Using multispectral ground sensors to improve crop phenology monitoring

Michael Cecil

Overview

-Using ground sensors to overcome cloud cover

- Tracking smallholder crops using data fused time-series VI series of vegetation indices.

- Mapping smallholder crop management practices

Arable Mark multispectral sensor

Background - Zambia

This project focuses on smallholder maize agriculture in Zambia.

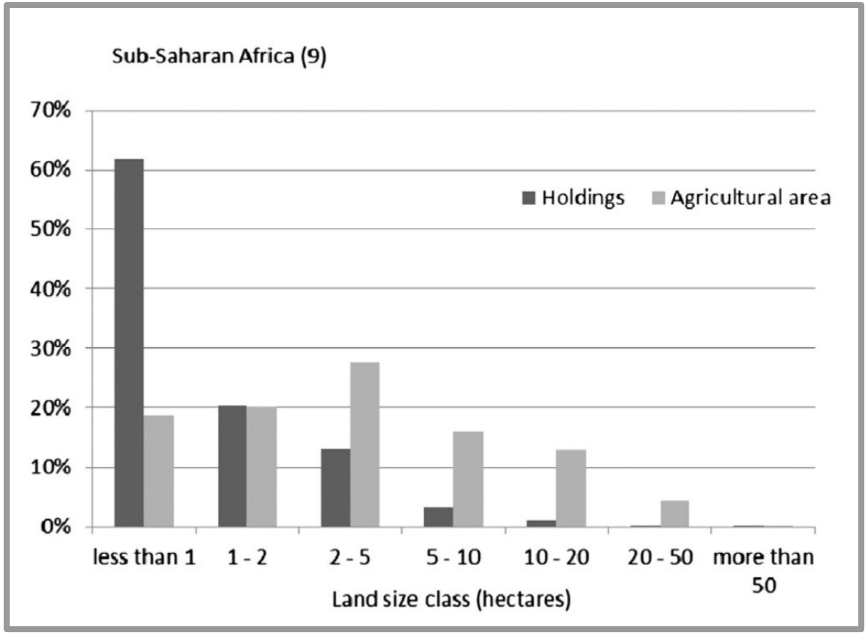
Why?

- Existing partnerships
- Data access
- Representative smallholder conditions
- Importance of Zambia regionally

Zambia Agriculture Research Institute seminar on participatory plant breeding
Source: ZARI Facebook

Smallholder Agriculture

- Smallholder farms produce 20 - 50% of global food supply. (Ricciardi et al. 2018)
- In sub-Saharan Africa (SSA), the most farms are< 2 ha. (Lowder et al. 2016)
- SSA projected to have increasing food demand and decreasing arable land (Ittersum et al. 2016)



Farm size distribution, sub-Saharan Africa (Lowder et al. 2016)

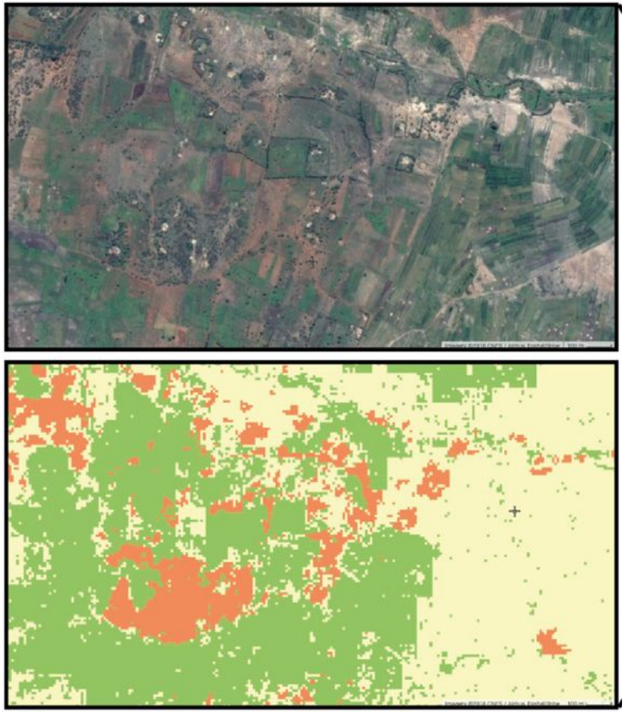
Limitations to Monitoring Smallholder Agriculture

Data scarcity

- Cloud cover
- Variable management practices
- Small field size

Shorter track record

- New methods developed for industrial agriculture often in US
- Less financial interest in crop monitoring for smallholder agriculture



Crop type mapping,
Kenya/Tanzania. Jin et al. 2019

Trial sites - Zambia

- Trials sites use different maturity cultivars
- 2020-21. 4 trial sites with 2-3 cultivars each.
- 2021-22. 1 trial site with 3 cultivars x 3 fertilizer levels.

Mark sensor in Zambia field trial

Additional sites - US

- About 50 Mark sensors installed in corn fields in CA, NE.
- 3 Mark sensors installed at Whittier Farms in MA, with weekly drone imagery.

US based sites provide additional training and validation data for model creation.

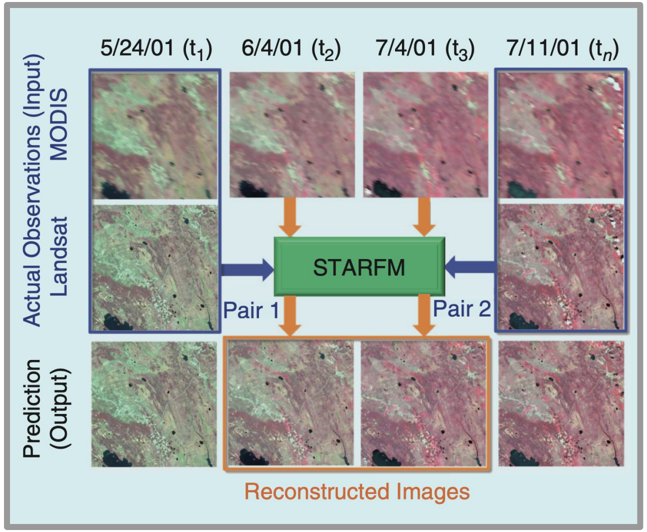
Mark sensor in Whittier Farms, MA

Data Fusion approach

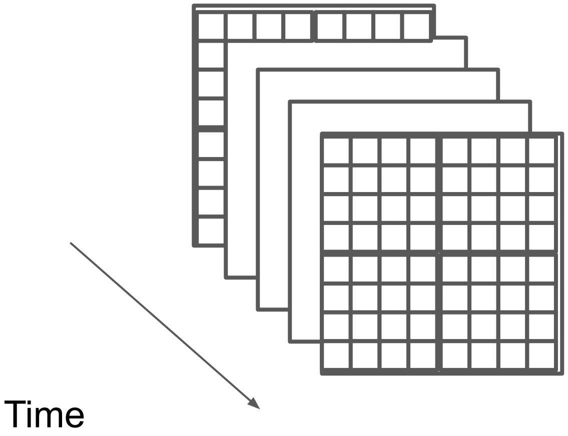
Existing data fusion methods

STARFM, STAIR (Luo et al 2018)

-Merge high frequency coarse sensor (MODIS) with less frequent, higher resolution (Landsat)



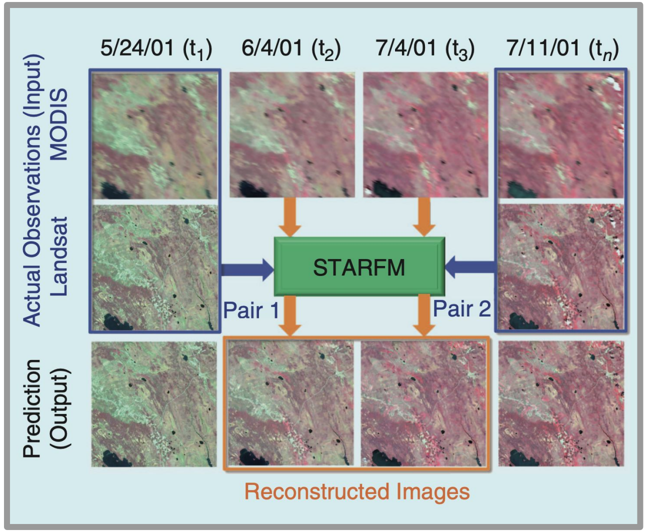
STARFM (Gao et al. 2006)



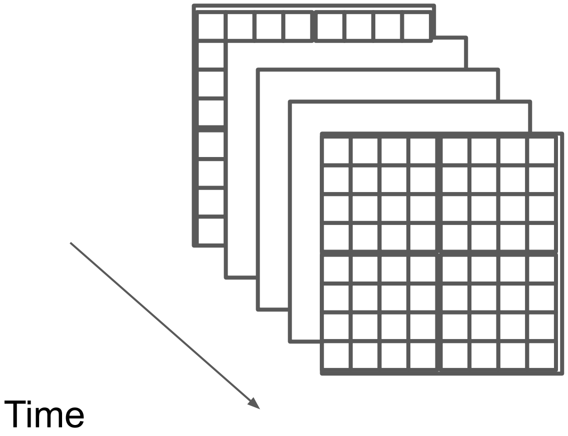
Existing data fusion methods

Limitations:

- Still affected by cloud cover
- Medium res sensors are still too coarse for smallholder agriculture



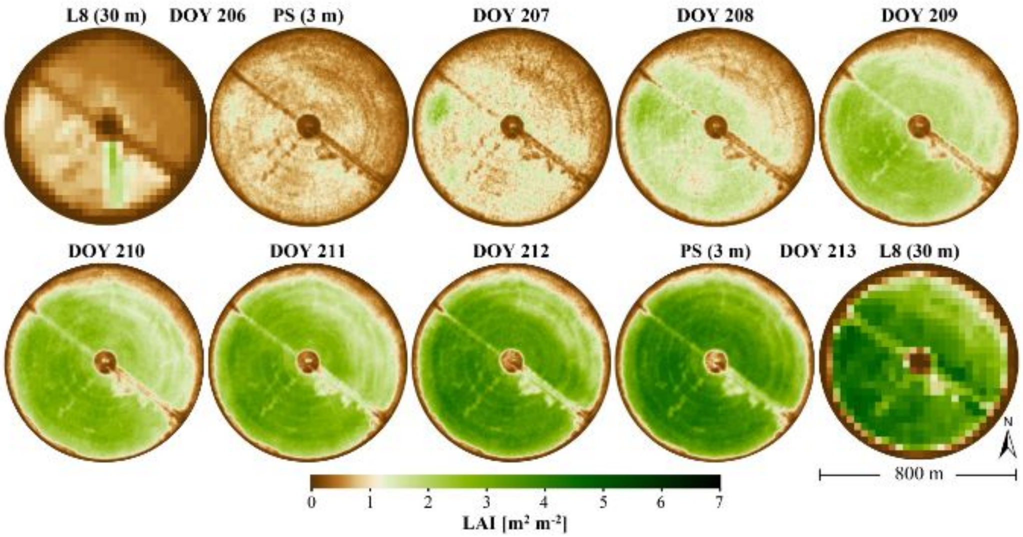
STARFM (Gao et al. 2006)



Existing data fusion methods

CESTEM

- Integrates Landsat, Sentinel-2 imagery to create radiometrically consistent product at Planet resolution (~3-4 m, near daily)
- Planet Fusion product recently released to public (March 2021)

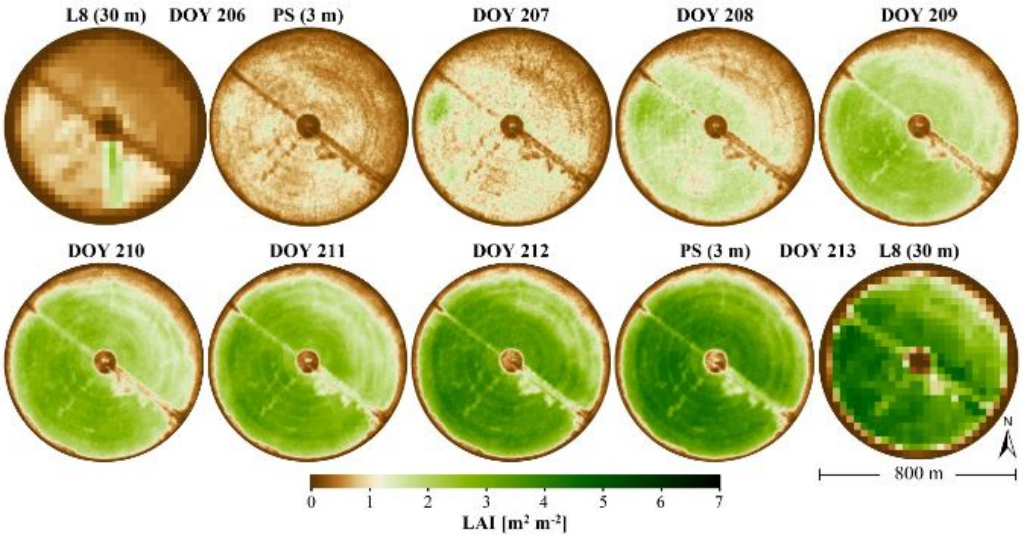


CESTEM (Houborg and McCabe 2018)

Existing data fusion methods

Limitations

- Cloud cover can still obscure imagery majority of time in cloudy regions (e.g. subtropical agriculture)
- Lacks integration of farmer management practices
- Not freely available



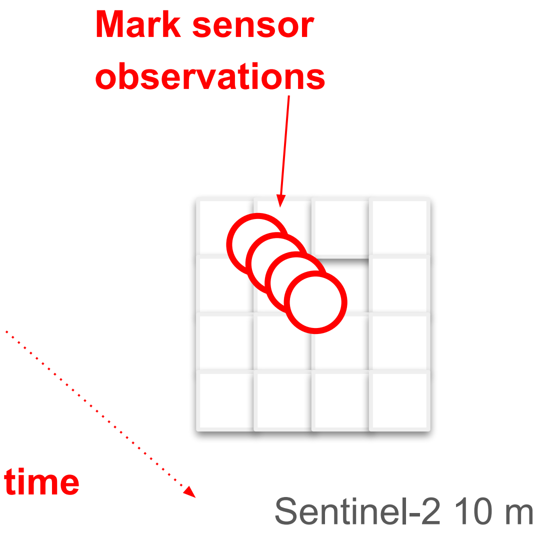
CESTEM (Houborg and McCabe 2018)

This project's approach

- Use ground-based multispectral sensors that track crop growth (and measure VI's) continuously
- Establish empirical relationship between satellite-based sensors and ground sensor VI

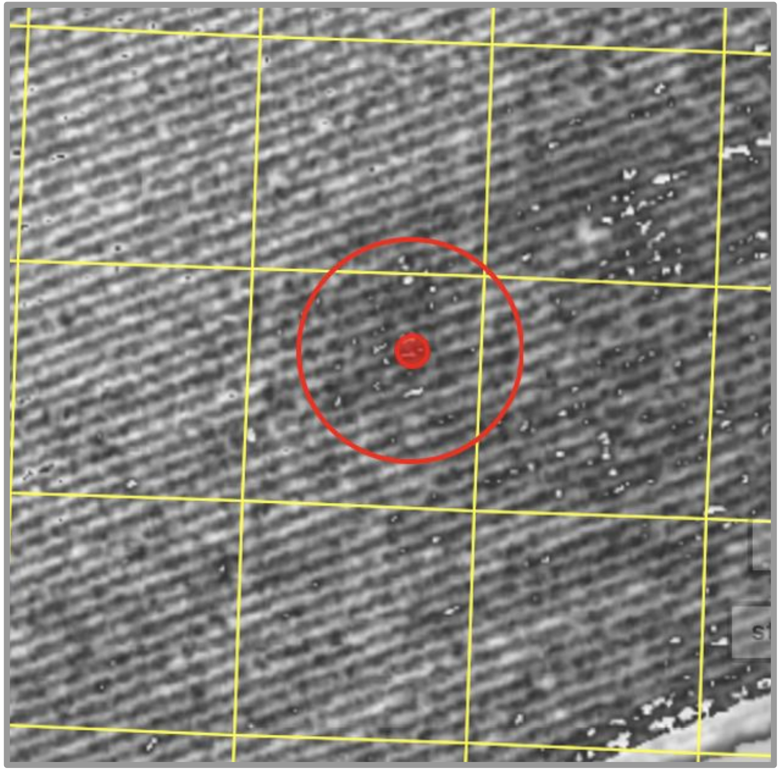
$$(1)\ \ S2\,VI_{fitted} + Planet\,VI_{fitted} + S1_{fitted} + var_{growth} \;{-}{-}{>}\; Mark\,VI$$

- Extrapolate model away from ground sensors



Scale (space)

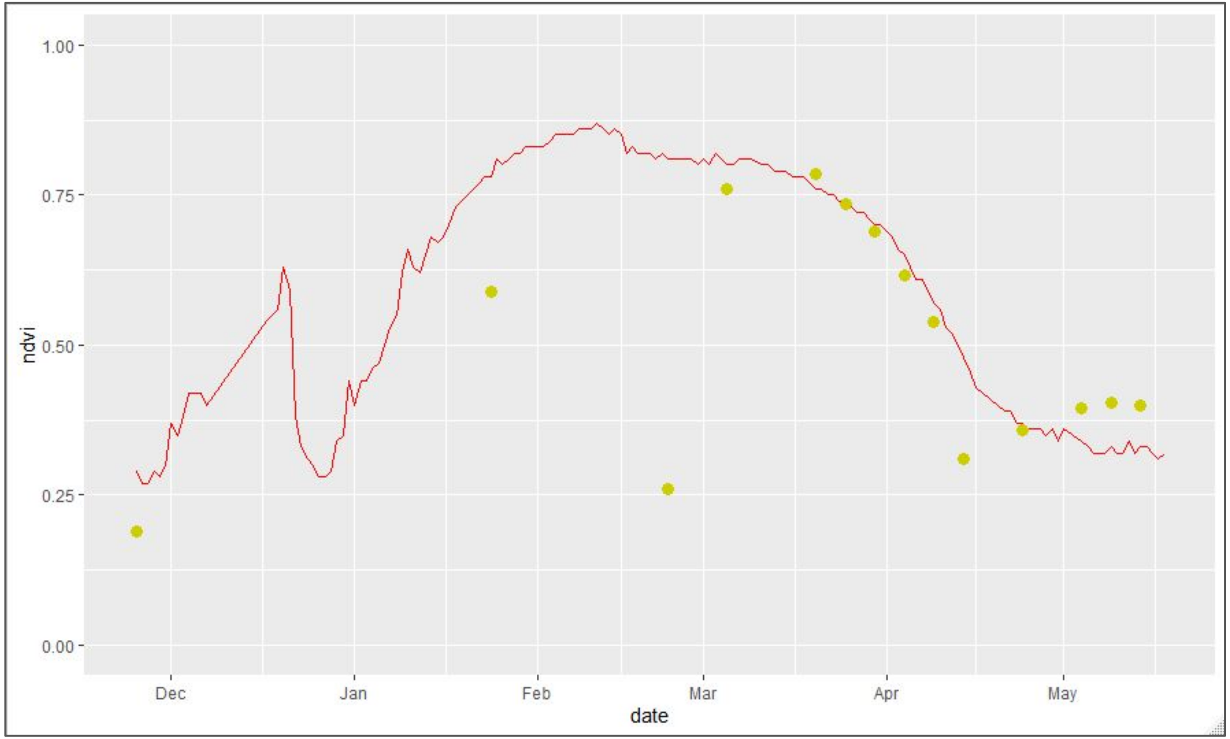
- Ground sensor footprint (10 meter radius) is roughly equal to Sentinel-2 resolution
- Mark sensor captures several rows of corn, but still a tiny percentage of field



Sentinel-2 grid (yellow), and
Mark sensor footprint (red)
Whittier Farms, MA

Scale (time)

- Mark sensors provide continuous coverage
- Sentinel-2 provides sporadic coverage, especially during greenup.



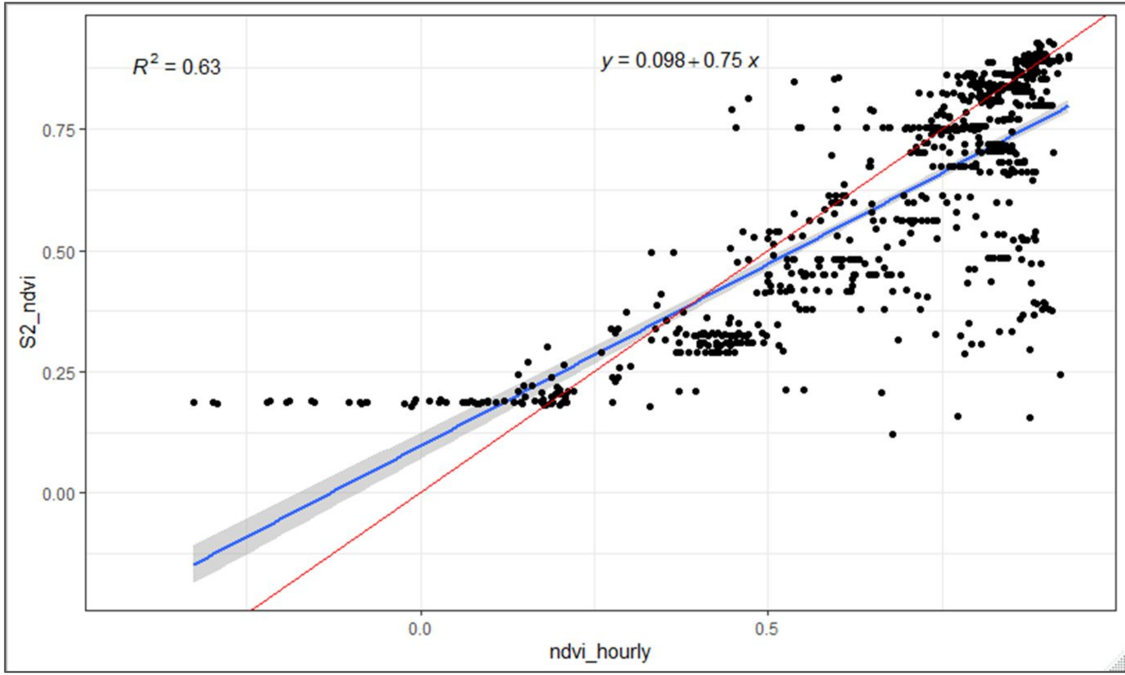
NDVI observations
Sentinel-2 (yellow),
Mark sensor footprint (red)
Zambia field trial

Creating a transformation model

$$(1)\ \ S2\,VI_{fitted} + Planet\,VI_{fitted} + S1_{fitted} + var_{growth} \text{ --> } Mark\,VI$$

First, need to understand direct relationship between variables.

- Data cleaning
- Partial cloud effects
- Choice of VI

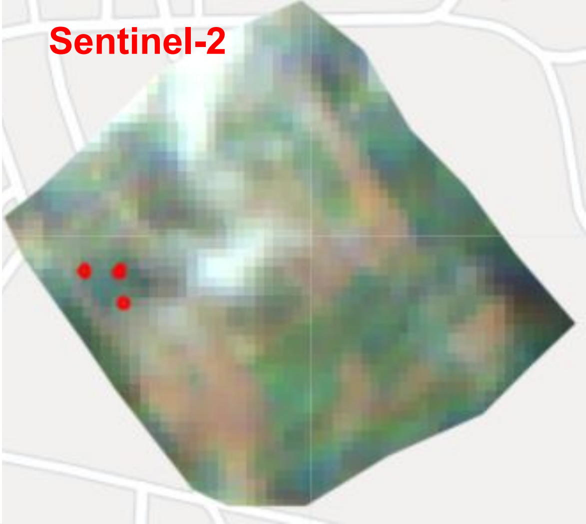


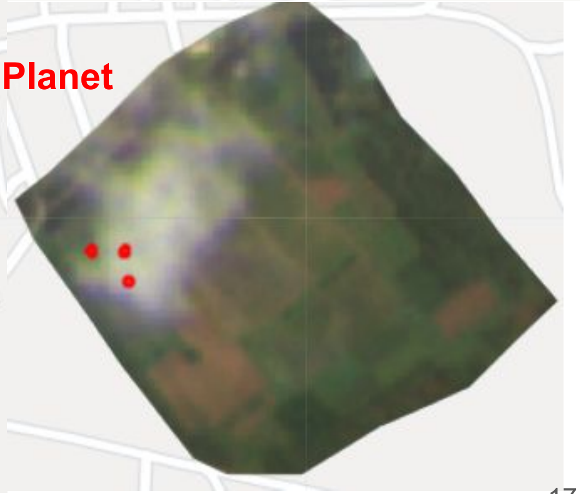
Integrating multiple data sets

$$(1)\ \ S2\,VI_{fitted} + Planet\,VI_{fitted} + S1_{fitted} + var_{growth} \dashrightarrow Mark\,VI$$

Questions:

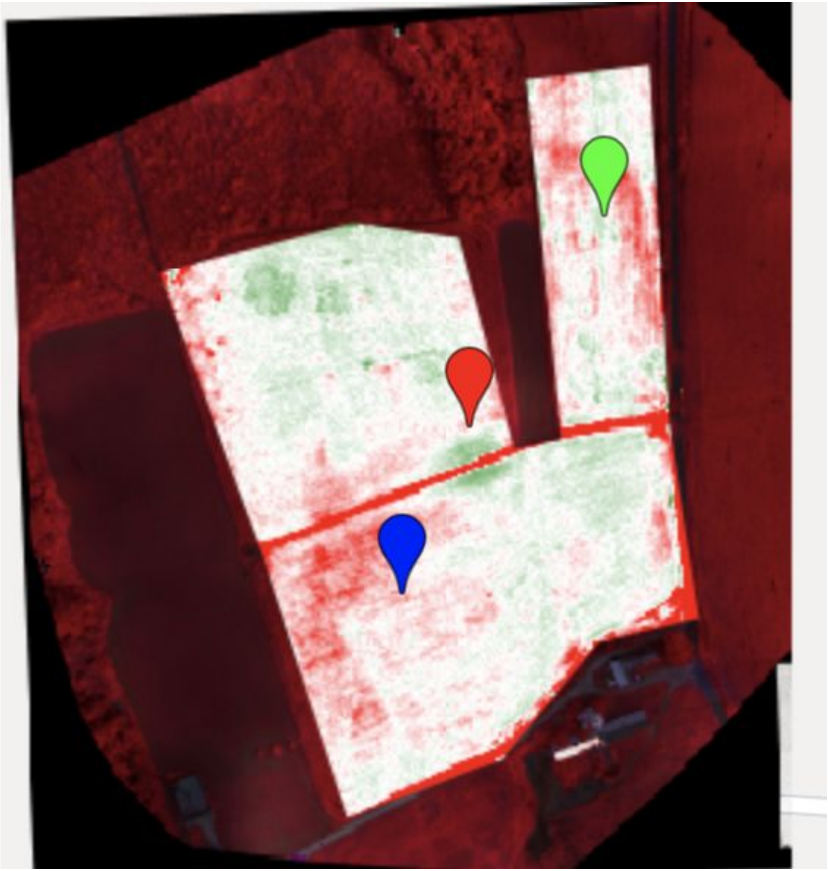
- Date inconsistency
- Curve-fitting
- Model type
  - Regression?
  - Machine learning?





Extrapolation

Extrapolation of model will first be tested on other Mark sites, using cross-validation.



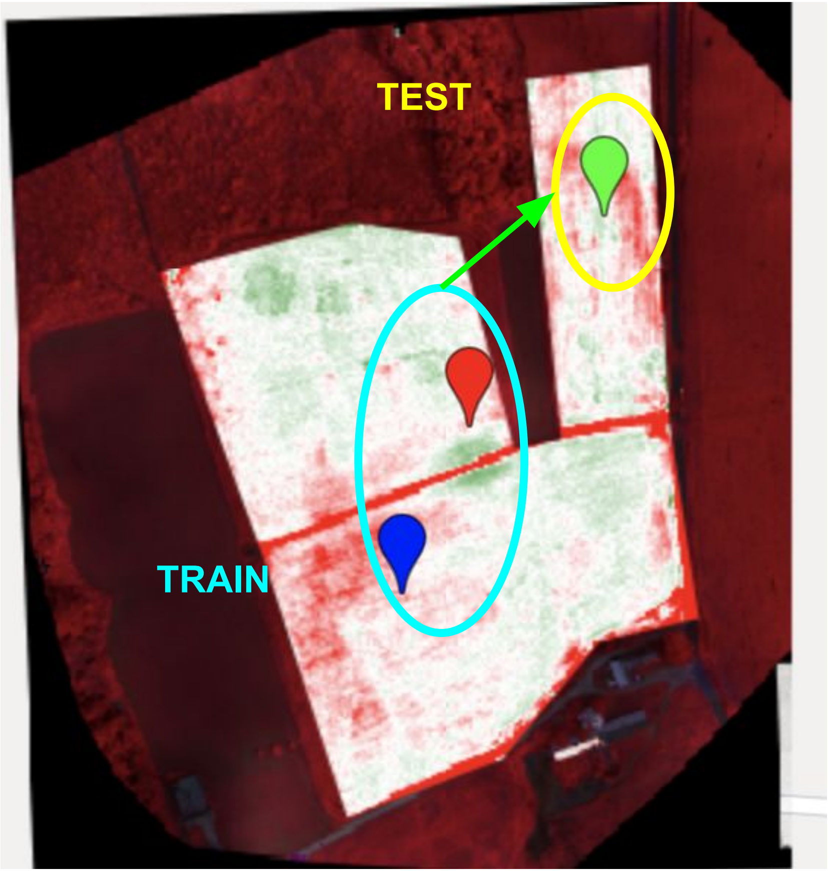
Mark sensors at Whittier Farms

Extrapolation

The transformation model will be trained on a subset of sensors and tested on the withheld sensors.

We also have data in smallholder fields in Kenya and Zambia from previous project.

In total, we have ~100 seasons of Mark data, but with gaps in some seasons.



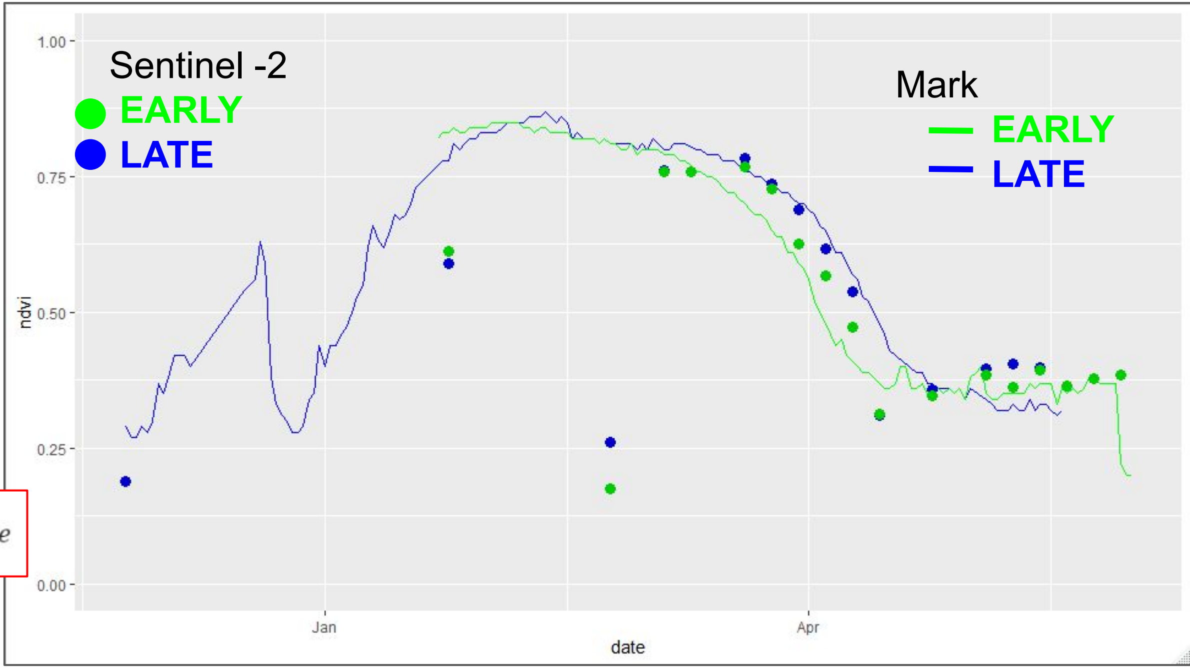
Mark sensors at Whittier Farms

Identifying crop management practices

Zambia trials include cultivars of different maturities.

Goal is to create model that estimates management practices from VI curves

$$(2)\ Data\ fused\ VI\ +\ \ met\ data\ -->\ Cultivar,\ Planting\ date$$



Zambia trial fields.

Identifying crop management practices

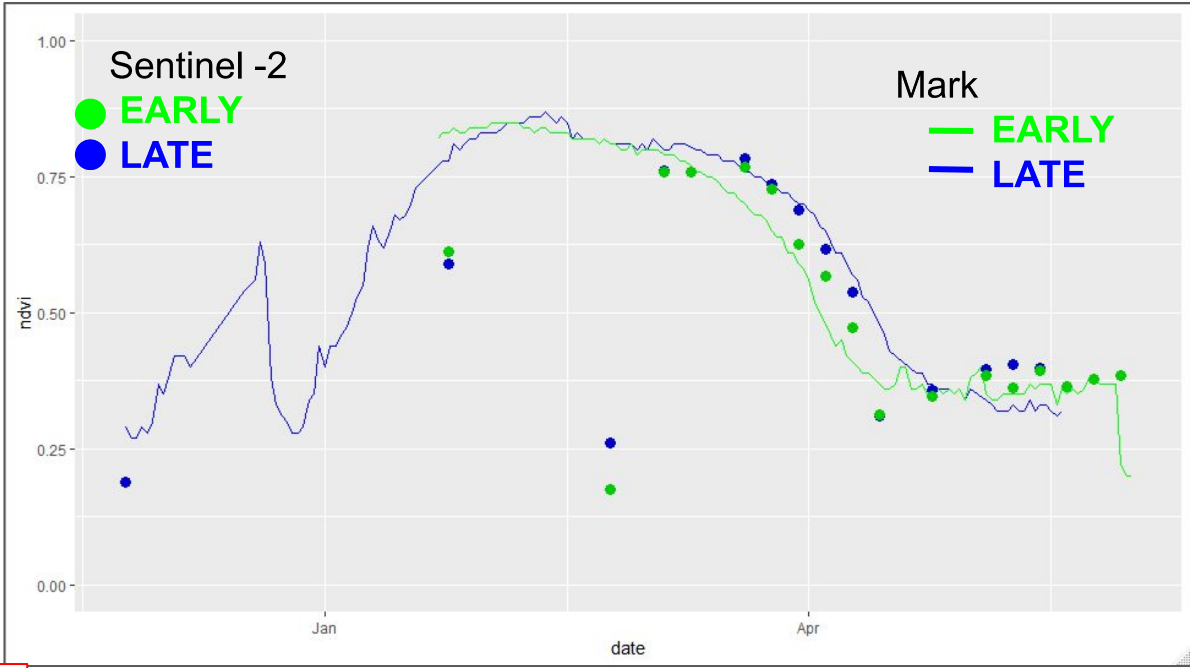
Planting date

- When does curve reach x% of max NDVI? (Urban 2018)

Cultivar

- How long does curve take to reach peak VI?

Data hungry

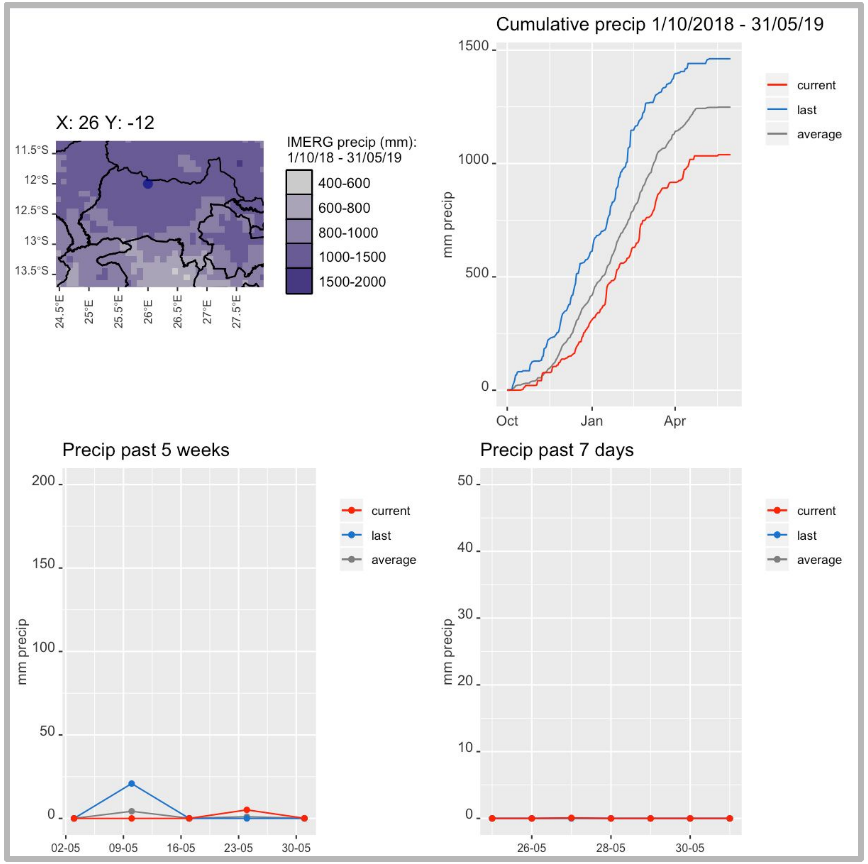


(2) *Data fused VI* + *met data* --> *Cultivar*, *Planting date*

Zambia trial fields.

Downstream applications

- Evaluate policy interventions
- Yield variance analysis, (integration with crop modeling)
- Regional crop monitoring



Dashboard for Mark sensor and precipitation monitoring, Zambia.

Importance of new sensors

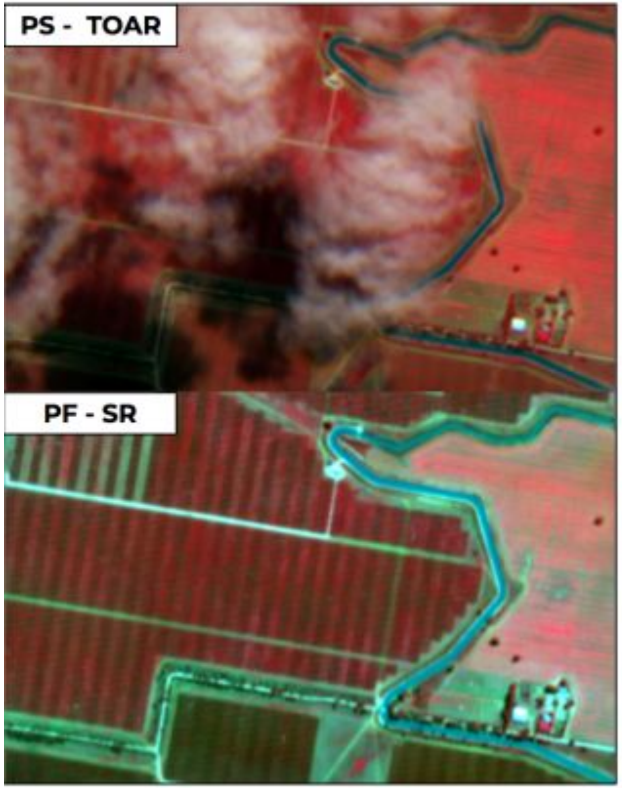
Arable

- Ground sensors are valuable. Ability to accurately integrate them with satellite data allows for scaling.

Planet Fusion

- Can potentially address partial cloud/shadow conditions

This project will evaluate how these new data sets improve models.

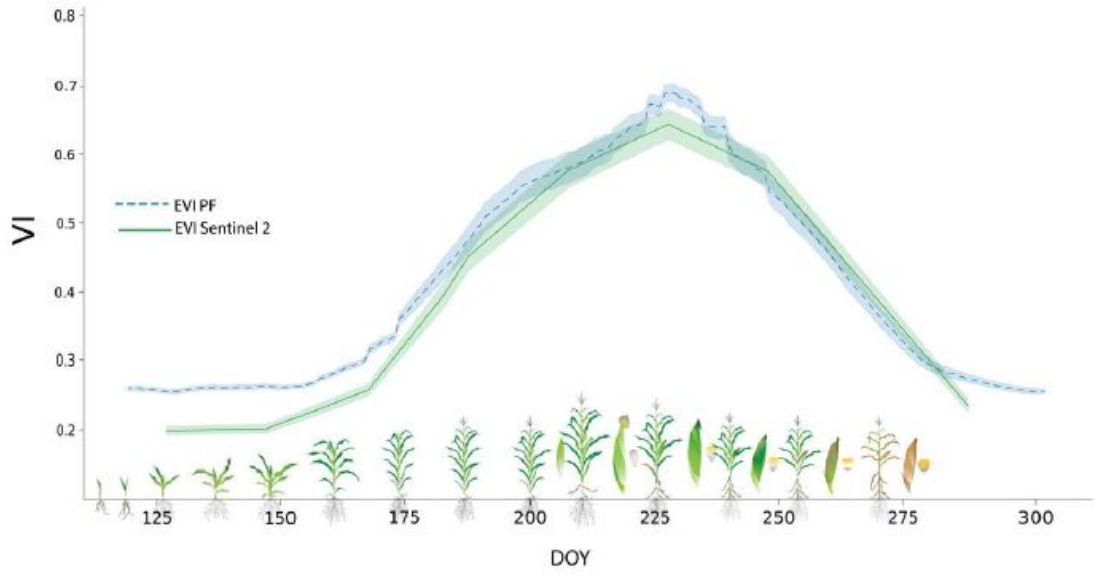


Planet Fusion product manual

Recent research

- New applications of Planet Fusion data

- BUT applications in the US, more challenging to apply in smallholder context



Maize phenological stage mapping
Nieto et al. 2022

Recent research

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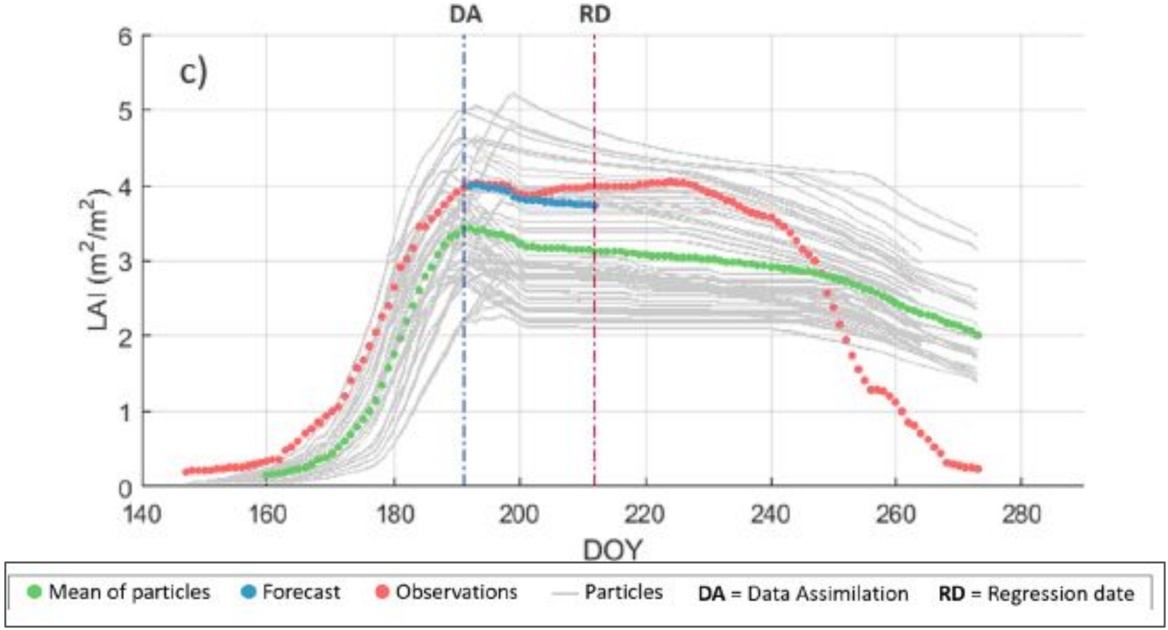

Integrating Planet Fusion data into crop models for earlier yield prediction.
Ziliani et al. 2022

Collaboration

I would like to hear from you!

Especially if your interests include

- Smallholder agriculture in SSA
- Data fusion
- Mapping agricultural practices with remote sensing

Acknowledgements

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Michael Cecil

mcecil@clarku.edu

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