EO (finally) delivers on crop monitoring

Prof. P. Lewis UCL/NCEO

UK: UCL, Assimila
China: CAU, CAAS
Ghana: GSSTI

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Newton Fund

Science and Technology Facilities Council

Natural Environment Research Council

EO promises for crop monitoring

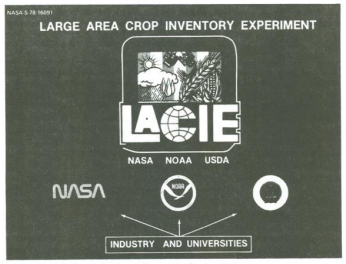


Figure 8.1 The three federal agencies participating in LACIE

Much of the groundwork and requirements laid in 1970s and 1980s: LACIE, AgRISTARS

- Crop models
- Drivers
- EO
  - vegetation / stress indicators
  - Crop type

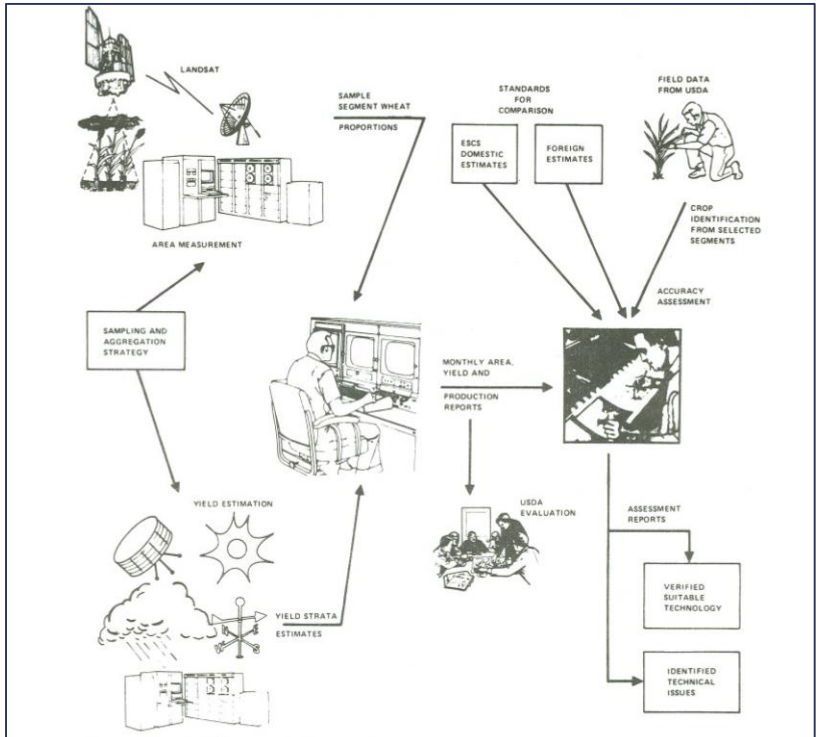
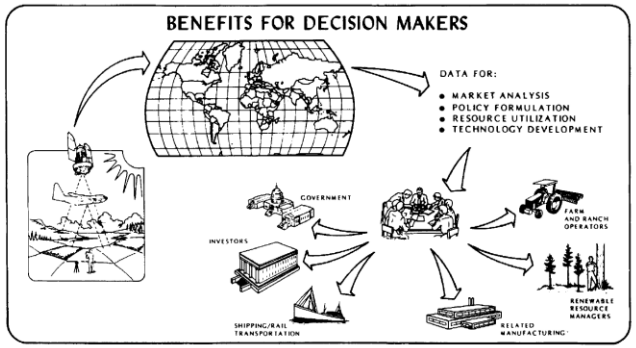


Figure 8.3 LACIE technical approach

Early promise



Remote sensing technology is being developed to give timely, reliable information to those concerned with the worldwide status of renewable resources.

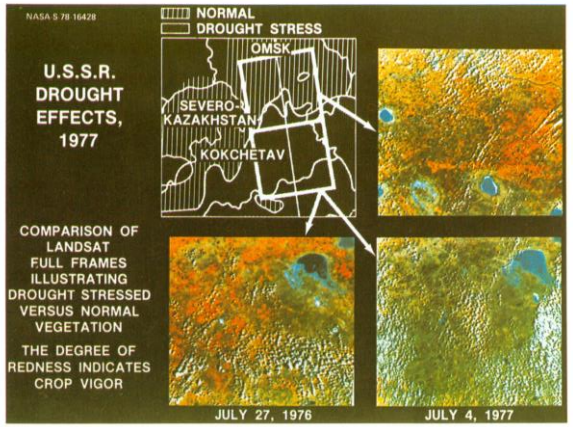


Figure 8.11 USSR drought effects visible on LANDSAT 1977

FY 1983

AgRISTARS

RESEARCH REPORT

A Joint Program for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing

AVHRR data have provided an efficient and inexpensive source of data for agricultural monitoring, condition assessment, and change detection to augment existing satellite, aircraft, and ground

PREFACE

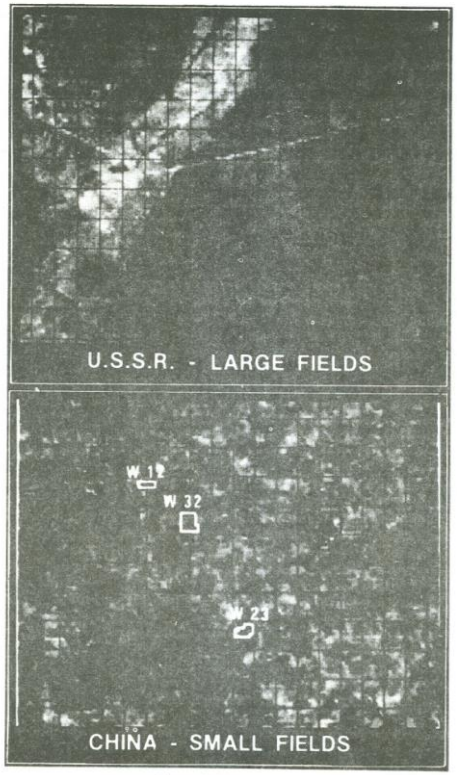
The AgRISTARS program was initiated in fiscal year 1980 in response to an initiative issued by the U.S. Department of Agriculture. Led by the USDA, the program is a cooperative effort with the National Aeronautics and Space Administration, the National Oceanic and Atmospheric Administration of the U.S. Department of Commerce, the U.S. Department of the Interior, and the Agency for International Development of the U.S. Department of State.

The program goal is to determine the usefulness, cost, and extent to which aerospace remote sensing data can be integrated into existing or future USDA systems to improve the objectivity, reliability, timeliness, and adequacy of information required to carry out USDA missions.

The program is well underway, with encouraging progress having been made in fiscal years 1980,* 1981,† 1982,§ and 1983 (as documented in this report). The outlook is that aerospace remote sensing will contribute to USDA information needs in a significant way and, more generally, that the AgRISTARS effort will advance this technology for use in other areas of national need.

Requirements

- **Improve information extraction**
  - Calibration
  - Cloud and atmospheric effects
  - Physically-based models
- **Models**
  - Calibration datasets
  - Improve drivers
  - ML vs explicit models
- **Data Assimilation**
  - multiple models and datasets
  - treatment of uncertainty
- **Processing**
  - volumes and databases
- **Match spatial and temporal sampling**
  - Higher resolution and revisit (SPOT, Landsat)



Z. Jin et al. Agricultural and Forest Meteorology 247 (2017) 207–220

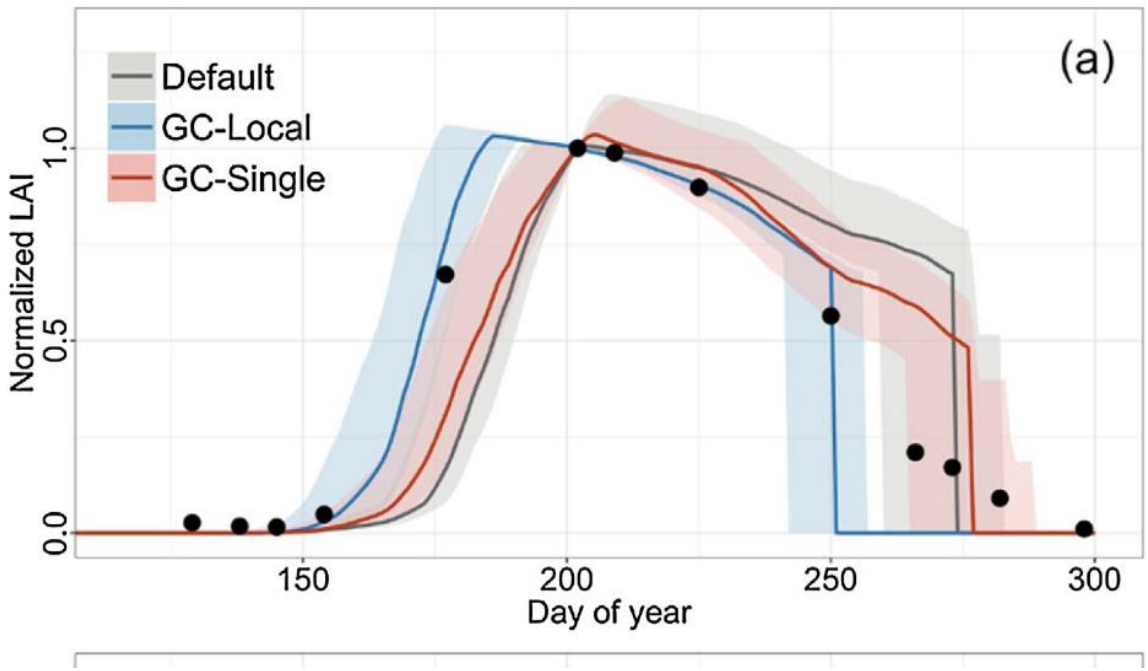


Fig. 4. The normalized LAI derived from simulations with default and calibrated phenology parameters for typical pixels from (a) Illinois (41.76N, −89.09E), and (b) Iowa (41.08N, −95.46E). Thick lines are simulations with the most likely sowing dates that are estimated based on the NASS state-level data and the geographic location. Shaded areas include simulations with sowing date between 20% and 80% quantile of the NASS reported state-level planting progress. Dots represent Landsat obsevations.

Remote Sensing of Environment 235 (2019) 111470

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No pixel left behind: Toward integrating Earth Observations for agriculture into the United Nations Sustainable Development Goals framework

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Requirements

The Role of Terrestrial Vegetation in the Global Carbon Cycle:
Measurement by Remote Sensing
Edited by G. M. Woodwell

CHAPTER 8
The LACIE Experiment in Satellite Aided Monitoring of Global Crop Production

J. D. Erickson
NASA Johnson Space Center, Houston, Texas, USA

ABSTRACT

The Large Area Crop Inventory Experiment (LACIE) demonstrated that improved accuracy in USDA predictions of wheat production can be achieved for the US Great Plains by the use of satellite imagery. LACIE experimenters also used their technique to predict with great accuracy the size of the 1977 Soviet wheat crop six weeks prior to harvest. This paper discusses the experiment as a potential model for other programmes designed to measure globally other terrestrial plant communities by remote sensing from satellites.

Higher temporal resolution 'drivers'
The need to develop yield models that are based on daily or weekly, rather than monthly, averages of temperature and precipitation, and that more closely simulate the critical biological functions of the wheat plant and its interaction with the external environment.

Need for higher (<80 m) spatial resolution observations
The need to develop techniques to deal more effectively with the spatial information in LANDSAT data and to improve the accuracy of area estimates in regions where a high percentage of the fields have effective sizes close to the resolution limit of LANDSAT. In addition, further investigation of the improvements resulting from the increased resolution power of LANDSAT-D, as well as the spatial resolution requirements for future LANDSAT satellites, is necessary.

Cloud and atmospheric impacts
The need for better quantification of the effects of cloud cover on the acquisition of LANDSAT data at critical periods in the crop season, particularly in more humid environments, such as the United States cornbelt.

Consider the trade-offs
The trade-offs between the need to shorten the time from data acquisition to reporting and the cost of obtaining a quicker response. Although it is possible to reduce this time span, doing so may require substantial additional costs.

The Role of Terrestrial Vegetation in
Measurement by Remote Sensing
Edited by G. M. Woodwell

CHAPTER 8
The LACIE Exp
Monitoring of G

J. D. Erickson
NASA Johnson Space Center,

The Large Area Crop Inventor
accuracy in USDA predictions o
Plains by the use of satellite ima
to predict with great accuracy th
harvest. This paper discusses
programmes designed to measure
sensing from satellites.

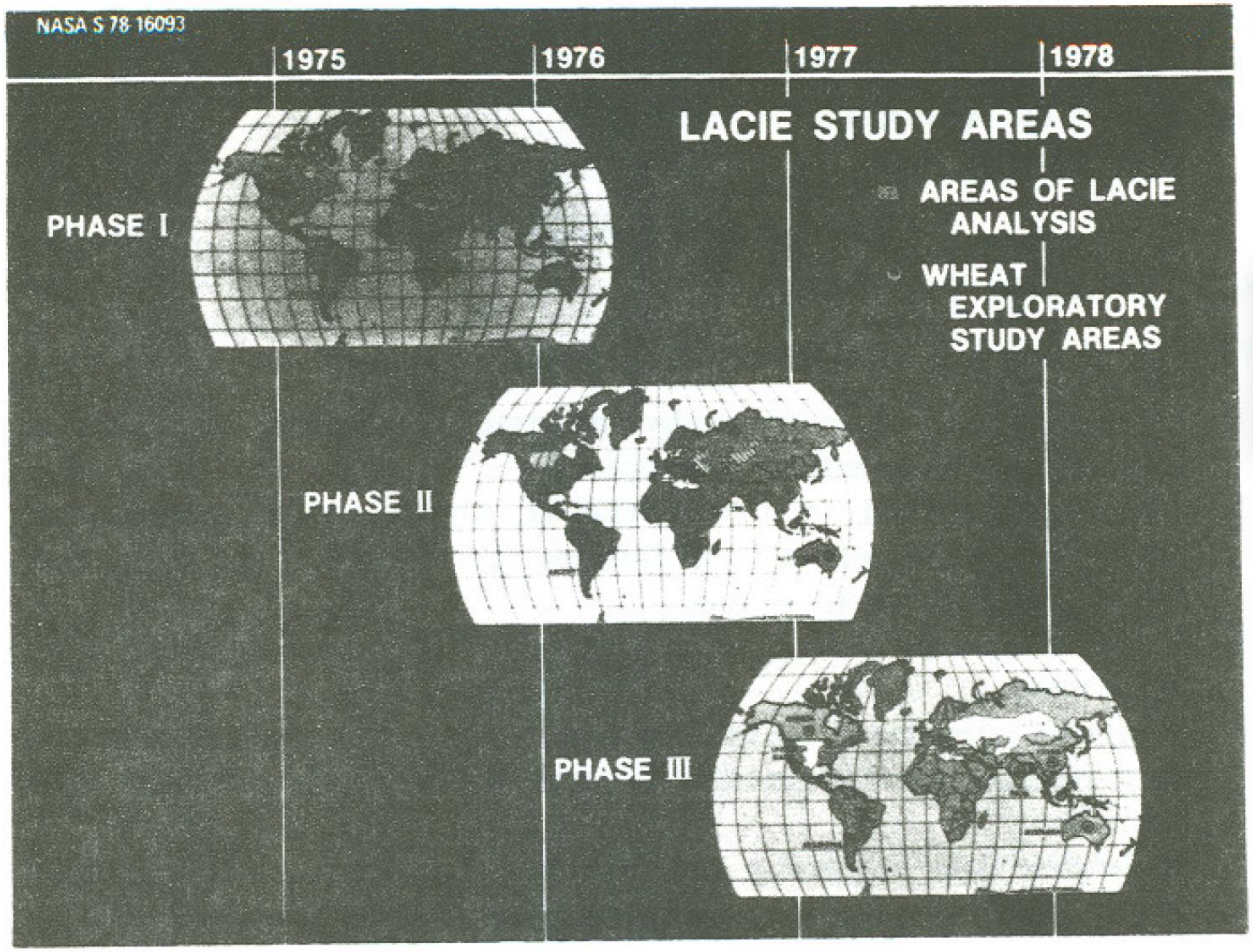


Figure 8.2 LACIE study areas

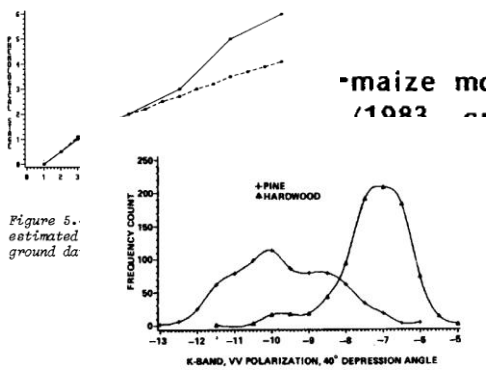
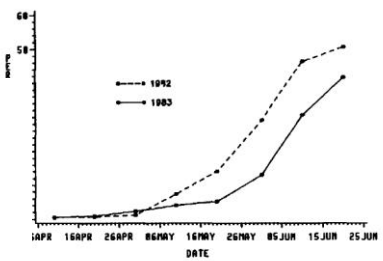


Figure 27.- Radar backscatter histogram: pine versus hardwood.

- A revised wheat yield redu model was transferred to the Fo Agricultural Service (FAS) and t in both the USSR and China. M results compared favorably with satellite data sources.

FAS also used the Crop Estim Environ winter w operational SR.



gure 7.- Estimated 1982 and 1983 eat yield reduction potentials for jor wheat provinces in China.

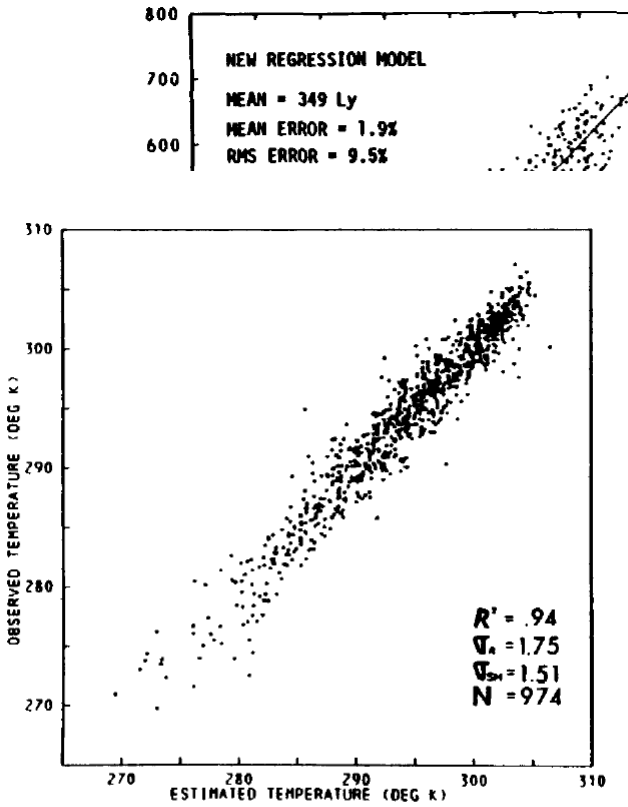


Figure 12.- Shelter temperature plotted against satellite estimates for clear and partly cloudy retrievals for April through July 1981.

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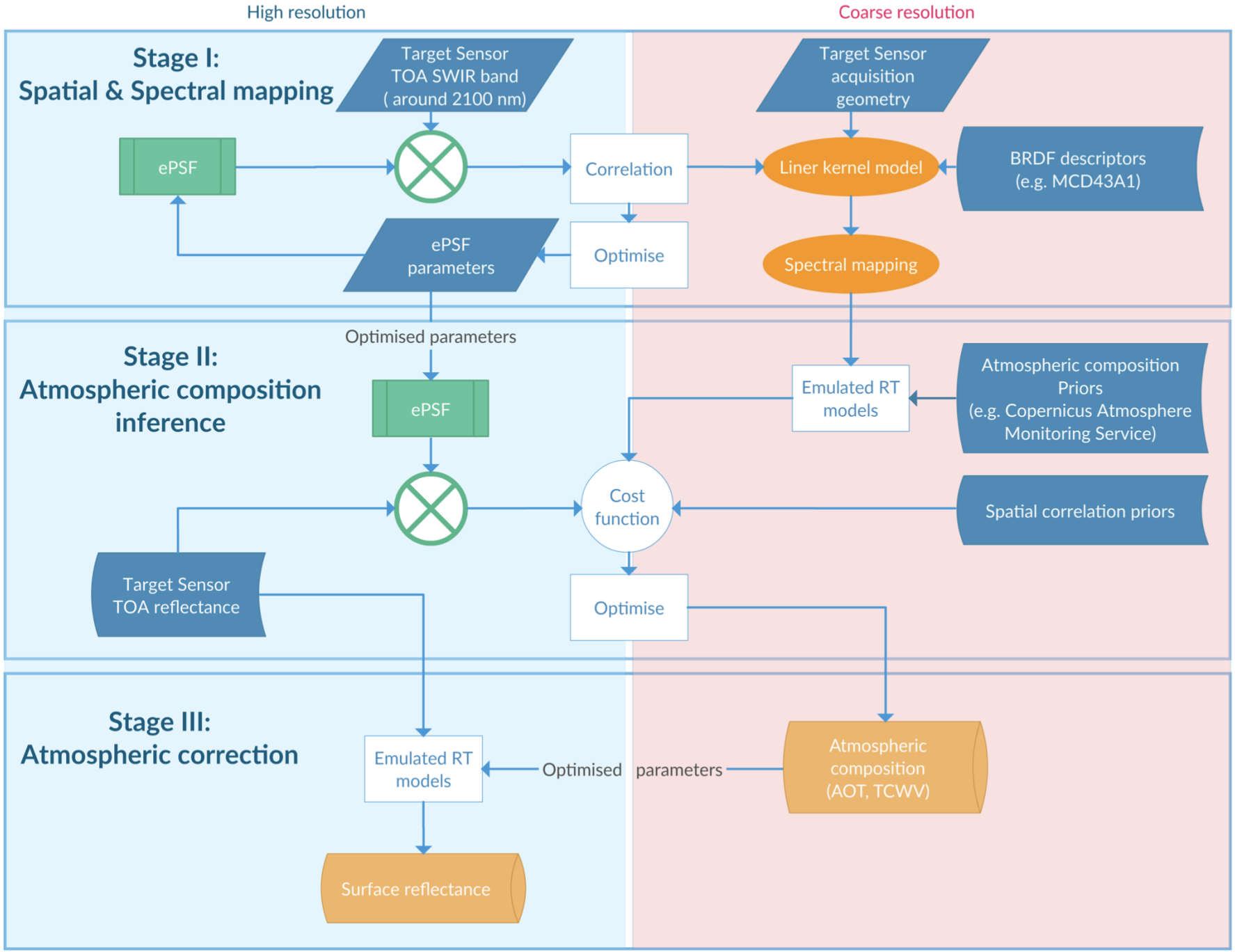

High resolution
Coarse resolution
Stage I:
Spatial & Spectral mapping
Target Sensor
TOA SWIR band
(around 2100 nm)
Target Sensor
acquisition
geometry
ePSF
Correlation
Liner kernel model
BRDF descriptors
(e.g. MCD43A1)
ePSF
parameters
Optimise
Spectral mapping
Optimised parameters
Stage II:
Atmospheric composition
inference
ePSF
Emulated RT
models
Atmospheric composition
Priors
(e.g. Copernicus Atmosphere
Monitoring Service)
Cost
function
Spatial correlation priors
Target Sensor
TOA reflectance
Optimise
Stage III:
Atmospheric correction
Emulated RT
models
Optimised parameters
Atmospheric
composition
(AOT, TCWV)
Surface reflectance

11

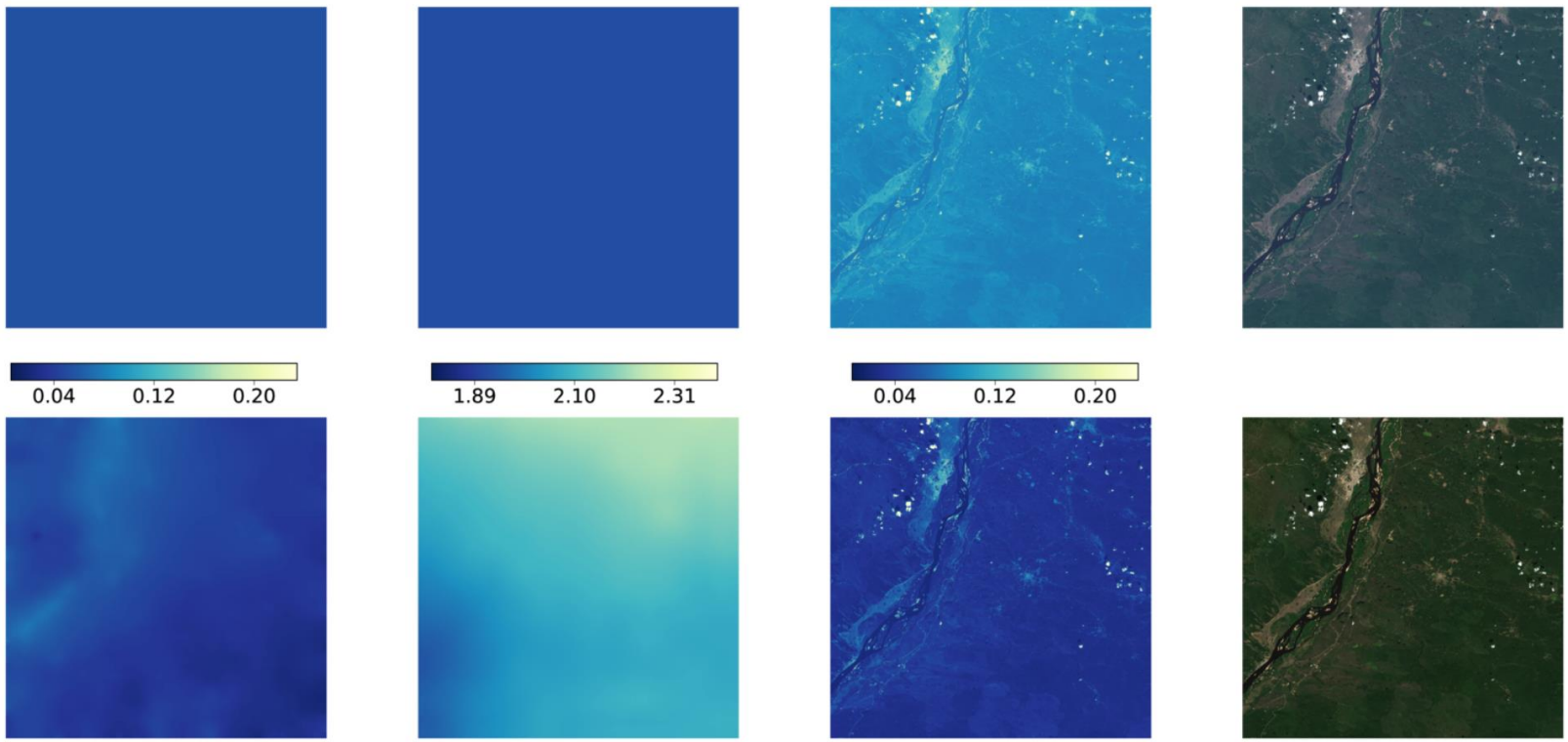


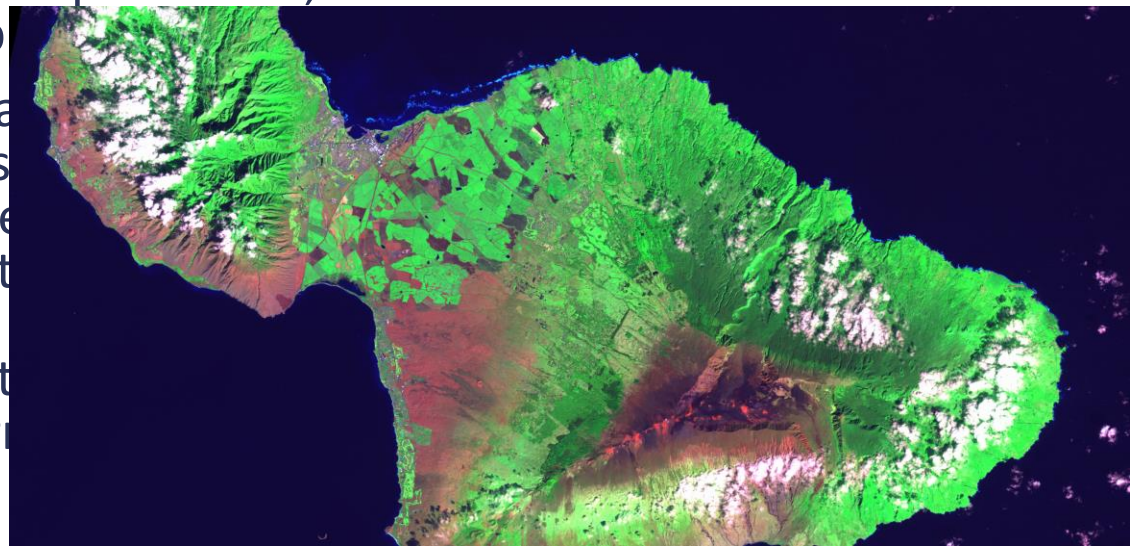
Figure 10: Example of retrieval on S2 data over Zvenigorod site (S2 Tile 37UCB, 24 Jul 2017). (Top row, left to right): AOT prior mean from CAMS, TCWV prior mean from CAMS, blue band TOA reflectance, TOA RGB composite (Bottom row, left to right): *A poteriori* AOT mean, *A poteriori* TCWV mean, blue band BOA reflectance, BOA RGB composite.

for L8 (top row) and S2 (bottom row), where the red markers stands for the median of those parameters.

Mira et al. (2015)

Earth Images Enable Near-Perfect Crop Predictions

- Using MODIS, NASA can make a near-perfect prediction when it comes to crop and harvest yields. The beta version of the TellusLabs Kernel, an intelligence product that allows viewing of the satellite images, predicted yields on U.S. corn and soy crops in 2016; ahead of all publicly availab
- Not only was it first, it was a According to NASA, Kernel's all within one percent of the yields. The U.S. Department actual reported yields were acre, and the MODIS satellit yields were reported to Kerr bushels per acre.




USDA United States Department of Agriculture
Foreign Agricultural Service
IPAD International Production Assessment Division
Reports and Briefs
Geospatial Data
Crop Calendars and Production Maps
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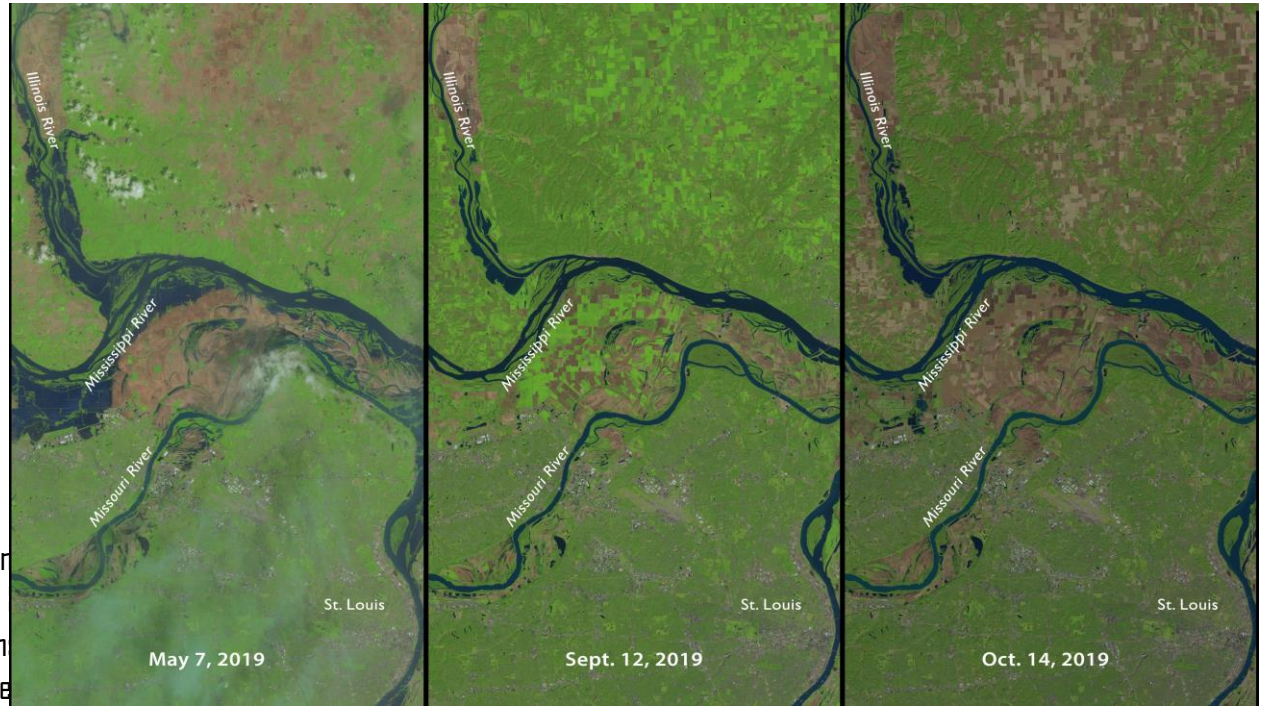
Crop Explorer
MODIS Rapid Response
Click on a region to view MODIS images
Click here to add your Comments/Feedback
Project Information
NASA Satellites Improve Response To Global Agricultural Change

- Satellite Imagery aids in:
- Yield Analysis Prior to Harvest
- Crop Identification and Determining Key Growth Stages
- Validation and Verification (V&V)



Three moments in a tur
in NASA-USGS Landsat
planting for many farm
signifying growing vege
On the right, Oct. 14, 2019, the light brown indicates harvested fields while darker brown are fields that have not been seeded or fallow all summer.

Credits: NASA

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Useful Links

SMOS (Soil Moisture and Ocean Salinity) Mission

Spacecraft | Launch | Mission Status | Sensor Complement | Ground Segment | References

SMOS is an ESA Explorer Opportunity science mission, a technology demonstratior Planet Program, in cooperation with CNES (France) and CDTI (Center for Technologi Madrid, Spain. 1) 2) 3) 4) 5)

Known as ESA's 'Water Mission', SMOS will improve our understanding of Earth needed data for modelling of the weather and climate, and increasing the skill in prediction. One of the highest priorities in Earth science and environmental policy is potential consequences of modification of Earth's water cycle due to climate chang atmospheric greenhouse gases and aerosols on atmospheric water vapor conc patterns and water availability must be understood in order to predict the conseq consumption and agriculture. 6)

The main science objective of the SMOS mission is to demonstrate observations of oceans and **SM** (Soil Moisture) over land to advance climatologic, meteorologic, applications. Soil moisture is a key variable in the hydrologic cycle. Over land, surface/atmosphere interface are strongly dependent upon soil moisture. SM is an weather and climate models as well as in surface hydrology and in vegetation mon distribution of salt in the oceans and of its annual and inter-annual variability, is cru the ocean and the climate system. Ocean circulation is mainly driven by the momen atmosphere/ocean interface, it is dependent on water density gradients, which observation of SSS and SST (Sea Surface Temperature). 7) 8) 9) 10) 11) 12) 13) 14) 15)

Soil moisture can be retrieved from brightness temperature observations. Due to the dry soil and water, the soil emissivity "epsilon" at a particular microwave frequer content. At L-band in particular, the sensitivity to soil moisture is very high, wh disturbances and surface roughness is minimal. 16) 17) 18)

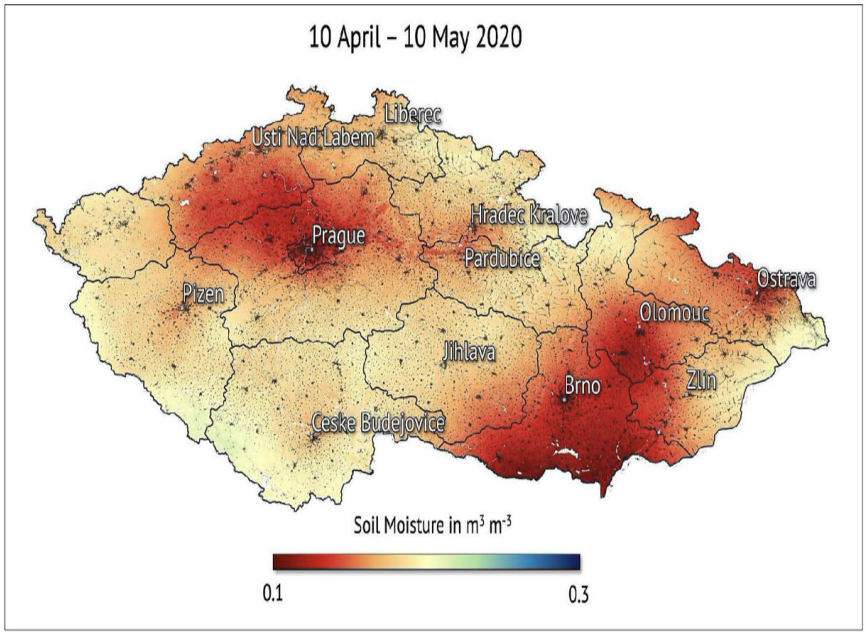
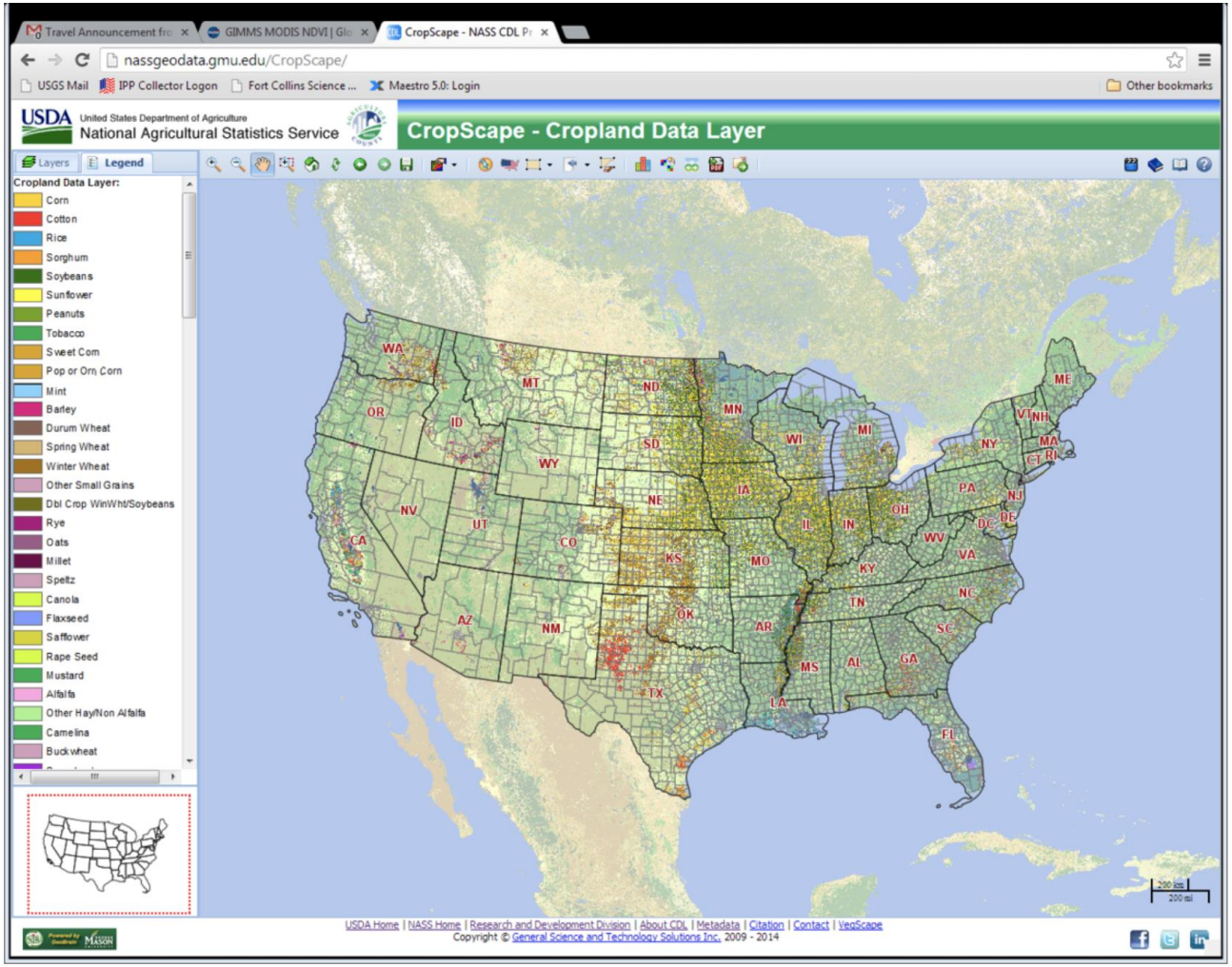


Figure 8: This map shows the average soil moisture conditions from 10 April to 10 May 2020. The map uses data from ESA's SMOS satellite, the EU's Copernicus Sentinel missions, along with data from NASA and the Japanese space agency JAXA missions (image credit: VanderSat)



The CropScape data portal allows for the display of the Cropland Data Layer by year from 1997 to the present, as well as supporting layers such boundaries, water, and roads.

Aims

- Common issues & national objectives (UK, Ghana ++)
  - increased productivity of smallholder agriculture
    - reducing rural poverty through the
- Demonstrate the practical benefits of EO-enabled crop monitoring and yield prediction for sustainable agriculture
  - policy makers, extension workers and other stakeholders
- Continue, and deepen collaborative partnerships between the UK and China
  - and extend its impact: develop a partnership with Ghana
    - adapt the approach to meet local needs and conditions.

Objectives

- Apply methods developed for EO-enabled crop monitoring and yield prediction for wheat in North China Plain to maize in China;
- Enhance the system by using other agrometeorological models and investigate multi-model ensembles;
- Develop an in-season forecasting system for yield for at least North China Plain;
- Engagement and capacity building in Ghana;
- Demonstrate application of crop monitoring and yield prediction to maize in Ghana.

- "With the fluorescence breakthrough, we can start to directly measure photosynthesis instead of color," Guan said.
-

Supersmart satellites reveal crops and fields like never before

Tech start-ups are putting cameras in orbit to monitor everything from flood damage to crop yield with greater frequency and detail than ever before

SPACE 7 June 2016

By **Hal Hodson**

Fertile territory
Jesse Allen/NASA EO-1 team/USGS

This startup uses machine learning and satellite imagery to predict crop yields

Artificial intelligence + nanosatellites + corn

By Alex Brokaw | Aug 4, 2016, 10:22am EDT

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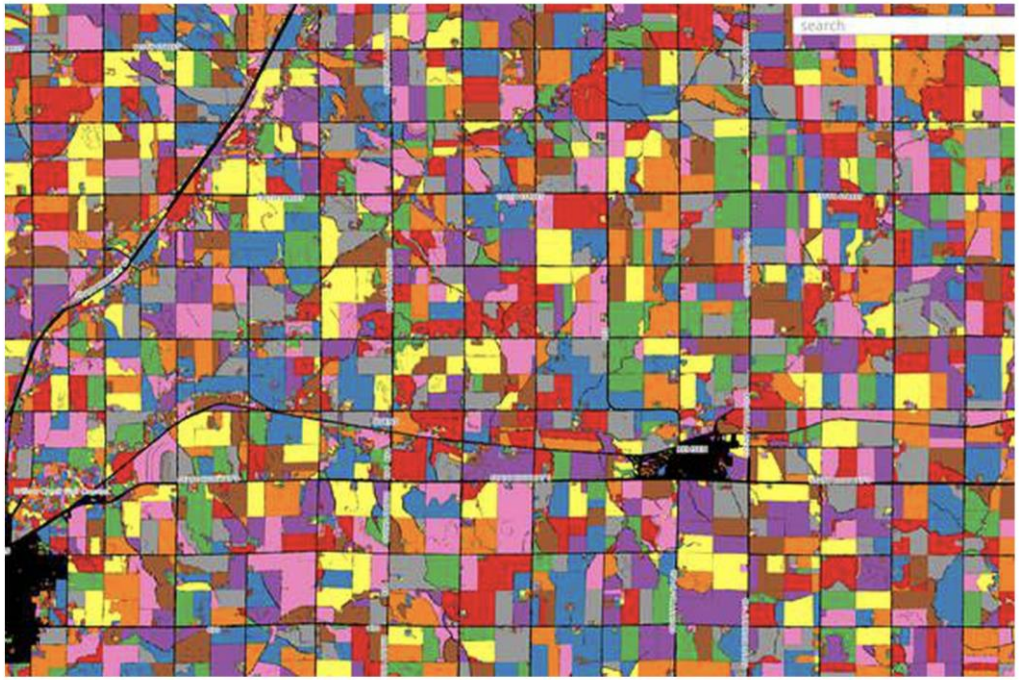


Descartes uses machine learning to segment different crop fields | Descartes Labs

Planet's New Rapid Revisit Platform To Capture Up To 12 Images Per Day

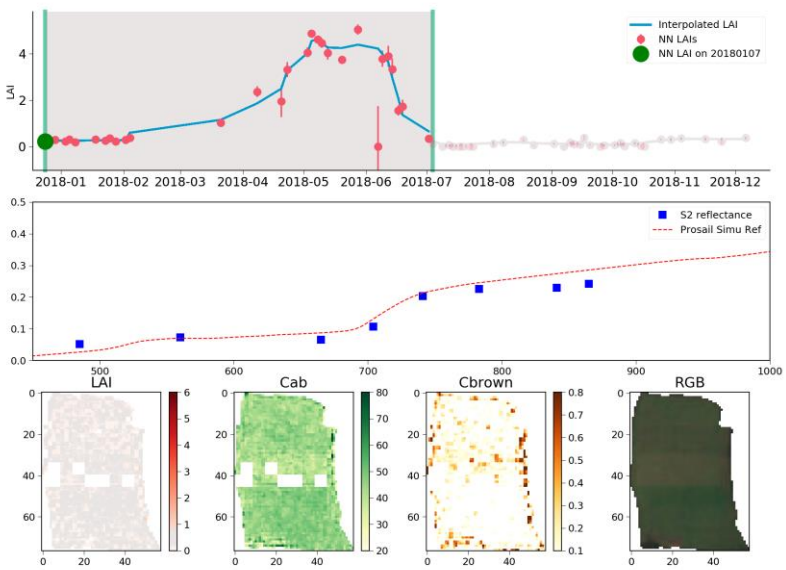
Martin Van Ryswyk | June 9, 2020

AUTHOR PROFILE

MARTIN VAN RYSWYK

Martin Van Ryswyk is Senior Vice President of Product at Planet.

Earth Observation



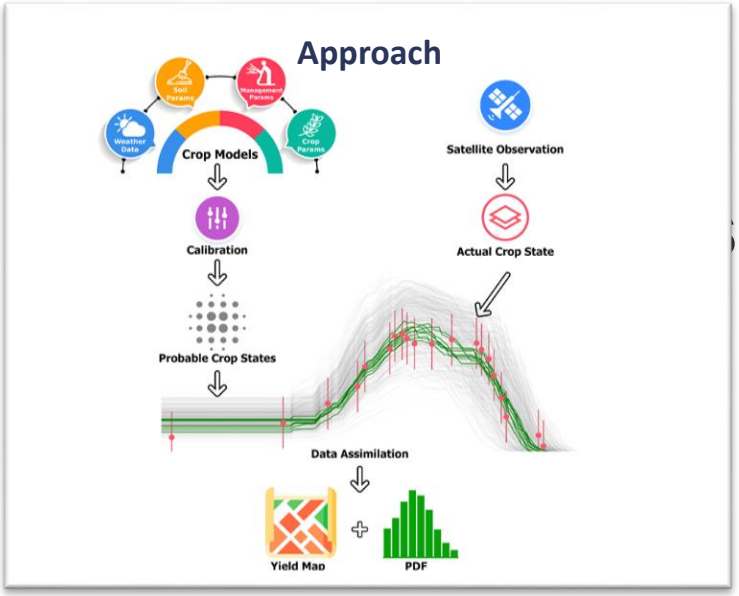
Leaf Area Index - LAI

Green

Brown

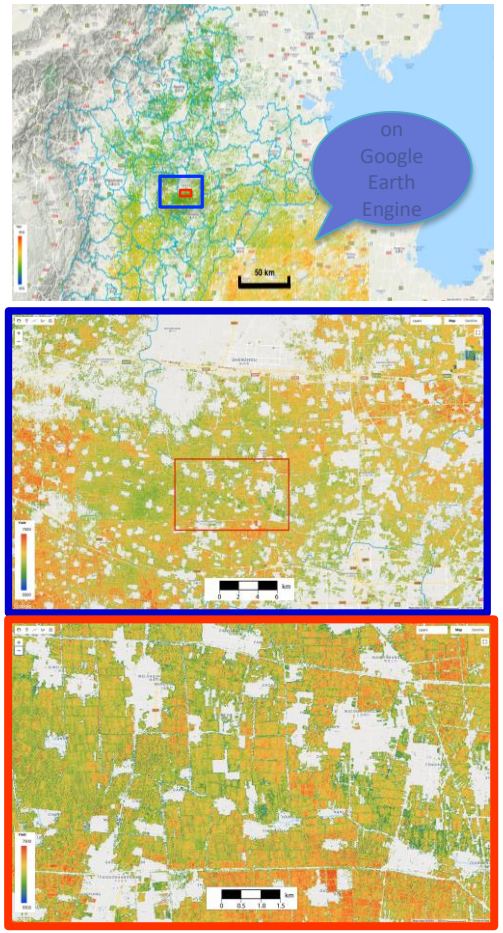
Colour Picture … with clouds

Interpret EO: radiative transfer (physics) and machine learning

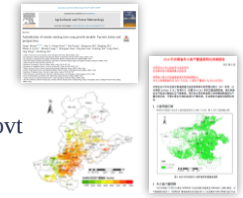


S

Result: Wheat yield: kg/ha



Main Impacts



- Papers, open source software
- Yield reports service for central and local govt
  - CHARMS (MARA), Henan
  - 10% prediction accuracy (~150 kg/ha RMSE)
  - New 10-20 m resolution: sub-field scale
- Workshop/training/competition
- Project videos and website
- Industrial partners

https://www.geog.ucl.ac.uk/research/research-projects/sentinels-of-wheat

Needs

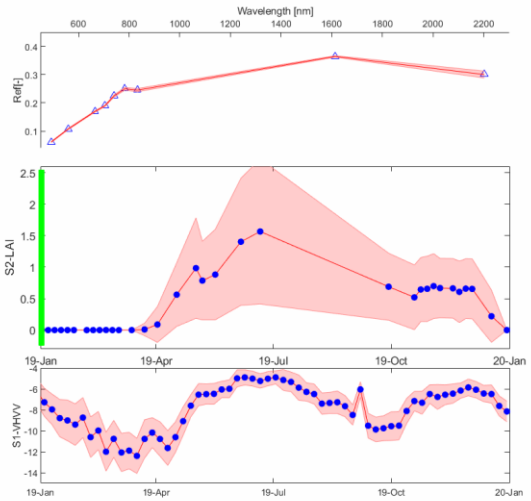
- Recent economic progress, but still entrenched poverty
- Rainfed, smallholder food crop (70% women) farmers
- Yields susceptible

Target

- Northern Ghana Maize smallholders

Approach

- Develop trilateral partnership
- Capacity building in food crop monitoring
  - Training in Earth Observation
  - Target women scientists
- Adapt system to Ghana: maize
- GSSTI
  - Government (planning)
  - Extension workers - farmers



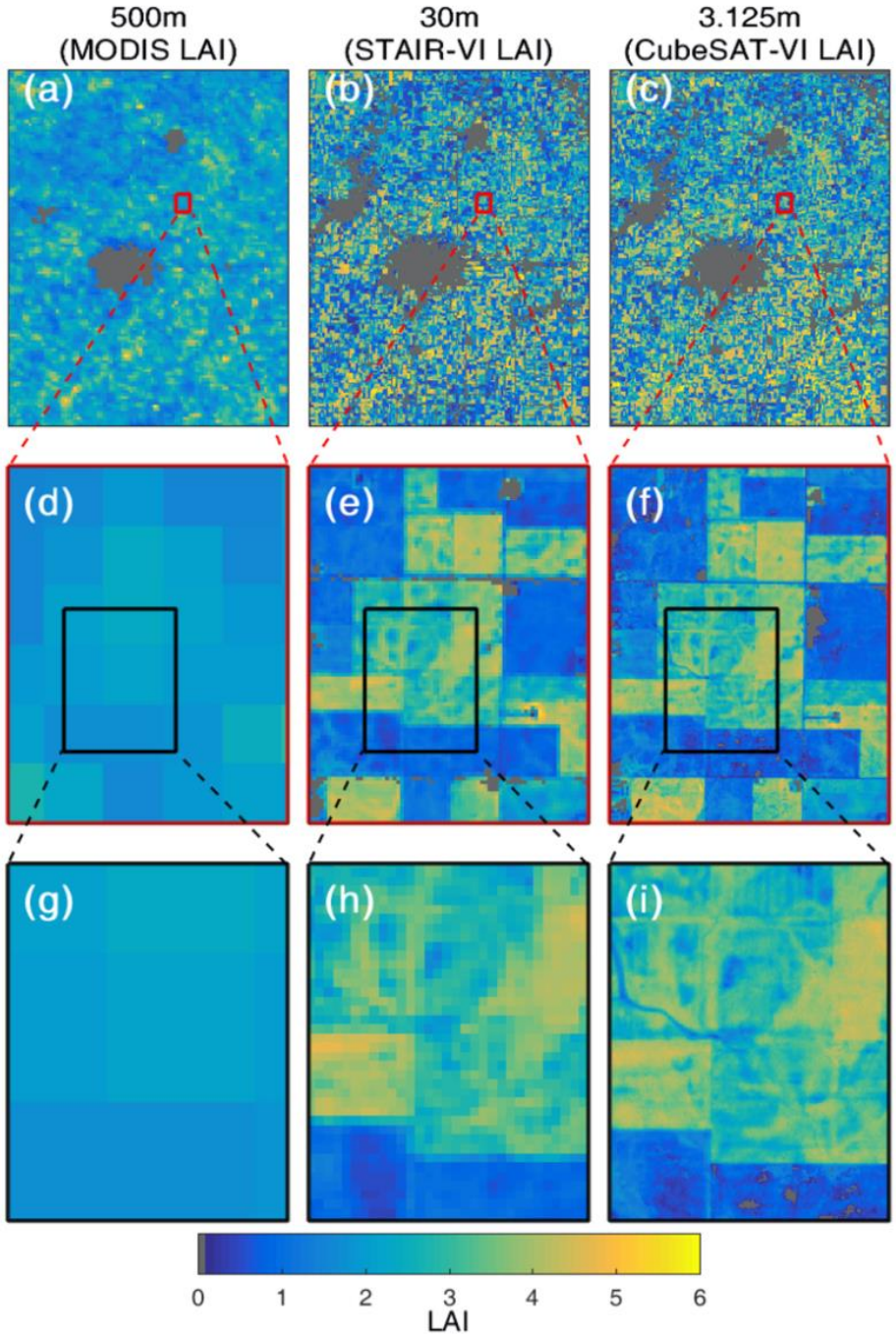


Fig. 6. An example visualization of LAI maps from MODIS, STAIR data, and CubeSat data on DOY of 177 (a-c), and zoom-in views at two levels (d-i).

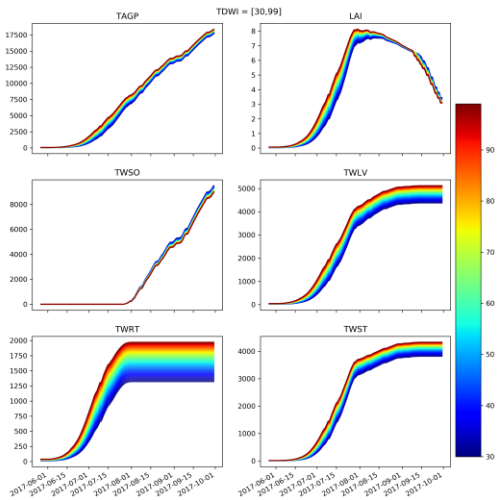
Other context

- **NEWTON Chair's prize 2019: Ghana**
  - Set up infrastructure & training
  - Capacity building in food crop monitoring
    - Training in Earth Observation
    - Target women scientists, extension workers & smallholder

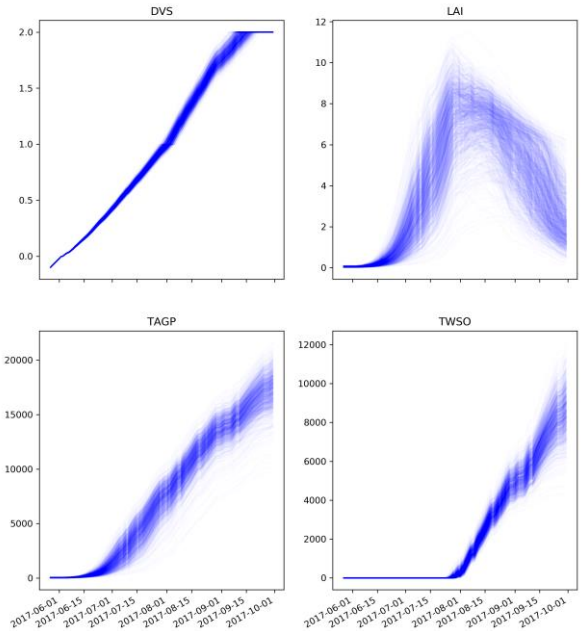
- **Taken over as UK Representative to GEOGLAM**
- **COVID delay of new project (& NEWTON prize)**
  - Nominally to end August
  - But not clear can effectively travel then
  - Only 24 months + 12 months of Prize
  - **Impacts**: staff, field data collection (Ghana & China), workshops & training (Ghana)
- **Extension granted for previous project**
  - Researchers stuck in China under lockdown
  - Preparing Maize calibrations for China
  - Linking biomass to microwave
  - Writing up

Initial maize calibration (China)

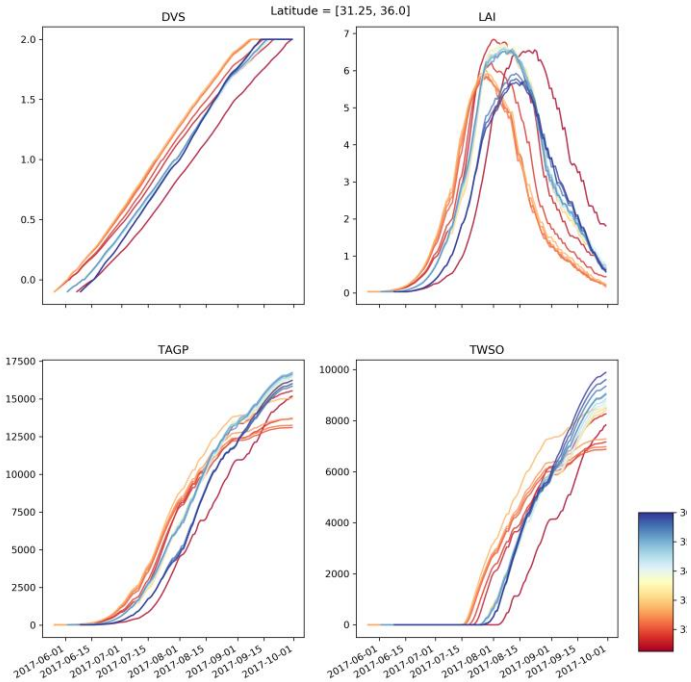
calibrated WOFOST simulation with variation of TDWI (Initial total crop dry weight);



ensembles of WOFOST with 1000 members in 20 parameters space;



Henan province



agrometeorological station data collected few years ago and county level yield statistics.

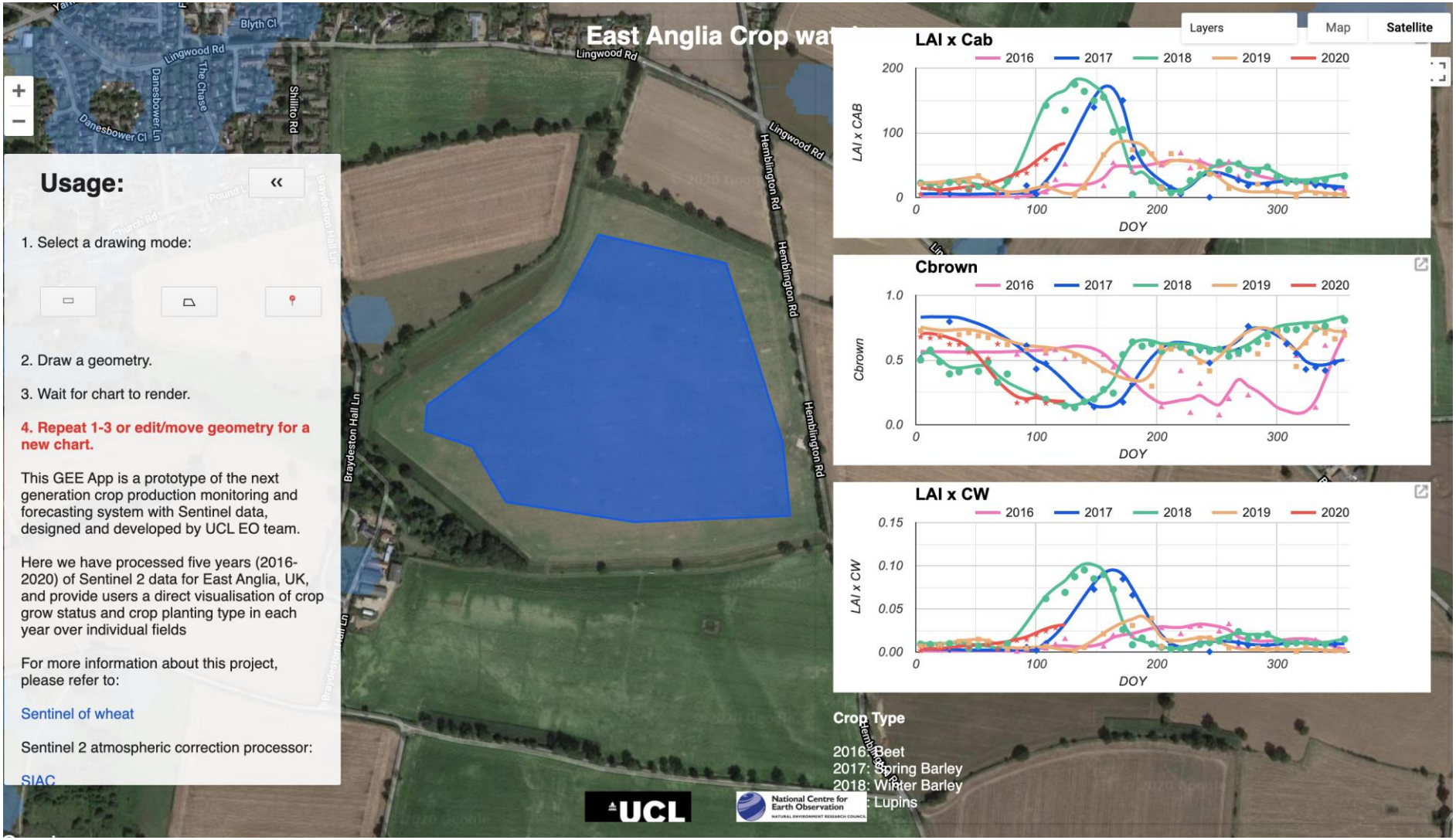
Other context

- UK DEFRA data services discussions
  - Exploratory application to COVID impacts
  - Discuss use for reduction in farmer reporting burdens

- **East Anglia: GEE implementation**
  - https://code.earthengine.google.com/?scriptPath=users%2Fmarcyinfeng%2Futils%3AInteractive_LAI

- DEFRA CROME (Crop map of England: 2016-19)

The Crop Map of England (CROME) South East is a polygon vector dataset mainly containing the crop types of England. The dataset contains approximately 32 million hexagonal cells classifying England into over 20 main crop types, grassland, and non-agricultural land covers, such as Woodland, Water Bodies, Fallow Land and other non-agricultural land covers. The classification was created automatically using supervised classification (Random Forest Classification) from the combination of Sentinel-1 and Sentinel-2 images during the period late January 2016 – August 2016. The dataset was created to aid the classification of crop types from optical imagery, which can be affected by cloud cover. The results were checked against survey data collected by field inspectors and visually validated. refer to the CROME specification document Attribution statement:



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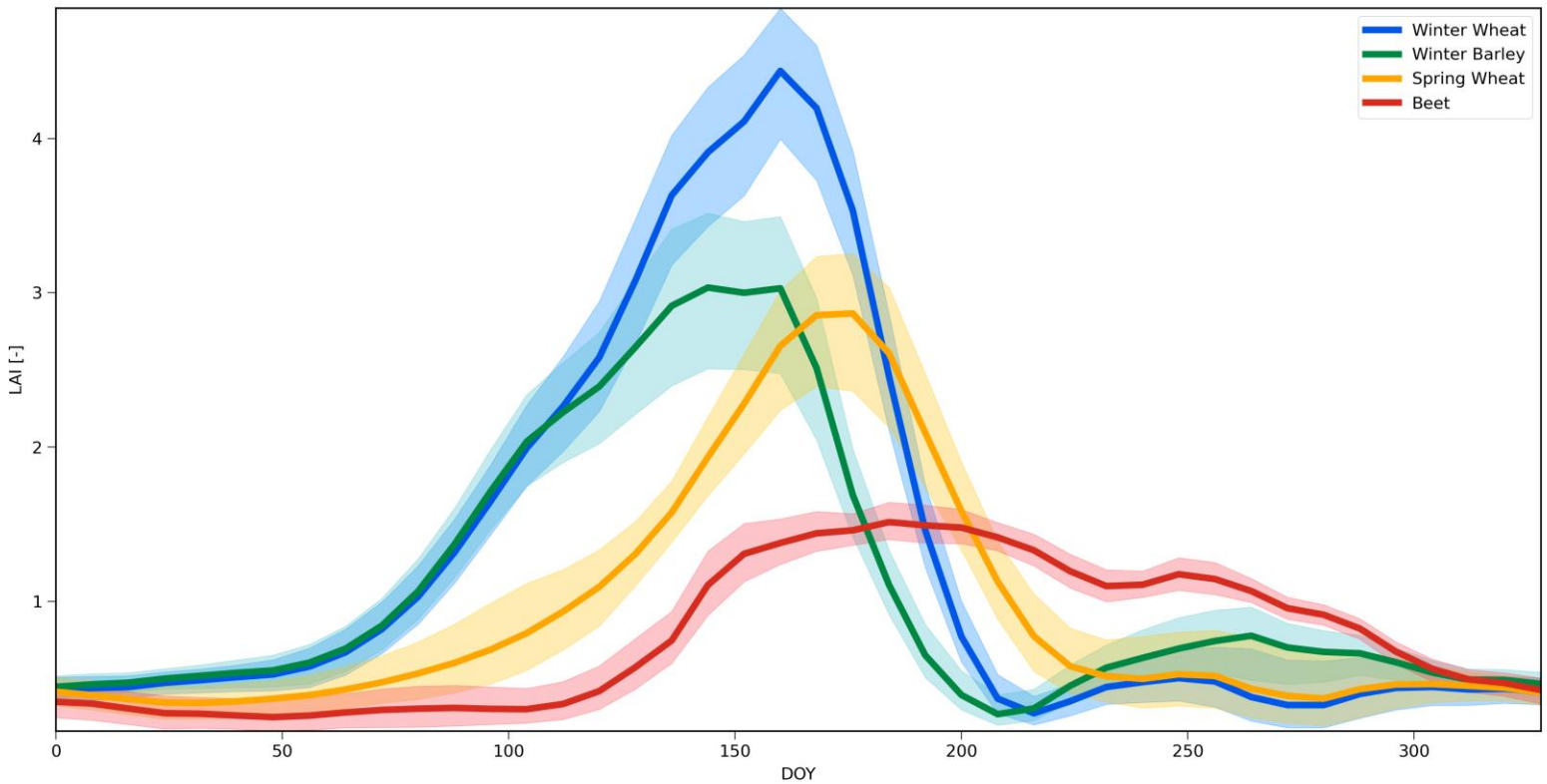
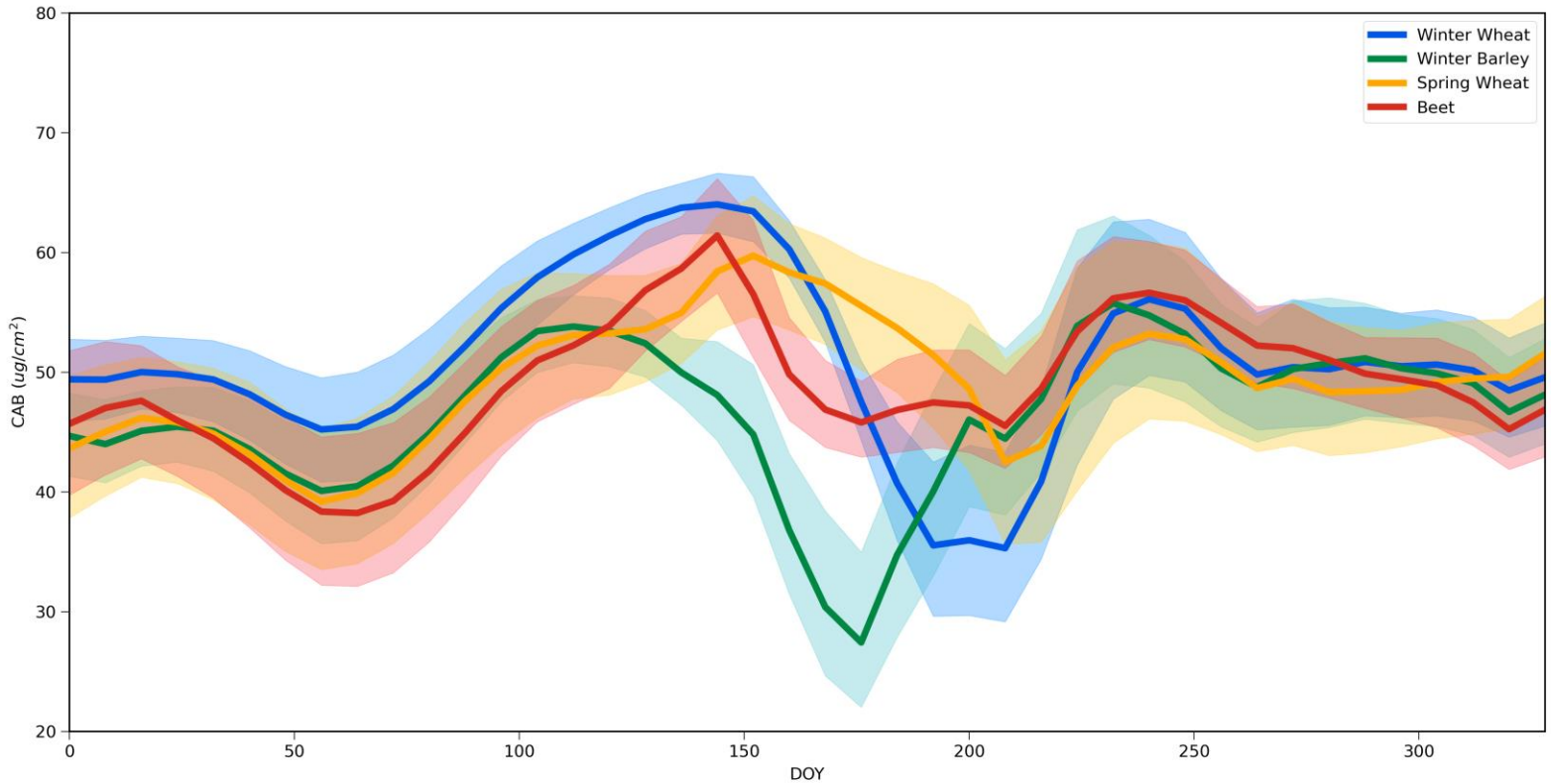
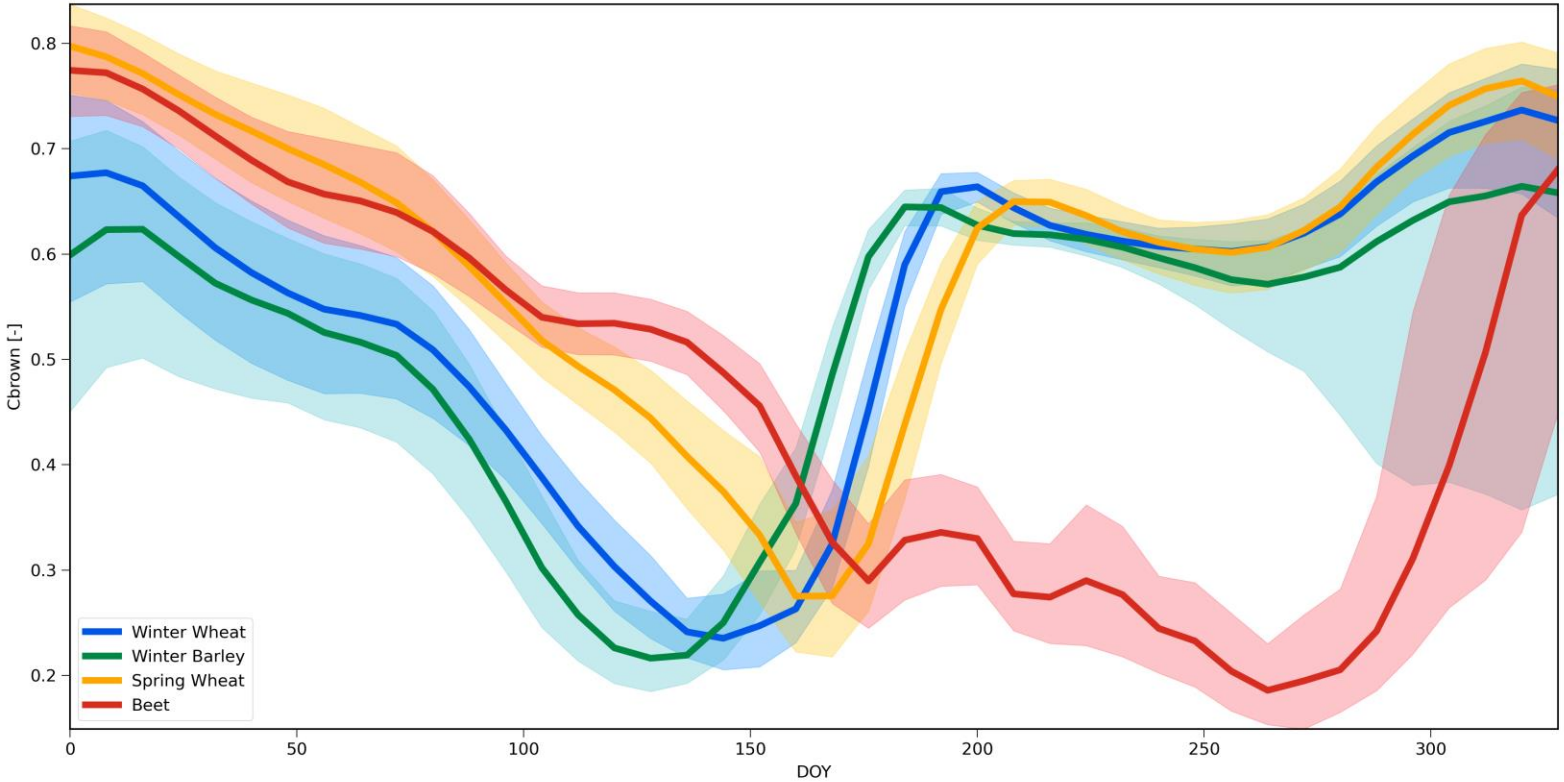
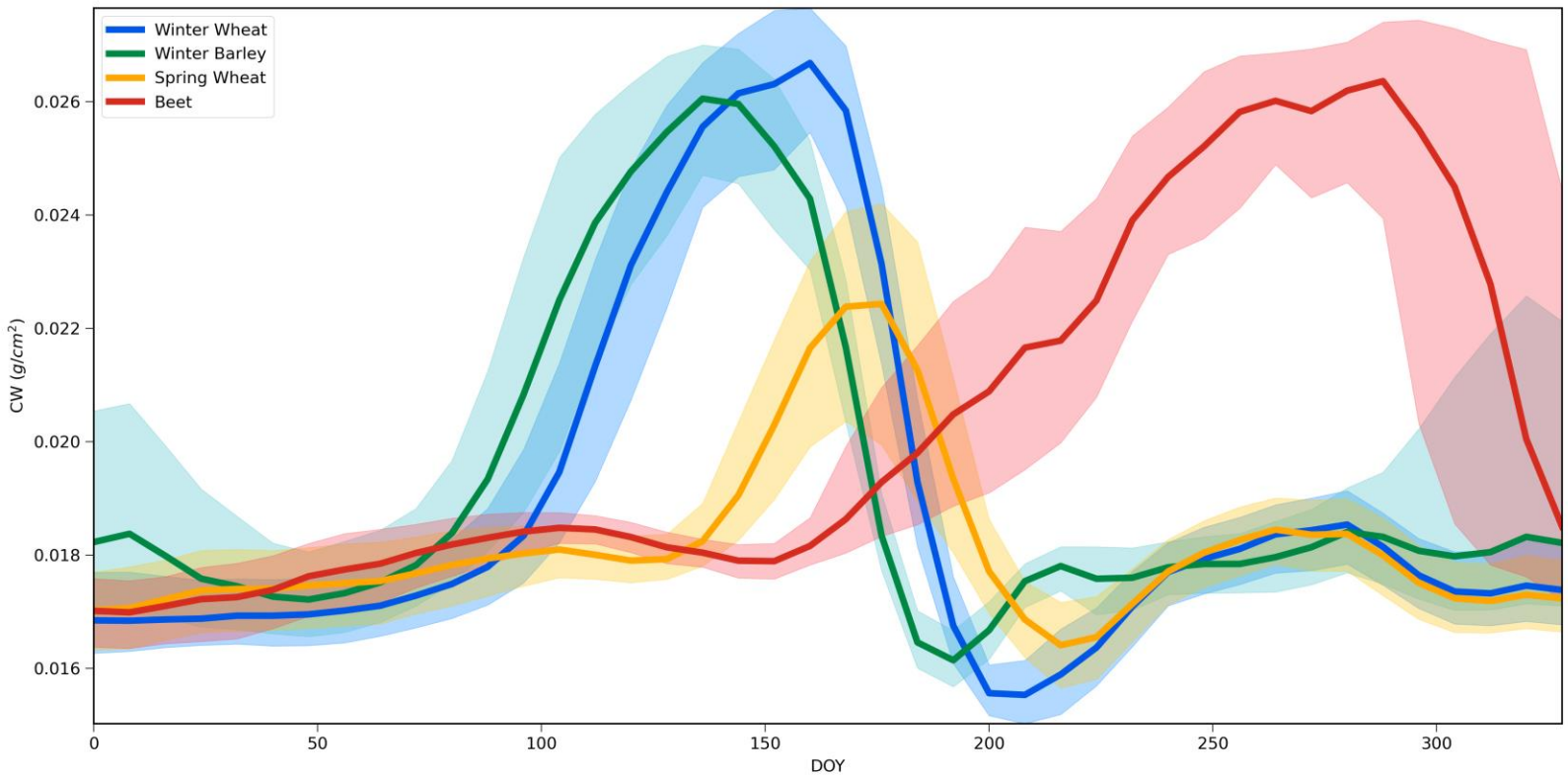
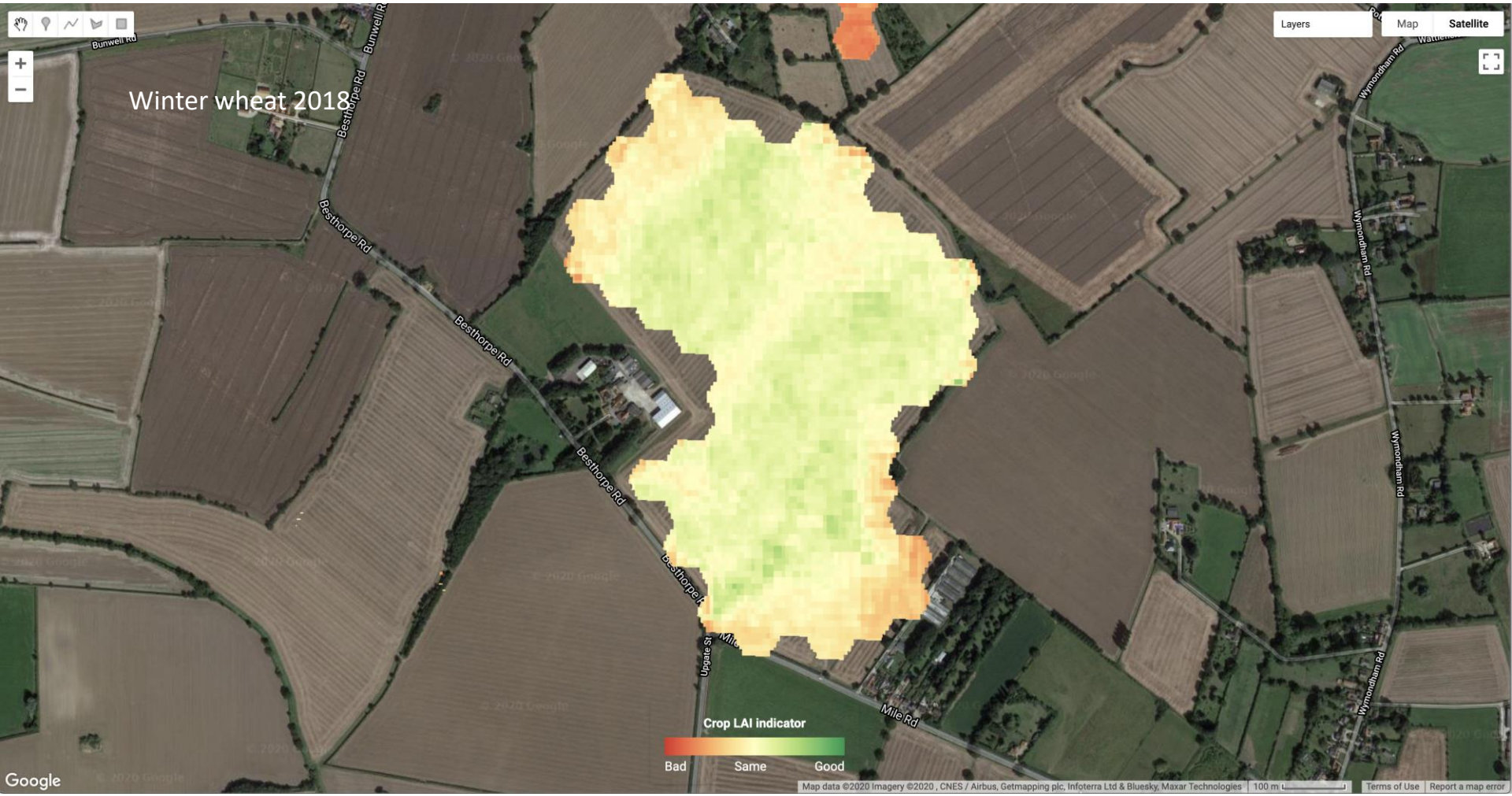

Winter Wheat
Winter Barley
Spring Wheat
Beet
LAI [-]
1
2
3
4
0
50
100
150
200
250
300
DOY


Winter Wheat
Winter Barley
Spring Wheat
Beet
CAB (ug/cm²)
DOY
80
70
60
50
40
30
20
0
50
100
150
200
250
300


0.8
0.7
0.6
0.5
0.4
0.3
0.2
Cbrown [-]
0
50
100
150
200
250
300
DOY
Winter Wheat
Winter Barley
Spring Wheat
Beet


Winter Wheat
Winter Barley
Spring Wheat
Beet
0.026
0.024
0.022
0.020
0.018
0.016
CW (g/cm²)
0
50
100
150
200
250
300
DOY



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Summary

- Using extension of previous grant
  - Writing up
  - Linking biomass with microwave
  - Exploring datasets (including UK)
    - Esp biophysical parameters
  - Initial maize calibration (China)
- Start new project(s) in September?
  - But concerns
    - over ability to achieve impact from training
    - Availability of yield (++) data
- Help from other projects?
  - Datasets
- Help to other projects?
  - EO biophysical parameters / patterns

EO (finally) delivers on crop monitoring

- **The 'finally' a little unfair**
  - Consistent progress over last 40-odd years
  - Main requirements understood and targeted in 1970s/80s
- **But huge advances in practical global monitoring in recent years**
  - Basic algorithms to provide analysis-ready data
    - surface reflectance: Machine learning for fast inverse models / data assimilation
    - Crop type maps routine produced
  - Crop growth models
    - Many – so can implement ensembles
    - Huge databases from USDA NASS
    - Machine learning approaches
  - Data & product heritage from NADA & USDA
    - MODIS & Landsat
  - Processing 'data cubes' and APIs
    - E.g. ESA ESDL, Google Earth Engine etc.
  - **Copernicus**
    - Including ECMWF CAMS datasets
    - Sentinel-2a,b
      - ~5-day revisit, 10-60m spatial resolution
      - good spectral coverage for biophysical parameters
    - Sentinel-1
    - Sentinel-5P: SIF
    - [Copernicus LSTM, ROSE-L] {CHIME? protein content}