Using Satellite Data for Area Yield insurance

Rose Goslinga,
Co Founder and CEO

PULA CGAP

May 8, 2018

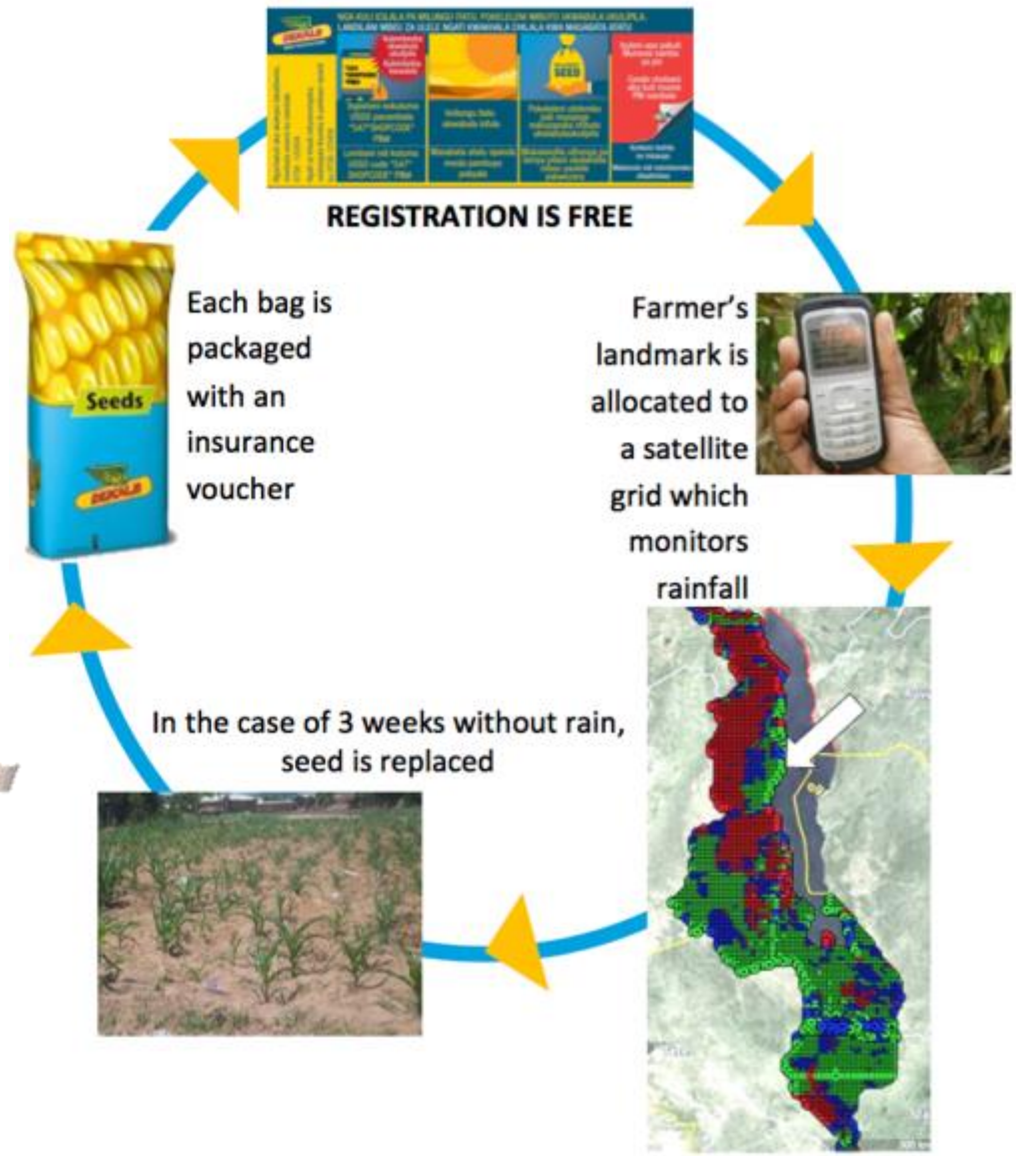
PULA

We develop and distribute insurance and farm advisory for small scale farmers

611,040 farmers used our products in 2017 across 9 countries

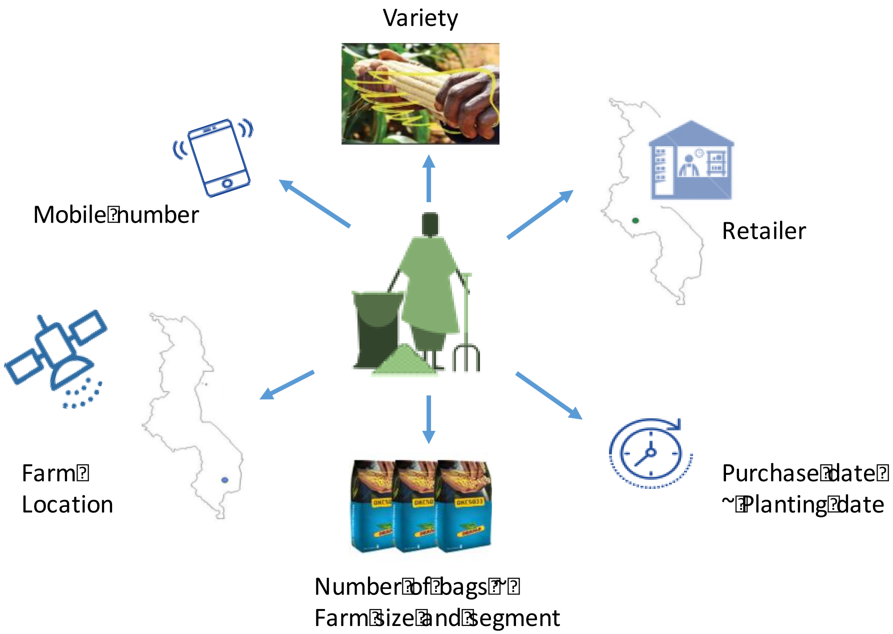
But farmers don't like buying insurance

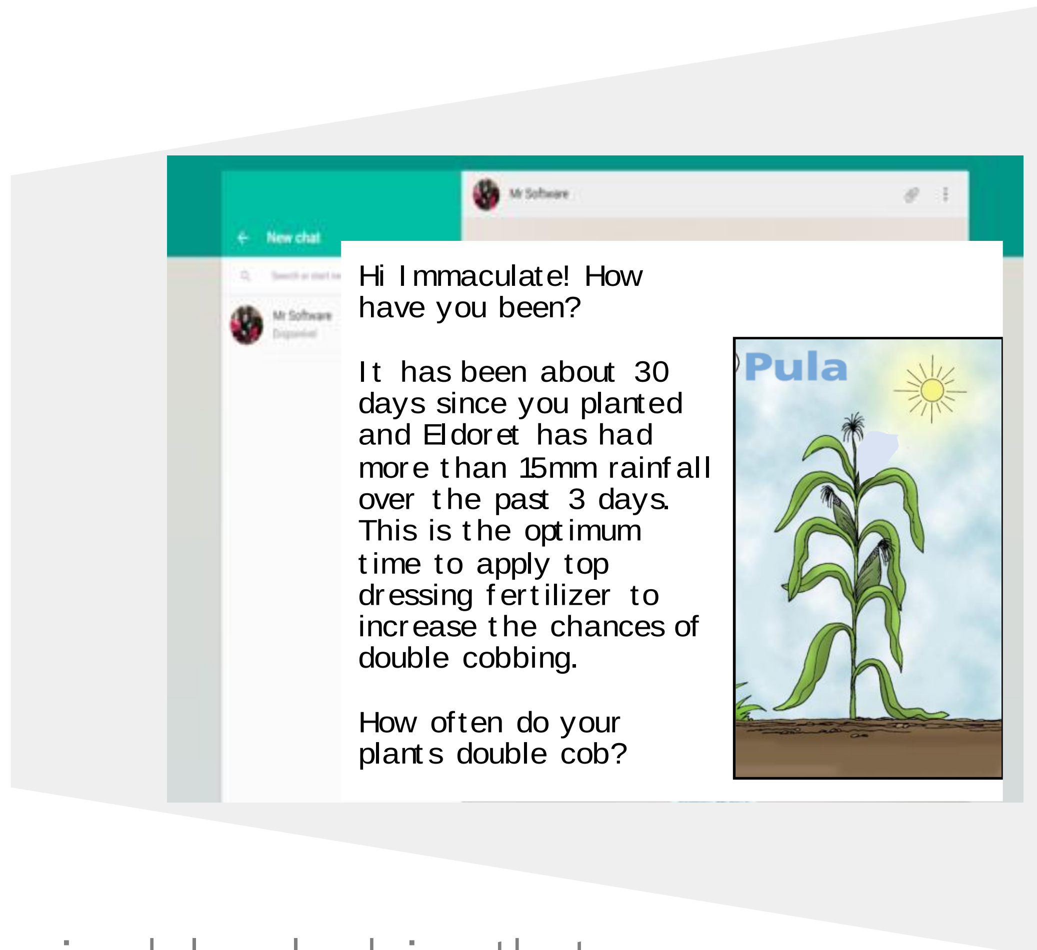
Which is why we package insurance with products farmers actually want like seeds, fertilizer and credit.



As part of our underwriting process

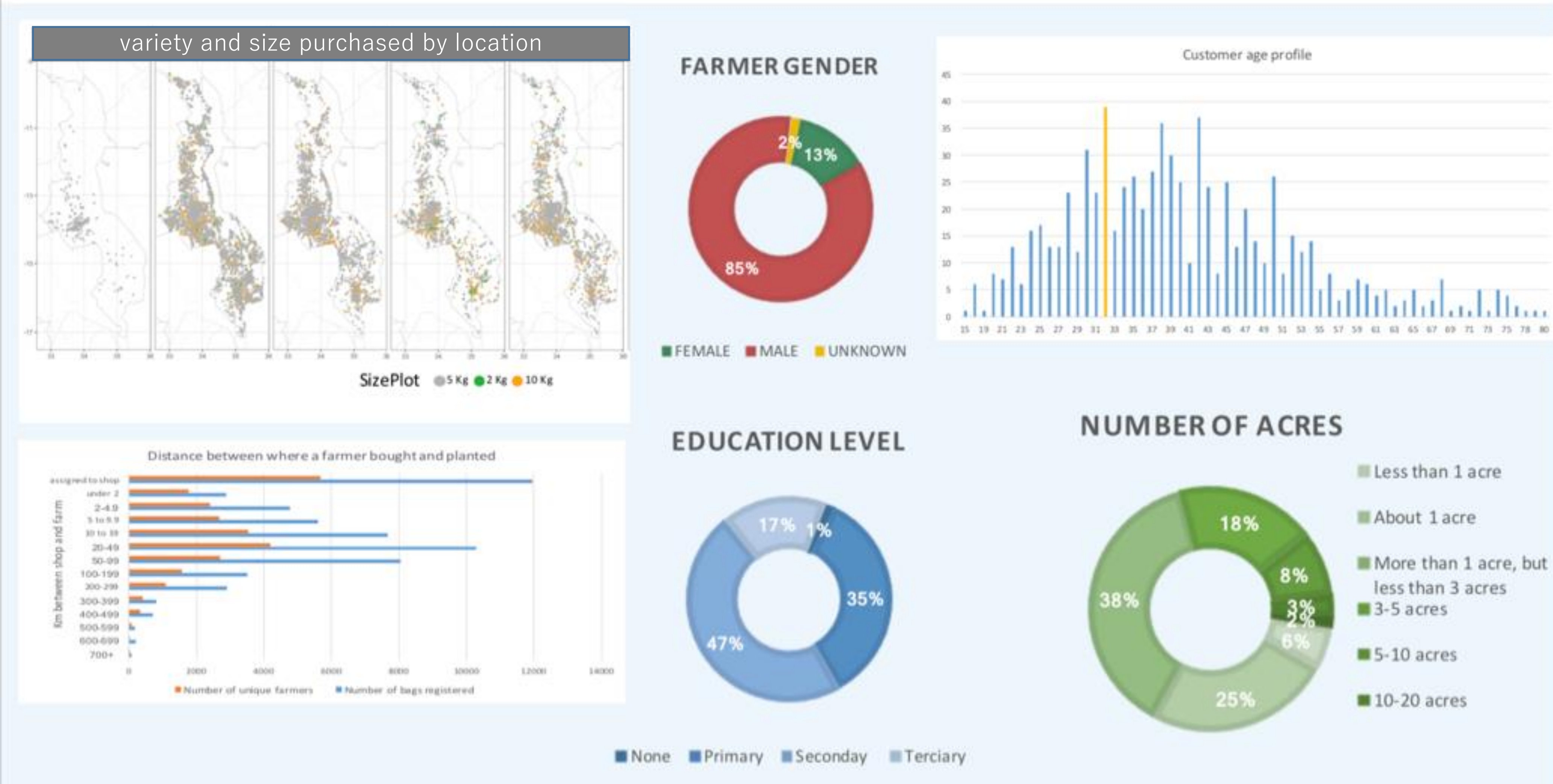
we collect unique farmer data that allows us to advise farmers





This proprietary data allows for synchronized, local advice that provides value **to all farmers** every season, and not just to those that are compensated.

Harnessing data to understand smallholders



- Customer distribution by variety and size across the country
- Distance from farm to shop
- Farmer age and sales profile

At scale, Pula is an ecosystem of agribusiness with insurance as the initial entry point

PULA

Insurers

Underwrite risks
Grow market

Credit Providers

Credit access
Grow loan book
Reduce credit risk

Seed & Fertilizer Co.

Pay Premiums
Customer & supply chain data
Combats counterfeits
Increase sales

Agro-Retailers

Explain and supports insurance
Awards
Increase sales

Farmers

Purchases inputs
Data
Free insurance
Tailored advisory
Improve yields and incomes

With **each** party both **receiving and providing** value along the chain

3 Variations of Insurance Bundles

Seeds+ Insurance to cover the planting stage

Weather index cover using satellite data

Operational in Malawi, Zambia, India

Fertilizers+ Insurance to cover the whole season

Area Yield index cover using ground +satellite data

Offered in Nigeria

Credit + Insurance to cover the season and **harvest income**

Area Yield index cover using ground + satellite data

Operational Nigeria, Kenya, Uganda, Rwanda, Malawi, Zambia, Tanzania

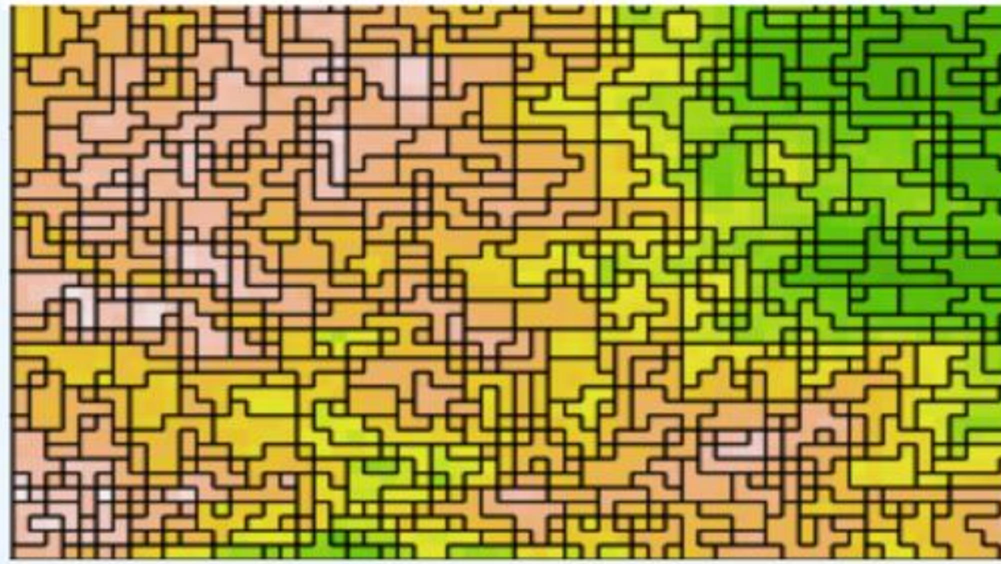
Data is the backbone of each product

Seed insurance uses satellite data algorithms to price premiums and enables farmers to sign up on any day and any location in a country.

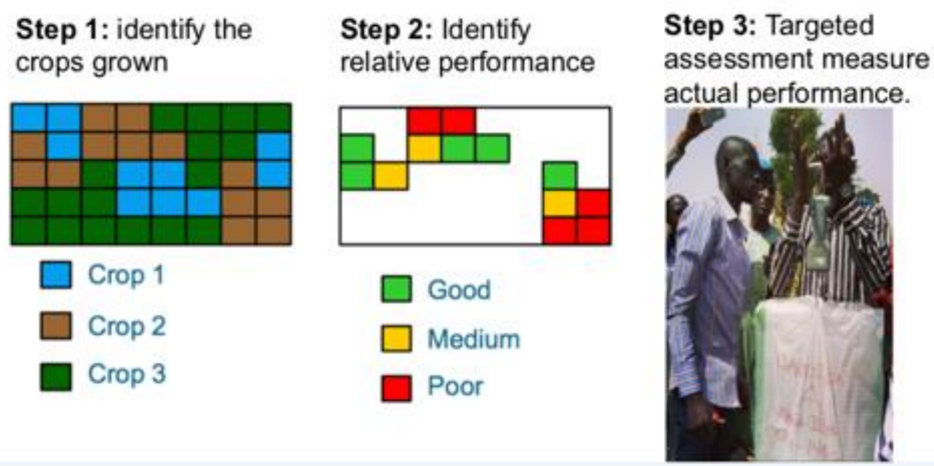
Fertilizer and credit insurance uses a combination of proprietary ground yield data collection processes and remote sensing data to estimate yields.

Where index insurance has struggled with basis risk, **we focus on products that limit basis risk** (area yield index and start of season weather index) and price in the cost of this risk as part of the premiums

Monitoring farm yields using remote sensing and machine learning



Fertilizer & Credit Insurance hybrid data process



Our go-to-market strategy is through public & private partners, targeting 1.2mln in 2018

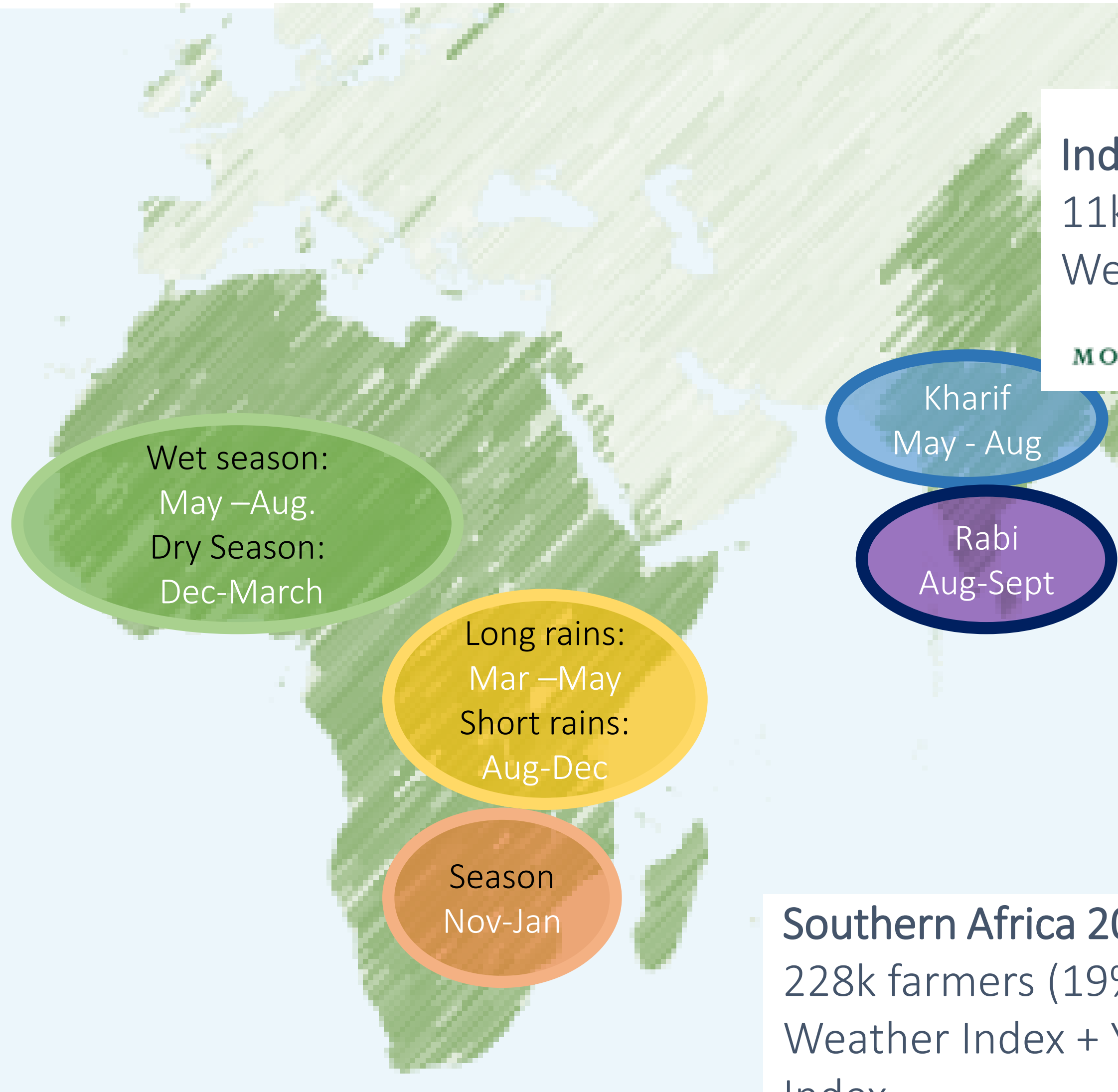
PULA

East Africa 2018
705k farmers (59%)
100% Yield index

WFP wfp.org
ONE ACRE FUND
BRACED Building Resilience and Adaptation to Climate Extremes and Disasters

Nigeria 2018
266k farmers (22%)
100% Yield index

NIRSAL
Babban Gona Mai Inganci
FMN Flour Mills of Nigeria Plc



India 2018
11k farmers (1%)
Weather Index

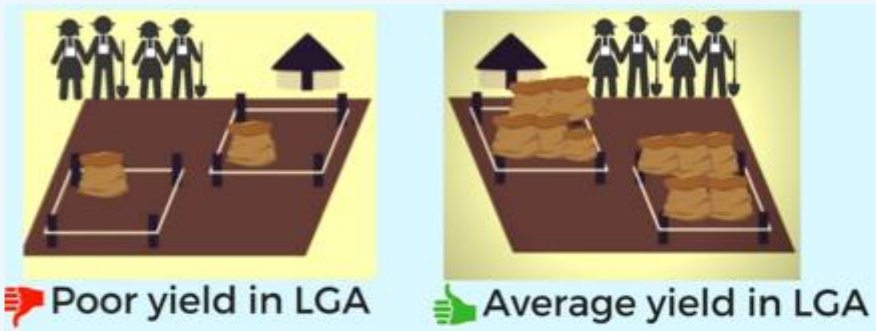
MONSANTO

Southern Africa 2018
228k farmers (19%)
Weather Index + Yield Index

MONSANTO

Yield index insurance has been key to our growth

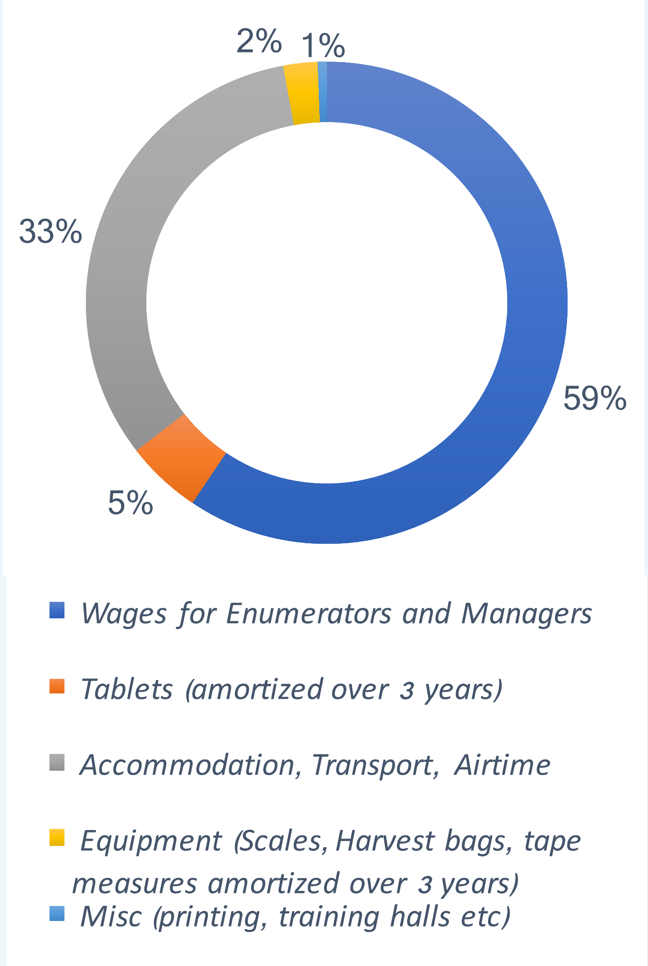
PULA

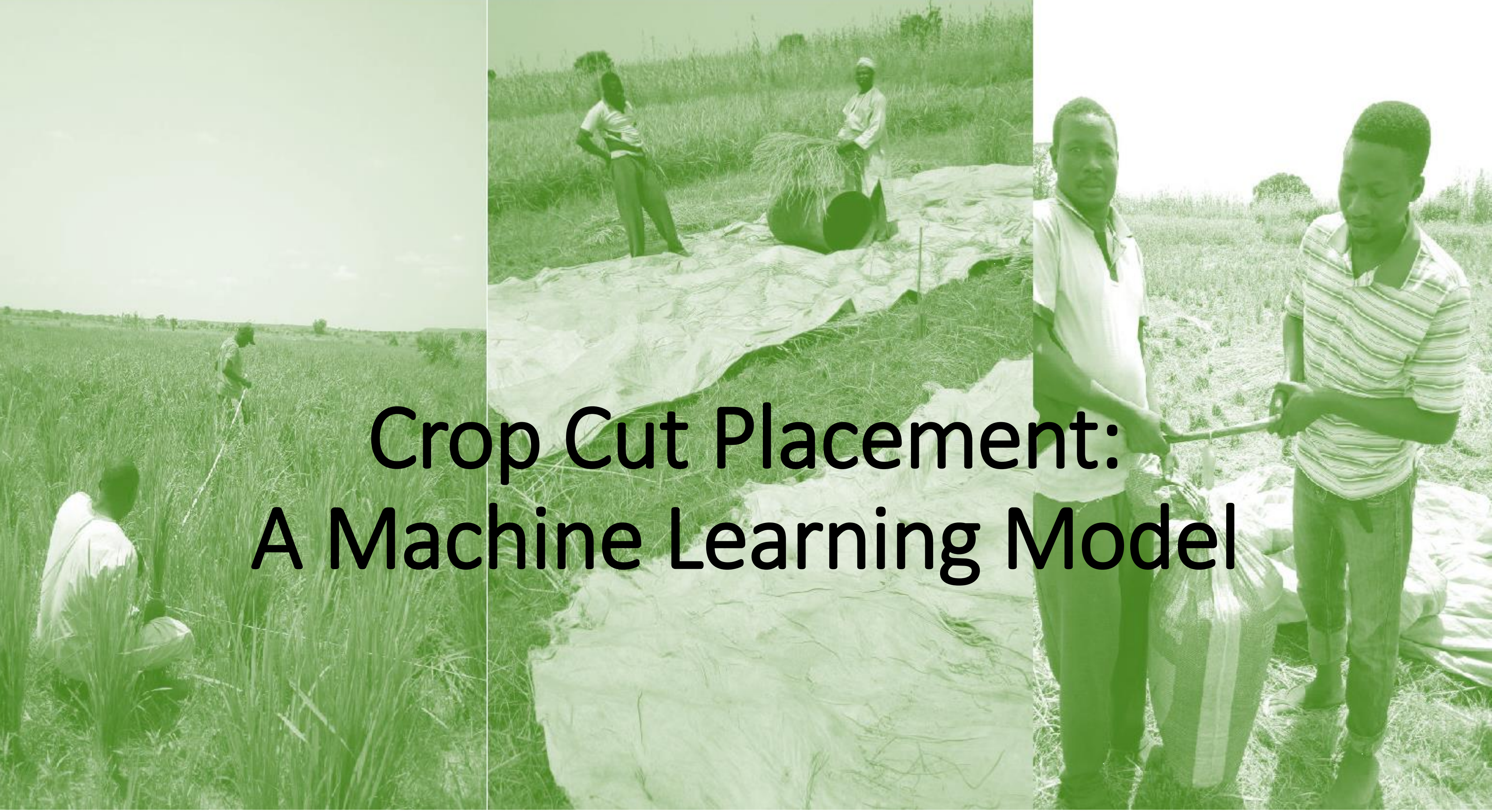


Farmers and their creditors want comprehensive, simple to understand coverage

Challenges to scale:

1) Yield insurance is in demand due to **comprehensive nature:**
   - Governments want it everywhere
   - Fertilizer companies want it but again, they want it everywhere
2) Our Yield product based on CCE's is labor and travel intensive
   - 92% of unit cost
3) Historical data to base pricing on is sparse
4) Key challenges to solve:
   - Manage the cost of CCE's
   - Gather a baseline of measurements





Crop Cut Placement: A Machine Learning Model

Victor Wang,

May 8, 2018

Crop Cut Selection: The Problem

Current Operations

- Sampling minimum of 25 crop cuts per LGA (Local Government Area)
- LGA's are not defined based on agricultural yield, so low correlation between them, and many need to be sampled

Target Issue

- A single crop cut can cost up to 36 USD
- Sampling every LGA becomes prohibitively expensive with expansion

Proposed Solution 1: Yield Data

Figure 1 individual yield prediction quality quality is based on Random Forest Model showing low predictive potential

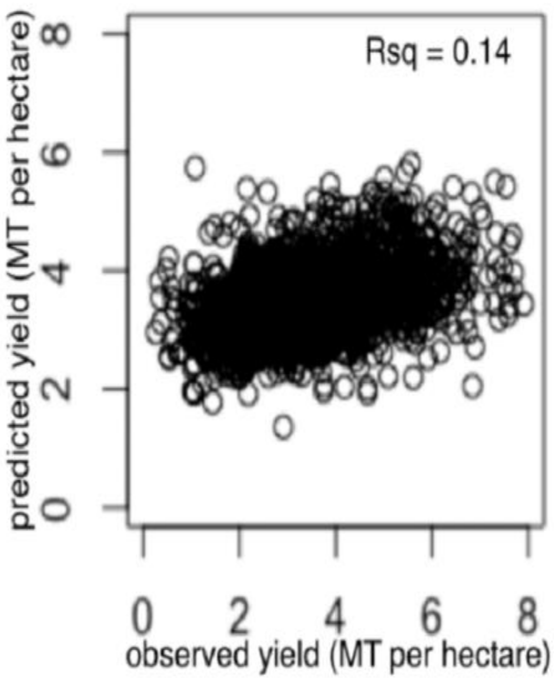
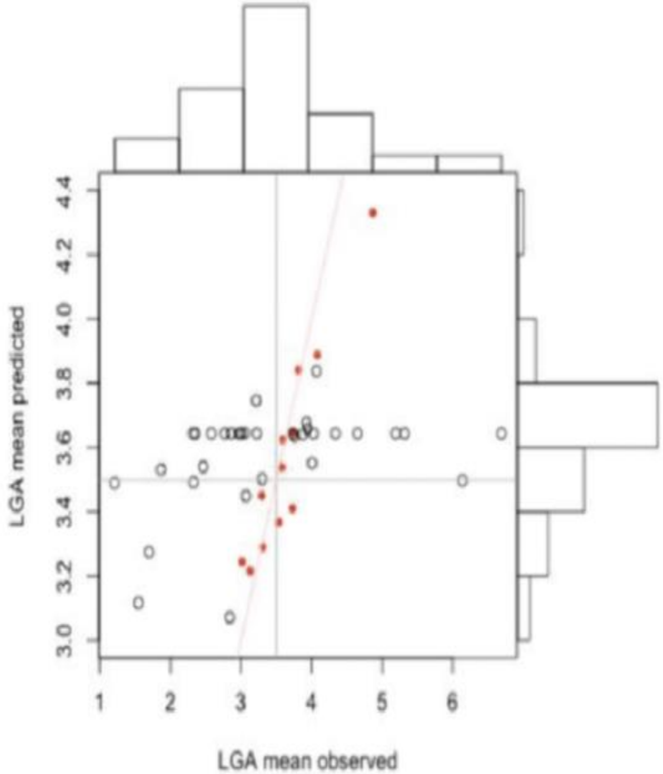


Figure 2: LGA yield prediction potentially more promising



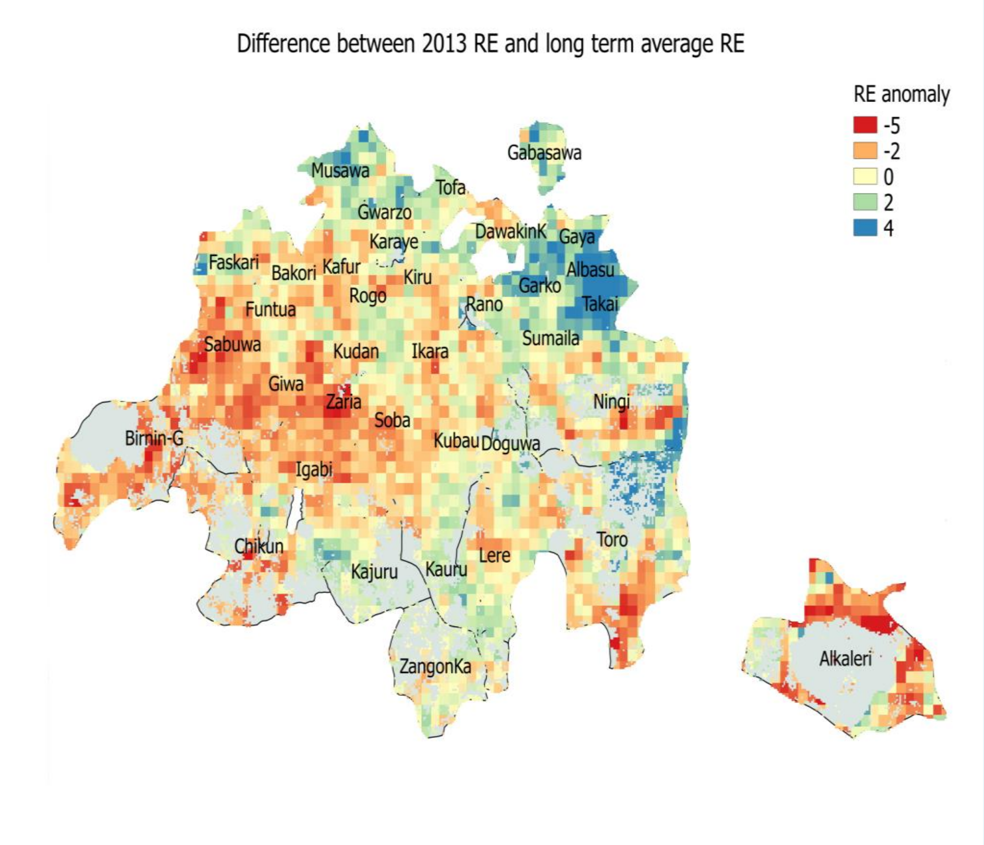
Proposed Solution 2: Evapotranspiration

EARS used the yield data provided by PULA in order to examine the possibility to assist the optimization of crop cut experiments using remote sensing data.

EARS (Environment Analysis & Remote Sensing Group) is the provider of the Meteosat Relative Evapotranspiration dataset with:

- ❑ Index Insurance experience in 18 countries, mainly in Africa
- ❑ 35 years of hourly / daily satellite data
- ❑ Full coverage of the African continent at 3 km spatial resolution

Proposed Solution 2: Evapotranspiration



Lack of signal:

For example, a country-wide dataset that shows non-drought yields is not as valuable to a model as a year with some success and some drought spots.

Crop Cut Selection: The Solution

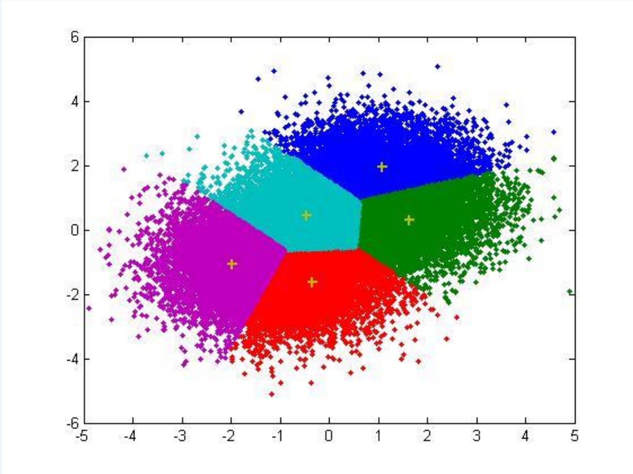
PULA

Target Solution

- Goal: Create districts to replace LGA's, that cover larger areas yet are more correlated
- Fewer districts that are more representative of their regions mean fewer crop cuts needed, dramatically lowering overall costs

Methodology

- Use K-Means (unsupervised machine learning algorithm) to create districts
- Based on latitude, longitude, historic rainfall
- Weighed appropriately to create mutually exclusive regions
- Normalized for planting seasons, precipitation caps, 30+ years of data (CHIRP)



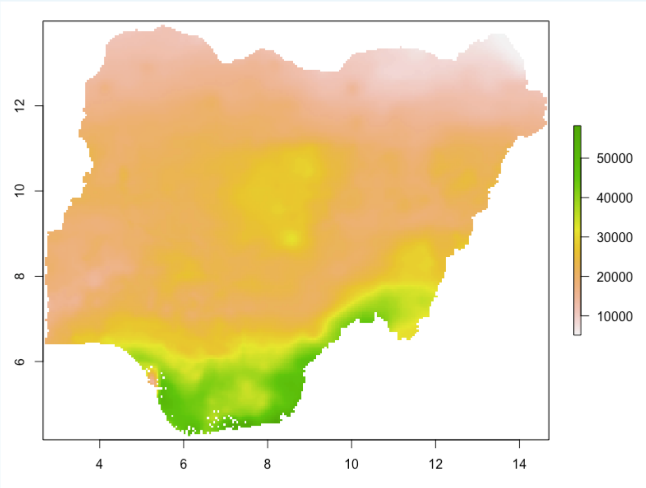
How It Works, Part 1: The Data

1) Data Preparation:

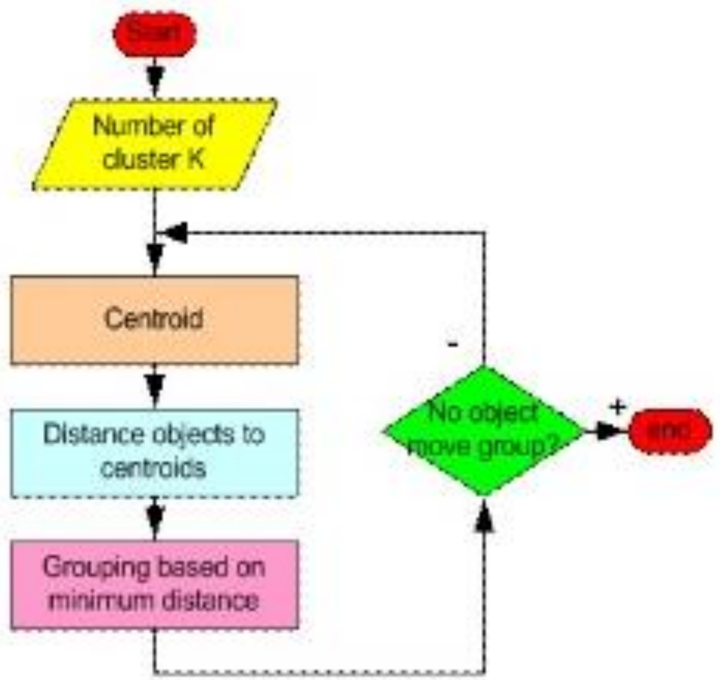
Extraction (Climate Hazards Group InfraRed Precipitation), Normalization (daily precipitation cap, restriction to planting season, etc.)

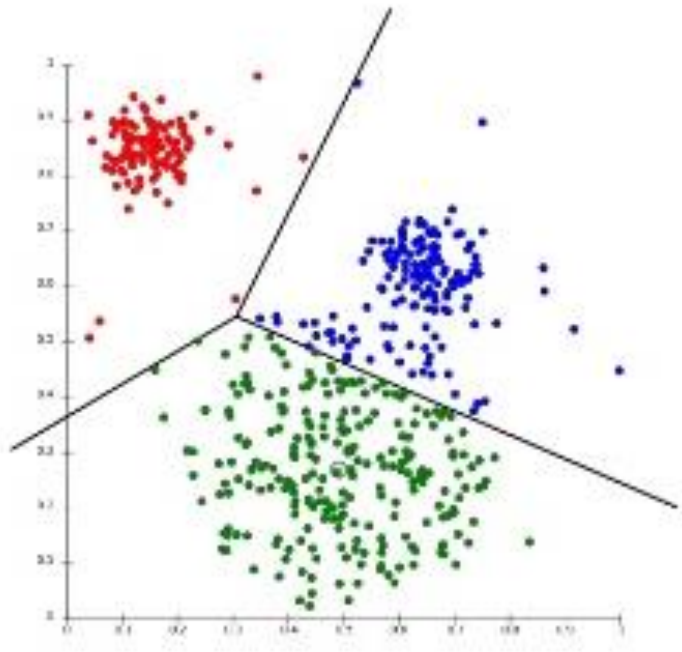
2) Data Maps:

Combine 30+ years of data, data clean-up (remove errors, N/A values)



An Aside: K Means Clustering





Guide to Clustering:

A) Pick X number of districts you want to create.
B) Randomly choose X points, use those as the centre of districts, and allocate all points to the nearest chosen point in X.
C) Repeat Step B (for a predefined number of times) until a set of X points is found to have the minimum total amount of distance from those X points.
D) The allocation of all points to chosen X points is then the generated districts.

How It Works: Machine Learning

K Means:

Machine learning (trial and error, varying results), Unsupervised (no “correct” districts), defined number clusters, scaling.

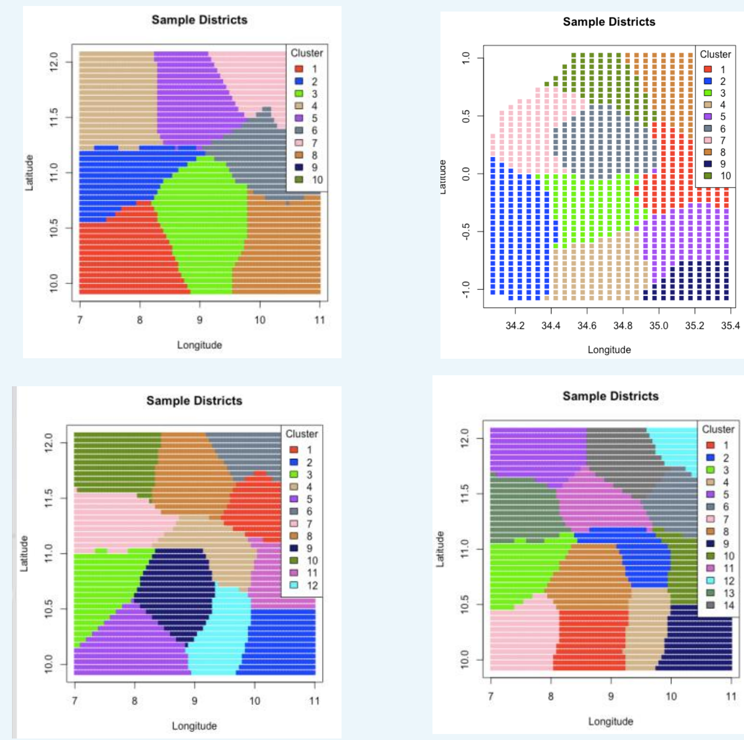
a) Clusters (ie. Number of Districts) needs to be decided in advance. Example on right shows results of various numbers of clusters. Decision needs to balance not having too many districts, and being able to pick up on drought.

:

b) Example: For Babban Gona, our recommendation was 14 districts, and for Nirsal it was 32, since farmers were in a greater area for Nirsal. For Babban Gona, 14 districts were required to detect lower yield areas (results in later slides).

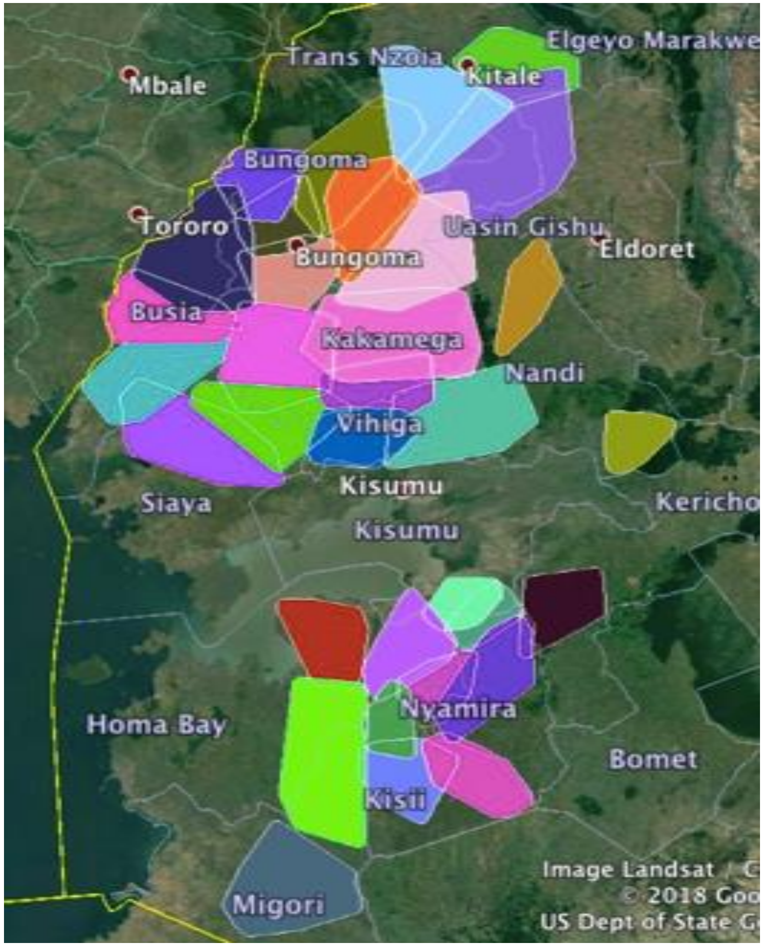
c) Note because of the nature of machine learning, there Is great flexibility of the program such as generating results for custom regions, custom years, and district shaping.

Cluster analysis for 8, 10, 12, 14 Districts, respectively:

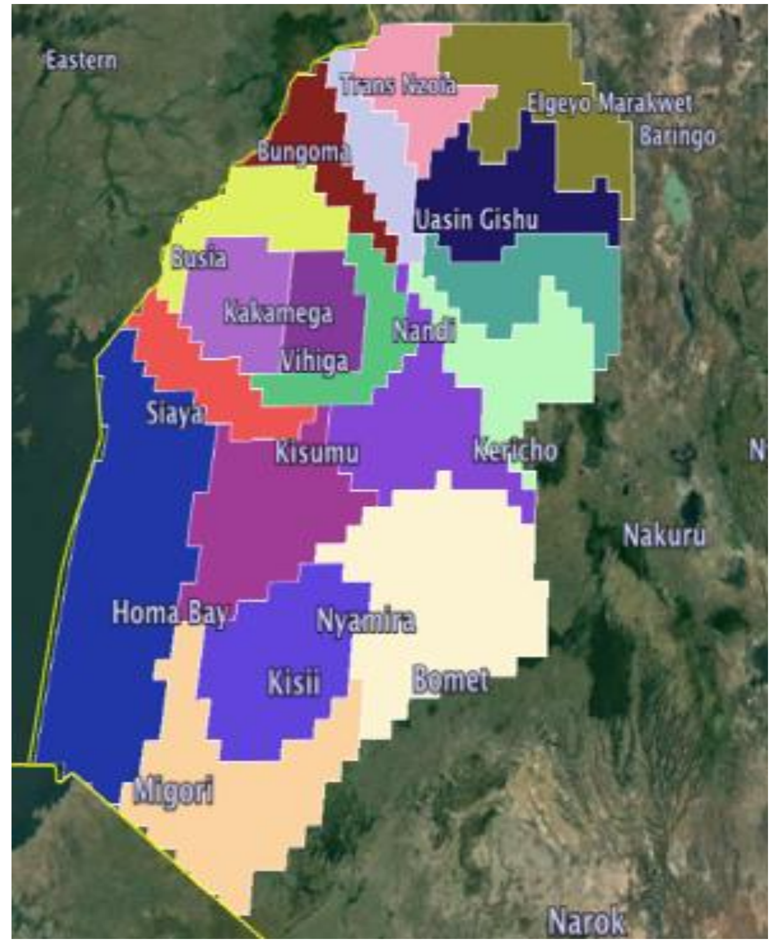


Unit areas of insurance: Past and Future

Based on administrative boundaries and operational limitations

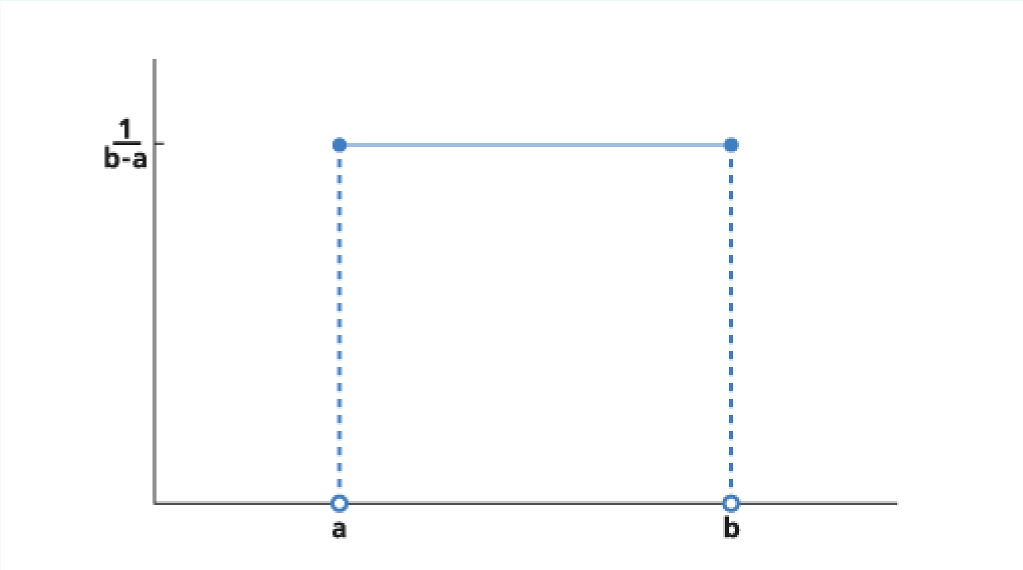


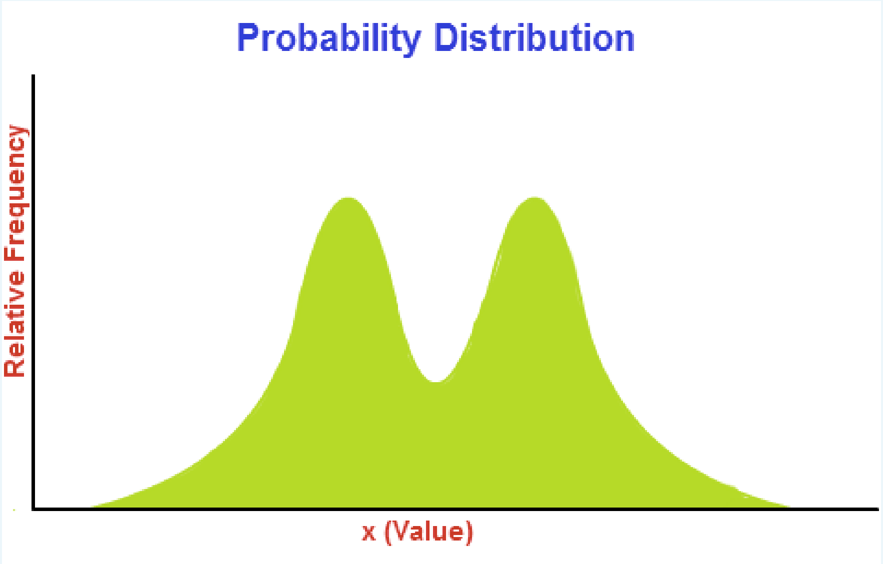
Based on machine leaning climatological features



Manage the number of areas → Manage the number of CCE's → **Scale faster**

Validation: Statistical Studies





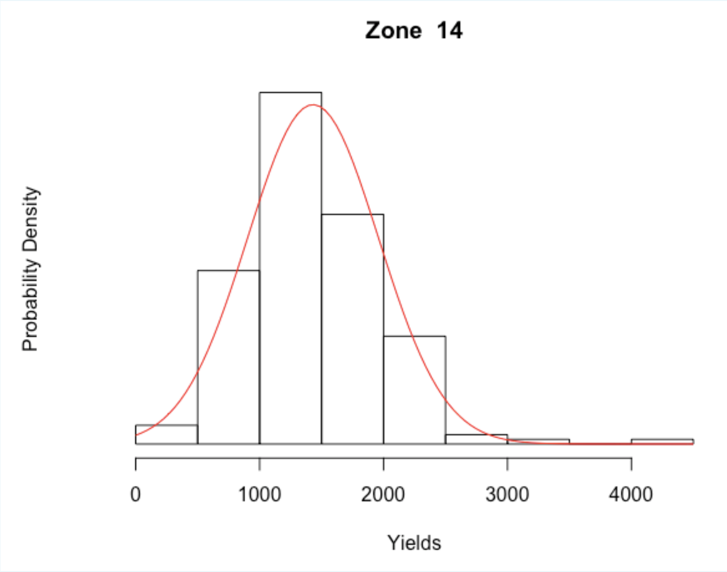
Uniform Distribution:

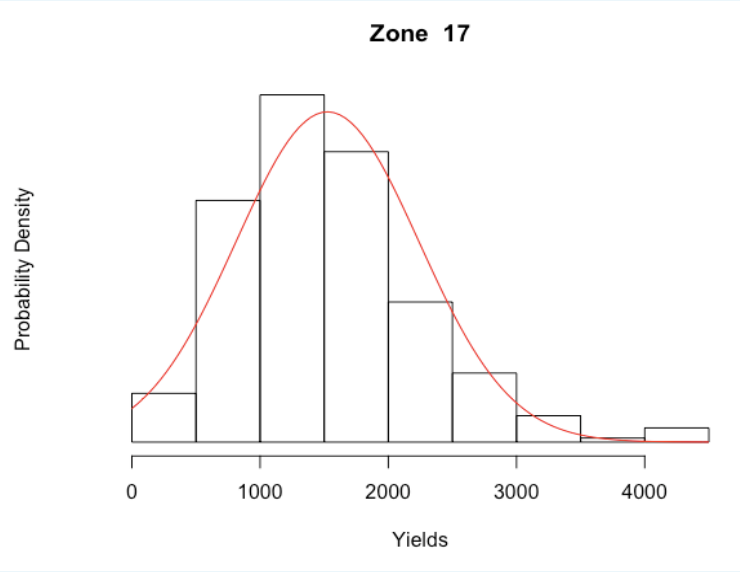
Would indicate area was generated effectively at random, similar to LGAs from before.

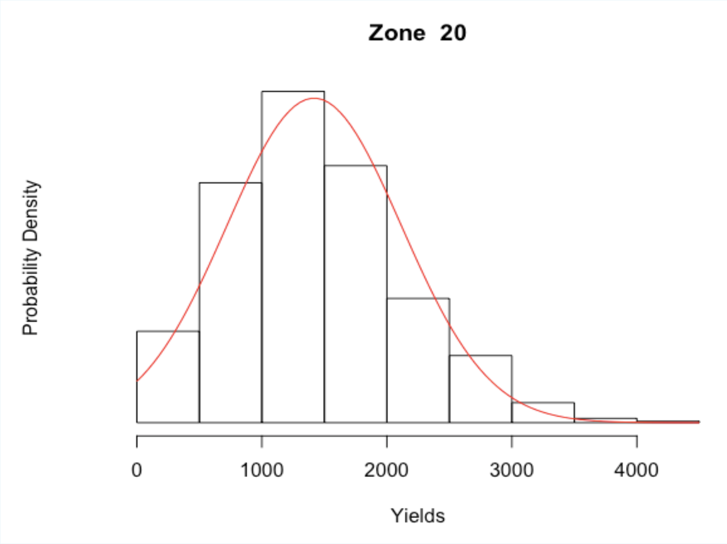
Bimodal Distribution:

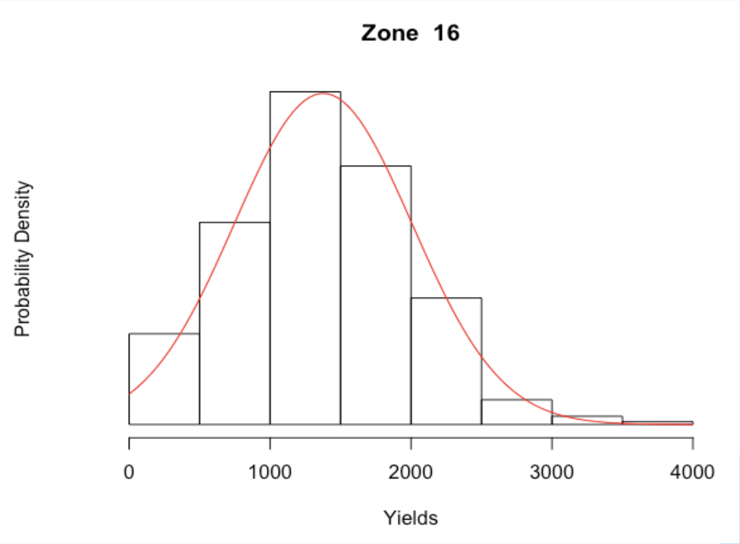
Would indicate AEZ needs to be split further into two separate AEZs.

Validation: Statistical Studies





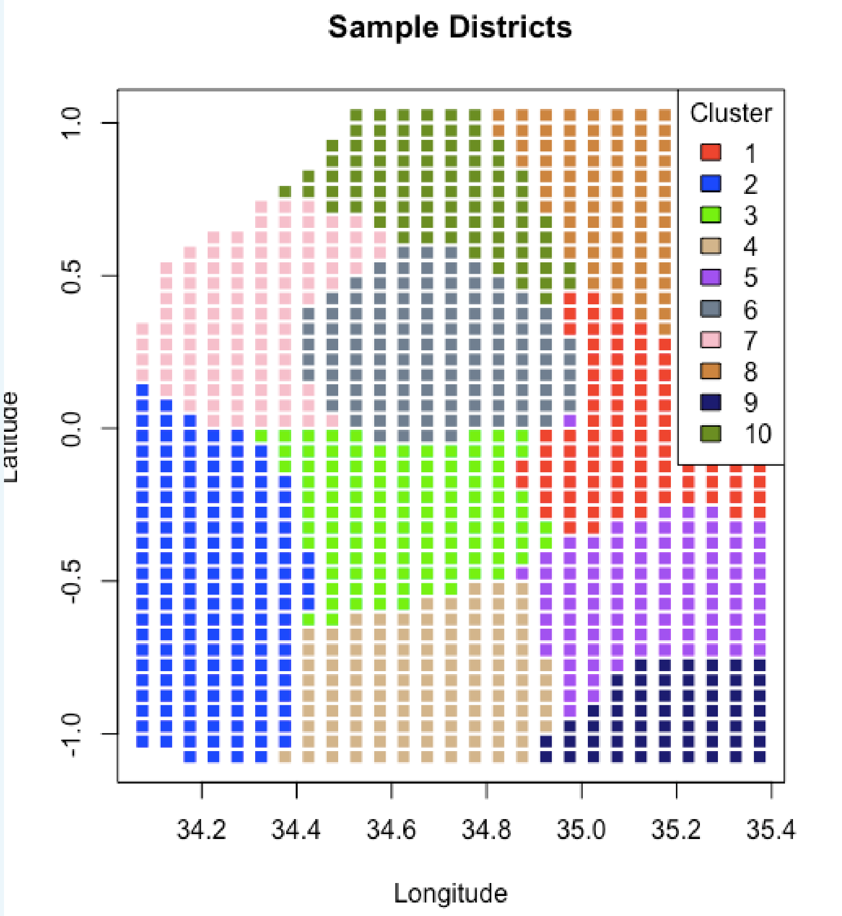




Validation: Empirical Studies in Kenya

		Average KGs Per Acre	
	Year	LR 2015	LR 2016
Cluster	1	No Data	1805
	2	No Data	807
	3	1595	1111
	4	1321	1304
	5	1802	1519
	6	1751	1250
	7	1608	976
	8	1879	1595
	9	1174	"No Data"
	10	2015	1794

Note in **Cluster 2 and 7,** the model is able to very clearly detect a payout, mirroring field experience in 2016 locations.

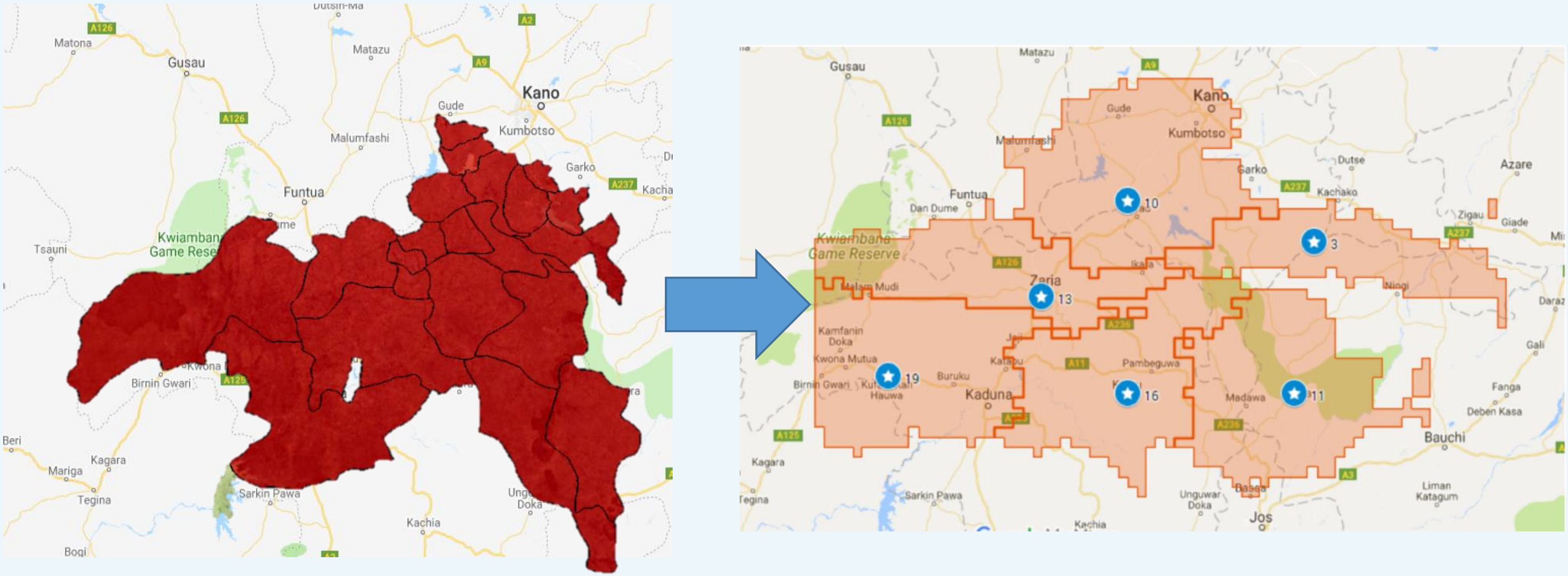


New proposed Districts, based on 1982 – 2016 data

Application in North Central Nigeria

UAI Based on administrative boundaries

UAI based on machine leaning climatological features

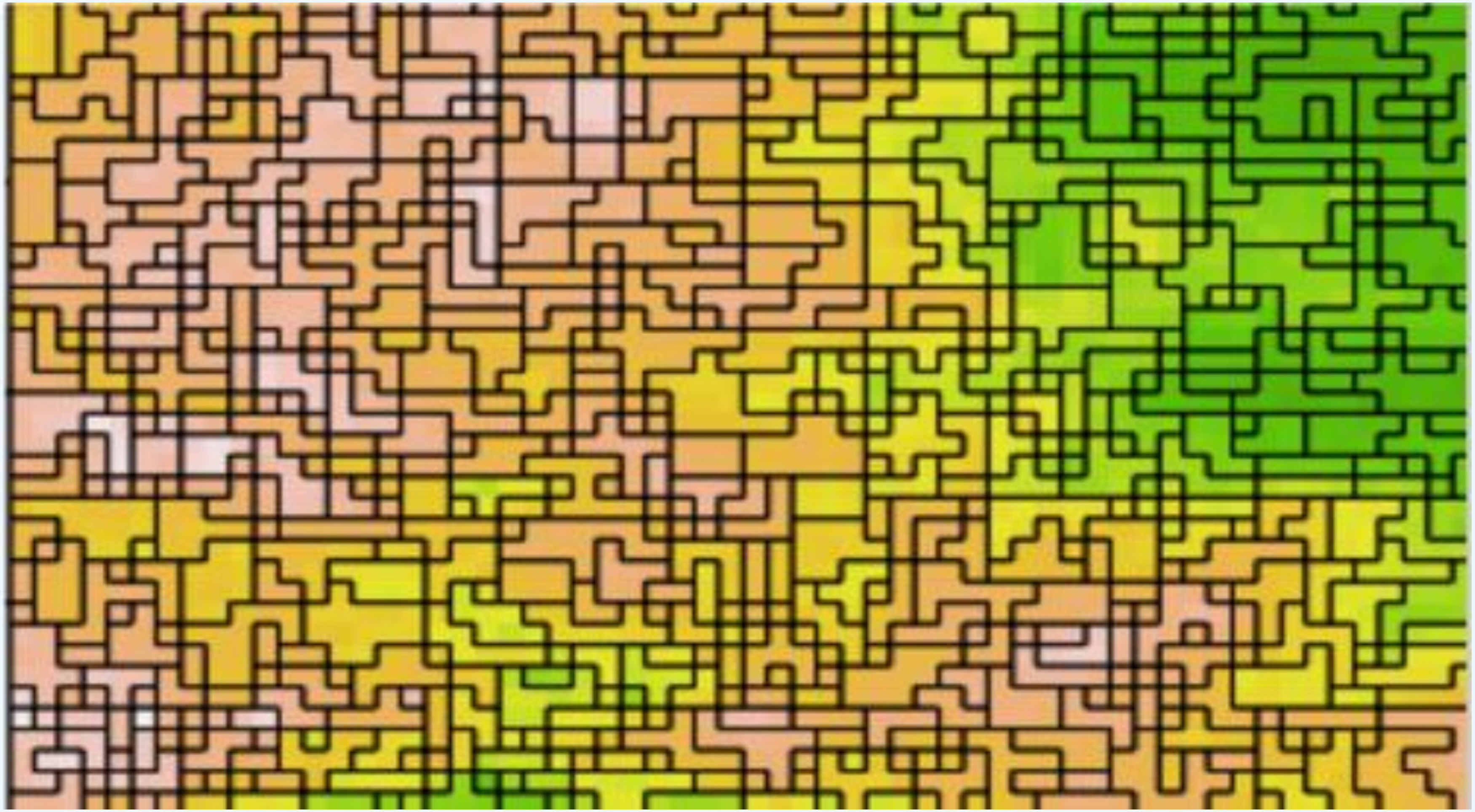


From 22 administrative boundaries to 5 agro ecologies

Cost was 22 x 30 CCE x 36 USD

Budget spend is now 5 x 75 CCE x 36 USD = 43% cost reduction

Future Applications: Hotspot Analysis



Using similar methodology, and real time vegetation estimates to understand potential poorly performing areas and ensure CCEs are placed proportionately, with the goal to limit basis risk.

Thank you.

Questions?