Ag Internet of Things, Big Data, and the Promise of Open Source for Agriculture

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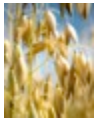
A. Balmos, E. Hawkins, M. Koester, A. Layton, S.Noel, Y. Wang, Y. Zhang

Today’s Plan

- Context / Background / Farmer Focus
- Three open source projects:
  - Mobile apps for meta data sensing
  - Isoblue / Candroid
  - The Open Ag Data Alliance
- Precision management zone estimation from multi-year yield data
- Observations on the “precision” of yield maps

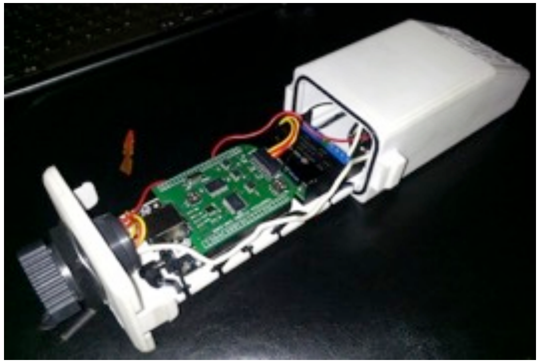


OATS Group Background

We are farmers:

- North Central Indiana (corn, soy, wheat, cattle)
- NE Colorado, Western Neb. (wheat, corn, millet, beans)

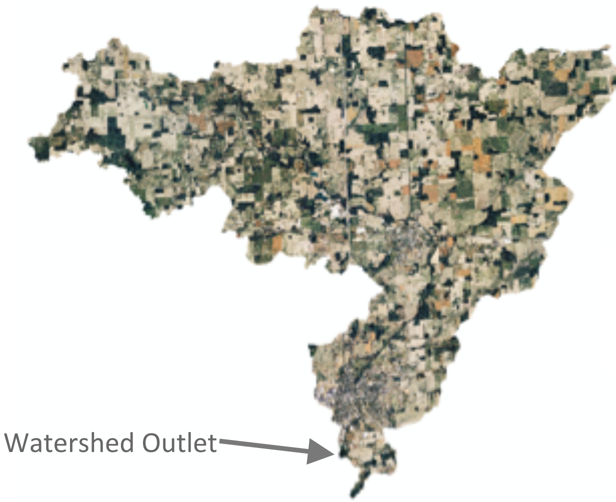
OATS Group Background



We are engineers:

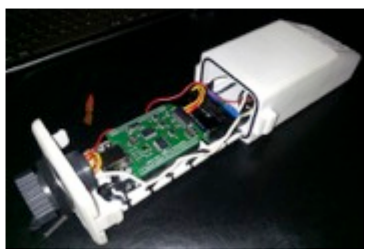
- Elec. and Comp. / Ag and Bio
- We make open source hardware and software
- We connect widgets to our machines to collect data

Three Open Source Projects



Watershed Delineation

- ❑ Mobile apps for meta data sensing
- ❑ Isoblue / Candroid



- ❑ The Open Ag Data Alliance

Mobile Apps / Autogenic Sensing

Rock

Field Work

Trello Sync

Elevations

Watershed Delineation

Spraying

Planting

Field Notebook

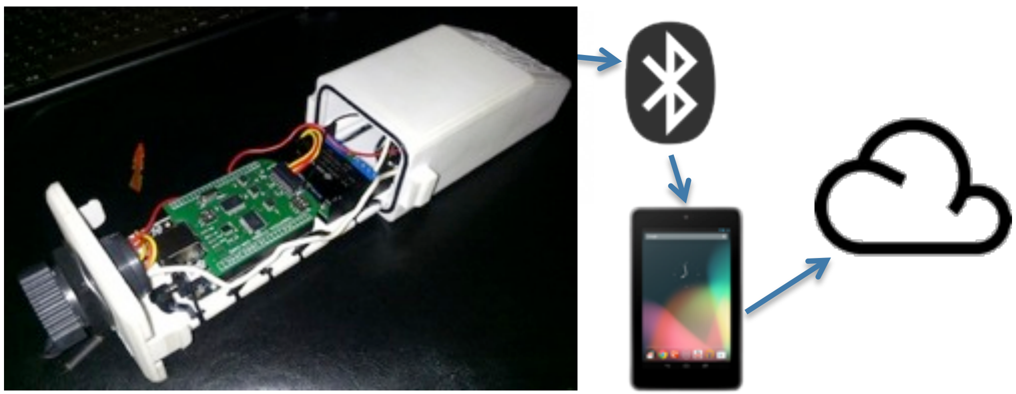
Coming Soon...

Machinery

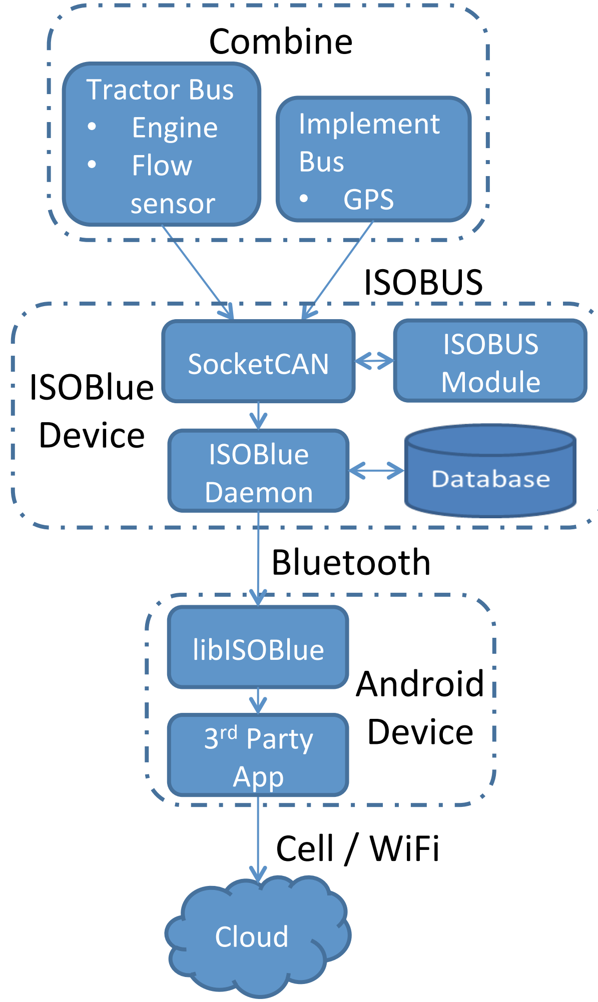
OADA Sync

Open Ag Toolkit: http://openagtoolkit.org

Real Time Internet of Things: Isoblue and CANDroid



ISOBlue Data Flow



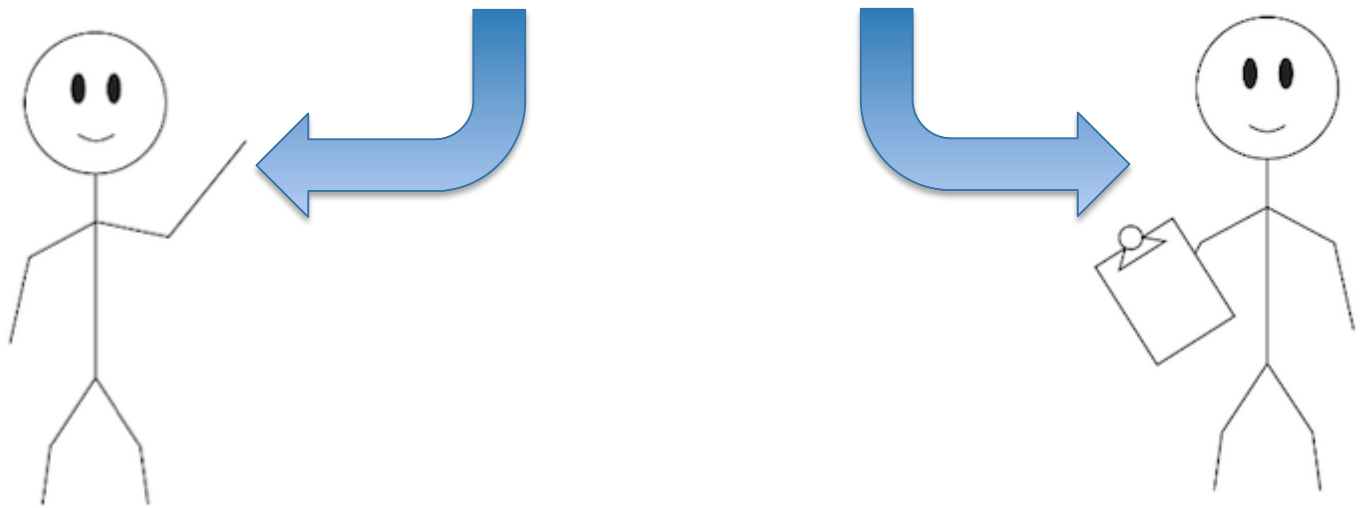
Isoblue: http://isoblue.org

The Open Ag Data Alliance:
http://openag.io

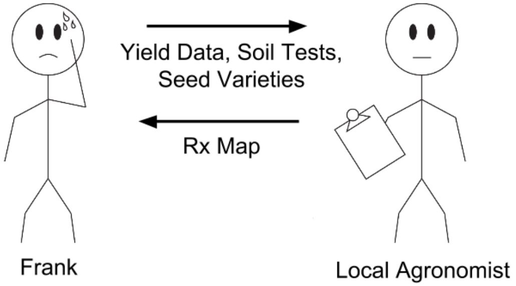
Ag Data Today: An Example

Prescription Planting Maps

Meet Frank and Andy.



Data Today: An Example



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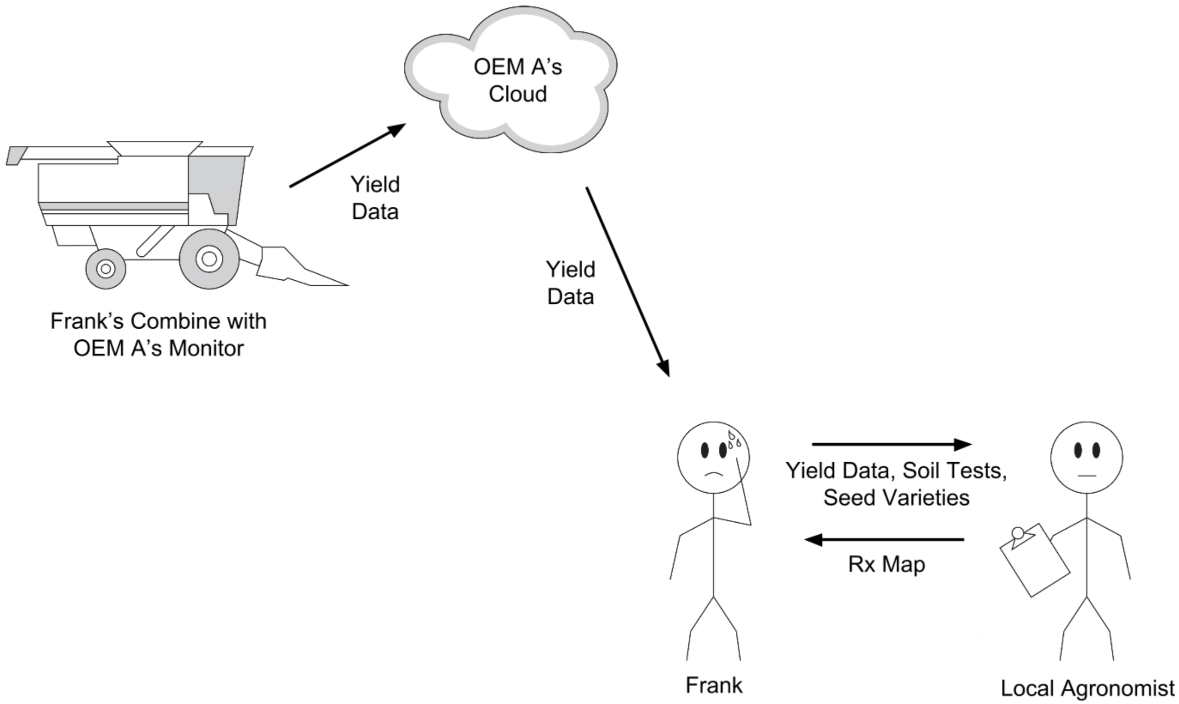

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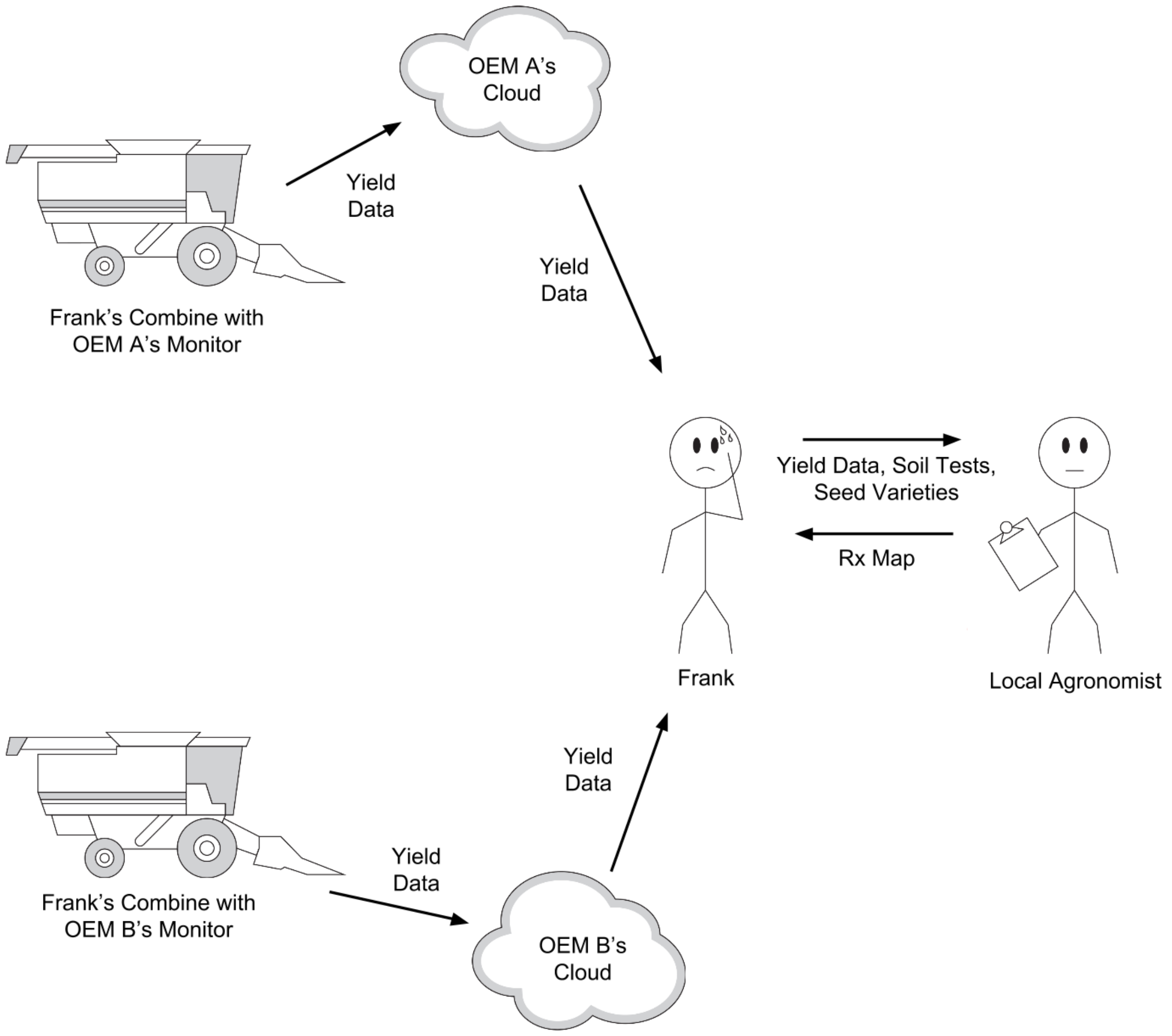

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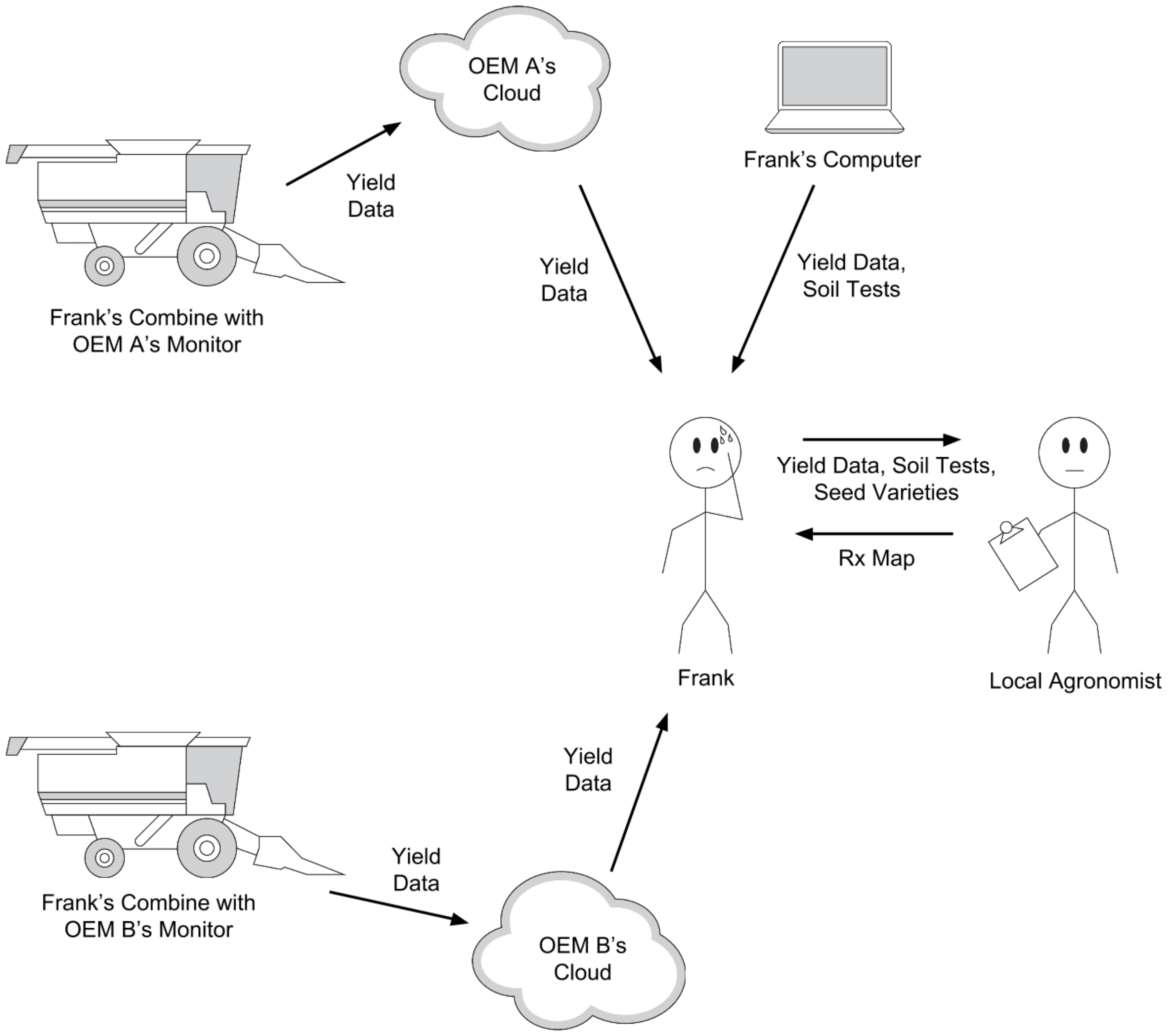

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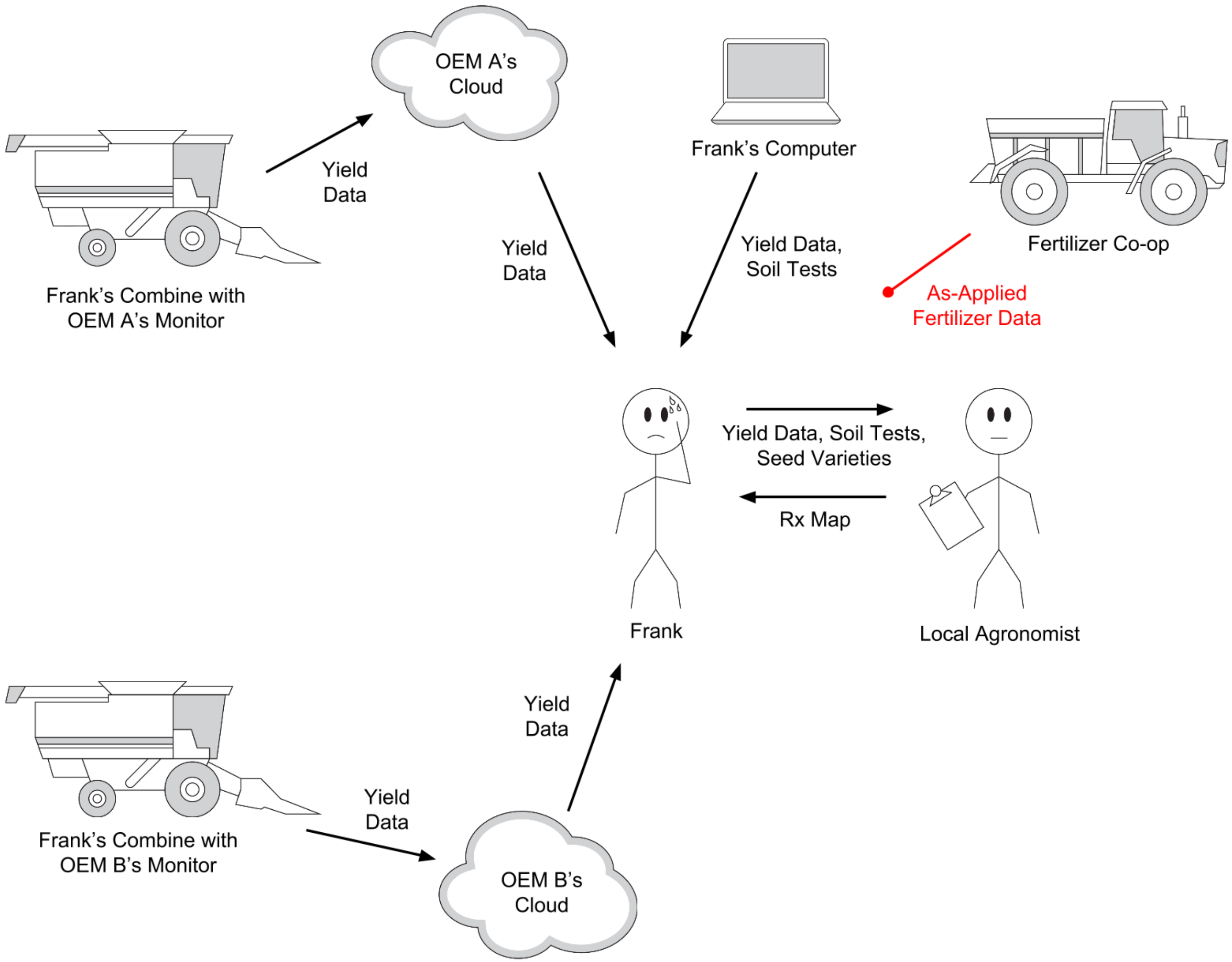

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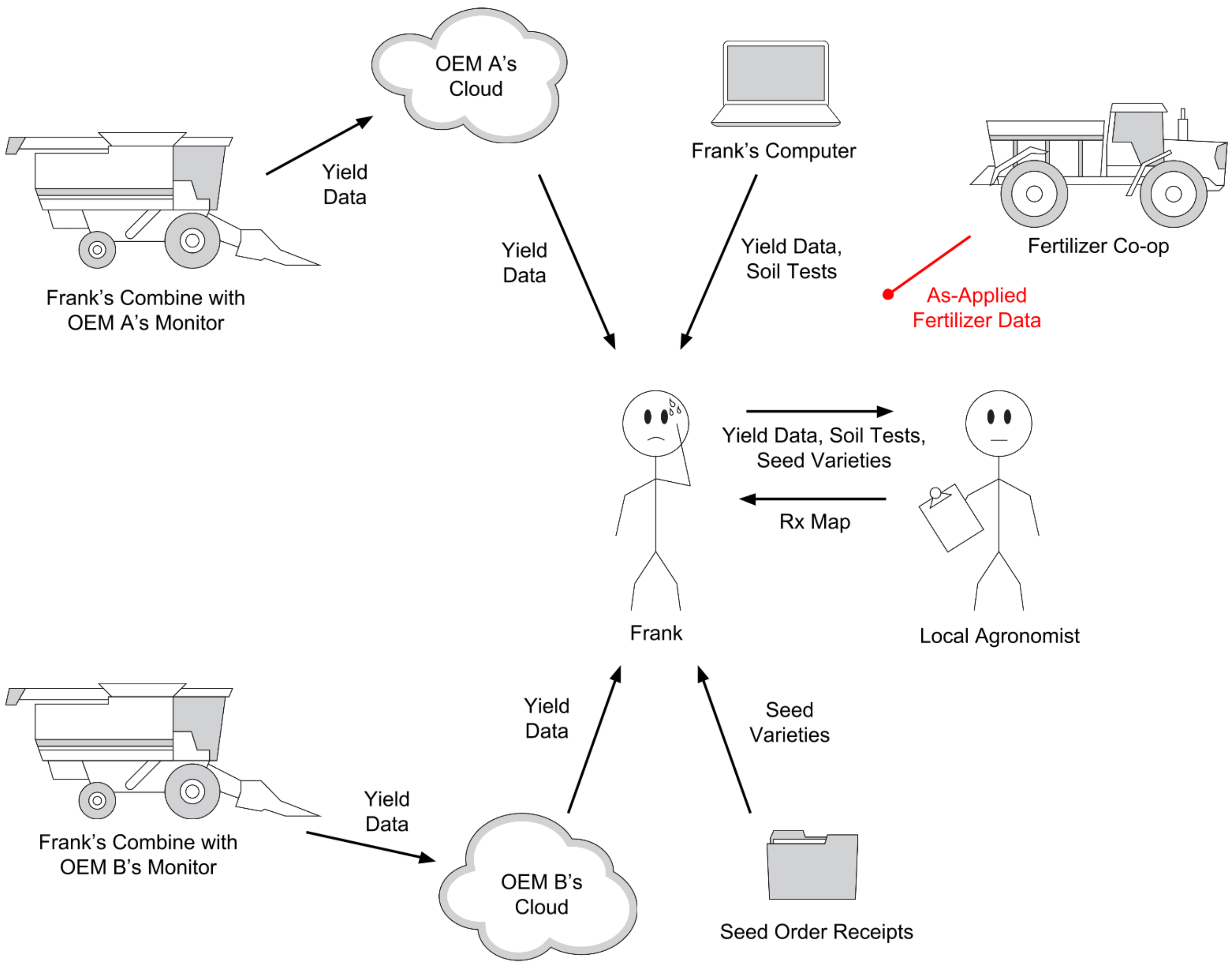

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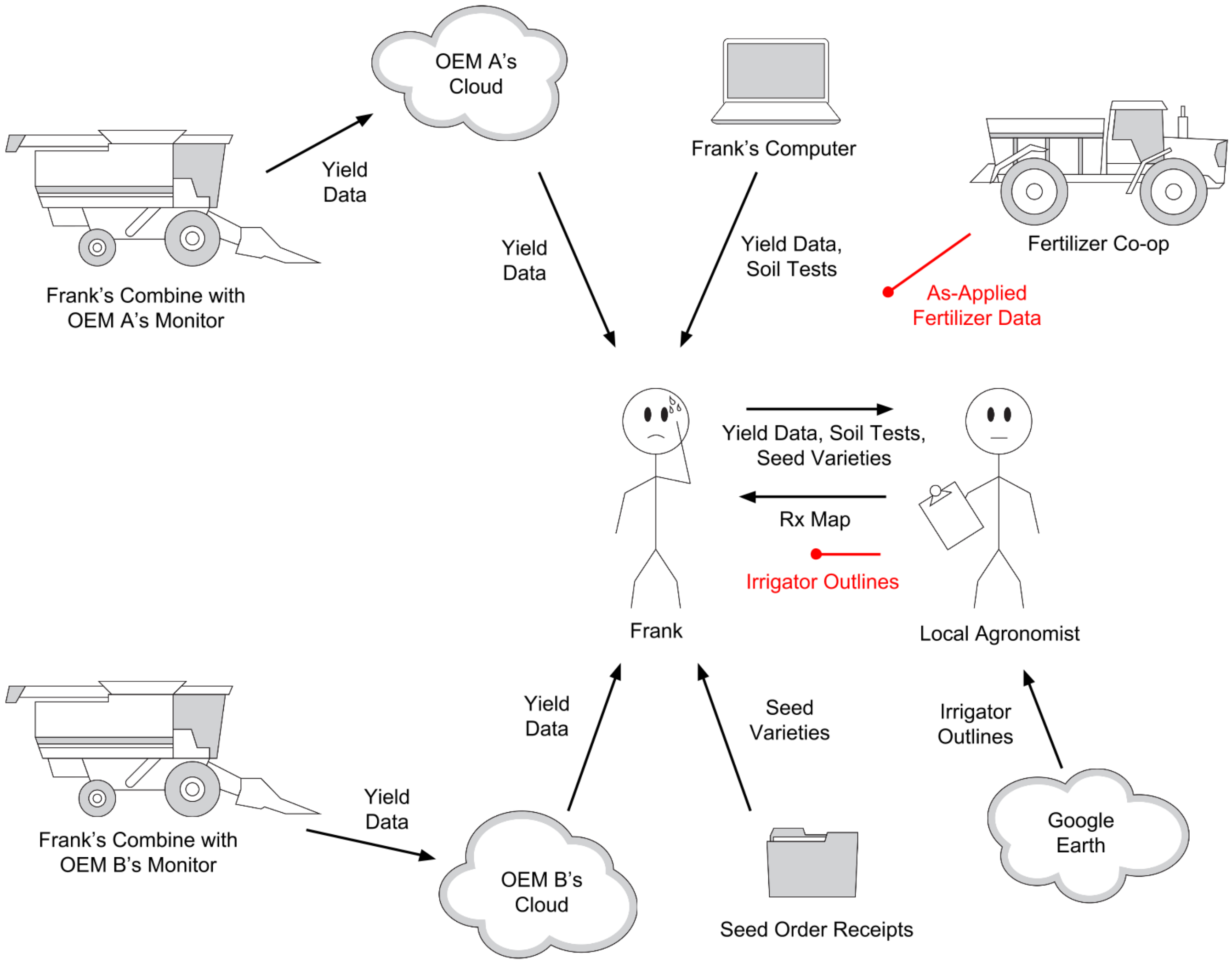

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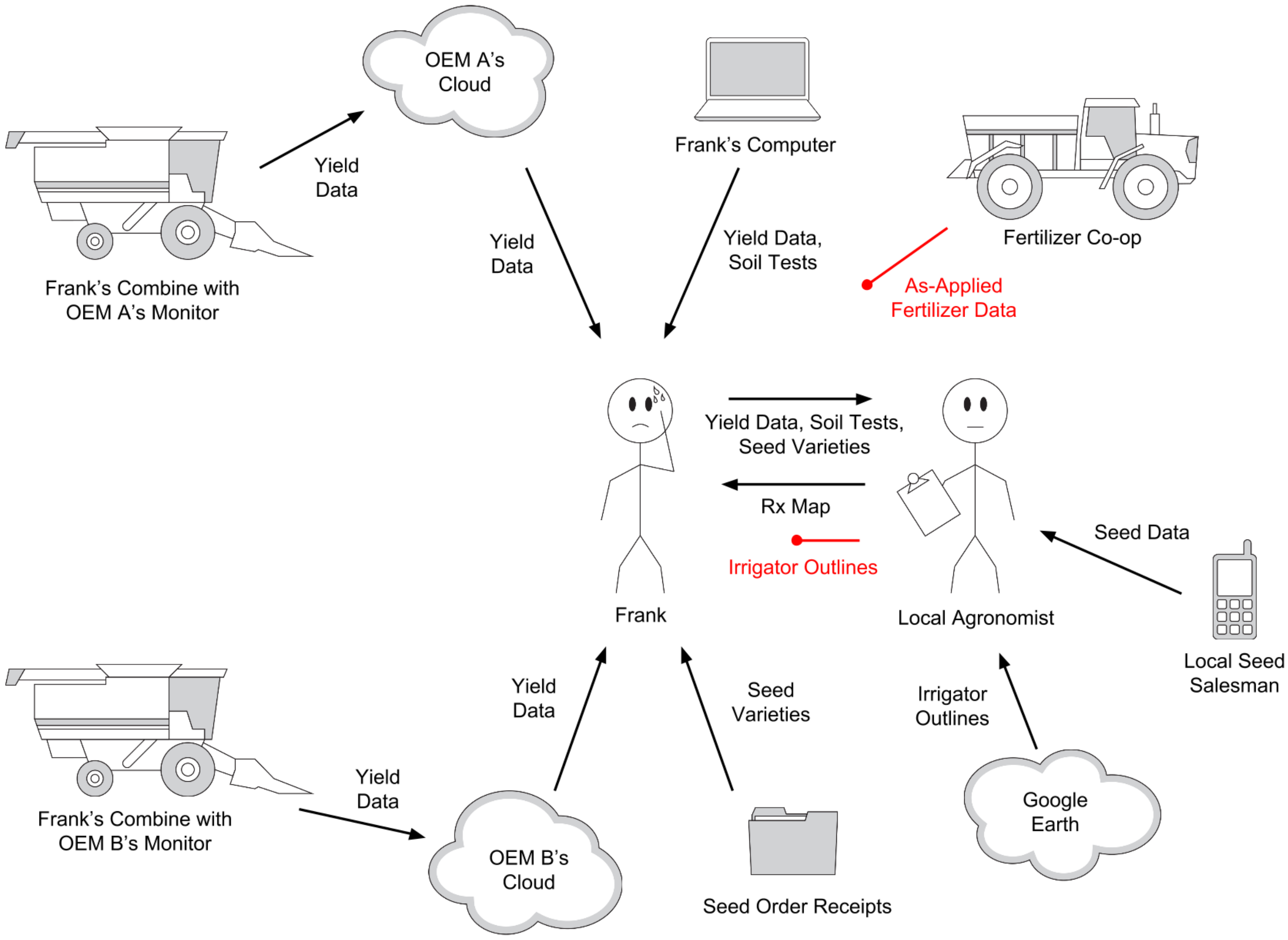

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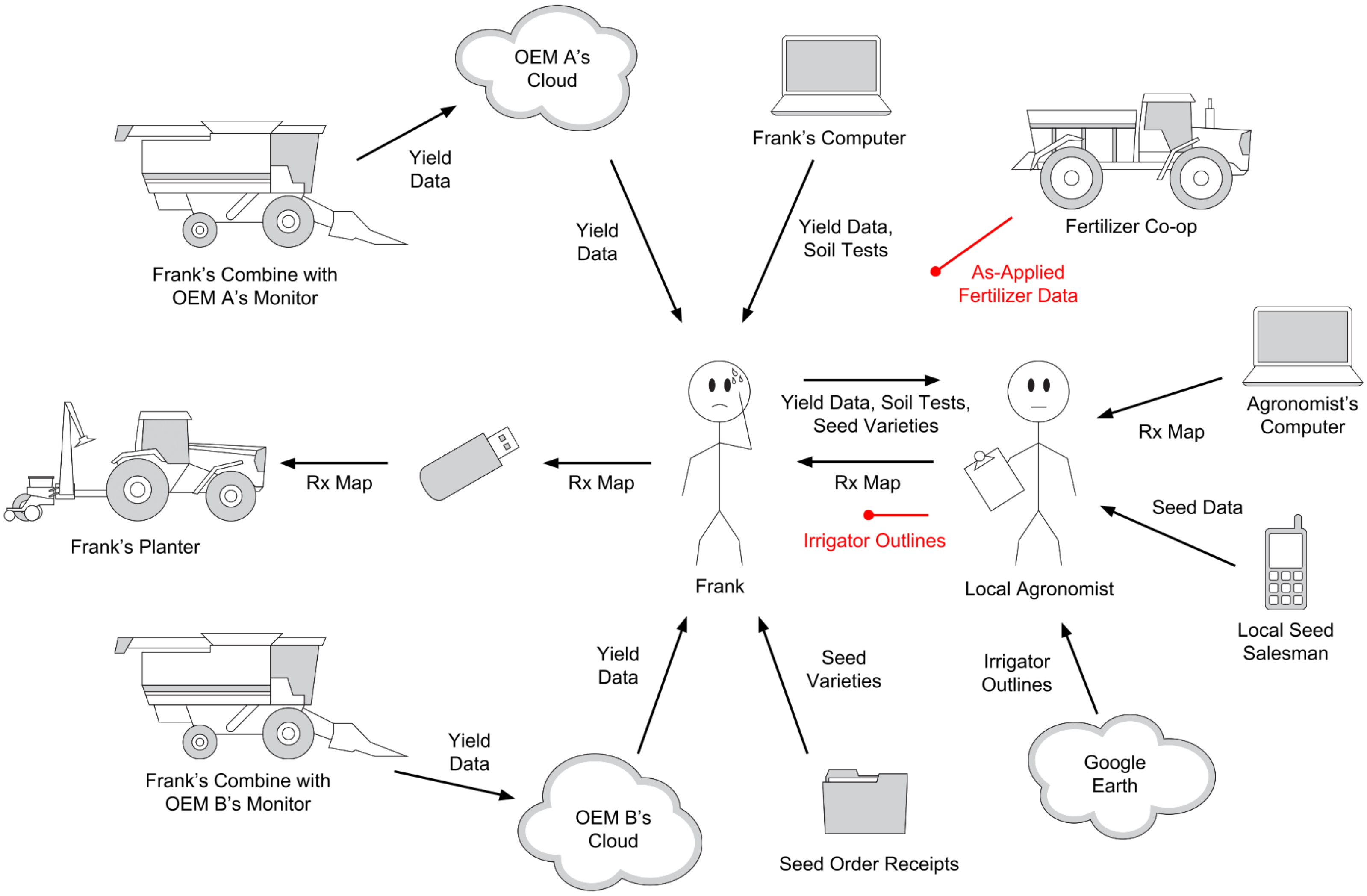

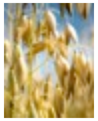

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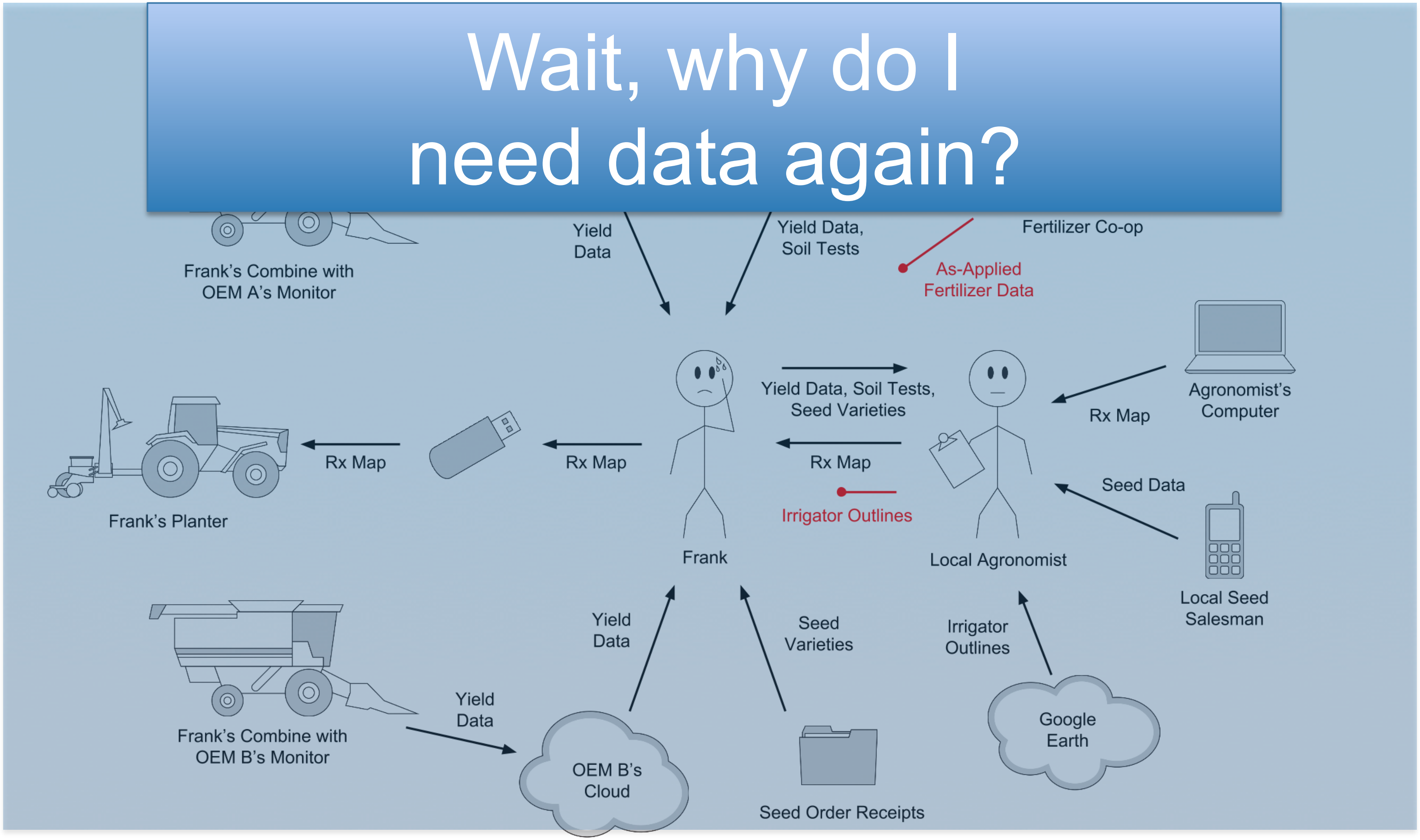

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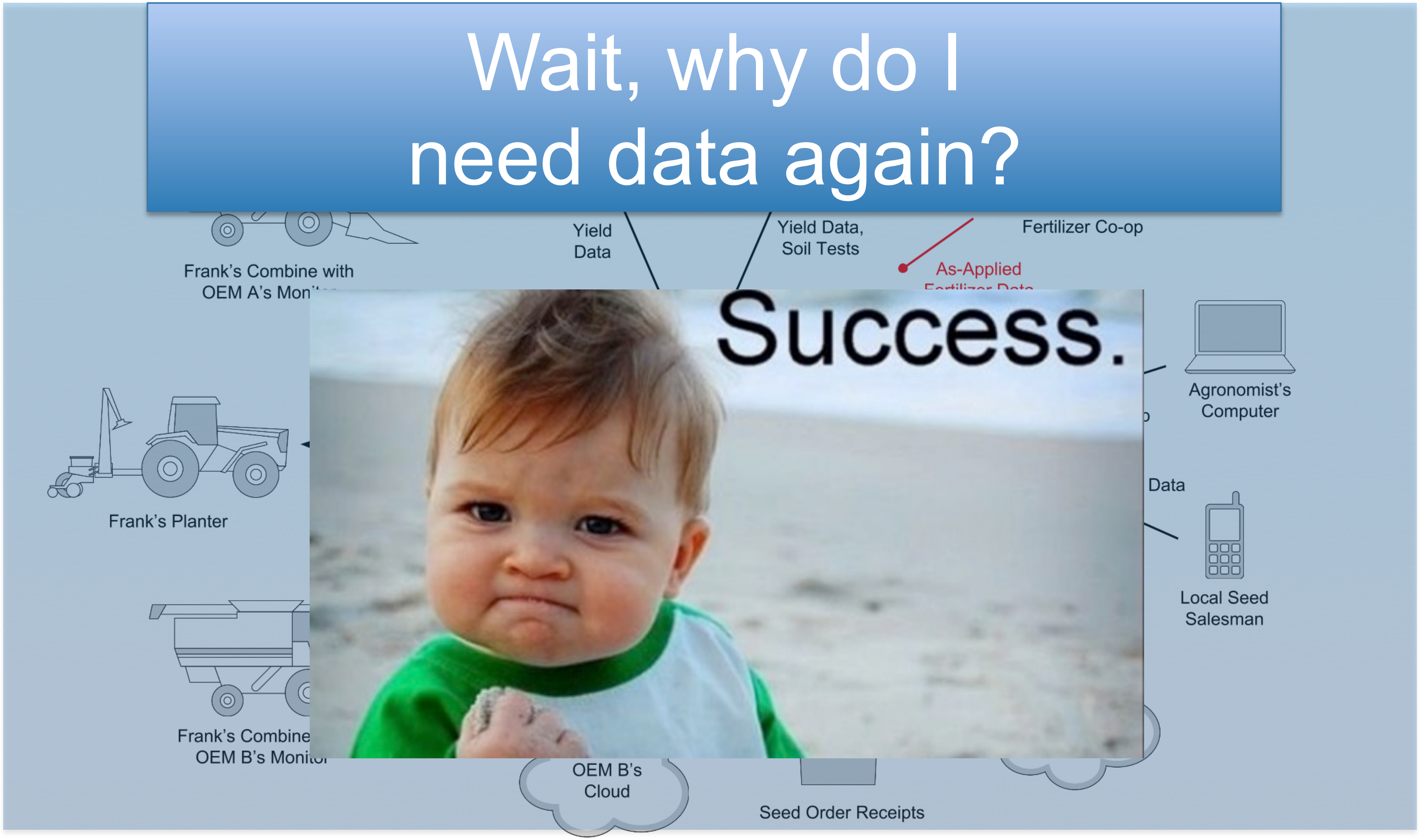

Wait, why do I need data again?

Success.

Value Proposition of Data?

A Farmer’s core business is logistics.

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Precision Ag has been around for 20 years.

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"A key challenge is that, with the exception of Precision Agriculture tools such as auto-steer, telematics, and row shut-offs, the **value for many of the products and services have not yet been clearly established**."

-- *Digital Transformation of Row-Crop Agriculture*, report to Iowa Ag State by the Hale Group, ***Dec. 2014***.
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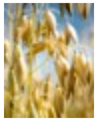

Value Proposition of Data?

Obvious Lessons from 20 Years of Fail:

1. It's really hard to turn data into value.

We still don't use data for logistics.

Or Evaluation.

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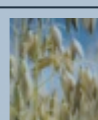

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Value Proposition of Data?

Obvious Lessons from 20 Years of Fail:

1. It's really hard to turn data into value.

We still don't use data for logistics.

2. There is no single "right" solution.

3. No single OEM can provide all data on any given farm.

Dec. 2014.

http://www.iowacorn.org/documents/filelibrary/membership/agstate/AgState_Executive_Summary_0A58D2A59DBD3.pdf

What Farmers Want from Data

Data should **flow**

from whatever source a farmer has

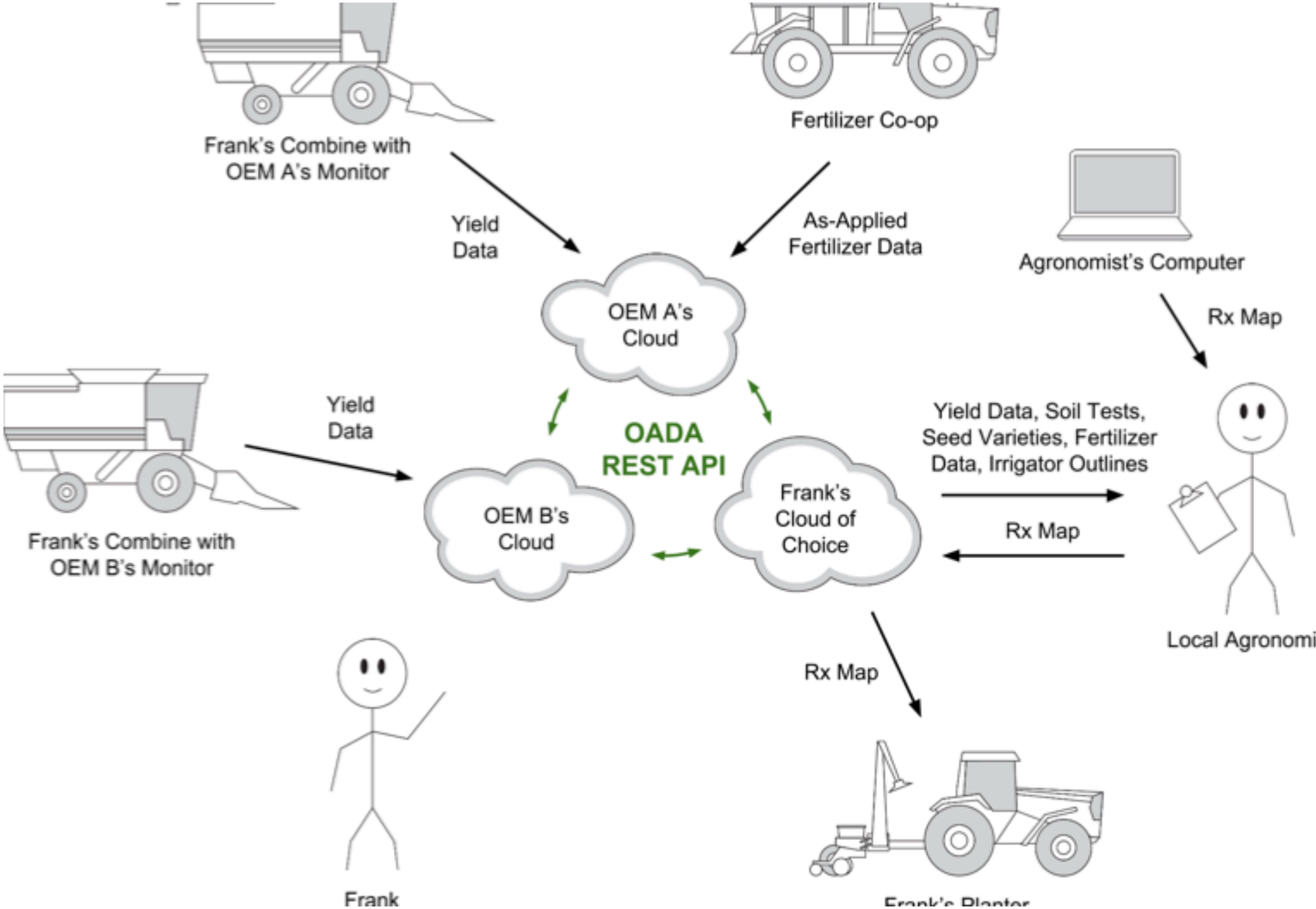
into whatever tool a farmer wants

without manual intervention

Data with OADA: An Example

Prescription Planting Maps

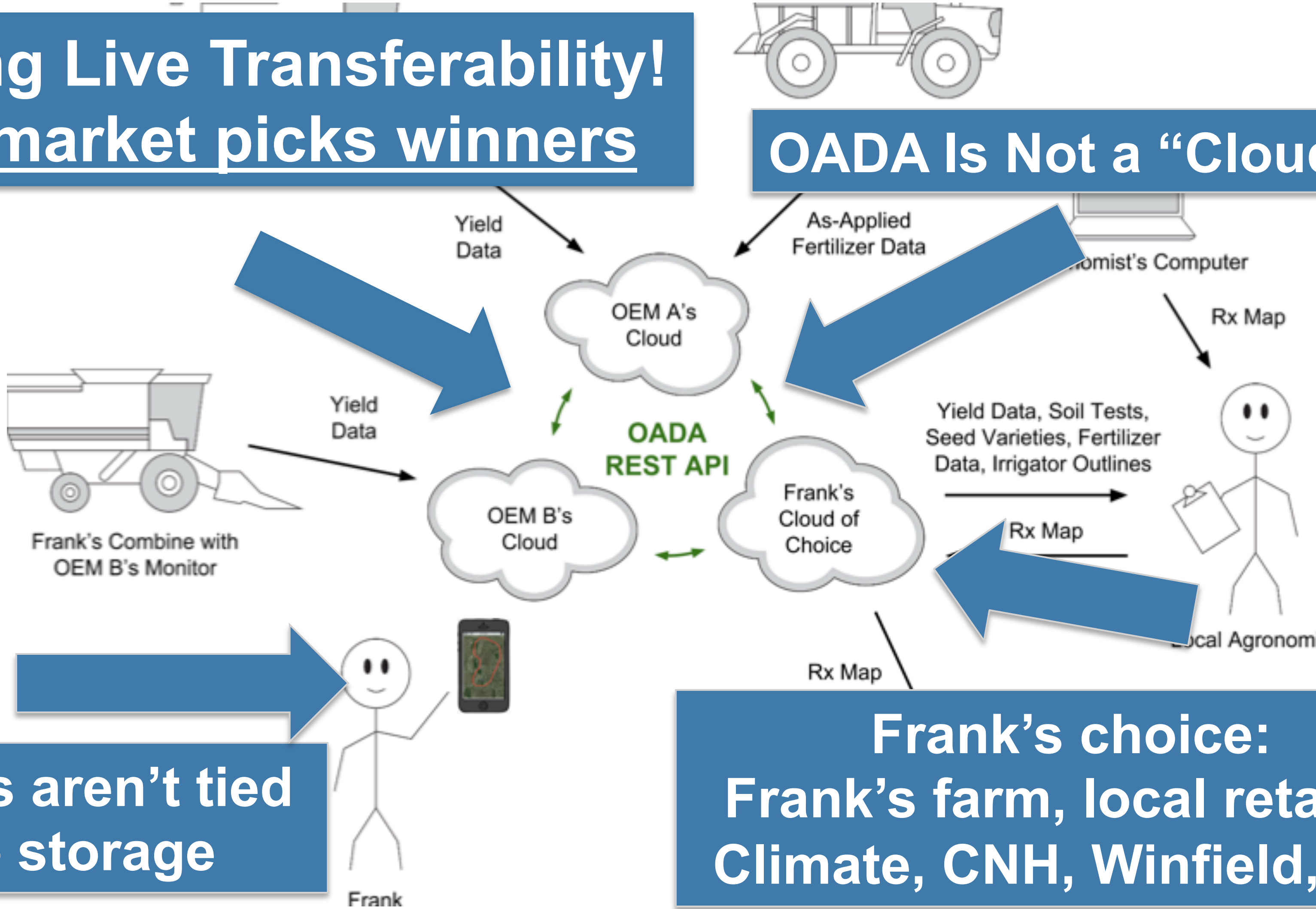
OADA Overview



OADA Overview

Long Live Transferability!
--> <u>market picks winners</u>

OADA Is Not a "Cloud"



Tools aren't tied to storage

Frank's choice:
Frank's farm, local retailer, Climate, CNH, Winfield, etc.

OADA Overview

Frank has complete control over who can see his data.

What Ag / Ag Research Need

Open Source

Volunteers/Industry writing freely available, public code

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>> Much of modern software ….

What Ag / Ag Research Need

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Open Standards

Standards grow out of implementation, not vice-versa

>> Example: Shapefiles...

What Ag / Ag Research Need

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Standards grow out of implementation, not vice-versa

Market Forces

There doesn't have to be only one way to do everything

OADA Milestones

Since beginning in March 2014:

CNH/Geosys Demo Finished 12/8/2014

Live Yield Monitor

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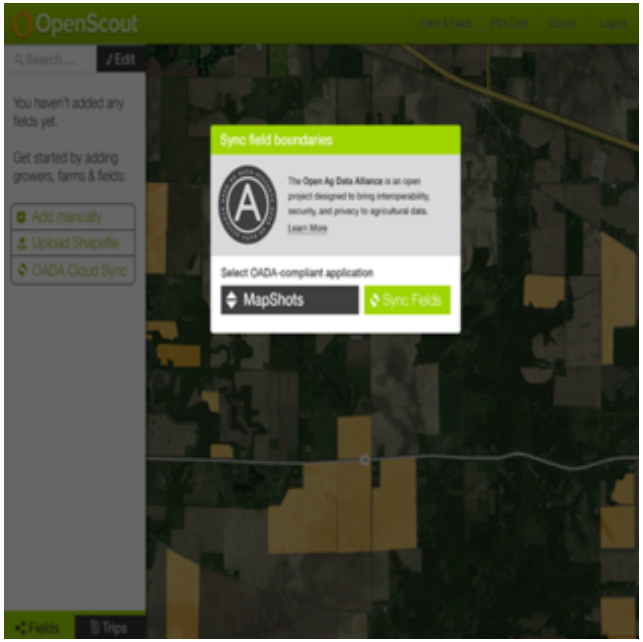
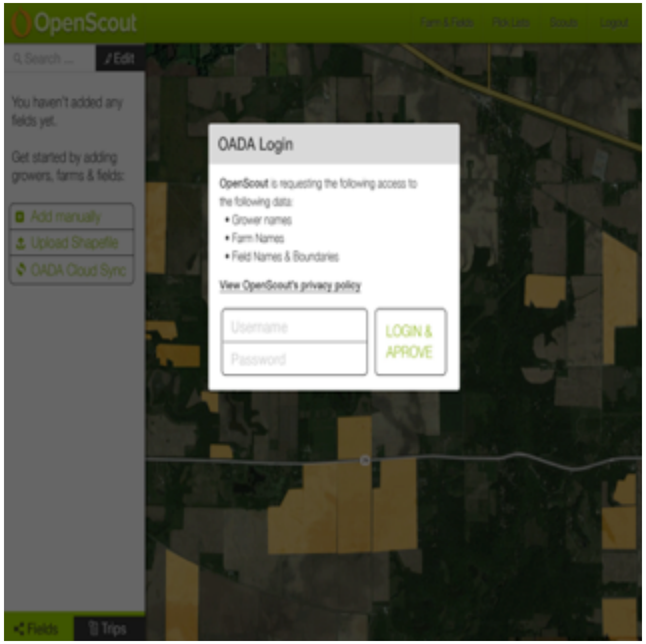
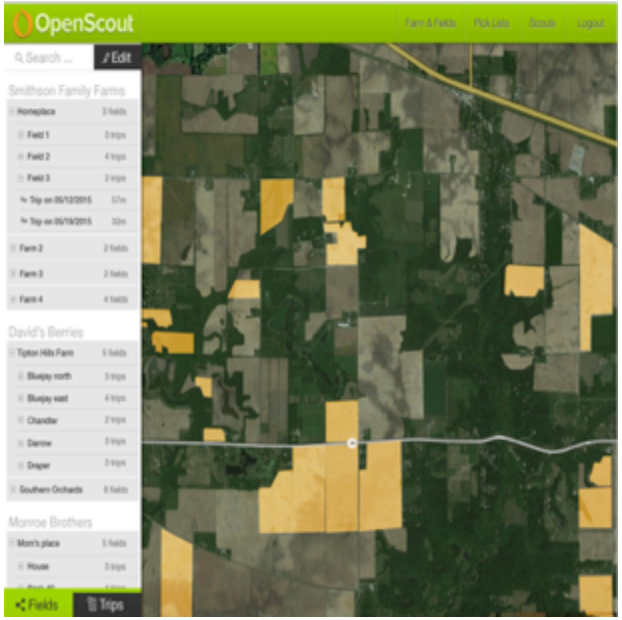
Winfield/Mapshots/OpenScout Demo Jan 2015

Field Boundaries and Common Login







OADA Milestones

Since beginning in March 2014:

- CNH/Geosys Demo Finished 12/8/2014
    - Live Yield Monitor
- Winfield/Mapshots/OpenScout Demo Jan 2015
    - Field Boundaries and Common Login
- ***Valley Irrigation's ValleyIX certified as OADA v1.0 conformant***

VALLEY®

The Leader in Precision Irrigation

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- ***Winfield building OADA-conformant "Data Silo"***

WINFIELD™ SOLUTIONS

OADA Milestones

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- Special thanks to our current funding partners!

… and currently 25+ supportive partners around the world!

Current Projects: Real Time Connections

NEWS RELEASE

August 1, 2016

Open Ag Data Alliance, Servi-Tech launch Real-Time Connections API for weather, soil moisture data

WEST LAFAYETTE, Ind. - The Purdue University-led Open Ag Data Alliance and partner Servi-Tech Inc. announced Monday (Aug. 1) a commercial demonstration of its Real-Time Connections initiative, continuing their mission to help farmers better use data in their daily decisions across all of their operations.

Current Projects: Real Time Connections

Publish formats

OADA API as base transport

Emphasis on working commercial, real-time system

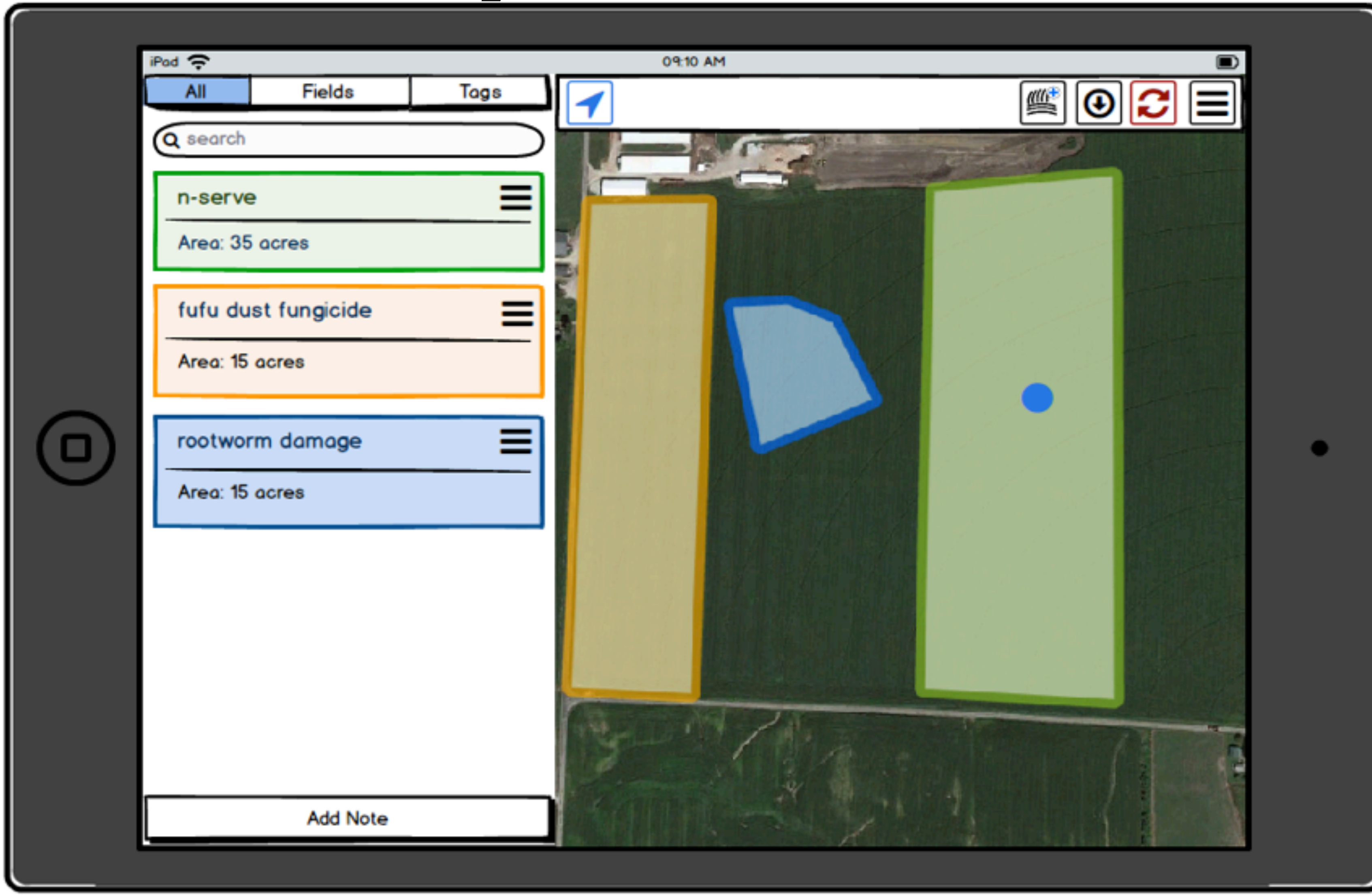
Can integrate with open source apps / SDKs

For more information:
aaron@openag.io

Current Projects: Trials Tracker

An open source app
we've been working on at Purdue,
designed to work with
OADA-conformant cloud providers

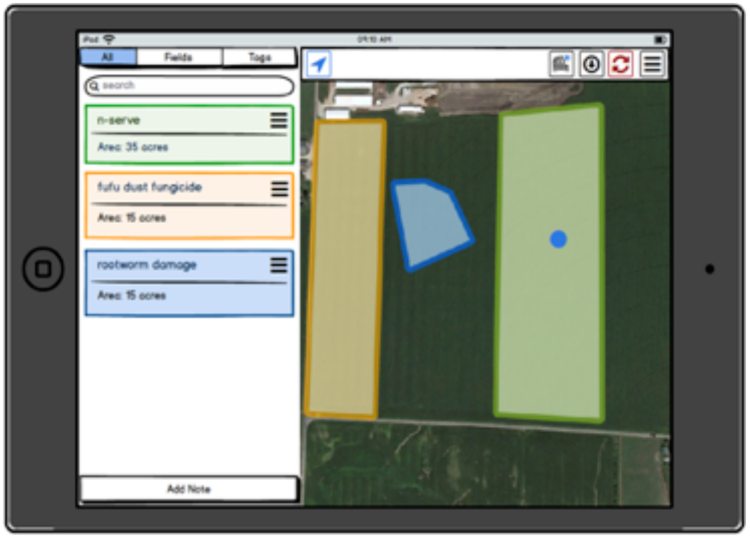
Current Projects: Trials Tracker



Current Projects: Trials Tracker

Without the cloud you can still:

- Take notes
- Draw areas
- Email shapefiles
- Work offline (cacheable map!)



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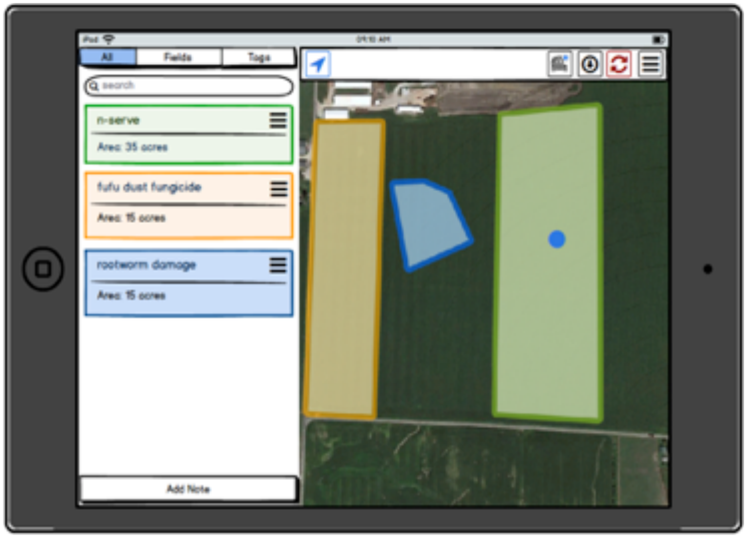
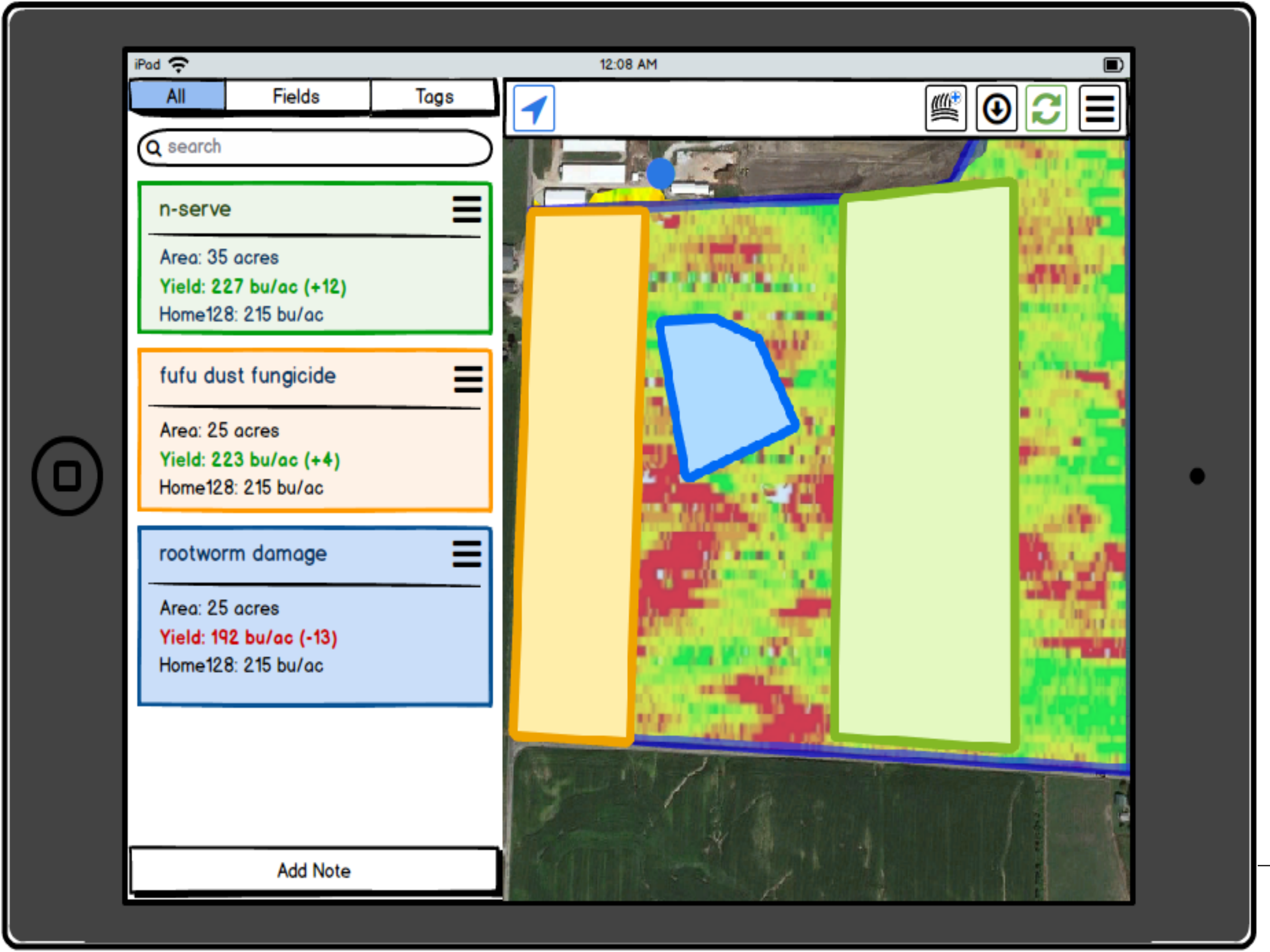


But with the cloud you can…

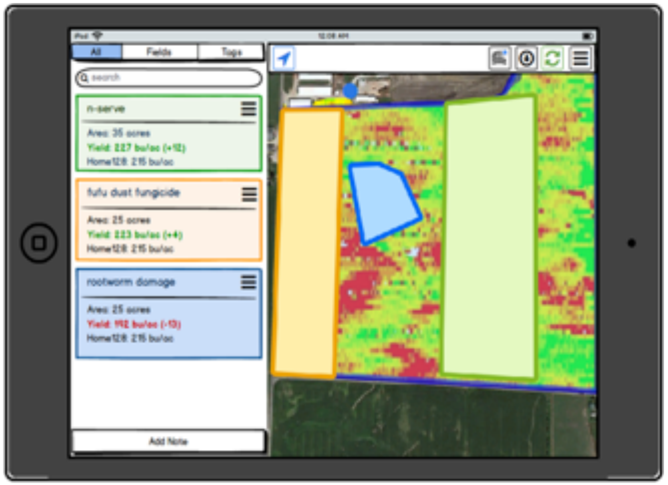


iPad
12:08 AM
All
Fields
Tags
search
n-serve
Area: 35 acres
Yield: 227 bu/ac (+12)
Home128: 215 bu/ac
fufu dust fungicide
Area: 25 acres
Yield: 223 bu/ac (+4)
Home128: 215 bu/ac
rootworm damage
Area: 25 acres
Yield: 192 bu/ac (-13)
Home128: 215 bu/ac
Add Note

Current Projects: Trials Tracker

But with the cloud you can…

Compare yields
Sync fields
Sync notes with employees/co-op
Load and analyze data FAST
Work offline
Stream live yield from combines
Get polygons from other operations



Current Project: Determine the Management Zones from Multiple Years of Yield Data

- Farm precision management refers to the use of site-specific agronomy for field management zones that respond similarly to similar inputs …
  - Soils, topography, organic material, water holding capacity vary spatially on the scale of a typical field
  - Farmers have ability to target inputs (seed, fertilizer, water) with high spatial resolution
- Goal: Algorithm for determining management zones from multi-year yield data

Current Project: Determine the Management Zones from Multiple Years of Yield Data

- Our data set:
  - North central Indiana (Rochester, IN)
  - About 3,500 acres
  - 7 to 10 years of calibrated yield data
  - Corn, soybean rotation
  - Case IH combines and OEM sensors, monitors
- The state of the art management zone algorithm is called **Management Zone Analyst (MZA)** – N. R. Kitchen with USDA-ARS Cropping Systems and Water Quality Research Lab, University of Missouri.

Example: Gott East 93

- 7 years of yield data
  - Corn years: 2007, 09, 11, 13
  - Soy years: 2010, 12, 14
- Soil series
- Elevation
- Precipitation
- Growing degree days

Example: Gott East 93

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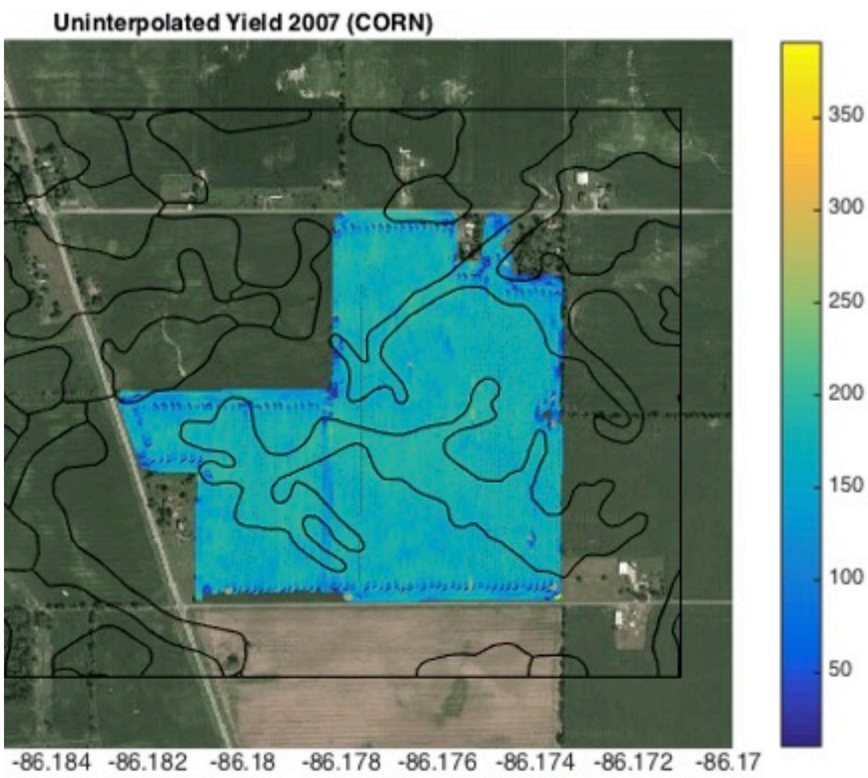
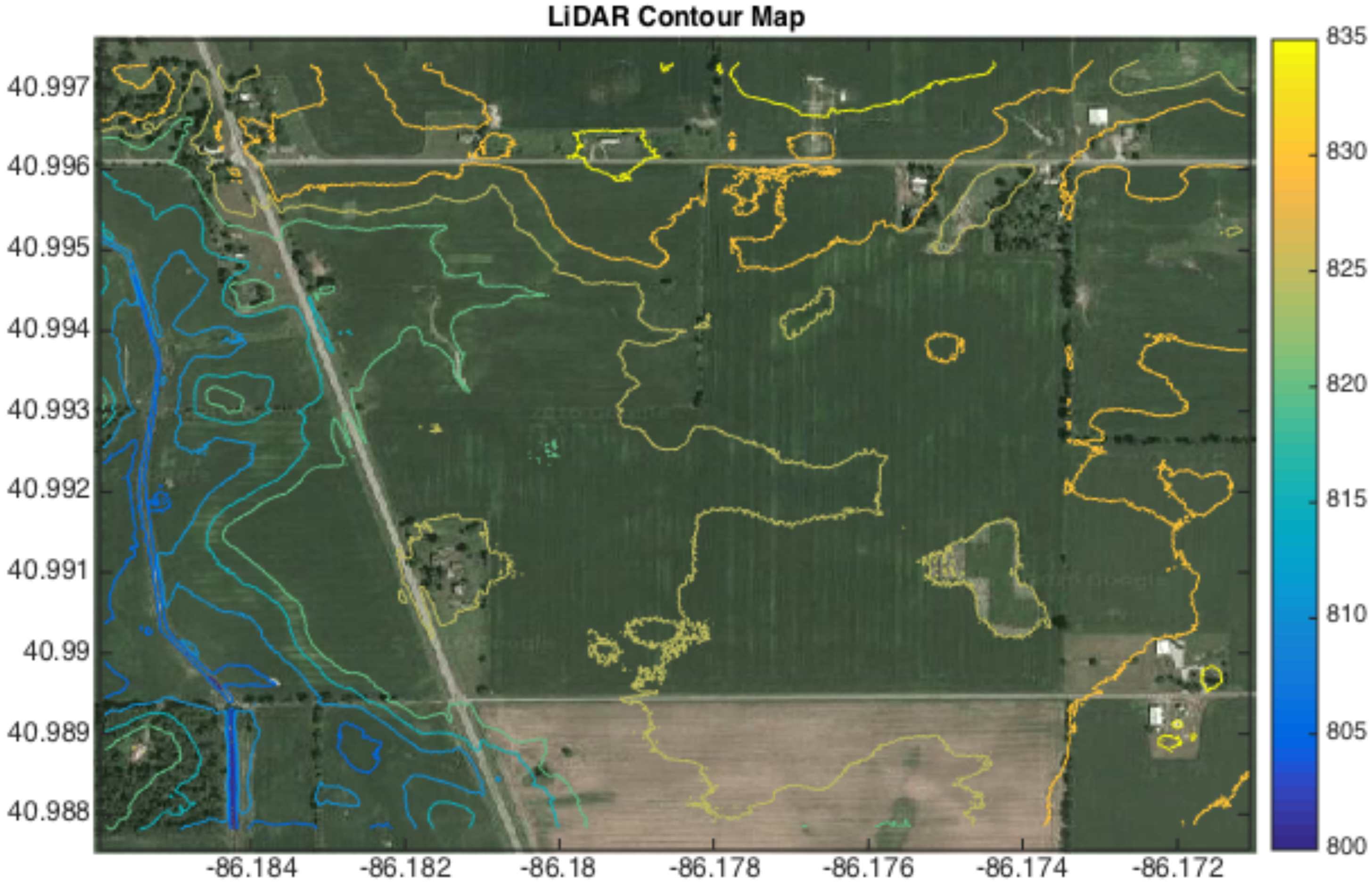
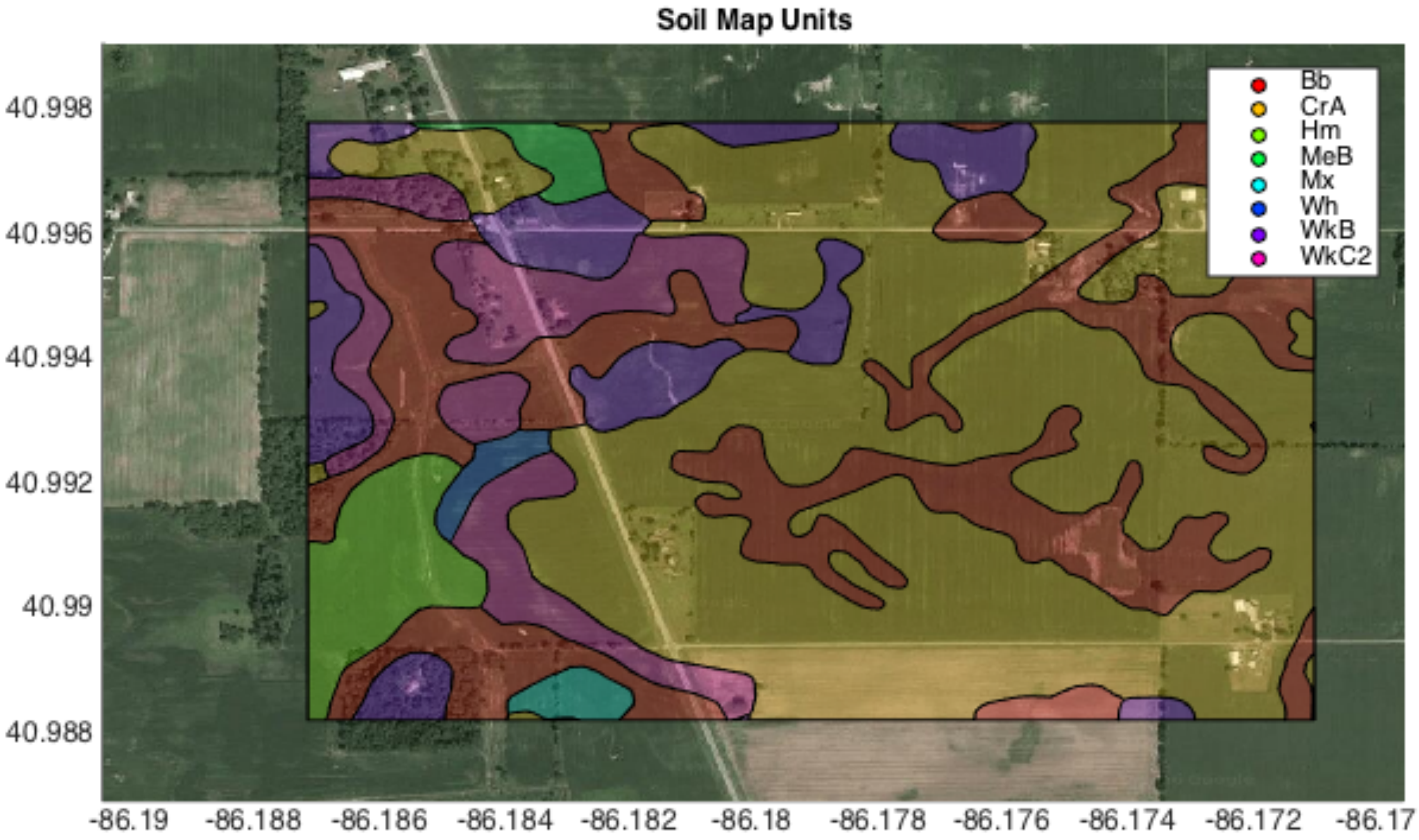


Gott East 93: Contours



Gott East 93: Soil Series



"Bb" = Barry loam

"CrA" = Crosier loam, 0 to 2 percent slopes

"Hm" = Houghton muck, drained

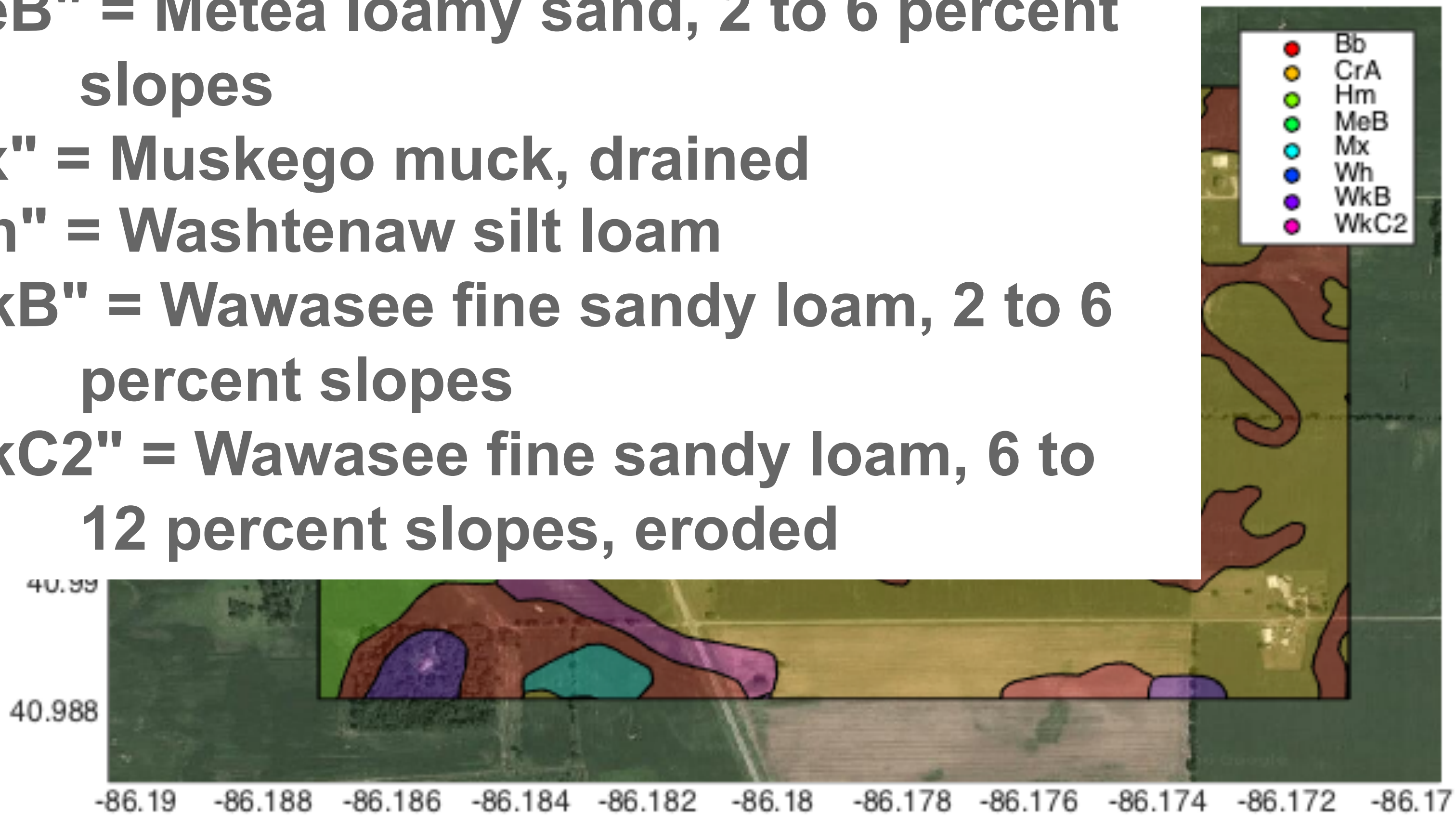
"MeB" = Metea loamy sand, 2 to 6 percent slopes

"Mx" = Muskego muck, drained

"Wh" = Washtenaw silt loam

"WkB" = Wawasee fine sandy loam, 2 to 6 percent slopes

"WkC2" = Wawasee fine sandy loam, 6 to 12 percent slopes, eroded



LOCATION CROSIER IN+MI

Established Series
Rev. RAB-FF-TRZ
07/2011

CROSIER SERIES

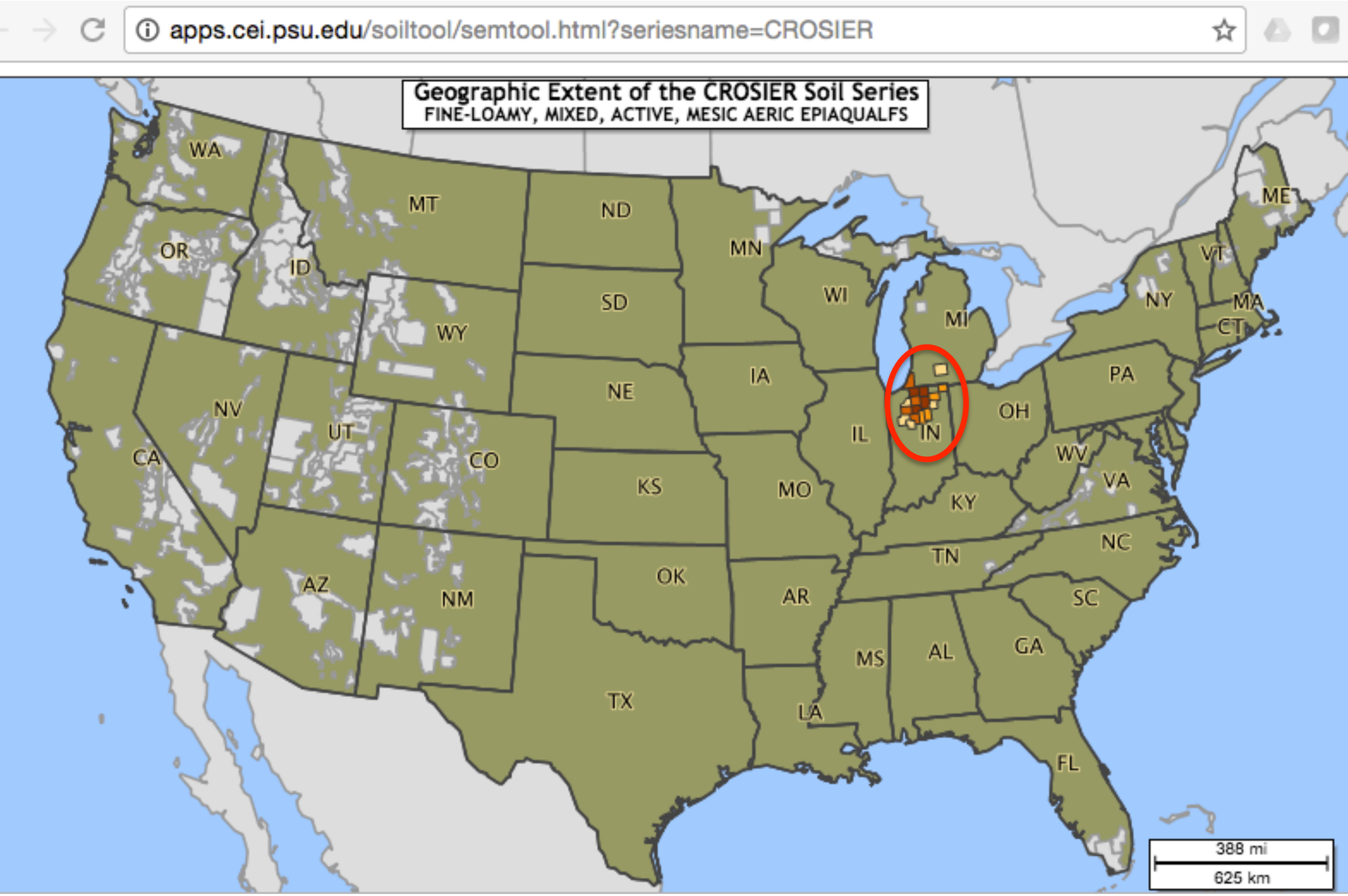
The Crosier series consists of very deep, somewhat poorly drained soils formed in till on till plains and moraines. They are moderately deep to dense till. Slope ranges from 0 to 4 percent. Mean annual precipitation is about 940 mm (37 inches), and mean annual temperature is about 10.0 degrees C (50 degrees F).

TAXONOMIC CLASS: Fine-loamy, mixed, active, mesic Aeric Epiaqualfs

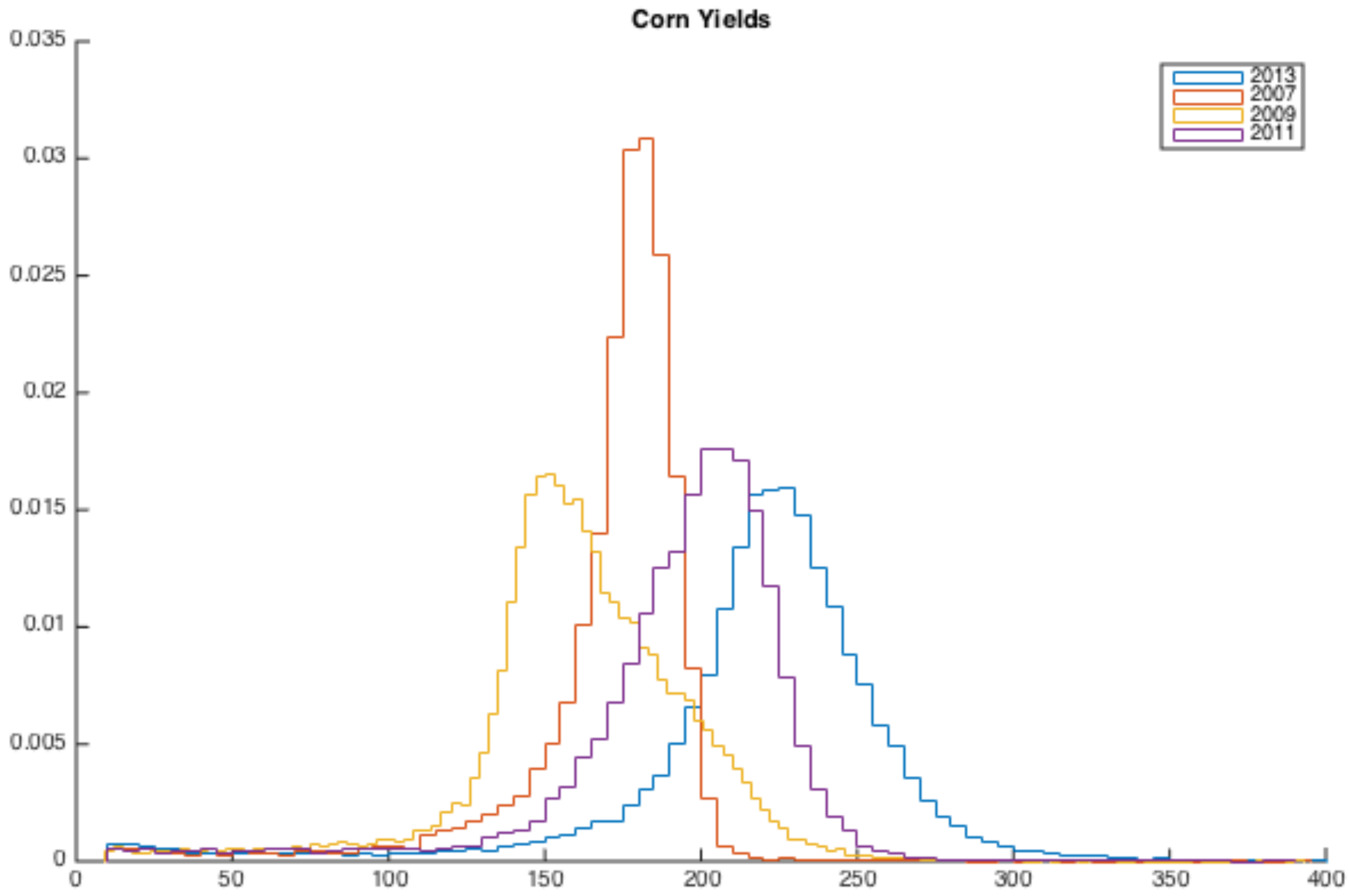
TYPICAL PEDON: Crosier loam, on a 1 percent slope in a cultivated field at an elevation of 260 meters (852 feet) above mean sea level. (Colors are for moist soil unless otherwise stated.)

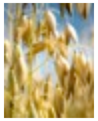
Ap--0 to 20 cm (0 to 8 inches); dark grayish brown (10YR 4/2) loam, light brownish gray (10YR 6/2) dry; weak fine granular structure; friable; 1 percent gravel; neutral; abrupt smooth boundary. [15 to 25 cm (6 to 10 inches) thick]

Eg--20 to 28 cm (8 to 11 inches); grayish brown (10YR 5/2) loam; weak medium subangular blocky structure; friable; common medium prominent yellowish brown (10YR 5/6) masses of oxidized iron in the matrix; common distinct light gray (10YR 7/1) clay depletions on faces of peds; 1 percent gravel; slightly acid; clear smooth boundary. [0 to 25 cm (10 inches) thick]

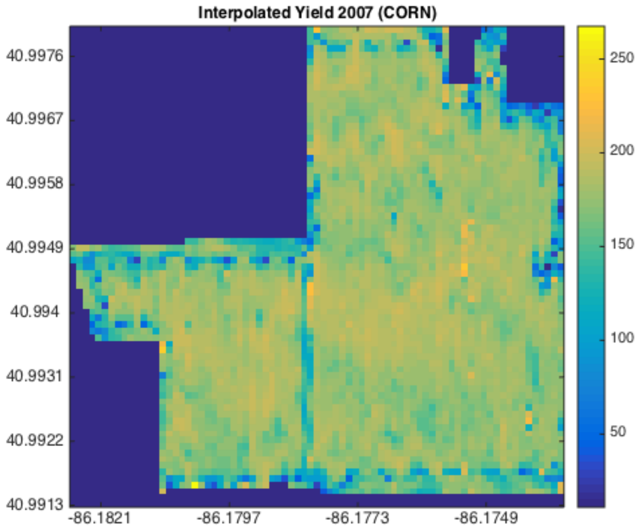

apps.cei.psu.edu/soiltool/semtool.html?seriesname=CROSIER
Geographic Extent of the CROSIER Soil Series
FINE-LOAMY, MIXED, ACTIVE, MESIC AERIC EPIAQUALFS
WA
OR
ID
MT
ND
MN
SD
WY
NV
CA
UT
CO
NE
IA
IL
IN
OH
MI
WI
KS
MO
KY
WV
VA
PA
NY
VT
ME
MA
CT
OK
AR
TN
NC
SC
AZ
NM
TX
LA
MS
AL
GA
FL
388 mi
625 km

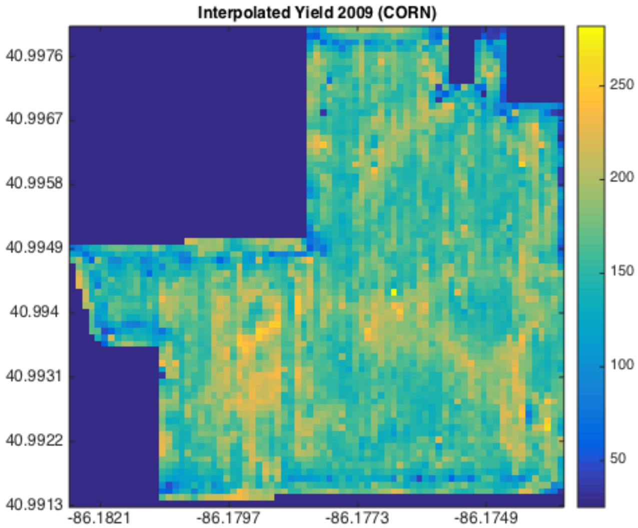
Gott East 93: 4 Years Corn Yield Histograms

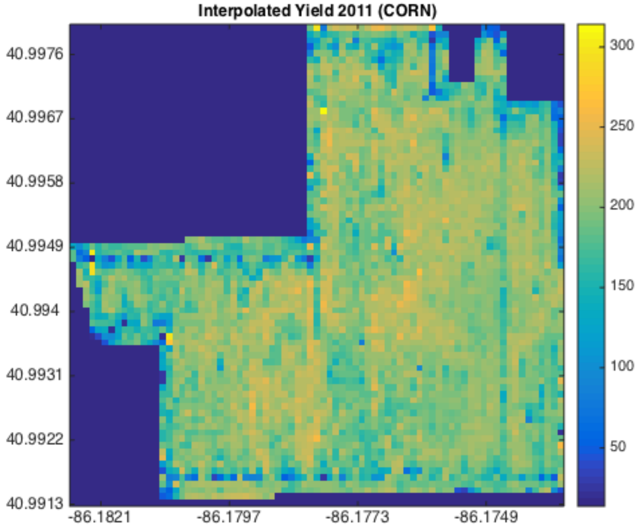


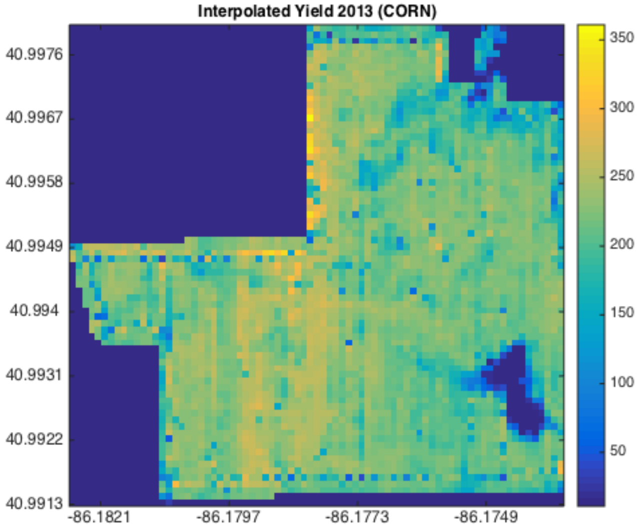


Gott East 93: 4 Years Yield Maps

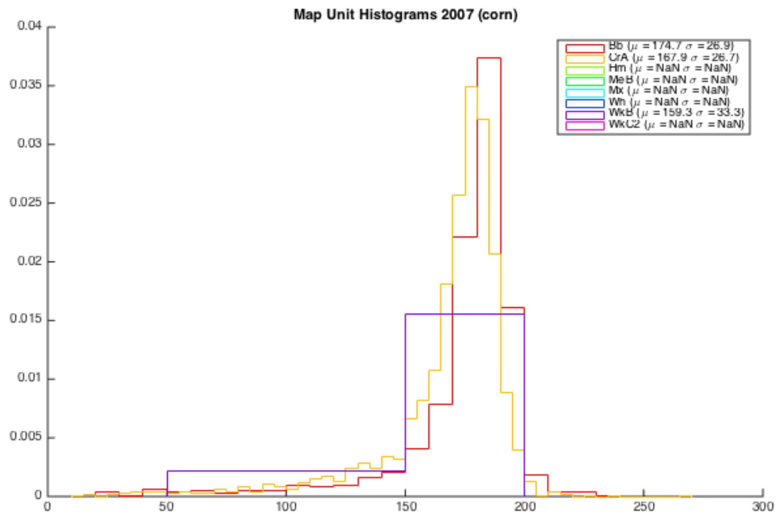


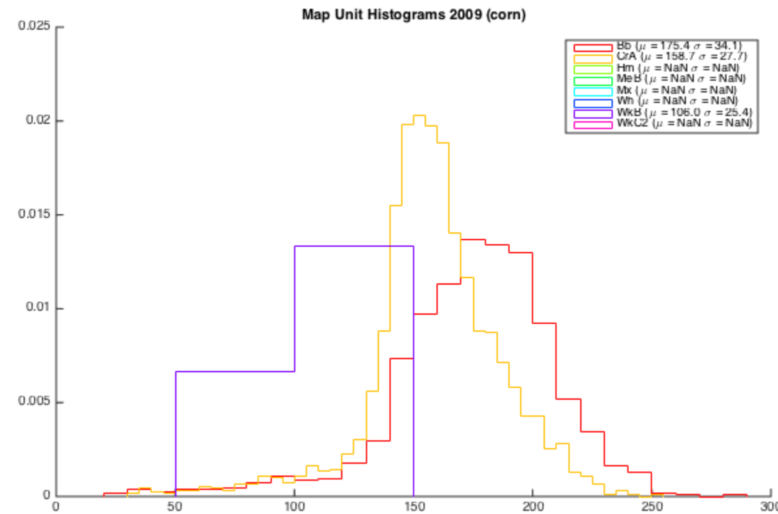


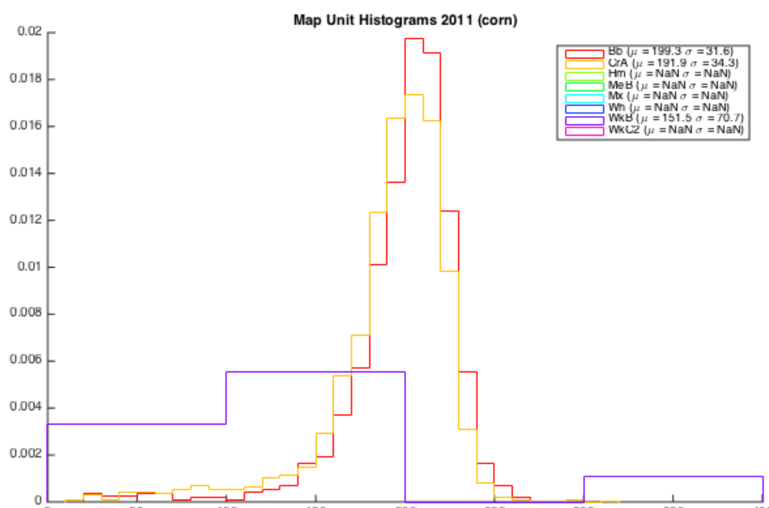


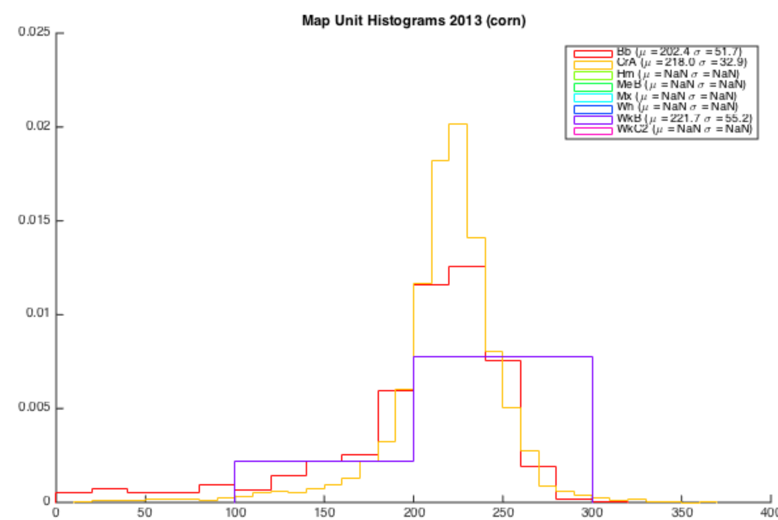


Gott East 93: Yields by Soil Type

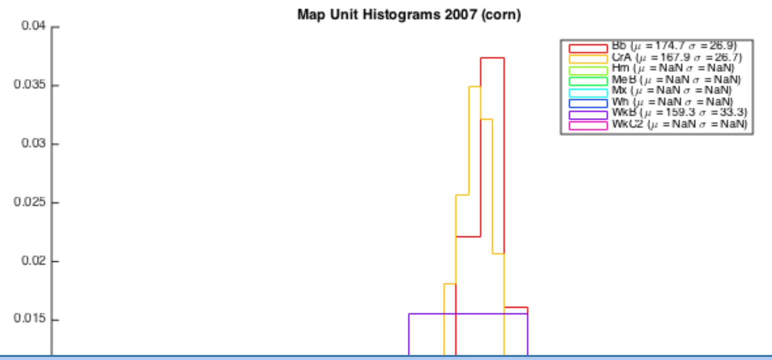


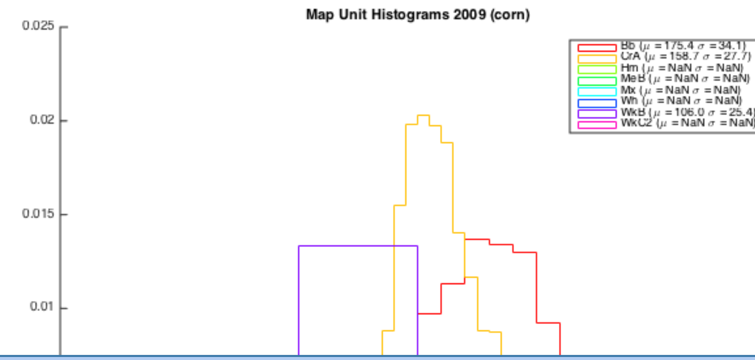




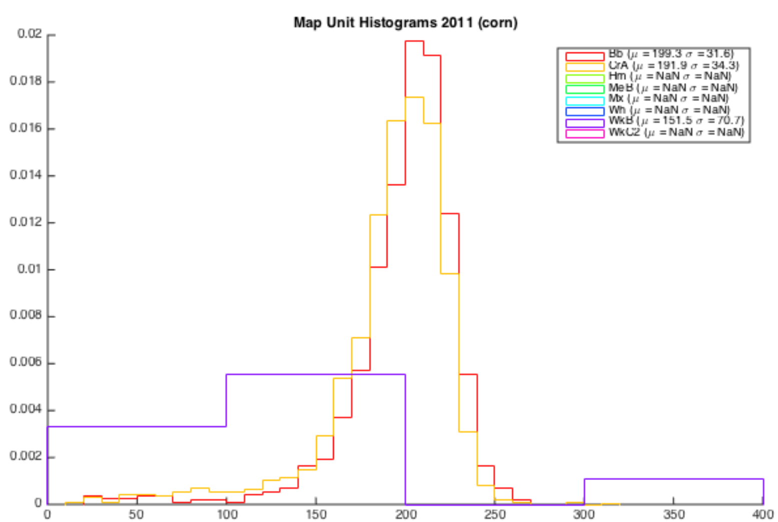


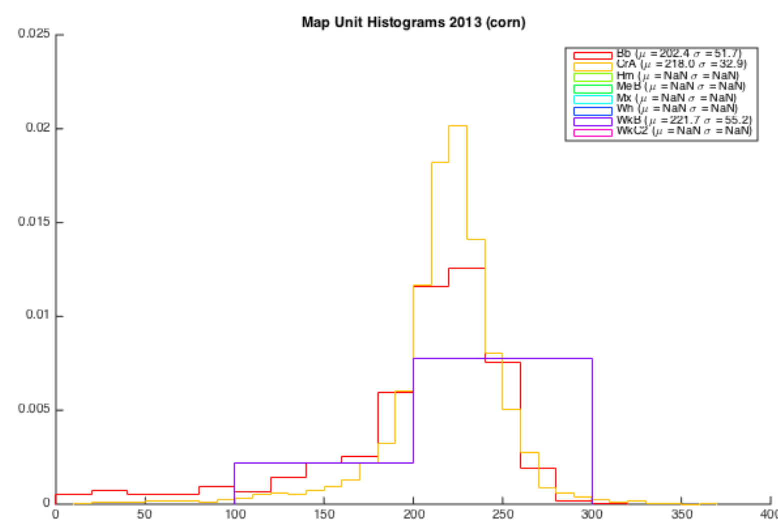
Gott East 93: Yields by Soil Type





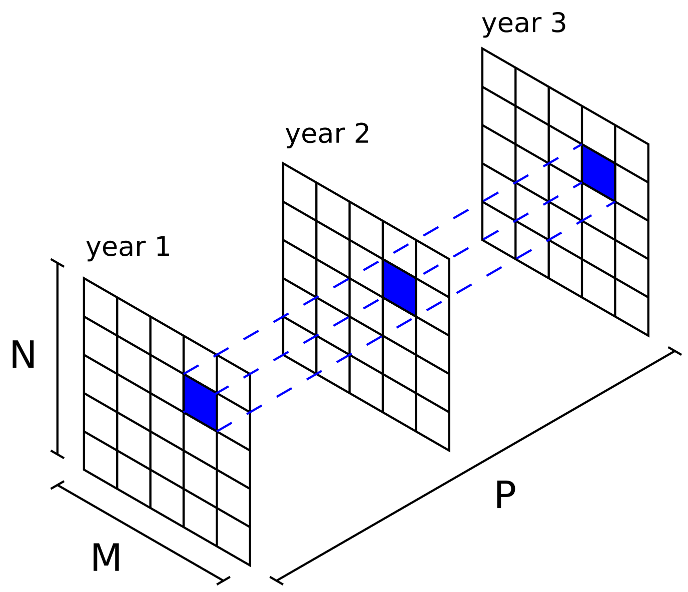
GE 93 (corn): does not appear one should manage by soil type alone





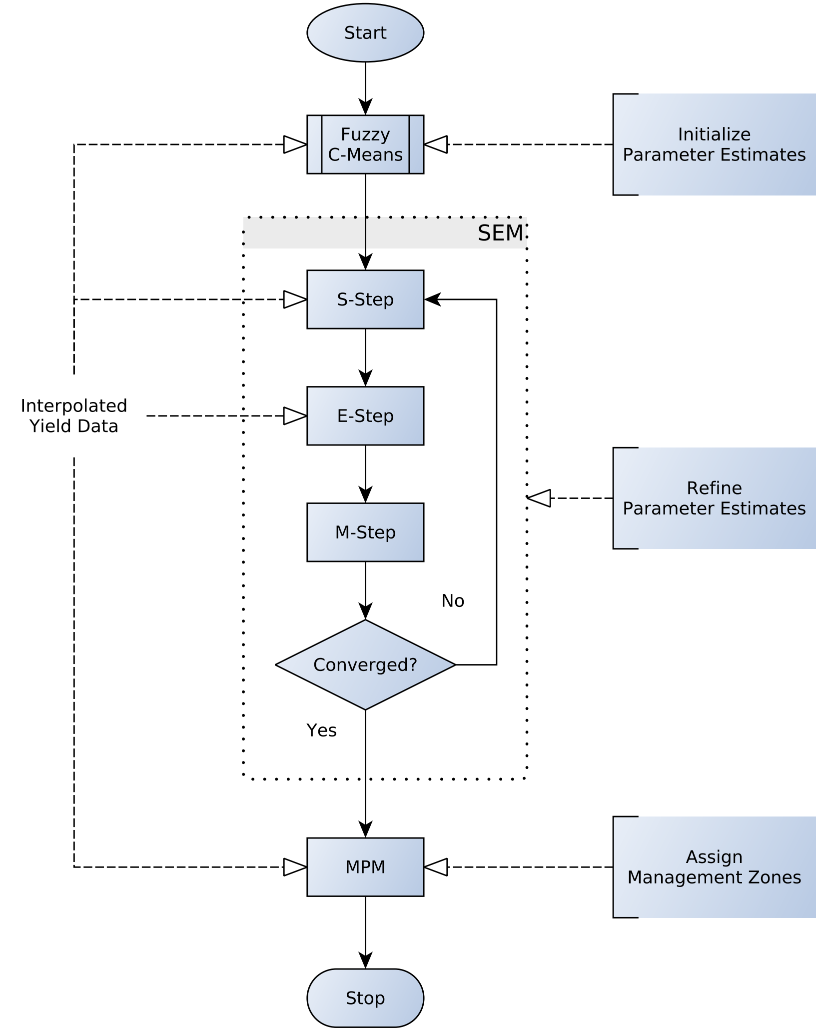
Another Model for Management Zone Estimation

- Management zones modeled as Markov random field
  - Labels “hidden”
  - Potts model for spatial relationships
- Multi-year yield vectors modeled as conditionally Gaussian

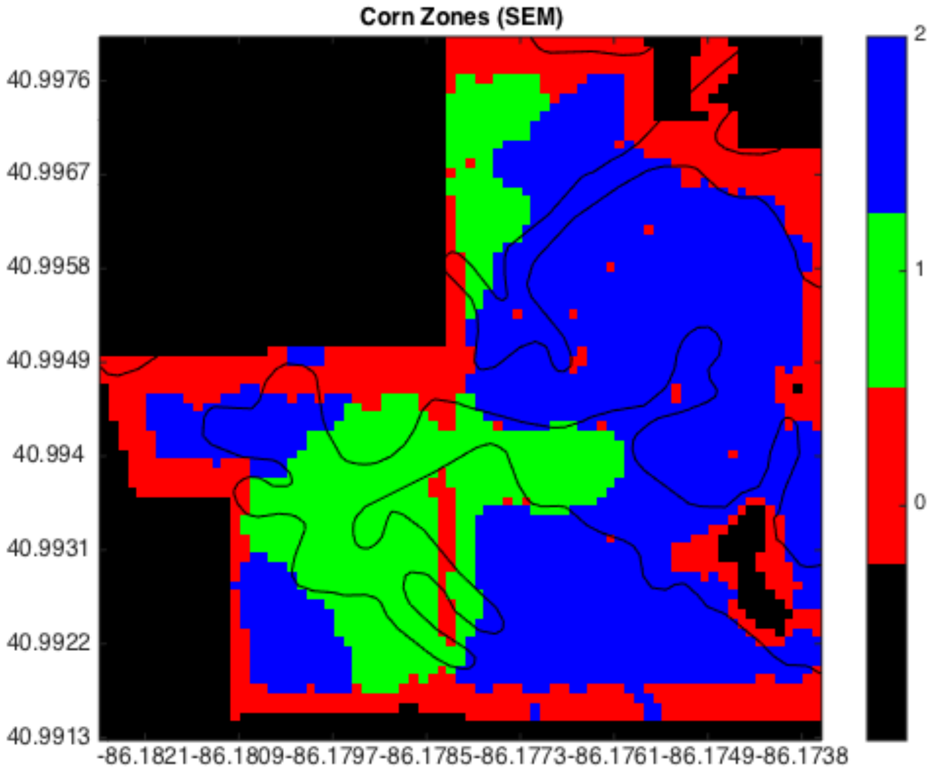


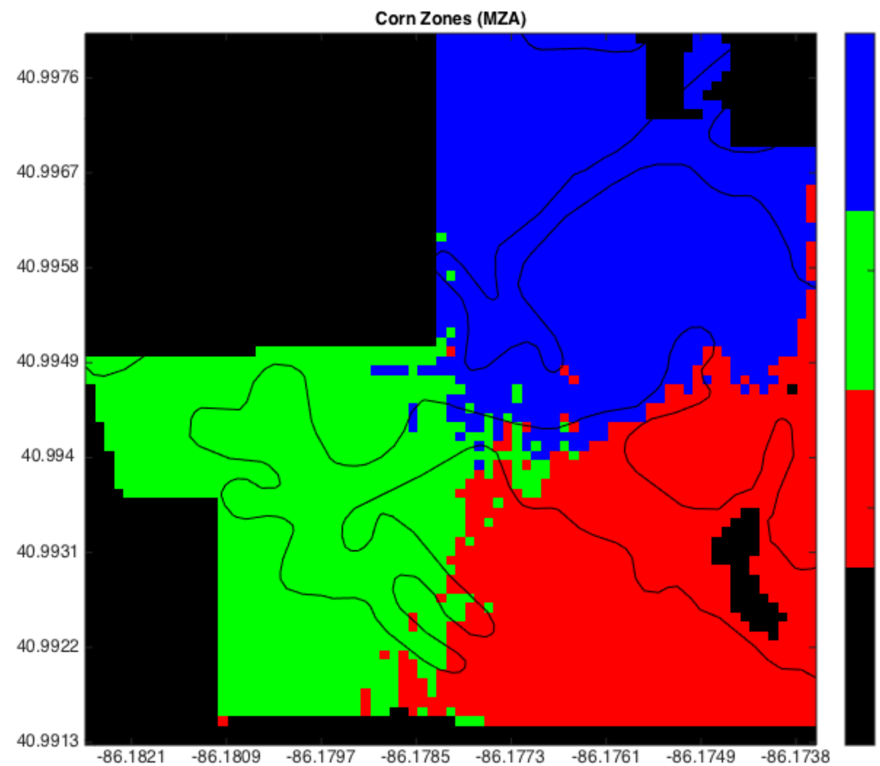
Algorithm: Stochastic Expectation Maximization (SEM)

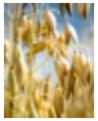
- Initialize with fuzzy c-means
- Assume order is known
  - Used: number of soil types + 1
- We compare to MZA algorithm



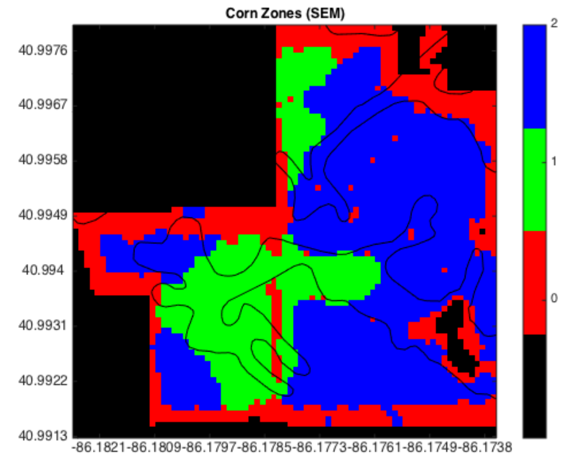
Management Zones: left = SEM, right = MZA (K = 3)

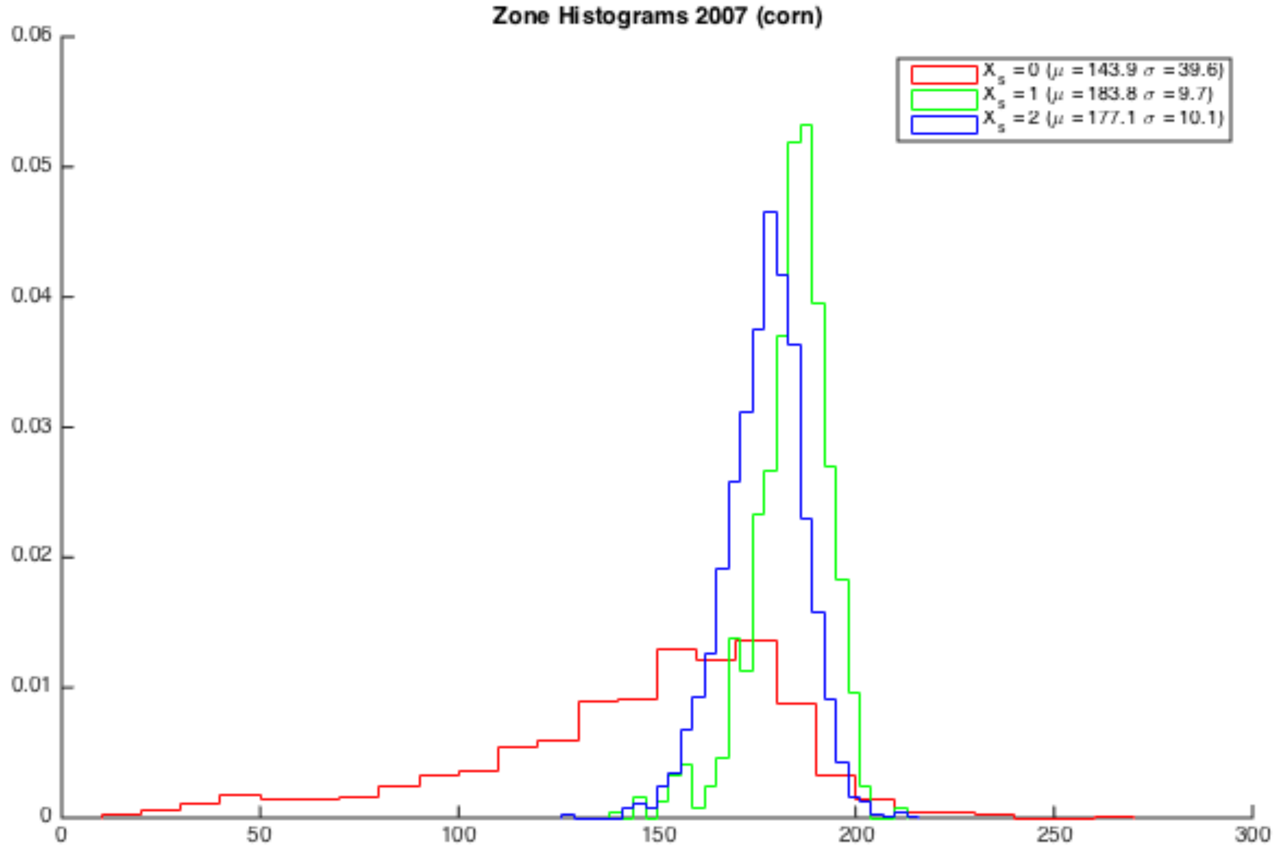




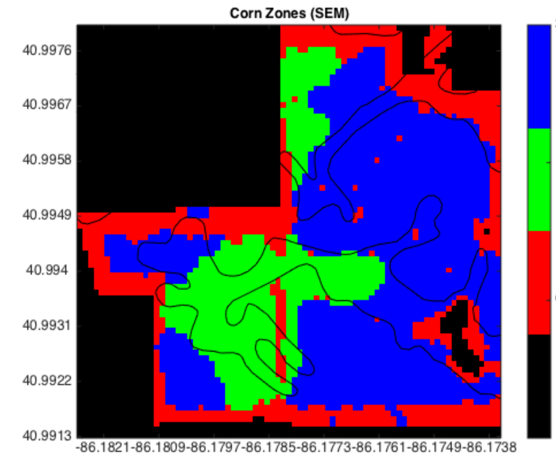


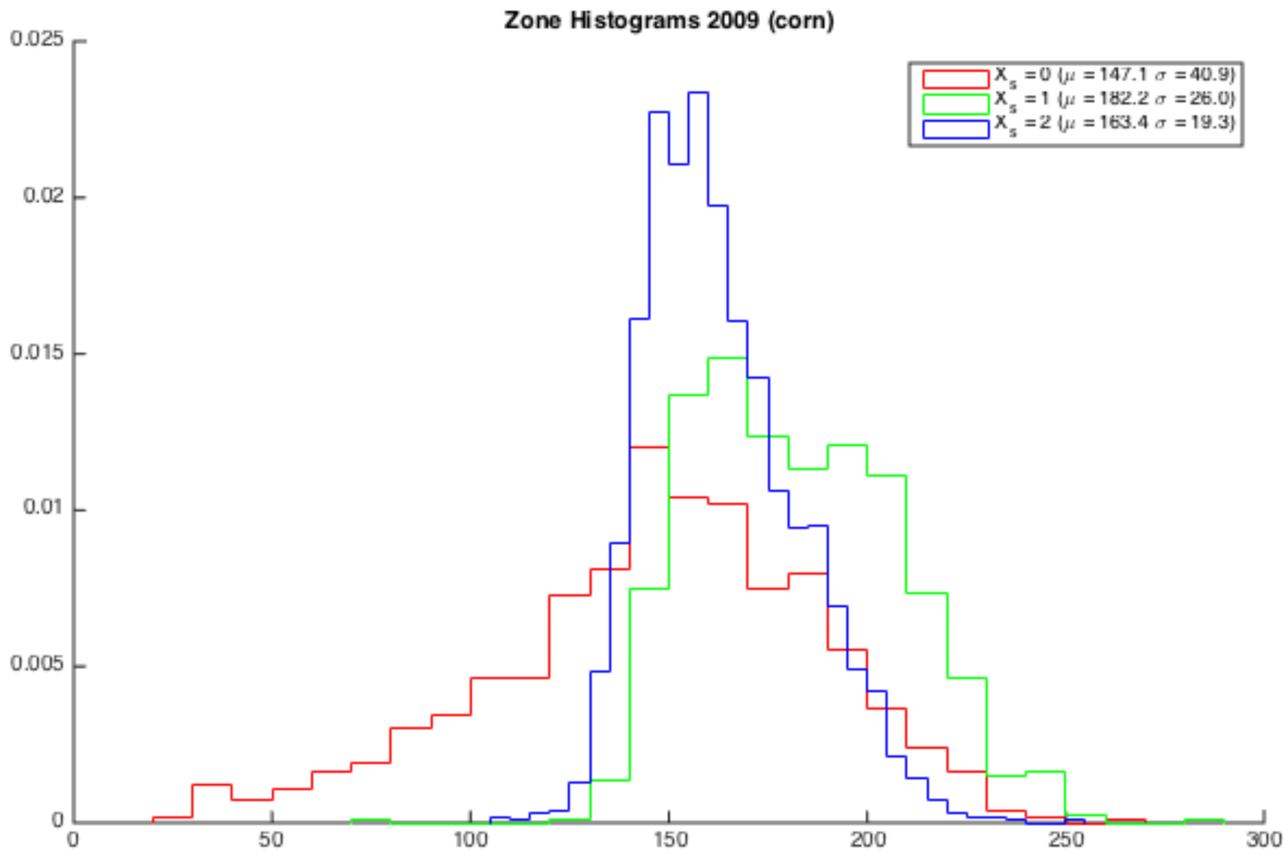
SEM Management Zone Histograms 2007



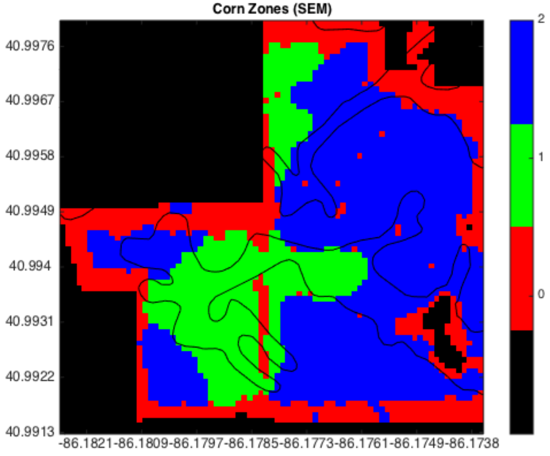


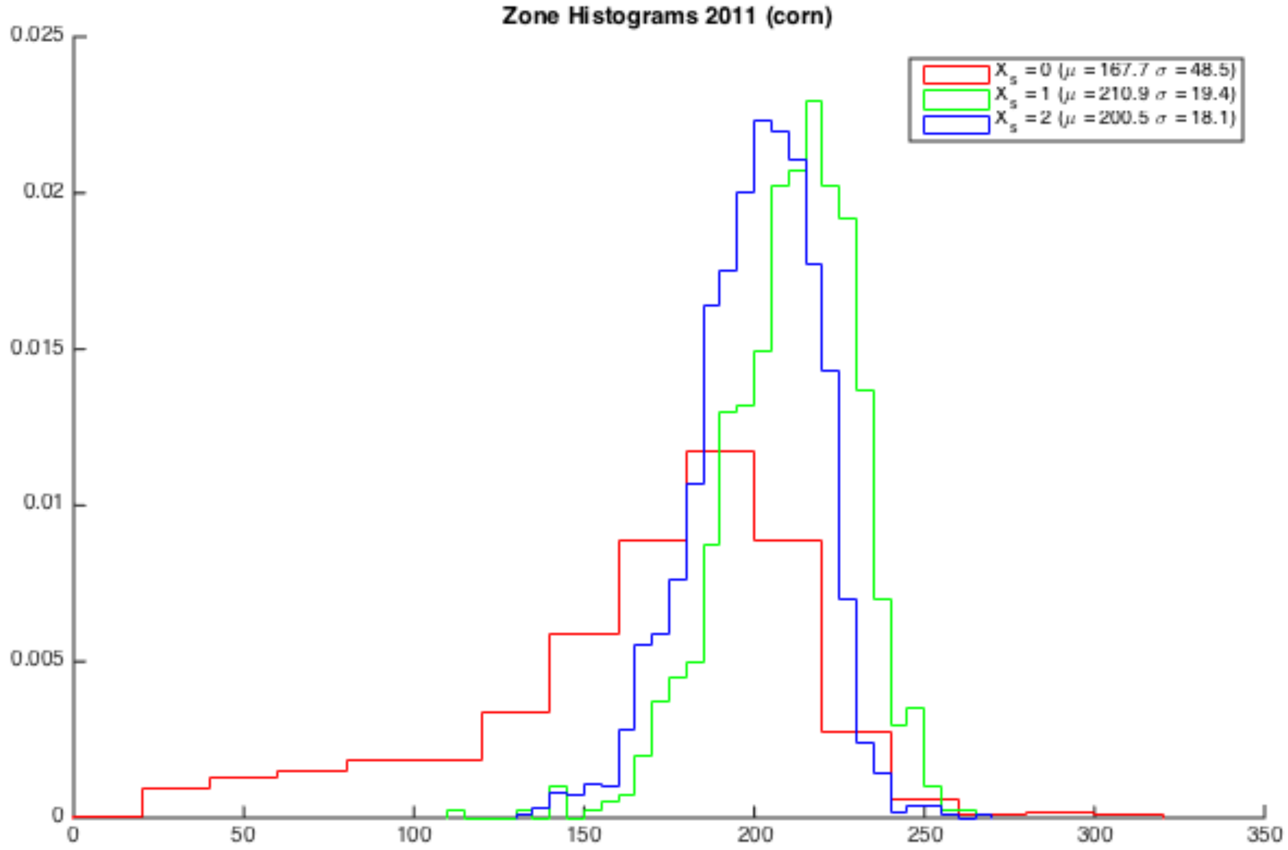
SEM Management Zone Histograms 2009



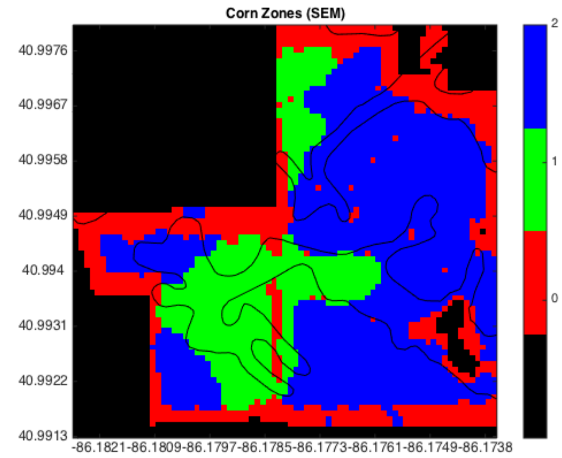


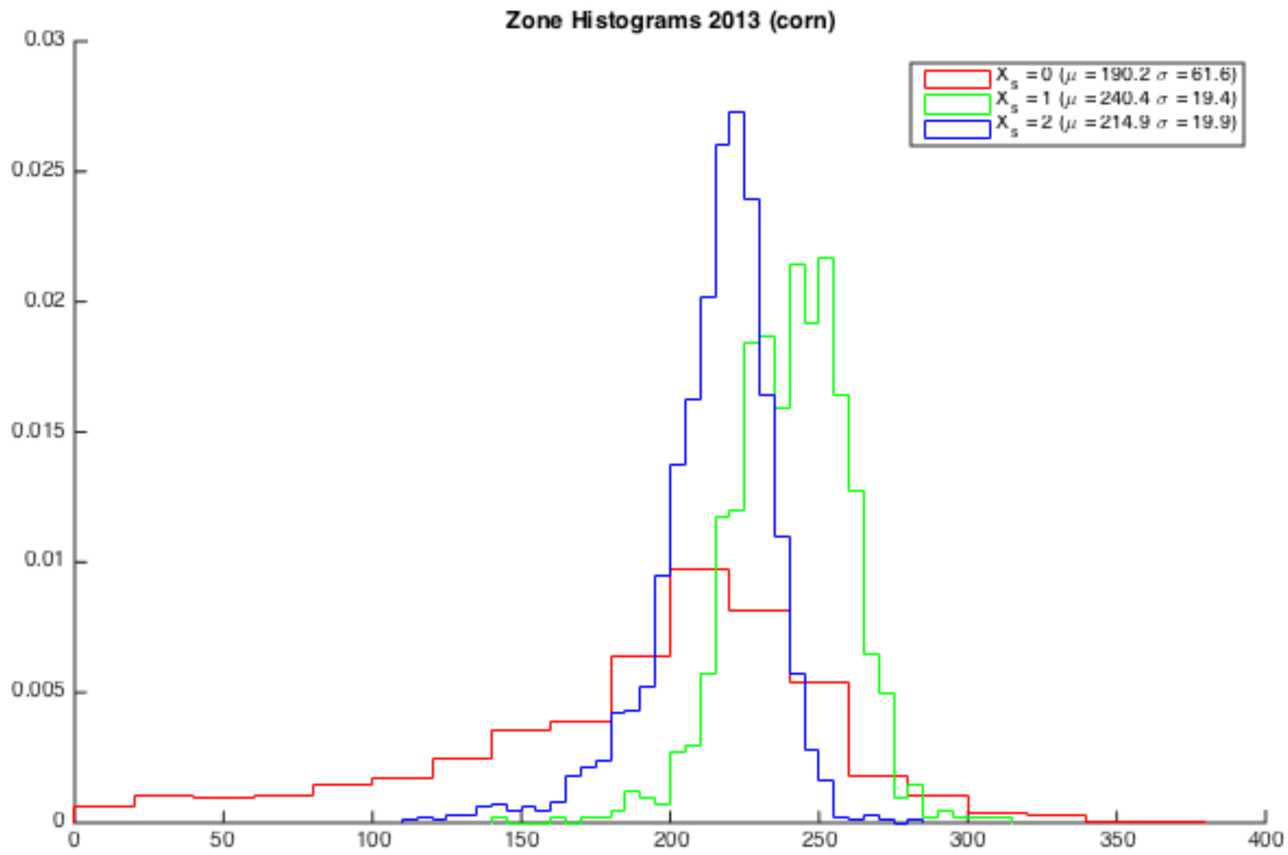
SEM Management Zone Histograms 2011





SEM Management Zone Histograms 2013





Management Zone Estimation: Preliminary Conclusions

- SEM derived management zones appear to cluster according to corn yield potential
- Not as evident in the MZA derived management zones
- Field boundary clearly needs special attention (compaction, yield map errors?)
- The “resolution” that can be achieved is unclear given this data
- Also (but not shown here):
  - Soybeans and corn should be treated separately for purposes of management zone estimation (SEM algorithm can combine them)
  - SEM finds significantly different zones for the two

Where will we go from here?

- Characterize sources of yield mapping errors
  - Models for mass flow, moisture sensor errors
  - Models for grain separation and flow in the combine
  - Couple with combine kinematic model

- Solve inverse problem: From sensor and machine position measurements, attribute the grain to a spot on the field

- Finally: How to design and analyze experiments, using precision farming technologies, which can be used to improve farm management.

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Is this precision attainable?

http://egnos-portal.gsa.europa.eu/discover-egnos/about-egnos/case-studies/egnos-yield-mapping-power-knowledge

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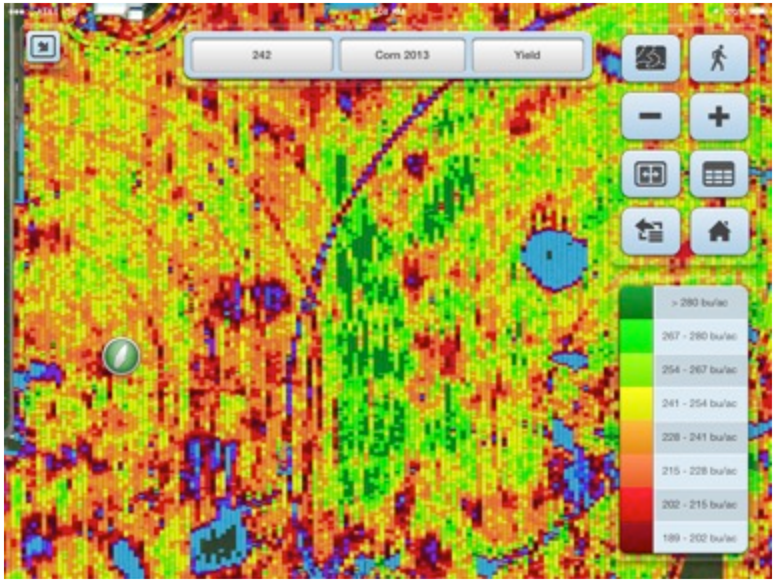
Or this?



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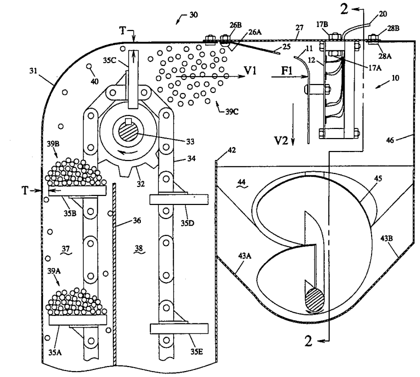

United States Patent [19] | [11] **Patent Number: 5,343,761**

Myers | [45] **Date of Patent: Sep. 6, 1994**

[54] **METHOD AND APPARATUS FOR MEASURING GRAIN MASS FLOW RATE IN HARVESTERS**

[76] Inventor: **Allen Myers**, R.R. 2, Ames, Iowa 50010

[21] Appl. No.: **716,293**

[22] Filed: **Jun. 17, 1991**

electrical communication with the force measuring apparatus calculates the average value of grain impact force, adjusts this value to compensate for the difference between an actual measured operating speed of the conveyor and a constant reference speed, and calculates grain mass flow rate utilizing a mass flow calibration characteristic which relates grain mass flow rate to average grain impact force, where this calibration char-

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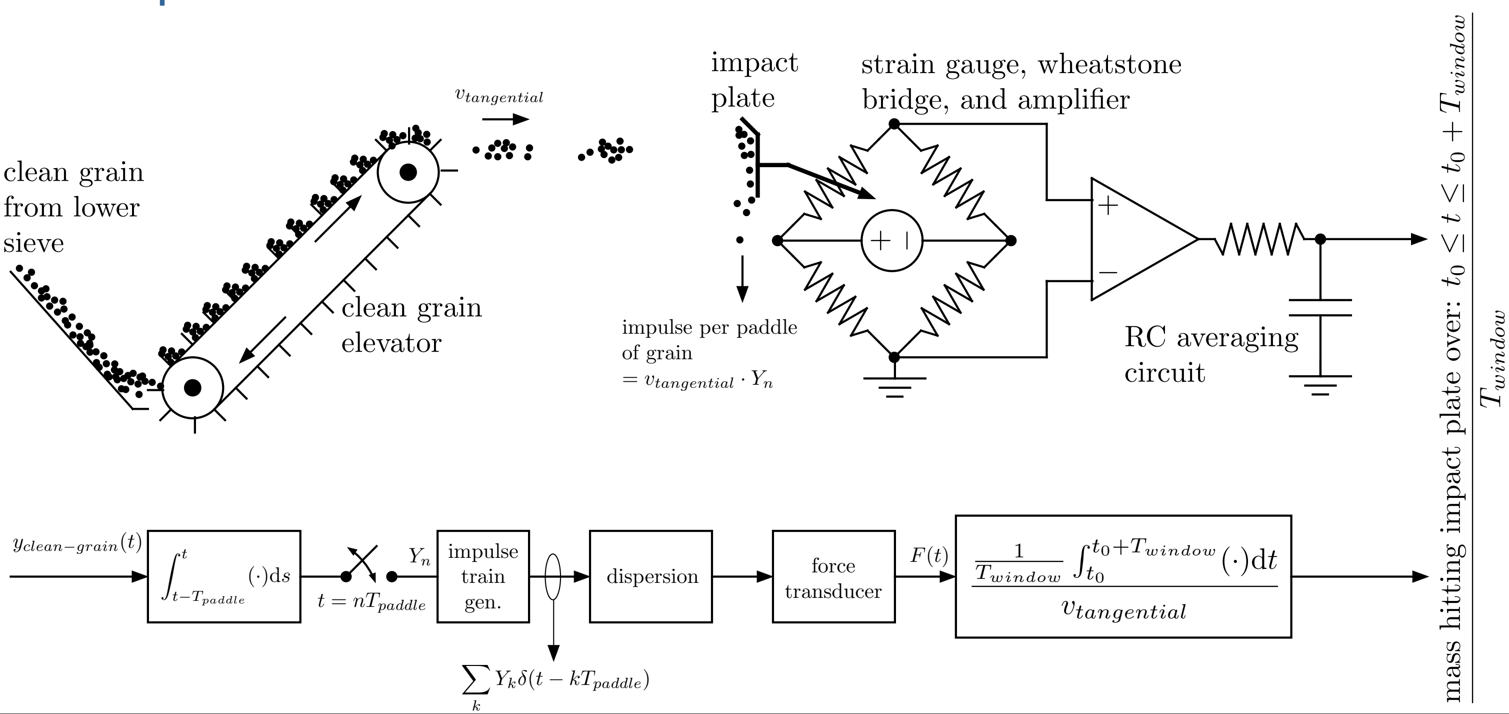

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Interesting video of mass flow sensor operation on a JD combine:

https://upload.wikimedia.org/wikipedia/en/transcoded/a/a0/GrainFlowSensorVideo.webm.480p.ogv

Where will we go from here?

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A Modern Rotary Threshing Combine Cutaway

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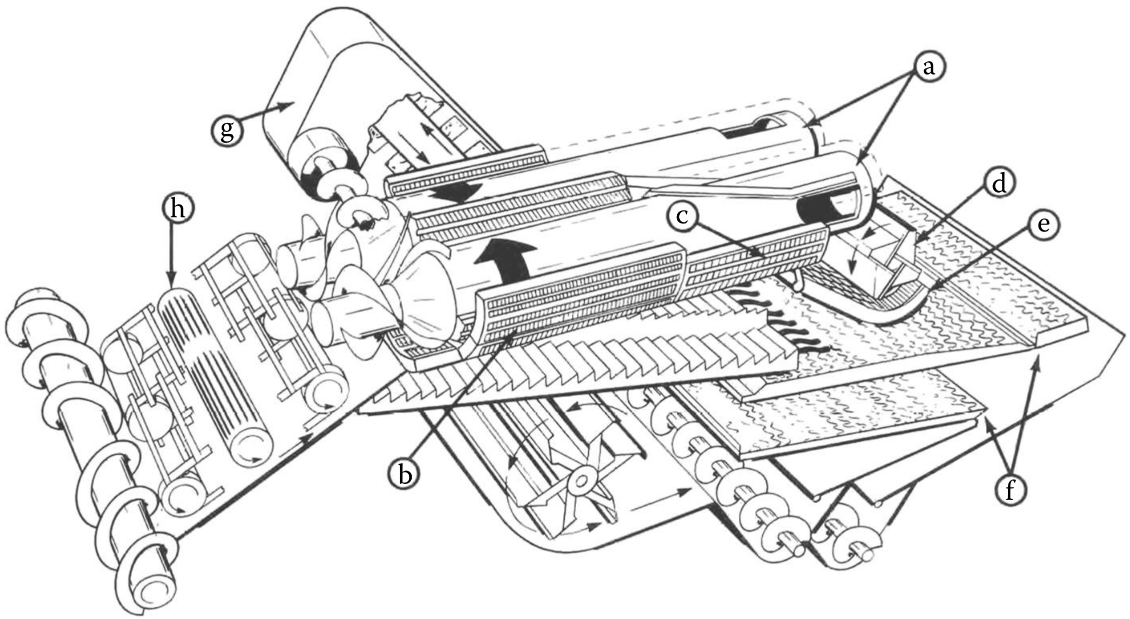
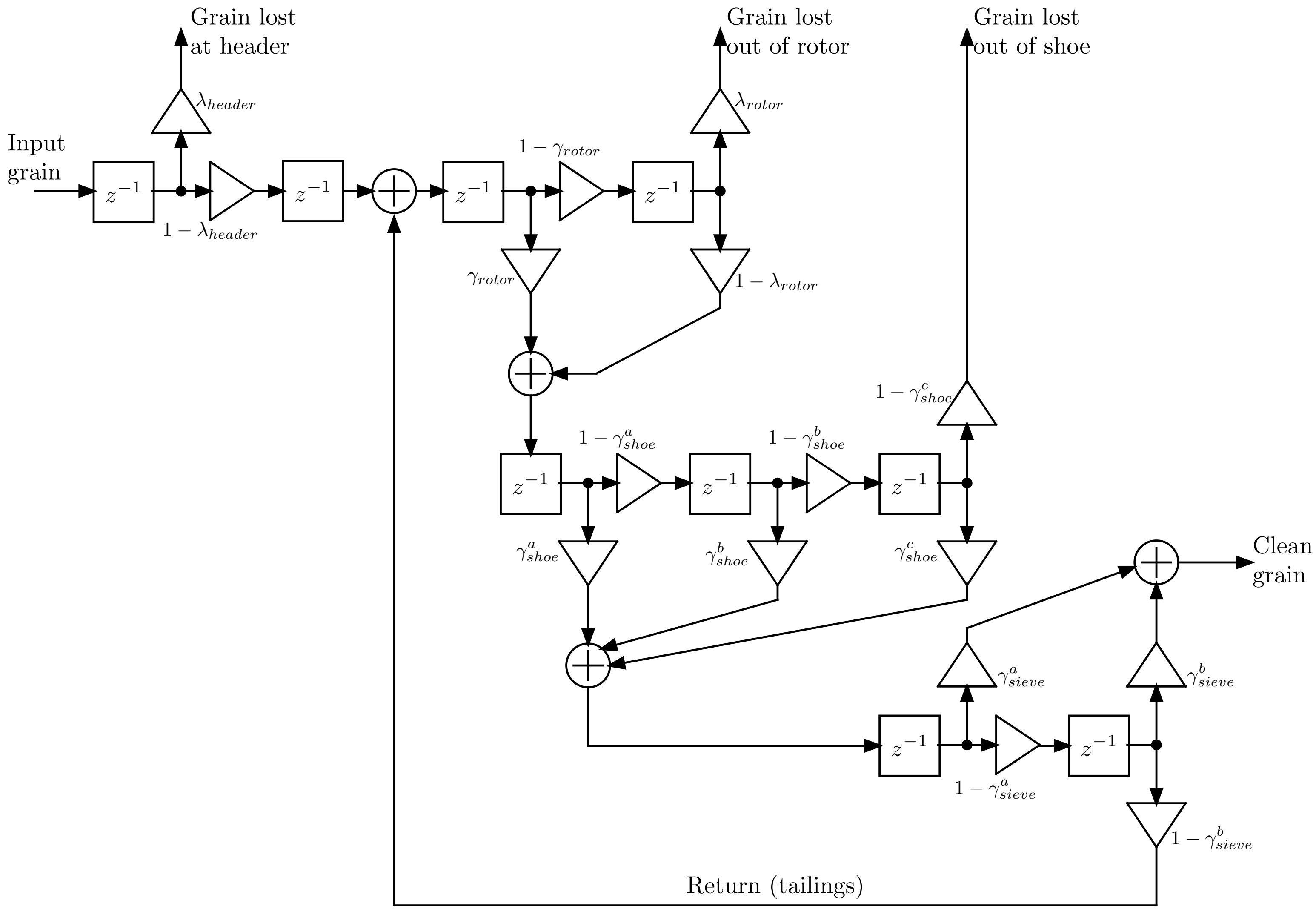


Model for Threshing / Separating



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- Finally: How to design and analyze experiments, using precision farming technologies, which can be used to improve farm management.

Thank you!

Well, even if the big data thing doesn't work out, we'll still have auto-steer:

Thank you!

;)