Weather shocks and migrations Intension in Western in Africa

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Our Motivation

Why we are doing this research ?

OBJECTIVE OF THIS STUDY

What is our goal?

Understand and interpret migration intensions

WHY?

Climate change has become a major issue!

Global temperatures expected to rise substantially over next century

Climate changes

Assess Damage Function

Evaluate Economic Implications

Migration!

Understand and interpret migration intensions in relation with climate changes

HOW?
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
  - 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.

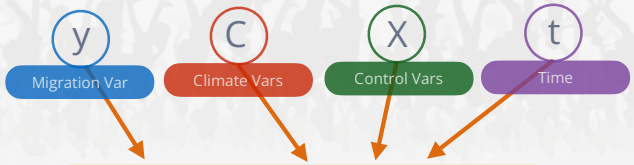
HOW?
Answering these research questions

- 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?

Interesting paper

Multilevel approach
Bertoli, Docquier, Rapoport, and Ruyssen

GENERAL MODEL
What is parameter learning ?



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

Global Model

WE ARE LOOKING FOR f

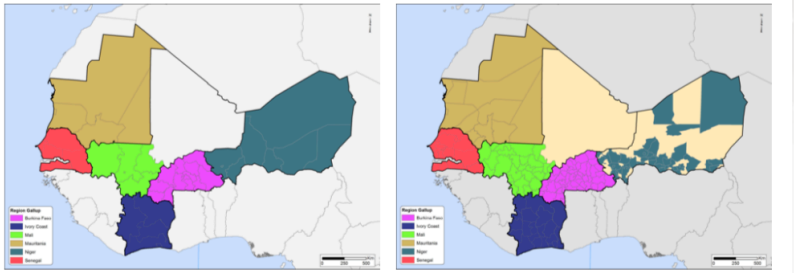
[1] Bertoli, S., Docquier, F., Rapoport, H., & Ruyssen, I. (2019). Weather shocks and migration intentions in Western Africa: Insights from a multilevel analysis Workshop on Climate change, Inequality and Human Migration, AFD, Oct 2019, Paris, France.

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 intensions => **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)**

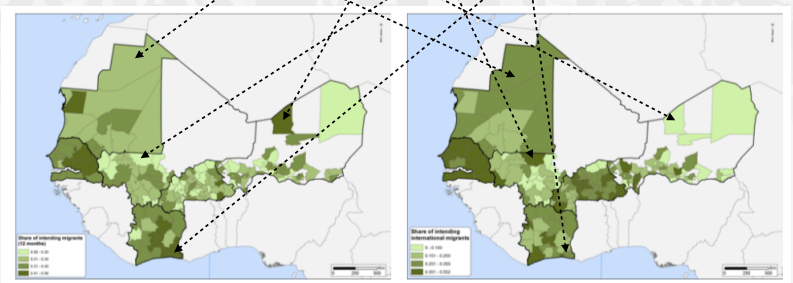
DATA DESCRIPTION
Regions granularity



(a) Coarse regions by country (b) Fine regions by country

DATA DESCRIPTION
Regions granularity

Opposite behaviors



(c) Moving intentions within 12 months (fine regions) (d) International migration intentions (fine regions)

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

- Economic variables => **Control variables.**
  - **hhsize** => 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, ∞))

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

DATA DESCRIPTION
Weather Shocks

- 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/

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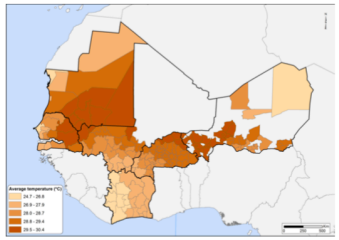
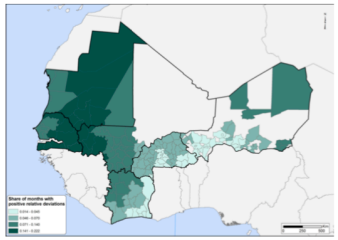
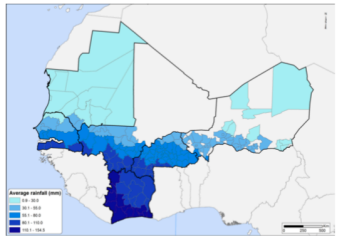


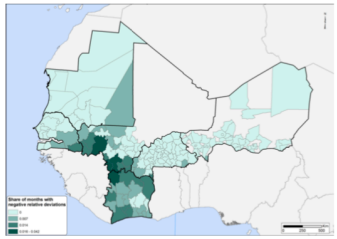
(a) Average temperature (fine regions)



(b) Adverse temperature shocks (fine regions)



(c) Average precipitation (fine regions)



(d) Adverse precipitation shocks (fine regions)

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)

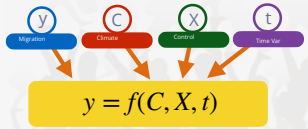
D1-D9
They differentiate between the size and direction of anomalies

C1-C36
The period cover by this variable (month-1, month-36)

https://gadm.org/metadata.html
https://www.dropbox.com/sh/b16zbcl6t3uh6v6/AAAjrKc_eJaYwjZzV5sYmJJma?dl=0
https://www.dropbox.com/sh/v8q74qt3uujrb5y/AACFl9wsmhHiEaQ7ECB27H2ta?dl=0

MULTILEVEL APPROACH MODEL
Regression

CONTRIBUTION



$$V_{\text{Person, Bamako, Mali, 2014}} = \alpha_{\text{Mali}} + \beta_{\text{Mali}} WS_{\text{Bamako, 2014}} + \gamma_{\text{Mali}} X_{\text{Person}} + \delta_{\text{Mali,1}} d_{\text{July}} + \delta_{\text{Mali,2}} d_{2014} + \delta_{\text{Mali,3}} d_{\text{Bamako}}$$

Climate term | Control term | Residues (errors terms)

REGRESSIONS AND CONCLUSIONS
310 000 logit regressions

- 310 000 logit regressions (= 6 x 7 x 3 x 3 x 36 x 2 x 2 x 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)

REGRESSIONS AND CONCLUSIONS
Conclusion

- 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**.

REGRESSIONS AND CONCLUSIONS
Conclusion

Considering the crop-growing season over the previous 12 months

- Analysis for **internal 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

Using Enriched dataset

Run machine learning algorithms to verify their results

ENRICHED DATASET

Gallup dataset + Weather Shocks dataset => join by region

- 39319 obs. x 8441 vars. (only 12 control variables)
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- **T, P, SPEI**
  Temperature, Rainfall or SPEI over 12 months (alternatives are 1, 3, 6, 18 or 24 months)
- **r,a**
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https://www.dropbox.com/sh/b16zbcl6t3uh6v6/AAAjrKe_eJaYwjZzV5sYmJJma?dl=0
https://www.dropbox.com/sh/x8q74qt3uujrb5y/AACFJ9wsmbHiEaQ7ECB27H2ta?dl=0

REGRESSIONS AND CONCLUSIONS

Conclusion

Considering the crop-growing season over the previous 12 months

- Analysis for **internal migration**
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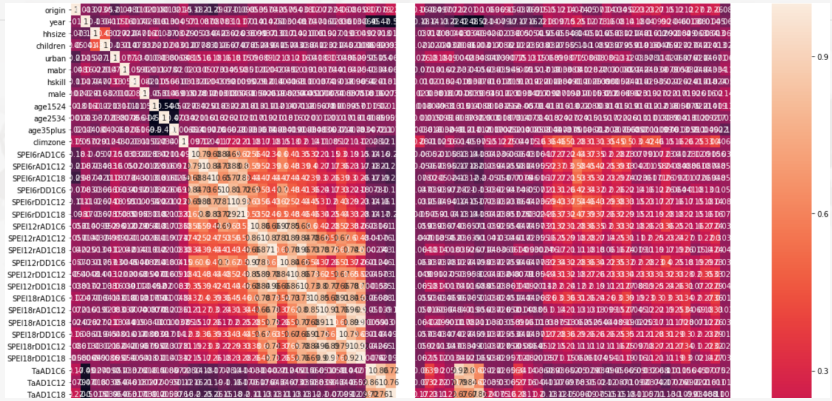
Visualization and Interpretation

How the data is structured?

CORRELATIONS BETWEEN VARIABLES

Climate variables are highly correlated



- Household and children have some correlations
- SPEI = $f(T, P)$ which shows correlation among them.

CORRELATIONS BETWEEN VARIABLES

Climate variables are highly correlated

	origin	year	hhsize	children	urban	mabr	hskill	male	age1524	age2534	...	PrAD1C6	PrAD1C12	PrAD1C1
origin	1.000000	0.012697	-0.072809	0.049683	-0.208720	-0.047966	-0.108850	0.020259	0.018323	0.001306	...	0.232402	0.230454	0.27021
year	0.012697	1.000000	-0.129381	-0.040967	0.014646	0.156363	0.017224	0.002869	-0.016424	0.012898	...	0.175220	0.040127	0.09927
hhsize	-0.072809	-0.129381	1.000000	0.432044	-0.027364	0.021810	-0.047280	-0.015952	0.111888	-0.036717	...	-0.048440	-0.015787	-0.01249
children	0.049683	-0.040967	0.432044	1.000000	-0.126701	-0.014201	-0.073283	-0.031681	-0.020963	-0.020158	...	-0.019112	-0.015787	-0.00468
urban	-0.208720	0.014646	-0.027364	-0.126701	1.000000	0.076852	0.131349	-0.010397	-0.030540	0.037749	...	-0.033172	-0.077641	-0.11133
mabr	-0.047966	0.156363	0.021810	-0.014201	0.076852	1.000000	0.059304	0.019543	0.011183	0.007810	...	-0.042241	-0.043260	-0.03936
hskill	-0.108850	0.017224	-0.047280	-0.073283	0.131349	0.059304	1.000000	0.082132	-0.112994	0.055675	...	-0.018102	-0.029112	-0.03529
male	0.020259	0.002869	-0.015952	-0.031681	-0.010397	0.019543	0.082132	1.000000	-0.052551	-0.013640	...	0.022951	0.019235	0.02674
age1524	0.018323	-0.016424	0.111888	-0.020963	-0.030540	0.011183	-0.112994	-0.052551	1.000000	-0.535159	...	-0.016166	-0.011720	-0.01216
age2534	0.001306	0.012898	-0.036717	-0.020158	0.037749	0.007810	0.055675	-0.013640	-0.535159	1.000000	...	0.010970	0.010864	0.01338
age35plus	-0.020534	0.003965	-0.079516	0.042649	-0.006782	-0.019757	0.061213	0.069047	-0.498185	-0.465851	...	0.005674	0.001125	-0.00099
climzone	0.146299	0.057197	0.029048	0.012373	0.047913	-0.019667	-0.031121	0.014979	-0.026818	0.033844	...	0.297204	0.415059	0.45952
SPEI6rAD1C6	-0.178773	0.100979	-0.050408	-0.077405	0.151266	0.030106	0.031797	0.002800	-0.034304	0.020915	...	0.076783	0.091376	0.06967
SPEI6rAD1C12	-0.206668	0.086837	-0.033672	-0.083482	0.156656	0.049850	0.019530	-0.001242	-0.024935	0.015993	...	0.042383	0.106001	0.05792
SPEI6rAD1C18	-0.289910	0.087270	-0.042212	-0.105401	0.175151	0.073352	0.042753	-0.001311	-0.018074	0.015948	...	0.023095	0.061045	0.07079
SPEI6rDD1C6	-0.070322	0.082585	-0.036439	-0.066133	0.156918	0.034401	0.009204	-0.001277	-0.032467	0.026338	...	0.140115	0.157342	0.12348
SPEI6rDD1C12	-0.113489	0.110943	-0.026186	-0.074241	0.178645	0.054648	0.010031	0.000538	-0.022292	0.020554	...	0.153900	0.231645	0.16942
SPEI6rDD1C18	-0.098096	0.170142	-0.035938	-0.078126	0.154318	0.085075	0.009466	0.003073	-0.017861	0.021477	...	0.145263	0.205195	0.18865

- Household and children have some correlations
- SPEI = $f(T, P)$ which shows correlation among them.

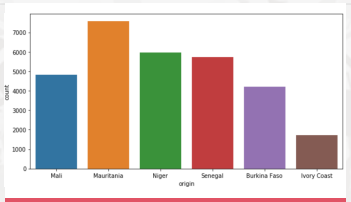
CORRELATIONS BETWEEN VARIABLES

Correlation > 0.08

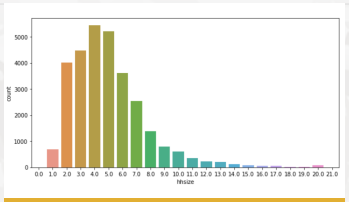
			Corr.	
Mabr	vs	year	0.156	Age 15-24 vs (hhsize, year)
Age15-24	vs	hhsize	0.112	
Mabr	vs	urban	0.076	Mabr vs (urban, skill, year)
Hskill	vs	urban	0.131	
Mabr	vs	BMIG_in	0.114	
Move	vs	BMIG_in	0.428	Mabr vs (BMIG_in, move, male, age 15-24)
male	vs	BMIG_in	0.142	
Age15-24	vs	BMIG_in	0.133	
Age35plus	vs	BMIG_in	-0.15	Move vs (mabr, male, hskill, year)
Move	vs	mabr	0.081	
Male	vs	move	0.123	
Age 15-24	vs	move	0.076	Age, move, hskill, and male
Age35plus	vs	move	-0.108	
Male	vs	hskill	0.082	
Age15-24	vs	hskill	-0.113	
Hhsize	vs	year	-0.129	

DISTRIBUTION OF VARIABLES

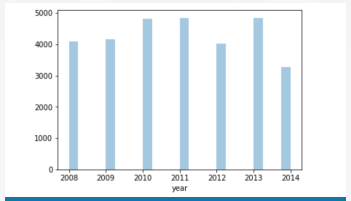
Origin, hhsize, year, children



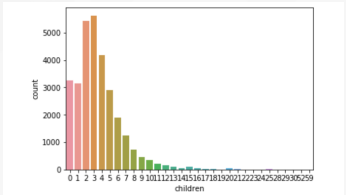
ORIGIN



HHSIZE



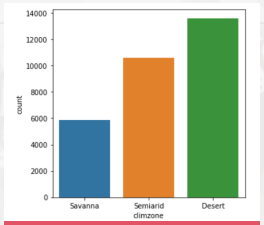
YEAR



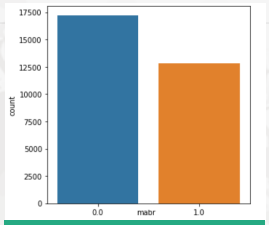
CHILDREN

DISTRIBUTION OF VARIABLES

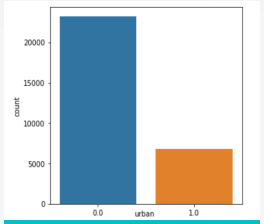
Climatezone, urban, mabr, male



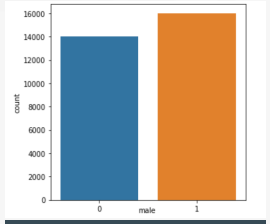
CLIMATE ZONE



MABR(friends)



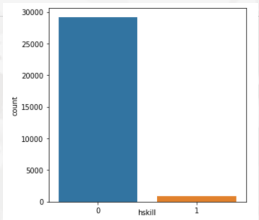
URBAN



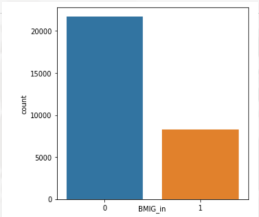
MALE

DISTRIBUTION OF VARIABLES

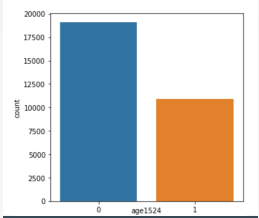
Hskill, Age15-24, BMIG_in (target), move (target)



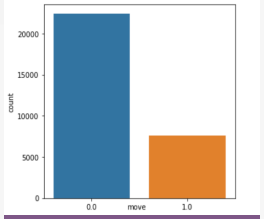
HSKILL



BMIG_in (target)

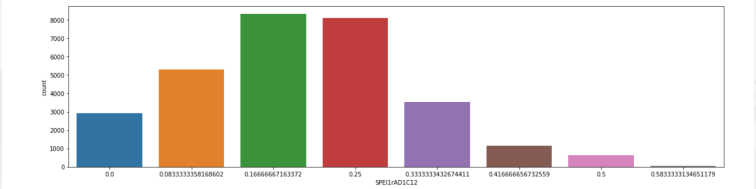


AGE15-24

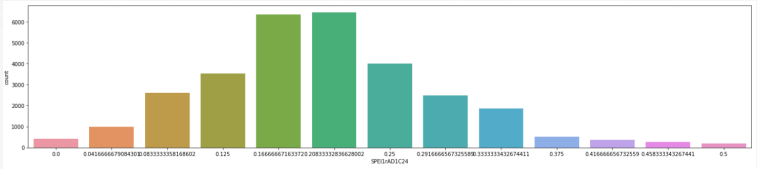


MOVE (target)

DISTRIBUTION OF VARIABLES

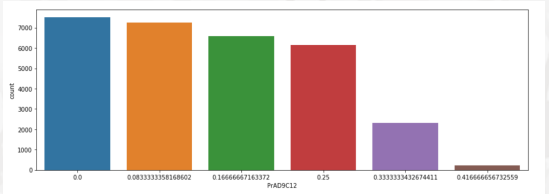


SPEI1rAD1C12

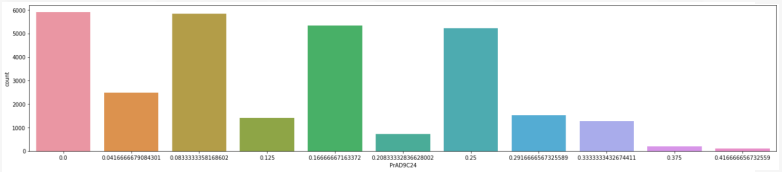


SPEI1rAD1C24

DISTRIBUTION OF VARIABLES



PrAD9C12



PrAD9C24

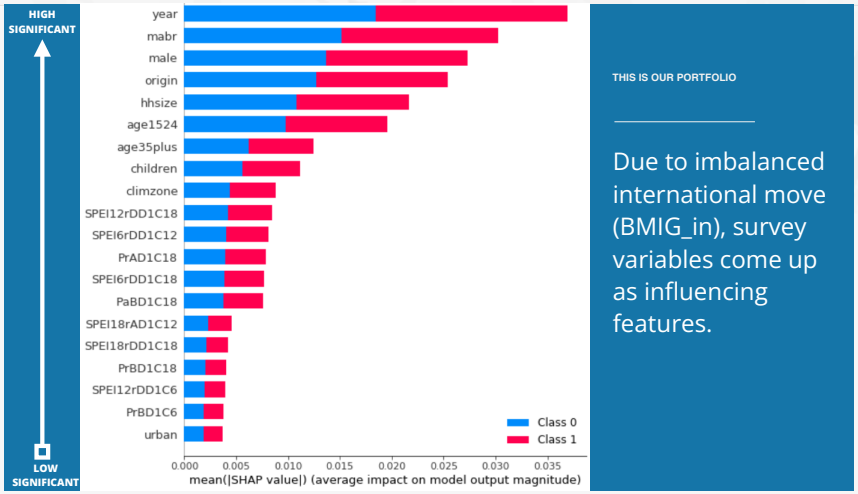
VARIABLES USED FOR SHAP (TRIAL 1)

Targeting BMIG_in

•'origin','year','hhsize','children','urban','mabr','hskill','male','age1524','age2534','age35plus','climzone',
•'SPEI6rAD1C6','SPEI6rAD1C12','SPEI6rAD1C18',
•'SPEI6rDD1C6','SPEI6rDD1C12','SPEI6rDD1C18',
•'SPEI12rAD1C6','SPEI12rAD1C12','SPEI12rAD1C18',
•'SPEI12rDD1C6','SPEI12rDD1C12','SPEI12rDD1C18',
•'SPEI18rAD1C6','SPEI18rAD1C12','SPEI18rAD1C18',
•'SPEI18rDD1C6','SPEI18rDD1C12','SPEI18rDD1C18',
•'TaAD1C6','TaAD1C12','TaAD1C18','TaBD1C6','TaBD1C12','TaBD1C18',
•'TaDD1C6','TaDD1C12','TaDD1C18','TrAD1C6','TrAD1C12','TrAD1C18',
•'TrBD1C6','TrBD1C12','TrBD1C18','TrDD1C6','TrDD1C12','TrDD1C18',
•'PaAD1C6','PaAD1C12','PaAD1C18','PaBD1C6','PaBD1C12','PaBD1C18',
•'PaDD1C6','PaDD1C12','PaDD1C18','PrAD1C6','PrAD1C12','PrAD1C18',
•'PrBD1C6','PrBD1C12','PrBD1C18','PrDD1C6','PrDD1C12','PrDD1C18',
'BMIG_in'

VARIABLES USED FOR SHAP (TRIAL 1)

SHAP solution (take two days)

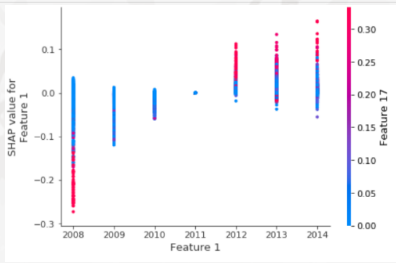


THIS IS OUR PORTFOLIO

Due to imbalanced international move (BMIG_in), survey variables come up as influencing features.

VARIABLES USED FOR SHAP (TRIAL 1)

SHAP solution (take two days)



YEAR vs SPEI6rDD1C18

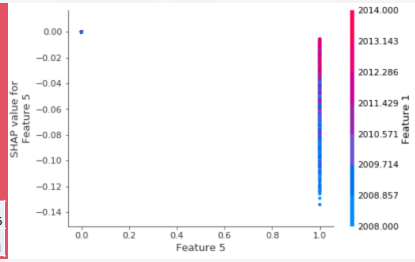
Higher SPEI relative, growing crop season, 18 months accumulated have dependency appeared recently

year'	1
SPEI6rDD1C18'	17

MABR vs YEAR

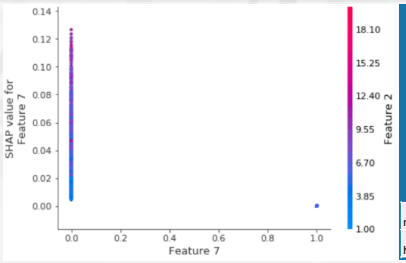
Having friends abroad appears recently than past.

mabr'	5
year'	1



VARIABLES USED FOR SHAP (TRIAL 1)

SHAP solution (take two days)



MALE vs HHSIZE

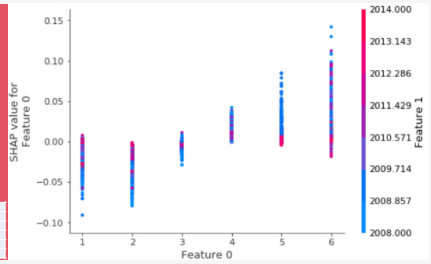
Male are not so much influenced by household size when making international move. Females are.

male'	7
hhsize'	2

ORIGIN vs YEAR

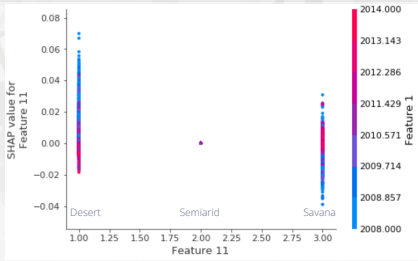
- More of Ivory Coast moved in the past. Niger is still actively international moving recently.
- Mauritania and Senegal are not so active but more movements recently.

origin'	0
year'	1



VARIABLES USED FOR SHAP (TRIAL 1)

SHAP solution (take two days)



CLIMATEZONE vs YEAR

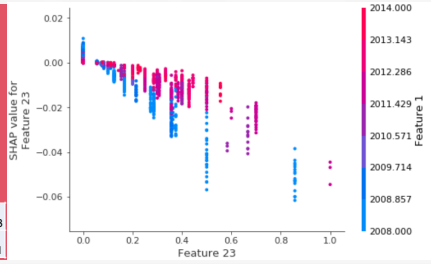
- Semiarid is not so influenced by year.
- Desert area movement was more in the past.
- Savanna area has more international movements recently.

climzone'	11
year'	1

SPEI12rDD1C18 vs YEAR

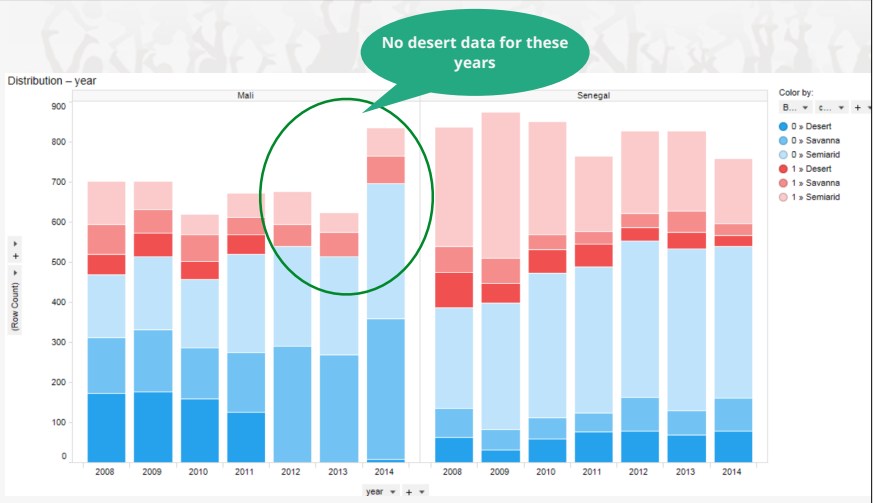
Higher SPEI 12 months, relative, growing crop season, accumulated for 18 months happens more recently influencing movement.

SPEI12rDD1C18'	23
year'	1



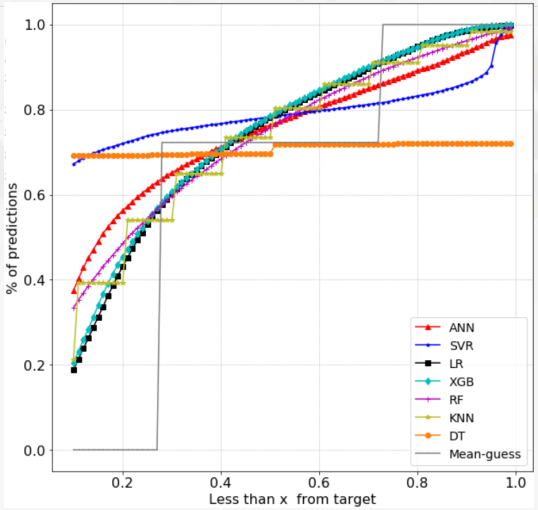
USING TABLEAU TO VISUALIZE VARIABLES (TRIAL 2)

Mali, Senegal => Climatezone, BMIG_in



USING TABLEAU TO VISUALIZE VARIABLES (TRIAL 2)

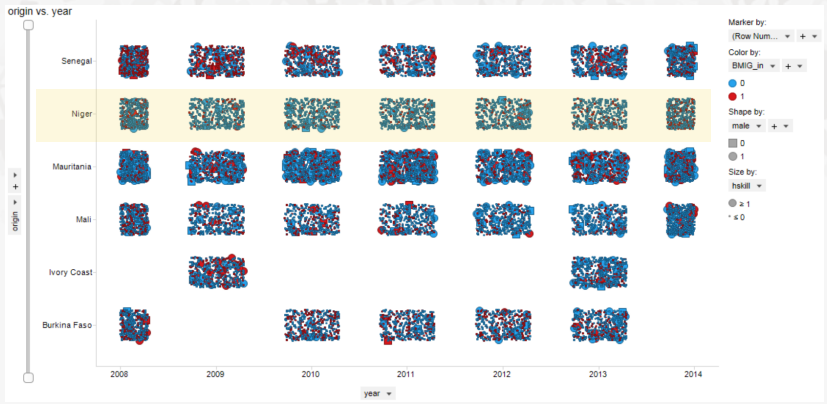
People in Niger don't want to move in general



- 'origin','year','hhsize','children','urban','BMIG_in','mabr','move','hskill','male','age1524','age2534','age35plus','climzone',
- 'SPEI6rAD1C6','SPEI6rAD1C12','SPEI6rAD1C18','SPEI6rAD1C24',
- 'SPEI6rDD1C6','SPEI6rDD1C12','SPEI6rDD1C18','SPEI6rDD1C24',
- 'SPEI12rAD1C6','SPEI12rAD1C12','SPEI12rAD1C18','SPEI12rAD1C24',
- 'SPEI12rDD1C6','SPEI12rDD1C12','SPEI12rDD1C18','SPEI12rDD1C24',
- 'SPEI18rAD1C6','SPEI18rAD1C12','SPEI18rAD1C18','SPEI18rAD1C24',
- 'SPEI18rDD1C6','SPEI18rDD1C12','SPEI18rDD1C18','SPEI18rDD1C24',
- 'SPEI24rAD1C6','SPEI24rAD1C12','SPEI24rAD1C18','SPEI24rAD1C24',
- 'SPEI24rDD1C6','SPEI24rDD1C12','SPEI24rDD1C18','SPEI24rDD1C24',

USING TABLEAU TO VISUALIZE VARIABLES (TRIAL 2)

People in Niger don't want to move in general



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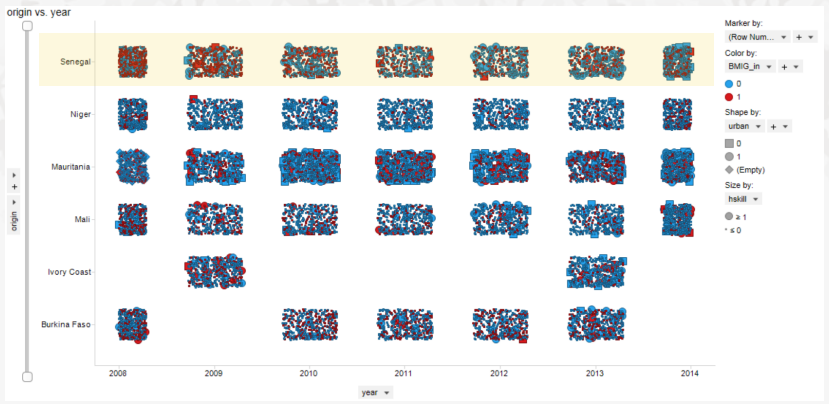
People in Niger don't want to move in general



Build new Algorithms from raw data

Running deep learning approaches (RNN)