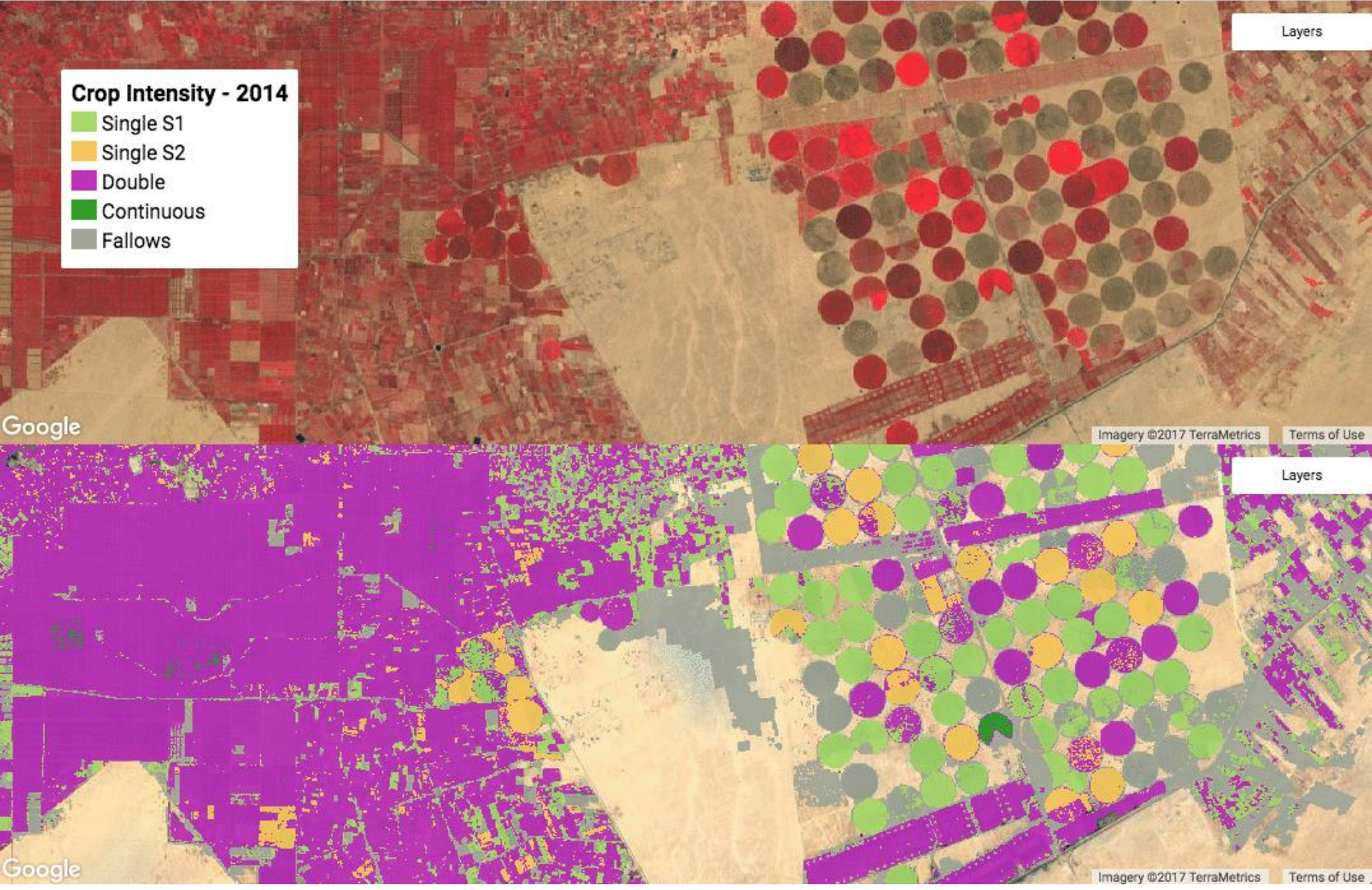


Global Cropland Mapping
Africa: Crop Extent and Intensity

Jun Xiong | Research Scientist

USGS
science for a changing world

Objectives of GFSAD30 Project

"Global Food Security Analysis-Support Data" aims to provide high resolution (30-m) global cropland products, including:

- Cropland extent/area
- Global major crop types:
- Irrigated versus rainfed
- Cropping intensities: single, double, continuous
- Cropland change

Story of African Agriculture

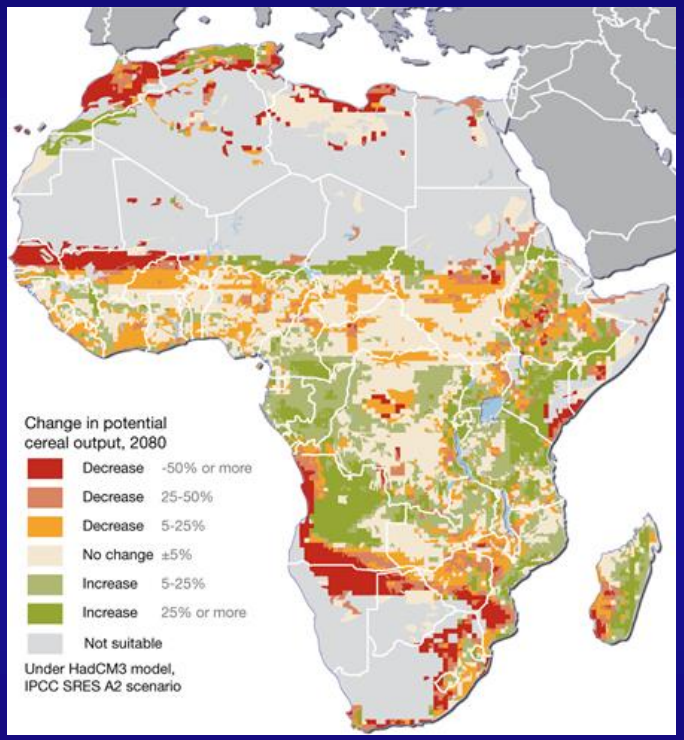
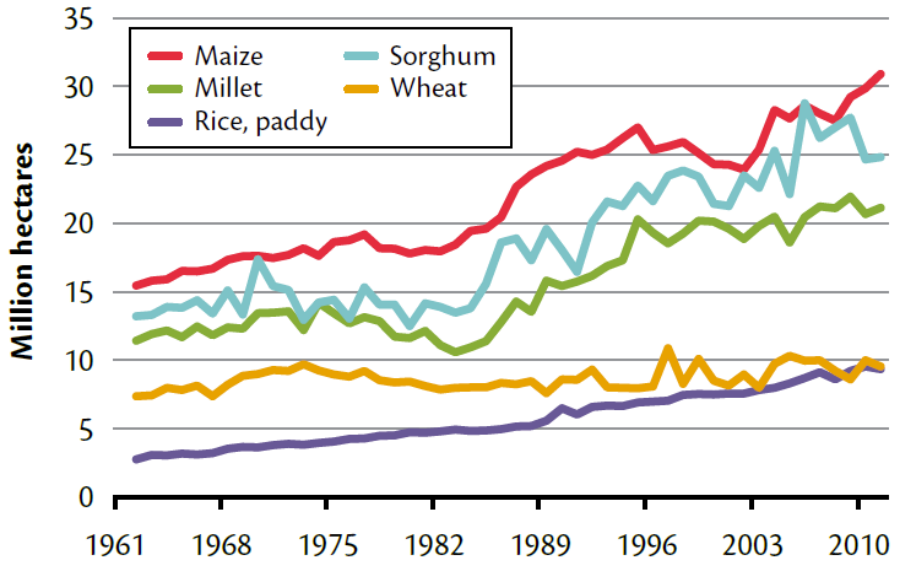


FIGURE 1 Area harvested of top five cereal crops



Data source: FAO 2012.

Story of African Agriculture

Image: national geographic magazine

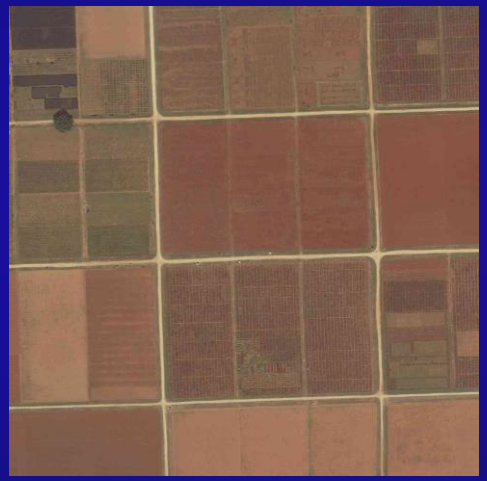
Previous studies

- The Africover maps (FAO) covering 10 countries (2000): Burundi, Egypt, Eritrea, Kenya, RDC, Rwanda, Somalia, Tanzania, Sudan and Uganda, http://www.africover.org/
- The land use/land cover (LULC) 2000 datasets produced by USGS covering 8 countries: Benin, Burkina-Faso, Ghana, Guinea, Guinee Bissau, Mali, Mauritania, Niger, Togo.
- The MODIS-JRC Crop mask derived from MODIS time series for the year 2009 over northern Nigeria and Benin
- JMARS-JRC 250-m crop mask (Christelle, 2013)

- GlobeLand30 (2010) from National Geomatics Center of China (NGCC) http://www.globallandcover.com/home/Enbackground.aspx
- FROM-GLC (Finer Resolution Observation and Monitoring of Global Land Cover), China http://data.ess.tsinghua.edu.cn/

Definition of “Crop Extent”

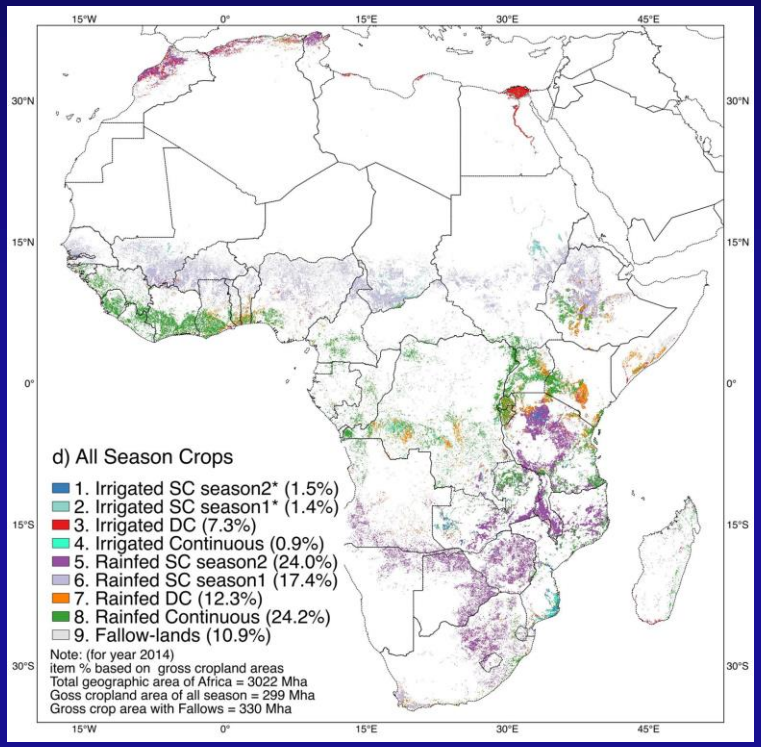
“Lands cultivated with plants harvested for food, feed, and fiber, include both seasonal crops and continuous plantations. It also includes areas equipped for cropping but may not be cropped in a particular season or year (cropland fallow) ”




Cropland extent layer aims to provide work-basis for other high-level products.

GFSAD250AF Products

- Automated Mapping Algorithm was deployed in Google Earth Engine (GEE) to process MODIS data from 2003 to 2014
- In 2014, the net and gross croplands areas are 296, 330 Mha respectively for continental Africa
- Accessible through Croplands.org



Citation:

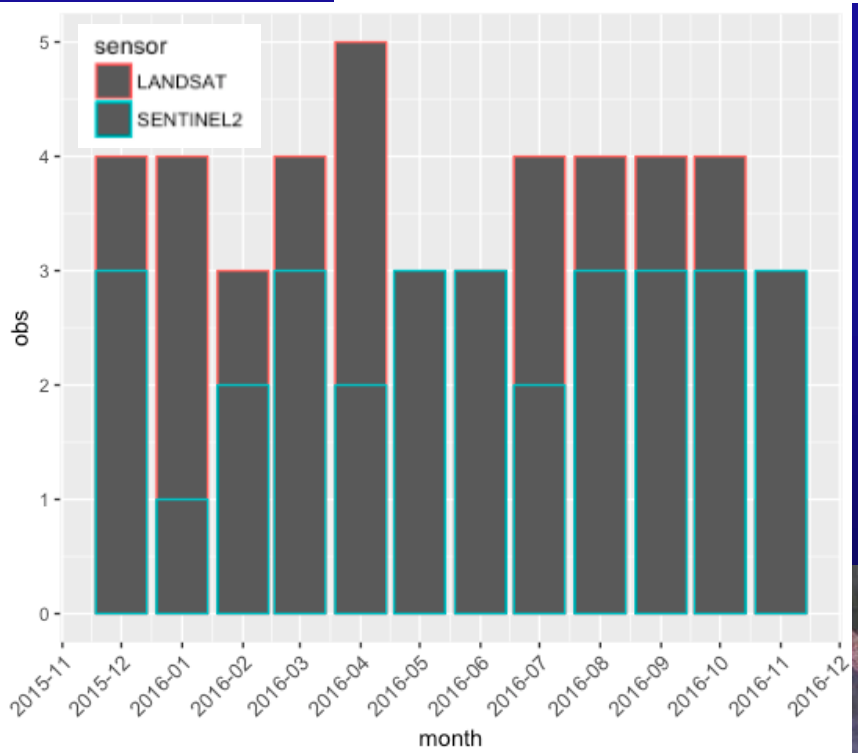
Xiong J, Thenkabail PS, Gumma, M., et al. Automated Cropland Mapping of Continental Africa using Google Earth Engine Cloud Computing. ISPRS Journal of Photogrammetry and Remote Sensing. 2017;doi:10.1016/j.isprsjprs.2017.01.019

Hybrid of classification and segmentation

- Input: Sentinel-2 MSI
- Crop/Non-crop reference samples selection
- Classification: Random Forest, SVM
- Segmentation: RHSEG
- Merging
- Accuracy assessment
- Data (beta) submission

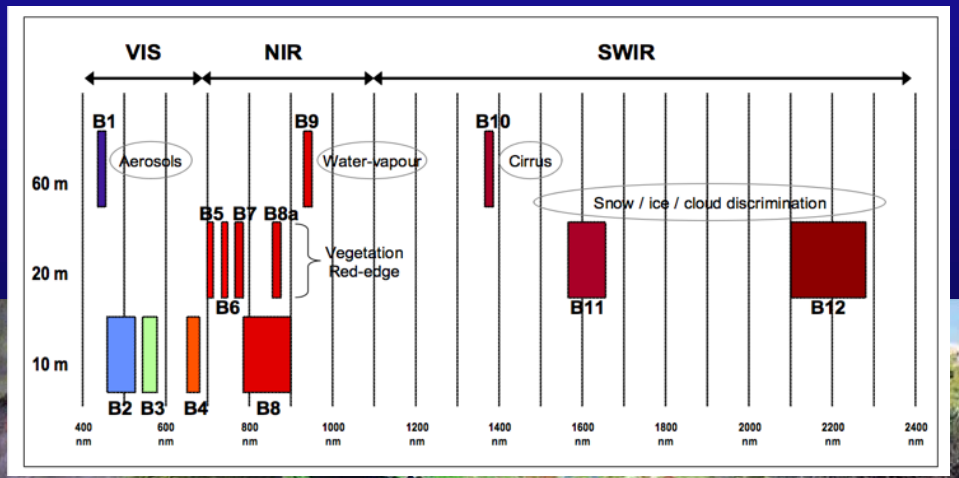
Sentinel-2 and Landsat 8

Sensors	Period	Band	Use	Wavelength	Resolution
Sentinel-2 multi-spectral imaging (MSI)	Season 1: March - June; Season 2: July - October	B2	Blue	490nm	10m
		B3	Green	560nm	10m
		B4	Red	665nm	10m
		B8	Near Infrared	842nm	10m
		B8A	Near Infrared	856nm	20m
Landsat 8	Season 1: March - June; Season 2: July - October	B2	Blue	450 - 510nm	30m
		B3	Green	530 - 590nm	30m
		B4	Red	640 - 670nm	30m
		B5	Near Infrared	850 - 880nm	30m
Shuttle Radar Topography Mission (SRTM) 30-m		Slope			30m

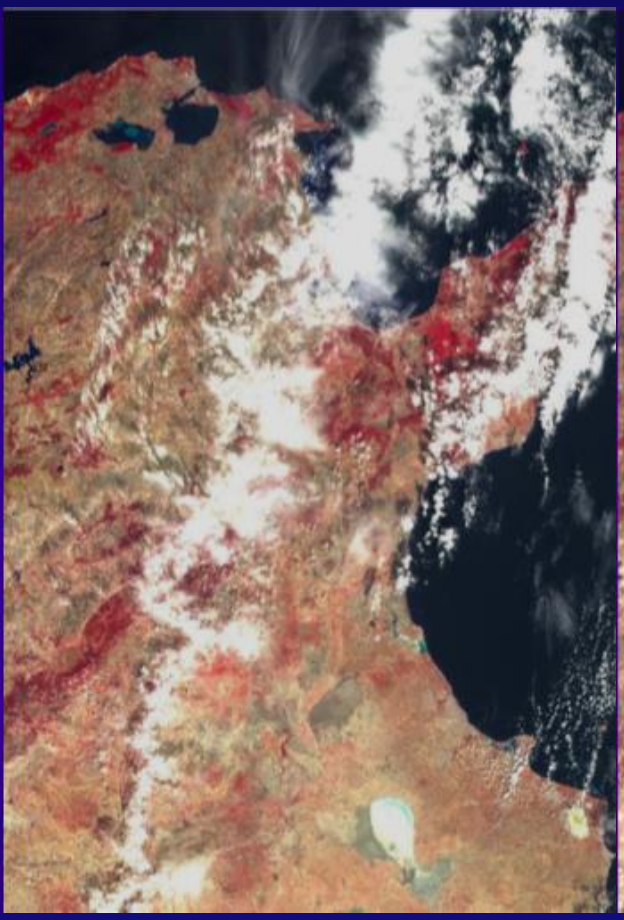


All bands are converted to TOA

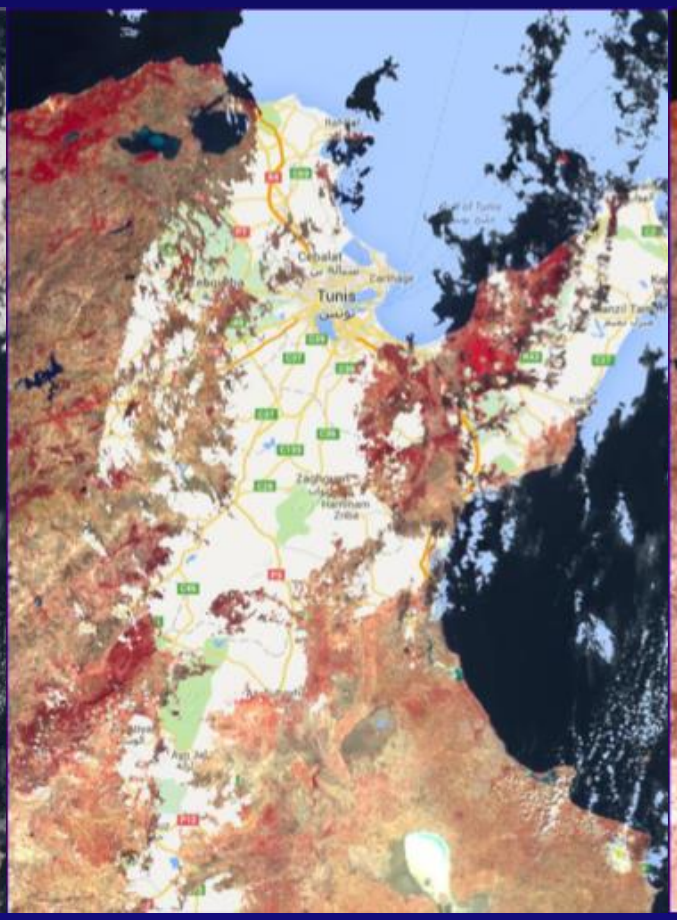
In order to match Landsat nir band (B5), Sentinel-2 B8A (856nm, 20m) is closer than B8 (842nm, 10m).



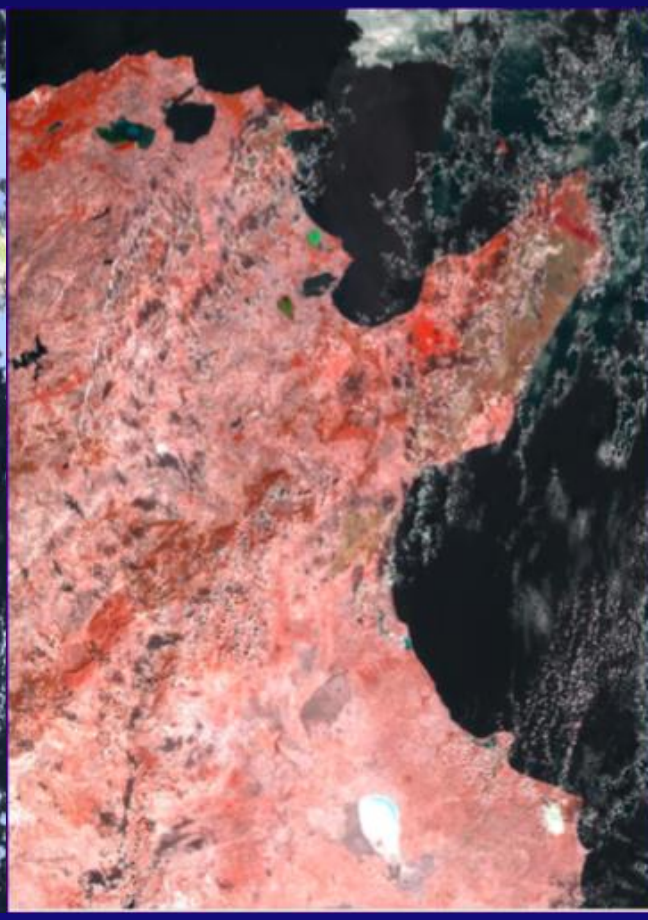
Gap-filling



Sentinel-2(B8/B4/B3) Season 2, 2015

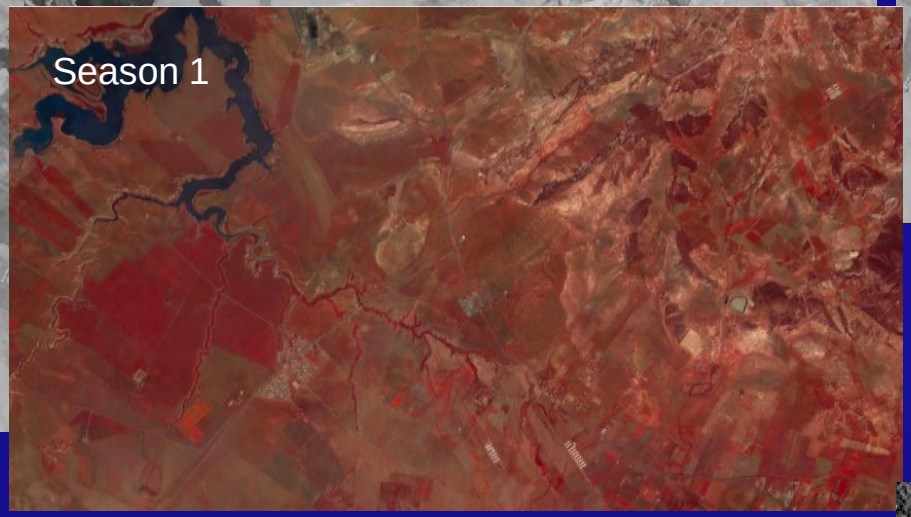


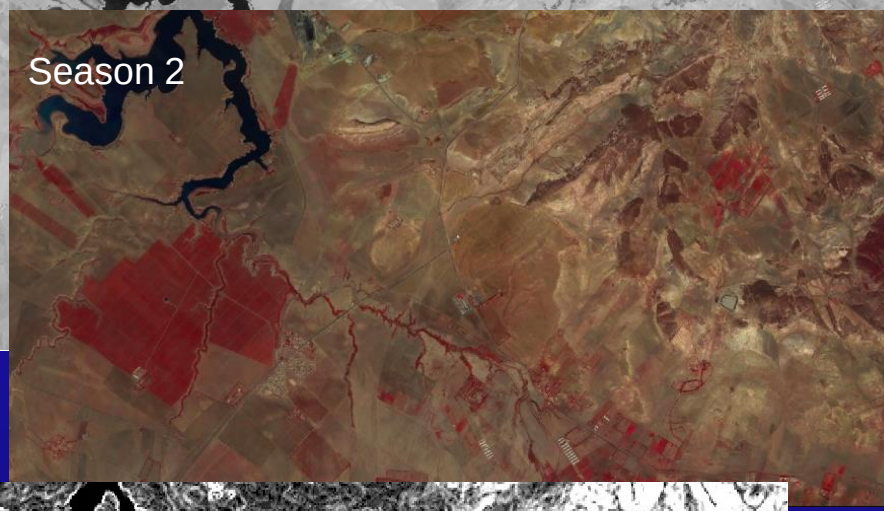
Sentinel-2 Cloud Mask



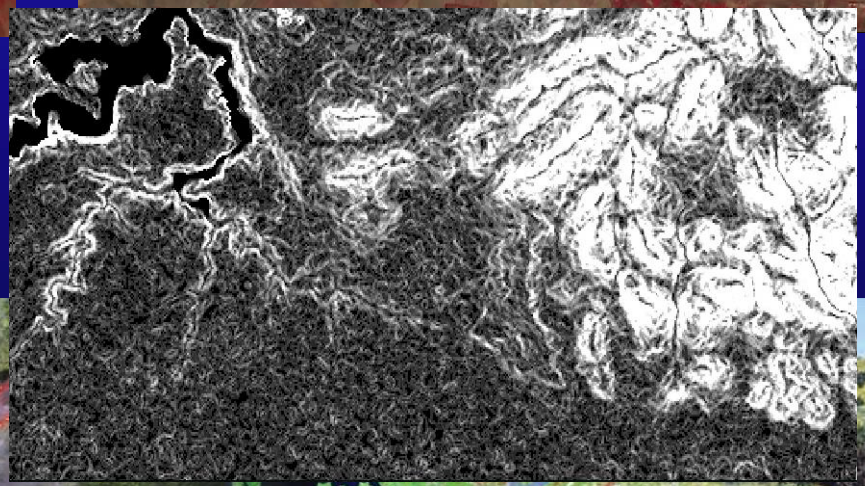
Sentinel-2 Gap-filling with Landsat

Nominal 30-m mosaic bands

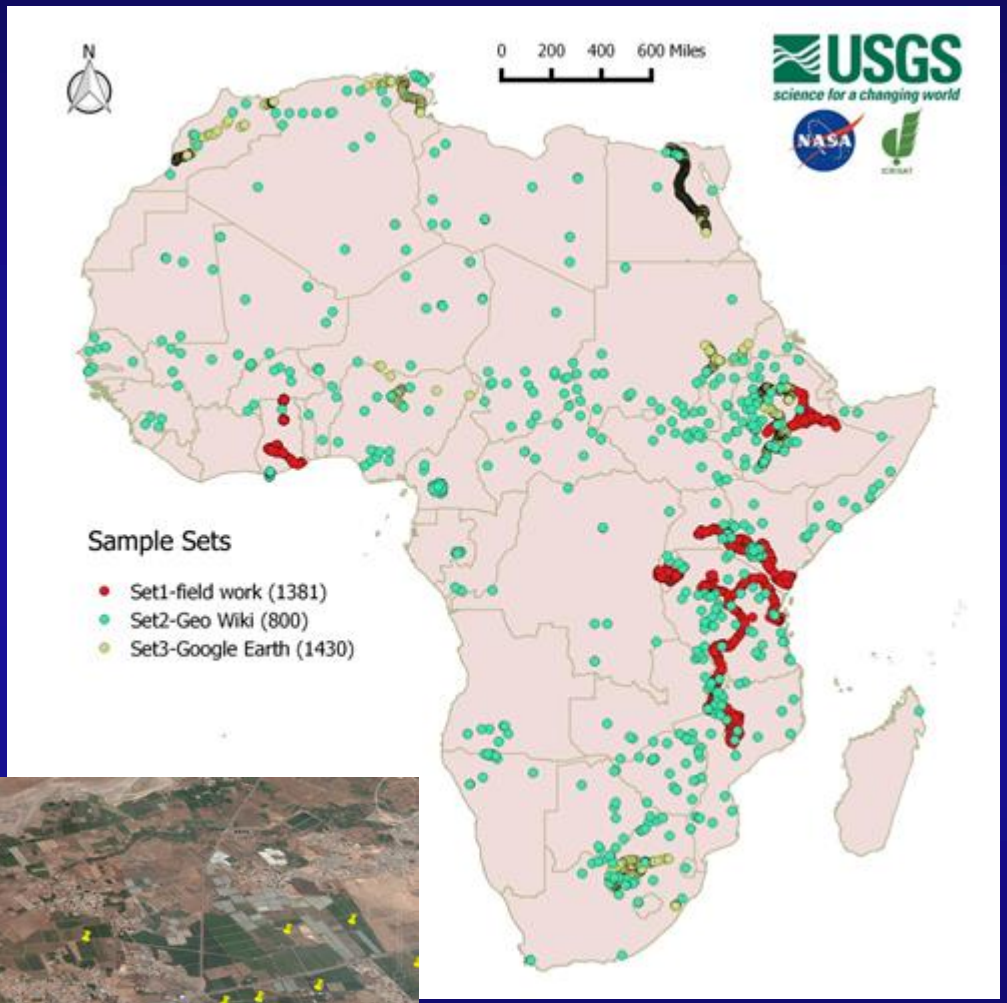


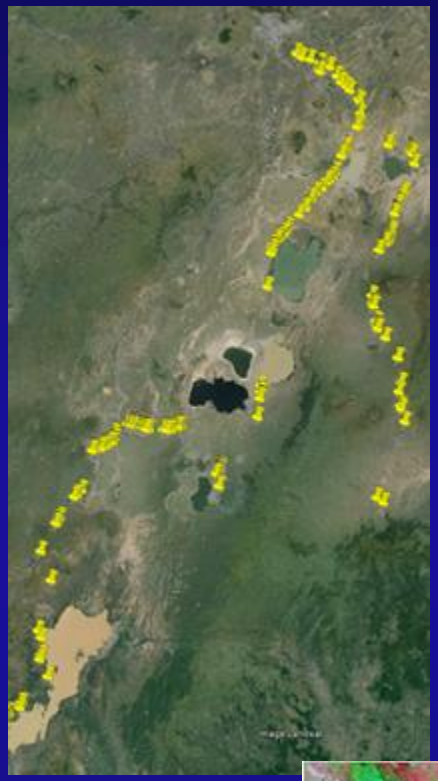


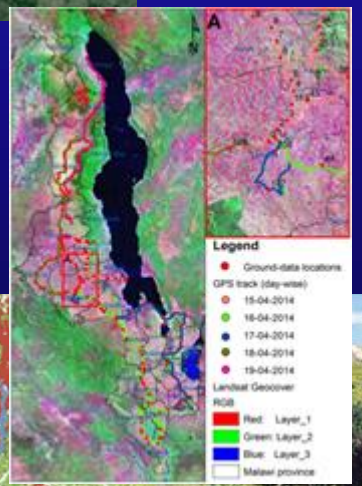
Season 1: March - June, Median Composite	B2	Season 2: July - October, Median Composite	B2
	B3		B3
	B4		B4
	B8A		B8A
	false color (B8,B4,B3)		false color (B8,B4,B3)
slope band from Shuttle Radar Topography Mission (SRTM) 30-m			



Ground campaigns in Africa







Ground data mobile collector

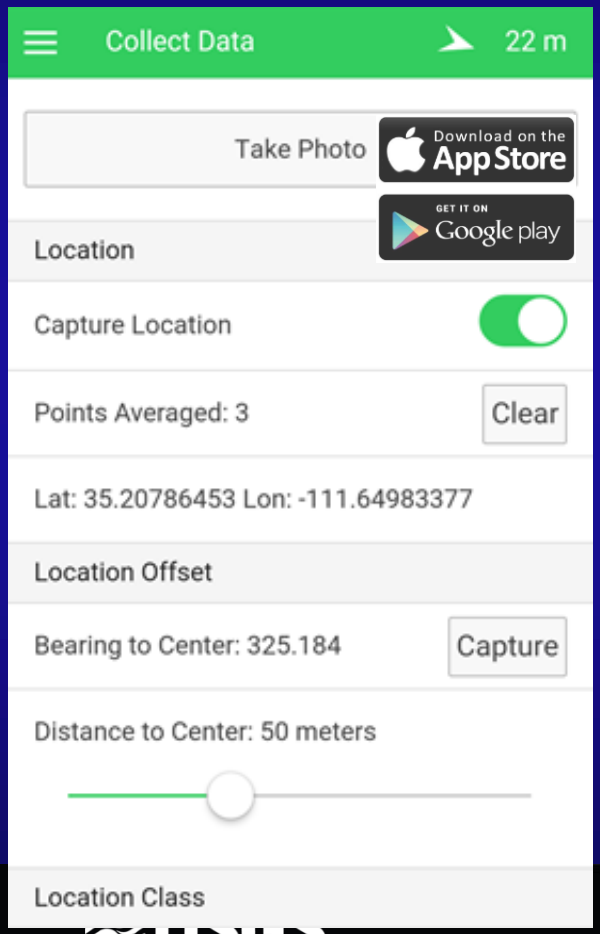
Download the app
croplands.org/mobile

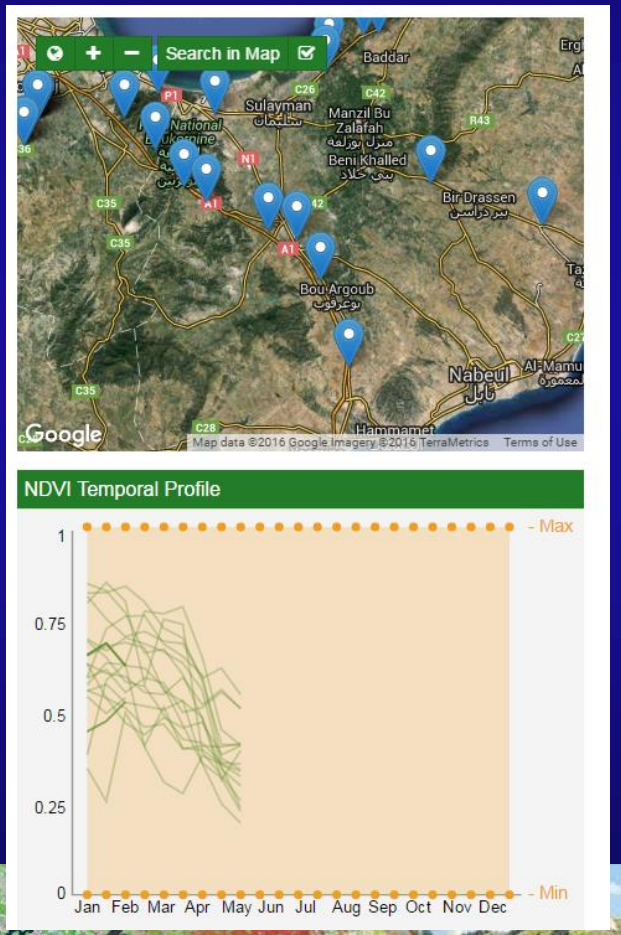
→

Collect data
in the field

→

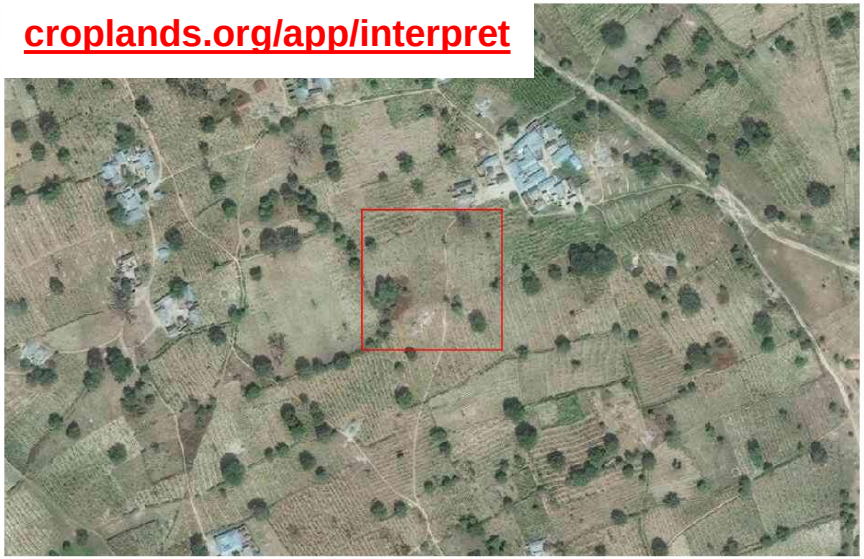
Ingest to database
croplands.org/app/data





Sample Interpreter for Validation

croplands.org/app/interpret

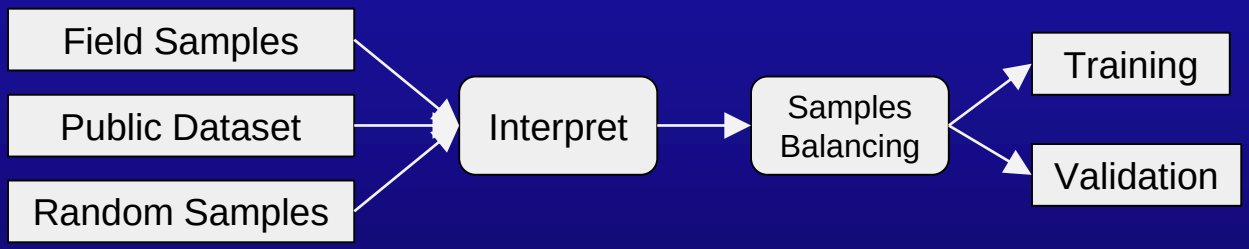


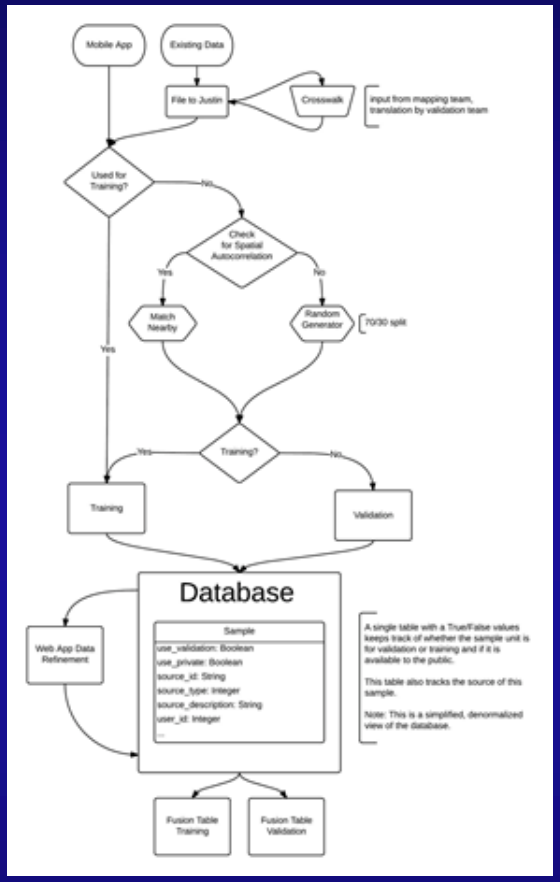
Select Class

- Pure Cropland
- Mixed Cropland
- Not Cropland
- Reject
- Skip

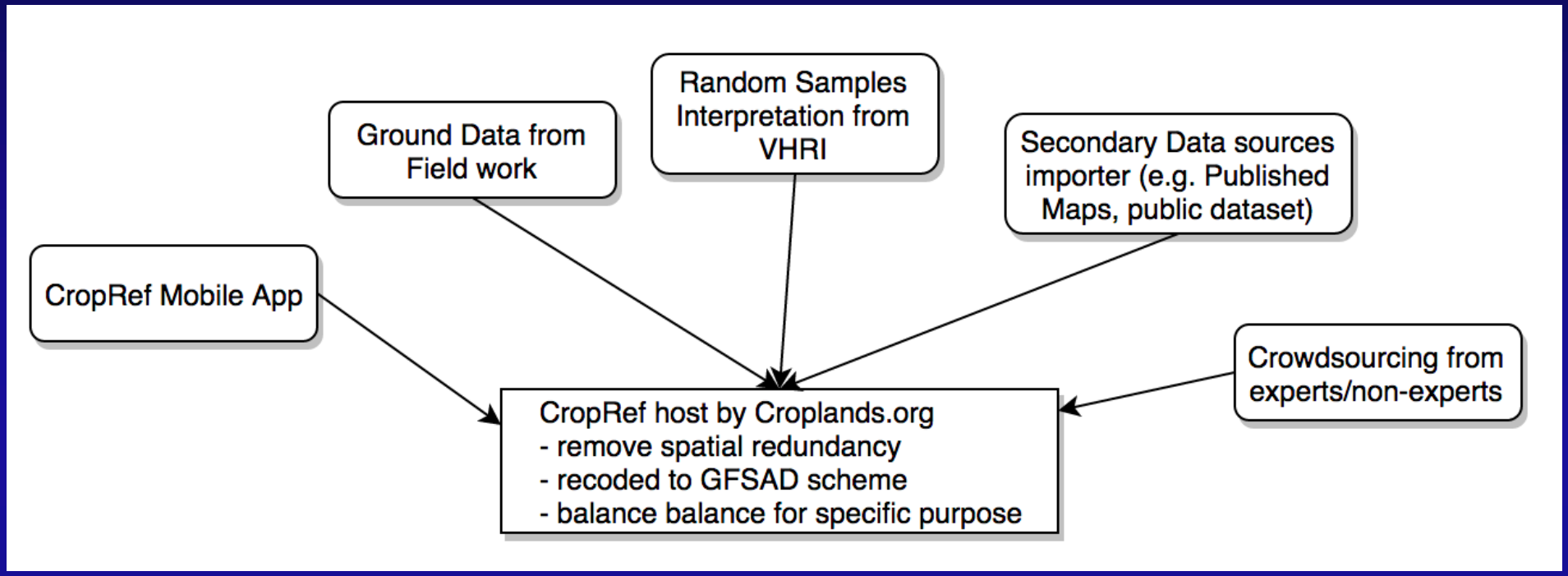
Keyboard Shortcuts

c	Pure Cropland
e	Mixed Cropland
d	Not Cropland
r	Reject
s	Skip
f	Zoom Out
g	Zoom In





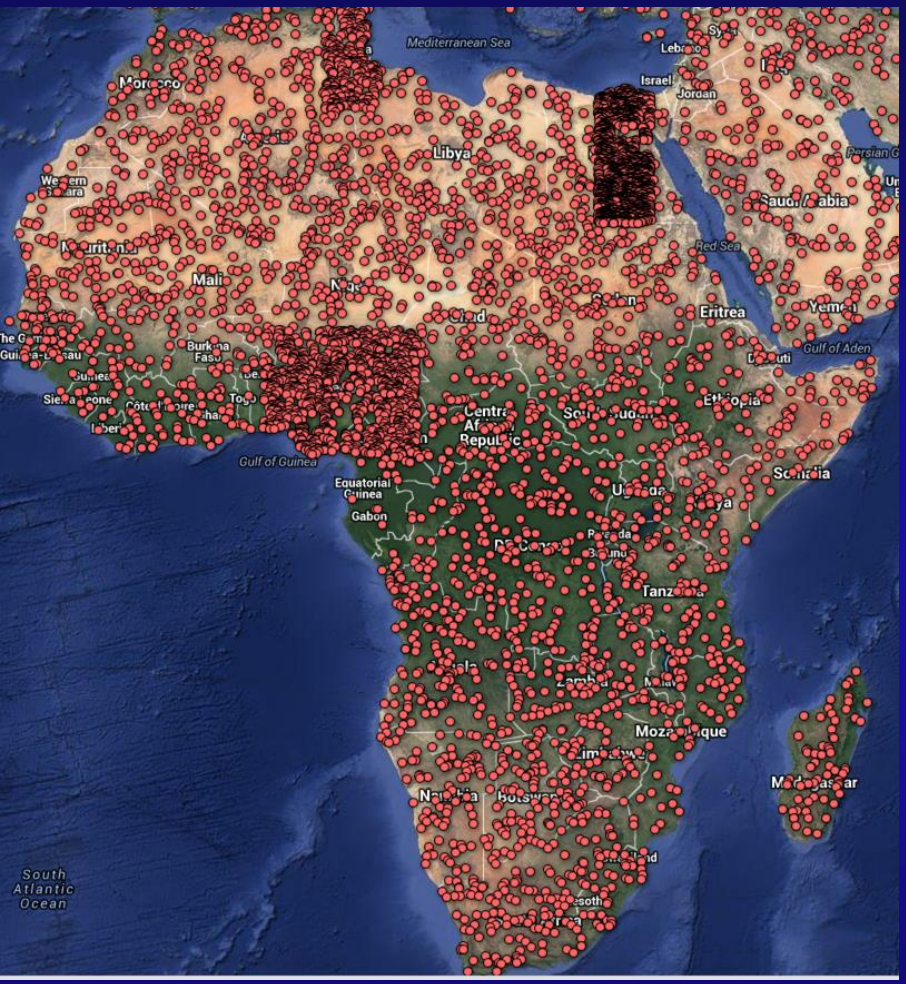
CropRef: Global Crop Reference Data for Community



GFSAD Global Derived Cropland Reference Dataset
Global Sample (Train/Testing, ~70,000; Validation: ~35,000) **Until Nov, 2016**

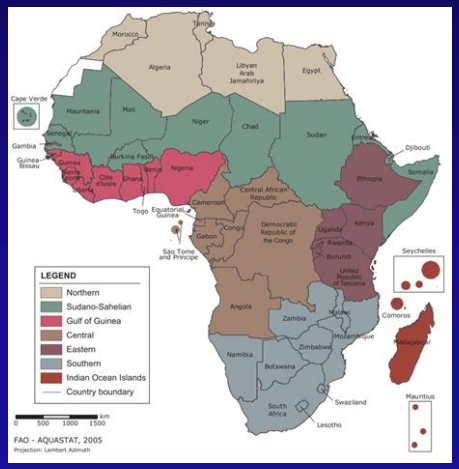
Xiong J, Thenkabail PS, Poehnelt, J., Teluguntla P, Congalton, R., Yadav K. Web-based Cropland Reference Database to improve global cropland mapping. Remote Sensing. 2017;(In Preparation).

Evaluation Samples Balancing

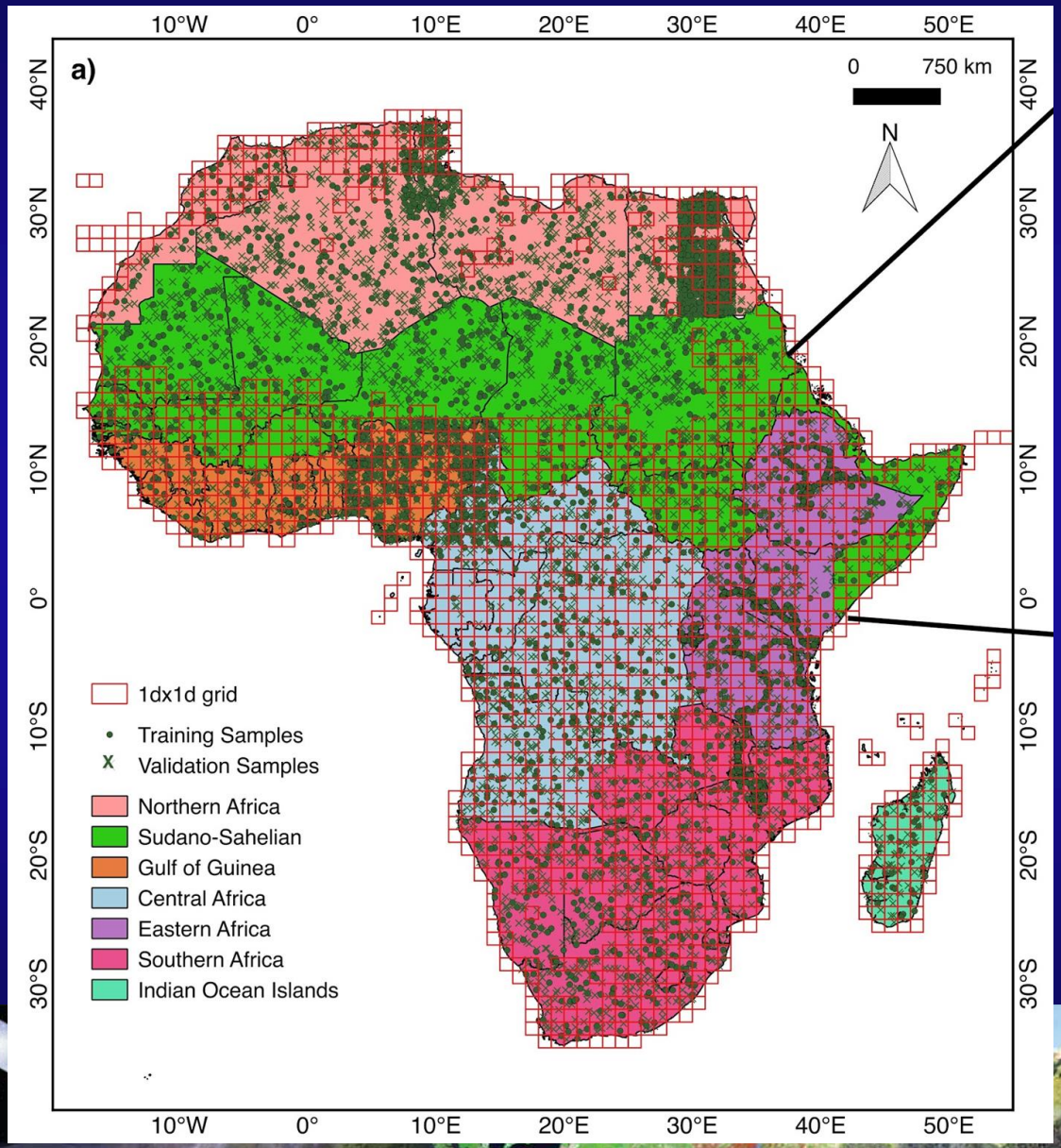


Total 8351 sites (left) were filtered to 5511 (right) to reach better even distribution

Distribution of Training/Testing Samples

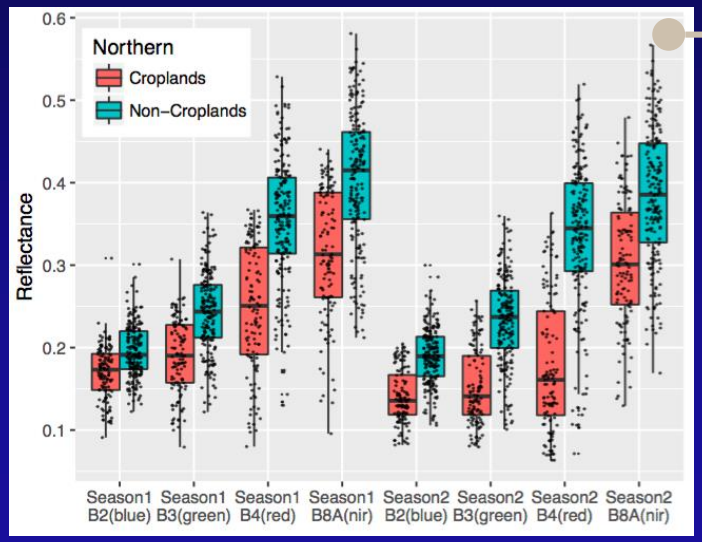


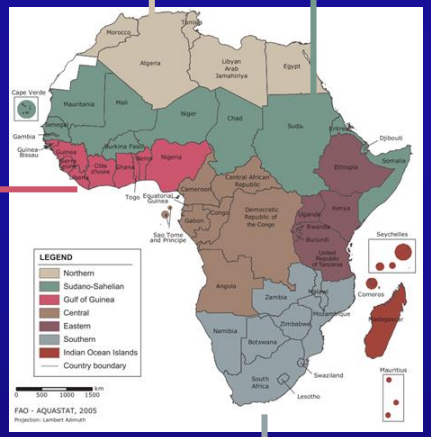
- Seven Divisions
- Total 3803 training samples were selected by hand
- Total 5511 validation samples were used for internal evaluation

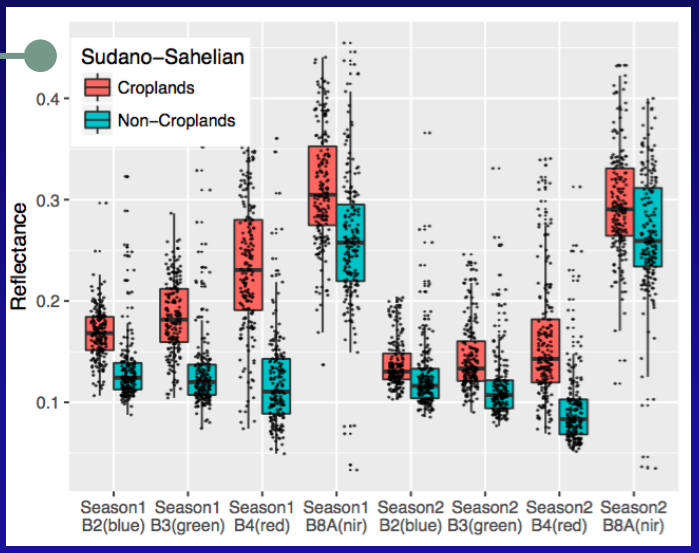


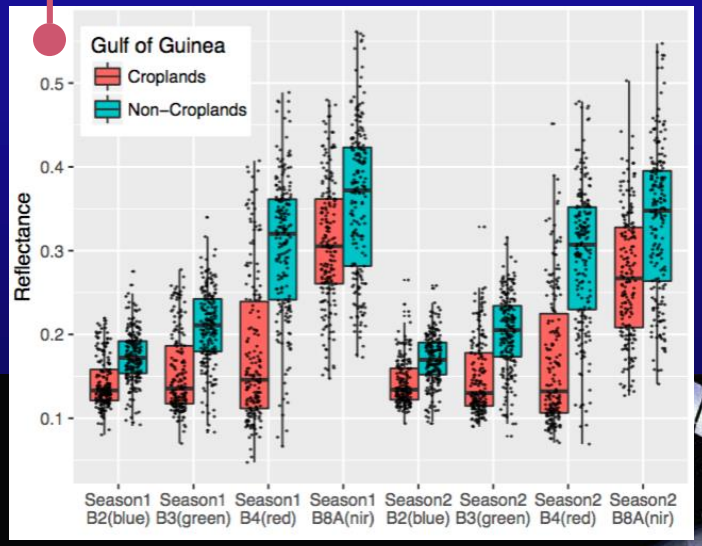
USGS
U.S. Department of the Interior
U.S. Geological Survey

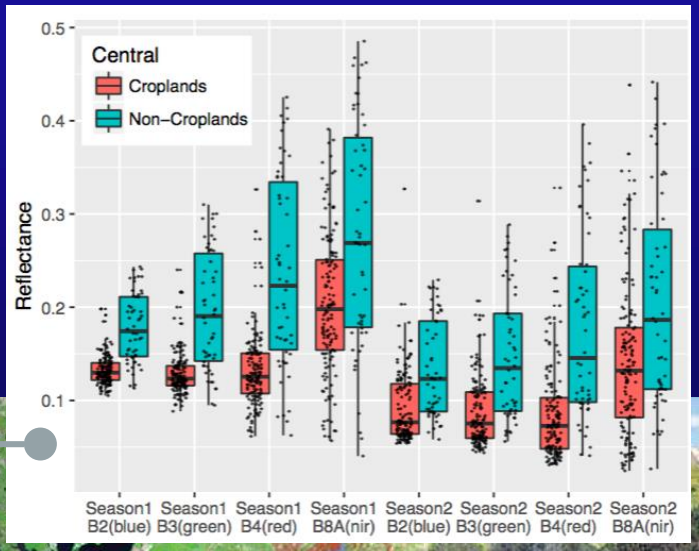
Signatures of Crop vs. Non-Crop











Classifier: Random Forest

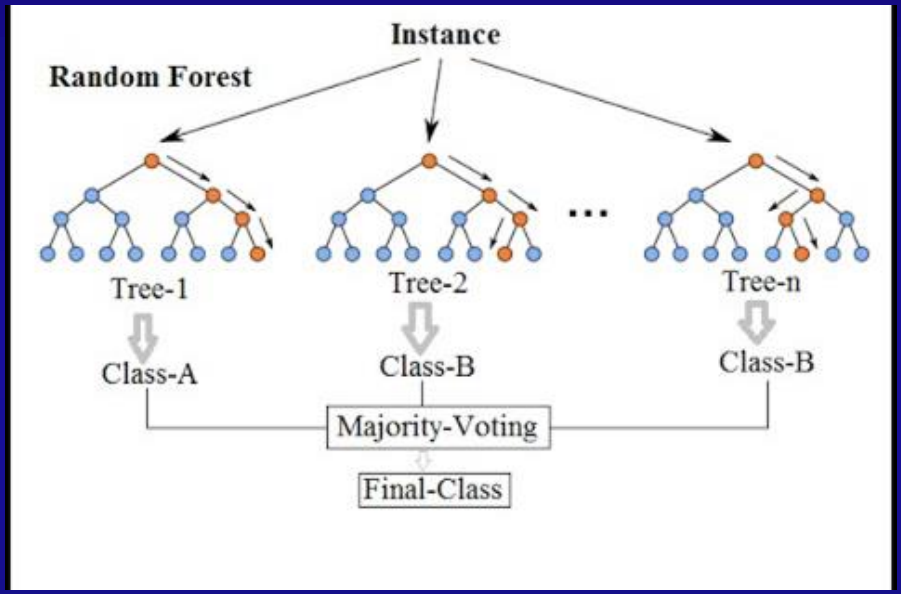
a bagging technique for both classification and regression

pro:

- ➢ easy to use (no need to select features)
- ➢ efficient for training - assessment - re-training process
- ➢ fast for very large area

con:

- ➢ overfitting for noisy inputs and complex classification

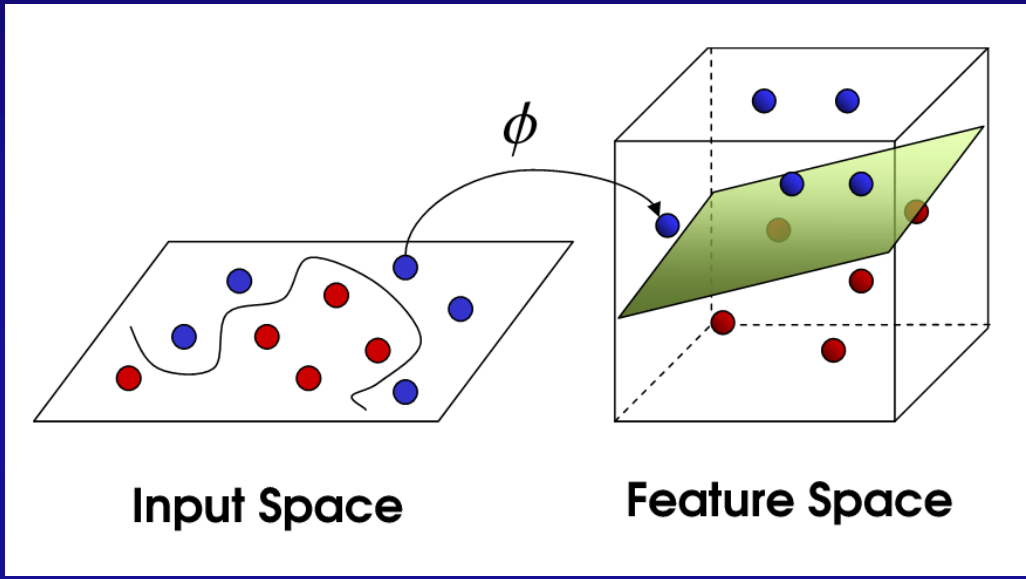


Classifier: Support Vector Machine

a discriminative classifier formally defined by a separating hyperplane

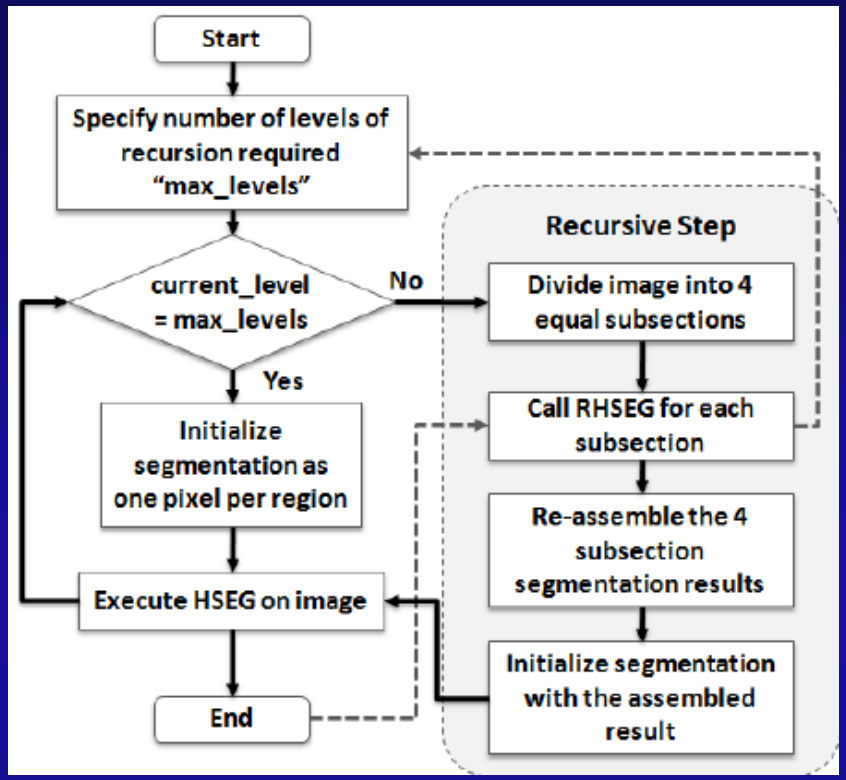
con:
(for cropland classification)

- ➢ not so predictable
- ➢ not so robust
- ➢ notoriously expensive for computing



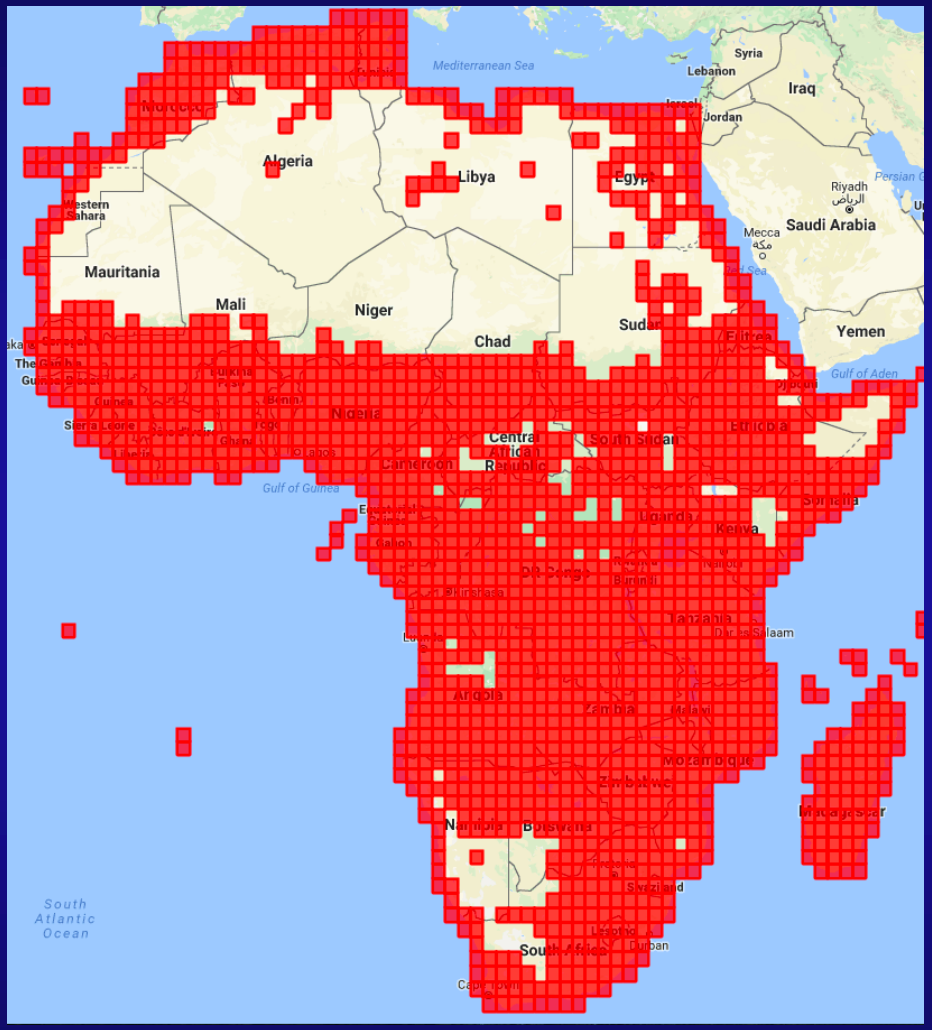
Demo 1a

Hierarchical Segmentation (RHSEG)



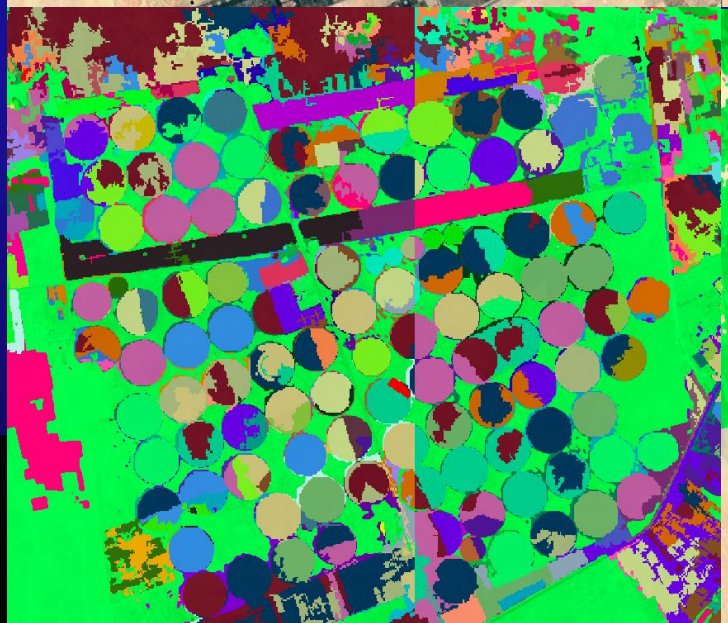
- Input: two season mosaic same as classification except slope bands
- Program: Recursive Hierarchical Image Segmentation (RHSEG)

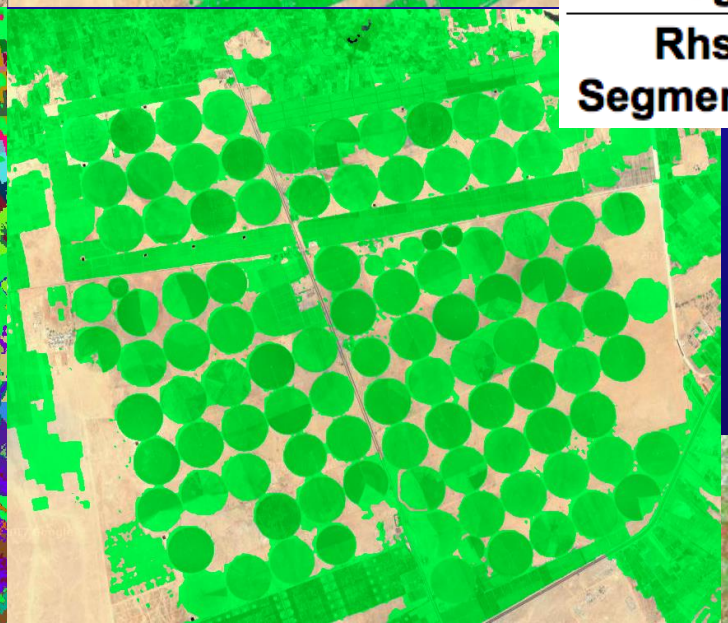
1d x 1d gridding of Africa



- Total 1919 grids by a 1° by 1° for non-desert area.
- Each grid is about 3720 x 3720 pixels
- 2 season mosaics (season 1: March-June, season 2: July-Oct) with NIR, red, green and blue bands.
- Utilizing both the Pleiades and Discover clusters, all segmentation processing is finished within 10 days.

Merging pixel-based and object-based



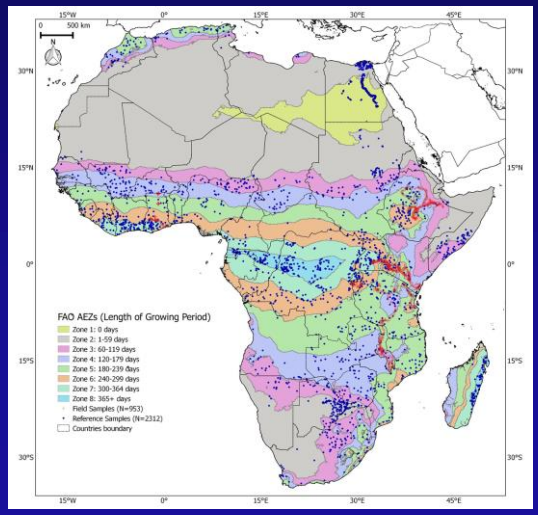


Google Imagery	Pixel-base classification
Rhseg Segmentation	Merging Results

Evaluate with CropRef data

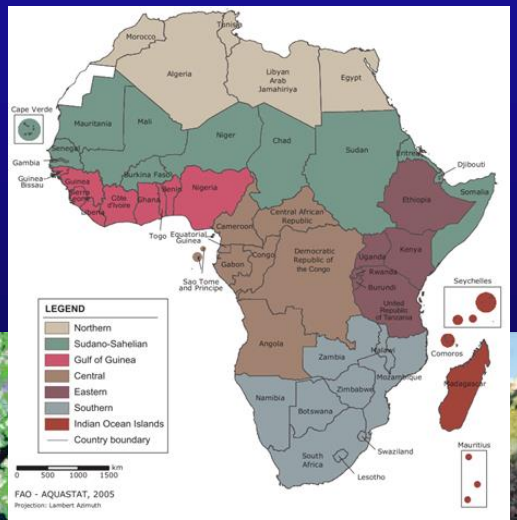
GFSAD30AF		CropRef Reference Data			
AE Zone	Class	Crop	No-Crop	Total	User Accuracy
1	Crop	24	6	30	80%
	No-Crop	1	1,068	1069	100%
	Producer Accuracy	96%	99%		
2	Crop	70	23	93	75%
	No-Crop	4	1,761	1765	100%
	Producer Accuracy	95%	99%		
3	Crop	64	25	89	72%
	No-Crop	8	383	391	98%
	Producer Accuracy	89%	94%		
4	Crop	40	18	58	69%
	No-Crop	8	441	449	98%
	Producer Accuracy	83%	96%		
5	Crop	61	32	93	66%
	No-Crop	9	595	604	99%
	Producer Accuracy	87%	95%		
6	Crop	32	16	48	67%
	No-Crop	10	350	360	97%
	Producer Accuracy	76%	96%		
7	Crop	24	7	31	77%
	No-Crop	5	168	173	97%
	Producer Accuracy	83%	96%		
8	Crop	31	3	34	91%
	No-Crop	9	215	224	96%
	Producer Accuracy	78%	99%		
All	Crop	346	130	476	73%
	No-Crop	54	4981	5035	99%
	Producer Accuracy	87%	97%		
Overall Accuracy (weighted)		95.92%		Kappa	0.716

AEZs Divisions



?

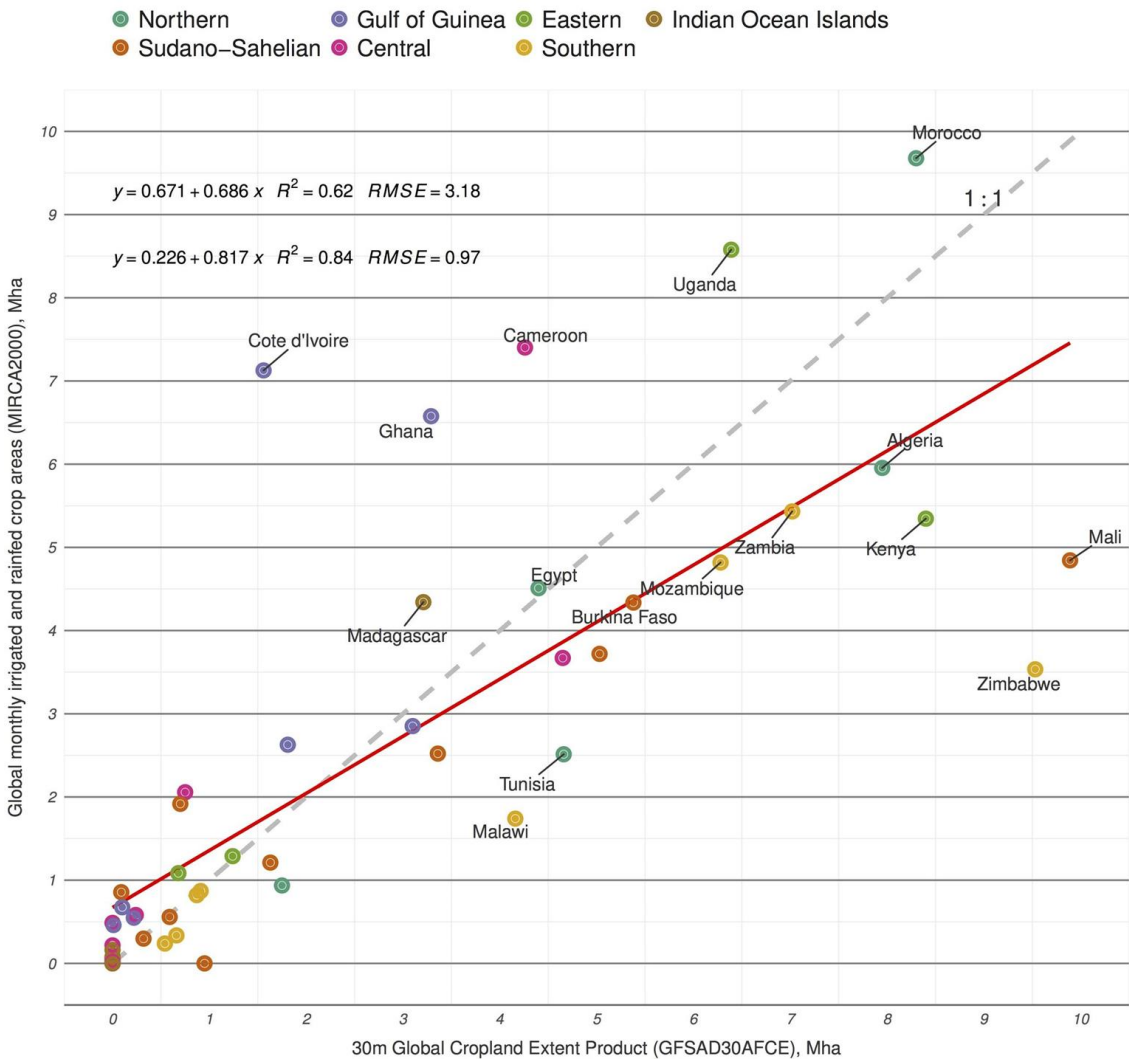
Geo-Divisions



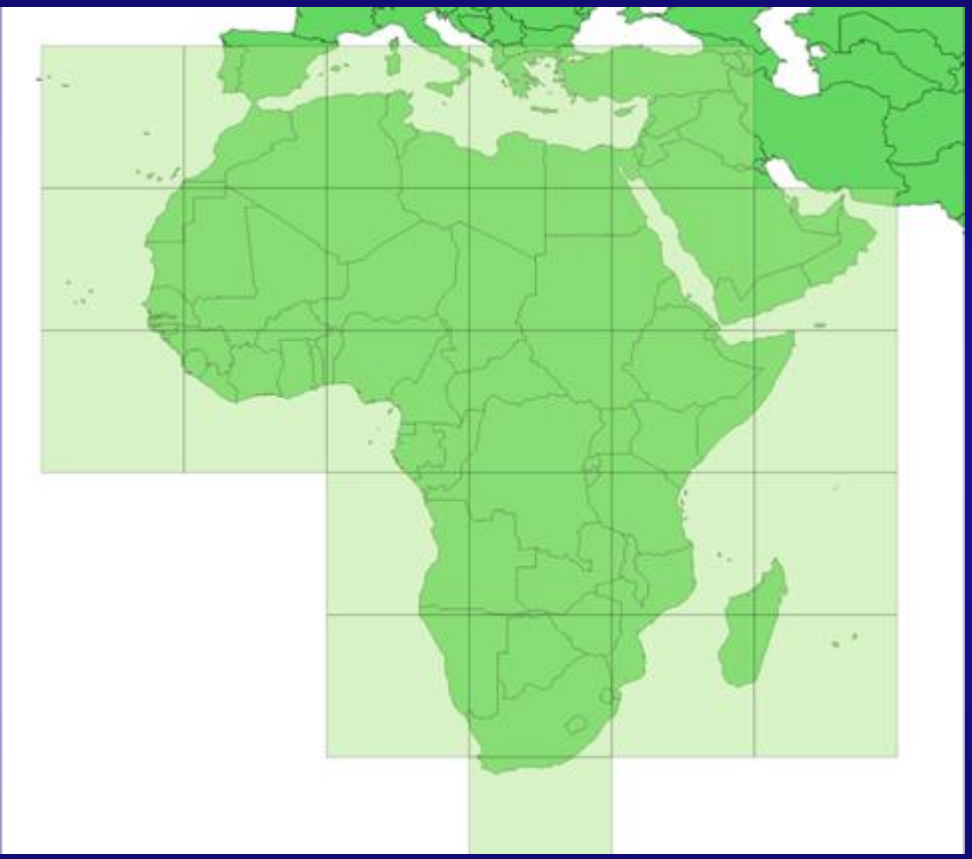
Country-wise Statistics (Top 22)

Country	Code	Land Area FAO-GAUL	Crop Area MIRCA2000	Crop Area This Study: GFSAD30AFCE
			vaiable	30-m
		Mha	Mha	Mha
Nigeria	182	90.56	38.62	29.43
Ethiopia	79	112.76	11.09	21.83
Sudan	6	186.88	18.40	19.09
United Republic of Tanzania	257	93.98	5.67	18.97
South Africa	227	122.00	15.70	15.58
Congo DRC	68	232.94	9.80	11.39
Mali	155	125.26	4.84	9.89
Zimbabwe	271	39.07	3.53	9.53
Kenya	133	59.34	5.35	8.4
Morocco	169	67.77	9.68	8.3
Algeria	4	231.27	5.96	7.95
Niger	181	118.12	14.53	7.34
Zambia	270	75.12	5.43	7.02
Uganda	253	24.13	8.58	6.39
Mozambique	170	78.57	4.82	6.28
Burkina Faso	42	27.39	4.34	5.38
Chad	50	127.09	3.72	5.03
Tunisia	248	15.50	2.51	4.66
Angola	8	124.71	3.67	4.65
Egypt	40765	98.22	4.51	4.4
Cameroon	45	46.50	7.40	4.26
Malawi	152	11.85	1.74	4.16
Senegal	217	19.52	2.52	3.36
Ghana	94	23.86	6.58	3.29
Madagascar	150	58.98	4.34	3.21
Benin	29	11.52	2.85	3.1
Togo	243	5.67	2.63	1.81
Libya	145	161.52	0.94	1.75
Somalia	226	63.26	1.21	1.63

Total net cropland: 249 Mha



Submission to LPDAAC



grid size: 15d x 15d

Total grids: 26

image dimension:

56,000 x 56,000

image size:

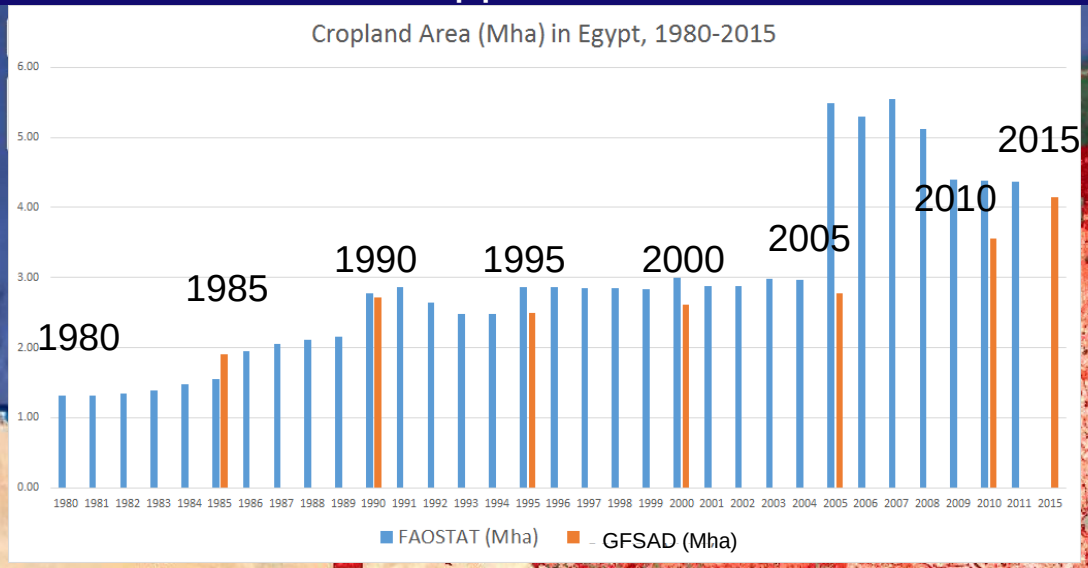
~ 100 MB after compressed

Google Cloud Storage is used to transfer dataset to LPDAAC

- *Xiong J, et al. User Guide of GFSAD30AF Crop Extent Product.*
- *Xiong J, et al. ATDB of GFSAD30AF Crop Extent Product.*

Expansion of Egypt Irrigation since 1985

- In the past 35 year, Egypt increased its irrigation area from 1.2 Mha to 4.1 Mha, most of them happened after 2005



Demo & Known Issues

- Low-density Cropland in West Africa
- ‘slash and burn’ agriculture

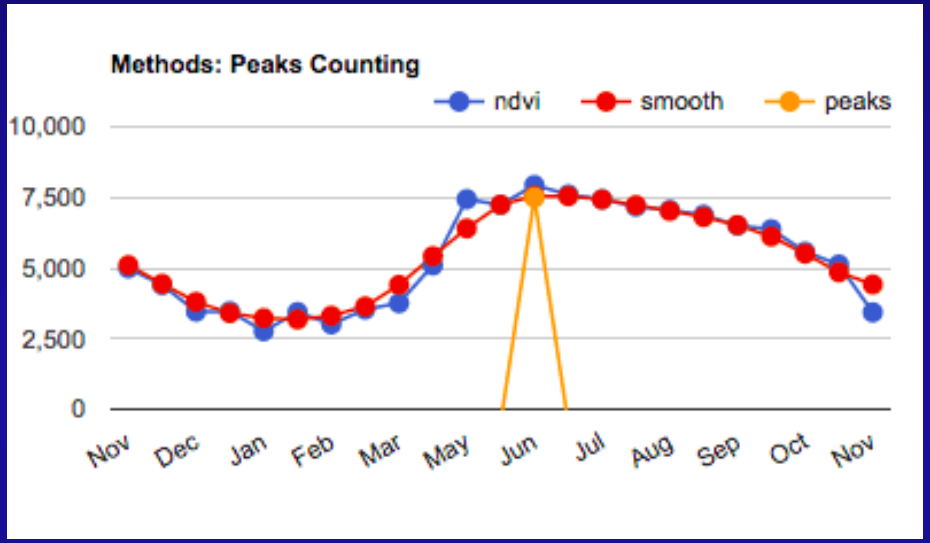
Xiong J, Thenkabail PS, Tilton, J., et al. A Nominal 30-m Cropland Extent of Continental Africa Using Sentinel-2 data and Landsat-8 by Integrating Random Forest and Hierarchical Segmentation Approach on Google Earth Engine. Journal TBD. 2017;(In Preparation).

Cropping intensity Mapping

- Cropping intensity can greatly affect net production
- Current studies using MODIS may not accurately map smallholder farms because of the resolution
- Landsat/Sentinel-2: coarse temporal resolution

Method 1: Peak Counting

1. Remove abnormal points
2. Smooth Time Series data
3. Locate the local max value (Peak)
4. Filter out global low-value peaks
5. Counting the number of Peaks



pro

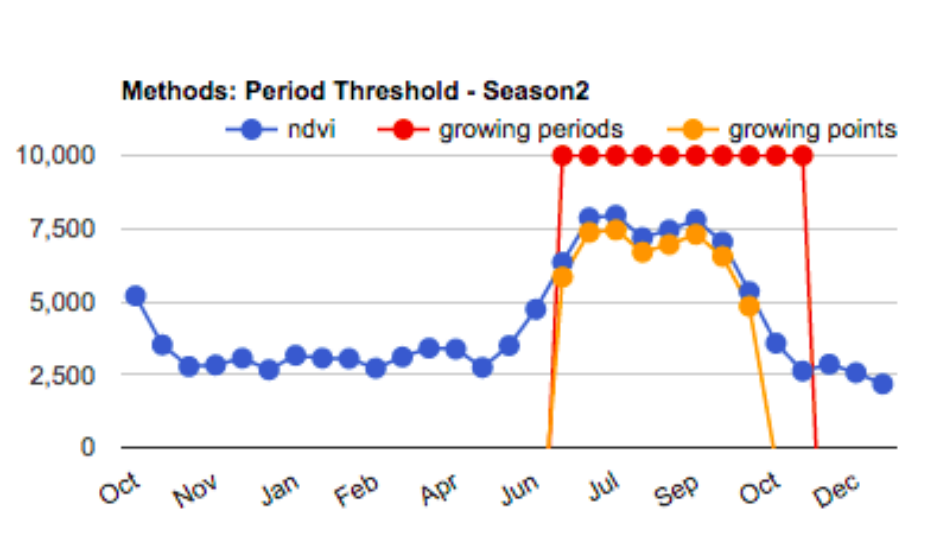
- ➢ no need of prior knowledge
- ➢ fast to implement

con

- ➢ depend on time series data quality
- ➢ uncertainty of smoother

Method 2: Growing Season Threshold

To identify if a pixel is cropped or uncropped during each growing season.



pro

- no need to smooth time-series
- workable for Landsat pixel
- computing for every season

con

- need prior input

Sage Crop Calendar Dataset

- Barley.crop.calendar.fill.nc.filled.index.tif
- Barley.crop.calendar.fill.nc.harvest.end.tif
- Barley.crop.calendar.fill.nc.harvest.range.tif
- Barley.crop.calendar.fill.nc.harvest.start.tif
- Barley.crop.calendar.fill.nc.harvest.tif
- Barley.crop.calendar.fill.nc.index.tif
- Barley.crop.calendar.fill.nc.plant.end.tif
- Barley.crop.calendar.fill.nc.plant.range.tif
- Barley.crop.calendar.fill.nc.plant.start.tif
- Barley.crop.calendar.fill.nc.plant.tif
- Barley.crop.calendar.fill.nc.tot.days.tif
- Barley.Winter.crop.calendar.fill.nc.filled.index.tif
- Barley.Winter.crop.calendar.fill.nc.harvest.end.tif
- Barley.Winter.crop.calendar.fill.nc.harvest.range.tif
- Barley.Winter.crop.calendar.fill.nc.harvest.start.tif
- Barley.Winter.crop.calendar.fill.nc.harvest.tif
- Barley.Winter.crop.calendar.fill.nc.index.tif
- Barley.Winter.crop.calendar.fill.nc.plant.end.tif
- Barley.Winter.crop.calendar.fill.nc.plant.range.tif
- Barley.Winter.crop.calendar.fill.nc.plant.start.tif
- Barley.Winter.crop.calendar.fill.nc.plant.tif
- Barley.Winter.crop.calendar.fill.nc.tot.days.tif
- Cassava.crop.calendar.fill.nc.filled.index.tif
- Cassava.crop.calendar.fill.nc.harvest.end.tif
- Cassava.crop.calendar.fill.nc.harvest.range.tif
- Cassava.crop.calendar.fill.nc.harvest.start.tif
- Cassava.crop.calendar.fill.nc.harvest.tif
- Cassava.crop.calendar.fill.nc.index.tif
- Cassava.crop.calendar.fill.nc.plant.end.tif
- Cassava.crop.calendar.fill.nc.plant.range.tif
- Cassava.crop.calendar.fill.nc.plant.start.tif
- Cassava.crop.calendar.fill.nc.plant.tif
- Cassava.crop.calendar.fill.nc.tot.days.tif
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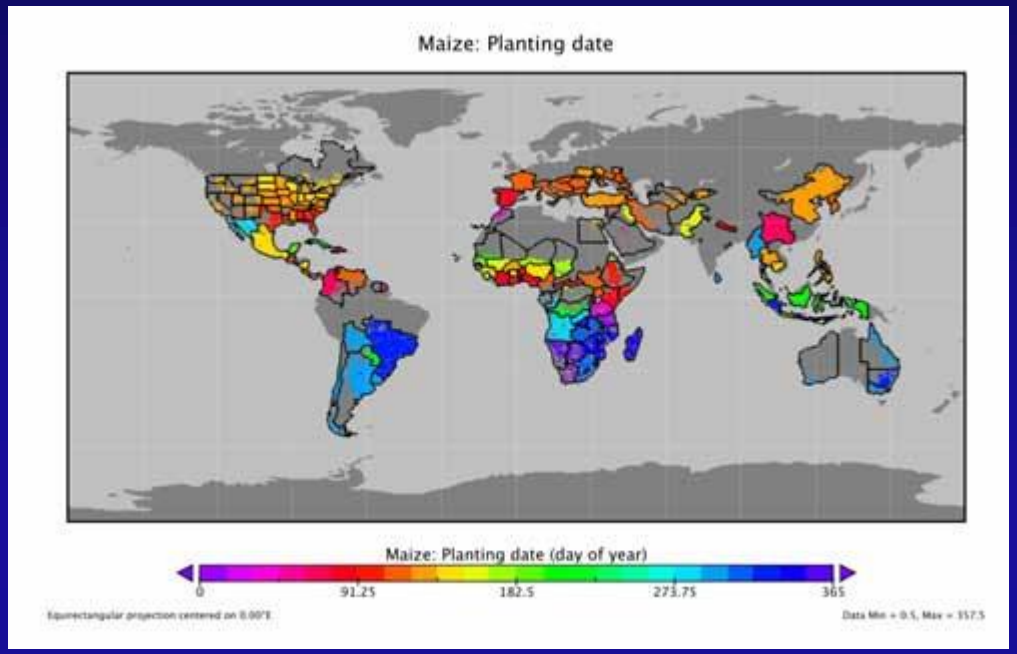
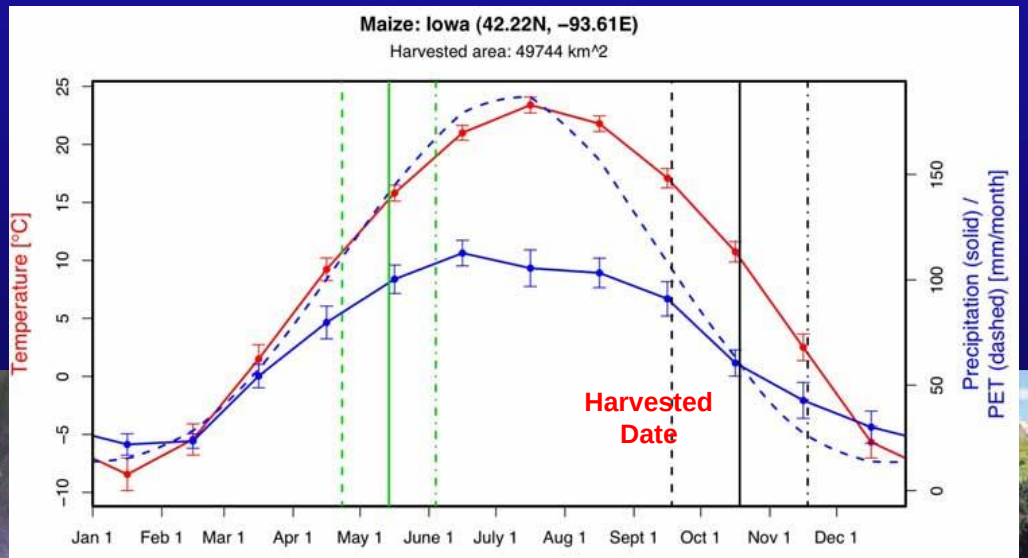
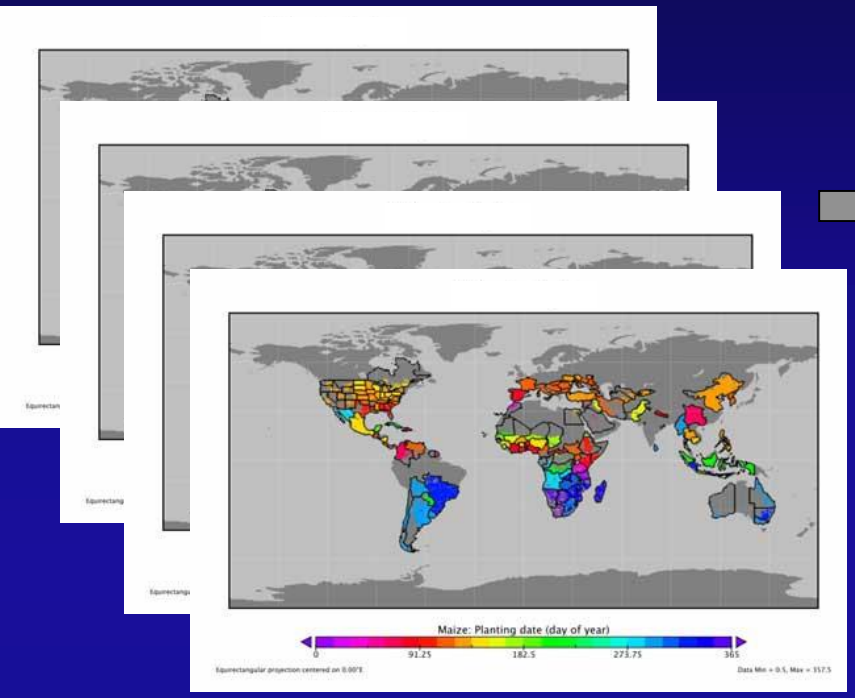
- Cotton.crop.calendar.fill.nc.harvest.end.tif
- Cotton.crop.calendar.fill.nc.harvest.range.tif
- Cotton.crop.calendar.fill.nc.harvest.start.tif
- Cotton.crop.calendar.fill.nc.harvest.tif
- Cotton.crop.calendar.fill.nc.index.tif
- Cotton.crop.calendar.fill.nc.plant.end.tif

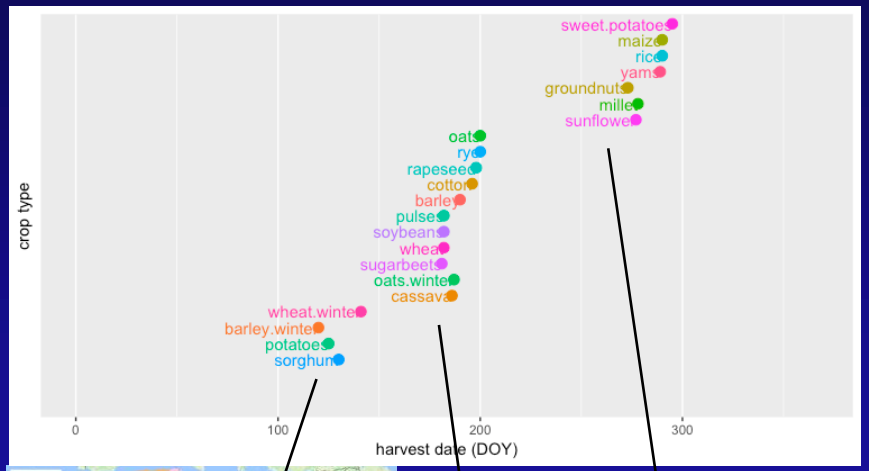


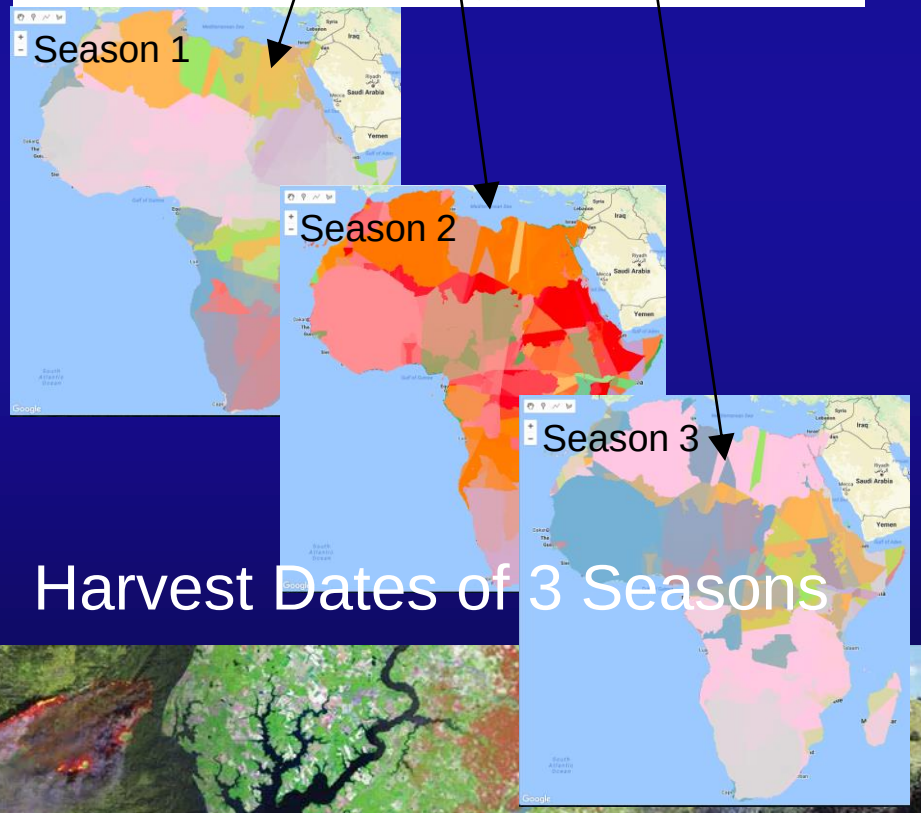


5min Harvest Dates Map (3 seasons)



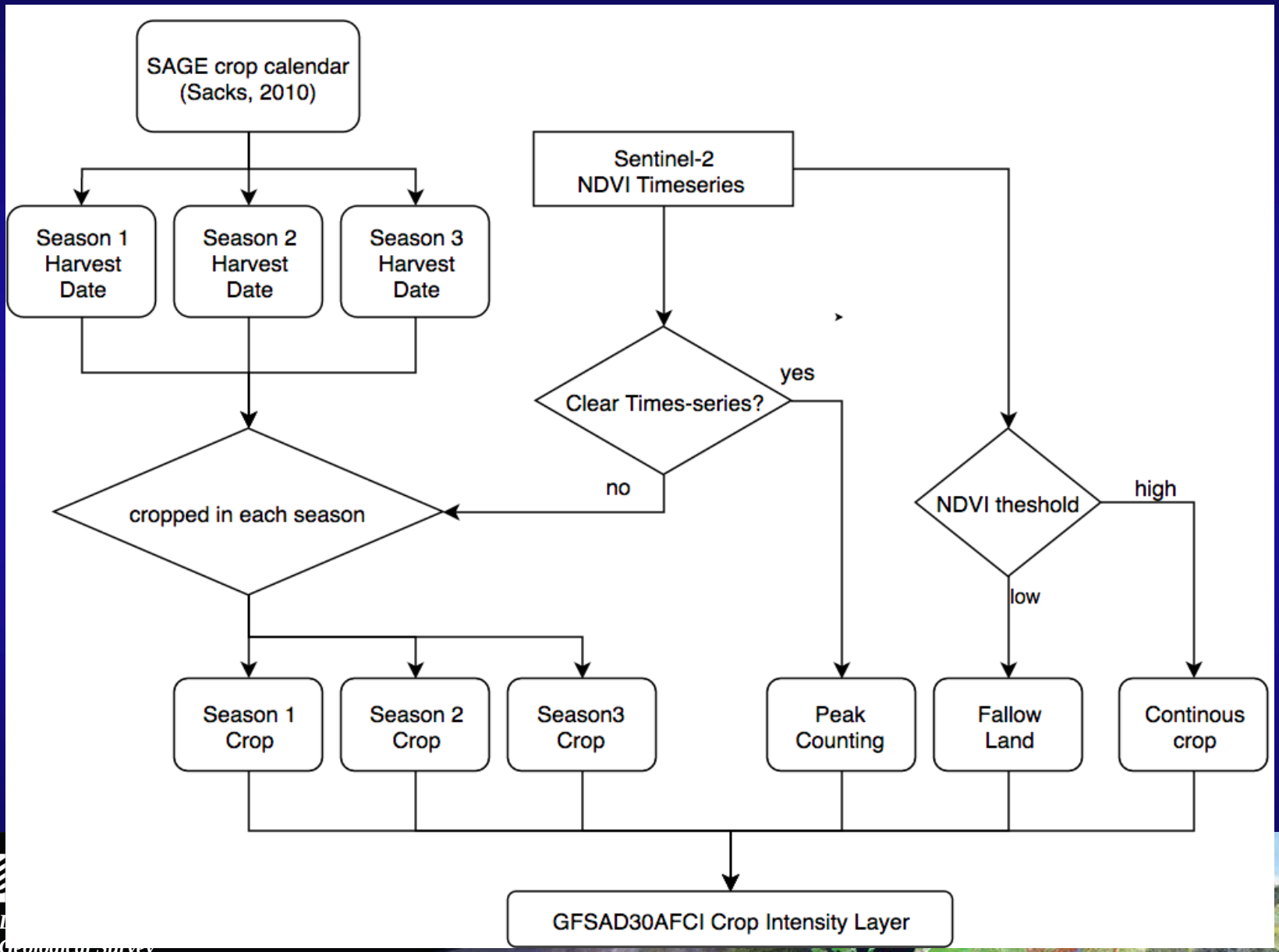
All 25 Crops Calendar Maps from Sage



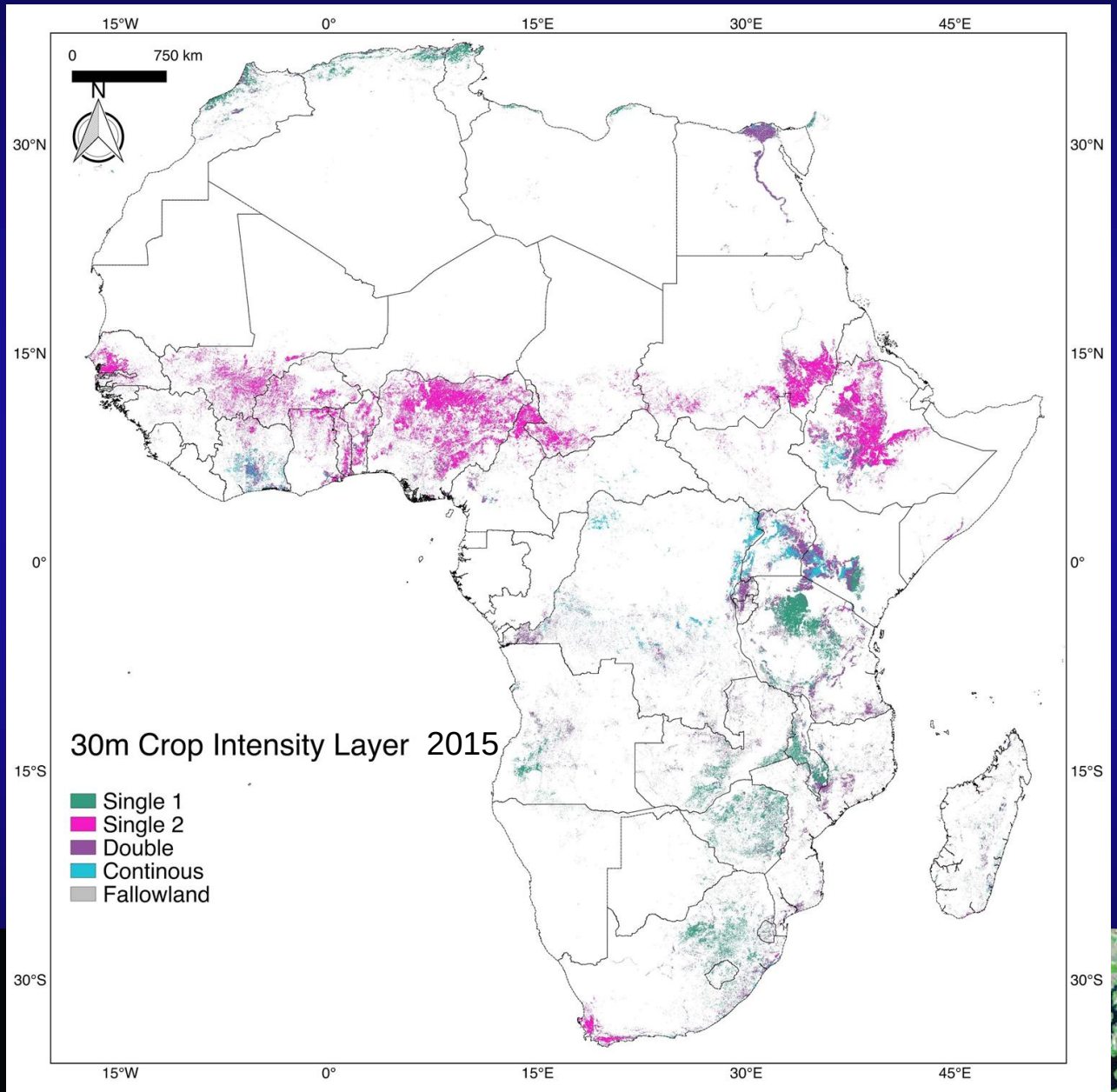


Harvest Dates of 3 Seasons

Flowchart of Crop Intensity Mapping



Demo 3: GFSAD30AFCI

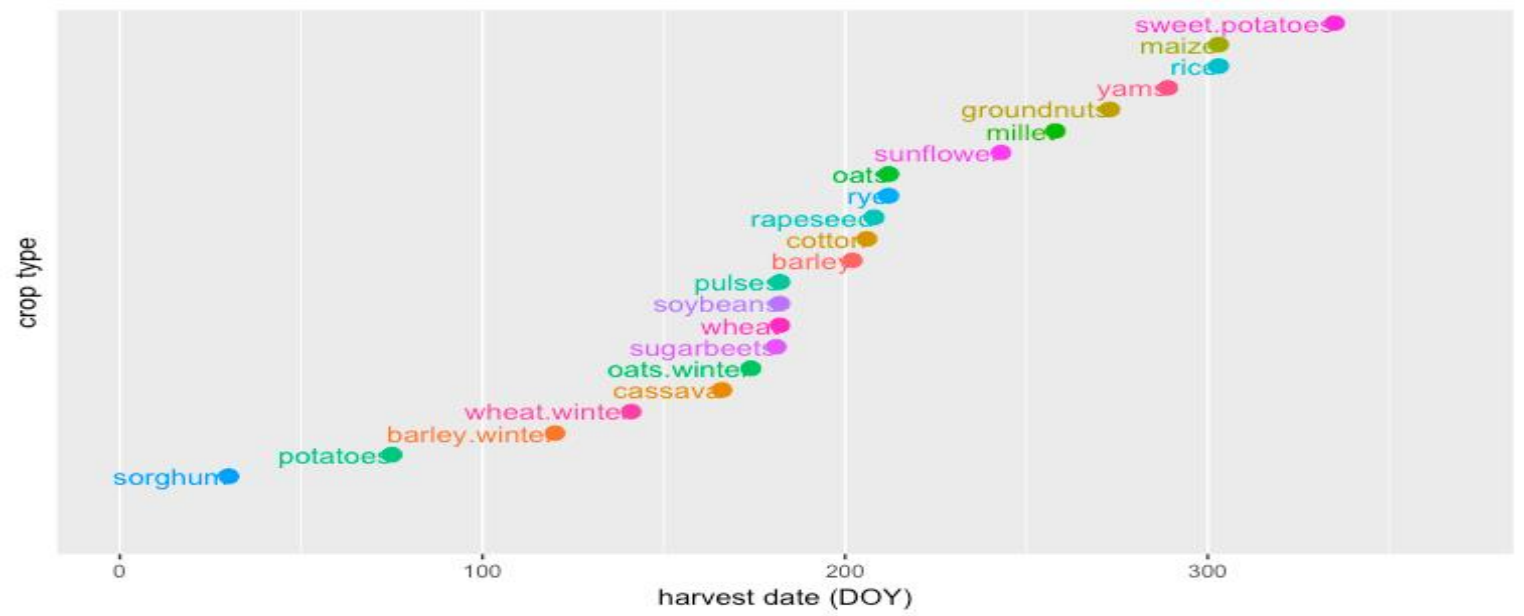


Crop Intensity Class	Area Mha	Percent %
Single 1	62.797	20.73%
Single 2	124.393	41.06%
Double	80.079	26.43%
Continuous	23.592	7.79%
Fallow-land	12.093	3.99%
Total Cropland	302.955	

Xiong J, Thenkabail PS, Teluguntla, P., et al. Mapping Cropping Intensity of Smallholder Farms Globally using Google Earth Engine. Journal TBD. 2017;(In Preparation).

Demo and Known Issues

- Gaps in satellite time series
- Mapping of fallow-land & continuous crops
- Evaluation & Validation
- Uncertainty in Crop Calendar data



Does Crop Intensity Help Mapping Type?

- Given Crop Intensity Information, are we able to map crop type in separate seasons?

or

- We can use Crop Intensity Layer as mask to filter out some spectrum-based misclassification?

Crop Type: Case Study in Tunisia

Harvest Periods

Class	MIRCA(ha)	%	Code	Jan	Feb Mar	Apr	May Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barley/Wheat	775925	45.78%	1										
Fababean	1816	0.11%	2										
Fodder	181572	10.71%	3										
Oats	2717	0.16%	4										
Orchard	722002	42.60%	5										
Sunflowers	10726	0.63%	6										






Crop Type: Case Study in Tunisia

Bands used, converted to TOA

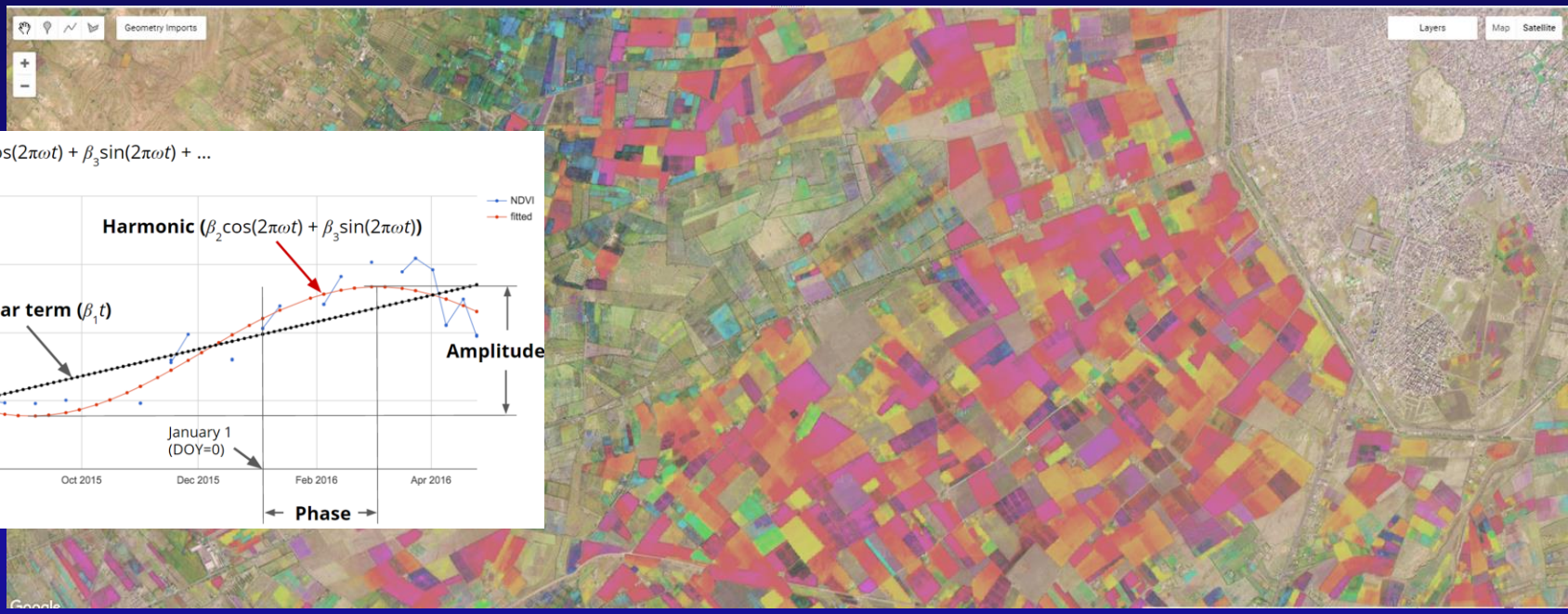
Sensors	Composite	Band	Use	Layer
Sentinel-2 MSI	March - Apri	B2	Blue	1
		B3	Green	2
		B4	Red	3
		B8A	Near Infrared	4
Sentinel-2 MSI	May - Jun	B2	Blue	5
		B3	Green	6
		B4	Red	7
		B8A	Near Infrared	8
Sentinel-2 MSI	Sep - Oct	B2	Blue	9
		B3	Green	10
		B4	Red	11
		B8A	Near Infrared	12
Sentinel-2 MSI		Phase of NDVI Timeseries	Temporal Signature	13

Ground Samples

Row Labels	Count of croptype
Barley/Wheat	117
Fababean	11
Fodder	10
Non-cropland	37
Oats	9
Olive	1
Orchard	112
Vegetable	14
(blank)	
Grand Total	**311**

Class	MIRCA(ha)	%	Code	Harvest Periods: Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barley/Wheat	775925	45.78%	1												
Fababean	1816	0.11%	2												
Fodder	181572	10.71%	3												
Oats	2717	0.16%	4												
Orchard	722002	42.60%	5												
Sunflowers	10726	0.63%	6												

Phase of NDVI time series



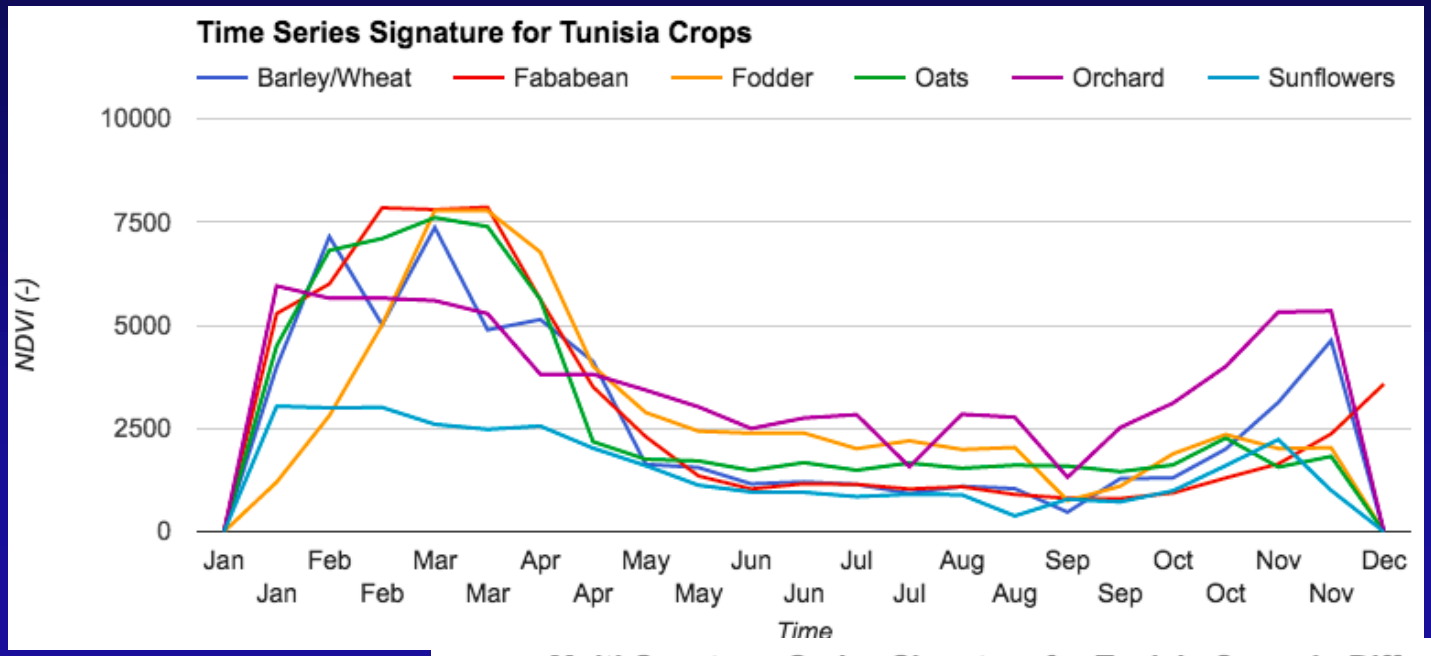
pro

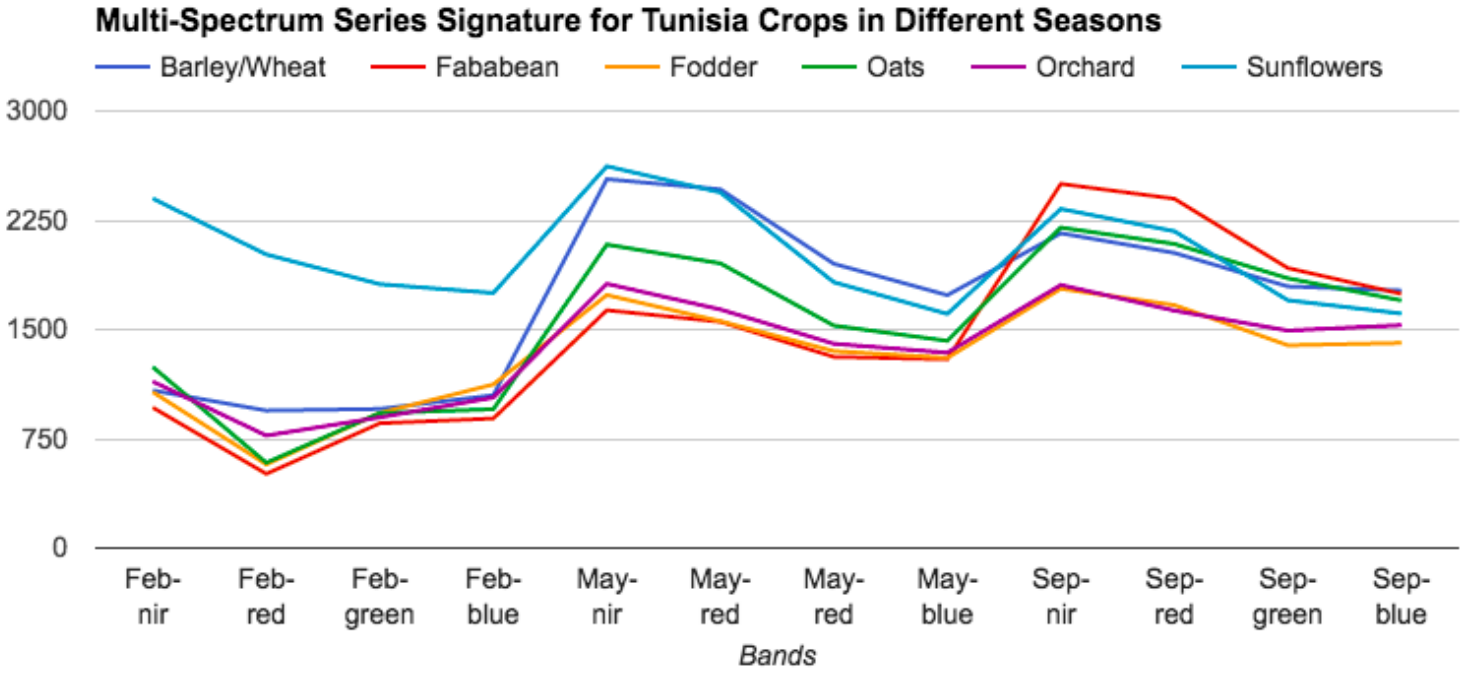
- good way to visualize phase layer
- provide temporal input
- fix missing data partly

con

- uncertainty with cloudy data
- unknown weight if used with spectrum bands

Signature





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U.S. Department of the Interio
U.S. Geological Survey

Tunisia Crop Type Map (Demo 4)

Class	MIRCA(ha)	%	GFSAD	%
Barley/Wheat	775,925	45.78%	654,113	37.28%
Fababean	1,816	0.11%	73,034	4.16%
Fodder	181,572	10.71%	72,497	4.13%
Oats	2,717	0.16%	66,113	3.77%
Orchard	722,002	42.60%	874,682	49.86%
Sunflowers	10,726	0.63%	13,967	0.80%

- Apply Continuous Crop Intensity in classified orchard area

Random Forest Classification

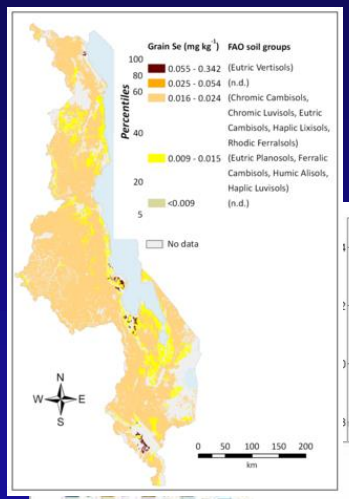
	Barley/Wheat	Orchard	Total	UA
Barley/Wheat	31	8	39	79.49%
Orchard	13	32	45	71.11%
Total	44	40		
PA	70.45%	80.00%		

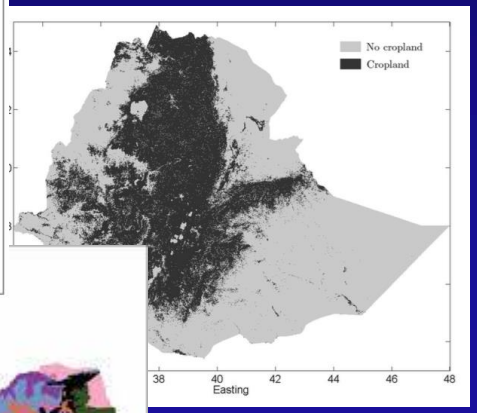
Apply "Continuous" Crop

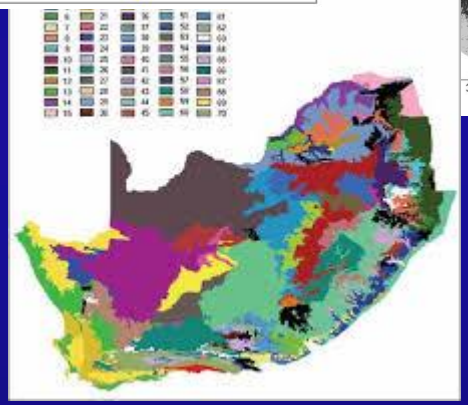
	Barley/Wheat	Orchard	Total	UA
Barley/Wheat	31	8	39	79.49%
Orchard	9	32	41	78.05%
Total	40	40		
PA	77.50%	80.00%		

Crop Type: Literature Review

- ✓ Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data
  J Meghan Salmon et al. | International Journal of Applied Earth Observation and Geoinformation, 2015 vol. 38 pp. 321-334
- ✓ Crop area mapping in West Africa using landscape stratification of MODIS time series and comparison with existing global land products
  E Vintrou et al. | International Journal of ..., 2012 vol. 14 (1) pp. 83-93
- ✓ Estimating Global Cropland Extent with Multi-year MODIS Data
  Kyle Pittman et al. | Remote Sensing, 2010 vol. 2 (7) pp. 1844-1863
- ✓ Comparison of global and regional land cover maps with statistical information for the agricultural domain in Africa
  Steffen Fritz et al. | International Journal of Remote Sensing, 2010 vol. 31 (9) pp. 2237-2256
- ✓ Crop planting dates: an analysis of global patterns
  William J Sacks et al. | Global Ecology and ..., 2010 pp. no-no
- ✓ Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium
  Prasad S Thenkabail et al. | International Journal of Remote Sensing, 2009 vol. 30 (14)
- ✓ Accurate mapping of forest types using dense seasonal Landsat time-series
  Xiaolin Zhu and Desheng Liu | ISPRS Journal of Photogrammetry and Remote Sensing, 2014 vol. 96 pp. 1-11
- ✓ Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services
  M Drusch et al. | Remote Sensing of Environment, 2012 vol. 120 pp. 25-36
- ✓ Mapping rice areas of South Asia using MODIS multitemporal data
  Murali Krishna Gumma et al. | Journal of Applied Remote Sensing, 2011 vol. 5 (1) pp. 053547-053547-26
- ✓ Mapping cropland extent at 30-m resolution using Google Earth Engine and its application for Continental Africa
  2016 pp. 1-15
- ✓ Land Cover Characterization in West Sudanian Savannas Using Seasonal Features from Annual Landsat Time Series
  Jinxiu Liu et al. | Remote Sensing, 2016 vol. 8 (5) p. 365
- ✓ Understanding the Spatial Temporal Vegetation Dynamics in Rwanda
  Felix Ndayisaba et al. | Remote Sensing, 2016 vol. 8 (2) p. 129
- ✓ Production of a Dynamic Cropland Mask by Processing Remote Sensing Image Series at High Temporal and Spatial Resolutions
  Silvia Valero et al. | Remote Sensing, 2016 vol. 8 (1) p. 55
- ✓ Global land cover share (GLC-SHARE) database beta-release version 1.0-2014
  J Latham et al. | FAO: Rome, 2014
- • A Comparative Study on Satellite- and Model-Based Crop Phenology in West Africa
  Elodie Vintrou et al. | Remote Sensing, 2014 vol. 6 (2) pp. 1367-1389







~60 research papers/reports about regional crop type mapping in Africa since 2004, in South Africa, Rwanda, Ethiopia, Malawi, Mali, Egypt, etc.

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Discussion: Data preprocessing

- Good practises on preprocessing with GEE's support, including and not limited to:
  - cloud mask
  - gap-filling
  - smooth
  - harmonizing of Sentinel-2 and Landsat

Discussion: Mapping & Validation

- Accurate Description of Continuous Crop, Cropland fallow

- Understand 'Uncertainty' better:
  - Uncertainty existing in input data on specific purpose (Crop Intensity, Crop Type), QC1 band
  - Uncertainty in classification methodology, QC2 band
  - Uncertainty in segmentation (?)
- Comprehensive accuracy of the products

Thank you!

Documentation: https://developers.google.com/earth-engine/

JavaScript Playground: https://code.earthengine.google.com/

Classical approach

1. pick a region
2. set the targets (how many primary crops, in how many seasons)
3. investigate the separability (input features, how many features)
4. data mining the knowledge based on reference dataset
5. build the classifiers
6. classification and accuracy assessment
7. no flexibility for training, all kinds of over/under-estimation
8. when you add a sample, you have to tell what kind of crop type it is.

single crop

1. pick a region (South Africa)
2. set the targets (how many primary crops, in how many seasons)
3. investigate the separability (input features)
4. flexibility: append training samples by image-interpretation as we need
5. when you add a sample, you just need to tell whether it belongs to current crop type.
6. These samples can be reused in other classification.

Outlines

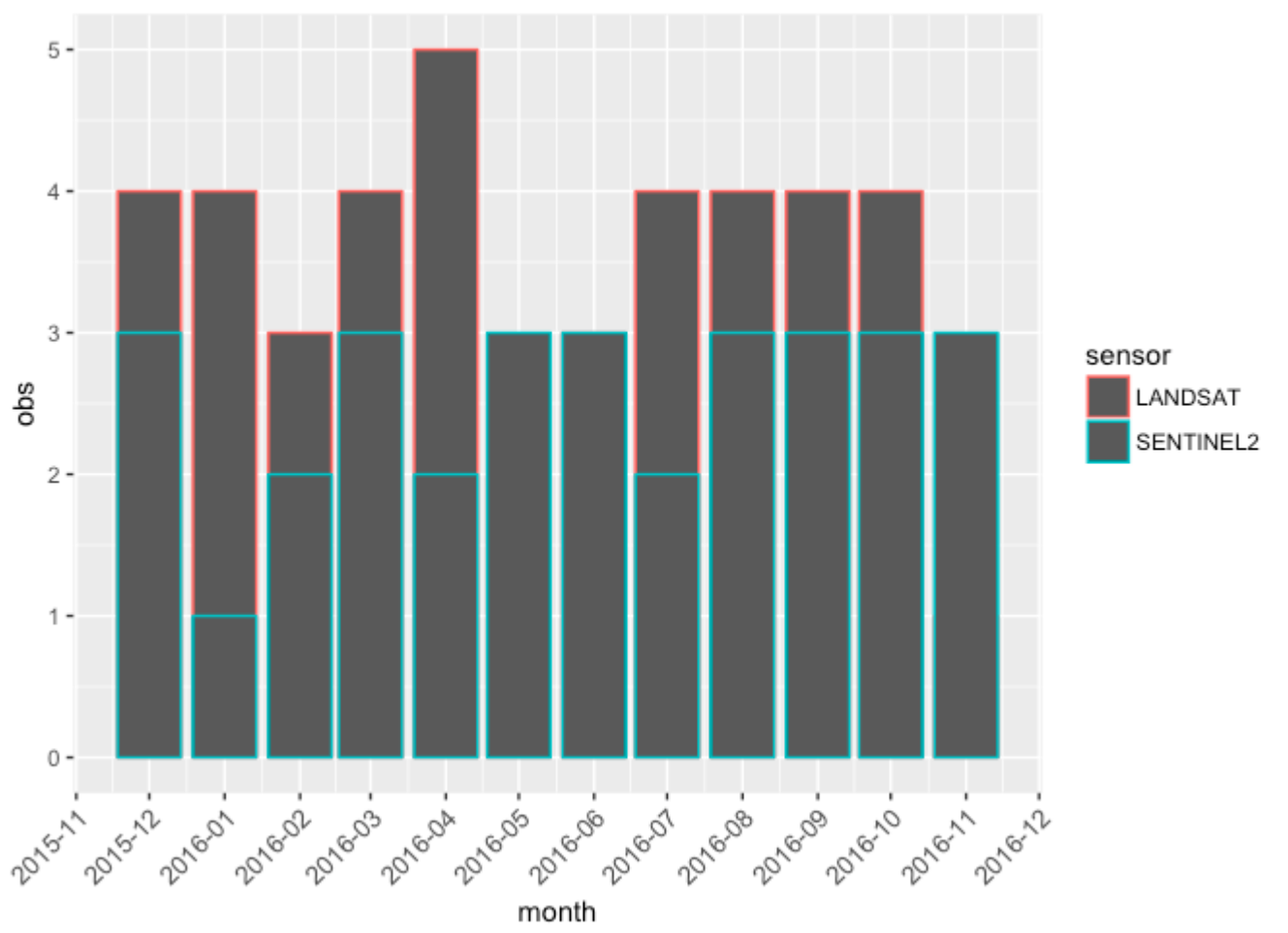
30-m Crop Extent Map
Study area
Data
- Landsat + sentinel
- table satellite data
- Table reference data

MLAs
Knowledge for MLAs
GEE cloud computing
Results
Africa 30-m cropland extent
Accuracy
Comparison with other products
- Spatial
- Area

Discussions
- how much cropland exists in Africa @ present relative to land area
- which are big countries
- area vs. productivity
- uncertainties

30-m Crop Intensity Map
30-m Maize Map of Africa
30-m Sorghum Map of Africa

Sentinel-2 + Landsat



Crop Intensity Layer @ 30m (GFSAD30AFCI)

Demo: MODIS vs. Sentinel-2 (script)

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science for a changing world

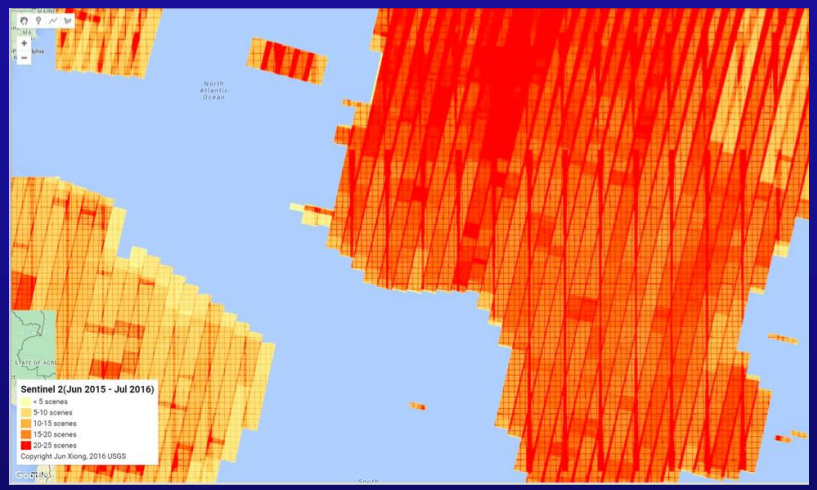
Mapping Global Cropland Dynamics Africa: Crop Extent, Intensity and Types

Jun Xiong

Feb 7th, 2017

Harvesting millet in northern Uganda. *Image: DFID via Flickr*

Sentinel-2 MSI

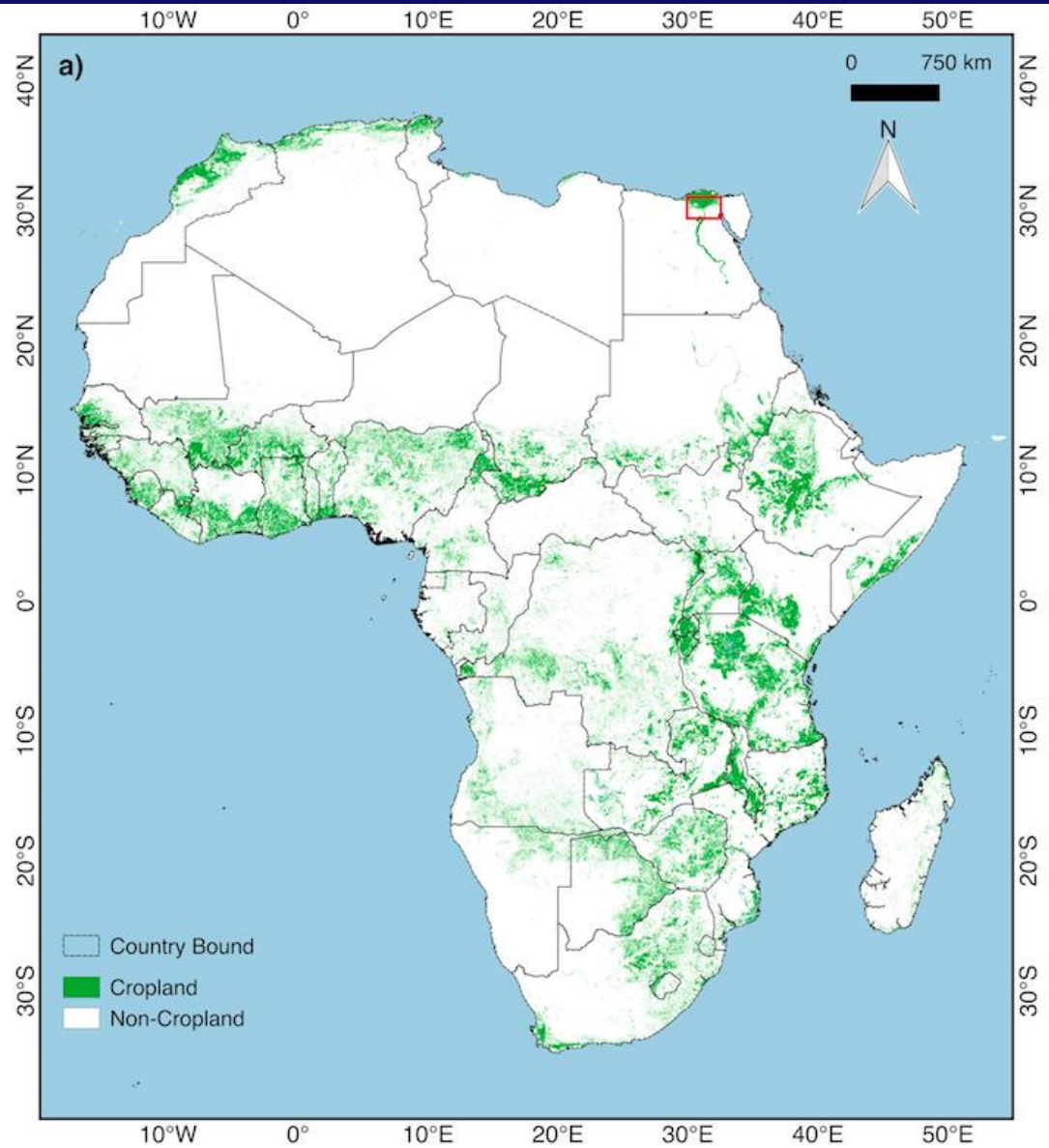


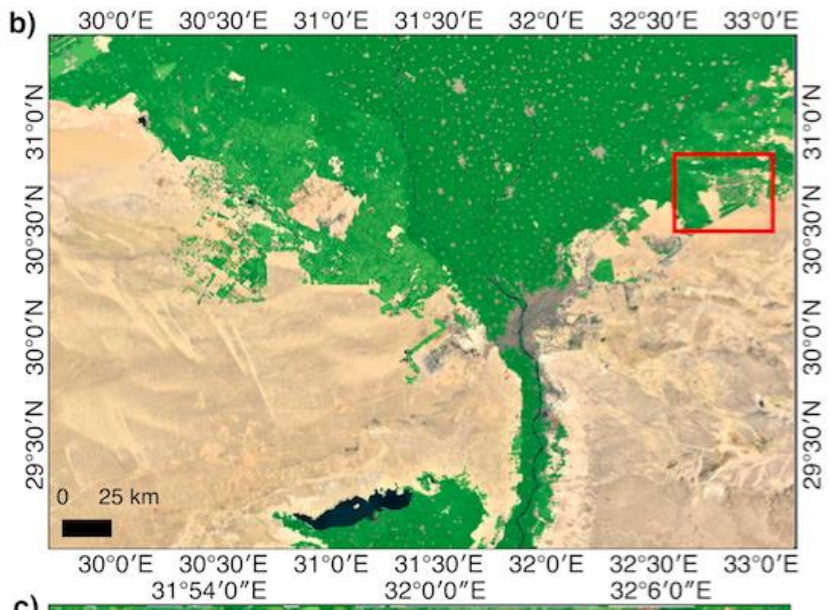
Feature	Description
Spacecrafts	2 operating in twin configuration
Instrument	MSI (Multi-Spectral Instrument) operating in pushbroom principle (filter based optical system)
Spectral bands	13 (VIS–NIR–SWIR)
Spatial Resolution	10m / 20m / 60m
Swath	290 km
Orbit	Sun-synchronous at 786 km (14+3/10 revs per day), with LTDN 10:30 AM
Revisit Periodicity	10-day with 1 satellite 5 day with 2 satellites
Lifetime	7.25 years, extendable to 12 years
Launch	**June 2015**

Available on Earth Engine

Crop Extent Layer @30m (GFSAD30AFCE)

Demo of 1km, 250m, 30m





Hybrid of classification and segmentation

Summary

Progress Chart, Next Action

Products	Shortname	Validation	LP DAAC Doc	Viewable on Croplands.org	Title of Manuscript	Journal	Manuscript Status
Africa 250m	GFSAD250AF	Done	Revision	Done	Automated Cropland Mapping of Continental Africa using Google Earth Engine Cloud Computing	ISPRS	Accepted
Crop Extent @30m	GFSAD30AFCE	Second Round	Revision	Done	A Nominal 30-m Cropland Extent of Continental Africa Using Sentinel-2 data by Integrating Pixel-based Classification and Hierarchical Segmentation Approach	RSE	Submission
Crop Intensity @30m	GFSAD30AFCI				Mapping cropping intensity of smallholder farms globally using Google Earth Engine	TBD	In Preparing
GFSAD30 Reference Data	GFSAD30Ref	---			Reference Datasets and techniques to improve global cropland mapping"	TBD	In Preparing

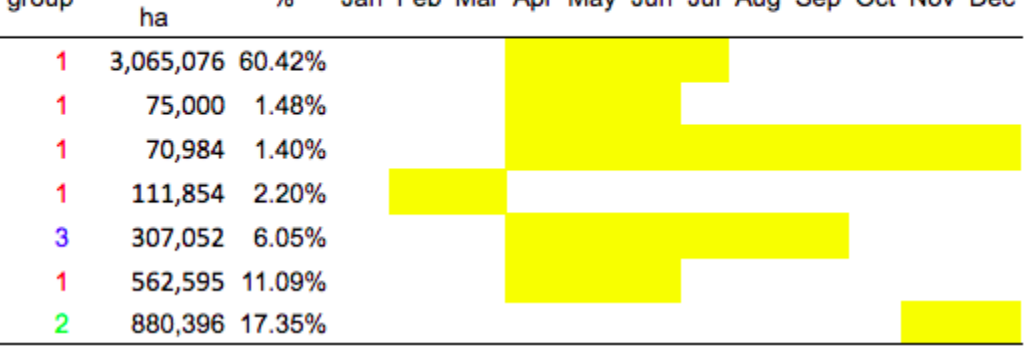
Staged
Done
In Processing

@article{Xiong:2017afci,
author = {Xiong, Jun and Thenkabail, P S and {Gumma, M.} and Teluguntla, P and {Poehnelt, J.} and {Congalton, R.} and Yadav, K},
title = {{Mapping Cropping Intensity of Smallholder Farms Globally using Google Earth Engine}},
journal = {Journal TBD},
year = {2017},
volume = {(In Preparation)}
}

Crop Type: Case Study in Tunisia

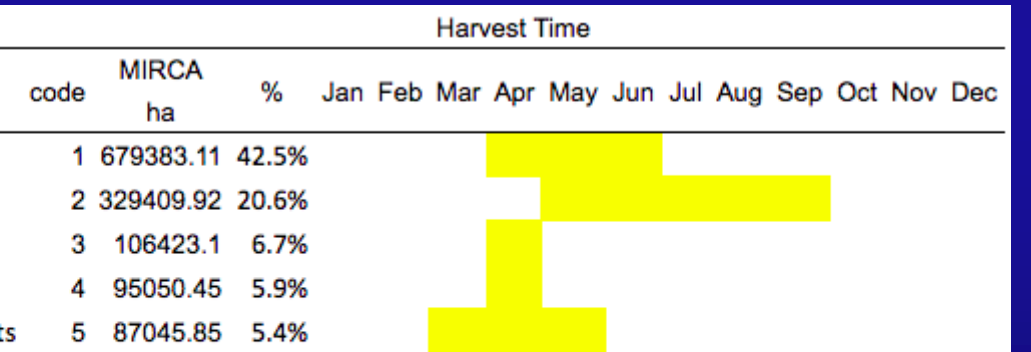
South Africa

Type	code	group	MIRCA ha	%
Corn	1	1	3,065,076	60.42%
Cotton	2	1	75,000	1.48%
Oranges	3	1	70,984	1.40%
Soybean	4	1	111,854	2.20%
Sugarcane	5	3	307,052	6.05%
Sunflower	6	1	562,595	11.09%
Wheat	7	2	880,396	17.35%

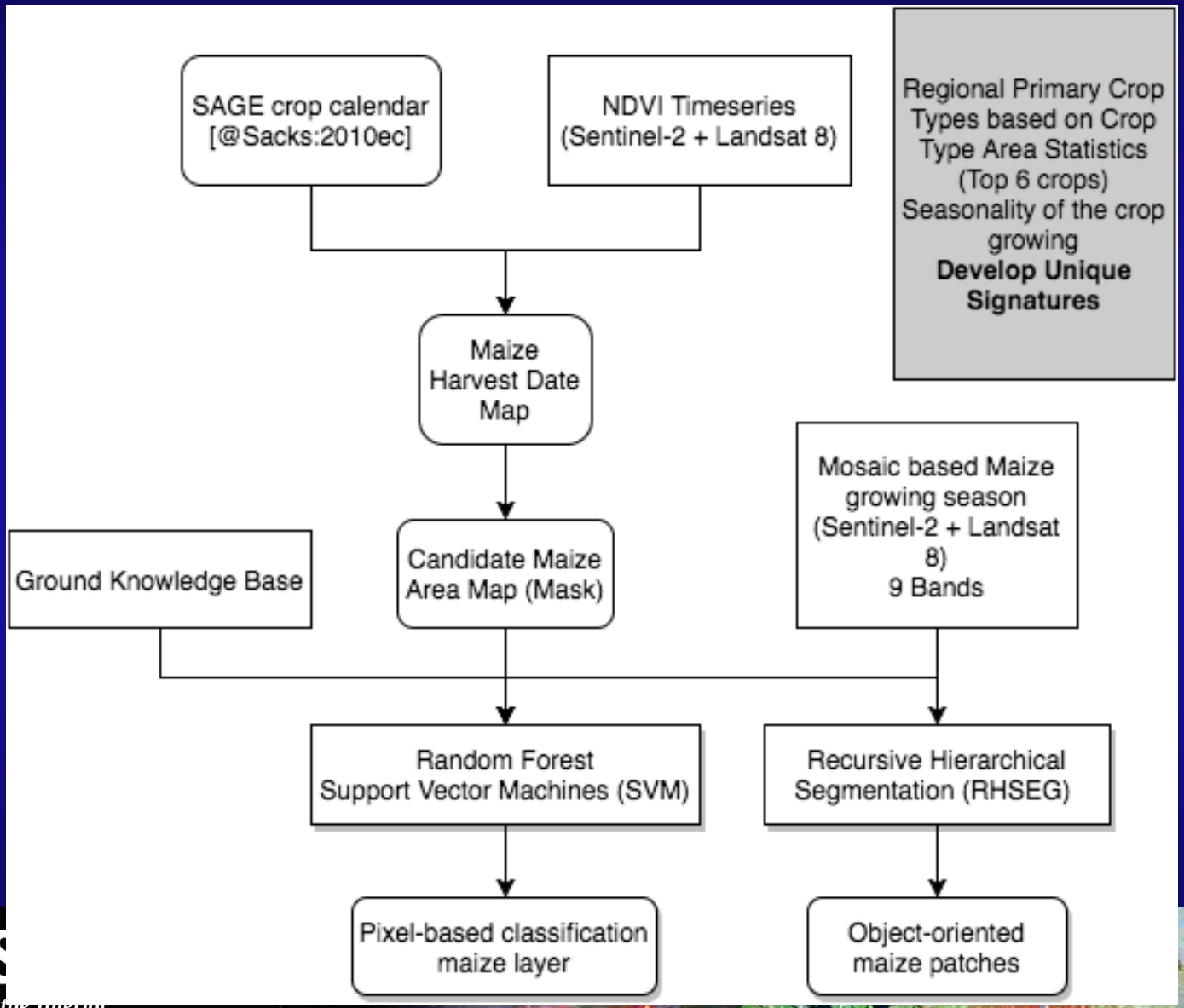


Malawi

Type	code	MIRCA ha	%
Maize	1	679383.11	42.5%
Pulses	2	329409.92	20.6%
Potatoes	3	106423.1	6.7%
Cassava	4	95050.45	5.9%
Groundnuts / Peanuts	5	87045.85	5.4%
Cotton	6	37144.58	2.3%
Rice	7	28390.08	1.8%
Sorghum	8	23755.15	1.5%
Sugarcane	9	21685	1.4%



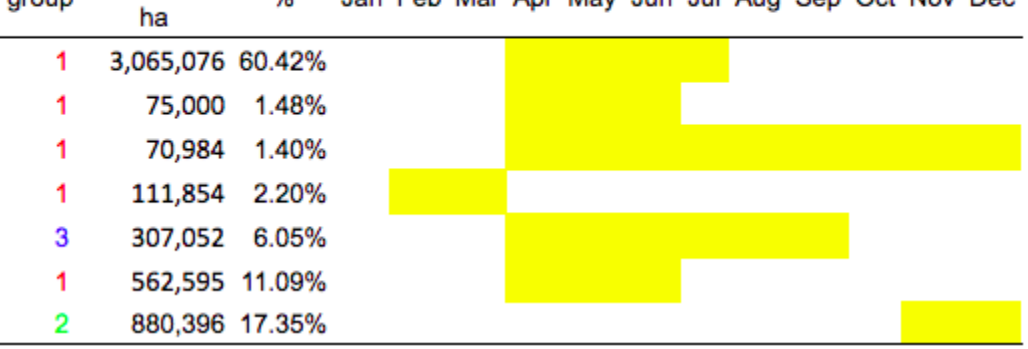
Flowchart


SAGE crop calendar [@Sacks:2010ec]
NDVI Timeseries (Sentinel-2 + Landsat 8)
Regional Primary Crop Types based on Crop Type Area Statistics (Top 6 crops) Seasonality of the crop growing
Develop Unique Signatures
Maize Harvest Date Map
Mosaic based Maize growing season (Sentinel-2 + Landsat 8) 9 Bands
Ground Knowledge Base
Candidate Maize Area Map (Mask)
Random Forest Support Vector Machines (SVM)
Recursive Hierarchical Segmentation (RHSEG)
Pixel-based classification maize layer
Object-oriented maize patches

Crop Type: Case Study in Tunisia

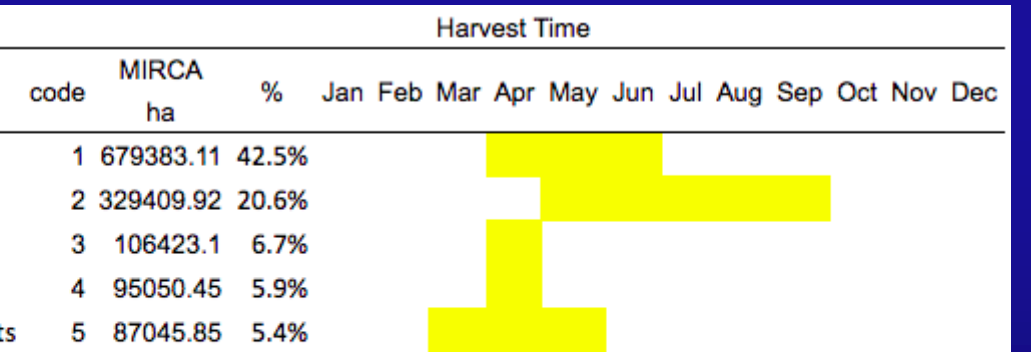
South Africa

Type	code	group	MIRCA ha	%
Corn	1	1	3,065,076	60.42%
Cotton	2	1	75,000	1.48%
Oranges	3	1	70,984	1.40%
Soybean	4	1	111,854	2.20%
Sugarcane	5	3	307,052	6.05%
Sunflower	6	1	562,595	11.09%
Wheat	7	2	880,396	17.35%



Malawi

Type	code	MIRCA ha	%
Maize	1	679383.11	42.5%
Pulses	2	329409.92	20.6%
Potatoes	3	106423.1	6.7%
Cassava	4	95050.45	5.9%
Groundnuts / Peanuts	5	87045.85	5.4%
Cotton	6	37144.58	2.3%
Rice	7	28390.08	1.8%
Sorghum	8	23755.15	1.5%
Sugarcane	9	21685	1.4%



Story of African Agriculture

Image: national geographic magazine

GFSAD30 Products

- Coarse-resolution products have limited ability to capture cropland patterns in complex landscapes.
- High Resolution Dataset (Landsat and Sentinel-2 Archive) and Petapixel Computing (Google Earth Engine) are proved to be feasible solutions to improving global cropland
- More accurate cropland can be achieved through open data sharing/hybrid solutions.
- Methodology of classification, mapping and validation will be redefined.