Farmer Perception, Recollection, and Remote Sensing in Weather Index Insurance: an Ethiopia Case Study

In Review, Remote Sensing

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International Research Institute for Climate and Society
EARTH INSTITUTE | COLUMBIA UNIVERSITY

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Experience

IRI has been working **for over a decade** in research, education and technical support for index insurance projects

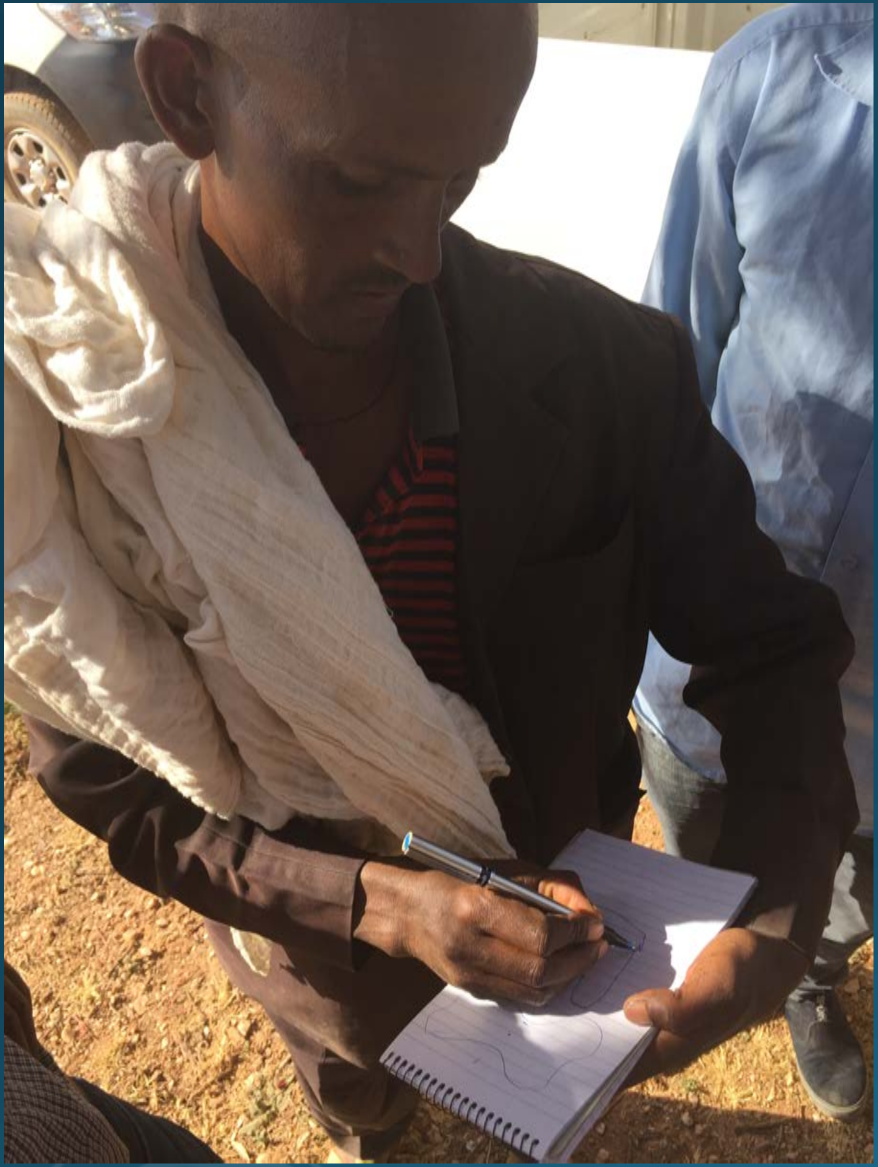
We support most of the index insurance projects that have gone to **large scales**.

We support dozens of projects across Africa, Latin America, and Asia, with **several hundreds of thousands** of farmers purchasing indexes we have helped build

Some partners:

CCAFS, USAIDe3, WFP, OXFAM, WB/IFC, Kilimo Salama/ACRE, UN-ILO, NASA, TAMSAT, NOAA, SWISSRe, MunichRe, USAID, FEWSNET as well as several academic institutions

Data in Index Insurance



To design *reliable* index insurance products we all know that we must rely on accurate, up to date and robust data

Limited formal datasets so projects increasingly rely on remote sensing data

- use of RS datasets require some form of **validation with ground data**

Literature on Biases in Farmer Recollection

-Likely to bias reporting to negotiate for higher payouts
-Reluctant to reveal info that may weaken negotiations in labor or rent
-Bias related to gender and representation of women
-Cognitive challenges of recalling historical events
  -Telescoping
  -Recall Delay
  -Anchoring
-Errors in surveys
-Increasing recall time increases bias

Other literature on Farmer Perceptions

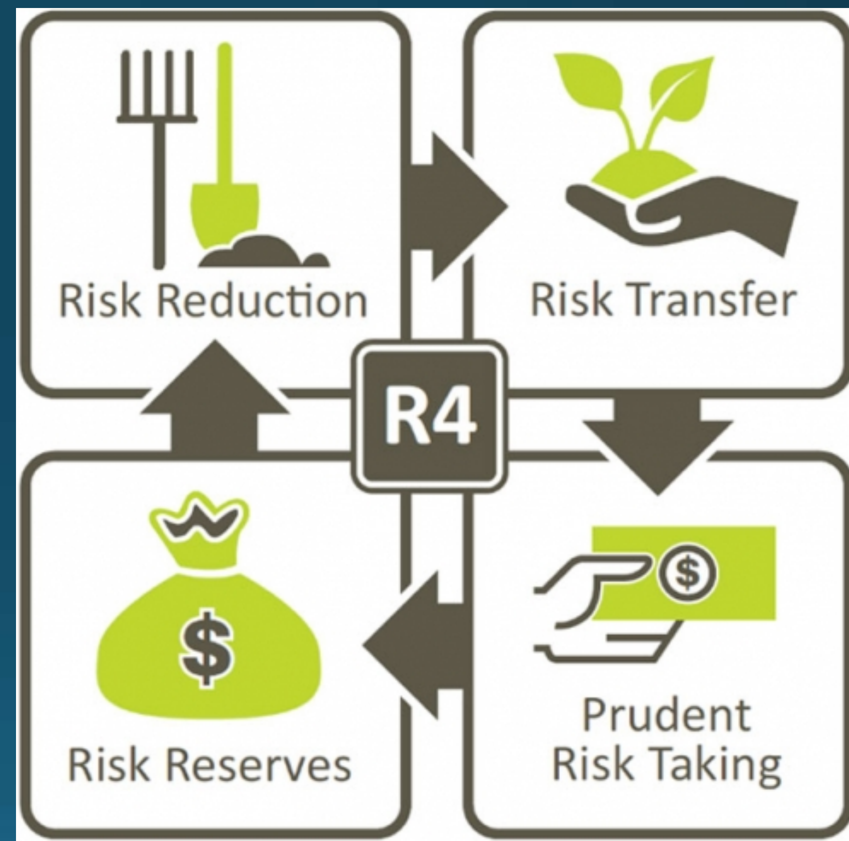
- Farmer recollection of climate variability
  - Temperature and precipitation
- Comparing Farmer perceptions with national meteorological data
- Affects of perception of climate variability on adaptation

WHAT IS MISSING?

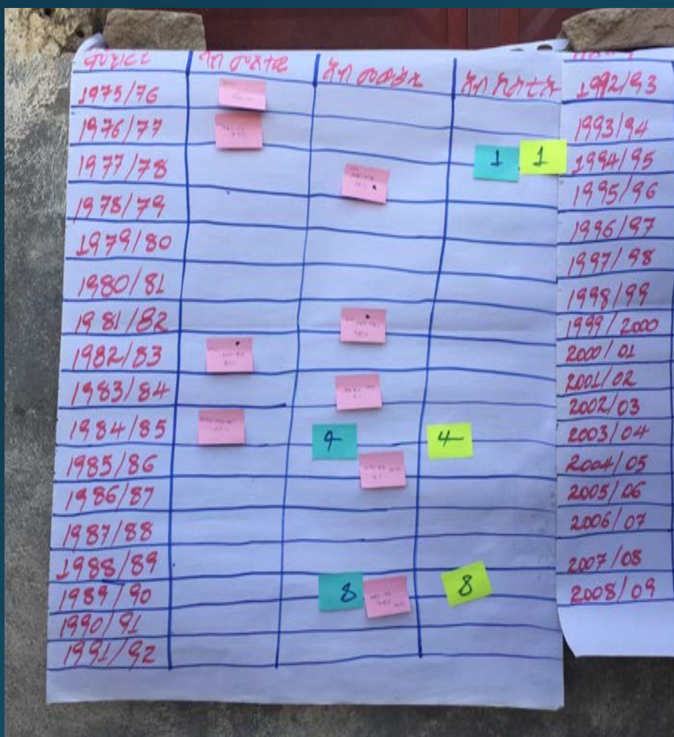
Farmer perception of long term weather impacts on agriculture

Test this in the context of index insurance!

Case Study: R4 Ethiopia



Participatory Approach to Index Design



Integration of local farmer and expert knowledge with index design

1st Year Dry Run:

- Games that simulate economic risks
- Interactive Drought Year Exercises
- Index is designed to closely target actual losses
- Exercises are conducted at the institutional level and capacity building trainings are conducted

2nd Year:

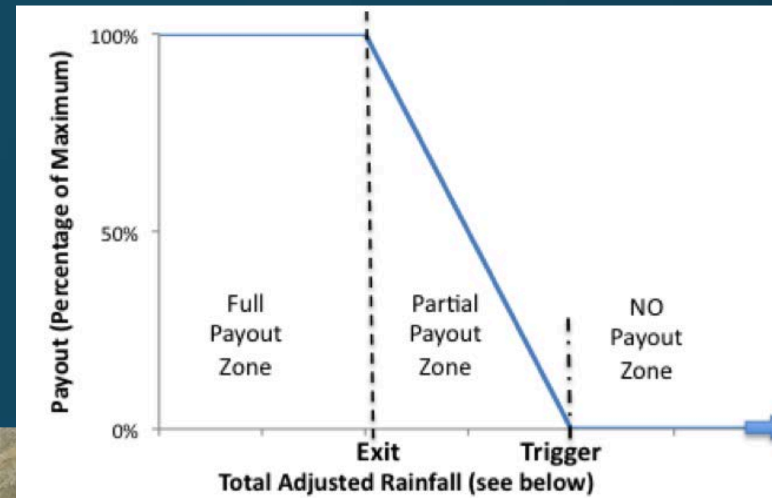
- Further refinement of indexes occurs, with scale up in feasible areas

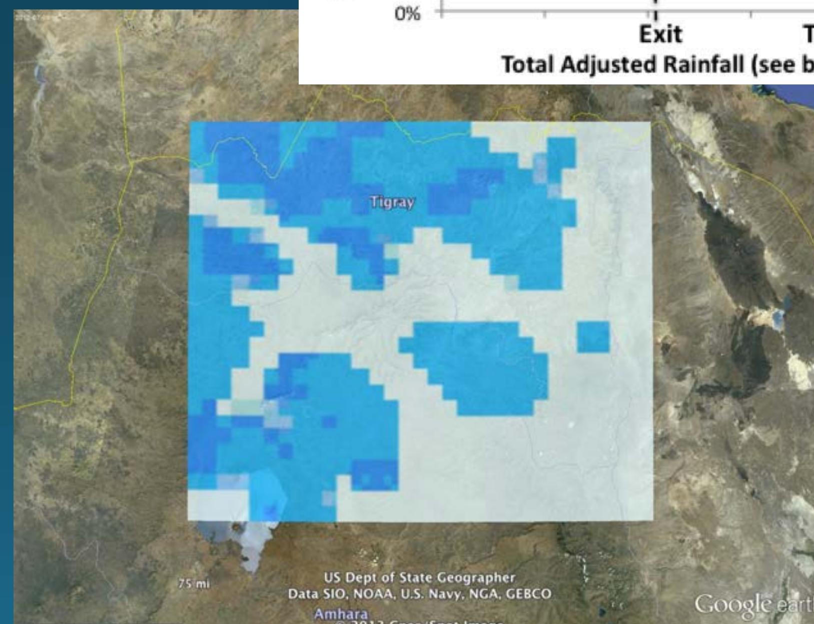
Subsequent Years:

- Scale up is feasible due to dry run process and index refinement process, with participatory exercises at the root

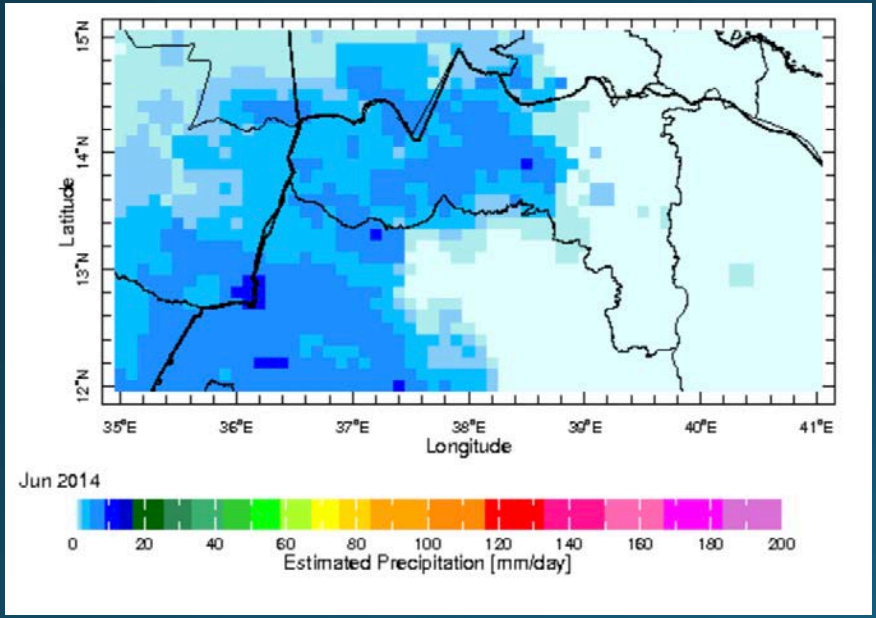
Simple indexes, based on satellite data

- R4 Ethiopia indexes are based on the 30+ year African Rainfall Climatology Version 2 (ARC2) dataset
- Parameters include a trigger, exit, cap
- Fractional payouts, partial payout between the trigger and the exit

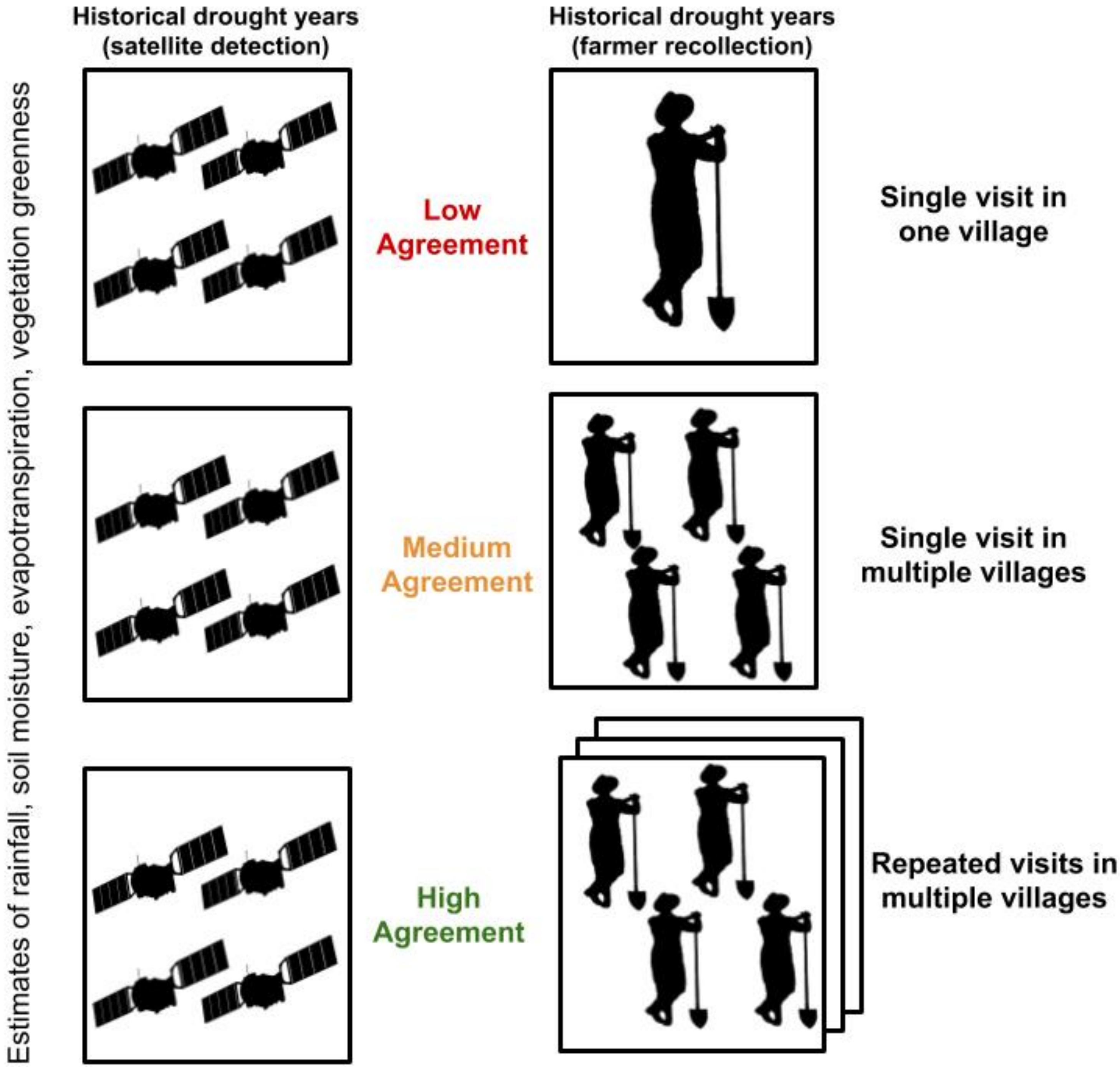




Satellite Estimates of Rainfall to Detect Drought



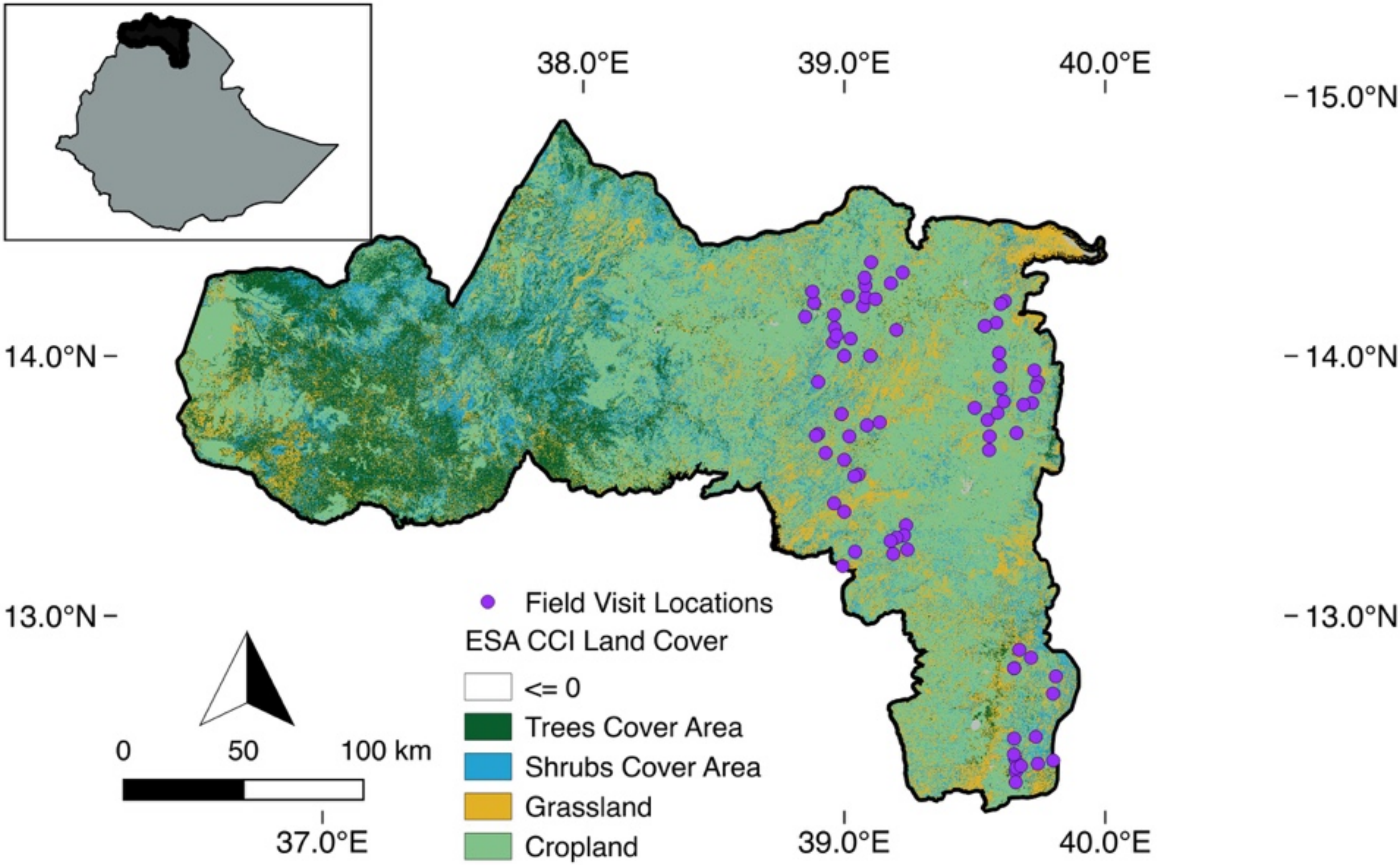
- R4 Index based on drought
- Sometimes satellite derived rainfall estimates don't capture droughts
- Hard to capture orographic (mountain) rainfall
- Spatial resolution
- Rain gauge data
- Ultimately, the technical feasibility of index insurance relies on being able to validate the remote sensing data


Historical drought years
(satellite detection)
Historical drought years
(farmer recollection)
Estimates of rainfall, soil moisture, evapotranspiration, vegetation greenness
Low
Agreement
Single visit in
one village
Medium
Agreement
Single visit in
multiple villages
High
Agreement
Repeated visits in
multiple villages

Data: Farmer Perception

- "Farmer bad years": historical drought years coming from farmers representing a community
- 81 villages, 21 villages visited multiple times
- Formal game exercises assist with recall
- Worst 8 years: community must have consensus

Location of Study Area in Ethiopia



Data: Satellite products

1983-2016

- ARC2 African Rainfall Climatology (ARC2)
  - Early and Late Window Rainfall Totals 10km
- CHIRPS
  - Early and Late Window Rainfall Totals 5km

2000 - 2016

- MODIS NDVI
  - 250m resampled to 10km
  - 1 month lag
- MODIS EVI
  - 250m resampled to 10km
  - 1 month lag
- ALEXI Evapotranspiration
  - Resampled to 25 km
- CCI ESA Surface Soil Moisture
  - Resampled to 25 km

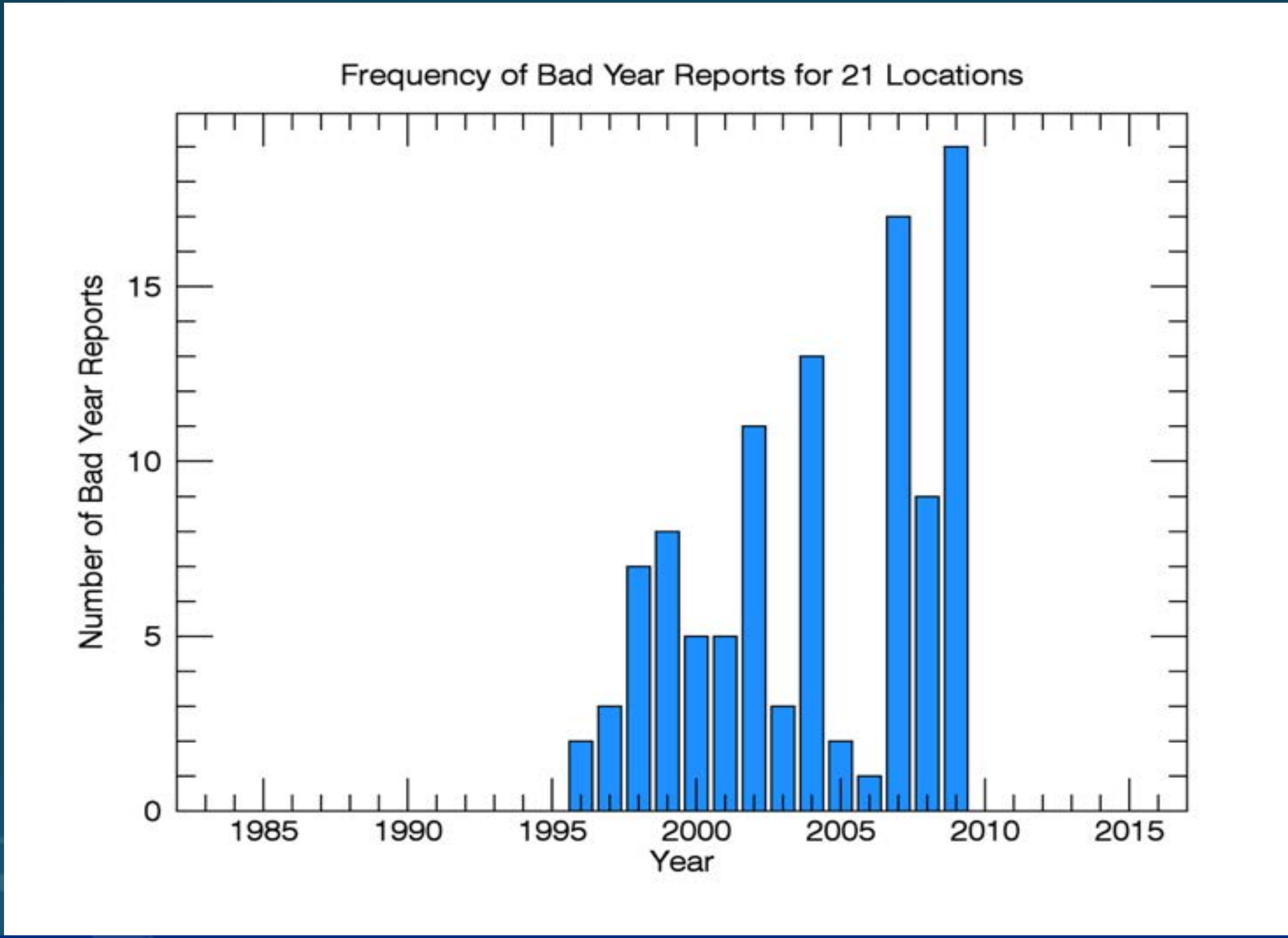
Methodology

1. 3 types of forecast verification (Heidke, Peirce, Equitable Threat Scores) to identify which part of the season agrees the most with farmer reported years
2. Logistic regressions test how well RS estimates can predict farmer recollection historical drought years in Ethiopia
3. Potential bias in reporting is filtered through both **temporal aggregation** (multiple village visits) and **spatial aggregation** (information aggregated from nearby villages)

Methodology, cont.

- Baseline exploration of 21 villages (subset of 81 total)
- Compared with data collected from second visit, a few years subsequent – exploring potential benefits of utilizing multiple visits over time
- Compare the multiple visits strategy to direct increase in sample size, exploring issues of spatial aggregation and reporting
- Finally, in one model we look at multiple satellite-derived variables to see if there is evidence for farmer bad years

Results: Temporal Aggregation Initial Diagnostics FIRST VISIT



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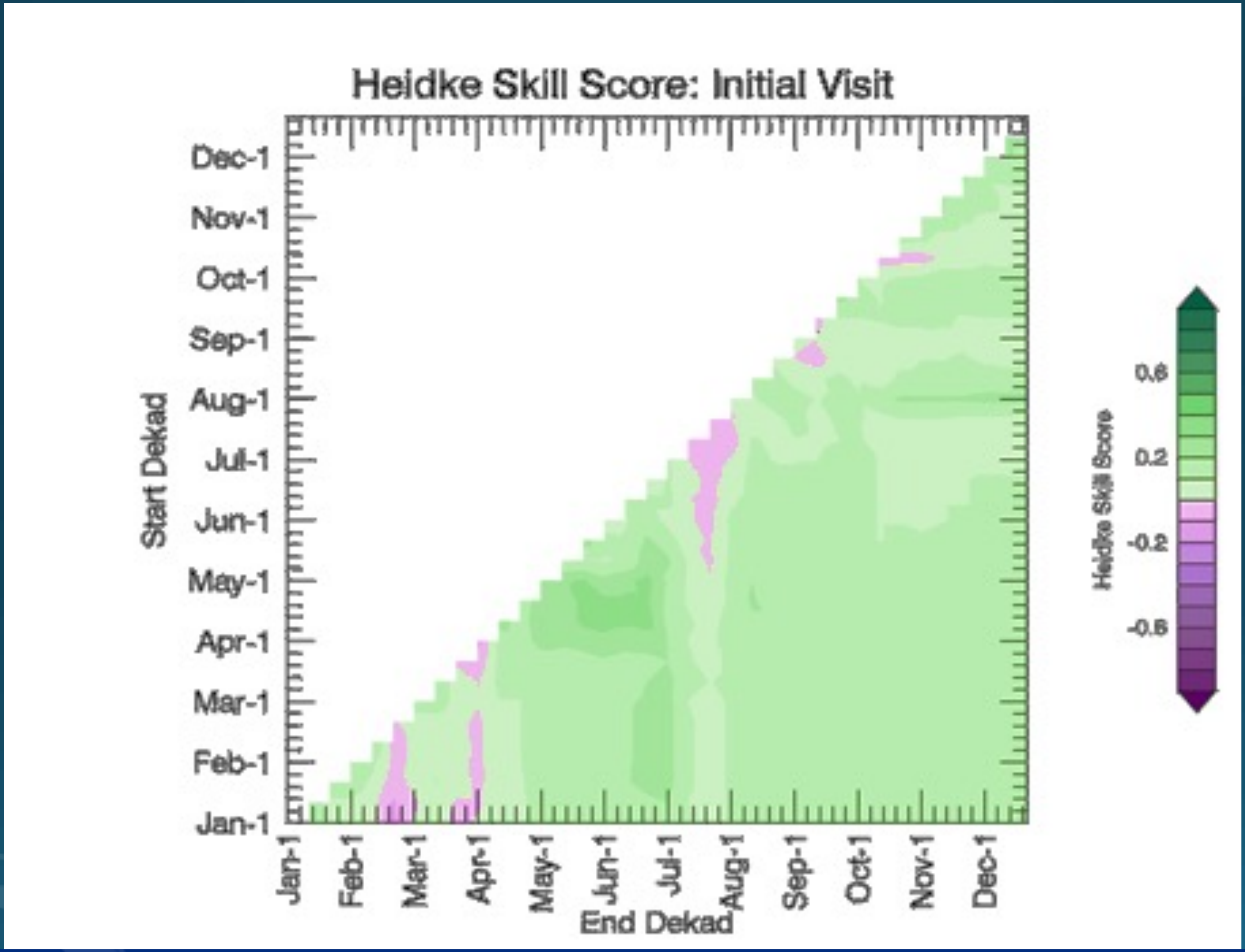
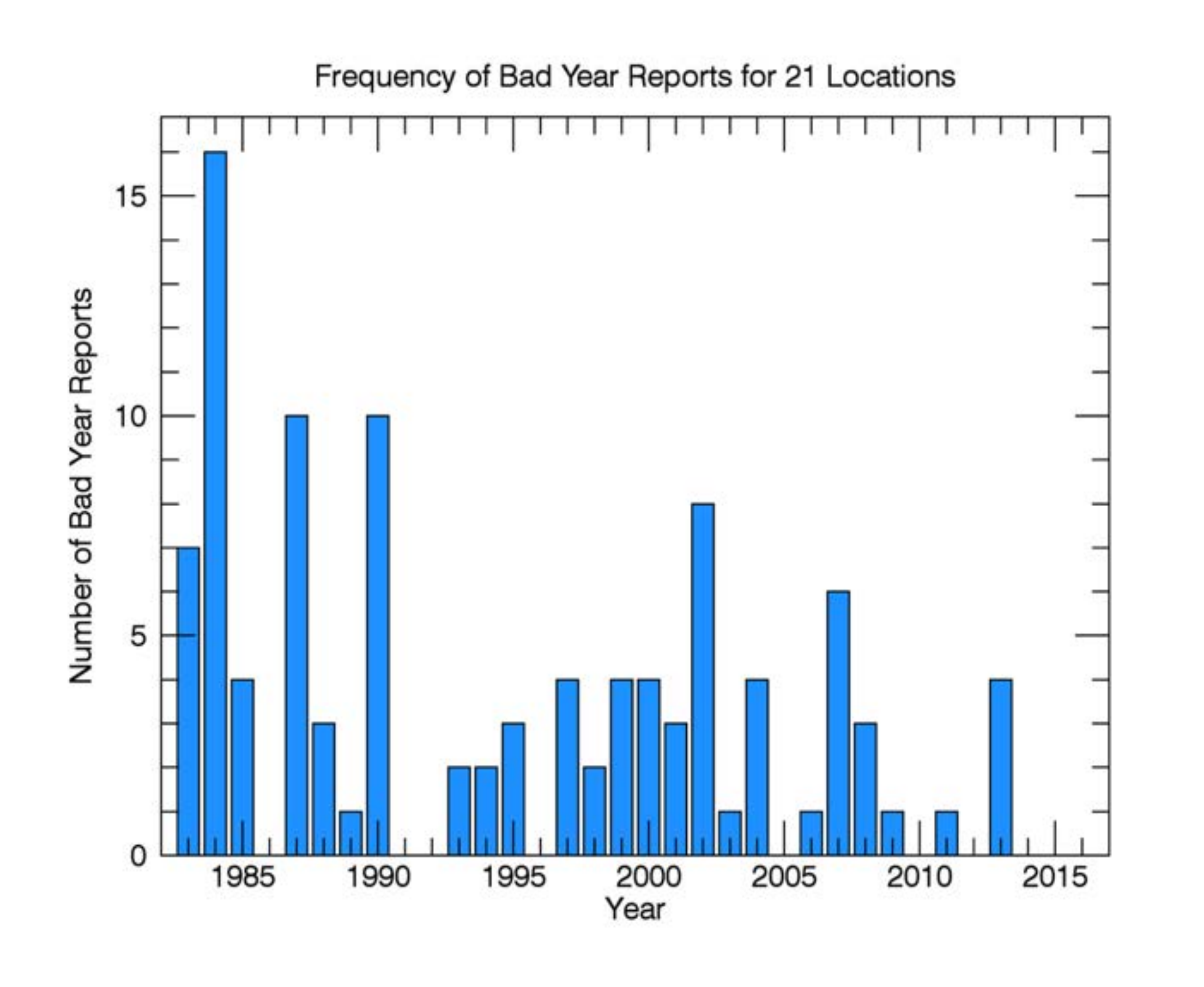


Results: Temporal Aggregation Initial Diagnostics SECOND VISIT



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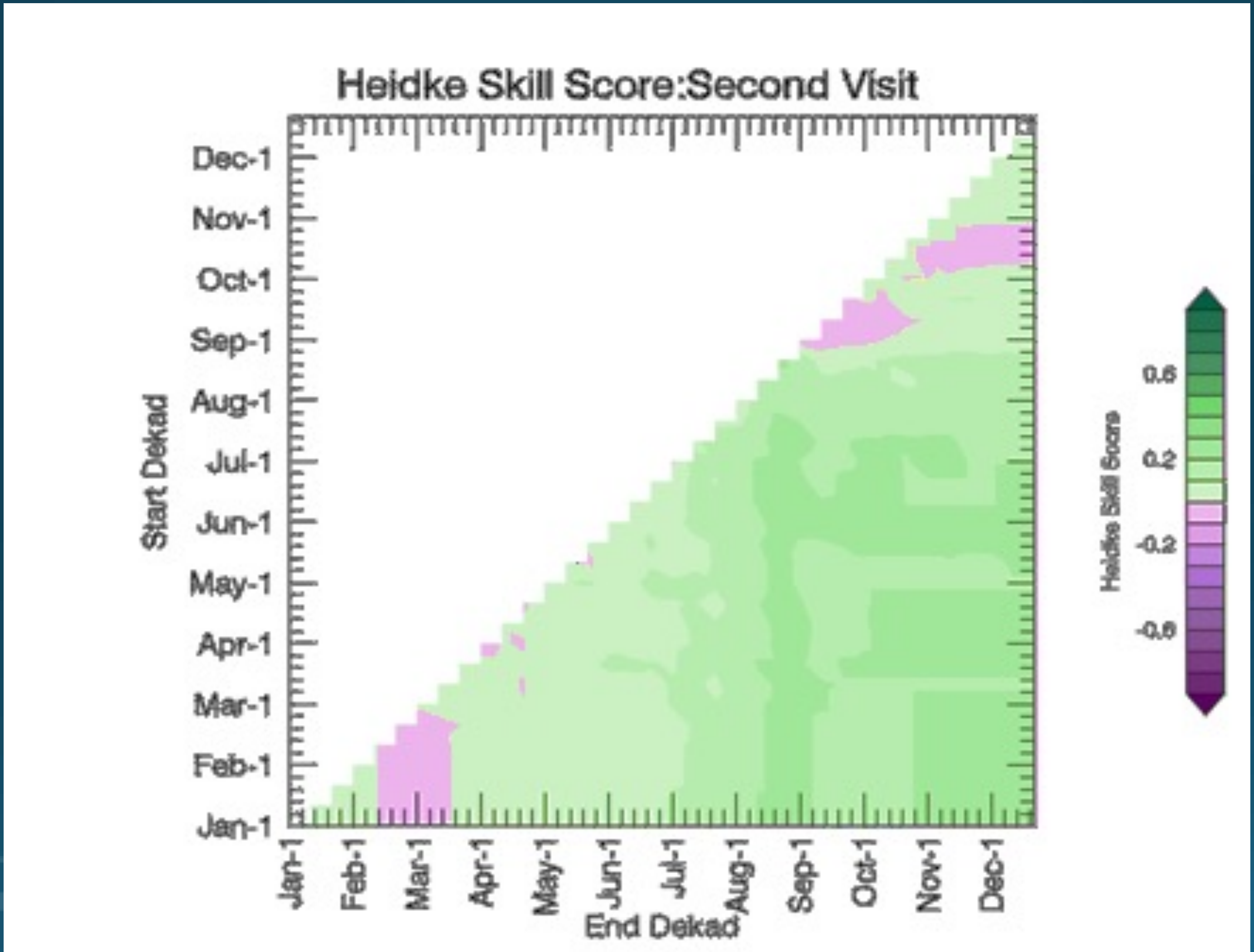
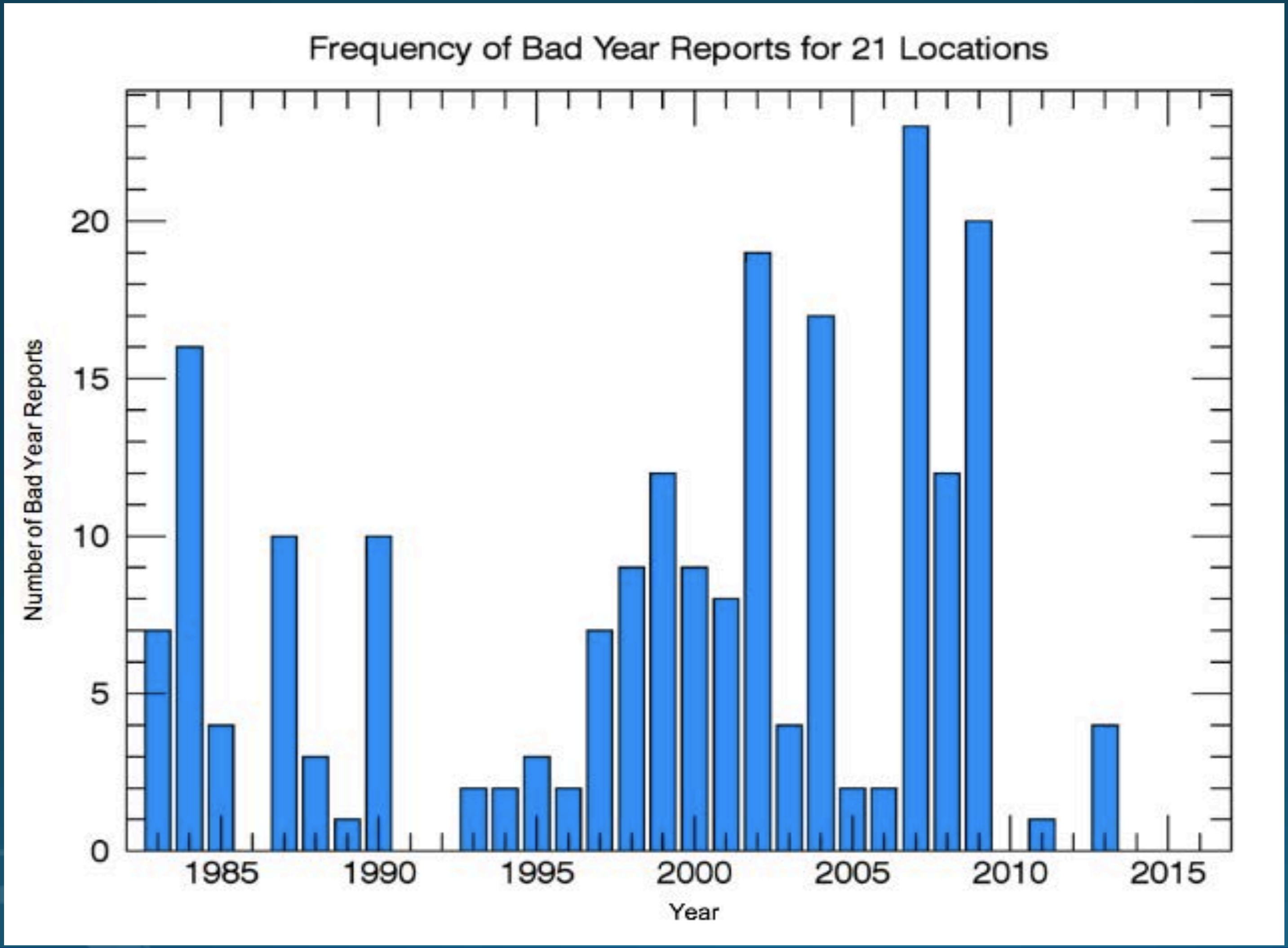


Results: Temporal Aggregation Initial Diagnostics 1st + 2nd COMBINED



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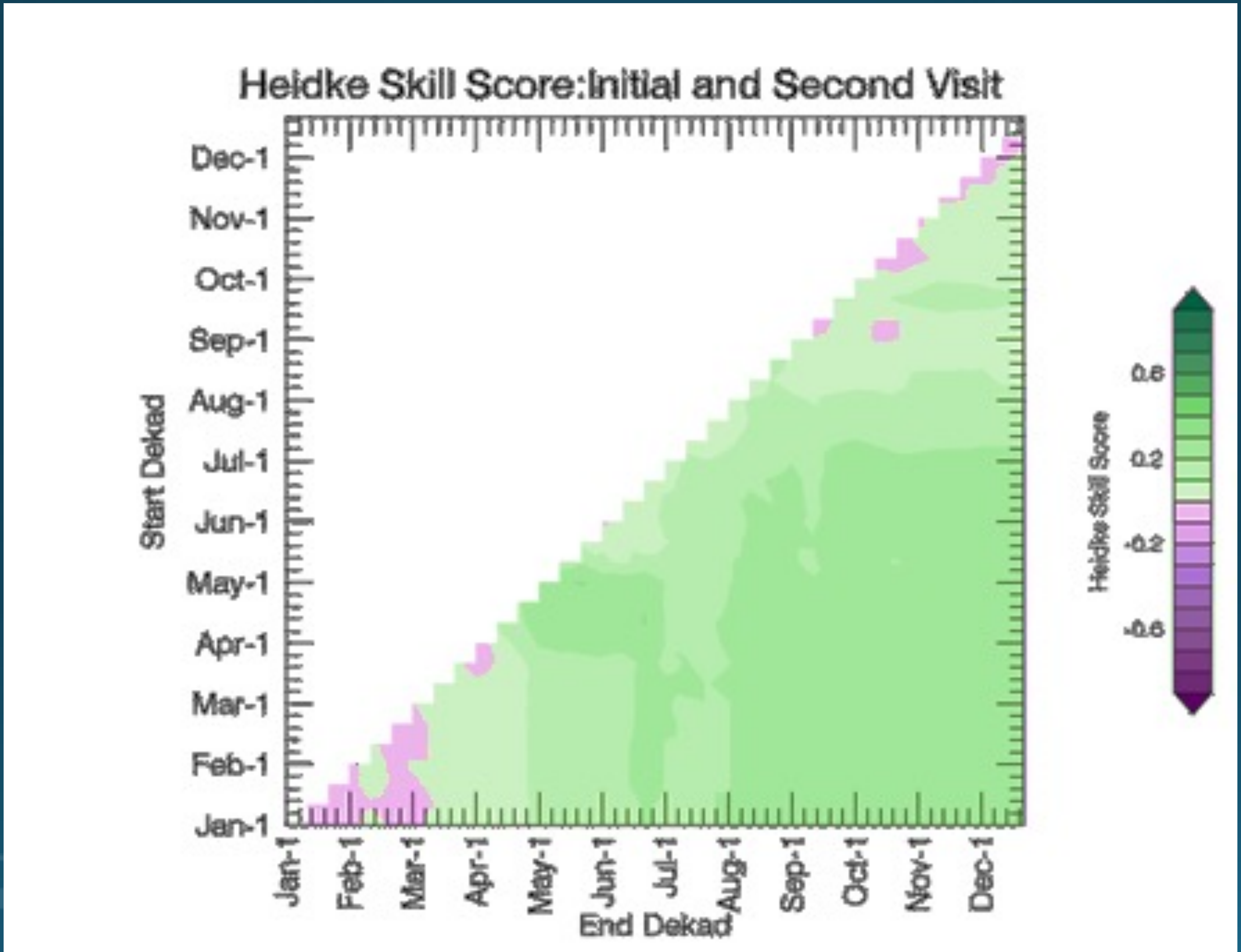

Results: Temporal Aggregation Logistic Regression

DEP VARIABLE	Village Bad Year		
Time	First Visit	Second Visit	First + Second
Early Rainfall	-0.00761***	-0.000964	-0.00492***
	(0.00251)	(0.00197)	(0.00175)
Late Rainfall	-0.00199	-0.00904***	-0.00653***
	(0.00201)	(0.00228)	(0.00170)
Constant	-1.157***	-0.907***	-0.0979
	(0.234)	(0.233)	(0.191)
Observations	693	693	693
Pseudo R2	0.0212	0.0311	0.0308
Logit Hits	26	27	75
p-value X2	0.999331	0.99975686	0.00344567
Bad Years	105	104	193
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

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Results: More observations Logistic Regression

DEP VARIABLE	Village Bad Year
Time	Village
Early Rainfall	-0.0115***
	(0.00151)
Late Rainfall	-0.00493***
	(0.000960)
Constant	-0.693***
	(0.124)
Observations	2,673
Pseudo R2	0.0445
Logit Hits	91
p-value X2	1
Bad Years	416
Standard errors in parentheses	
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Results: More observations Logistic Regression

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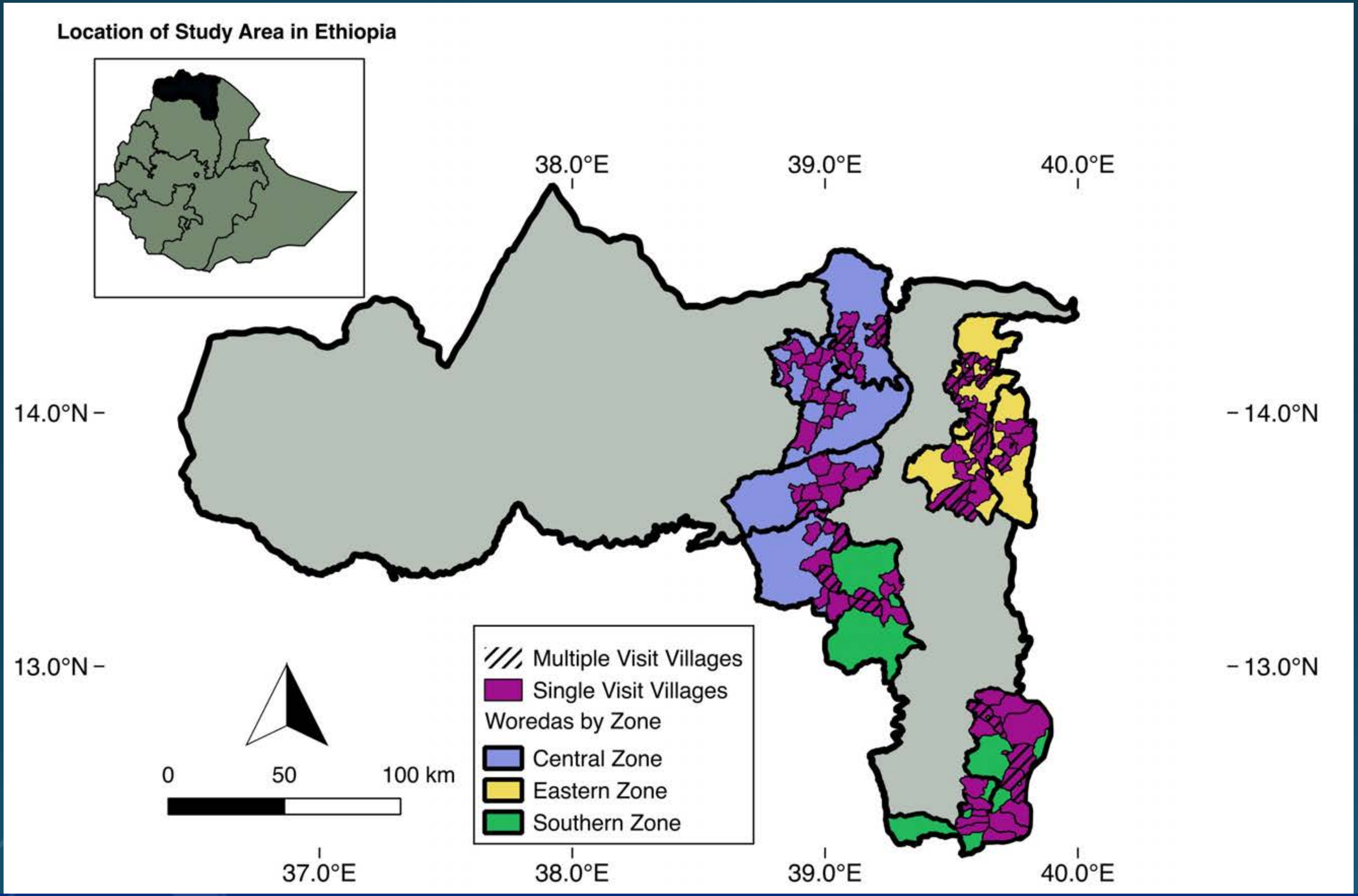
Results: Spatial Aggregation



Results: Spatial Aggregation Logistic Regression

DEP VARIABLE	Bad Year First + Second			
Time	Village	Woreda	Zone	Tigray
Early Rainfall	-0.00492***	-0.00181	-0.00224	0.00845
	(0.00175)	(0.00234)	(0.00453)	(0.0174)
Late Rainfall	-0.00653***	-0.00761***	-0.0159***	-0.0229*
	(0.00170)	(0.00248)	(0.00517)	(0.0129)
Constant	-0.0979	0.537*	2.178***	3.214**
	(0.191)	(0.301)	(0.629)	(1.497)
Observations	693	264	99	33
Pseudo R2	0.0308	0.0306	0.0829	0.112
Logit Hits	75	56	43	24
p-value X2	0.00344567	0.00024069	0.04361193	0.45069452
Bad Years	193	111	61	26
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Results: Extremes Diagnostic Logistic Regression

DEP VARIABLE	Bad Years First + Second
Time	Village
Early Pay Out	0.00590*
	(0.00351)
Late Pay Out	0.0107***
	(0.00352)
Constant	-1.126***
	(0.101)
Observations	693
Pseudo R2	0.0151
Logit Hits	73
p-value X2	0.00128046
Bad Years	193
Standard errors in parentheses	
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Results: All Datasets

DEP VARIABLE	Village Bad Years First + Second Visit					
Early ARC	-0.00492***	-	-	-	-	-
	(0.00175)					
Late ARC	-0.00653***	-	-	-	-	-
	(0.00170)					
Early CHIRPS	-	-0.00556***	-	-	-	-
		(0.00193)				
Late CHIRPS	-	-0.00139	-	-	-	-
		(0.0231)				
Early HainET25	-	-	0.0263	-	-	-
			(0.0177)			
Late HainET25	-	-	-0.00722	-	-	-
			(0.00966)			
Early EVI	-	-	-	-0.975	-	-
				(1.576)		
Late EVI	-	-	-	-9.161***	-	-
				(3.130)		
Early NDVI	-	-	-	-	-1.353	-
					(1.246)	
Late NDVI	-	-	-	-	-7.412***	-
					(1.999)	
Early ESA CCI	-	-	-	-	-	0.737
						(1.552)
Late ESA CCI	-	-	-	-	-	-5.674*
						(3.383)
Standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Results: All Datasets Village Bad Years

DEP VARIABLE	Village Bad Years First + Second Visit					
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	(0.00175)					
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			(0.0177)			
Late HainET25	-	-	-0.00722	-	-	-
			(0.00966)			
Early EVI	-	-	-	-0.975		-
				(1.576)		
Late EVI	-	-	-	-9.161***	-	-
				(3.130)		
Early NDVI	-	-	-	-	-1.353	-
					(1.246)	
Late NDVI	-	-	-	-	-7.412***	-
					(1.999)	
Early ESA CCI	-	-	-	-	-	0.737
						(1.552)
Late ESA CCI	-	-	-	-	-	-5.674*
						(3.383)
Standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Results: All Datasets Village Bad Years

DEP VARIABLE	Village Bad Years First + Second Visit					
Early ARC	-0.00492***	-	-	-	-	-
	(0.00175)					
Late ARC	-0.00653***	-	-	-	-	-
	(0.00170)					
Early CHIRPS	-	-0.00556***	-	-	-	-
		(0.00193)				
Late CHIRPS	-	-0.00139	-	-	-	-
		(0.0231)				
Early HainET25	-	-	0.0263	-	-	-
			(0.0177)			
Late HainET25	-	-	-0.00722	-	-	-
			(0.00966)			
Early EVI	-	-	-	-0.975	-	-
				(1.576)		
Late EVI	-	-	-	-9.161***	-	-
				(3.130)		
Early NDVI	-	-	-	-	-1.353	-
					(1.246)	
Late NDVI	-	-	-	-	-7.412***	-
					(1.999)	
Early ESA CCI	-	-	-	-	-	0.737
						(1.552)
Late ESA CCI	-	-	-	-	-	-5.674*
						(3.383)
Standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Key Findings Summary

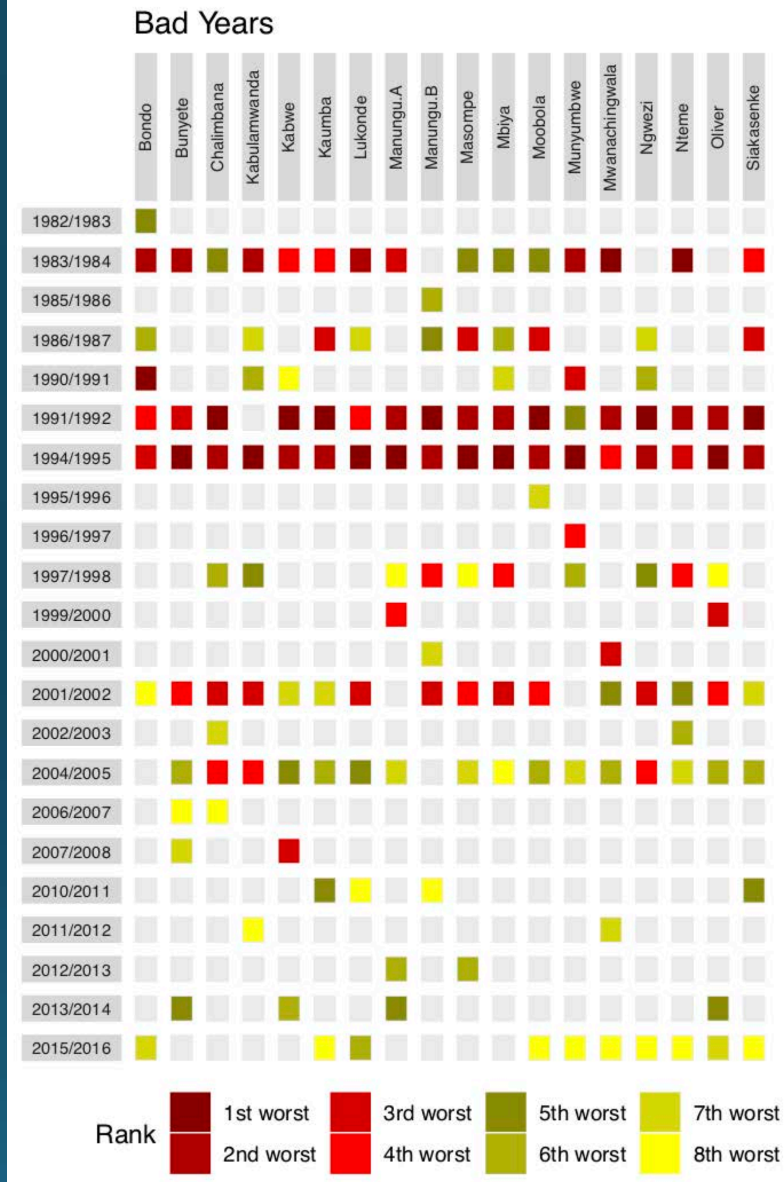
Temporal and Spatial Aggregation may help reduce bias

Strategies such as multiple visits to a village and spatial aggregation lead to improved predictions

Multiple RS Datasets validate farmer bad years

Farmer reported events are reflected in multiple RS datasets = evidence that farmer bad years are related to actual drought years

Current Research & Technology



Year	Mentions	Average.Rank	Year	Mentions	Average.Rank
1982/1983	1	5	2000/2001	2	5
1983/1984	15	3	2001/2002	16	4
1985/1986	1	6	2002/2003	2	6
1986/1987	10	5	2004/2005	16	5
1990/1991	6	5	2006/2007	2	8
1991/1992	17	2	2007/2008	2	5
1994/1995	18	1	2010/2011	4	6
1995/1996	1	7	2011/2012	2	7
1996/1997	1	4	2012/2013	2	6
1997/1998	10	5	2013/2014	4	5
1999/2000	2	3	2015/2016	10	7

NASA Interdisciplinary Science (IDS) Project

Exploiting the convergence of evidence in satellite data for advanced weather index insurance design

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Thank you !