Migration intentions => **migration var**
  - Q1 (internal migration). In the next 12 months, are you likely or unlikely to move away from the city or area where you live? **(BMIG\_in)**
  - Q2 (international migration). Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country? **(move)**



# DATA DESCRIPTION

From the Gallup World Polls data (1,7 millions of obs. x 2,600 of vars.)

📌 Economic variables => **Control variables.**

📌 **Lnhhincpc** => Household size

📌 **hhsiz** => Household size

📌 **children** => Number of children

📌 **urban** => Urban/Rural area

📌 **mabr** => Connexion abroad (network variable)

📌 **hskill** => Education (Highly/ educated

📌 **male** => Gender

📌 **age1524, age2534 and age35plus** => age variables (intervals  
[15, 24], [25,34], [35, 45] )

In the paper, they showed why these control variables are important



- Temperature and Rainfall from CRU-TS 4.01 gridded datasets  
=> **Climate variables**
  - Compute long-term mean and (Relative and absolute) Standard deviations.
    - Over 36 months.
- Standardized precipitation Evapotranspiration Index (SPEI) => **Climate variables**
  - Drought index used to determining the onset, duration and magnitude of drought conditions
  - It depends on several climate variables such as rainfall, temperature, and evapotranspiration.

[https://crudata.uea.ac.uk/cru/data/hrg/cru\\_ts\\_4.01/](https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.01/)



# ENRICHED DATASET

Gallup dataset + Weather Shocks dataset => join by region

39319 obs. x 8441 vars. (only 12 control variables)

## Names of climate variables



- T, P, SPEI  
Temperature, Rainfall or SPEI over 12 months (alternatives are 1, 3, 6, 18 or 24 months)
- r,a  
Absolute (a) or relative (r) deviations from the mean
- A,B,D  
A denotes that all months (regardless of the growing season) have been considered (B indicates only months falling within the planting season were considered; D indicates only months falling within the planting+harvesting season were considered)
- D1-D9  
They differentiate between the size and direction of anomalies
- C1-C36  
The period cover by this variable (month-1, month-36)

<https://gadm.org/metadata.html>

[https://www.dropbox.com/sh/b16zbc16t3uh6v6/AAAJrKc\\_eJaYwjZzV5sYmJJma?dl=0](https://www.dropbox.com/sh/b16zbc16t3uh6v6/AAAJrKc_eJaYwjZzV5sYmJJma?dl=0)

<https://www.dropbox.com/sh/v8q74qt3uuurb5y/AACF19wsmhHiEaQ7ECB27H2ta?dl=0>



# REGRESSIONS AND CONCLUSIONS

310 000 logit regressions

- 310 000 logit regressions ( $= 6 \times 7 \times 3 \times 3 \times 36 \times 2 \times 2 \times 7$ )
  - Six countries
  - Seven weather variables of interest (T, P, 5 SPEIs)
  - Three types of weather shocks
  - Three measures of the intensity of the shocks (1, 2, 3 deviations)
  - 36 months
  - Two anomaly period specifications (all months or only crop-growing season)
  - Two types of regional identifiers (finer or coarser)
  - Seven samples (full sample, urban/rural areas, low/high-educated respondents, with/without connection abroad)



- 📌 The predictive power is maximized when :
  - 📌 using **negative SPEI** shocks (i.e., droughts),
  - 📌 measuring shocks as the share of months with **at least 2 relative standard deviations** below the local SPEI long-term value **over the last 12 months**,
  - 📌 focusing on the **crop-growing season** (not all months)
  - 📌 focusing on the subsample of **individuals living in rural areas**.



Considering the crop-growing season over the previous 12 months

▣ Analysis for **people migration**

▣ higher probability of intending to move for **Senegal, Niger, and Ivory Coast.**

▣ Insignificant for the other countries.

▣ Analysis for **international migration**

▣ higher probability of intending to move from **Niger** only.





# Our Approach

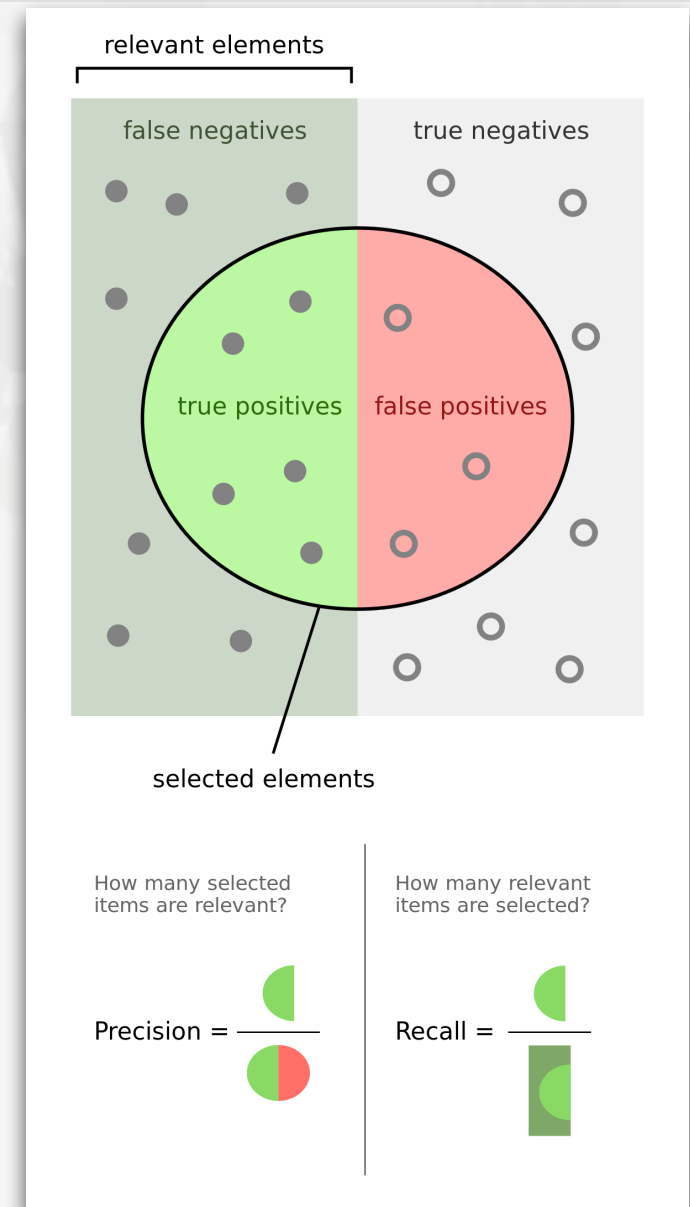
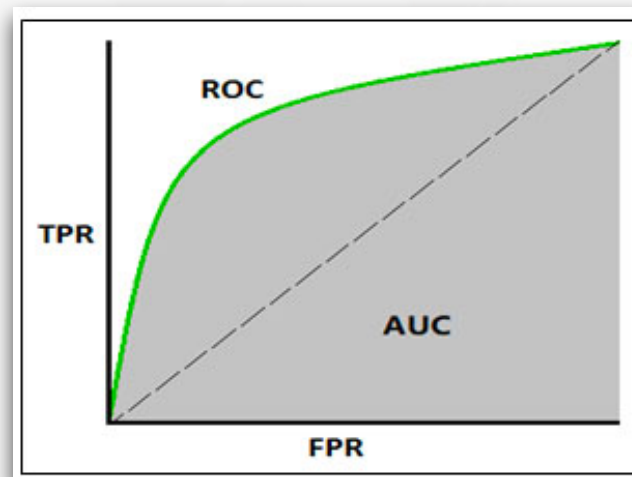
New lines of research (machine learning)



# MACHINE LEARNING APPROACHES

## Differences with manual regression

- Splitting data into **train and test sets** and train set into train and cross validation sets (avoiding overfitting, robustness against noise).
- Measuring the performance of the learning using metrics such as **Precision, Recall, Accuracy, F-measure and the Area Under the curve (AUC)**.





- ❖ Confirming the result of the paper ? Drawing further conclusions.
- ❖ Using the **Enriched dataset** (the same as the paper).
- ❖ Preprocessing the enriched data into a **Raw dataset** (i.e. we have the real SPEI values not a ratio).
- ❖ **Visualizing** the dataset in many ways (find correlations, dependencies, outliers, hints, ...)
- ❖ Running several **machine learning algorithm** (mainly tree based method which are really interpretable).
- ❖ **Interpreting** the results (i.e. finding the important features) and validating the results with experts.



# Visualization and Interpretation

Check this link





## Using Enriched dataset

Run machine learning algorithms to verify the paper conclusions



# ENRICHED DATASET

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<https://www.dropbox.com/sh/v8q74qt3uuurb5y/AACF19wsmhHiEaQ7ECB27H2ta?dl=0>



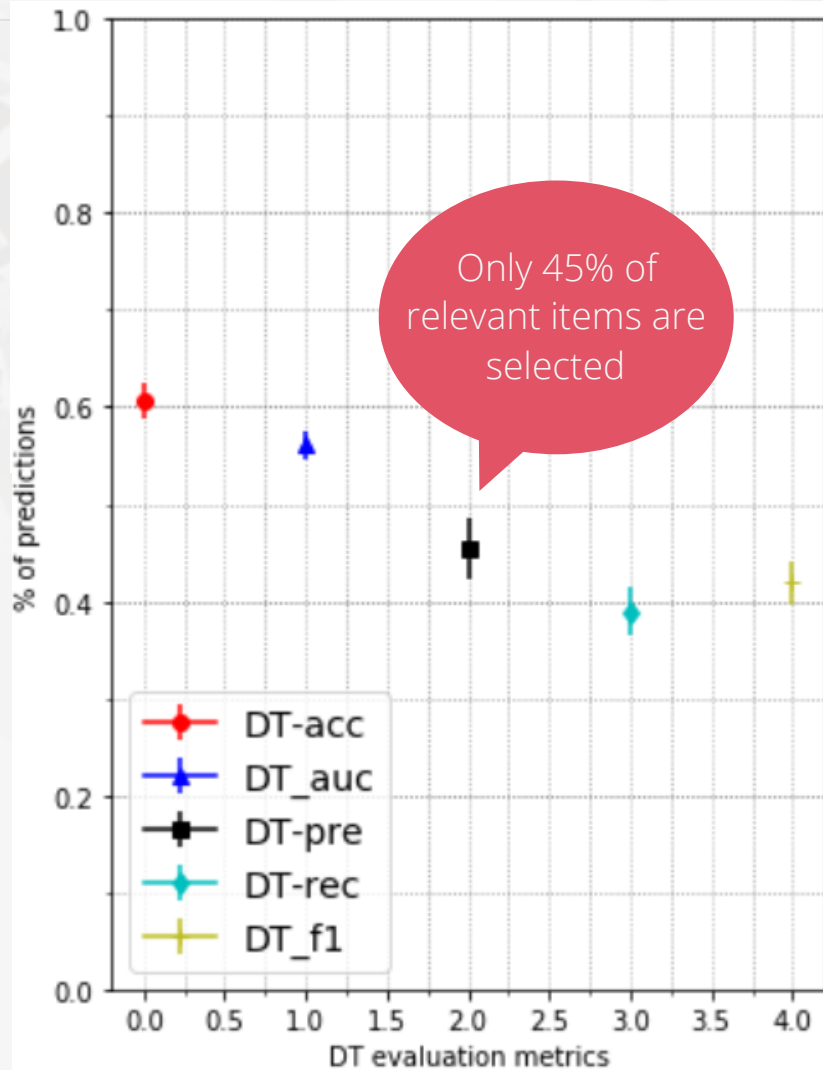
# VARIABLES USED FOR SHAP (TRIAL 1)

SHAP solution (take two days)

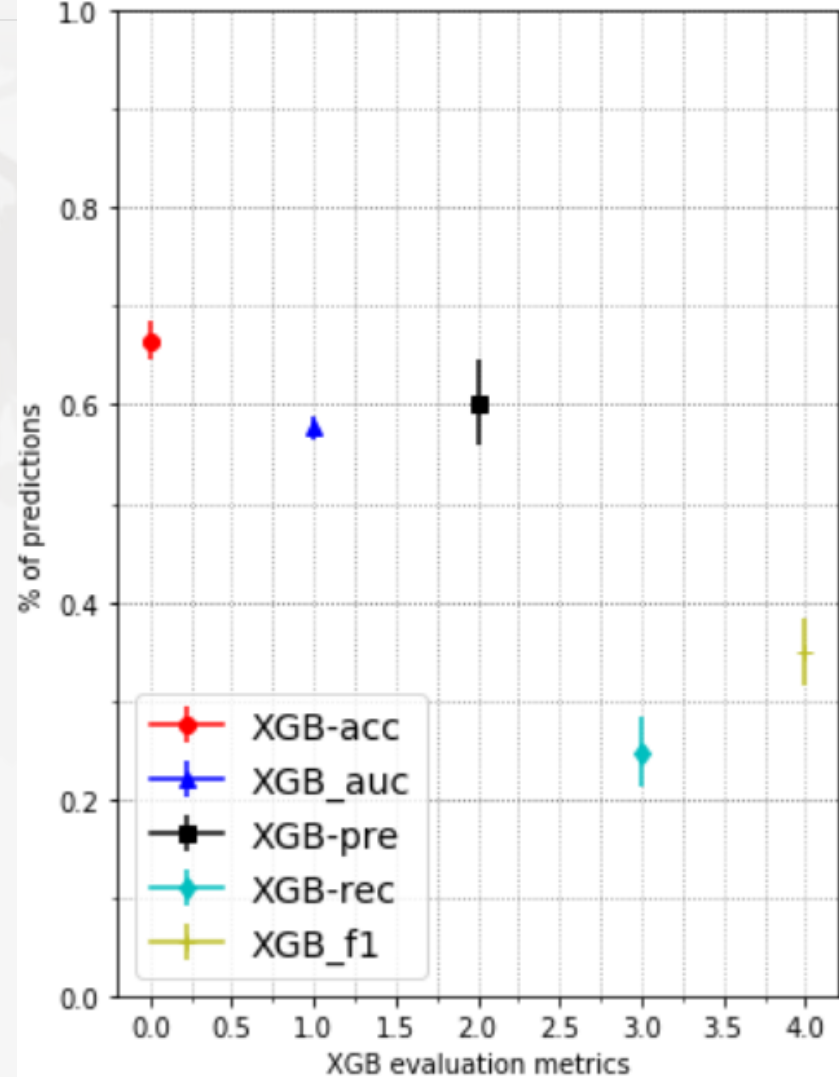
HIGH  
SIGNIFICANT



LOW  
SIGNIFICANT



ORIGIN

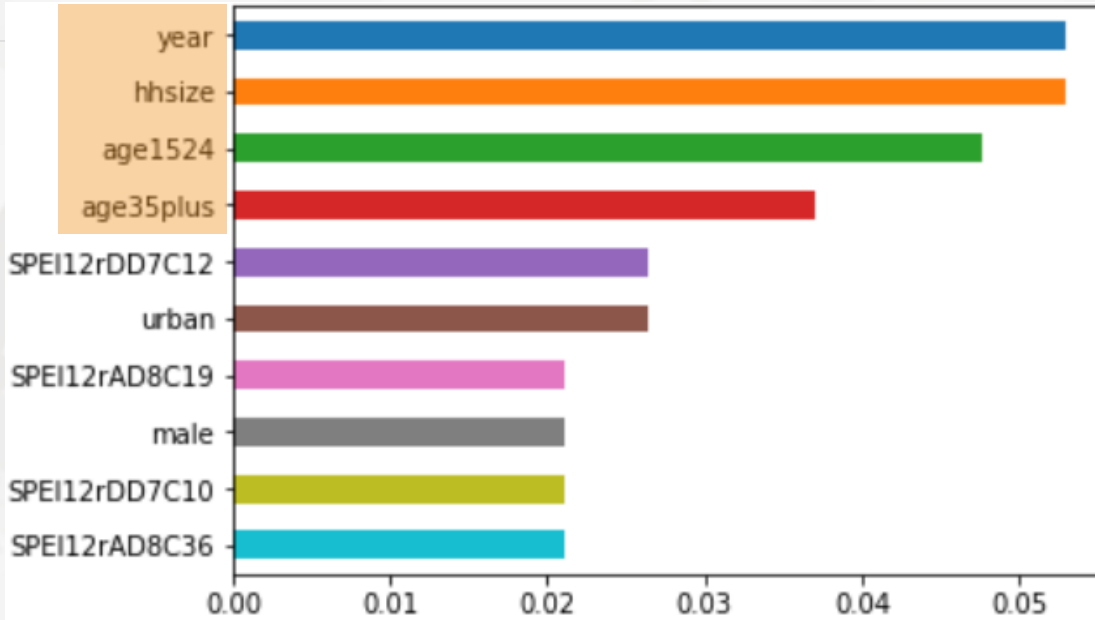


HHSIZE



# PERFORMANCE OF XGB

## Feature importance



Feature importance

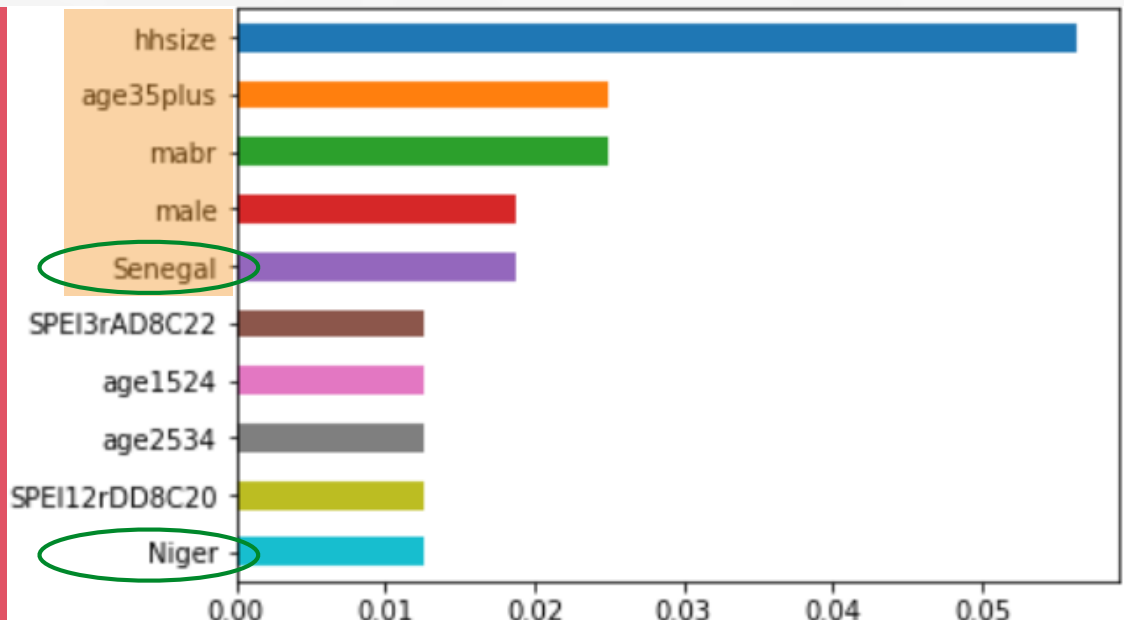
### Xgboost: Global feature importance metrics (Senegal)

year'	1
Household (hhsize)	2

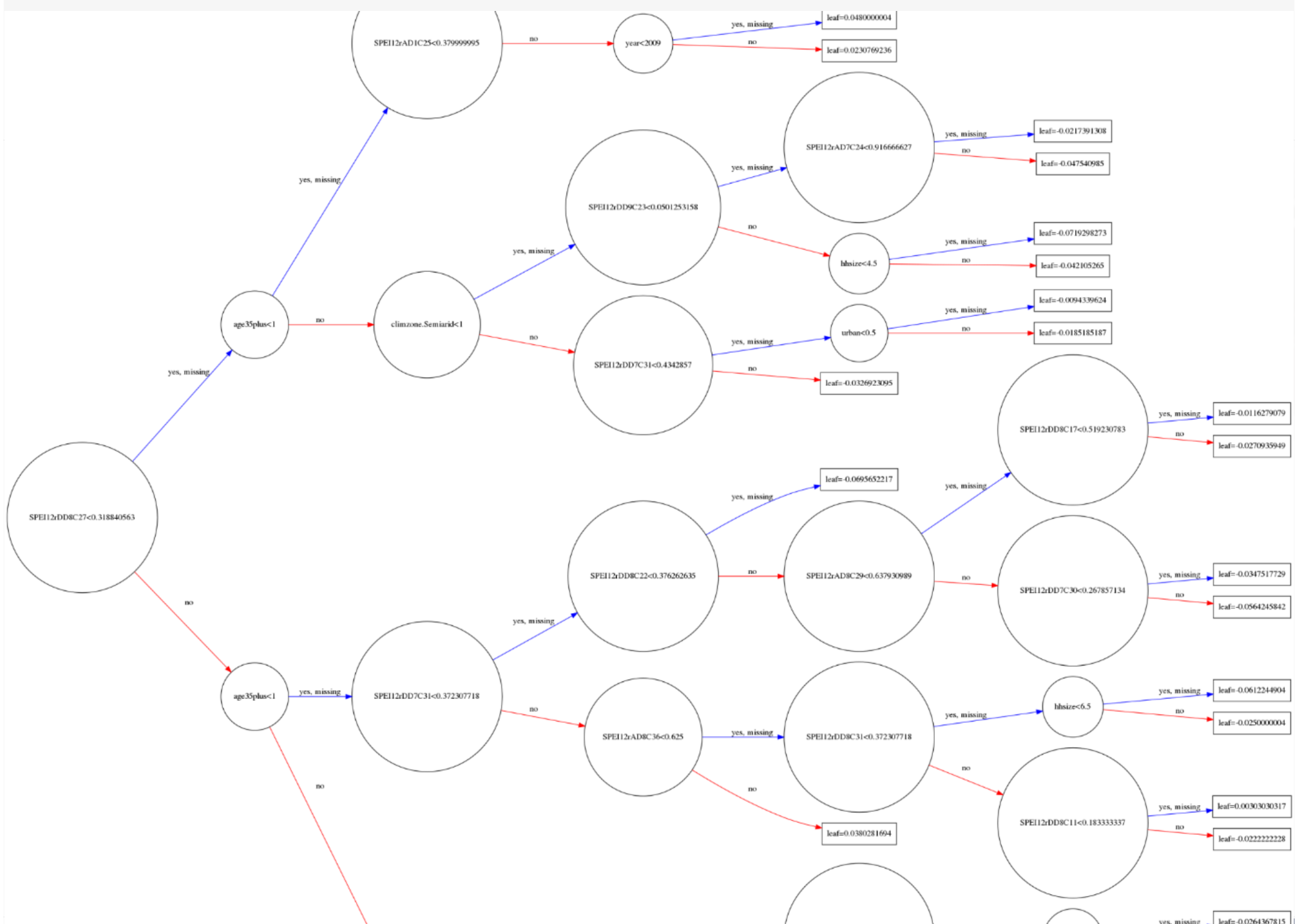
Feature importance

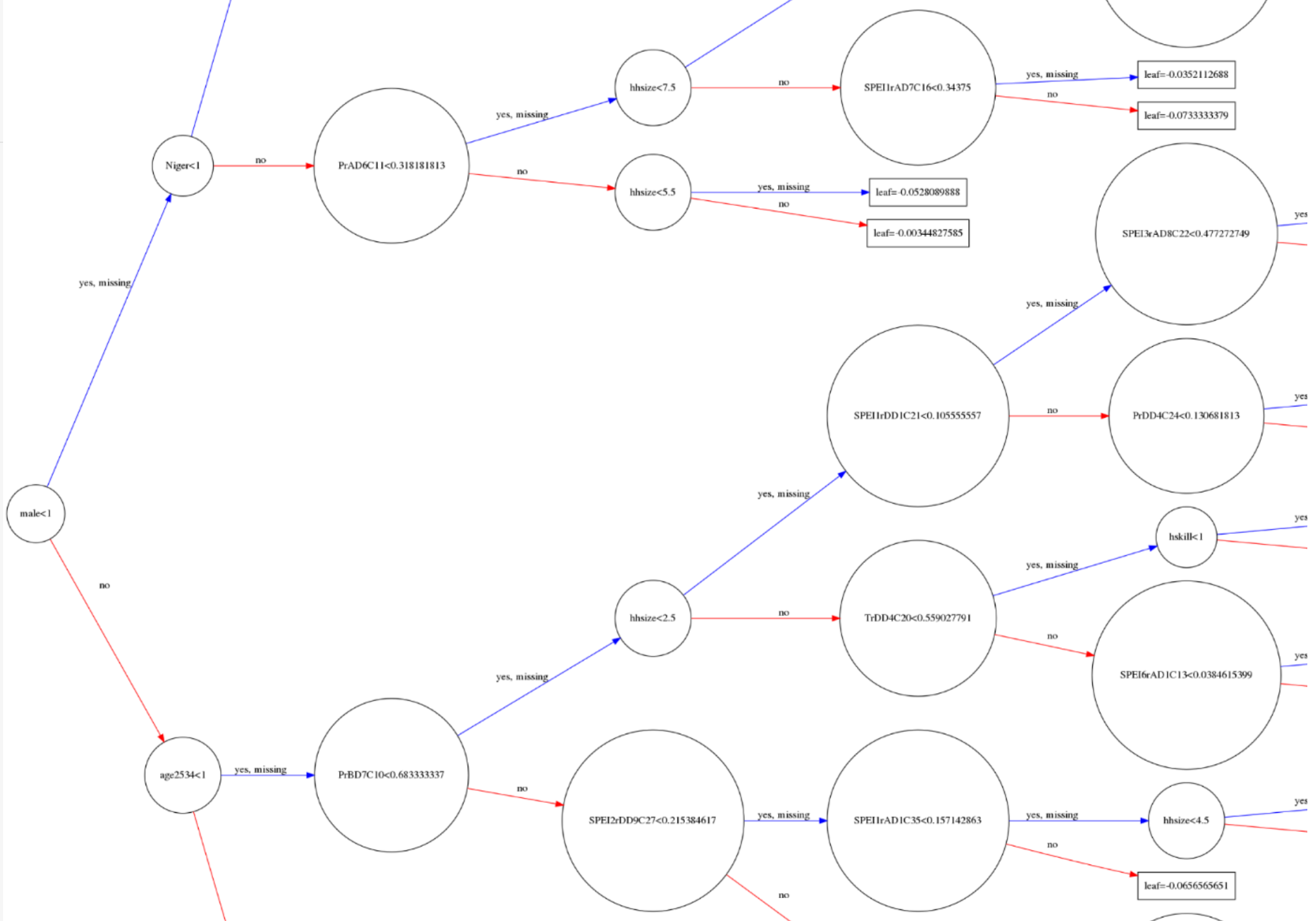
### Xgboost: Global feature importance metrics (All countries) - removed age > 35plus no move

Household (hhsize)	1
One-distance Connection Abroad (mabr)	1











# Build new Algorithms from raw data

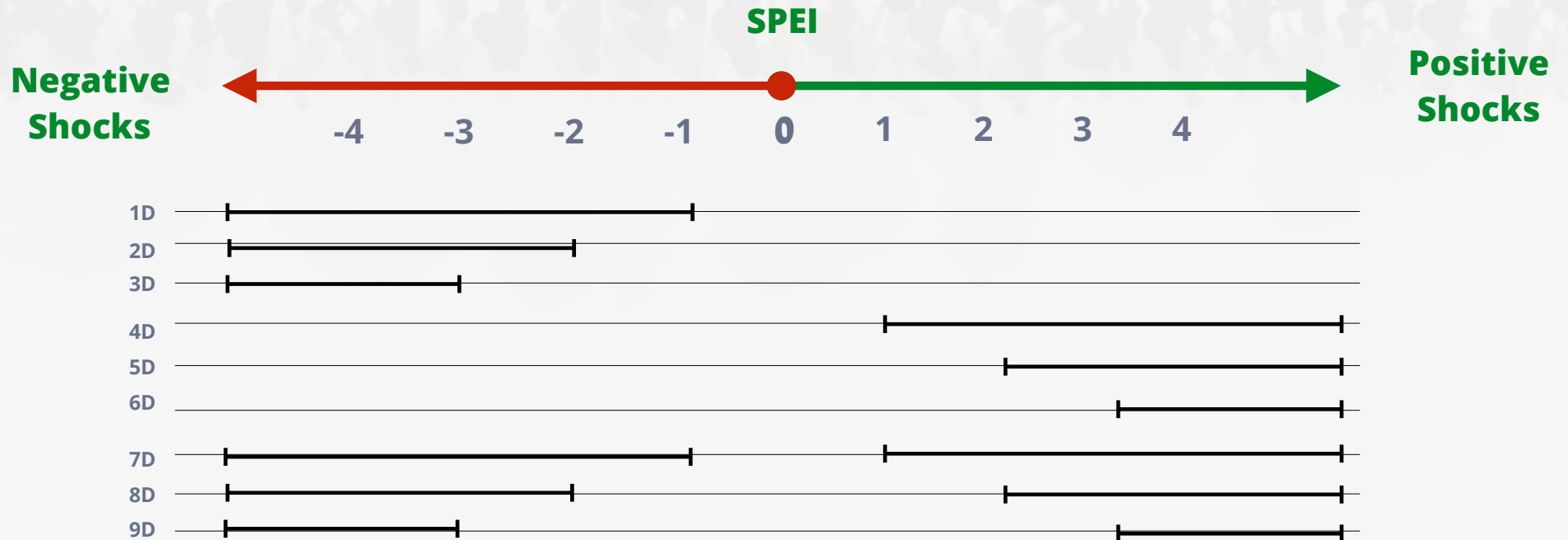
Running deep learning approaches (RNN)



# RAW DATASET

Gallup dataset + Weather Shocks dataset => join by region

- 39319 obs. x 8441 vars. (only 12 control variables)
- 12 Gallup Variables (Same as in the enriched data)
- Climate Variables (Binarize SPEI + cropping and growing seasons)



- 48 Climate variables monthly lags

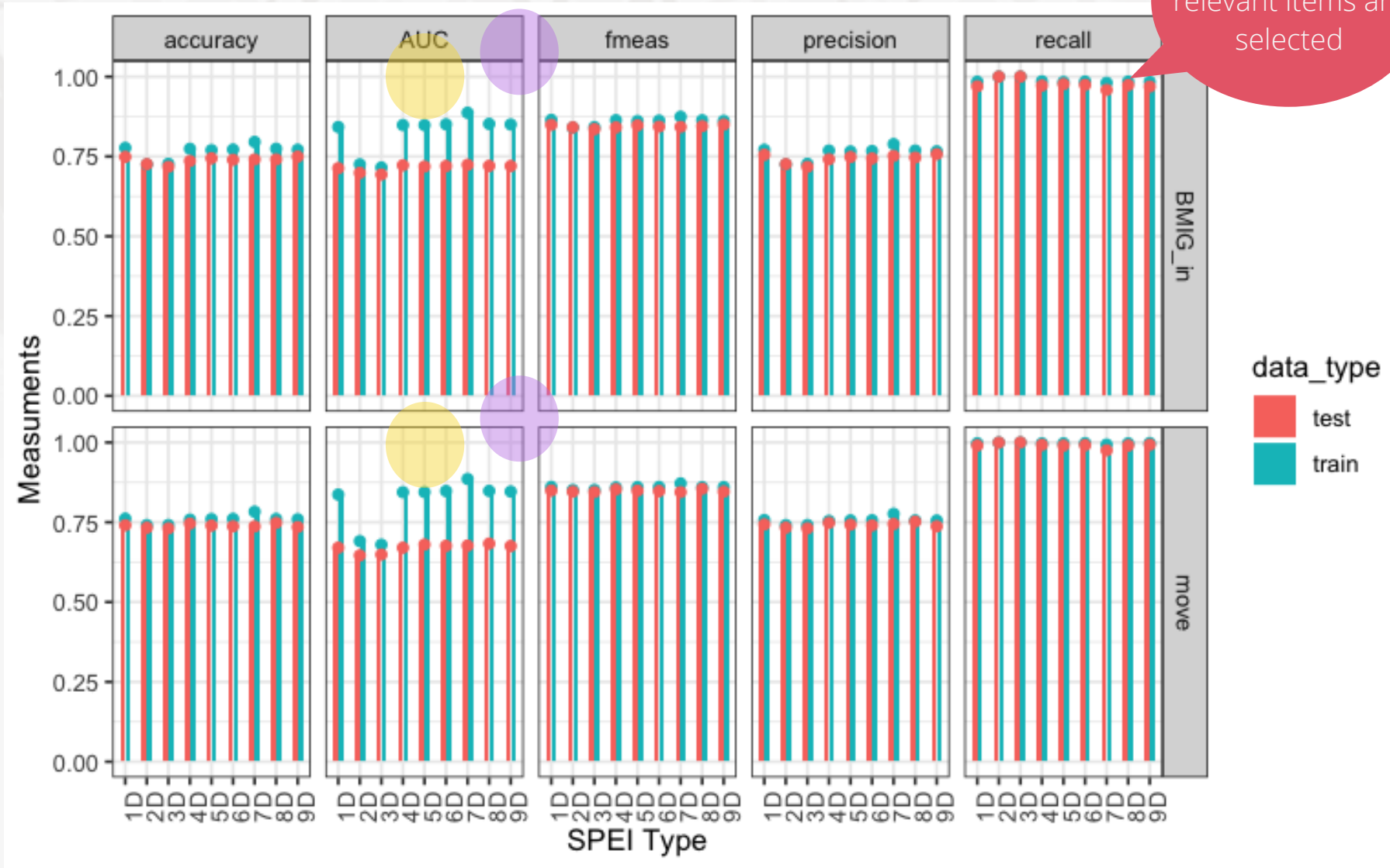


# Performances



# PERFORMANCE USING RANDOM FOREST (RF)

Accuracie and AUC are higher than the other when we have shocks

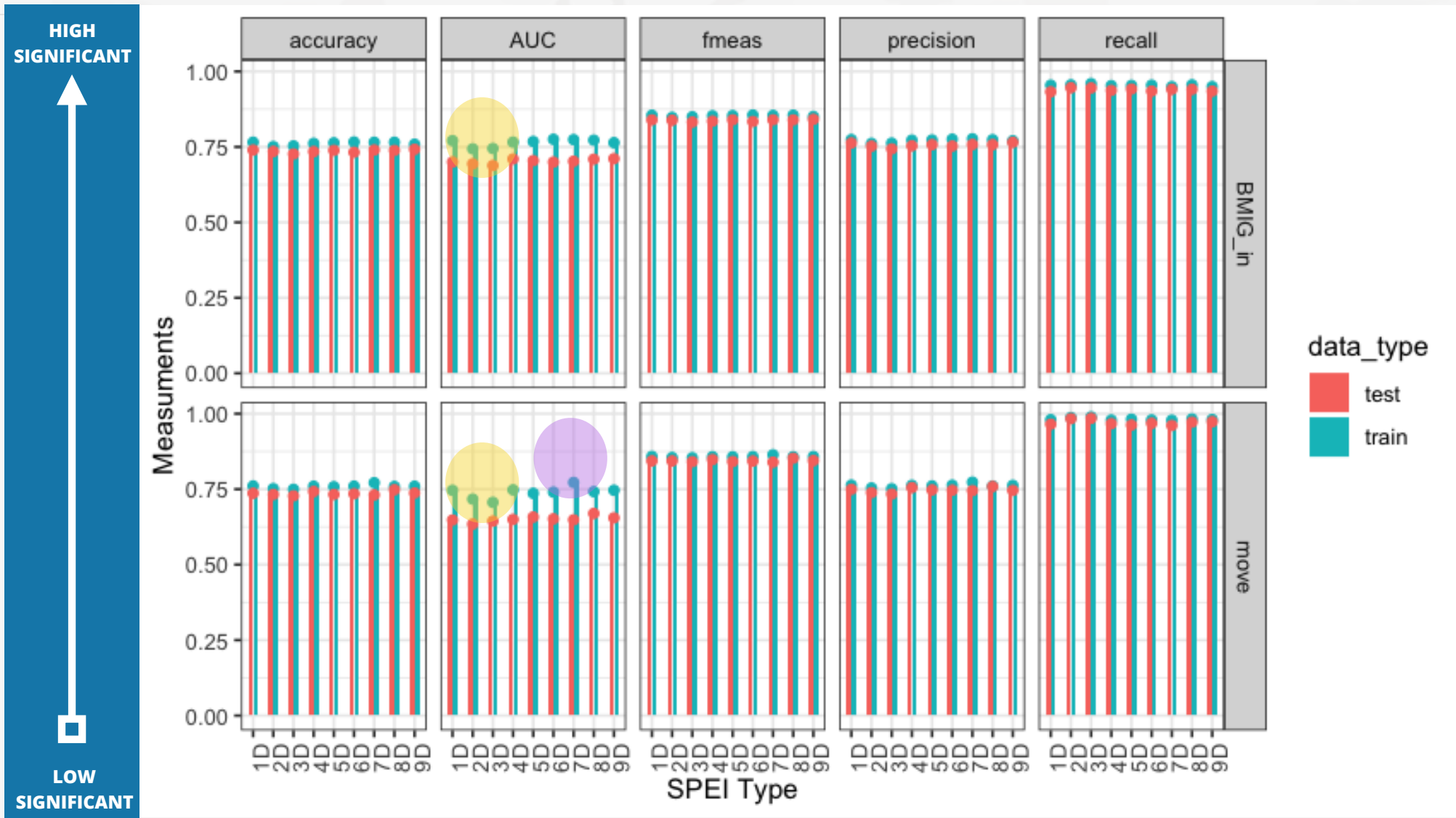


Almost all of the relevant items are selected



# PERFORMANCE USING GRANDIENT BOOSTED TREES (XGB)

Accuracie and AUC are higher than the other when we have shocks





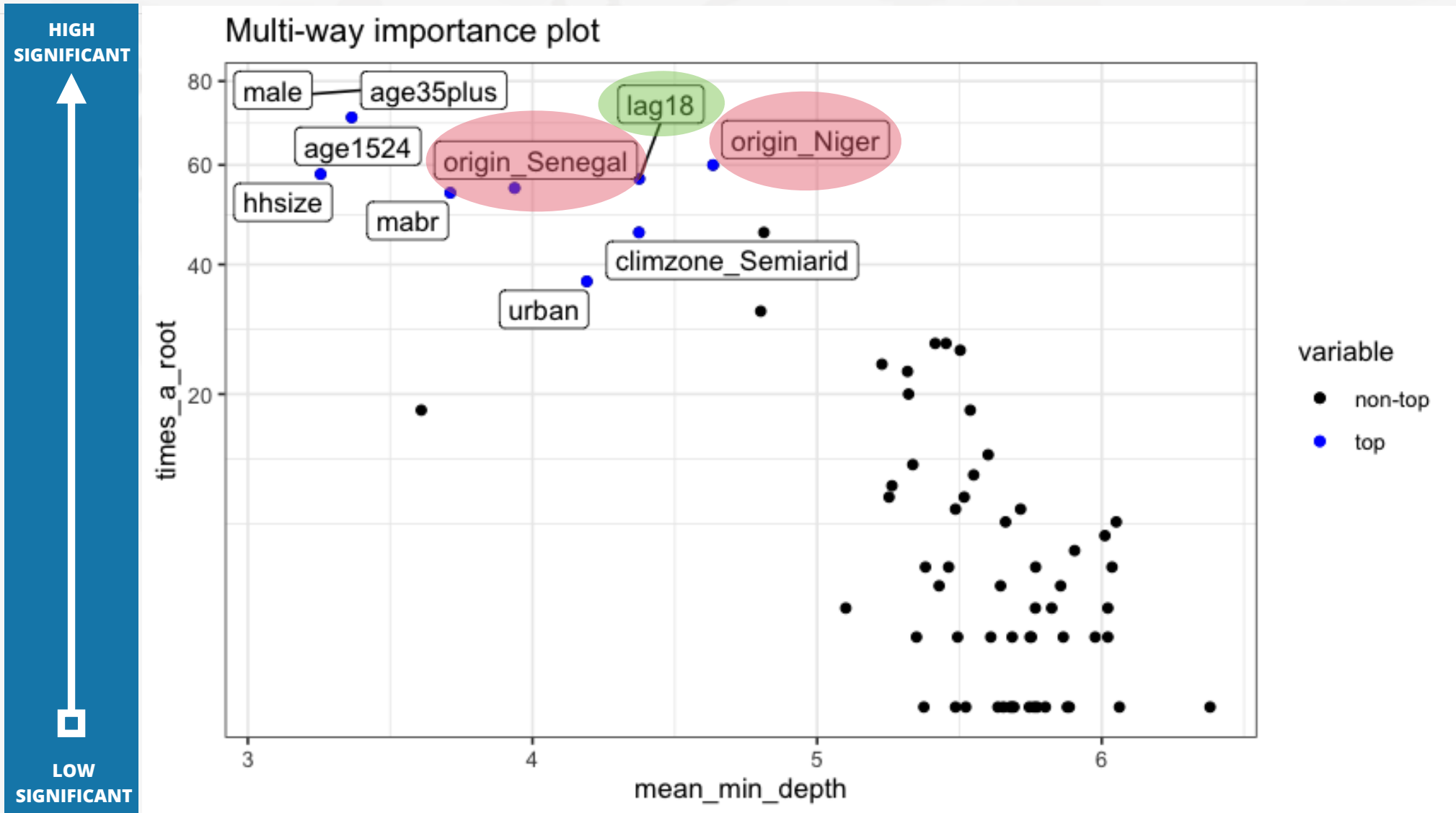
# International Move





# INVESTIGATION OF THE RF MODEL (INTERNATIONAL MOVE)

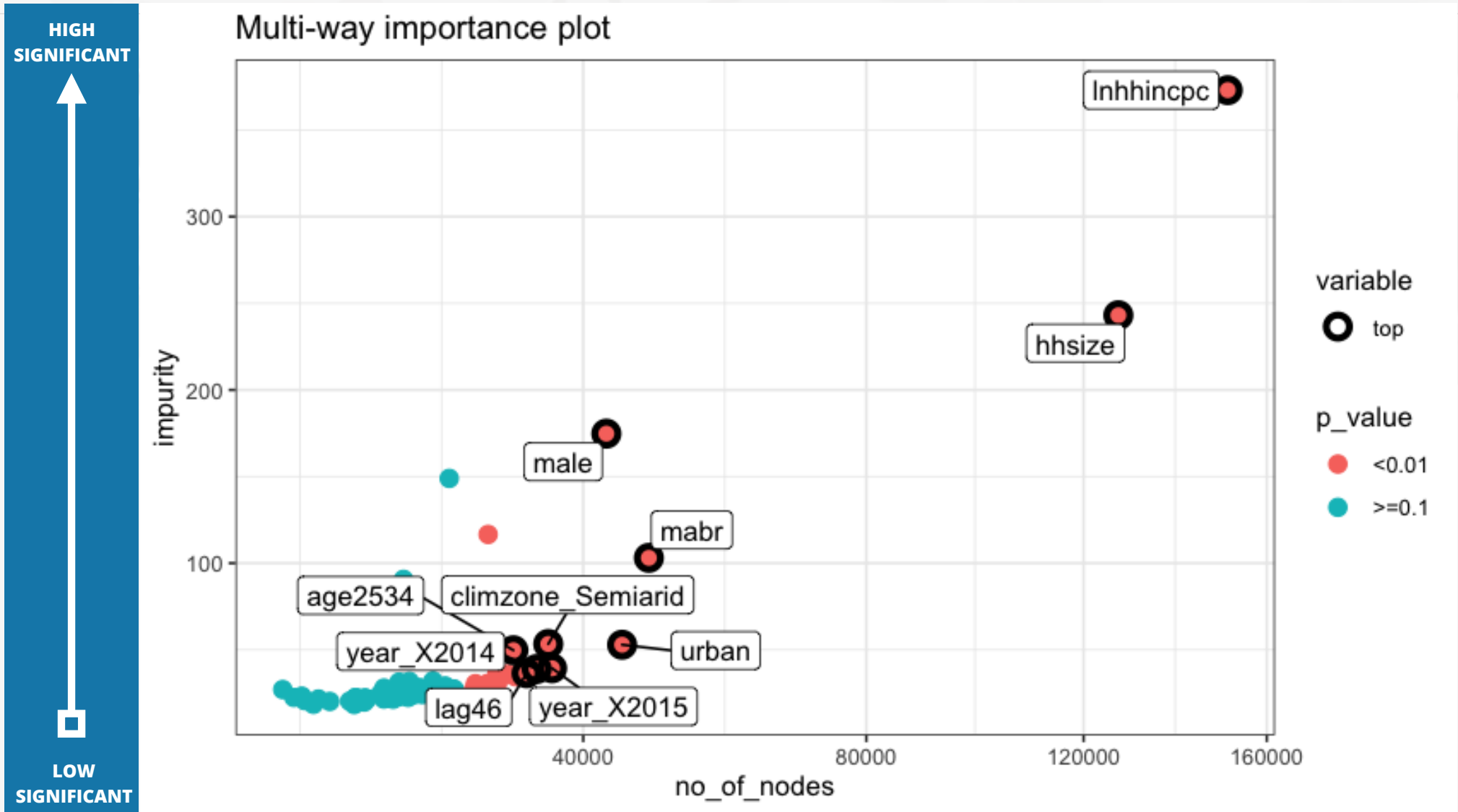
Feature importance





# INVESTIGATION OF THE RF MODEL

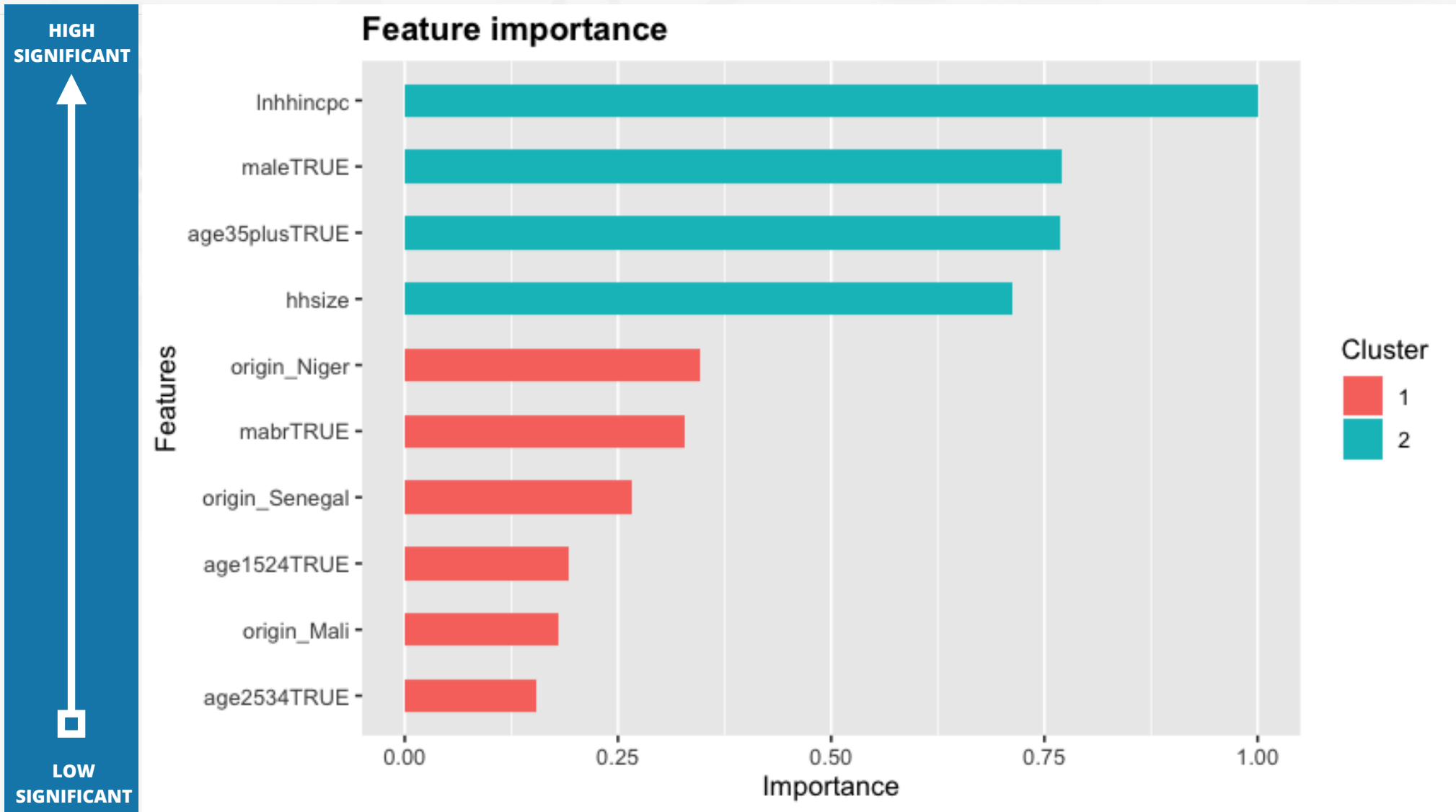
Feature importance (level of noise)





# INVESTIGATION OF THE XGB MODEL (INTERNATIONAL MOVE)

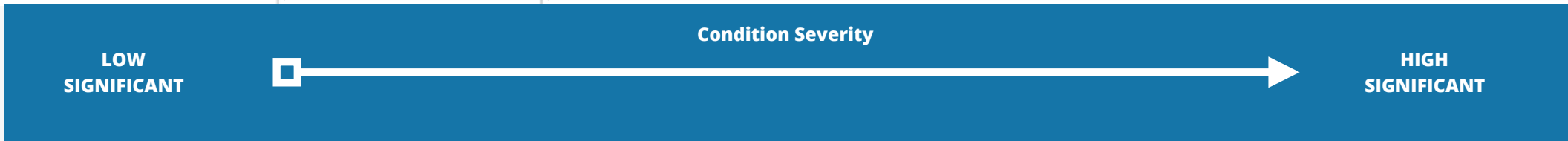
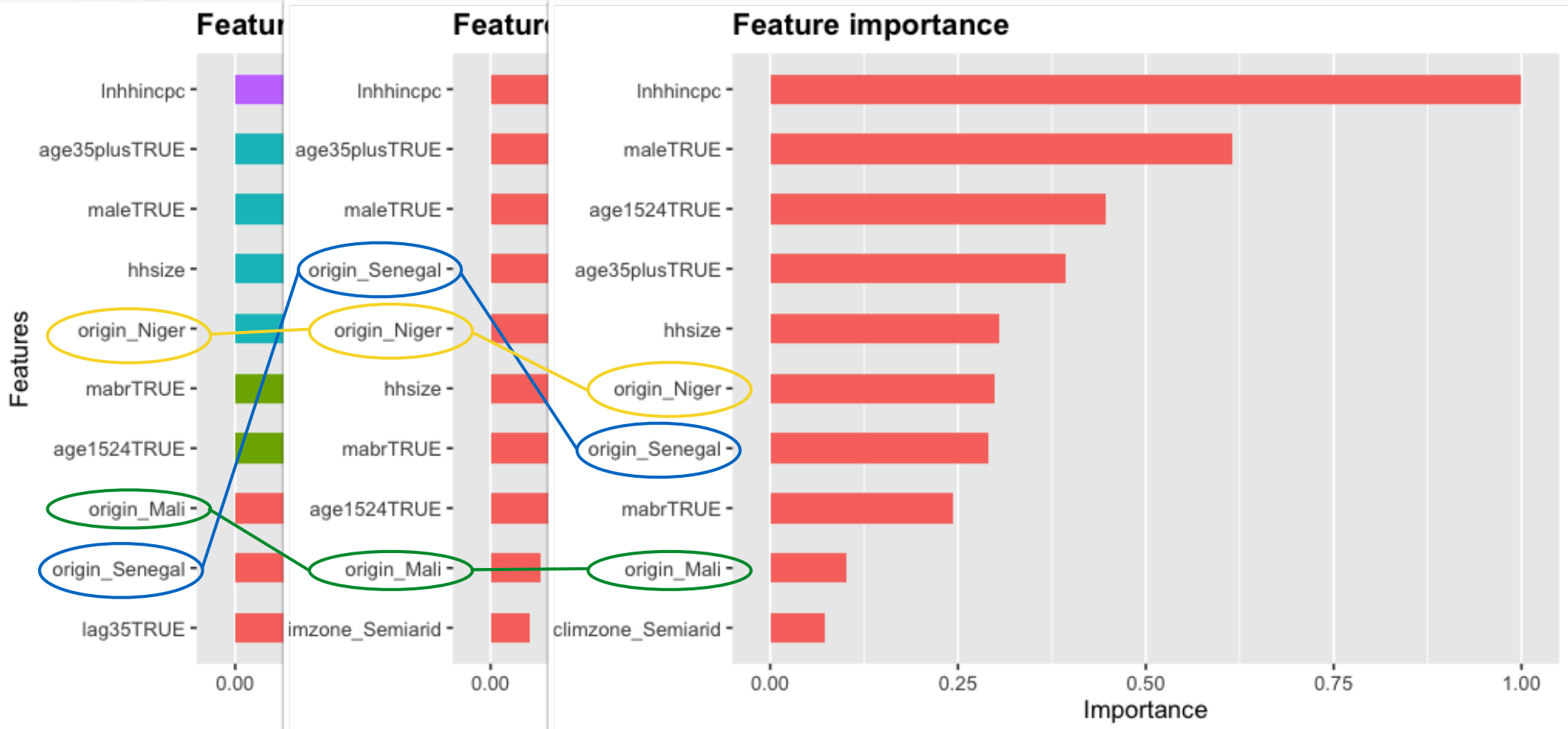
Features importance (spei < -1)





# INVESTIGATION OF THE XGB MODEL (INTERNATIONAL MOVE)

Features importance (severe condition)





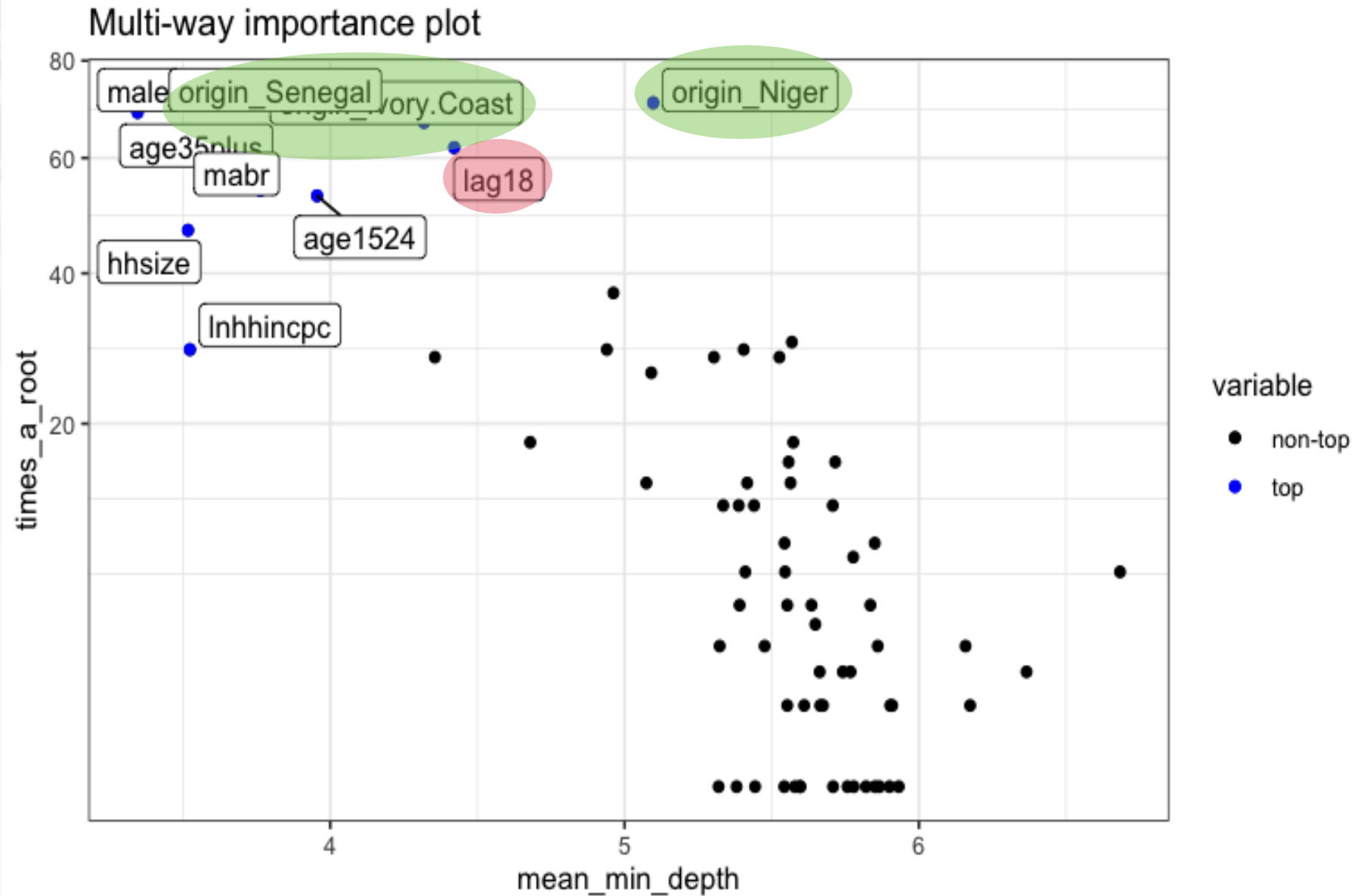
**Move**



# INVESTIGATION OF THE RF MODEL (MOVE)

Feature importance

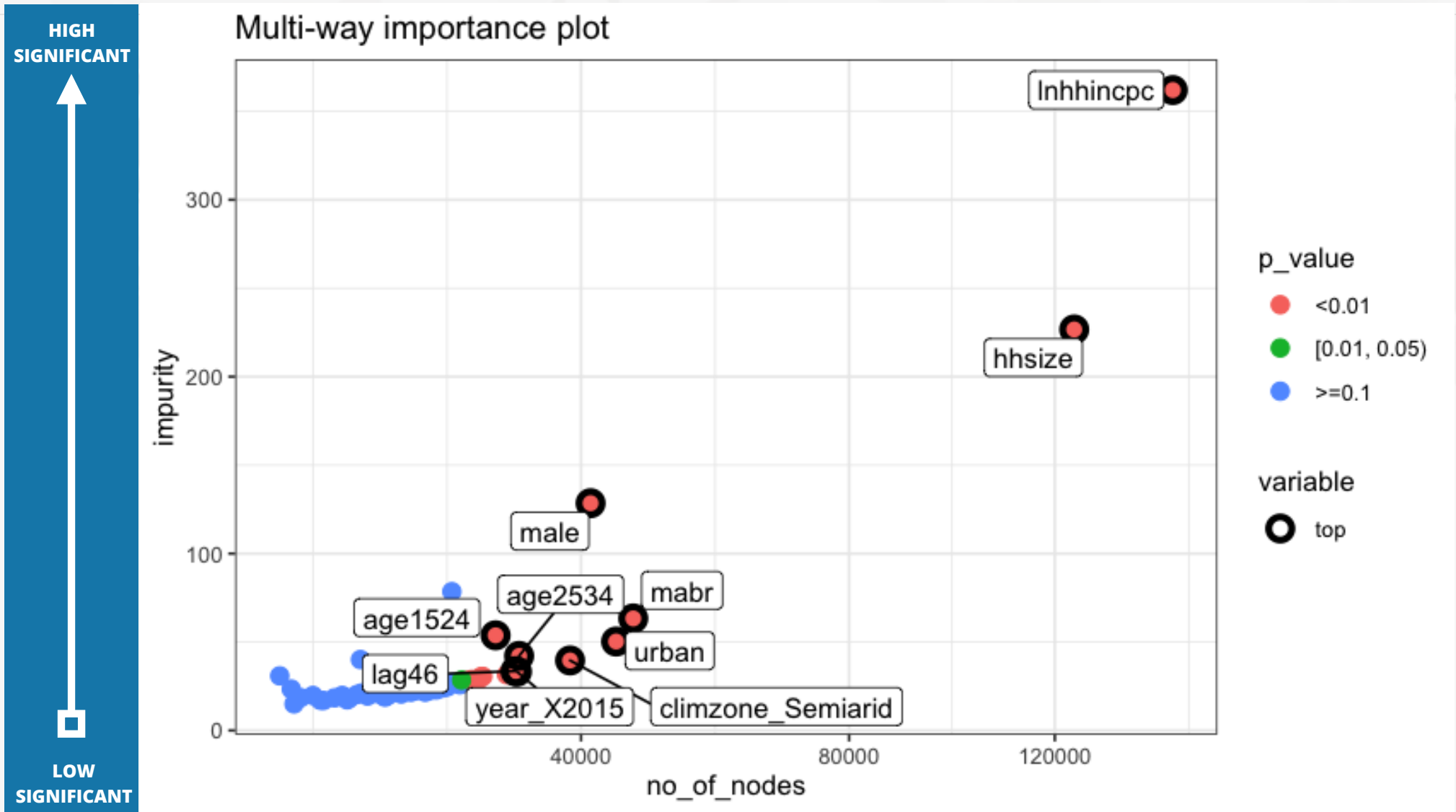
HIGH SIGNIFICANT  
↑  
LOW SIGNIFICANT





# INVESTIGATION OF THE RF MODEL

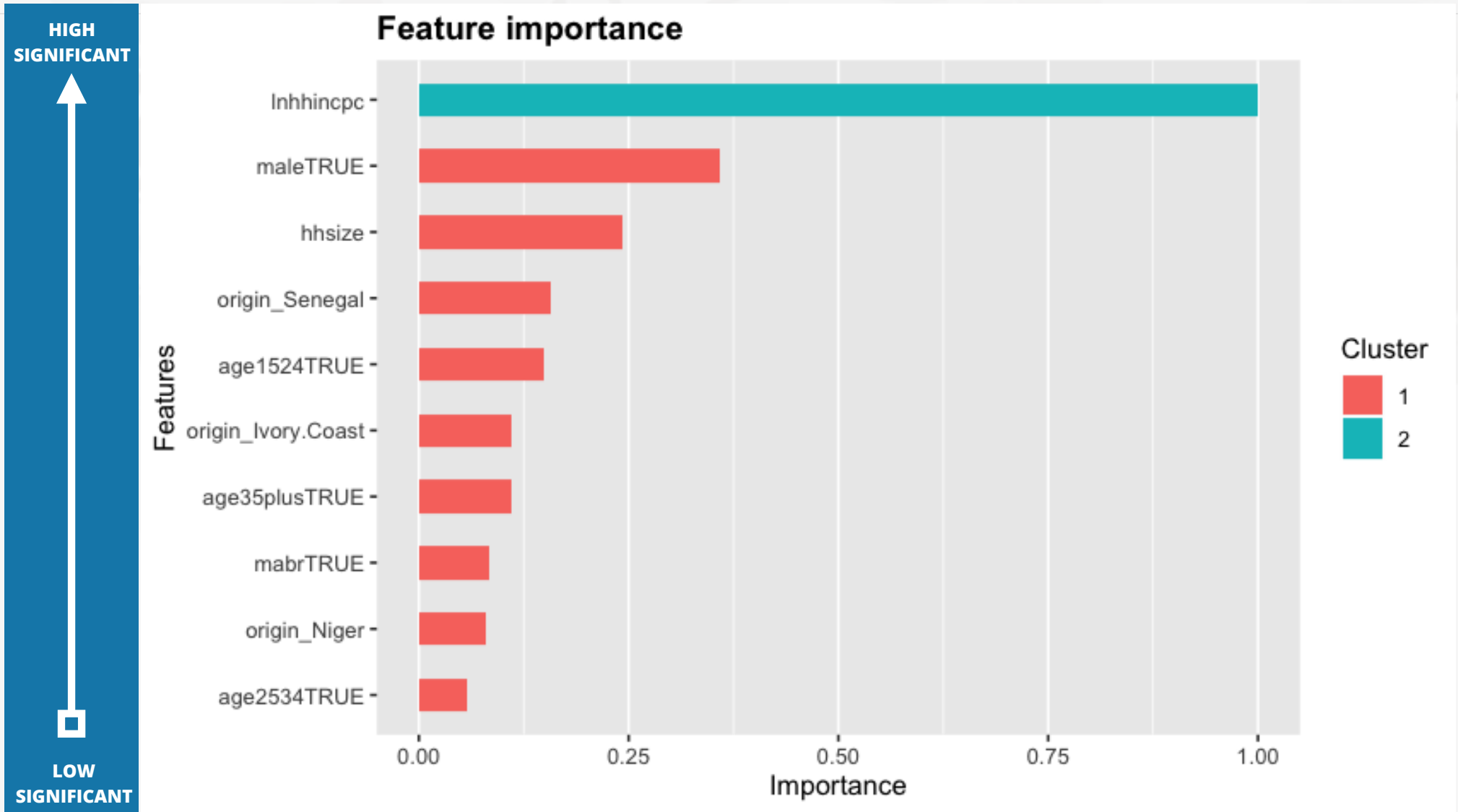
Feature importance (level of noise)





# INVESTIGATION OF THE XGB MODEL

Features importance (spei < -1)

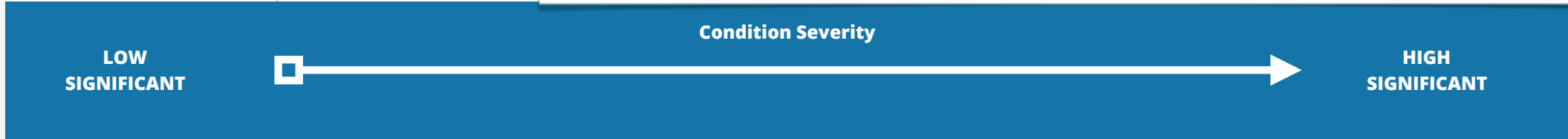
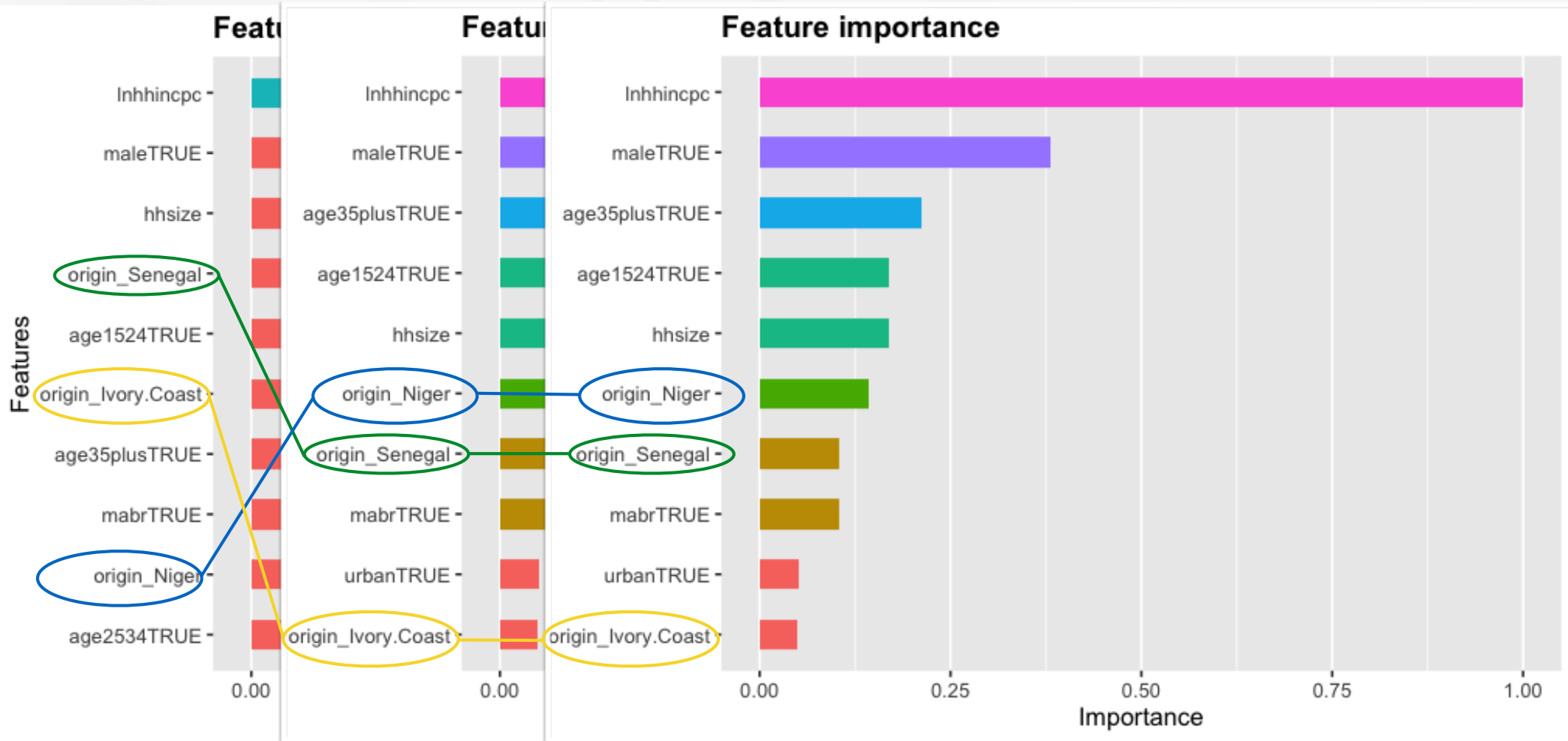






# INVESTIGATION OF THE XGB MODEL (MOVE)

Features importance (severe condition)





Considering the crop-growing season over the previous 12 months (SPEI)

- ◆ **Income, Gender, Household size and age** play an important role in the people intension to move.
- ◆ **18 months** before the interview month is the only interesting weather shocks feature that matters  
(=> **Difficult to establish a clear link between migration and climate here**)
- ◆ **At least 1 degree/stdv above or below LR mean SPEI** affects the people migration intensions.

Findings



Considering the crop-growing season over the previous 12 months (SPEI)

### Analysis for **people migration**

- Higher probability of intending to move for **Senegal, Niger, and Ivory Coast.**

- Insignificant for the other countries.

### Analysis for **international migration**

- higher probability of intending to move from **Niger and Senegal in the semi-arid climate zone.**

Same  
conclusion as in  
the paper



## Next Steps

Time Series + Deep learning approaches (RNN)



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## Extra Slides