

# Monitoring and modeling the field-level crop productivity and water uses for large-scale applications

Dr. Kaiyu Guan (kaiyug@Illinois.edu)

Assistant professor, Dept. of Nature Resources and Environmental Sciences Blue Waters Professor, National Center for Supercomputing Applications

Website: http://faculty.nres.illinois.edu/~kaiyuguan

University of Illinois at Urbana Champaign



NESA

The 2018 MOISST Workshop, UNL, Jun 4-7, 2018

## Current Research Directions in my lab

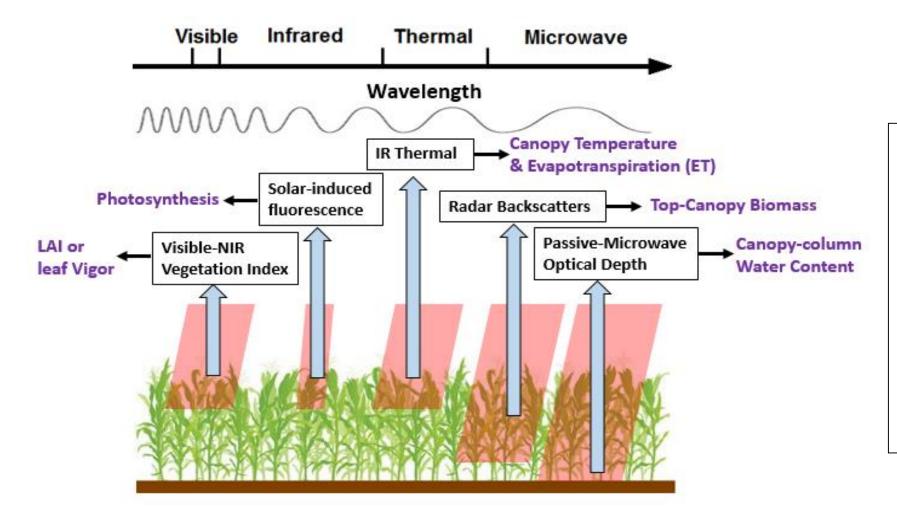
(1) Multi-sensor integration for monitoring/predicting crop productivity (yield, GPP)

(2) Long-term sensing network for agricultural ecosystems

(3) High-resolution satellite fusion and field-level mapping

(4) Measuring/Modeling crop responses to drought and heat stress

### A New Era of Earth Observation from Satellite: Vegetation Properties



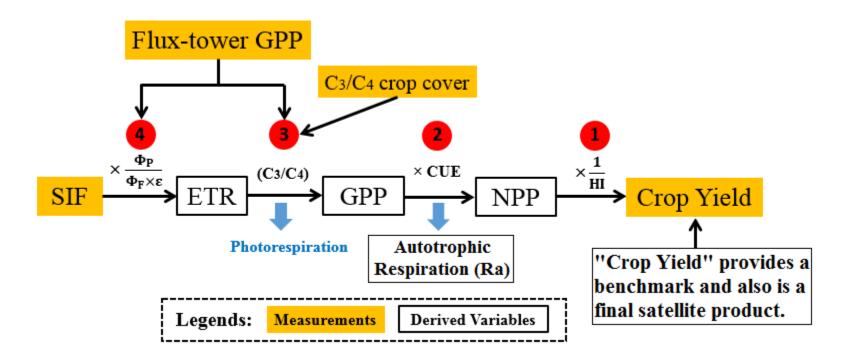
### Take home message:

All the satellite data share some common information.

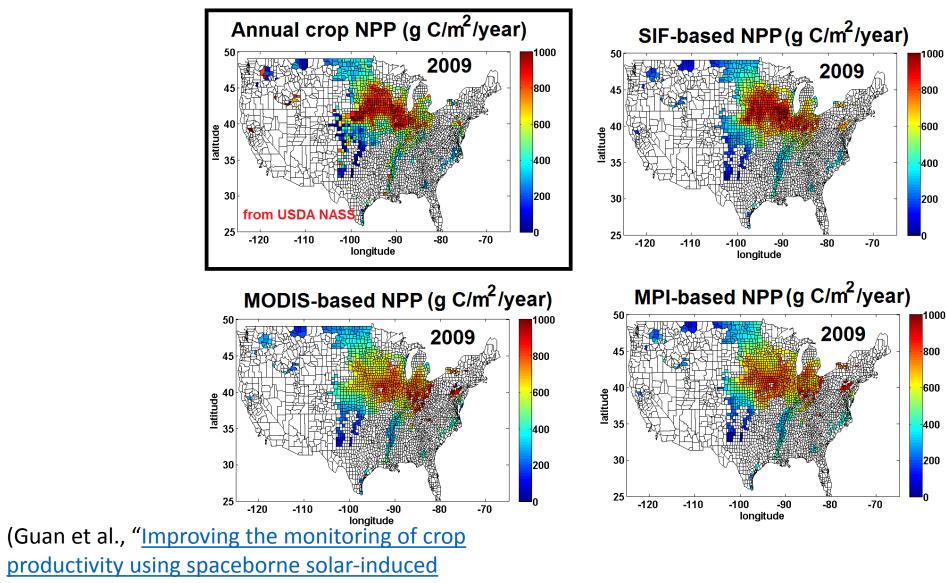
However, when excluding this common information, many data contain their unique information that tremendously improve our understanding of vegetation growth.

(Guan et al., RSE, 2012; Guan et al., Ecosphere, 2013; Guan et al., IEEE, 2014; Guan et al., JGR, 2014; Guan et al., GCB, 2016; He et al., RSE, 2016; Guan et al., RSE, 2017)

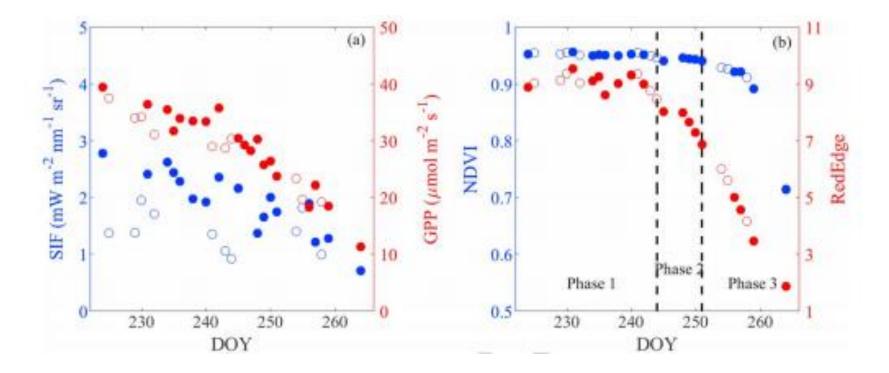
# A new framework of using SIF for crop monitoring



(Guan et al., "<u>Improving the monitoring of crop</u> productivity using spaceborne solar-induced <u>fluorescence</u>", Global Change Biology, 2016)



fluorescence", Global Change Biology, 2016)



Daily mean time series at the soybean field from 11 August to 20 September (day of year 224 to 264): (a) Sun induced chlorophyll fluorescence (blue) and gross primary productivity (red); (b) Normalized Difference Vegetation Index (blue) and Rededge Index (red). The solid circles represent for sunny days and open circles for cloudy days.

 <u>Miao, G.\*</u>, <u>Guan, K.\*</u>, Yang, Xi, et al. (2018). "<u>Sun-induced Chlorophyll Fluorescence, Photosynthesis, and Light</u> <u>Use Efficiency of a Soybean Field from seasonally continous measurements</u>", *Journal of Geophysical Research-Biogeosciences*.

#### Remote Sensing of Environment 199 (2017) 333-349

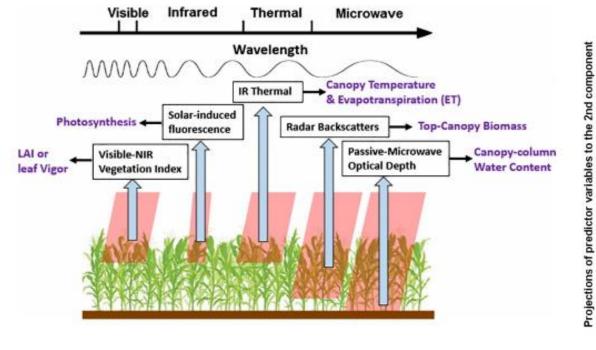


(b) yield-based NPP (g C/m<sup>2</sup>/year) (c) -dBmr 년 -11-일 -dB\_ 700 -12 6 7 8 9 10 11 12 1 2 3 5 month Longitude (d) - EVI -SIF-GPP ¥ 0.8 -ALEXI ET +dB ₿ 0.6 -δ(dB) VOD N 0.4 b 0.2 10 9

month

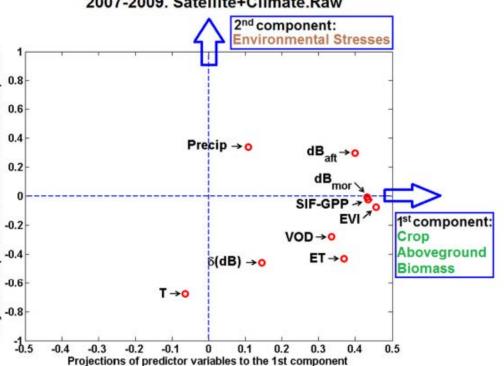
The shared and unique values of optical, fluorescence, thermal and microwave satellite data for estimating large-scale crop yields

Kaiyu Guan<sup>a,\*</sup>, Jin Wu<sup>b</sup>, John S. Kimball<sup>c,d</sup>, Martha C. Anderson<sup>e</sup>, Steve Frolking<sup>f</sup>, Bo Li<sup>g</sup>, Christopher R. Hain<sup>h</sup>, David B. Lobell<sup>i</sup>



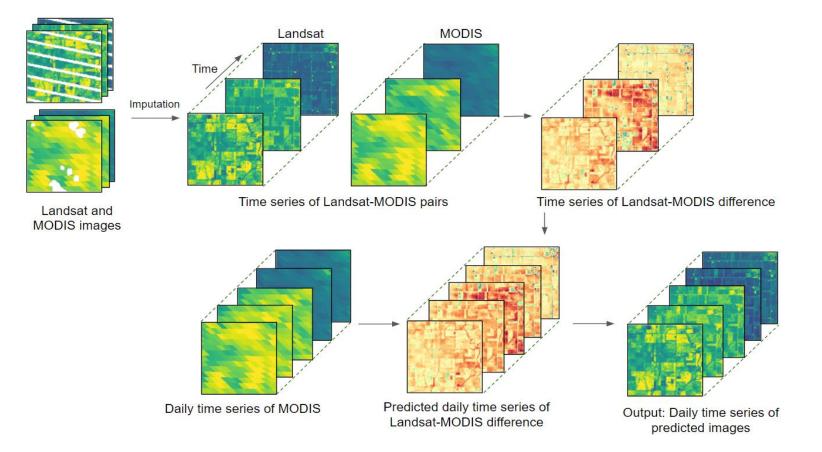
2007-2009. Satellite+Climate.Raw

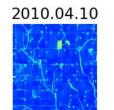
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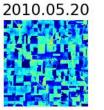


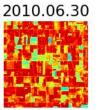
## We have generated 10 meter, daily, cloud-free/gap-free surface reflectance data by <u>fusing multiple sensors</u>; we can do it anywhere in this planet.

Luo, Y., Guan, K.\*, and Peng, J.\* (2018) "STAIR: A generic and fully-automated method to fuse multiple sources of optical satellite data to generate a high-resolution, daily and cloud-/gap-free surface reflectance product", *Remote Sensing of Environment*.



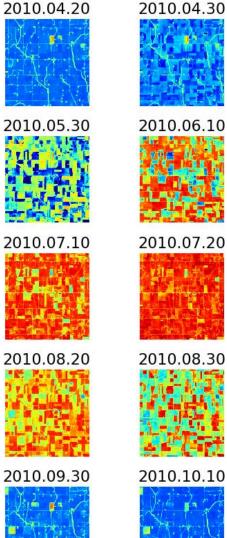


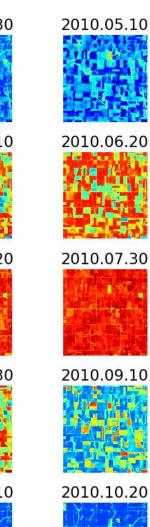


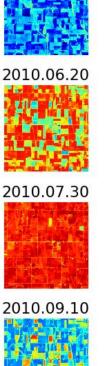












Luo, Y., Guan, K.\*, and Peng, J.\* (2018) "STAIR: A generic and fully-automated method to fuse multiple sources of optical satellite data to generate a high-resolution, daily and cloud-/gap-free surface reflectance product", Remote Sensing of Environment.

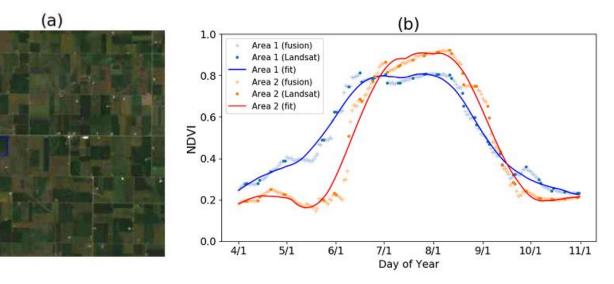
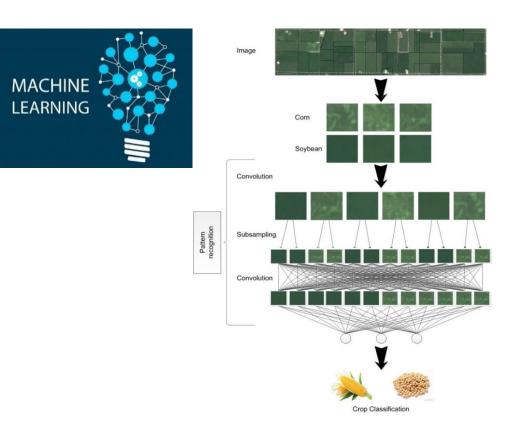


Figure 8. Temporal patterns of NDVI. (a) Two regions with different land covers in a subarea (North of Champaign County, IL), Area 1 and Area 2 (highlighted by blue and red boxes, respectively), were selected to compute their NDVI time series. (b) NDVI values derived from Landsat data and fusion data, and fitted curves for Area 1 and Area 2. Fitted curves were built using the Savitzky Golay algorithm.

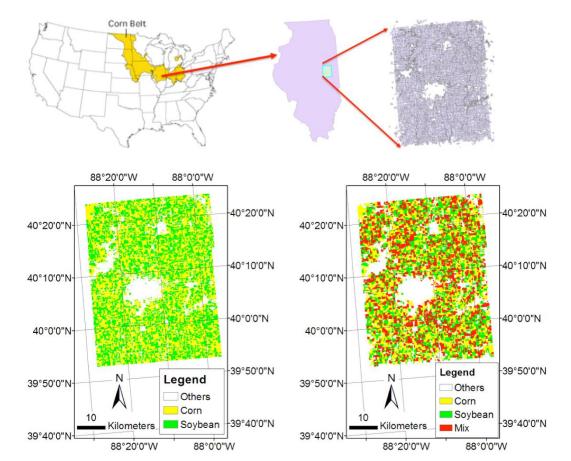
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

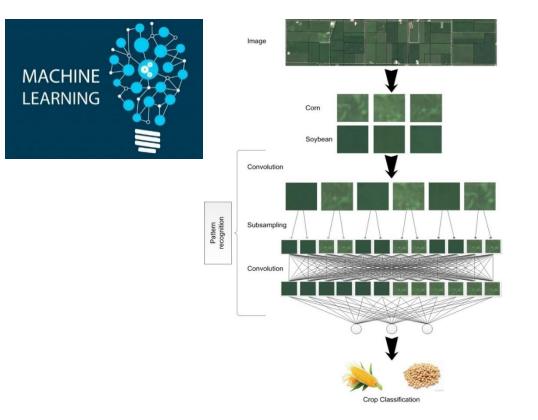
## We can identify crop types for the concurrent year, with 96% accuracy in late July.



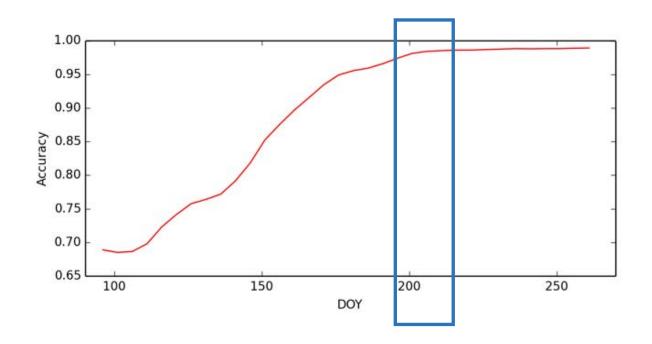
Schematic diagram of using Convolutional Neural Network and satellite image features to classify crop types.

Cai, Guan, Peng et al. "A high-performance and time-lead classification system of field-level crop types using time-series Landsat data and a machine learning approach." (Remote Sensing of Environment, 2018)





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