

Tuesday May 12, 2026 starting at 11:20 am CDT

Session 2: HLS in Action

Goals:

- Showcase real-world use of HLS across sectors and application areas, including methodology.
- Discuss the benefits and challenges to adopting HLS for downstream impact.

Time (CDT)	Topics	Format	Speaker
11:20 - 11:25 (5 min)	Introducing Impactful Applications of HLS	Presentation & Interactive 	Stephanie Jiménez, NSITE & UAH
11:25 - 11:45 (20 min)	Monitoring Cover Crops for Agroecosystem Assessment Using HLS Data	Presentation	Feng Gao, USDA-ARS
11:45 - 12:05 (20 min)	Near-Real Time Processing of HLS for Rangeland Management	Presentation	Sean Kearney, Thunder Basin Grassland Prairie Ecosystem Association
12:05 - 12:25 (20 min)	HLS Applications Challenges, Questions, and Needs	Interactive 	NSITE MCs
12:25 - 1:25 (60 min)	Lunch		



We are a part of an **ecosystem**

Users & Decision-makers

Fed, state & local gov,
general public, private sector,
and others



Private Sector LLMs,
Consultancies,
Value-added Data Resellers



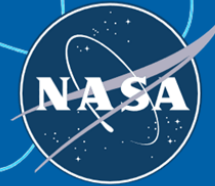
Commercial Satellite
Data Providers



Other public EO data
providers



Researchers



NASA
Earth Science

Understanding our relationships helps guide solution
development and engagement priorities



More efficient streamflow monitoring in Alaska

Protecting Lives and Livelihoods:

USGS measures and provides river flow and water level data, essential for protection of life and property, and water management.

Traditional flow measurements are hazardous and costly, especially in remote locations like Alaska.

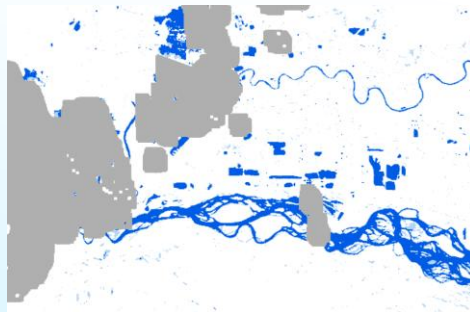
The high temporal resolution of Observational Products for End-Users from Remote Sensing (OPERA) surface water extent (DSWx) –HLS enables USGS to conduct more efficient streamflow monitoring from space. Including more locations that are hazardous or costly to monitor and reducing risk to USGS field personnel.



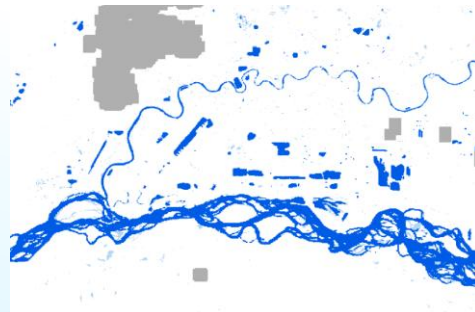
Ferrying traditional flow measuring equipment across Ikalukrok Creek, Alaska (credit: USGS)



Traditional surveying on the Yukon River, Alaska, (credit: Jeff Conaway, USGS)



Surface water extent **June 16,** 2024



Surface water extent **June 17,** 2024

Session 2: HLS in Action

Presenters



Feng Gao

Research Physical
Scientist

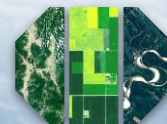
USDA - ARS



Sean Kearney

Spatial Ecologist

Thunder Basin
Grassland Prairie
Ecosystem
Association,
USDA - ARS



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Agricultural Research Service
U.S. DEPARTMENT OF AGRICULTURE

HLS Workshop, May 12, 2026 11:25-11:45 AM

Monitoring Winter Cover Crops for Agroecosystem Assessment Using HLS Data

Feng Gao

USDA-ARS, Hydrology and Remote Sensing Laboratory

Beltsville, MD 20705, USA

USDA is an equal opportunity provider and employer

Winter Cover Crops (WCC)

- ☐ Winter cover (intermediate) crops are planted between summer cash crops.
- ☐ Improve soil health and water quality
- ☐ Reduce nutrient runoff to the watershed
- ☐ Suppress weeds by competing for light, space, and nutrients
- ☐ Supported by federal and state incentive programs
 - ☐ USDA NRCS Environmental Quality Incentives Program (EQIP)
 - ☐ USDA RMA Pandemic Cover Crop Program (PCCP)
 - ☐ State-wide WCC Incentive Programs
 - Mid-Atlantic (e.g., Delaware, Virginia, Maryland)
 - Midwest (e.g., Illinois, Indiana, Iowa)
 - Southern (e.g., Missouri, North Carolina)



WCC Mapping Needs

When were WCC planted and terminated?

(WCC Phenology)

Where were/are WCCs planted?

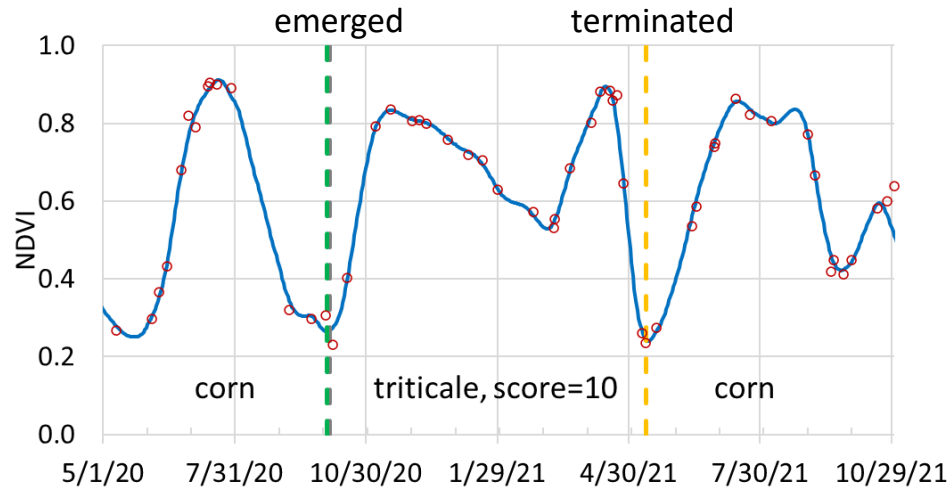
(WCC Presence)

Understanding where and when WCC are planted and their performance is essential for evaluating ecosystem services and for hydrologic and ecosystem modeling

WCC Phenology Needs

I. Emergence Date

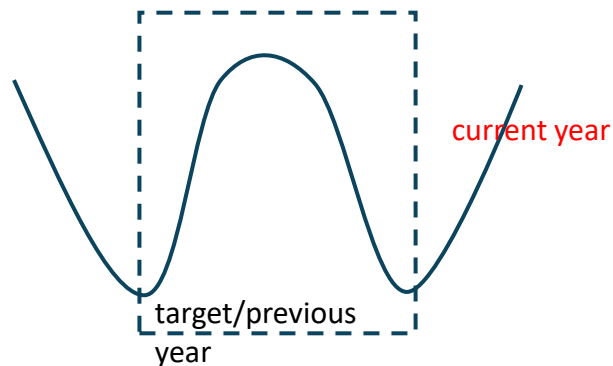
II. Termination/Harvest Date



Remote Sensing Phenology

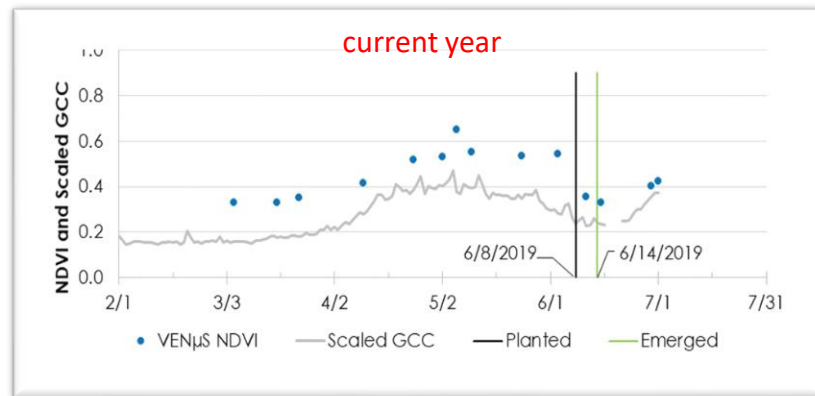
❑ After-season (conventional) approaches

- use prepended and appended observations
 - MODIS uses three years of data (+/- one year)
 - VIIRS and HLS use two years of time-series data (+/- 6 months)
 - 6-12 months after growing season
- cover a complete cycle of vegetation growth



❑ In-season or near-real-time (NRT) approaches

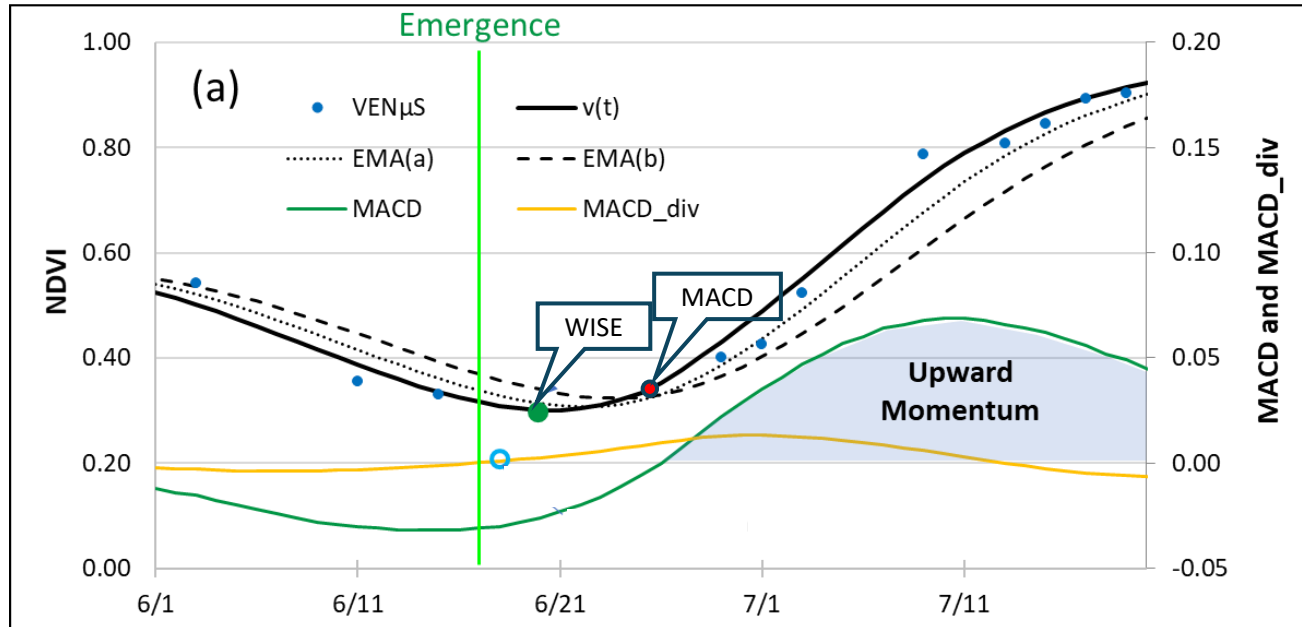
- use any period (partial year) of time series
- for specific crop growth stages
- more useful for operational uses



I. Within-Season Emergence (WISE) Detection

Step 1: Gap-filling and Smoothing: Modified Savitzky–Golay

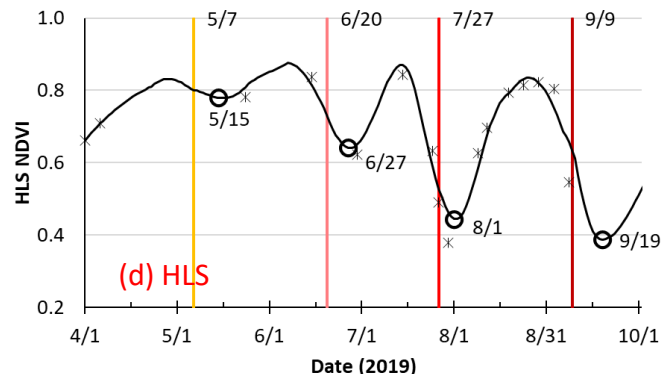
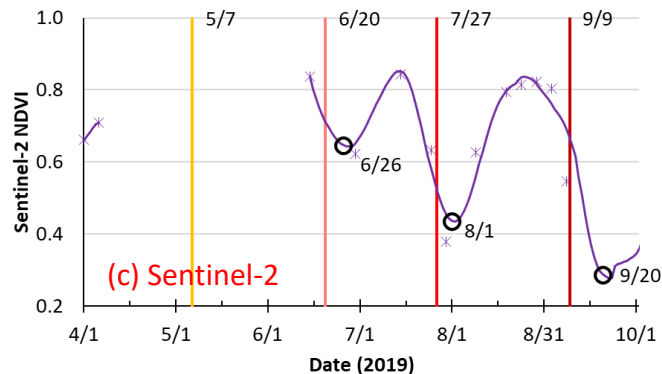
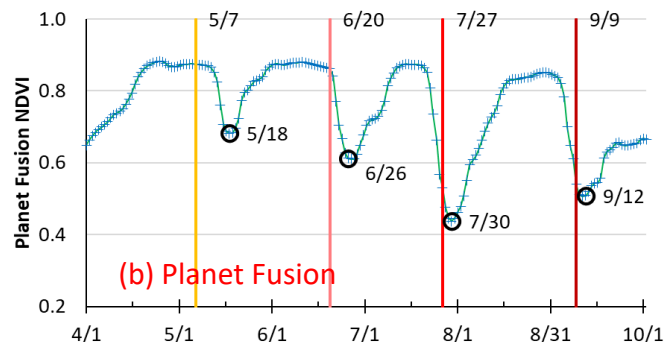
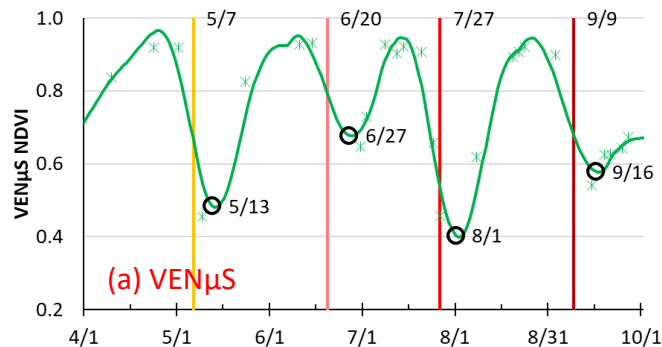
Step 2: Extracting Transition Points: Moving Average Convergence Divergence (MACD) & VI-test



Case Studies on

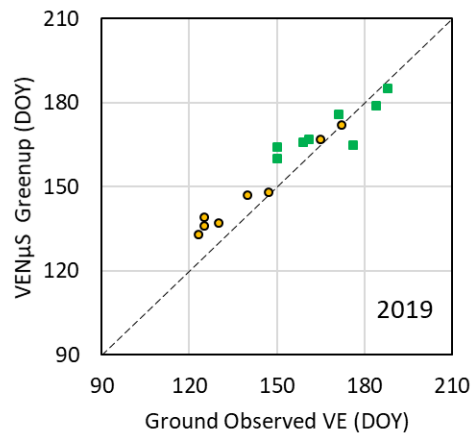
- ☐ Fields
- ☐ BARC area
- ☐ Maryland
- ☐ Corn belt states
- ☐ CONUS

Requirement of Temporal Resolutions (Alfalfa)

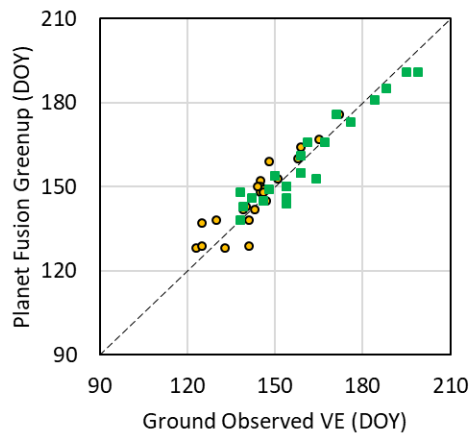


* Sentinel-2 ○ Greenups — Harvest_1 — Harvest_2
 — Harvest_3 — Harvest_4 — Gap-filled

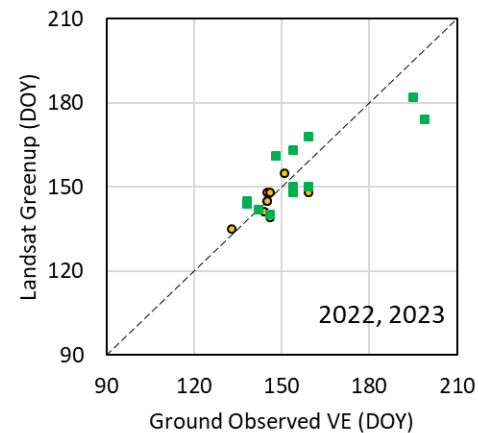
* HLS ○ Greenups — Harvest_1 — Harvest_2
 — Harvest_3 — Harvest_4 — Gap-filled



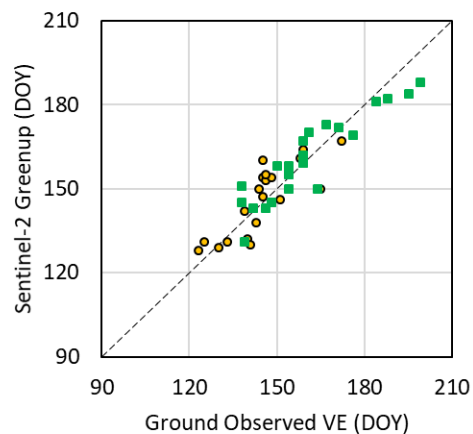
(a) VENμS



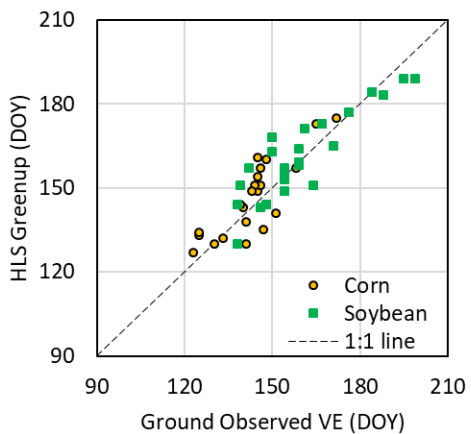
(b) Planet Fusion



(c) Landsat

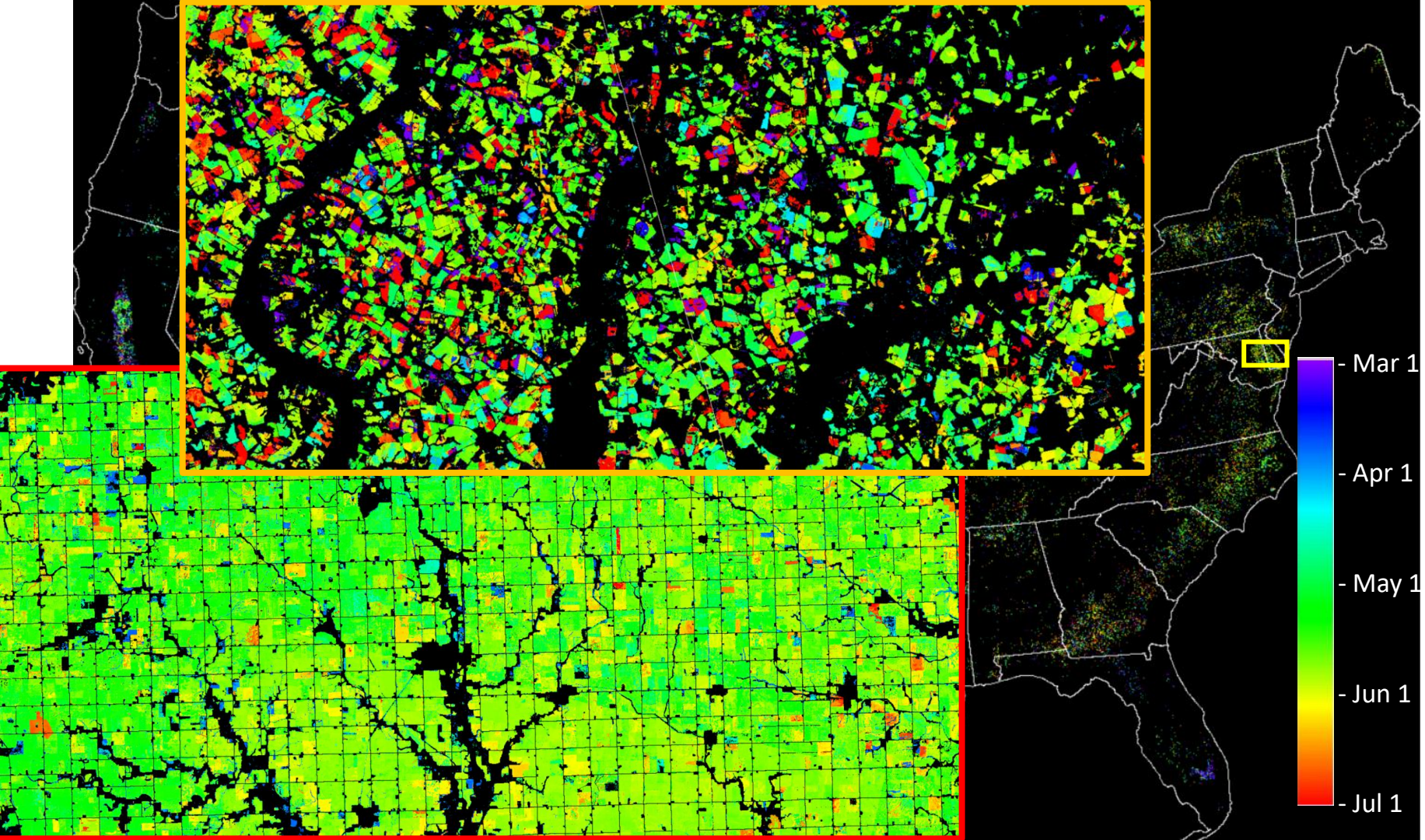


(d) Sentinel-2



(e) HLS

Data	Detected	Bias	MAD	RMSE	R ²
PF	100%	0.7	4.6	5.5	0.88
Landsat	44%	-1.4	6.6	8.7	0.73
S2	91%	0.4	6.1	7.2	0.82
HLS	100%	2.2	6.5	7.9	0.80



State-level Assessment

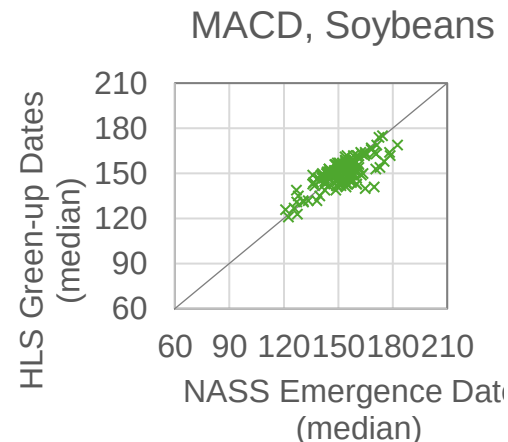
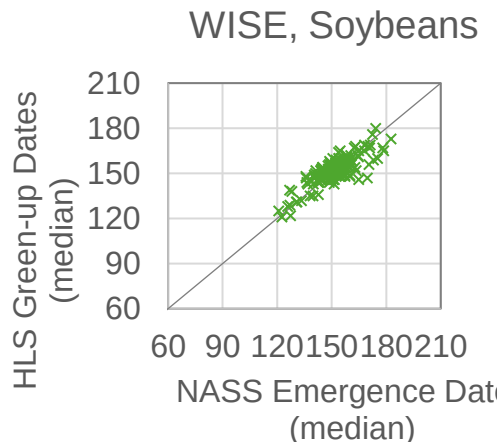
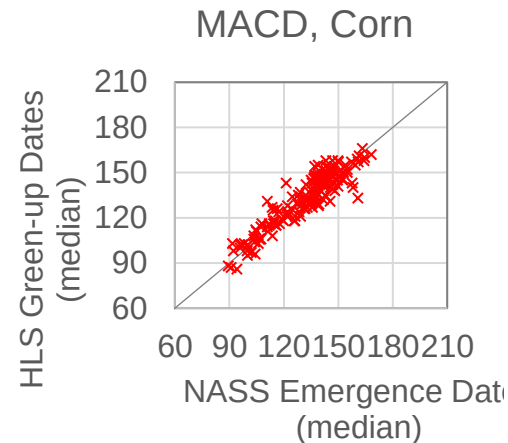
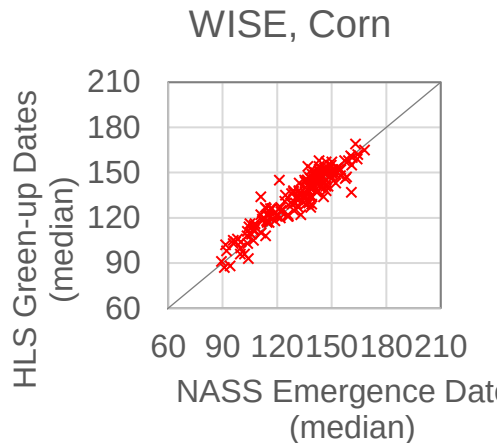
- 2018 – 2023
- Corn and soybean
- Major crop states (~25)
- Median VE dates from NASS CPR
- Median green-up dates

Mean differences for WISE and MACD

Corn: 5.7 and 3.7 days

Soybean: 1.3 and -0.5 days

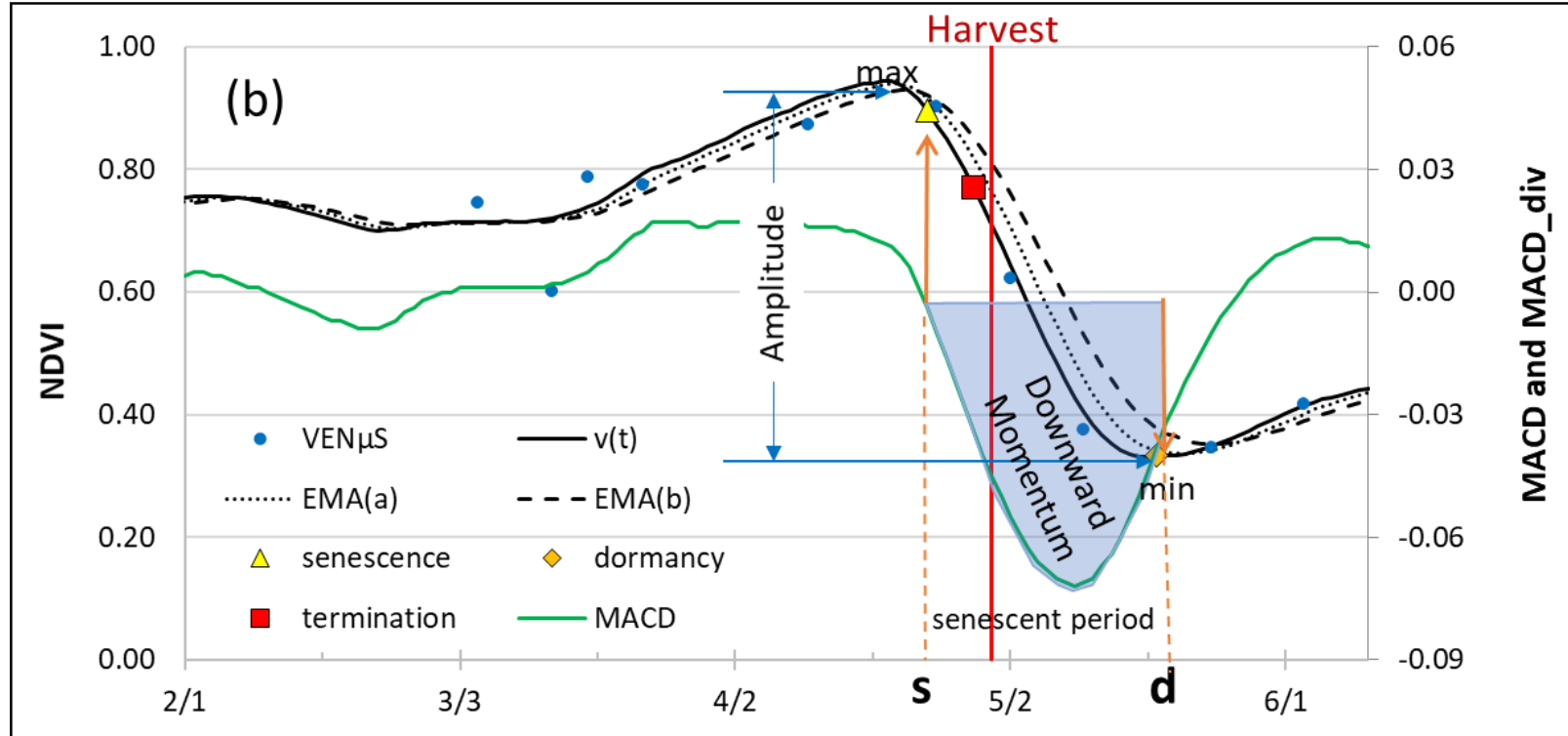
- WISE has less pixels than MACD, so they are not directly comparable for state-level median values
- MACD was earlier than WISE for the state-level statistics, which means the missing detections from WISE are mostly early green-ups



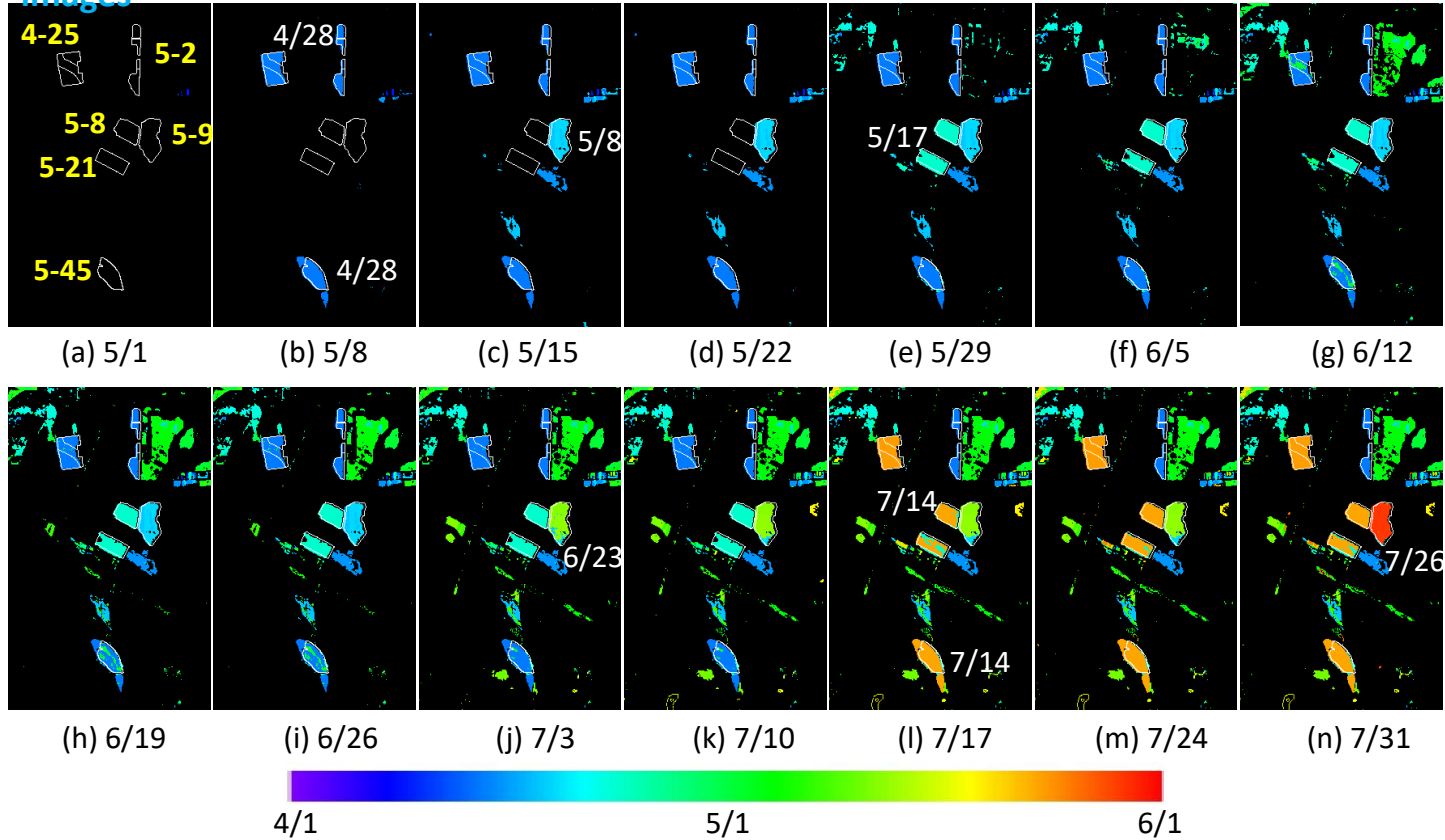
II. Within-Season Approach for Detecting Cover Crop Termination

- The Maryland Department of Agriculture (MDA) cost-share program uses cover crop termination dates to determine incentive payments
 - occurs between March 1, 2020, and June 14, 2020
 - eligible for additional incentive payments after May 1
- Termination dates need to be collected timely from fields.
- Remote sensing termination date helps to reduce field visits since 2020

Within-Season Termination (WIST) Algorithm



Cover crop termination maps from weekly near-real-time simulations using VENμS images



Cover crop field names (yellow text) are shown in (a). Newly detected termination dates from six fields in the 2019 weekly simulations are shown beside the field (white text).

HLS Assessment I: Roadside Survey

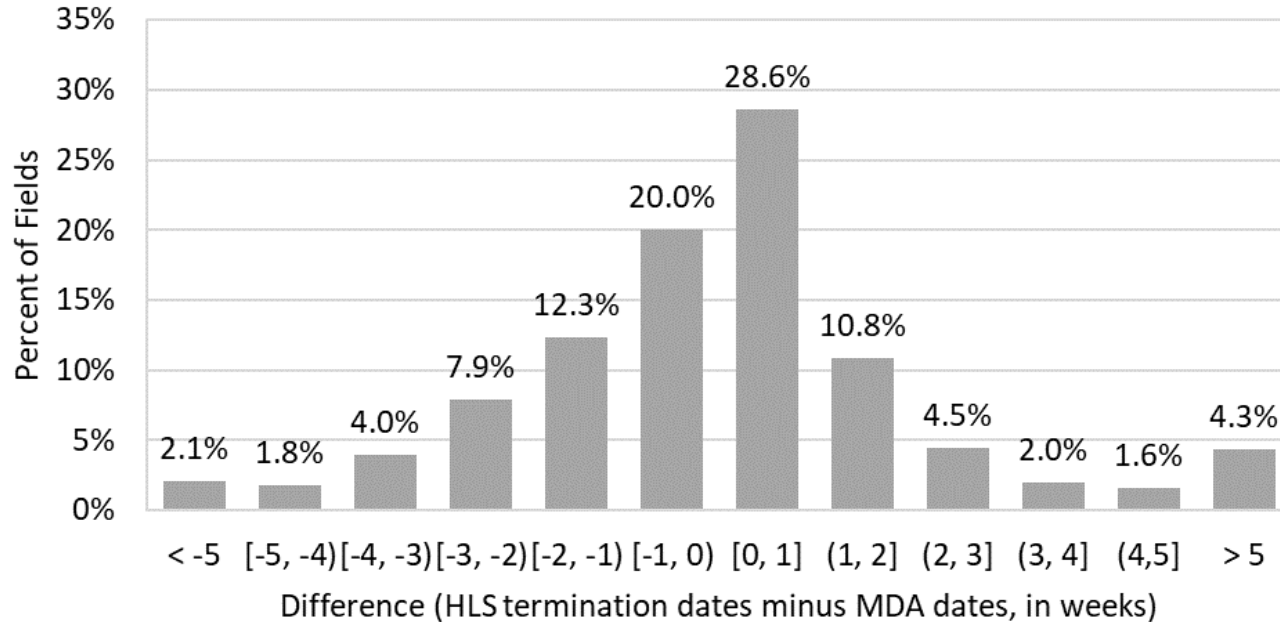
Statistics	Photos /Points	Percent in terms of all points (N=396)	Percent in terms of WIST detected (N=330)
Total number of photos	396	N/A	N/A
WIST failed to detect (no result)	66	16.7%	
WIST succeeded and returned results	330	83.3%	
Correctly detected terminated fields	189	79.3%	95.2%
Correctly detected unterminated fields	125		
Falsely detected termination fields	4	4.0%	4.8%
Falsely detected unterminated fields	12		



Survey Date	Terminated Fields	Un-terminated Fields
4/30/21	99	52
5/3/21	128	43
5/14/21	30	44
Total	257	139



HLS Assessment II: Reported Dates



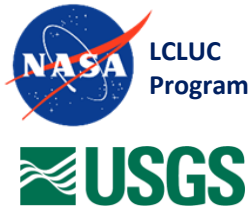
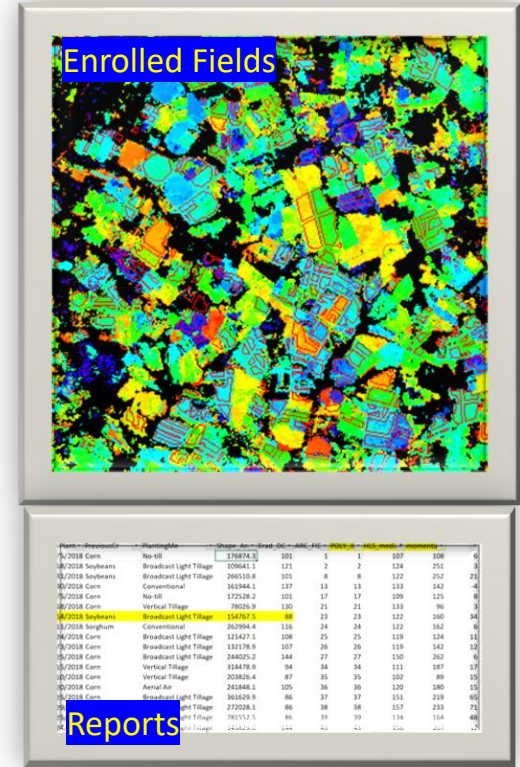
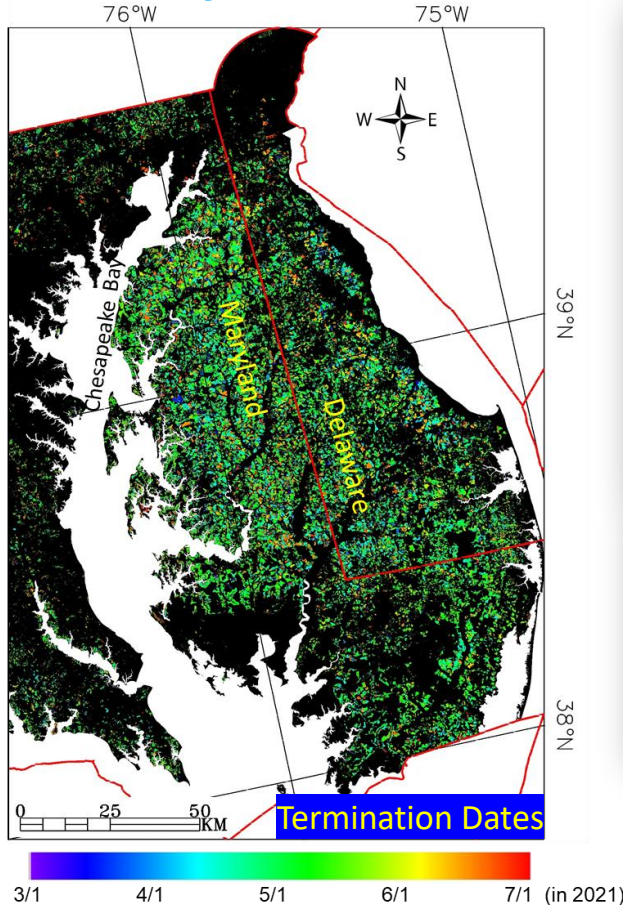
~48.6%, 71.8%, 84.2%, and 90.2% of detected fields were within 1, 2, 3, and 4 weeks of agreement in the 2020-2021 season

**monitoring of winter cover crops
to support ecosystem assessment**

Using HLS data, WISE and WIST algorithms, we have detected winter cover crop emergence and termination dates for Maryland and Delaware operational incentive programs since 2020

Gao et al., 2020. Remote Sensing.
<https://doi.org/10.3390/rs12213524>

Gao et al., 2022. Science of Remote Sensing.
<https://doi.org/10.1016/j.srs.2022.100073>



Mapping WCC Presence

❑ Remote Sensing Methods

- ❑ Traditional classification methods
- ❑ Operational Tillage Information System (OpTIS) (Landsat, MODIS, Sentinel-2)
- ❑ UIUC (Landsat and MODIS data fusion)

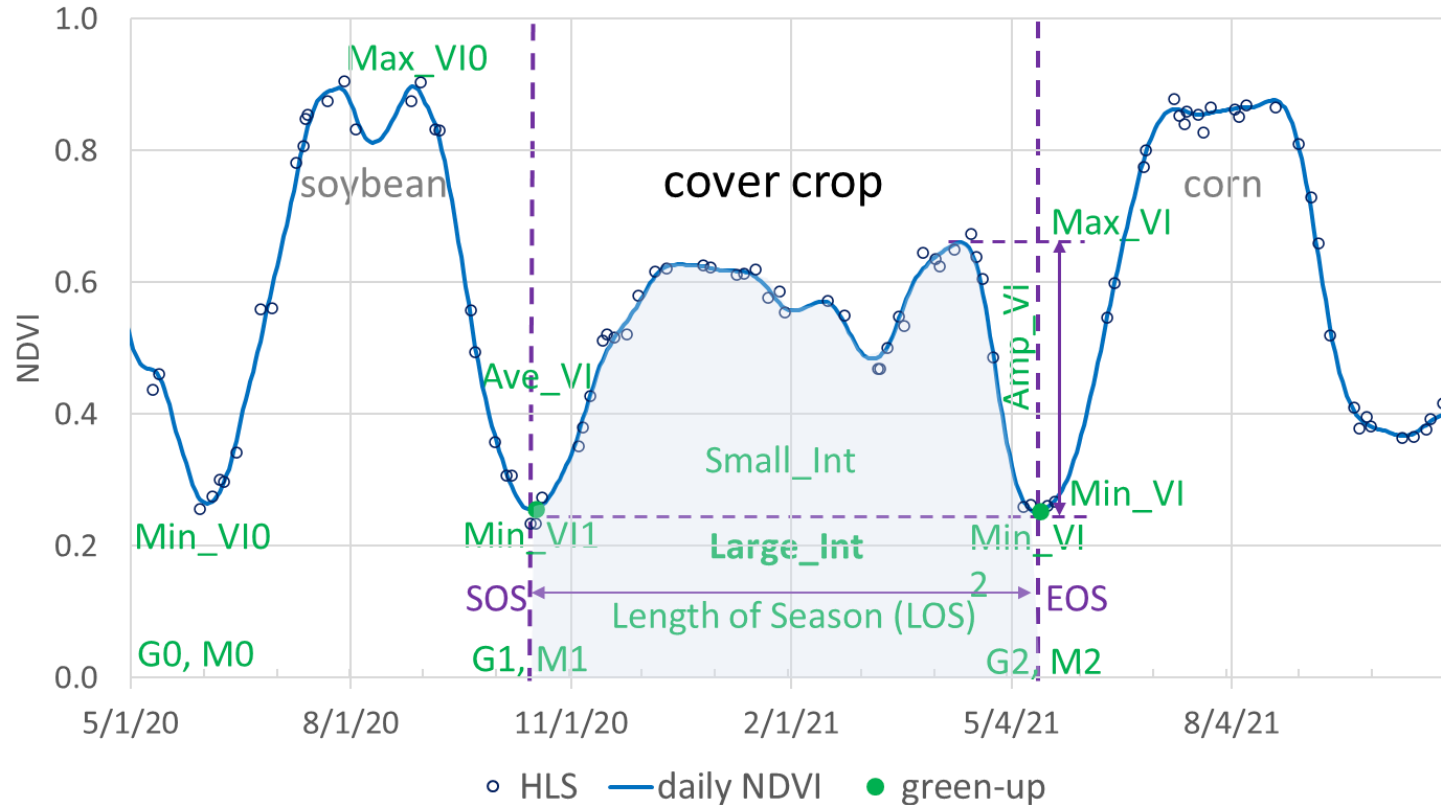
❑ Challenges

- ❑ After-season methods delay decision-making
- ❑ Confusion with weeds, winter wheat and WCC
- ❑ Binary maps oversimplify WCC performance

Develop an operational remote sensing method to map WCC presence during and post the WCC growing season

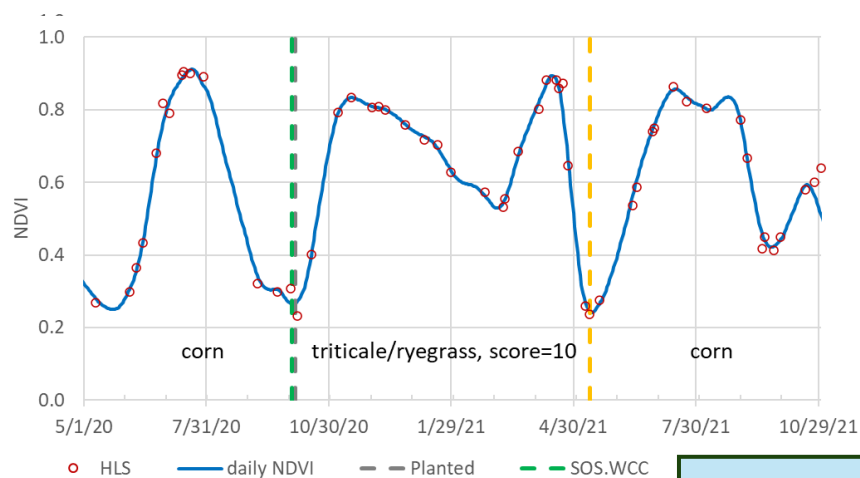


WCC Presence Detection using Remote Sensing Phenology

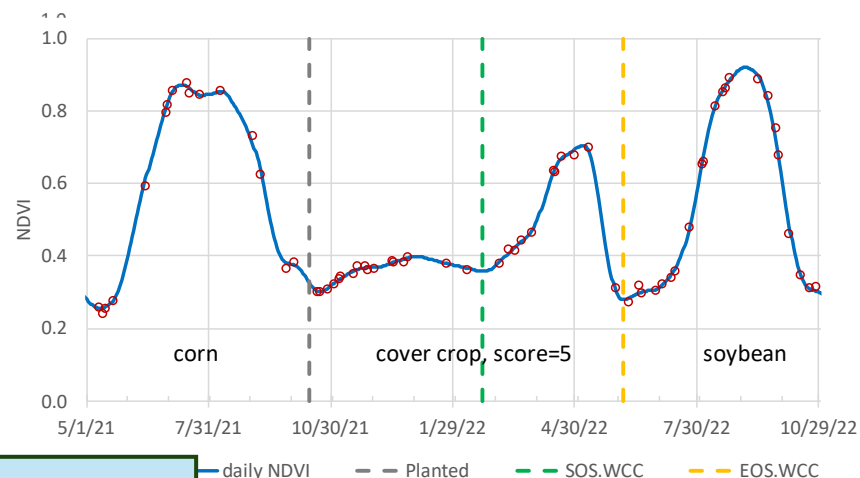


Remote Sensing Phenology-Based Approach

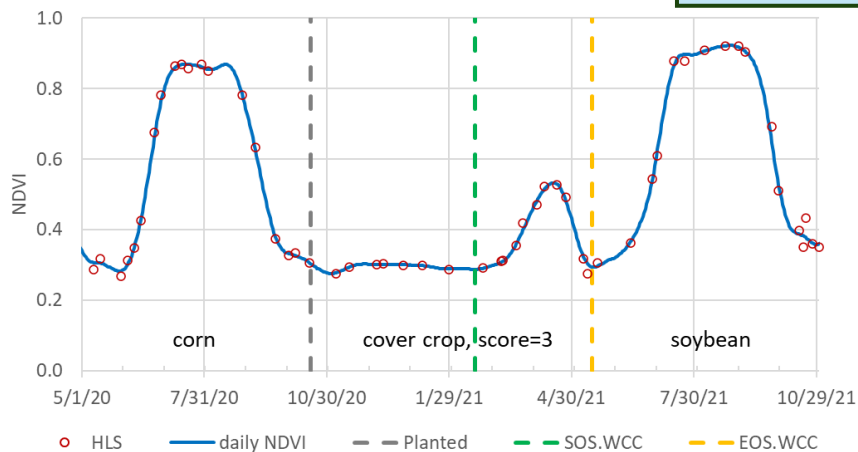
- ❑ Satisfy minimum requirements for WCC
- ❑ Used four phenological metrics to compute likelihood score
 - Absolute NDVI: max and large Integral
 - Relative NDVI: amplitude and small integral
- ❑ Normalized with a sigmoid function to scale metrics from 0 to 1
- ❑ Generate WCC likelihood score with a scale of 1 to 10
(10 means most likely with strong performance)



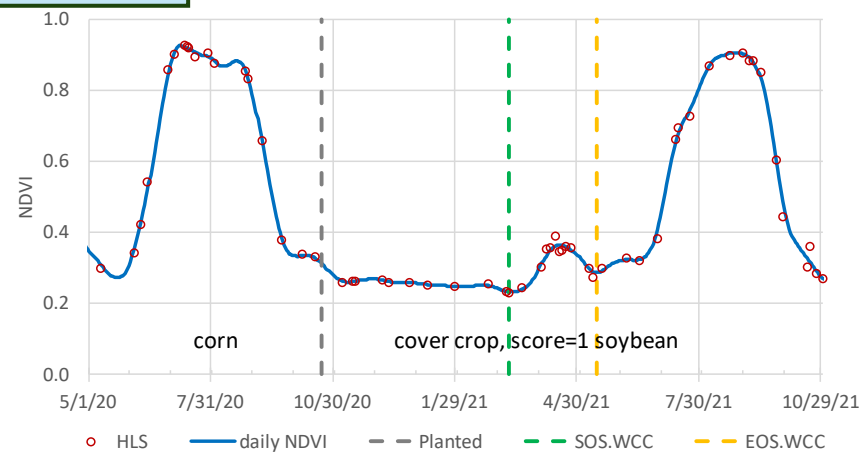
(a) Field #4-7



(b) Field #5-23

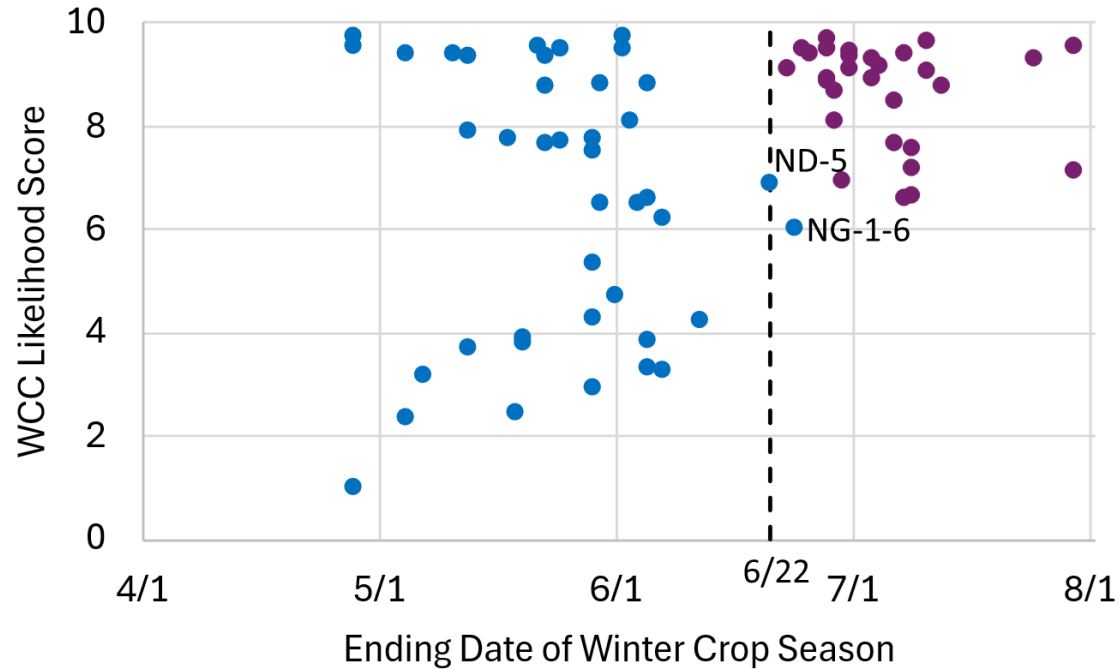


(c) Field #6-60



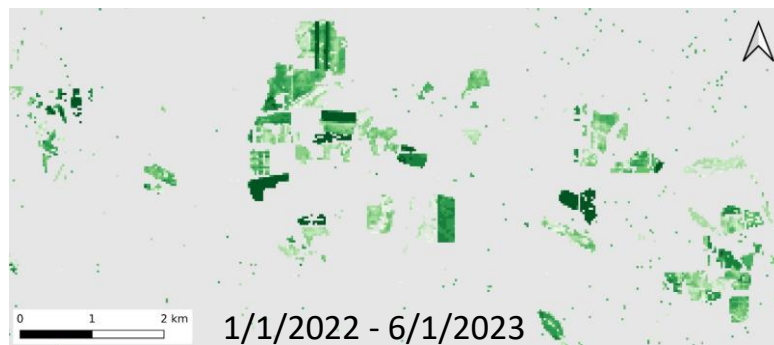
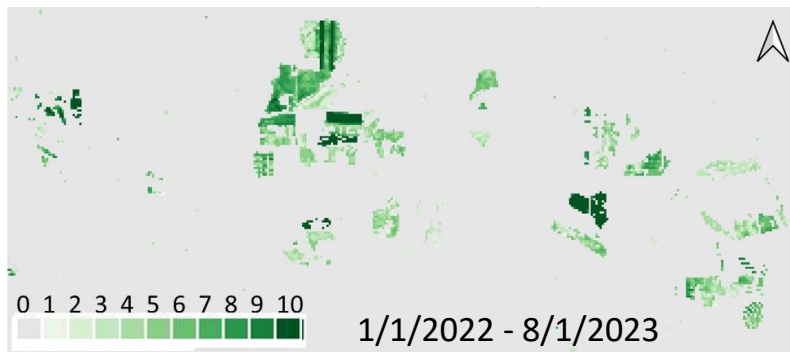
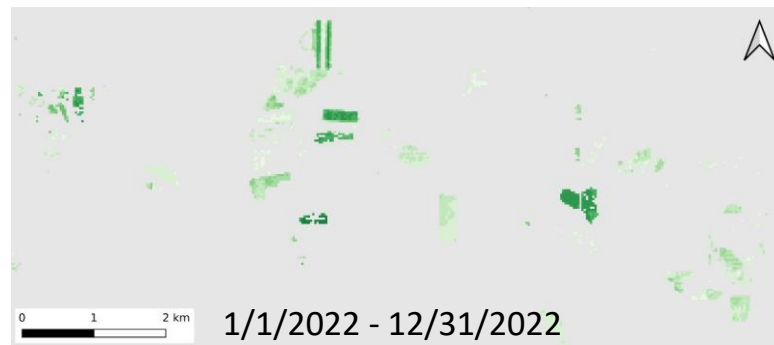
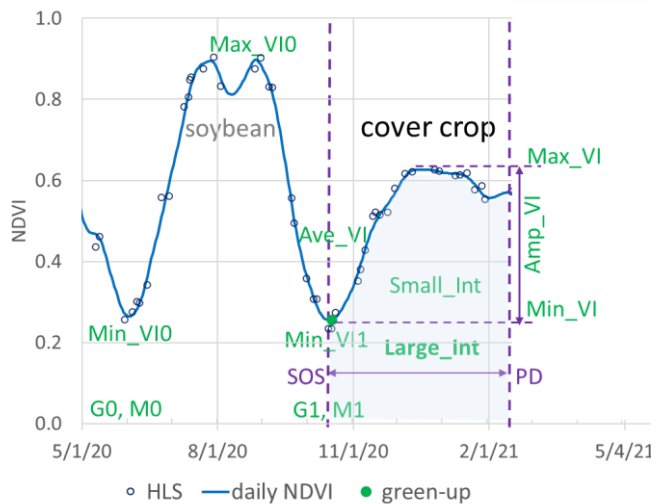
(d) Field #2-71

Incentive WCC



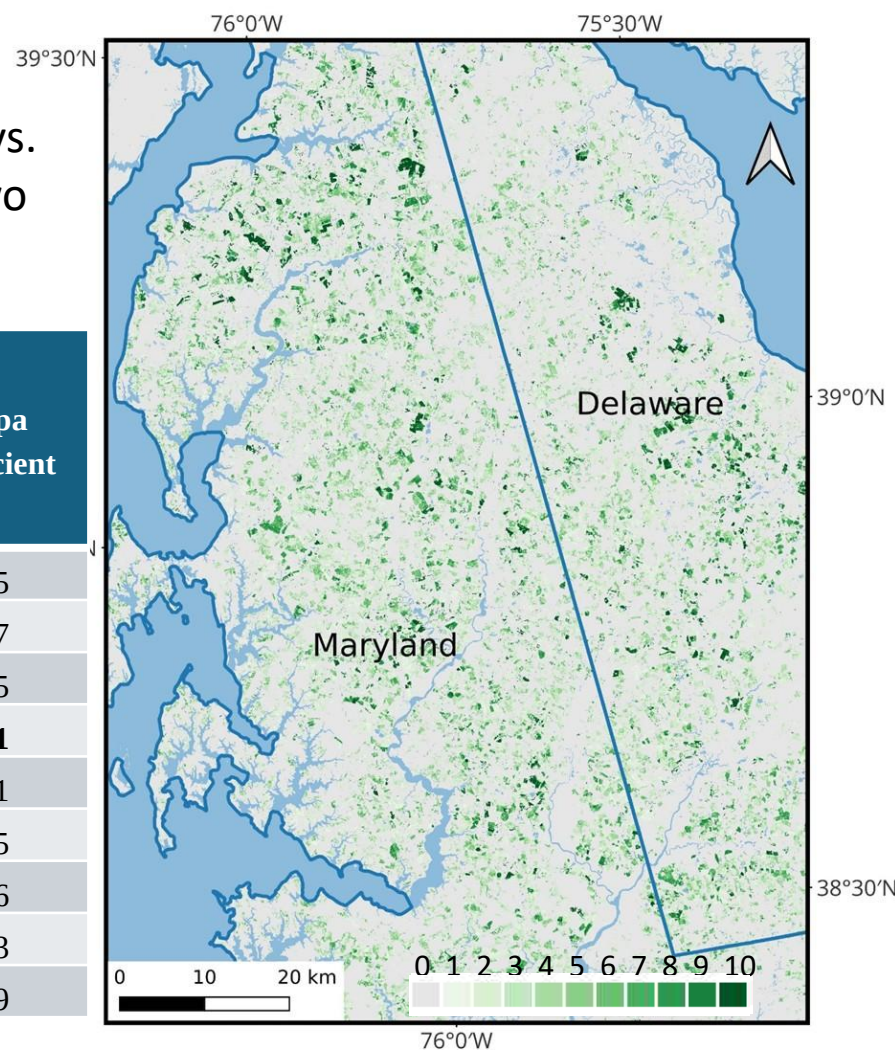
● harvested wheat ● incentive WCC - - - Earliest Harvest

In-season WCC Mapping Using Phenological Metrics



Incentive WCC and non-WCC detected from HLS vs. MDA enrolled and unenrolled WCC fields from two seasons (2019-2020 and 2020-2021)

WCC Score Thresholds (ST)	Producer's Accuracy of WCC	User's Accuracy of WCC	Balanced Overall Accuracy	Kappa Coefficient
ST >= 1	89.0%	58.5%	68.3%	0.35
ST >= 2	88.8%	64.4%	74.1%	0.47
ST >= 3	86.3%	70.5%	78.2%	0.55
ST >= 4	80.3%	77.5%	80.5%	0.61
ST >= 5	71.6%	84.1%	80.2%	0.61
ST >= 6	60.9%	87.9%	76.9%	0.55
ST >= 7	49.1%	89.5%	72.2%	0.46
ST >= 8	34.7%	88.9%	65.5%	0.33
ST >= 9	20.4%	87.6%	59.0%	0.19



Summary

Winter cover crop emergence and termination dates are mapped in 1-3 weeks after the events when HLS are timely available

The presence and likelihood of winter cover crop are mapped (>80% overall accuracy) either during or after WCC season using HLS

For HLS data products: short latency and reliable cloud mask are critical for the in-season winter cover crop mapping

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Near-Real Time Processing of HLS for Rangeland Management

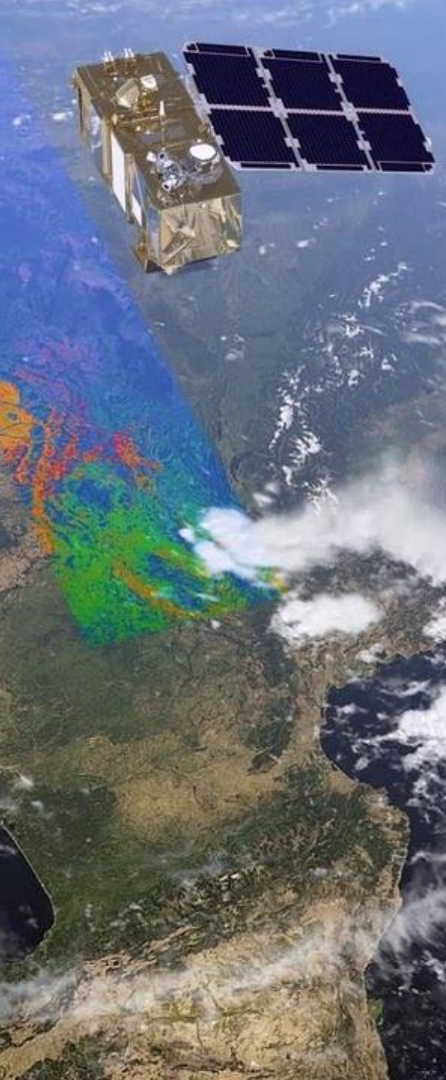
Sean Patrick Kearney, Lauren M. Porensky, David J. Augustine, Justin D. Derner, Martha Anderson, Feng Gao, Haoteng Zhao, Melissa Johnston, David Hoover, Erika Peirce, Mikael Hiestand, John Ritten, Gonzalo Irisarri











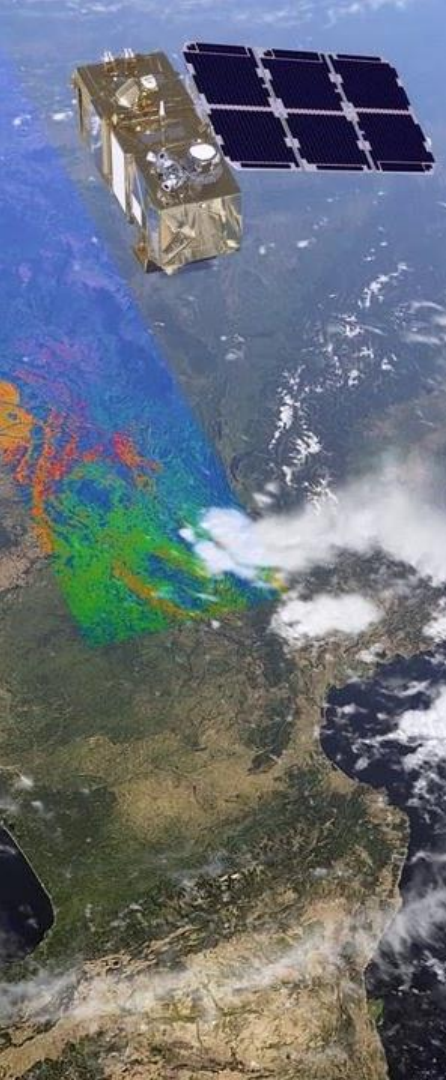
Objective: Support within-season decision-making

Why HLS?

- Temporal frequency
 - Explore time series and trends
 - Change over time (30-day change)
- Near-real time
 - Low latency (very important!)
 - Current conditions (within days or weeks)
- Historical comparisons
 - Go back in time
 - Compare to long-term average

Products/metrics

- Herbaceous standing biomass
- Cover (fractional)
- Crude Protein (diet quality)
- Leaf area index
- Evapotranspiration



Article

Predictions of Aboveground Herbaceous Production from Satellite-Derived APAR Are More Sensitive to Ecosite than Grazing Management Strategy in Shortgrass Steppe

Erika S. Peirce ¹, Sean P. Kearney ², Nikolas Santamaria ³, David J. Augustine ⁴ and Lauren M. Porensky ^{1,*}

¹ Rangeland Resources and Systems Research Unit, US Department of Agriculture (USDA)—Agricultural Research Service (ARS), Fort Collins, CO 80526, USA; erika.peirce@usda.gov (E.S.P.); sean.kearney@usda.gov (S.P.K.); david.augustine@usda.gov (D.J.A.)
² Applied Data Science Program, New College of Florida, Sarasota, FL 34243, USA; nikolas.santamaria@nfc.edu
³ Correspondence: lauren.porensky@usda.gov

Abstract: The accurate estimation of aboveground net herbaceous production (ANHP) is crucial in rangeland management and monitoring. Remote and rural rangelands typically lack direct observation infrastructure, making satellite-derived methods essential. When ground data are available, a simple and effective way to estimate ANHP from satellites is to derive the empirical relationship between ANHP and plant-absorbed photosynthetically active radiation (APAR), which can be estimated from the normalized difference vegetation index (NDVI). While there is some evidence that this relationship will differ across rangeland vegetation types, it is unclear whether this relationship will change across grazing management regimes. This study aimed to assess the impact of grazing management on the relationship between ground-observed ANHP and satellite-derived

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ARTICLE



Predicting spatial-temporal patterns of diet quality and large herbivore performance using satellite time series

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¹USDA-Agricultural Research Service (ARS) Rangeland Resources and Systems Research Unit, Fort Collins, Colorado, USA

²USDA-ARS Rangeland Resources and Systems Research Unit, Cheyenne, Wyoming, USA

³USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville, Maryland, USA

Correspondence:
 Sean P. Kearney
 Email: sean.kearney@usda.gov

Funding information:
 U.S. Department of Agriculture - Agricultural Research Service

Abstract

Adaptive management of large herbivores requires an understanding of how spatial-temporal fluctuations in forage biomass and quality influence animal performance. Advances in remote sensing have yielded information about the spatial-temporal dynamics of forage biomass, which in turn have informed rangeland management decisions such as stocking rate and paddock selection for free-ranging cattle. However, less is known about the spatial-temporal patterns of diet quality and their influence on large herbivore performance. This is due to infrequent concurrent ground observations of forage conditions with performance (e.g., mass gain), and previously limited satellite data at fine spatial and temporal scales. We combined multi-temporal field observations of diet quality (weekly) and mass gain (monthly) with satellite-derived phenological metrics (pseudo-daily, using data fusion and interpolation) to model daily mass gains of free-ranging yearling cattle in shortgrass steppe. We used this



Monitoring standing herbaceous biomass and thresholds in semiarid rangelands from harmonized Landsat 8 and Sentinel-2 imagery to support within-season adaptive management

Sean P. Kearney ^{1,*}, Lauren M. Porensky ², David J. Augustine ³, Rowan Gaffney ^{3,4}, Justin D. Derner ⁵

¹ USDA-Agricultural Research Service (ARS) Rangeland Resources and Systems Research Unit, Fort Collins, CO 80526, USA

² USDA-ARS Rangeland Resources and Systems Research Unit, Cheyenne, WY 82006, USA

³ UNAVCO, Inc., Boulder, CO 80301, USA

ARTICLE INFO

ABSTRACT

Keywords:
 Harmonized Landsat Sentinel
 Image time series
 Herbaceous biomass
 Vegetation index
 Adaptive rangeland management

Adaptive management requires rangeland managers to respond to changing forage conditions (e.g., standing herbaceous biomass) within the grazing season at the scale of individual pastures. While within-season biomass can be measured or estimated in the field, it is often impractical to make field measurements in extensive rangeland systems with adequate frequency and spatial representation for responsive decision-making by rangeland managers. We sought to develop a single model to accurately predict daily herbaceous biomass across seasonally and annually varying conditions from the Harmonized Landsat-Sentinel satellite time series. We also sought to

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OPEN Bringing cross-validation into the real world to evaluate transferability of satellite-based vegetation models

Sean P. Kearney ^{1,2,3}, David J. Augustine ⁴, Lauren M. Porensky ², Erika S. Peirce ^{1,2}, Mikael P. Hiestand ² & Justin D. Derner ²

Near-real-time mapping of vegetation using satellite imagery is becoming increasingly common and valuable across a wide range of ecosystems. The availability of large datasets has led many researchers to complex machine learning algorithms (MLAs) to train satellite models. However, complex MLAs may underperform for the inherently extrapolative applications required for real-world vegetation monitoring. We used a dataset of nearly 10,000 training samples of standing herbaceous grazingland biomass collected over ten years to train progressively more complex MLAs, test them across progressively more extrapolative cross-validation (CV) groupings, and evaluate their transferability and consistency. The performance of all MLAs decreased substantially when tested against more extrapolative CV groupings. The commonly used approach of random k-fold CV produced overly optimistic performance (R^2 : 0.71–0.78) compared to a more realistic task of predicting for an unseen year (R^2 : 0.49–0.54). Simpler MLAs, such as partial least squares regression, were more consistent and outperformed complex MLAs for the most extrapolative tasks, and performance was less sensitive to the distinctness of unseen test data. We conclude that random k-fold CV likely produces unrealistically optimistic expectations for real-world applications of satellite vegetation models, and could be associated with major prediction misses when models are used in novel environmental conditions.

CARM Goal

“To pass the land on to future generations ecologically and economically”

CARM Objectives



Profitable Ranching

Maintain or increase livestock weight gain

Reduce economic impacts of drought

Maintain or reduce operating costs



Vegetation

Increase percentage of cool-season grasses and non-shortgrass native plants by weight and number of plants

Increase variation in vegetation structure, composition, and density within and among pastures

Maintain or increase size of four-wing saltbush and winter-fat shrubs



Wildlife

Increase populations of mountain plover

Maintain populations of McCown's longspur, western meadowlark and horned lark

Increase populations of grasshopper sparrow, Cassin's sparrow, Brewers sparrow, and lark bunting

Maintain control of prairie dog populations (No prairie dogs.)

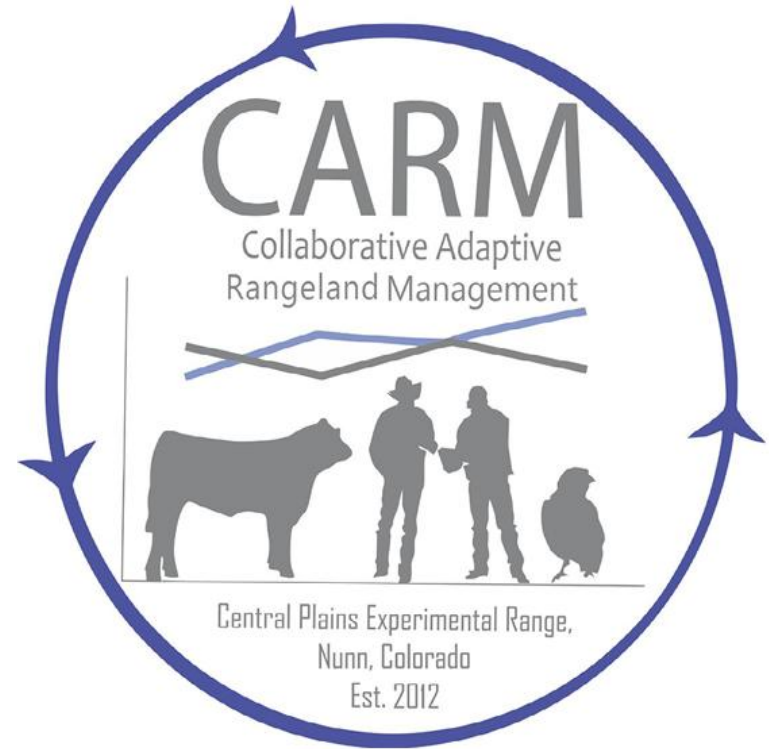


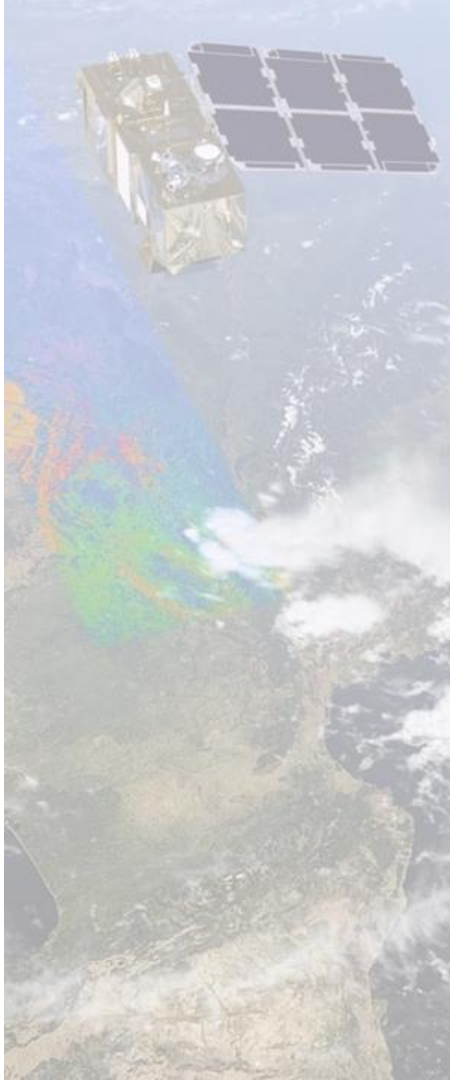
Social Learning

Stakeholders and researchers co-produce new knowledge

Increase respect, understanding and trust among stakeholders and researchers

Apply new knowledge and CARM in new areas





Methods

Going from spectra to vegetation metrics

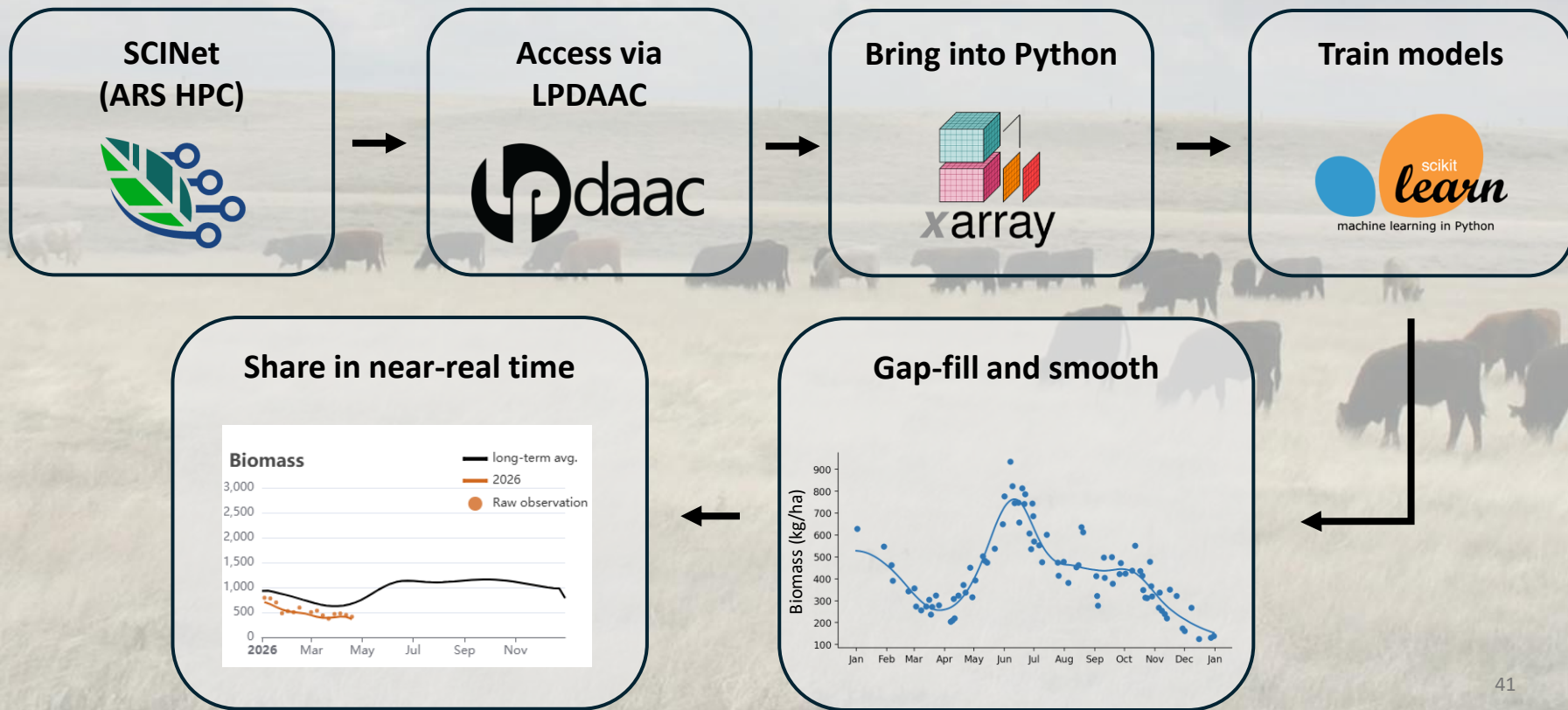
Methods – training/validation

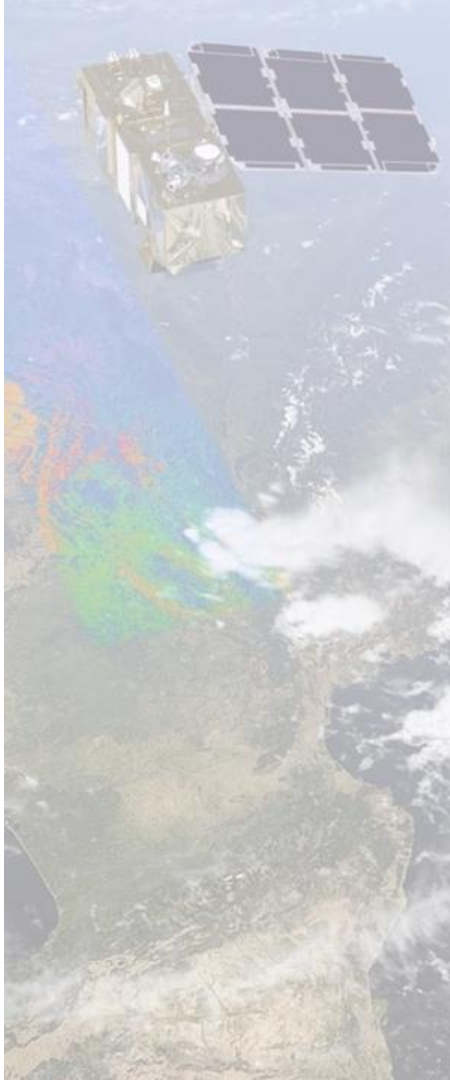
Extensive field data

- > 10,000 samples (rapid methods)
- > 10 years (long-term research)
- > 8 projects (CO, WY, OK, TX, MI, NM, ID, FL)



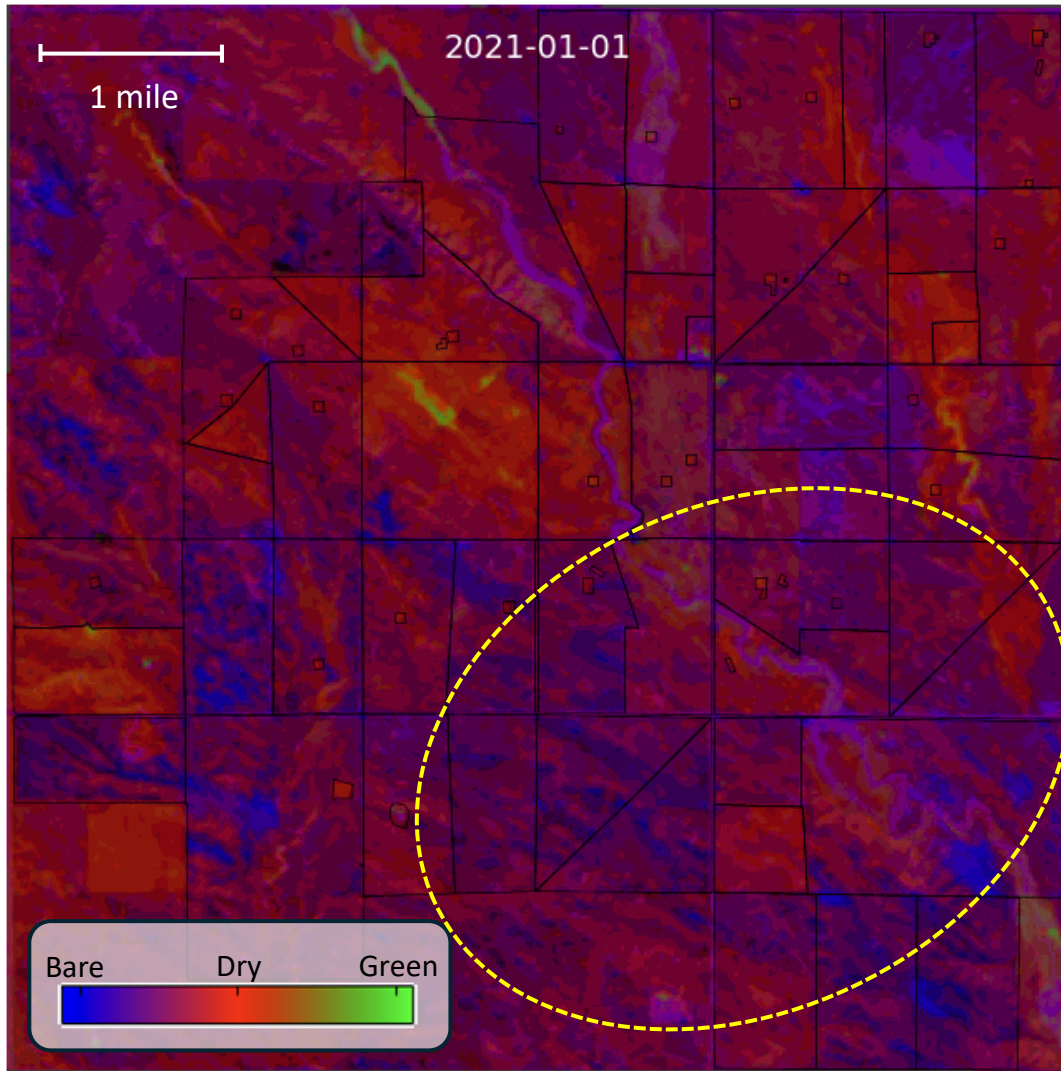
Methods – Data processing





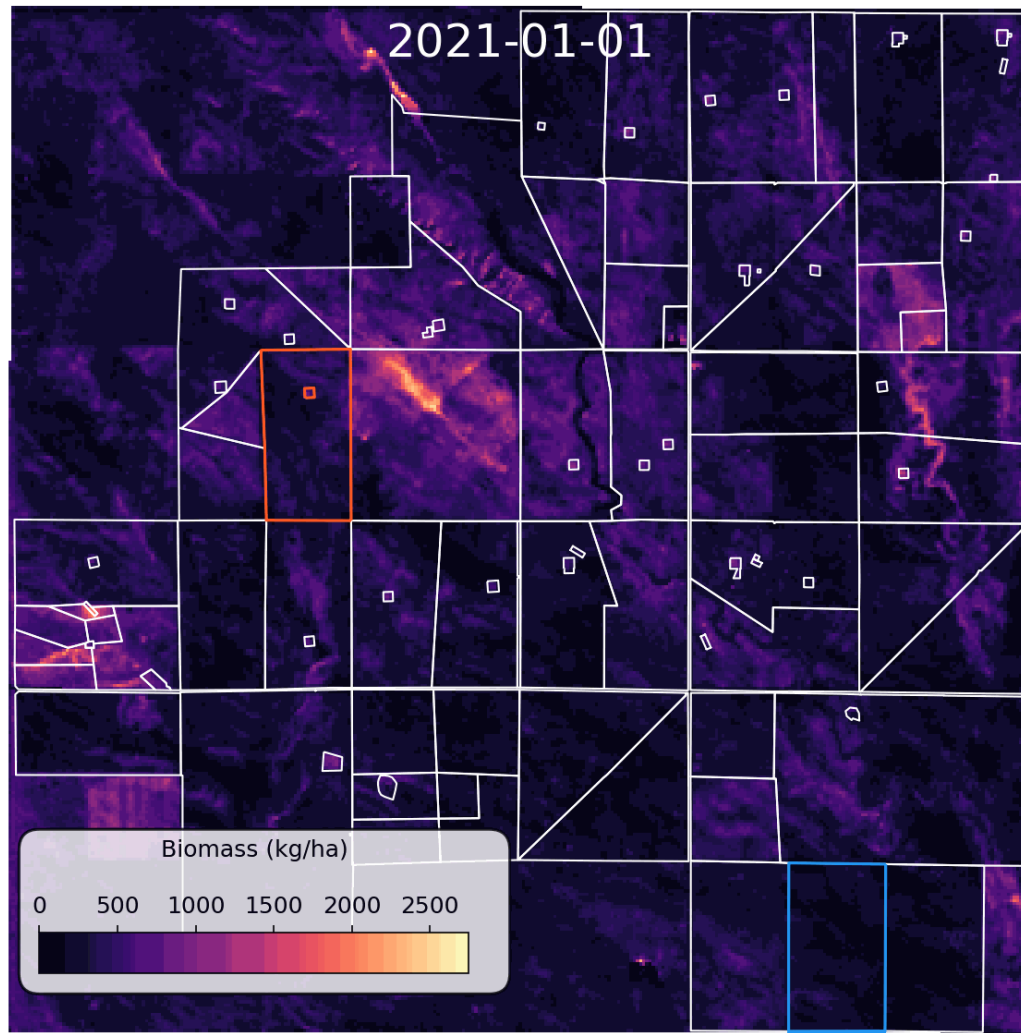
Examples

Using HLS products to inform rangeland research



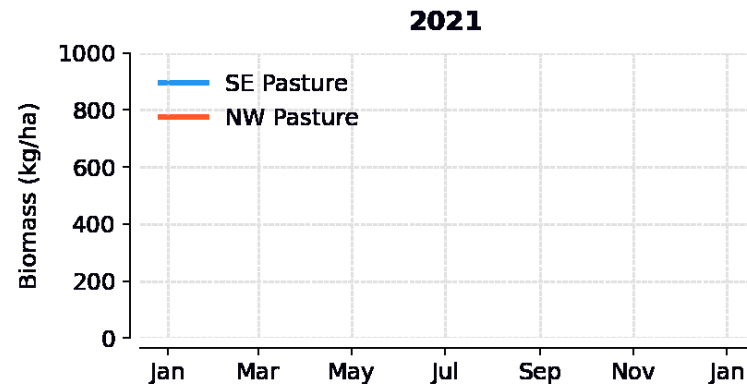
Weather effects

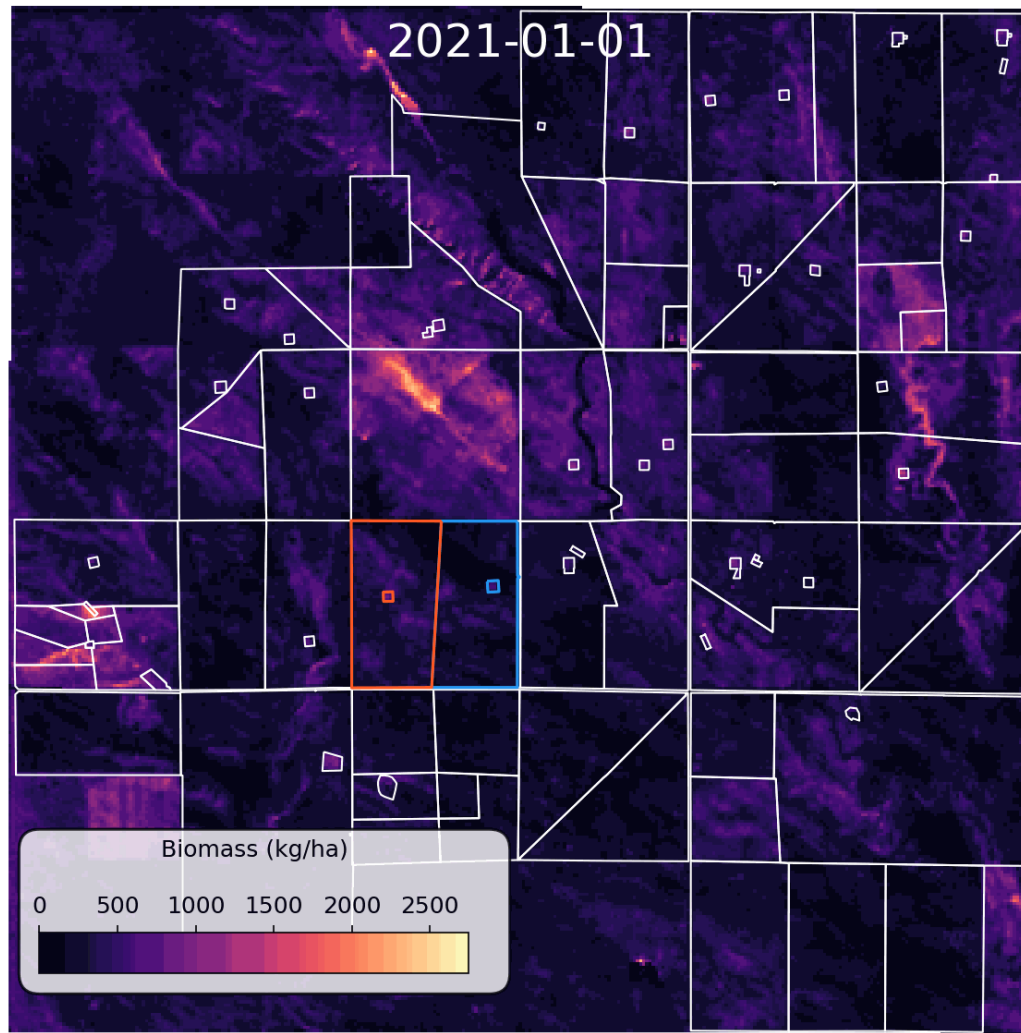
Outcomes of spatially variable rainfall



Weather effects

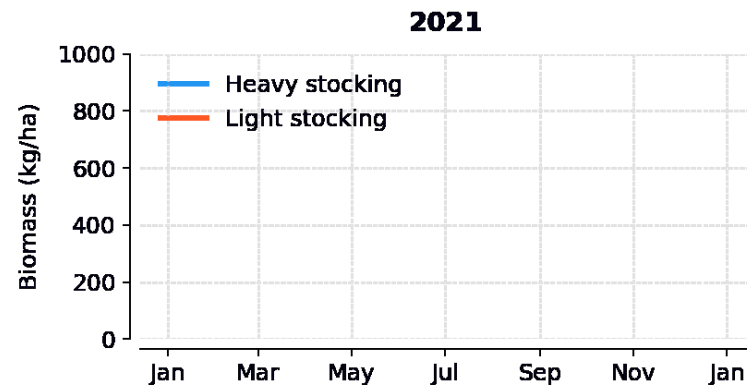
Outcomes of spatially variable rainfall

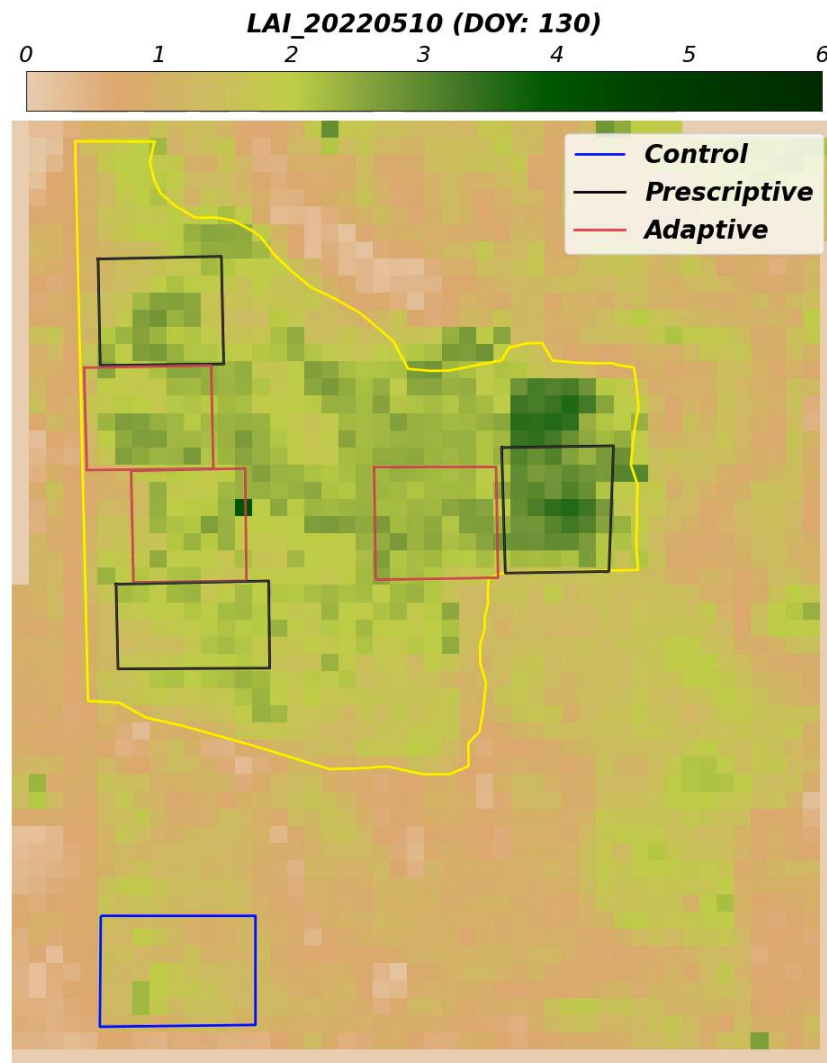




Management effects

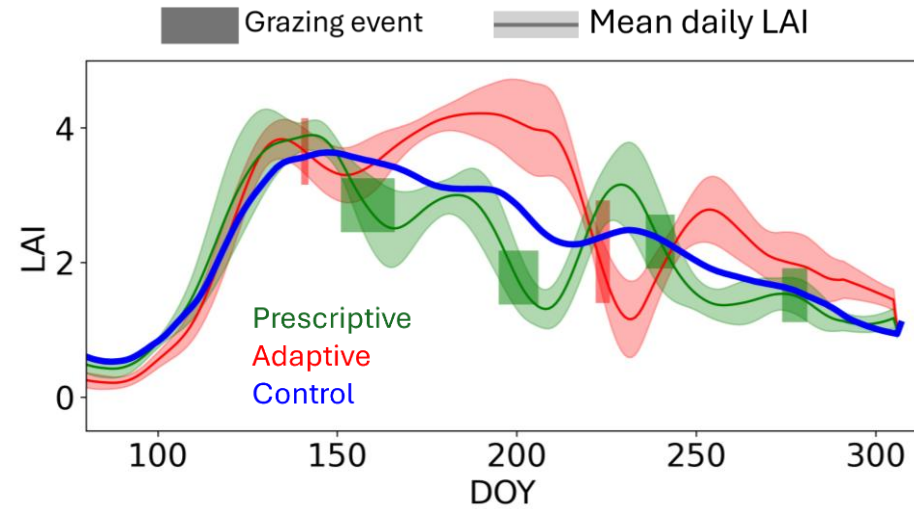
Outcomes of grazing intensity





Management effects

Recovery after grazing events



Average year (2011)

Early year (2018)

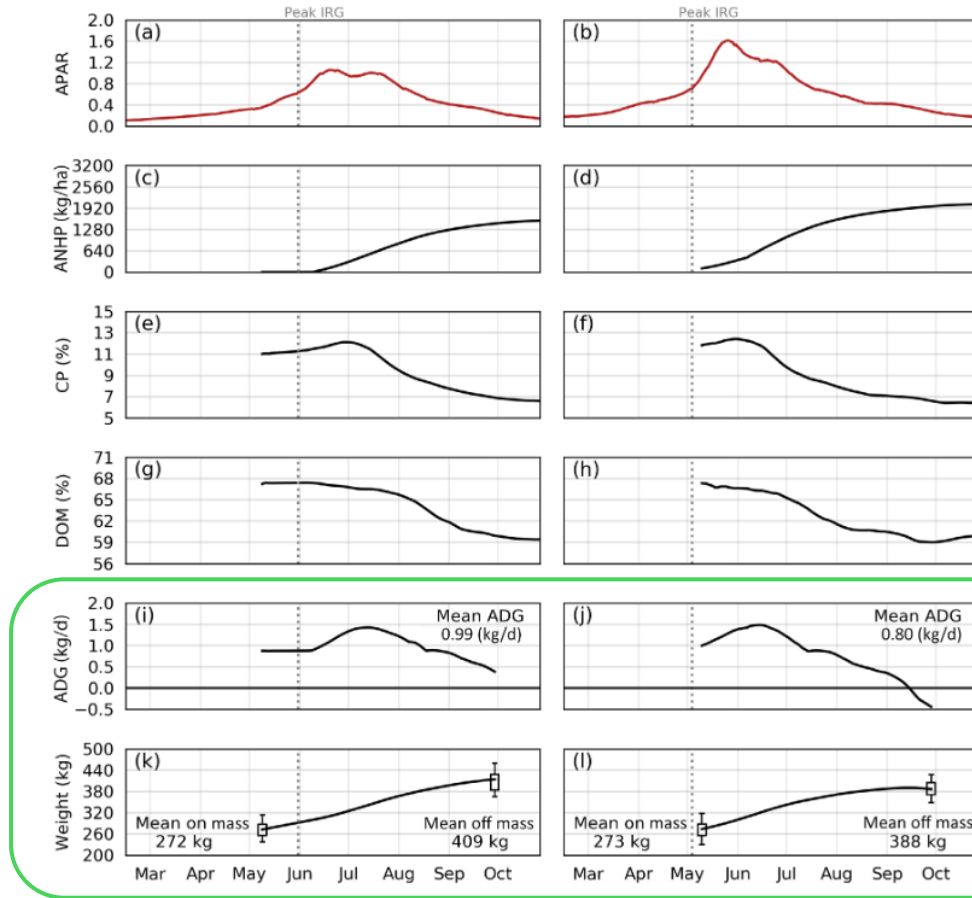


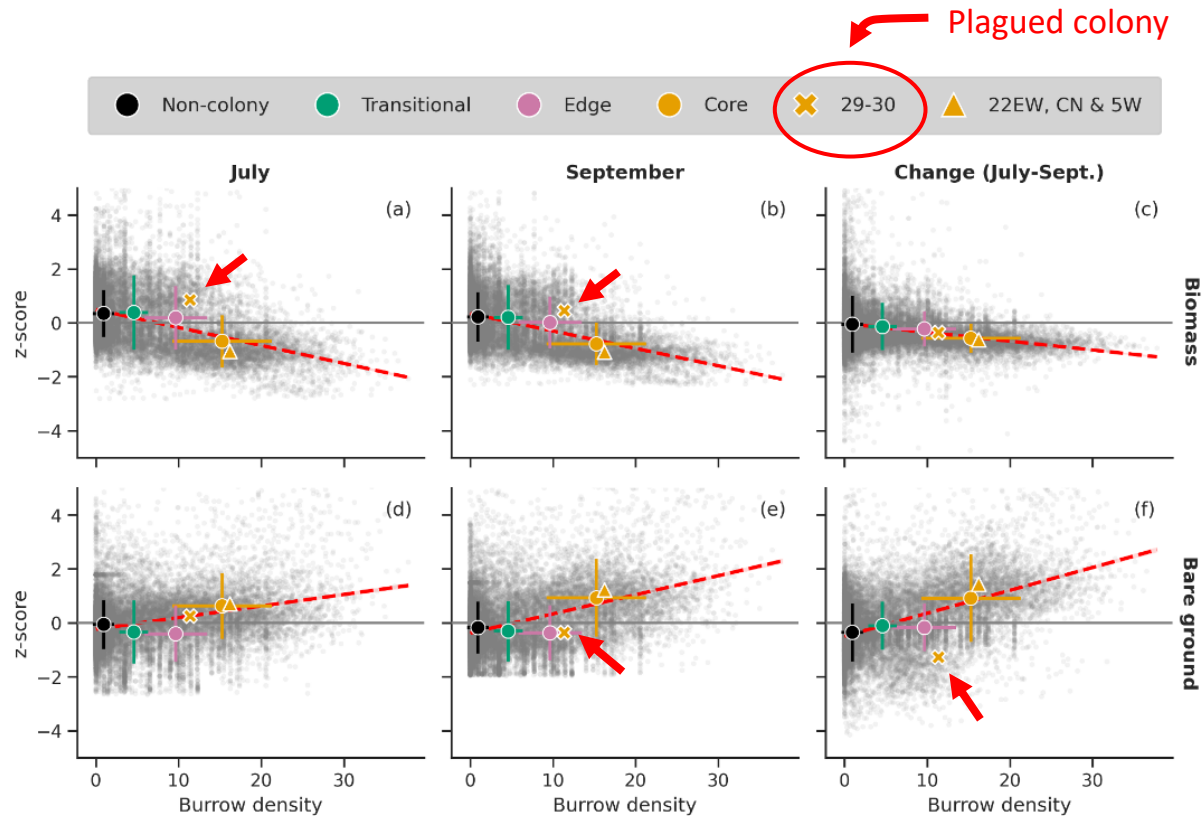
FIGURE 6 Example from paddock 31E of (a, b) satellite-derived APAR, (c, d) predicted forage quantity (ANHP), (e–h) diet quality (CP and DOM), (i, j) pseudo-daily mass gain (ADG), and (k, l) cattle mass during the grazing season for a typical “average” year (2011) and an “early” year with earlier-than-average forage green-up. Box plots in panels k and l show the observed on and off mass for all cattle in that paddock

Cattle weight gain (ADG)

Timing grazing with peak forage quality

When greenup started early, cattle weight gains were reduced by ~20%, despite adequate forage biomass.

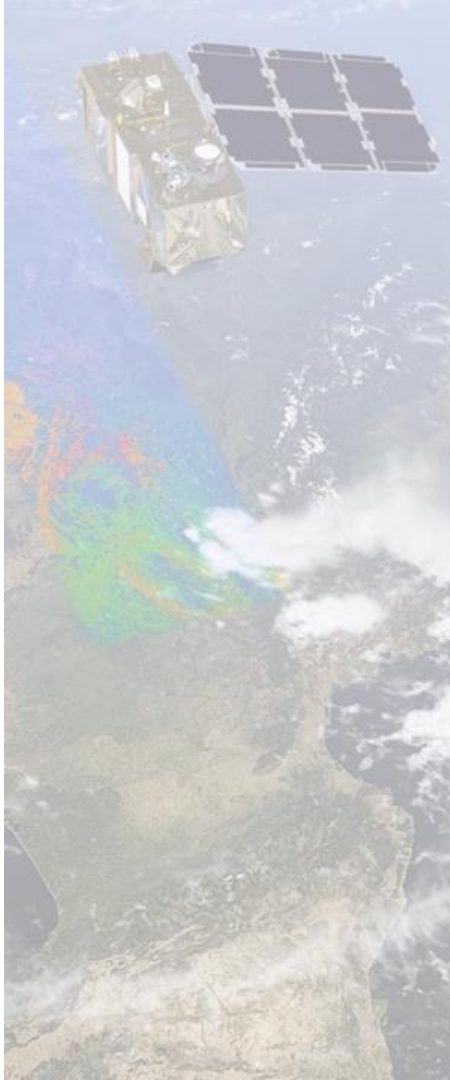
Kearney et al. (2022)
Ecological Applications



Prairie Dog Colonies

Detecting recent plague events

Fig. 10. Scatterplots of burrow density (within a 25 m radius) and satellite-derived metrics for July, September and the slope of the change in metrics over the July-September period. Grey dots represent individual 30 m pixels for the entire Central Plains Experimental Range (CPER) and are z-score standardized by subtracting the mean and dividing by the standard deviation of the entire CPER. Red dotted lines show the linear relationship for all CPER for each variable pair. Means (circles) and standard deviations (lines) are shown for the four model prediction classes (Non-colony, Transitional, Edge, Core) across the four study pastures. Means (symbols) are also shown separately for the Core areas in pasture 29-30, which experienced plague in 2020/21 ('X' symbol), and for the other three pastures with large, active colonies ('Δ' symbol for mean of 22EW, CN, 5 W). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



Interactive mapping tool

A near-real time prototype for collaborative adaptive
rangeland management

Map options

Select map year
2026

Select date
2026-04-19

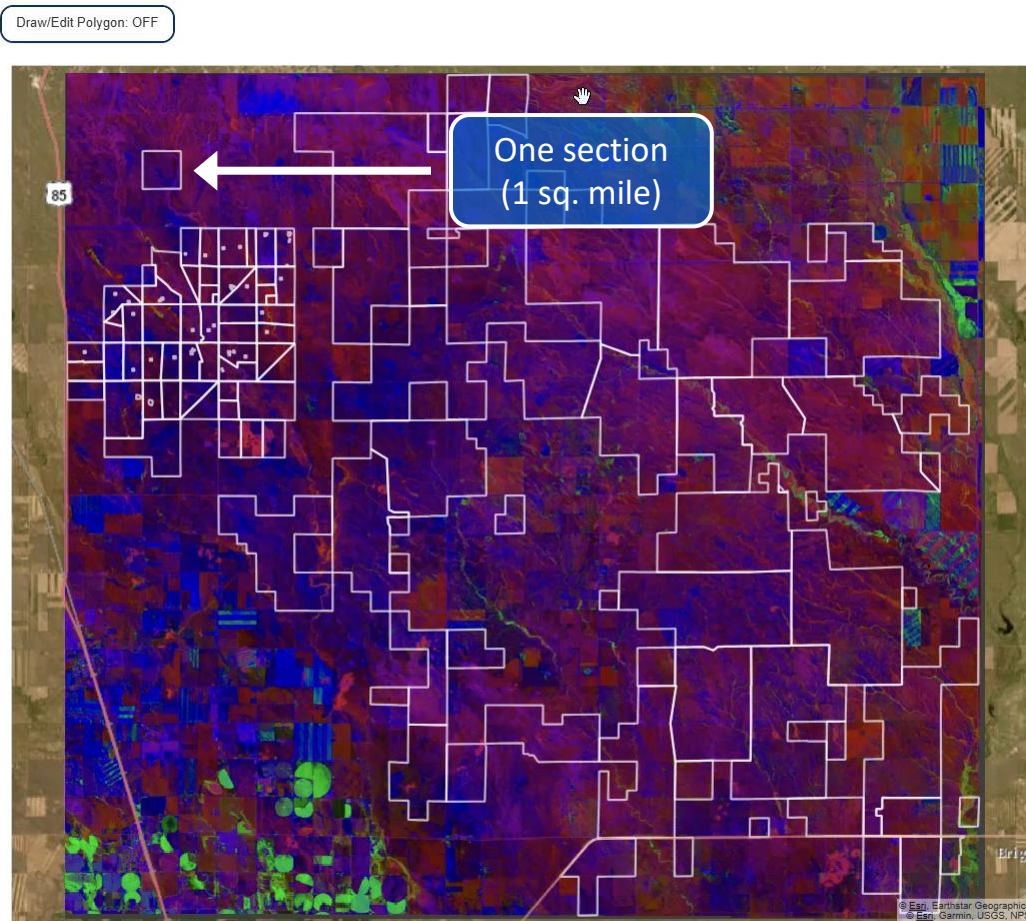
Basemap
Cover
Greenness (NDVI)
Biomass
Crude protein
Bare ground change
Greenness change
Biomass change
Crude protein change
Relative greenness
Relative biomass
Relative CP
Biomass threshold

Map legend

Bare Dry Green

Chart options

Comparison year
None



Pasture stats Time-series Drawing stats

No pasture selected

Apr 19, 2026

0 500 1000 1500 2000 2500
0 lbs/ac
Biomass

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
0 %
Crude protein

Cover

Fractional vegetation cover (%)

Dry veg Litter

Green veg Bare ground

Biomass variability

97% of the area is less than the threshold of 400 lbs/ac

100 %

Map options

Select map year

2026

Select date

2026-04-19

Basemap

Cover

Greenness (NDVI)

Biomass

Crude protein

Bare ground change

Greenness change

Biomass change

Crude protein change

Relative greenness

Relative biomass

Relative CP

Biomass threshold

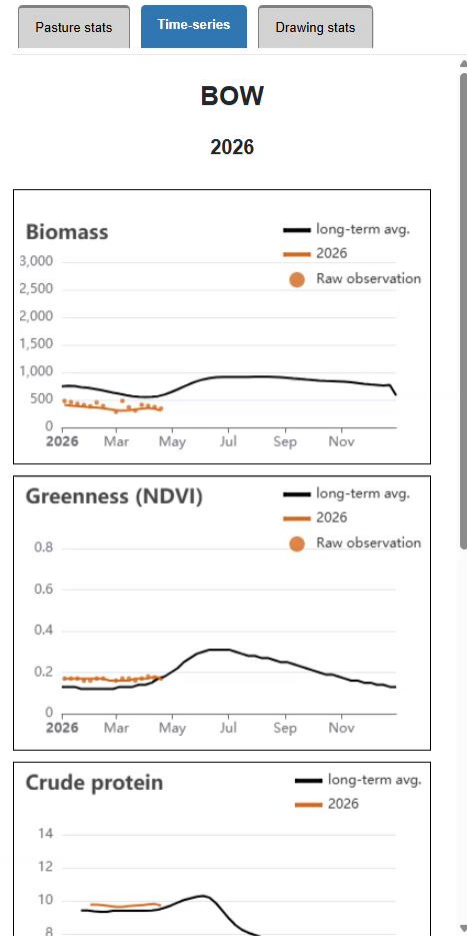
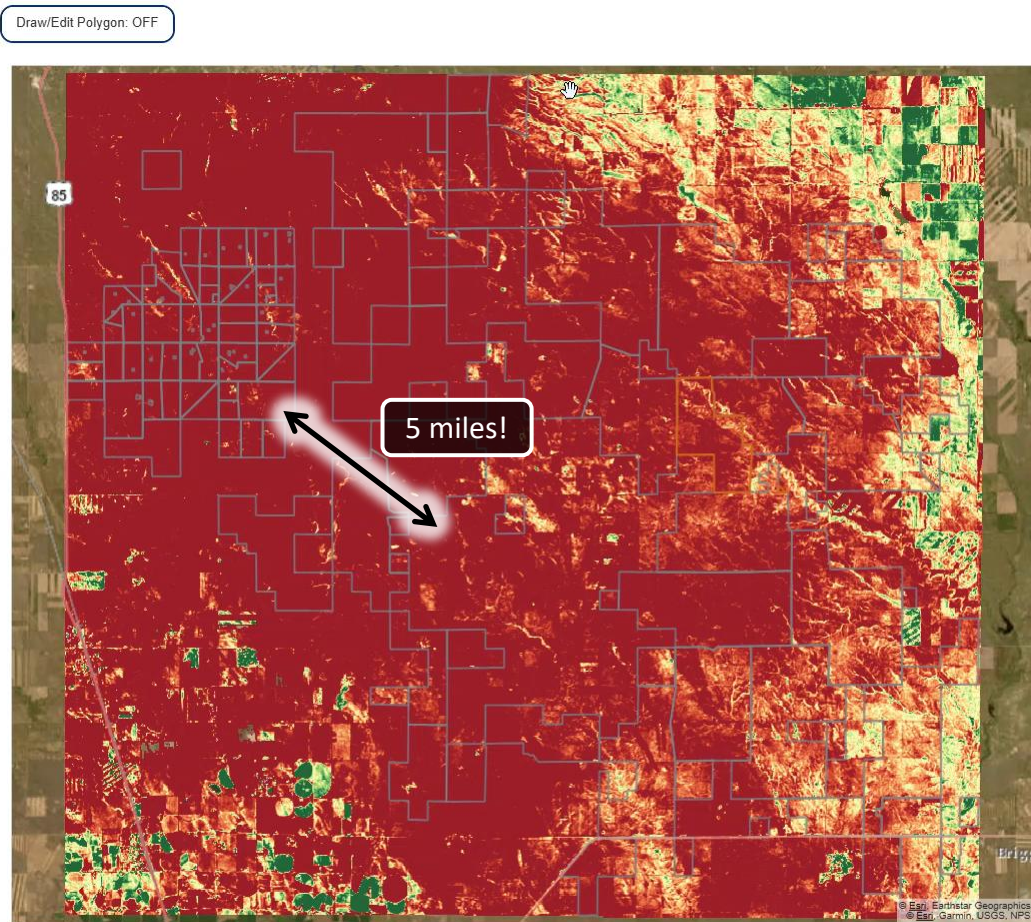
Map legend

50% 75% Avg. 125% 145%

Chart options

Comparison year

None



Challenges

Near-real-time availability

- Clouds
- Wildfire
 - Smoke
 - Data access – AK ground station
- NASA funding and staffing

Cloud/shadow masks

- Higher omission error for S2?



Trees torch on the Bear Creek Fire burning west of the Parks Highway, north of Healy on Friday, June 20, 2025. (Photo provided by Denali Borough)

Thank you!

Questions?

sean.kearney@tbgpea.org

Thunder Basin
Research Initiative



FOUNDATION FOR
FOOD & AGRICULTURE
RESEARCH



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Tuesday May 12, 2026 starting at 11:20 am CDT

Session 2: HLS in Action

Goals:

- Showcase real-world use of HLS across sectors and application areas, including methodology.
- Discuss the benefits and challenges to adopting HLS for downstream impact.

Time (CDT)	Topics	Format	Speaker
11:20 - 11:25 (5 min)	Introducing Impactful Applications of HLS	Presentation & Interactive 	Stephanie Jiménez, NSITE & UAH
11:25 - 11:45 (20 min)	Monitoring Cover Crops for Agroecosystem Assessment Using HLS Data	Presentation	Feng Gao, USDA-ARS
11:45 - 12:05 (20 min)	Near-Real Time Processing of HLS for Rangeland Management	Presentation	Sean Kearney, Thunder Basin Grassland Prairie Ecosystem Association
12:05 - 12:25 (20 min)	HLS Applications Challenges, Questions, and Needs	Interactive 	NSITE MCs
12:25 - 1:25 (60 min)	Lunch		



HLS in Action

Presenter Insights

1. Why did you choose to use HLS over other data?
2. What advice would you give to somebody in your field who is interested in using HLS?
3. What would be possible in your work if you had access to **HLS 10 m, HLS Vegetation Indices, or HLS Vegetation Index composites?**



HLS in Action

Questions from the Audience

What other **questions do the participants have** that we haven't answered yet?

What else could the presenters help with?

Participants, please post your questions in the Webex Q&A



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Tuesday May 12, 2026
break from
12:25 - 1:25 pm CDT

Lunch

2026
Harmonized
Landsat
and
Sentinel-2
(HLS)
Workshop

HLS is the most downloaded NASA dataset on the LP DAAC

Guess the number of downloaded HLS files, in billions

