Freshwater Cooperation (in Africa)

Work (very much) in Progress

Jillian Stallman

Development Lunch

May 6, 2024

The New York Times

Drought Pushes Millions Into 'Acute Hunger' in Southern Africa

The disaster, intensified by El Niño, is devastating communities across several countries, killing crops and livestock and sending food prices soaring.

Share full article 75

A farmer in Zimbabwe last month. Several countries have declared national emergencies. Tsvangirayi Mukwazhi/Associated Press

By Somini Sengupta and Manuela Andreoni

April 18, 2024

svt NYHETER | Nyheter | Lokalt | Sport | SVT Play | Barn

UTRIKES

En pappa hjälper sin undernärda son att gå. Bilden är tagen i Kenya där torka, vattenbrist och undernäring har blivit en dödlig kombination för många barn. Nu varnar Unicef att undernäring och vattenbrist riskerar miljoner barns liv på Afrikas horn. Foto: Brian Inganga/AP/TT

Antalet drabbade av torka på Afrikas horn nästan fördubblat

UPPDATERAD 23 AUGUSTI 2022 PUBLICERAD 23 AUGUSTI 2022

Afrikas horn har drabbats av svår torka och svält. Bara mellan februari och juli i år har antal människor påverkade av torkan ökat från 9,5 miljoner till 16,2 miljoner, varnar Unicef. Detta kommer drabba barnen hårdast, säger Unicefs generaldirektör Catherine Russell i ett pressmeddelande.

ANALYSE

Les crises de l'eau menacent la paix dans le monde

À l'occasion de la journée mondiale de l'eau, ce 22 mars, l'ONU rappelle l'urgence de gérer cette ressource essentielle de façon durable et équitable. 2,2 milliards de personnes n'ont toujours pas accès à une distribution d'eau potable. Et pour ne rien arranger, le changement climatique perturbe gravement le cycle de l'eau sur Terre.

Publié le : 22/03/2024 - 05:09 Modifié le : 22/03/2024 - 11:34 9 mn

De l'eau potable s'écoule d'un robinet au Burundi. © Banque africaine de developpement/projectsportal.afdb.org

RÍO COLORADO

A la sequía del norte de México se suma la incertidumbre del río Colorado

Se avecinan fuertes cortes de agua en los estados de EEUU que usan agua del río Colorado, lo que significa que México también podría enfrentar más cortes.

Por AP • Publicado el 12 de septiembre del 2022 • Actualizado a las 2:59 pm del 12 de septiembre del 2022

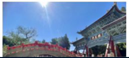
El río Colorado se queda sin agua después de cruzar a México el 6 de julio de 2022 en Mexicali, Baja California. El camino natural de los ríos se convierte en arena y malezas a menos de una milla después de cruzar la frontera en Mexicali, México.

2023
08/28
10:55:21
来源：新华网

埃及、埃塞俄比亚、苏丹三国就“复兴大坝”争端展开新一轮谈判

字体： 小 中 大 分享到：

深度观察



新华全媒头条丨人文经济视野下的武威观

DÉPÊCHES | REGIONS | SOCIÉTÉ

SENEGAL-COLLECTIIVITES-HYDRAULIQUE / Dagana : sept villages de la commune de Mbane confrontés à une pénurie d’eau

publié 23 avril 2024 à 14h51

AFRIQUE-MONDE-SPORT / L’AIPS célèbre son centenaire à Santa Susana, lundi

DÉPÊCHES REGIONS SOCIÉTÉ

SENEGAL-EDUCATION-HYDRAULIQUE / Kédougou : l'école élémentaire Bakary Dansokho sans eau courante depuis six ans (enseignant)

publié 22 avril 2024 à 12h58

Beni : la société civile déplore le manque d'eau potable à Mwangaza

Publié le sam, 13/04/2024 - 16:20 | Modifié le sam, 13/04/2024 - 16:21

Chercher

Dans la même catégorie

Bandundu : plus de 200 accouchements précoces recensés au premier trimestre 2024

06/05/2024 - 09:49

Société, Actualité / grossesse précoce, Sensibilisation, VBG

Tchad: l'accès à l'eau, l'une des principales préoccupations des électeurs à Abéché

Au Tchad, la campagne électorale bat son plein et l'eau est source de débat, notamment dans la ville d'Abéché, à l'Est du pays. Rare et donc coûteuse, l'eau est à l'origine de problèmes entre certains locataires et bailleurs.

Publié le : 21/04/2024 - 11:42 1 mn

Écouter - 01:17

Le problème de l'approvisionnement en eau est l'une des questions de la campagne électorale à Abéché au Tchad où la ressource est rare et chère (avril 2024). © Olivier Monodji / RFI

Globally

- Managing freshwater resources is hard
    - Common pool resources (Ostrom, 1990)
    - Up- and downstream externalities
    - Human rights politics
- Formal cooperation is hard to interpret (causality $\Leftrightarrow$)
- Informal cooperation is hard to document
- Markets and well managed property rights are the exception (Wheeler, 2021)

In Africa

- Agriculture accounts for 85% of water withdrawn in Africa (ReliefWeb, 2020)
- Irrigation is very low, $\approx$ 7% of ag. land (International Water Management Institute, 2024).
- Climate change affects levels, variability, onset of rains (Monerie et al., 2021; Persson et al., 2012)
- Water markets when they exist are often incomplete or informal (Mapunda et al., 2018)
- Many arrangements are informal or implicit (Nemarundwe and Kozanayi, 2003)
- Opinions on basin-level management have been mixed

  Too many cooks in the kitchen?
  Opposing / too many goals?
  Geopolitics (Wolf, 1999; Wolf et al., 2003)

Research question(s):

1. How do communities share water along rivers in practice, and what factors are associated with "good" management (ie marginal utilities co-move, all else equal)?
2. What implications does this have for on-the-ground outcomes (production, livelihoods)?
3. (Eventually: How might climate change affect these *de facto* arrangements?)

Strategy:

- **Descriptive:** What's the relationship between rainfall, water availability on rivers, and outcomes for small rivers (for now)
- **Model:** Dictator Game: upstream town(s) can allow water to pass to downstream town(s) (also considering: Self-Enforcing Agreements? Difficulty: transfers)
- **Empirics:** Examine Demographic Health Surveys (DHS); satellite lights; greenness. Compare as a function of precipitation and water flow over a broad geography (for now)
- **Identification:** IV / DiD changing **costs** to sending water or **benefits** from cooperation (e.g. shift-share for outside option; tech improvements for irrigation; NGO RCTs)

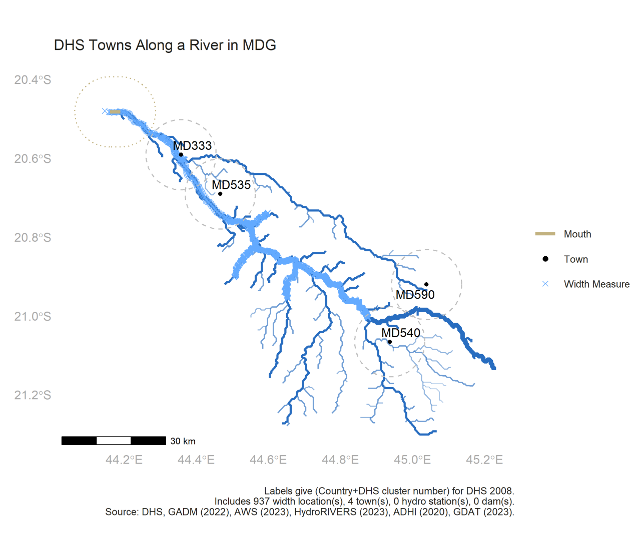
Short-term Goal:

- Trace out how rainfall $\rightarrow$ water flow $\rightarrow$ affects final outcomes (currently infant mortality)
- Consider how allocations vary according to the usual suspects (borders, language, ethnicity, conflict prevalence, formal agreements, basin committees)
- Interpretation: shifters of bargaining / Pareto weights

Medium/ Long-term Goals:

- Back out "selfishness" of upstream actors
- Add identification (shift-share for population growth? Policy roll-out? Forced displacements?) changing outside option
- Use this to parameterize how river allocation changes with precipitation affects final outcomes
- Consider climate change counterfactuals

Why I'm Not Showing You Stylized Facts



Water Externalities:

Remote sensing to allow consideration of quantity, and upstream-downstream relationships rather than common-pool considerations (Ostrom, 1990; Lipscomb and Mobarak, 2017; Ryan and Sudarshan, 2022) Pics

Water cooperation/conflict:

More granular outcomes than conflict; planning to explore mechanisms (McGuirk and Nunn, ming; Burke et al., 2015; Persson et al., 2012; García and Belmar, 2023)

Highlighting informal arrangements. Novel(?) use of DHS and remote sensing data to look at *revealed* agreements (Wolf, 1999; Dinar et al., 2019; Munshi and Rosenzweig, 2016)

Modelling:

Taking seriously the lack of commitment/enforcement throughout

Application of a model that generates predictions about when actors would act less cooperatively, lets us investigate what works (Ligon et al., 2002; Meghir et al., 2019)

What I do not expect to observe:

1. **Transfers** from downstream to upstream
   - $\Rightarrow$ Then I don't think I can *test* limited commitment on rivers

Things I may be able to observe (eventually)

1. Production!
2. Consumption!

* Contexts in which (informal) agreements are documented? (Sri Lanka, Chile)

For the meantime:

* How about we just have upstream put a weight on downstream?
* Higher weight if downstream is paying transfers / could credibly invade / has collateral / is "friendly" etc.

Setting:

- Two towns $i \in \{u, d\}$ (upstream, downstream)

Timing:

1. Endowments of water $\varepsilon_u, \varepsilon_d$ fall from the sky/flow down from the hills and are observed by upstream
2. Upstream chooses a quantity of water to transfer to downstream, and keeps the rest
3. Everyone receives payoffs

Simplifications:

- One-shot game (for now)
- Just consider upstream's choices (for now)
- Not considering whole-river solutions (for now) (but downstream weight is actually *all* downstream towns)
- Just droughts, not floods (for now)

Want corner solutions (e.g. ephemeral rivers)

$$U_u(x_u, x_d) = \theta_u u_u(x_u - b_u) + \theta_d u_d(x_d - b_d) \tag{1}$$

- u_i: utility i receives from just the water. $u_i' > 0, u_i'' < 0$
- b_i: minimum acceptable payoff for i (from u's perspective)
- θ_u, θ_d: u's Pareto weights to u, d
- x_u: water quantity kept by upstream
- x_d: water quantity received downstream (assuming no loss)

Normalizations

- $\theta_u + \theta_d = 1$: (Cobb-Douglas-like)
- $b_u + b_d = 0 \Rightarrow u$ has to trade off who they guarantee.

Interpretation

- $b_i < 0 \Rightarrow u$ is able to conceive of i getting a minimum acceptable payoff
- If $b_u > 0$: u guarantees itself $\Rightarrow$ sometimes u keeps everything

If towns have some sort of arrangement over their water consumption:

- Could we run a (variation of a) Townsend test?
- This could be run for the entire river with a DEM, so here's a full-river specification for town i in a given river basin

$$x_i = \beta_0(\sum_j \varepsilon_j) + \beta_1(\varepsilon_i) + FE_i$$

But there's a twist. Subject to:

$$x_i \leq \sum_{j \text{ upstream of i}} \varepsilon_j$$

Then we would want production (NVDI proxy?) and consumption data to see if *goods* consumption would yield different results.

$$\max_{x_u, x_d} U_u(x_u, x_d) = \theta_u u_u(x_u - b_u) + \theta_d u_d(x_d - b_d) \tag{2}$$

such that

$$\begin{aligned} 0 &\leq x_u & &\text{NN1 } (\mu_1) \\ x_u &\leq \varepsilon_u & &\text{NN2 } (\mu_2) \\ x_u + x_d &\leq \varepsilon_u + \varepsilon_d & &\text{BC } (\lambda) \end{aligned}$$

$$\max_{x_u, x_d} U_u(x_u, x_d) = \theta_u u_u(x_u - b_u) + \theta_d u_d(x_d - b_d) \tag{2}$$

Kuhn-Tucker Conditions:

$$\begin{aligned}
\theta_u u_u'(x_u - b_u) &= \theta_d u_d'(x_d - b_d) && \iff 0 < x_u < \varepsilon_u && \text{(Interior)} \\
\theta_u u_u'(x_u - b_u) &= \theta_d u_d'(x_d - b_d) - \mu_1 && \iff x_u = 0 && \text{(All to } d\text{)} \\
\theta_u u_u'(x_u - b_u) &= \theta_d u_d'(x_d - b_d) + \mu_2 && \iff x_u = \varepsilon_u && \text{(All to } u\text{)}
\end{aligned}$$

If utilities are logs:

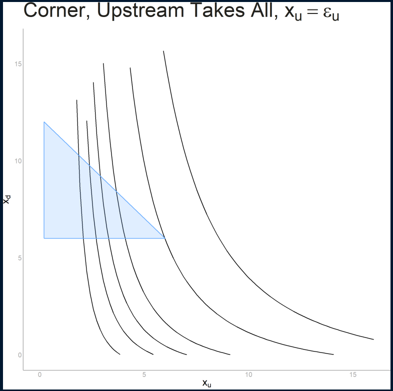
- We can see how u's choice varies with the endowments and its lower bounds of acceptable minima for u and d
- Recall $\theta_d = 1 - \theta_u$ and $b_u + b_d = 0$
- Define $\Gamma := b_u + \theta_u(\varepsilon_u + \varepsilon_d - b_u - b_d)$

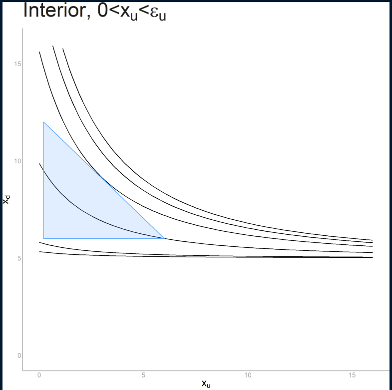
Upstream's choices

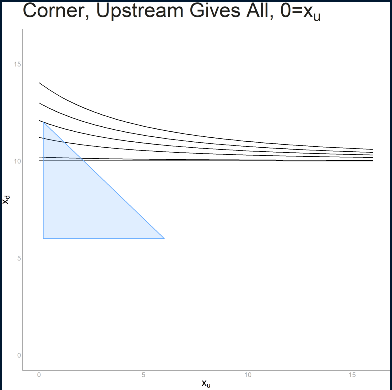
$$\begin{aligned}
x_u &= \theta_u\varepsilon_u + \theta_u\varepsilon_d - \theta_u b_d + \theta_d b_u && \text{(Interior)} \iff \Gamma \in (0, \varepsilon_u) \\
&= b_u + \theta_u(\varepsilon_u + \varepsilon_d - b_u - b_d) \\
x_d &= \theta_d\varepsilon_u + \theta_d\varepsilon_d + \theta_u b_d - \theta_d b_u && \text{(Interior)} \iff \Gamma \in (0, \varepsilon_u) \\
x_u &= \varepsilon_u && \text{(All to } u\text{)} \iff \Gamma \geq \varepsilon_u \\
x_u &= 0 && \text{(All to } d\text{)} \iff \Gamma \leq 0
\end{aligned}$$

Given θ_u, rearrange for b_u. Given b_u, get shifters of θ_u?

Visual Solutions (Moffatt and Zevallos, 2021)







Rain: European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) (0.25°, 31km) (change to CHiRP at 0.05°?)

Rivers: HydroSHEDS river networks (plus R `riverdist`) and Global Long Term River Width, LANDSAT2 images of river widths over time (1984-2020) Map

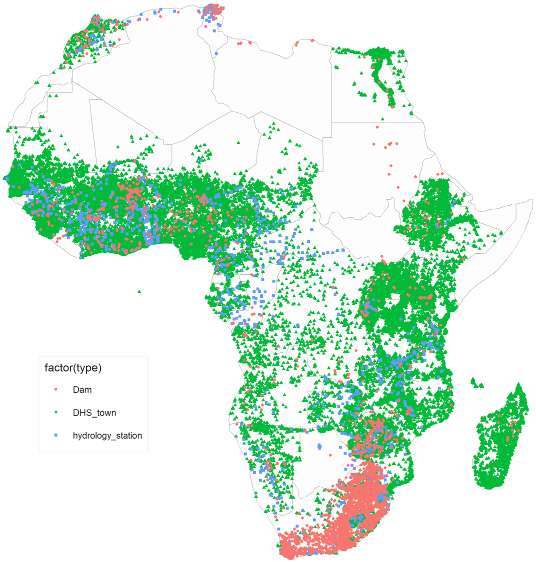
Demographics: **Demographic Health Surveys (DHS)**: 158 surveys in Africa from 1990-2022 in 1.87 million HHs Re: Infant Mortality

Borders: Global Administrative Areas (GADM)

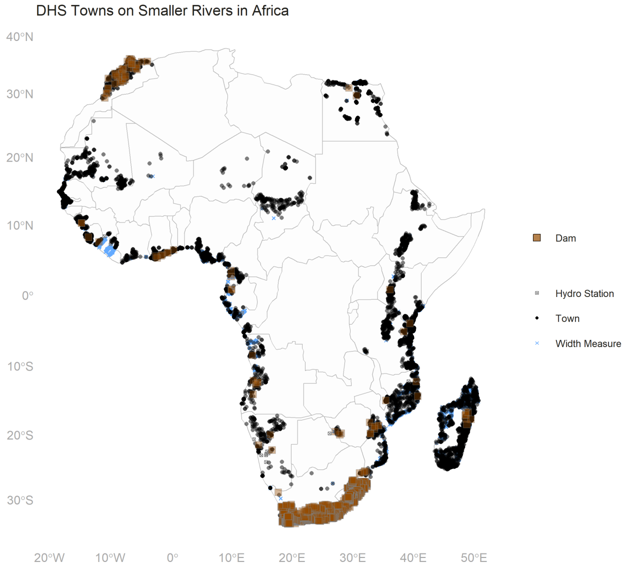
Dams: Global Dams Tracker (GDAT): panel, includes some construction dates Map

Hydro stations: African Database of Hydrometric Indices (ADHI) 1,467 stations, 1950-2018

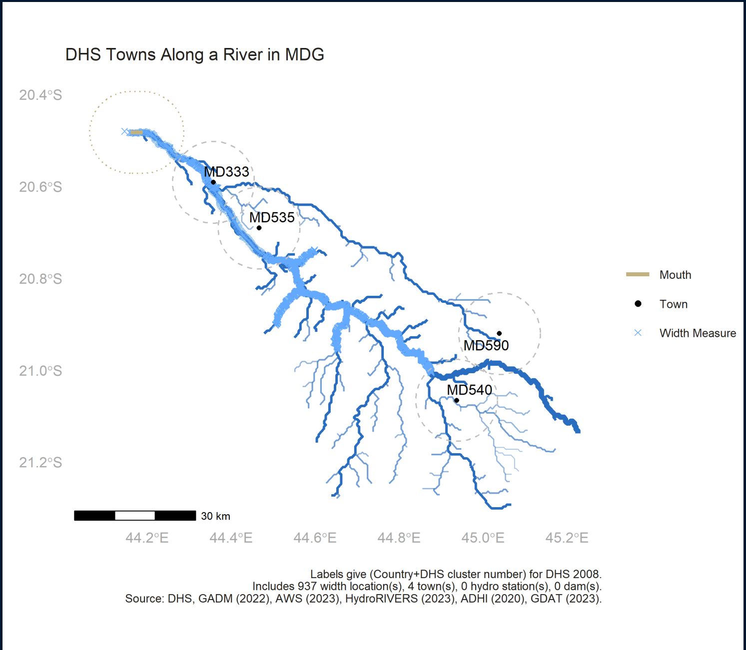
Dams, Hydro Stations, and DHS Clusters in Africa



Data from GDAT (2023), DHS (2023), ADHI (2019)

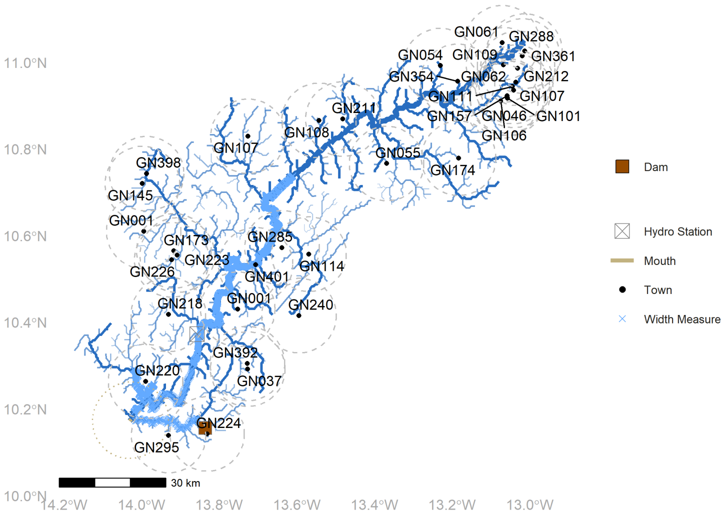


Includes 150840 width locations, 11038 towns, 281 hydro stations, 2725 dams.
Source: DHS, GADM (2022), AWS (2023),
HydroRIVERS (2023), ADHI (2020), GDAT (2023).



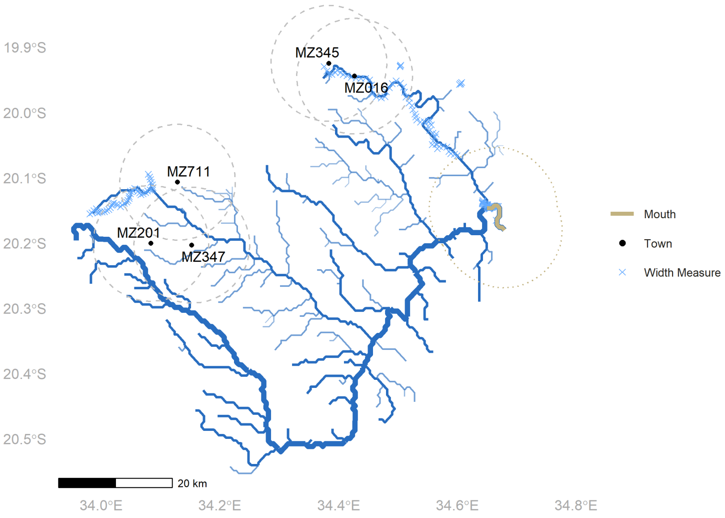
DHS Towns Along a River in MDG
20.4°S
20.6°S
20.8°S
21.0°S
21.2°S
MD333
MD535
MD590
MD540
30 km
44.2°E
44.4°E
44.6°E
44.8°E
45.0°E
45.2°E
Mouth
Town
Width Measure
Labels give (Country+DHS cluster number) for DHS 2008.
Includes 937 width location(s), 4 town(s), 0 hydro station(s), 0 dam(s).
Source: DHS, GADM (2022), AWS (2023), HydroRIVERS (2023), ADHI (2020), GDAT (2023).

DHS Towns Along a River in GIN



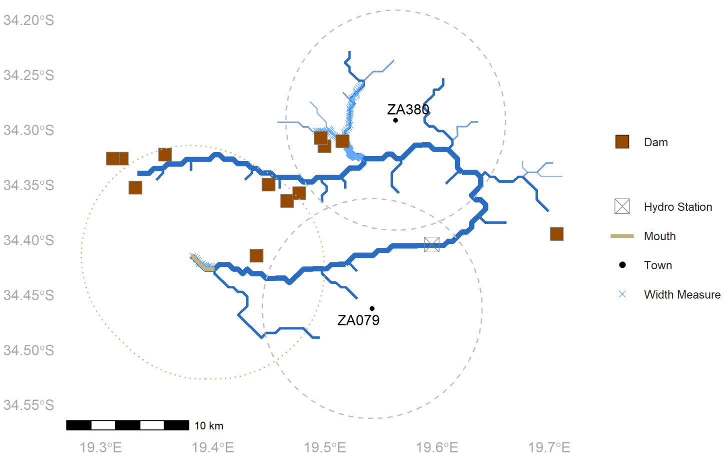
Labels give (Country+DHS cluster number) for DHS 1999.
Includes 806 width locations, 36 towns, 1 hydro stations, 2 dams.
Source: DHS, GADM (2022), AWS (2023), HydroRIVERS (2023), ADHI (2020), GDAT (2023).

DHS Towns Along a River in MOZ



Labels give (Country+DHS cluster number) for DHS 2011.
Includes 132 width location(s), 5 town(s), 0 hydro station(s), 0 dam(s).
Source: DHS, GADM (2022), AWS (2023), HydroRIVERS (2023), ADHI (2020), GDAT (2023).

DHS Towns Along a River in ZAF



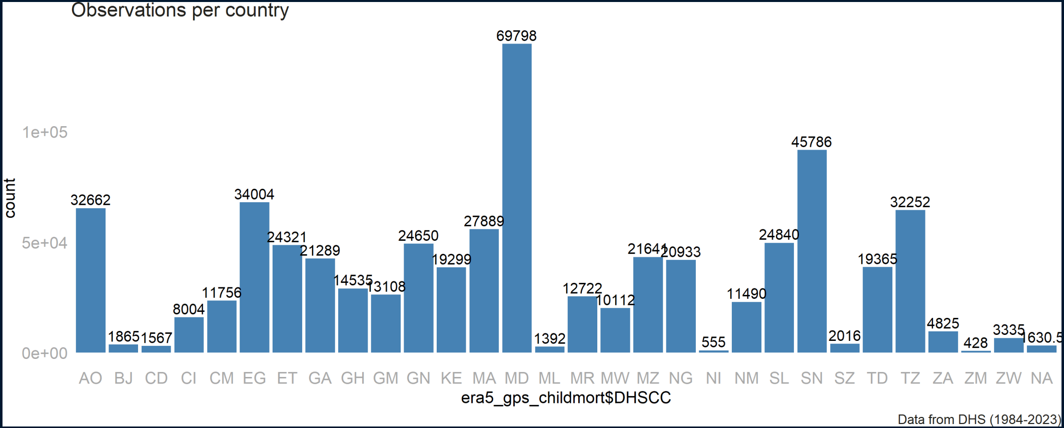
Labels give (Country+DHS cluster number) for DHS 2017.
Includes 116 width locations, 2 towns, 1 hydro stations, 12 dams.
Source: DHS, GADM (2022), AWS (2023), HydroRIVERS (2023), ADHI (2020), GDAT (2023).

Statistic	N	Min	Mean	Median	Max	St. Dev.
Year	248,678	1,957	1,999.38	2,000	2,022	11.09
Average annual precip. (mm/month)	248,678	0.00	0.001	0.001	0.01	0.001
Long-run avg. precip (mm/month)	248,678	0.0000	0.001	0.001	0.01	0.001
Annual precipitation Z-score	248,678	−2.45	−0.18	−0.30	8.59	0.84
3-year avg. precip.	248,678	0.0000	0.001	0.001	0.01	0.001
5-year avg. precip.	248,678	0.0000	0.001	0.001	0.01	0.001
Infant Mortality (/1000 births)	248,678	0	57.21	0	1,000	232.25
Infant Mort., Exposure-weighted	248,678	0.00	28.56	0.00	1,000.00	134.74
Rural	248,678	0	0.58	1	1	0.49
On a Dammed River	248,678	0	0.13	0	1	0.34
On a River with Width Obs	248,678	0	0.41	0	1	0.49
On a River with Hydro Station	248,678	0	0.20	0	1	0.40
N infants per town	248,678	0.50	53.08	48.50	178.00	28.86
N infants per year	248,678	1.50	7,831.37	8,575.50	10,813.00	2,713.27
N infants/town/year	248,678	0.50	2.60	2.00	12.50	1.79

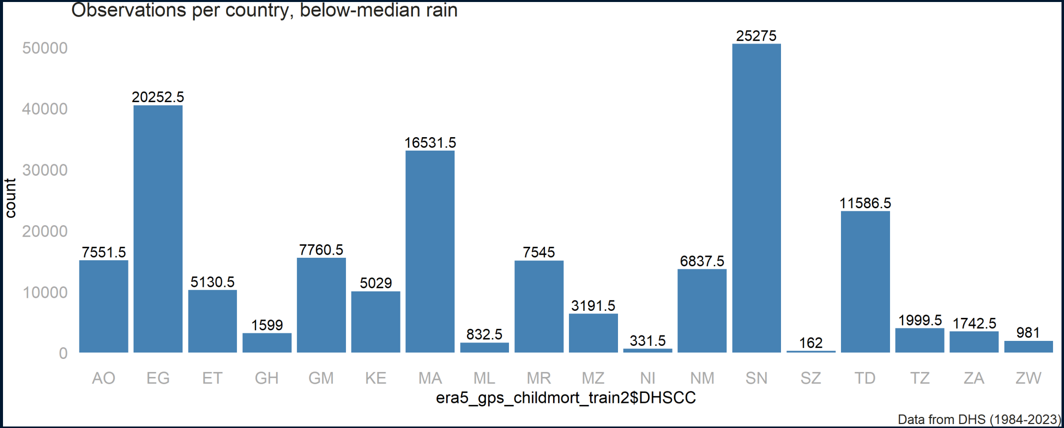
N is infant-by-year. Precipitation data from Hersbach et al. (2020) in mm per month, averaged over the year. Mortality data from over 100 DHS surveys. Currently unweighted by DHS weights for survey probabilities. River data from HydroATLAS (2022), additional calculations use `riverdist` package in R. Data restricted to 60% of cluster-years on rivers with < 100 towns (7223 clusters)

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	26.031			25.828		
	(0.466)			(0.467)		
Annual avg precip	-428.899	780.196	1412.516	-366.323	781.712	1415.134
	(943.647)	(947.642)	(1005.618)	(943.808)	(947.673)	(1005.608)
5-year avg precip	2724.538	6829.531	-2314.844	2132.502	6390.520	-1194.588
	(1000.256)	(2150.993)	(2314.810)	(1006.695)	(2435.252)	(2582.609)
5-yr precip x Dist to source				26.242	16.730	-43.234
				(5.023)	(47.202)	(47.310)
Mean	28.56	28.56	28.56	28.56	28.56	28.56
Cluster FE	N	Y	Y	N	Y	Y
Year FE	N	N	Y	N	N	Y
Num.Obs.	248678	248678	248678	248678	248678	248678
R2	0.000	0.029	0.033	0.000	0.029	0.033

Notes:
Outcome is infant deaths per 1000 infants observed. Precipitation data from ERA5 (2023), in millimeters per month (averaged over the year); river data from HydroSHEDS (2022); DHS surveys from 1988 to 2023, covering 3488 towns on 533 rivers over 1957-2022. Omits Madagascar and any rivers with rainfall above the median of river-level mean precipitation.



Observations per country
count
1e+05
5e+04
0e+00
32662
1865
1567
8004
11756
34004
24321
21289
14535
13108
24650
19299
27889
69798
1392
12722
10112
21641
20933
555
11490
24840
45786
2016
19365
32252
4825
428
3335
1630.5
AO
BJ
CD
CI
CM
EG
ET
GA
GH
GM
GN
KE
MA
MD
ML
MR
MW
MZ
NG
NI
NM
SL
SN
SZ
TD
TZ
ZA
ZM
ZW
NA
era5_gps_childmort$DHSCC
Data from DHS (1984-2023)


Observations per country, below-median rain
count
50000
40000
30000
20000
10000
0
7551.5
20252.5
5130.5
1599
7760.5
5029
16531.5
832.5
7545
3191.5
331.5
6837.5
25275
162
11586.5
1999.5
1742.5
981
AO
EG
ET
GH
GM
KE
MA
ML
MR
MZ
NI
NM
SN
SZ
TD
TZ
ZA
ZW
era5_gps_childmort_train2$DHSCC
Data from DHS (1984-2023)

Analysis:

1. Run it all the way through
2. More careful on river width measurements

Analysis:

1. Show results
2. Give interesting correlates of shifters on Pareto weights

   Economic: Basin management committee, water market in existence, within a country with fossil fuel subsidies across areas? (defines price for pumping)
   Socio-cultural: religion, ethnicity, language
   Physical: ruggedness, potential yields, dam/canal infrastructure

Model:

1. Extend / change?

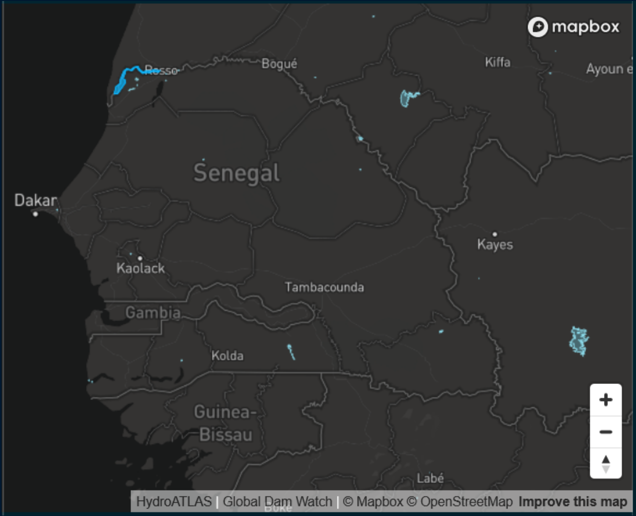
Empirics:

1. Explore whether an ML method with higher-res images would help clean up some of the issues with measurement (river widths / agricultural yields)

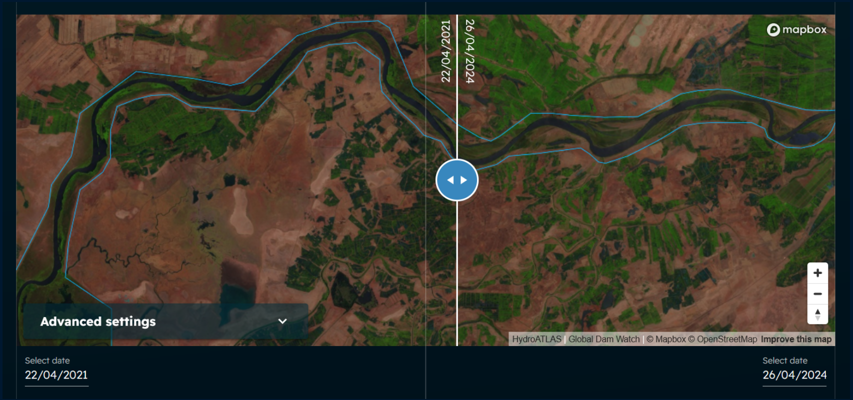
- Potential yield (richer downstream, better contracts?) (also run NN?)
- Technology change (better outside insurance, better contracts?) e.g. cell tower roll-out, shift-share
- Introduction of water markets (not too common in low-income?)
- Forced relocations e.g. after dams on different river systems (changes number of towns / people on river); some instrument of population growth (trade shock?)
- **Other ideas?**

Country-level sub-analysis?

- Data that would be helpful to show mechanisms more clearly:
    - Higher-resolution rainfall data
    - Census-level outcomes (*all* towns/HHs on a river)
    - Better agricultural yields measures
    - Closer crop prices
    - Better measures of HH-level outcomes (e.g. wealth) and choices (irrigated area, crops planted)



Source: Global Water Watch (2024)



Source: Global Water Watch (2024)

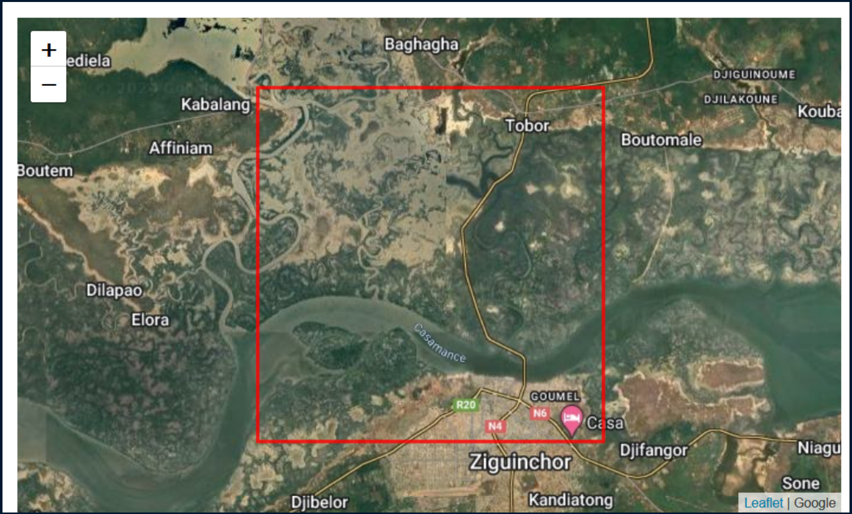
Sentinel-1 Mission

Resolution: approximately 20 meters

Timing: Every 12 days, from April 2014/2016- 2022

What is SAR (Synthetic Apertur Radar)

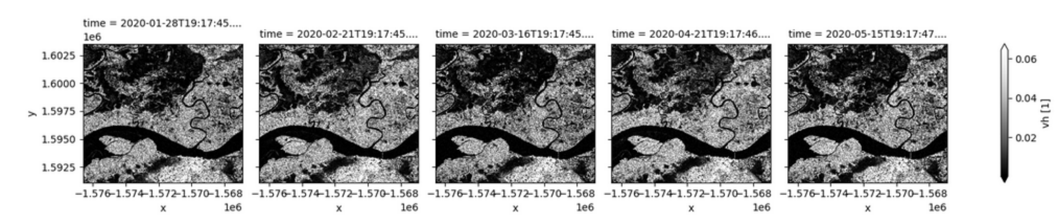
- Measures radar back-scatter, not visible light
- Day or night, clouds or no
- **Rocks** at mapping water, including changes (always-wet, sometimes wet, dry)



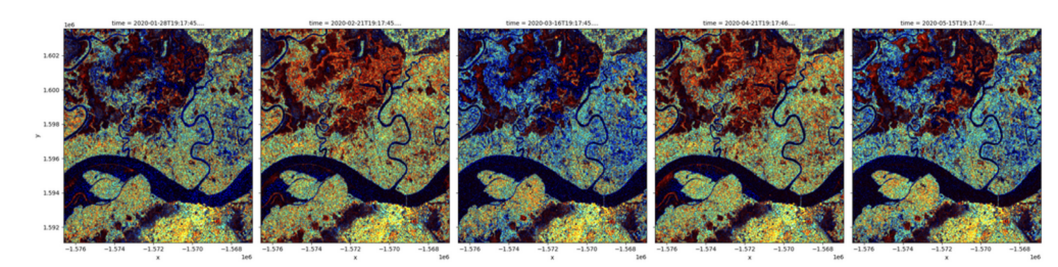
Source: Digital Earth Africa

Example: Water Changes

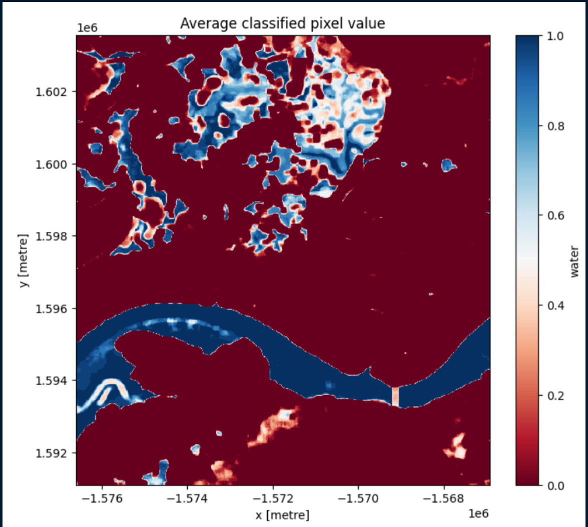
Back to Overview



Source: Digital Earth Africa



Source: Digital Earth Africa



Source: Digital Earth Africa

Infant mortality is sensitive to water availability:

- Water availability affects: agricultural outcomes (e.g. nutrition); hygiene (e.g. diarrhea); disease vectors (e.g. malaria). All these have been found to influence infant mortality (e.g.(Persson et al., 2012))

Spatio-temporal comparability:

- Retrospectively asking about fertility isn't subject to (too much) recall bias
- Can build out panel-esque information from many cross-sections over a wide geography (71k towns,30-some countries), 1954-now

Mechanisms also of interest:

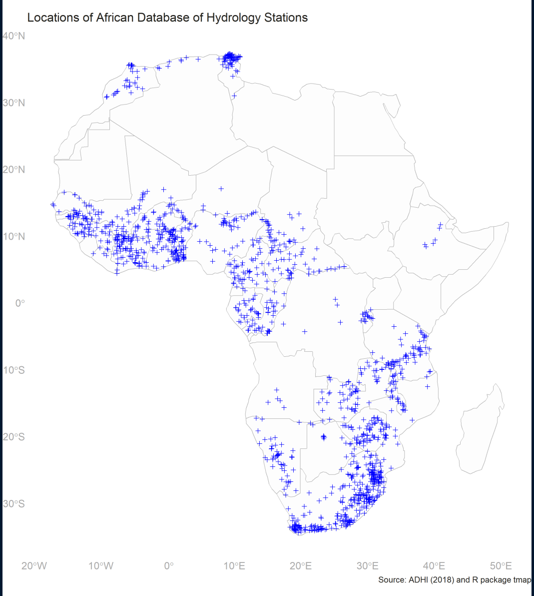
- Mechanisms for water → infant mortality include: in-HH asset accumulation (can get some with DHS household); agricultural productivity and overall community incomes (satellite data: lights, greenness (caveat, only 1992-on))

Not the only analysis?:

- Country-specific section with... better data? better time? more institutional analysis? really lucky identification?
- e.g. dams on River Senegal re-flooding
- Big caveat: short-term for now, *given* infrastructure

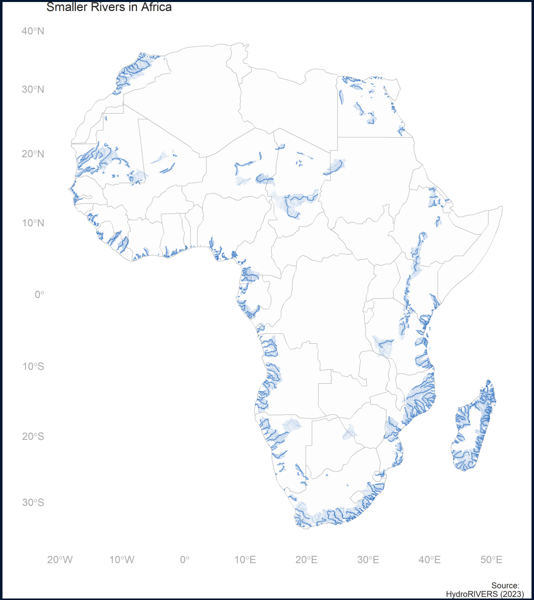
Hydrology Stations

Back



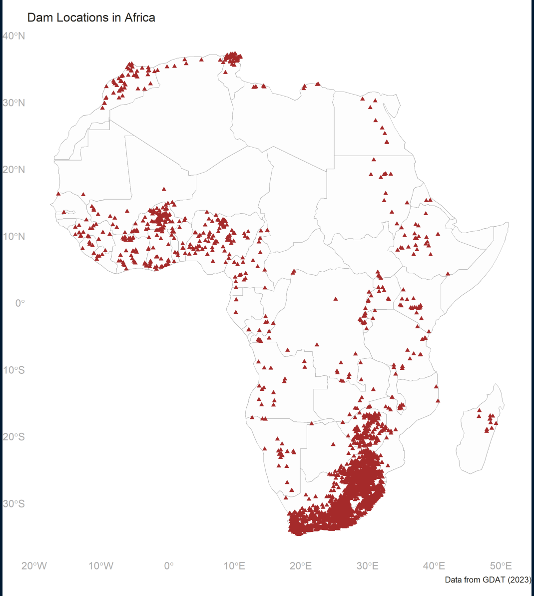
Rivers Currently Being Considered

Back

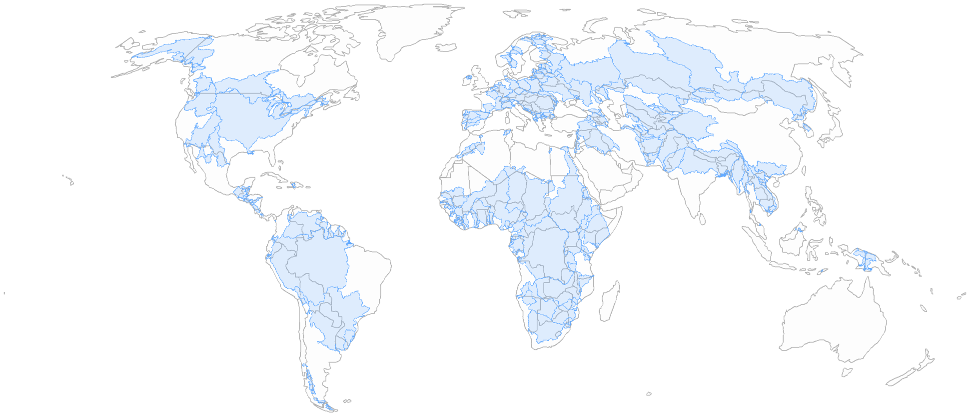


Dams

Back


Dam Locations in Africa
40°N
30°N
20°N
10°N
0°
10°S
20°S
30°S
20°W
10°W
0°
10°E
20°E
30°E
40°E
50°E
Data from GDAT (2023)

International Water Basins



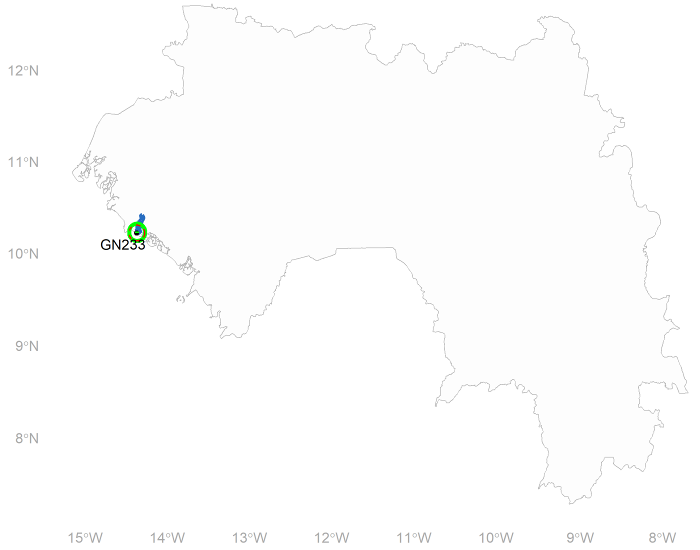
Data from Transboundary Freshwater Dispute Database, Oregon State University 2022

310 total international basins.

Back

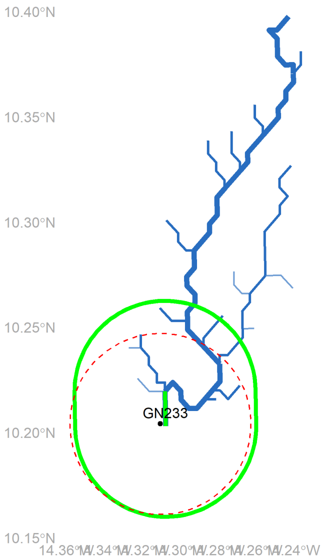

Morocco
Algeria
Libya
Egypt
Western Sahara
Saudi Arabia
Mauritania
Mali
Niger
Chad
Sudan
Burkina Faso
Guinea
Nigeria
Ethiopia
Ghana
Kenya
Gabon
DRC
Tanzania
Mozambique
Zambia
Angola
Madagascar
Zimbabwe
Namibia

Example: River Distance Calculations,GIN 2017 DHSs



Reported cluster in black; buffer of 10 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number)
Data from a compilation of DHS surveys in 2012-2017GADM (2022), AWS (2023), HydroRIVERS (2023).

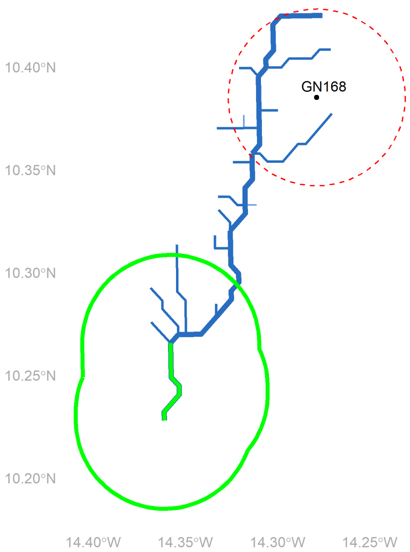
Example: River Distance Calculations,GIN 2017 DHS



Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2017)GADM (2022), AWS (2023), HydroRIVERS (2023).

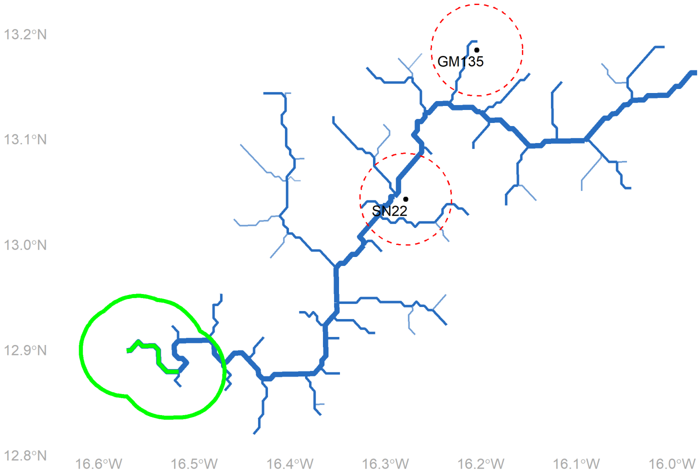

Bandeyehde
Yarita
Wakiriy
Lougame
Madine
Pourou

Example: River Distance Calculations,GIN 2016 DHS



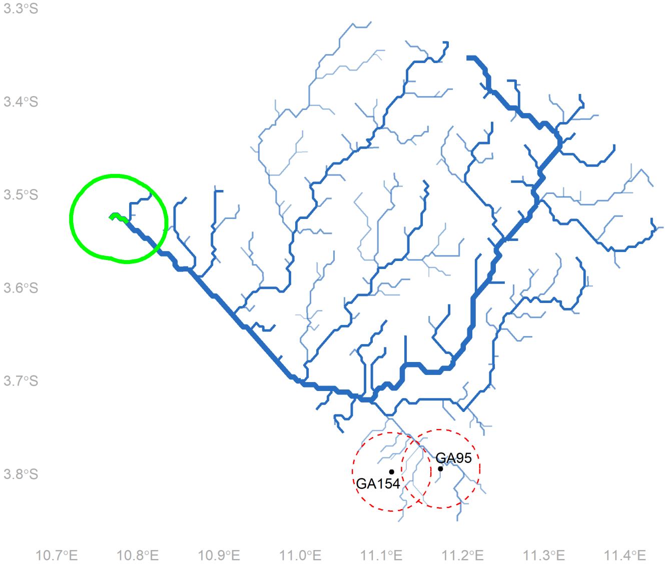
Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2016)GADM (2022), AWS (2023), HydroRIVERS (2023).

Example: River Distance Calculations,GMB SEN 2018-2020 DHSs



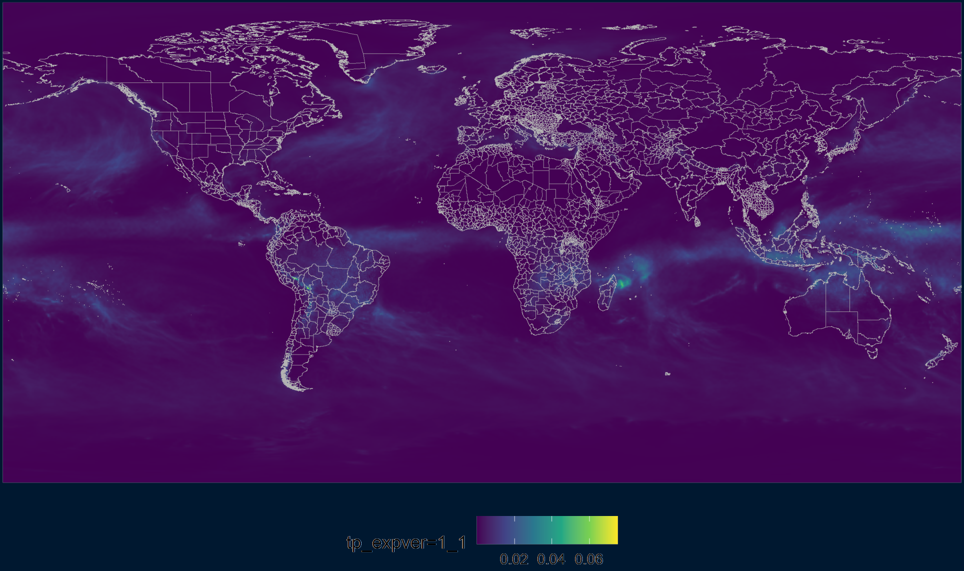
Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2018-2020)GADM (2022), AWS (2023), HydroRIVERS (2023).

Example: River Distance Calculations,COG GAB 2010 DHS



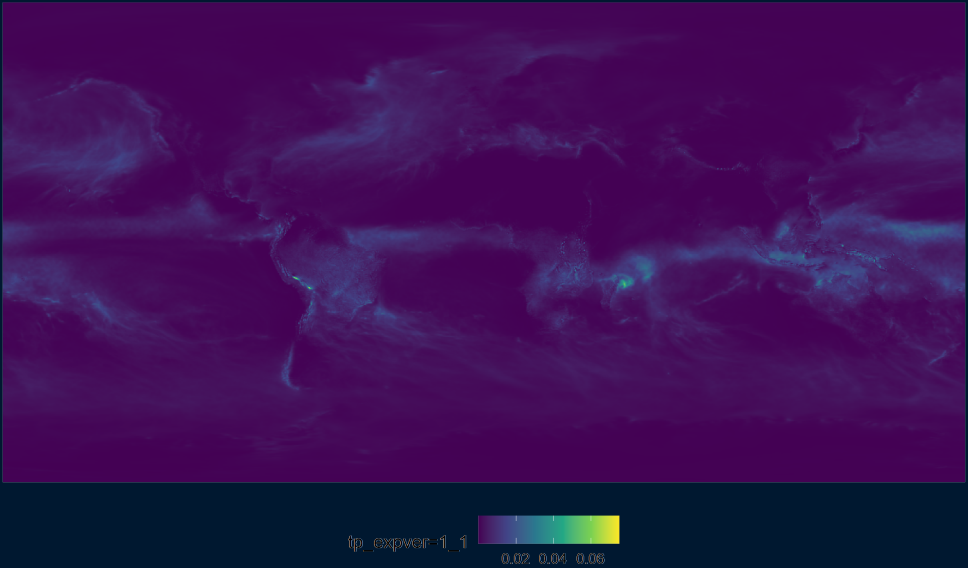
Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2010)GADM (2022), AWS (2023), HydroRIVERS (2023).

Rainfall Data More Visualization



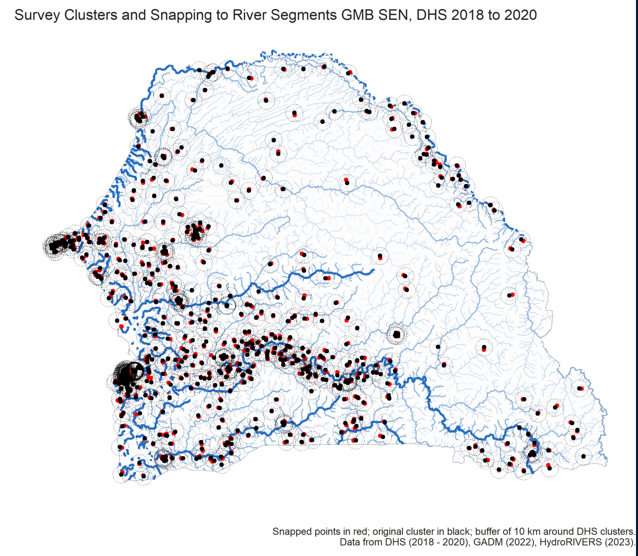
Rainfall Data

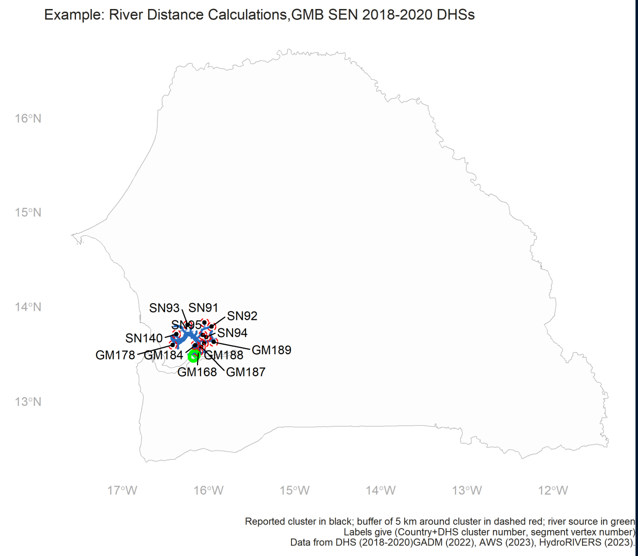
More Visualization

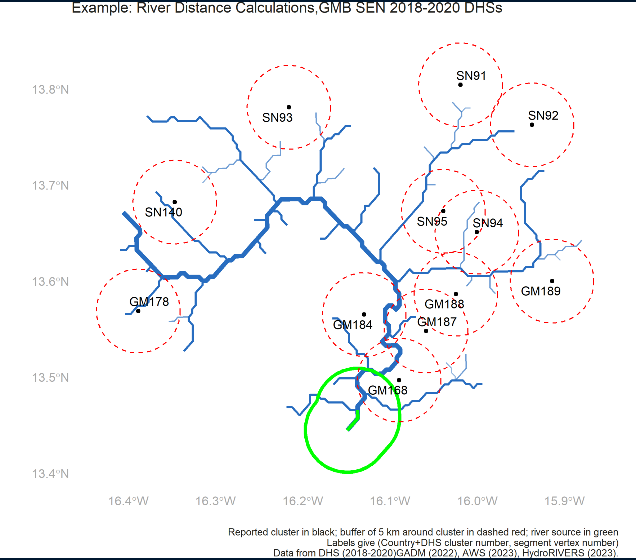


River Networks

Other River Network Examples

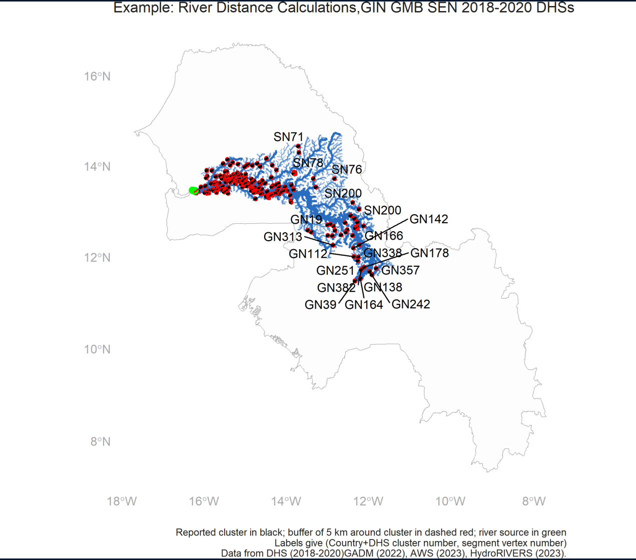



Example: River Distance Calculations,GMB SEN 2018-2020 DHSs
16°N
15°N
14°N
13°N
17°W
16°W
15°W
14°W
13°W
12°W
SN93
SN91
SN92
SN95
SN94
SN140
GM178
GM184
GM188
GM189
GM168
GM187
Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2018-2020)GADM (2022), AWS (2023), HydroRIVERS (2023).


Example: River Distance Calculations,GMB SEN 2018-2020 DHSs
13.8°N
13.7°N
13.6°N
13.5°N
13.4°N
16.4°W
16.3°W
16.2°W
16.1°W
16.0°W
15.9°W
SN91
SN93
SN92
SN140
SN95
SN94
GM178
GM189
GM188
GM184
GM187
GM168
Reported cluster in black; buffer of 5 km around cluster in dashed red; river source in green
Labels give (Country+DHS cluster number, segment vertex number)
Data from DHS (2018-2020)GADM (2022), AWS (2023), HydroRIVERS (2023).

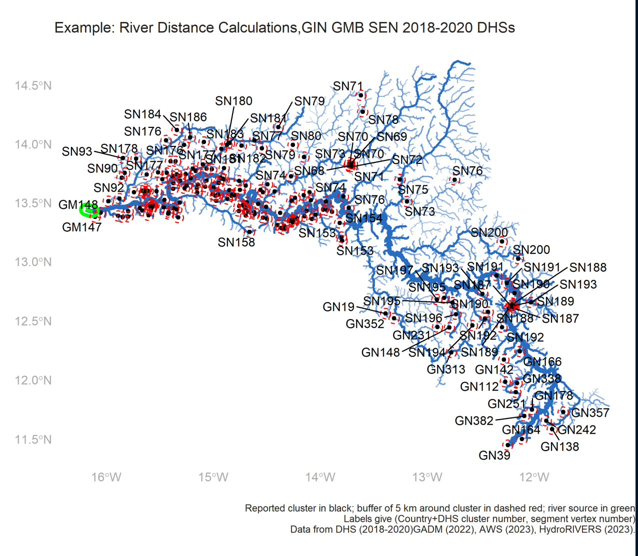
River Networks

Back to Main River Network



River Networks

Back to Main River Network



Statistic	N	Min	Mean	Median	Max	St. Dev.
Year	15,005	1,988	2,007.05	2,010	2,018	8.43
Average annual precip. (mm/month)	15,005	4.13	44.08	38.30	132.79	25.66
Annual precipitation SD (mm/month)	15,005	6.03	74.05	66.46	238.66	39.06
Annual precipitation Z-score	15,005	−0.83	−0.54	−0.57	2.67	0.27
Neonatal Mort. Rate (NNMR)	15,003	0.00	29.87	16.26	500.00	40.53
Infant Mortality Rate (IMR)	15,003	0.00	51.12	41.67	600.00	54.12
Under-5 Mort. Rate (U5MR)	14,999	0.00	87.16	70.81	602.32	79.77
Under-10 Mort. Rate (U10MR)	14,993	0.00	100.08	82.54	625.71	85.46
NNMR Weighted Number (WN)	15,005	0	26.47	21	233	20.58
IMR WN	15,005	0	32.84	27	297	25.10

N is number of cluster-by-years, for clusters on rivers intersecting with Senegal. Precipitation data from Hersbach et al. (2020) in mm per month, averaged over the year. Border data from GADM (2022). Mortality data from various DHS surveys. NNMR denotes neonatal mortality rate (months 0-1) per 1,000 live births; IMR denotes infant (months 0-12) mortality rate per 1,000 live births, calculated with modification of the R package `DHS.rates`. Weighted numbers are DHS weights for survey probabilities. Mortality truncated between median and 90th percentile due to small exposed populations.

Summary Statistics

Full Sum Stats

Statistic	N	Min	Mean	Median	Max	St. Dev.
Year	8,624	1,988	2,009.49	2,012	2,019	6.45
Cluster distance (m)	8,624	475.53	42,496.11	25,383.45	251,488.90	47,437.44
International	8,624	0	0.002	0	1	0.04
Cross-Adm 1 (state)	8,624	0	0.24	0	1	0.43
Cross-Adm 2 (county)	8,624	0	0.60	1	1	0.49
Urban U, Urban D	8,624	0	0.22	0	1	0.41
Urban U, Rural D	8,624	0	0.05	0	1	0.22
Rural U, Urban D	8,624	0	0.24	0	1	0.43
Rural U, Rural D	8,624	0	0.49	0	1	0.50
(NNMR U)/(NNMR D)	8,624	0.12	1.23	1.09	7.74	0.73
NNMR Weighted N (U)	8,624	15	51.70	49	166	25.93
NNMR Weighted N (D)	8,624	15	41.85	35	183	25.66
(IMR U)/(IMR D)	8,624	0.34	1.19	1.08	3.62	0.52
IMR Weighted N (U)	8,624	15	51.17	47	174	25.77
IMR Weighted N (D)	8,624	15	41.42	34	183	25.26

N denotes a dyad-year, only dyad-years with NNMR and IMR within 50-90th percentiles (to avoid small sample infinite values). Cluster distance is along-river flow-connected distance between dyads. International denotes crossing an international border; Cross-Adm 1 is crossing a state/province border; Cross-Adm 2 is crossing a county/district border. Urban U, Urban D denotes urban up and downstream clusters.

Summary Statistics

Full Sum Stats

Statistic	N	Min	Mean	Median	Max	St. Dev.
Year	181,020	1,988	2,006.27	2,011	2,019	9.53
Cluster distance (m)	181,020	434.98	36,429.00	4,138.88	292,775.30	49,679.83
International	181,020	0	0.001	0	1	0.03
Cross-Adm 1 (state)	179,870	0	0.23	0	1	0.42
Cross-Adm 2 (county)	179,870	0	0.77	1	1	0.42
Urban U, Urban D	181,020	0	0.55	1	1	0.50
Urban U, Rural D	181,020	0	0.05	0	1	0.21
Rural U, Urban D	181,020	0	0.25	0	1	0.44
Rural U, Rural D	181,020	0	0.15	0	1	0.36
(NNMR U)/(NNMR D)	118,319	0.00	Inf.00	1.28	Inf.00	
NNMR Weighted N (U)	181,020	0	38.49	32	236	30.56
NNMR Weighted N (D)	181,020	0	28.04	22	236	23.48
(IMR U)/(IMR D)	141,614	0.00	Inf.00	1.26	Inf.00	
IMR Weighted N (U)	181,020	0	38.22	32	233	30.13
IMR Weighted N (D)	181,020	0	27.84	22	233	23.12

N denotes a dyad-year, all dyad-years included. Cluster distance is along-river flow-connected distance between dyads. Internation denotes crossing an international border; Cross-Adm 1 is crossing a state/province border; Cross-Adm 2 is crossing a county/district border. Urban U, Urban D denotes urban up and downstream clusters.

- Because of Markov structure and since the SCs are forward-looking, sustainable continuation contracts depend on current state s only
- Pareto frontier at time t state s depends on s and not past history
- **Want to Know**: Shape of Pareto frontier and where it's defined
- **First need:**
    1. Convexity of set of sustainable contracts
    2. Convexity of set of sustainable discounted surpluses (i.e. $\exists$ a sustainable contract delivering such surpluses) for each representative consumer

Show that a convex combination of two sustainable contracts is a sustainable contract:

- For $\alpha \in (0, 1)$, consider two original contracts $\mathcal{T}(\cdot) = \{\tau(\cdot), \omega(\cdot)\}$ and $\hat{\mathcal{T}}(\cdot) = \{\hat{\tau}(\cdot), \hat{\omega}(\cdot)\}$, and define the consumption and water transfers respectively after each history h_t to as follows:

$$\alpha\tau(h_t) + (1 - \alpha)\hat{\tau}(h_t)$$

$$\alpha\omega(h_t) + (1 - \alpha)\hat{\omega}(h_t)$$

- $u(\cdot)$ and $v(\cdot)$ are concave, so this new average contract offers at least the average of surpluses from the original $\mathcal{T}$ and $\hat{\mathcal{T}}$ for both consumers from any history h_t, so SCs (Equations **??** and **??**) hold, i.e. this is a sustainable contract.

« Include subset of characterization from original Ligon et al. (2002), see what might be different » Additional Slides

Because of

1) Markov structure (can be irreducible)
2) Efficient contract $\Rightarrow$ efficient continuation contract
3) Concavity of period utility functions

The set of sustainable discounted surpluses for each household is an interval!

Because of

1) Markov structure (can be irreducible)
2) Efficient contract $\Rightarrow$ efficient continuation contract
3) Concavity of period utility functions

The set of sustainable discounted surpluses for each household is an interval!

For Upstream: $[\underline{U}_s, \bar{U}_s]$, and $\underline{U}_s \geq -P_1(s)$

For Downstream: $[\underline{V}_s, \bar{V}_s]$, and $\underline{V}_s \geq -P_2(s)$

Let $V_s(U_s)$ be the ex-post Pareto efficient frontier.

Goal: Be on the Pareto Frontier $V_s(U_s)$

$$V_s(U_s) = \max_{\tau_s,(U_r)_{r=1}^S} (v(y_2(s)) + \tau_s) - v(y_2(s)) + \delta \sum_{r=1}^{S} \pi_{sr} V_r(U_r)$$

Subject to:

1) Upstream getting surplus at least U_s (LM: λ)
2) Upstream not walking away (LM: ϕ_r)
3) Downstream not walking away (LM: μ_r)
4) Upstream's nonnegativity of consumption (LM: ψ_1)
5) Downstream's non-negativity of consumption (LM: ψ_2)

Proposition 1: Constrained-Efficient Contract

A constrained-efficient contract is a transfer scheme where there exist S state-dependent intervals $[\underline{\lambda}_r, \bar{\lambda}_r]$, $r = 1, 2, \ldots, S$ such that $\lambda(h_t)$ is given by, for r the state at $t+1$:

$$\lambda(h_{t+1}) = \begin{cases} \underline{\lambda}_r & \text{if } \lambda(h_t) < \underline{\lambda}_r := -V_r'(\underline{U}_r) \\ \lambda(h_t) & \text{if } \lambda(h_t) \in [\underline{\lambda}_r, \bar{\lambda}_r] \\ \bar{\lambda}_r & \text{if } \lambda(h_t) > \bar{\lambda}_r := -V_r'(\bar{U}_r). \end{cases} \tag{3}$$

This characterizes the contract completely for initial value λ_0

- If you can get first-best, don't change λ
- If you can't, change as little as possible to get into the new interval

Main Slides

- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0, 1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Identical prefs $\Rightarrow \xi_{hh} = \xi_{\ell\ell} = 1$

- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0,1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Low period:

$$y_\ell = y_h - d$$

Expected income per period:

$$y_h - pd$$

- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0,1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Low period:

$$y_\ell = y_h - d$$

Expected income per period:

$$y_h - pd$$

Four states (Upstream,Downstream): $(h\ell), (hh), (\ell\ell), (\ell h)$

- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0, 1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Low period:

$$y_\ell = y_h - d$$

What's the full-insurance transfer?

- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0, 1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Low period:

$$y_\ell = y_h - d$$

What's the full-insurance transfer?

$\tau_{h\ell} = \frac{d}{2}$, Upstream gives Downstream half

$\tau_{\ell h} = -\frac{d}{2}$

$\tau_{\ell\ell} = \tau_{hh} = 0$

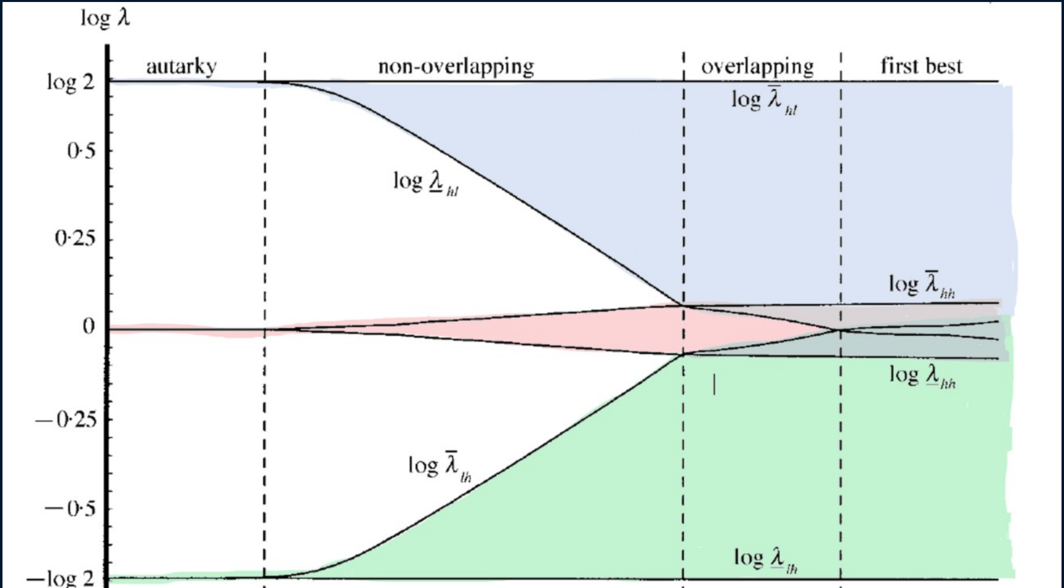
- IID income shocks, no punishments
- Two states y_h, y_ℓ
- Each HH suffers loss d with probability $p \in (0,1)$
- Identical log preferences $u(c) = v(c) = log(c)$

Because of the log, $[\underline{\lambda}_{hh}, \bar{\lambda}_{hh}] = [\underline{\lambda}_{\ell\ell}, \bar{\lambda}_{\ell\ell}]$

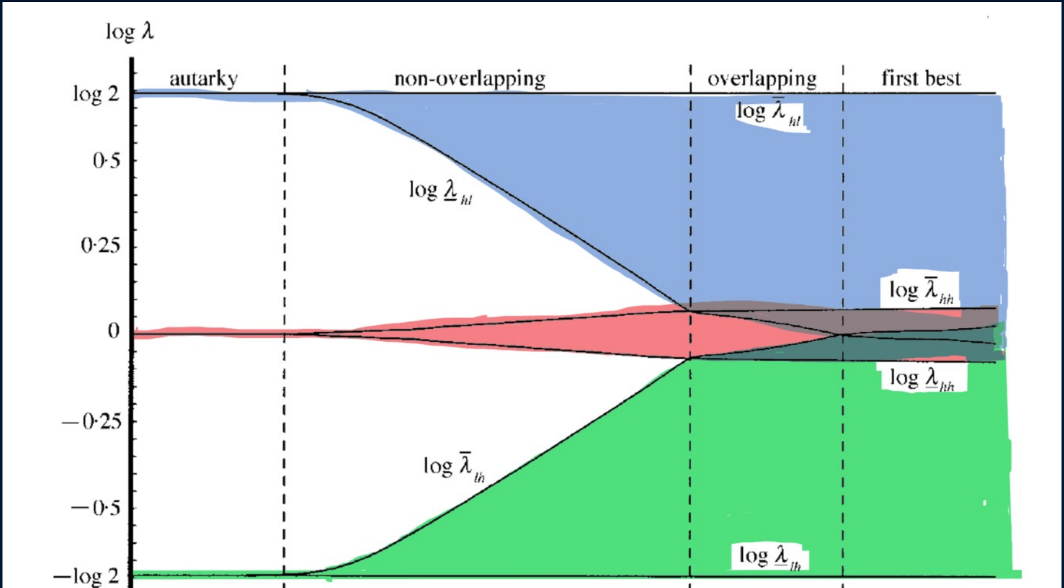
By symmetry:

$$\underline{\lambda}_{h\ell} = \frac{1}{\bar{\lambda}_{\ell h}}$$
$$\underline{\lambda}_{\ell h} = \frac{1}{\bar{\lambda}_{h\ell}}$$
$$\underline{\lambda}_{hh} = \frac{1}{\bar{\lambda}_{hh}}$$

Example: $p = 0.1$, $\frac{d}{y_h} = 0.5$ Main Slides



Example: $p = 0.1$, $\frac{d}{y_h} = 0.5$ Main Slides



1) Suppose we're in $\delta \in (.935, .965)$

2) Upstream gets a bad shock: ℓh

3) $\lambda \to \bar{\lambda}_{\ell h}$, for $1 > \bar{\lambda}_{\ell h} > \xi_{\ell h} = \frac{1}{2}$

4) Downstream transfers $\tau < \frac{d}{2}$ to Upstream s.t. $\frac{v'(c^2)}{u'(c^1)} = \bar{\lambda}_{\ell h}$

5) Updating rule: $\frac{v'(c^2)}{u'(c^1)} = \bar{\lambda}_{\ell h}$ *until* $h\ell$ occurs ($hh, \ell\ell$ Upstream $\to$ Downstream. Why?)

6) At $h\ell$, situation reverses: $\lambda \to \underline{\lambda}_{h\ell}$

7) Like a debt contract that gets repaid until another bad shock hits only one HH

- If both HHs hit, still repay

- If one HH hit, the previous history is forgiven, start fresh

Professors (frequent discussants): Giovanni Maggi, Mark Rosenzweig, Lauren Bergquist, Mushfiq Mobarak

Professors (occasional): Rohini Pande, Ken Gillingham, Robert Jensen

Ideas: Pam Jakiela, Owen Ozier, Carl Obst

Peers:

Fellowships: SYLFF

DHS contains:

HV101: relationship to household head (use for: do parents live in household)
HV221: whether household has telephone
HV236: person fetching water (only old DHS)
Child Labor Module Variables: worked for someone outside household, hours worked,fetched wood or water (hours); worked for family member (hours); did domestic household work (hours)
V130: religion; V131 Ethnicity (for size of other possible insurance networks?)
V167: number of trips away from home for one or more nights in last 12 months
V740: whether respondent works on own land, family land, rented land, or someone else's land (not core DHS VII anymore)

DHS contains:

HV111: whether mother of household member is still alive (base: children < 18)
HV113: whether father of household member is alive (base: children aged < 18)
H11: whether child had diarrhea in last 24 hours or last 2 weeks

DHS contains:

HV201: main source of drinking water
HV202: main source of water for use other than drinking
HV204: time taken to get water source for drinking water
HV244: owns land usable for agriculture; HV245 hectares for agricultural land

DHS contains:

HV205: type of toilet
HV 20x: whether household has certain durables
HV21x: materials of floors and roofs
HV221: whether household has telephone
HV24x: assets, including most livestock
HV244: owns land usable for agriculture; HV245 hectares for agricultural land
HV270: wealth index
MV484: smoking per week

DHS contains:

V104: nubmer of years living in the village/town/city of being interviewed
V705: partner's occupation groups; V717 respondent's occupation group
MV605: desire for more children; MV613: ideal number of children; MV621 whether partner agrees
MV72x: working, at home or away; worked in the last 12 months; seasonal, occasional, or annual worker
MV740: whether respondent works in own, family, rented or someone else's land (not core DHS VII anymore)
V169: owns mobile telephone (and uses for financial transactions)
V167-168: times away from home for 1 night or more in last 12 months

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