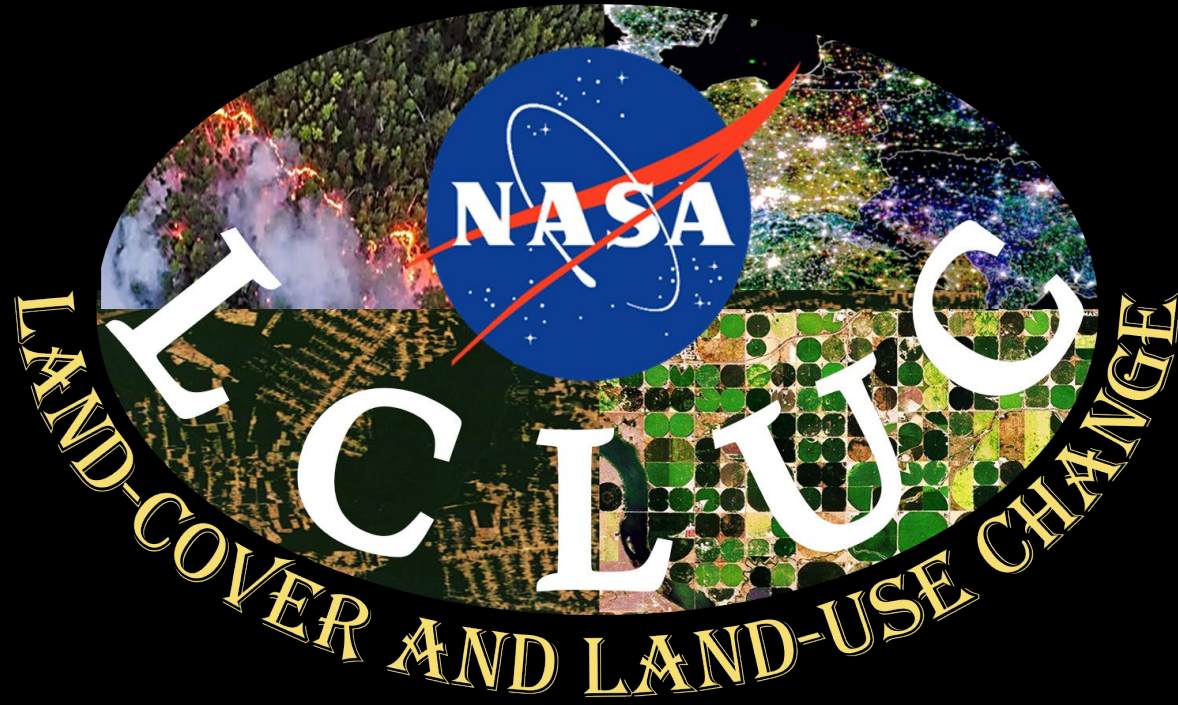


**LCLUC Science Team Meeting April 2-4, 2024**



**Poster Lightning Introductions**



**Abstract:** The WILDFUSE project integrates data from the Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) and the Earth Surface Mineral Dust Source Investigation (EMIT) to refine Land Surface Temperature (LST) estimations through a physics-based fusion of Visible to ShortWave Infrared (VSWIR) and Thermal Infrared (TIR) measurements. This methodology enhances the accuracy of ECOSTRESS’s Temperature-Emissivity Separation (TES) by integrating water vapor estimates and prior LST derived from EMIT.

### VSWIR

The EMIT sensor captures the solar radiation reflected from the Earth’s surface and atmosphere across 285 spectral bands in the VSWIR range of 350-2500 nm. Within this spectral domain, interactions such as absorption, scattering, and reflectance occur with atmospheric gases and particles, as well as with surface materials. Employing atmospheric correction techniques enables the deciphering of spectral surface signatures and atmospheric conditions for each pixel in the image.

### TIR

ECOSTRESS is a multispectral TIR (7-12 micron) sensor. It captures radiation originating at Earth’s surface, modulated by the surface’s temperature and emissivity. TES algorithms are used to decouple the two parameters, retrieving LST and surface emissivity. LST is then used to assess evapotranspiration (ET) and evapotranspiration stress index (ESI), a level 2 product for ECOSTRESS.

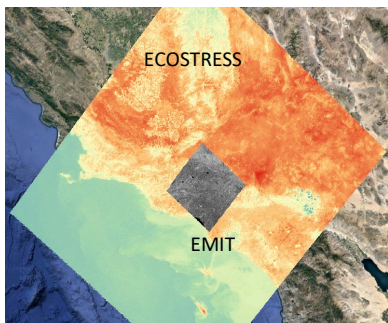


Fig 1: EMIT and ECOSTRESS simultaneous view from the ISS

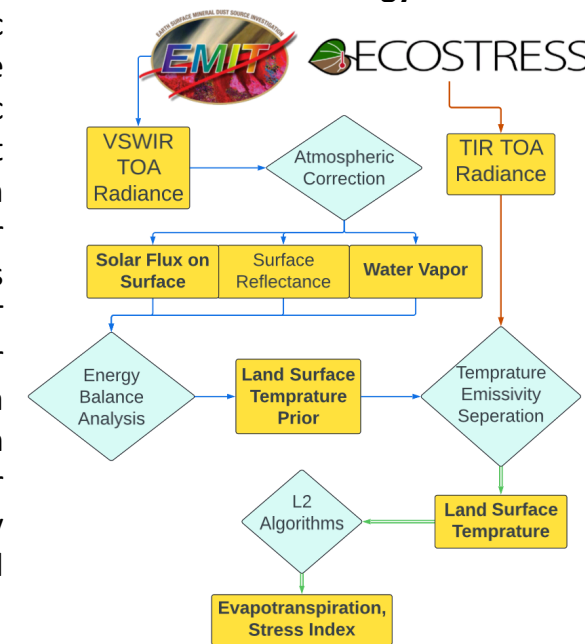
### Conceptual Framework

VSWIR spectrometers such as EMIT can estimate atmospheric conditions, namely the water vapor concentration, and surface reflectance from the radiance measurement using atmospheric correction routines. In contrast, multispectral TIR instruments must rely on auxiliary data and models to determine key unknown parameters required for the TES, namely the water vapor columnar concentration. Even then, separating temperature from emissivity is an ill-posed problem. In this project we are focusing on fusing EMIT data to support TES in two ways. First, we will estimate water vapor and use those estimates to inform TES. Second, we are developing a novel approach that estimates energy absorption using EMIT, and in combination with land cover classification, estimate a prior distribution LST. These two advancements will help significantly constrain and improve TES and downstream products, namely ET and ESI.

### Pre- and Post- Wildfire Analysis

We will calculate a set of plant traits related to wildfire risk (pre-fire) and forest rehabilitation (post-fire) using both EMIT and the improved ECOSTRESS LST product. From EMIT we will map functional properties such as Chlorophyll, Leaf Area Index (LAI), Brown Pigments, and more, based on PROSAIL top of canopy reflectance model. From ECOSTRESS we will incorporate ESI, which will be improved compared to the standard product due to the reduction of errors following our data fusion approach.

### Data Fusion Methodology





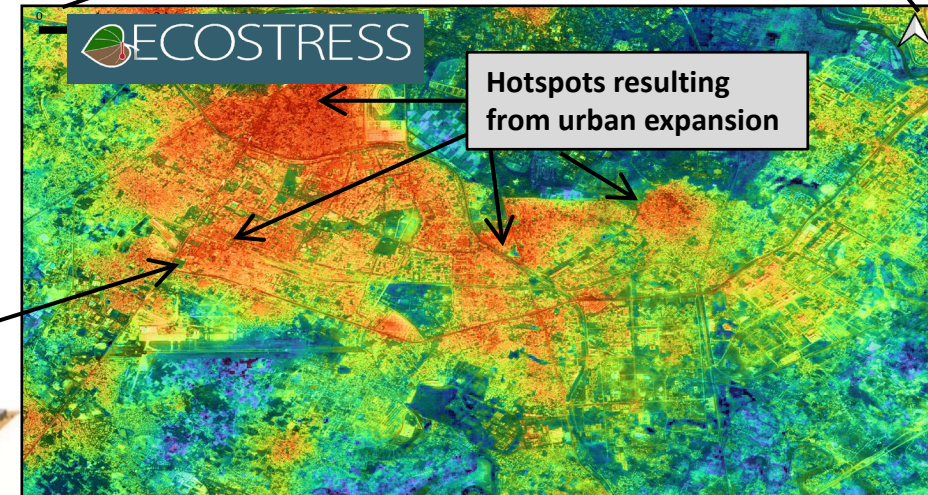
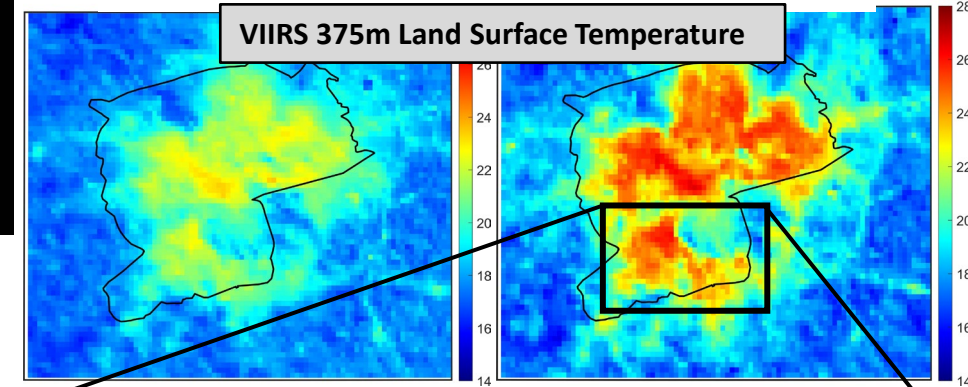
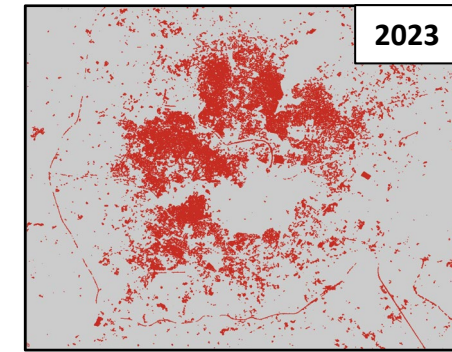
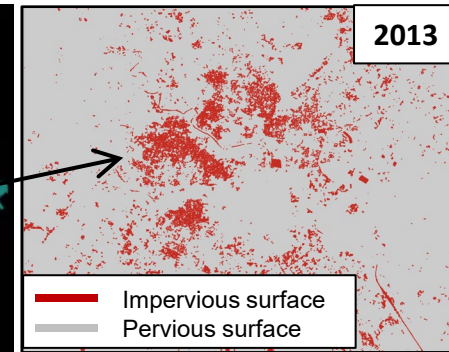
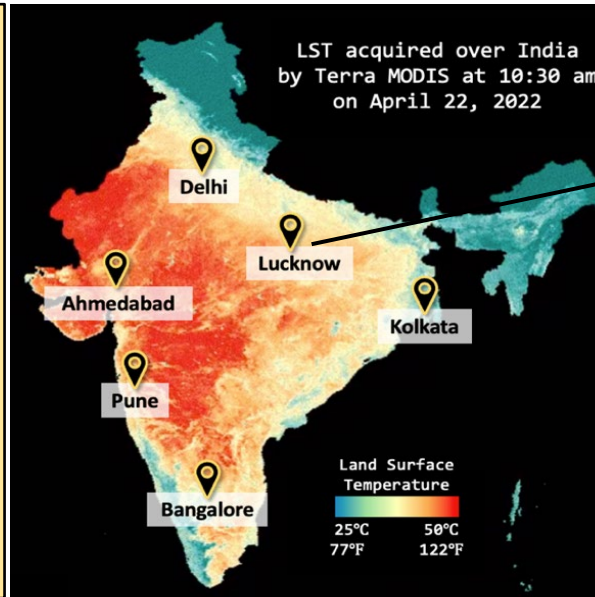


Glynn Hulley

# Quantifying connections between urban LCLUC and extreme heat in rapidly growing Indian cities

## Problem Statement:

- Rising extreme heat exposure from a combination of climate warming and urbanization threatens growing urban settlements in India.
- There is an urgent need to characterize where **urban growth** and the **emergence of extreme heat** intersects for rapidly growing cities.
- Understanding these interactions will aid cities in pin-pointing areas requiring tailored adaptation measures to mitigate heat risk.



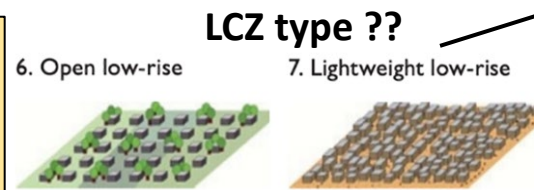
**Objective 1:** Produce mean annual **VIIRS Land Surface Temperature** summertime composites over the six Indian cities from 2013-2024 using VIIRS 375-m data.

**Objective 2:** Identify regions of rapid urban change using **Landsat Local Climate Zone (LCZ)** maps and VIIRS LST time-series composites from Obj. 1

**Objective 3:** Quantify connections between LCLU properties and LST for the regions of rapid change identified in Obj. 2 using **ECOSTRESS Land Surface Temperature**

### Project Team:

Dr. Anamika Shreevastava, California Institute of Technology  
 Dr. Vimal Mishra of Indian Institute of Technology, Gandhinagar  
 Dr. Ronita Bardhan of University of Cambridge, UK







Shijuan Chen

# Urbanization and Fire Risk at the Global Wildland-Urban Interface: A Multi-sensor Study of Past and Future Trends

## Goals and plans:

- Identify hotspots of historical urbanization within the global wildland-urban interface (GWUI) and analyze the intensity of urbanization.
- Assess forest degradation within urbanization hotspots in the WUI.
- Investigate the effects of urbanization and forest degradation on land surface temperature within urbanization hotspots in the WUI.
- Explore the effects of changes in land surface temperature on fire hazards.
- Project future WUI in the urbanization hotspots and identify areas with potential high risk.

Karen C. Seto (PI)

Shijuan Chen (Co-PI)

Volker Radeloff (Co-I)

Franz Schug (Collaborator)

Jennifer Balch (Co-I)



Yale University



WISCONSIN  
UNIVERSITY OF WISCONSIN



University of Colorado  
Colorado Boulder



# Detecting and Mapping War-Induced Damage to Agricultural Fields in Ukraine using Multi-Modal Remote Sensing Data

S. Skakun<sup>1</sup>, I. Becker-Reshef<sup>1</sup>, E. Duncan<sup>1</sup>, N. Kussul<sup>2,3</sup>, A. Shelestov<sup>2,3</sup>, M. Adegbenro<sup>1</sup>, C. Abys<sup>1</sup>



<sup>1</sup>University of Maryland, College Park, MD; <sup>2</sup>National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine; <sup>3</sup>Space Research Institute of National Academy of Sciences of Ukraine and State Space Agency of Ukraine

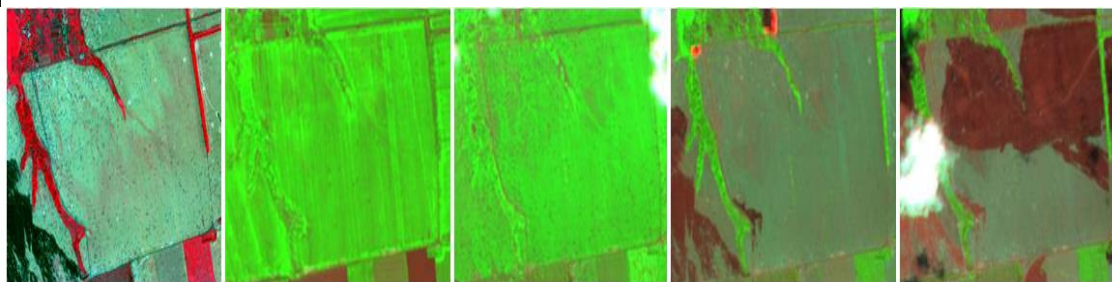
## Motivation

- ❖ The Russian invasion of Ukraine in 2022 led to a widespread distribution of **Unexploded Ordnances (UXO)** from artillery/rocket shelling
- ❖ Large demand for detection of craters for future **humanitarian demining** efforts, remote sensing only way to conduct this **safely** and at **large-scale**

## Key Expected Outcomes

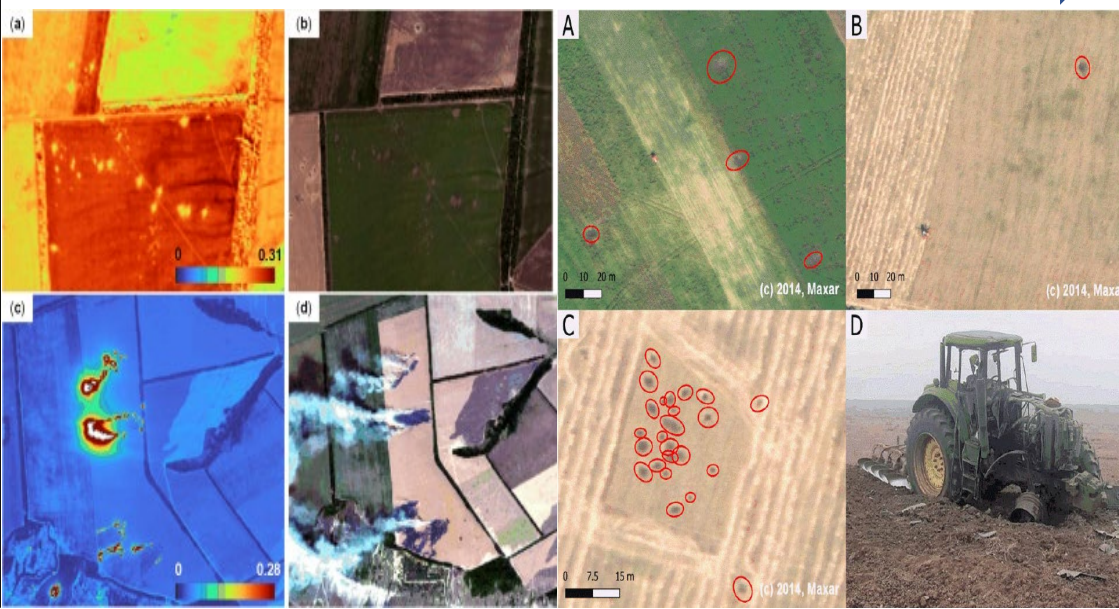
- ❖ **Classification model** for artillery crater detection
- ❖ **Multi-Modal Data Fusion** with the latest in remote sensing data
- ❖ Develop new **nomenclature system** and methods to identify and map them within the context of damaged agricultural lands

**Shelling** in mid-June detected by Sentinel-2 led to healthy vegetation in farm field being **abandoned**

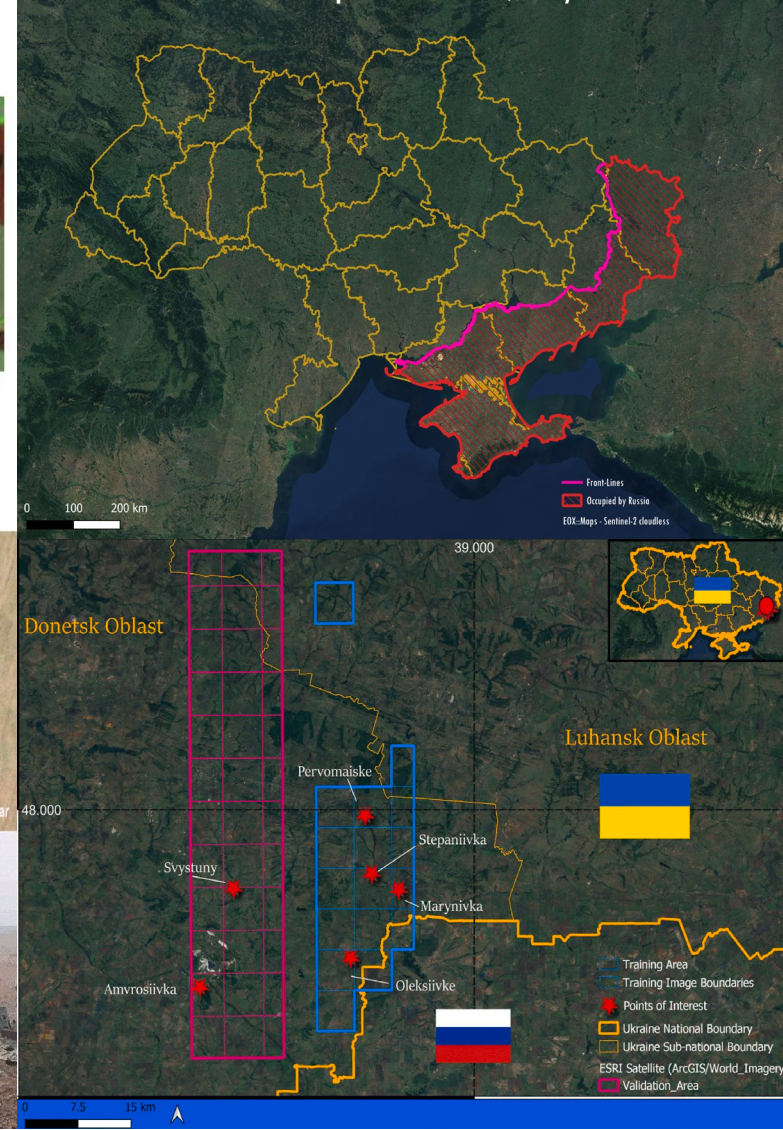


(a) 2022-07-02 (b) 2022-05-08 (c) 2022-06-12 (d) 2022-07-07 (e) 2022-07-17

Multi-modal data fusion for crater detection



## Ukraine Occupation Status, May 2023

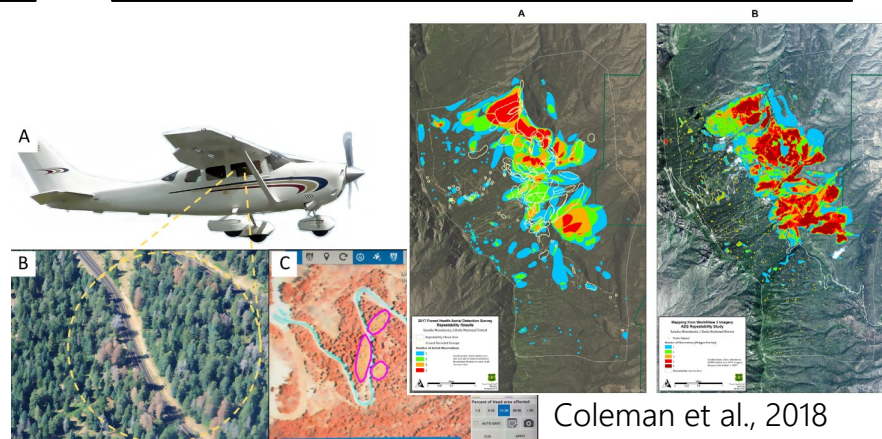




Increased heat waves and drought are driving forest mortality events in western US forests, threatening carbon, water, and fire risk

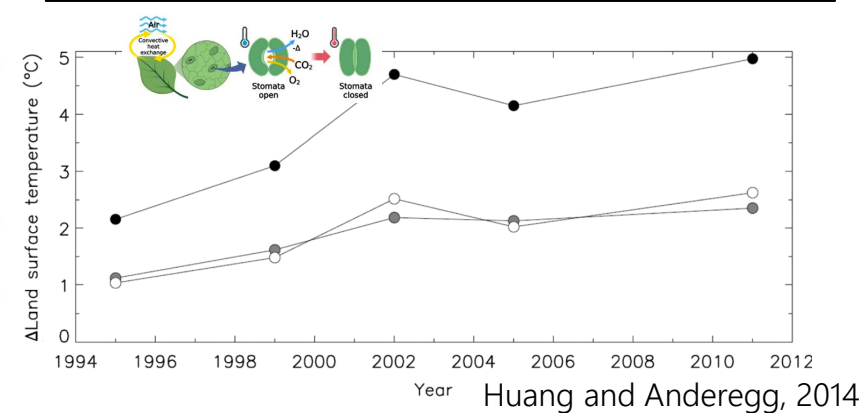


Current aircraft surveys are coarse, limiting understanding of trends, spatial patterns, and environmental feedbacks

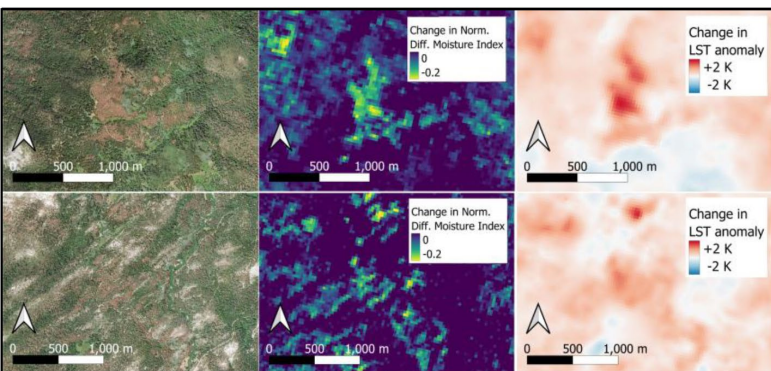


Coleman et al., 2018

Water stress induces stomatal closure or defoliation, reducing transpirational cooling and raising land surface temperatures (LST)

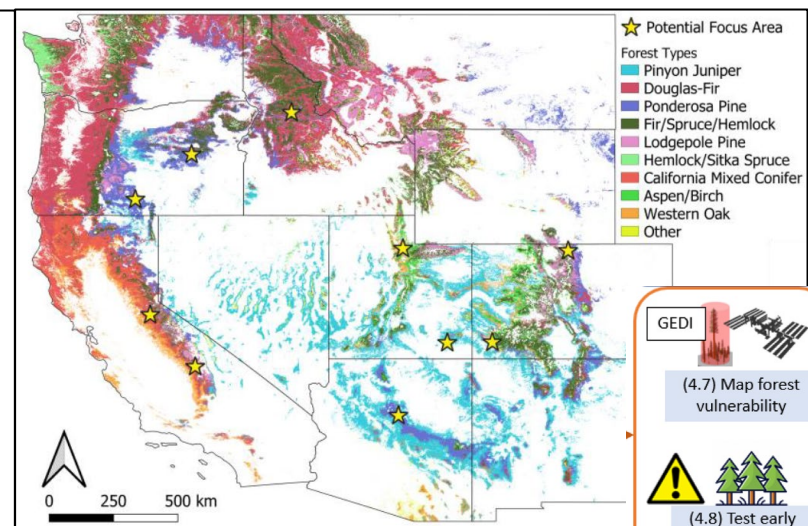


Are spatial anomalies of LST a reliable signal of forest mortality? We will improve detection and mapping forest mortality using Landsat Collection 2 LST and SR



### Expected Outcomes:

1. Reference data of individual tree status from high res imagery, airborne lidar, and drones in focus areas
2. 30 m map of annual percent forest mortality from 1984-2024 using LST and SR
3. Analyze drivers of vulnerability (e.g. height, density, elevation) across multiple forest types and ecoregions



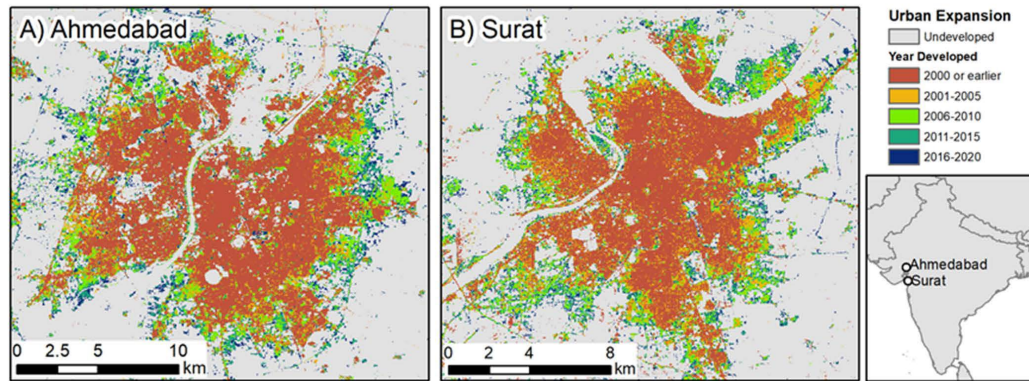
GEDI (Global Ecosystem Dynamics Investigation) satellite icon.

(4.7) Map forest vulnerability

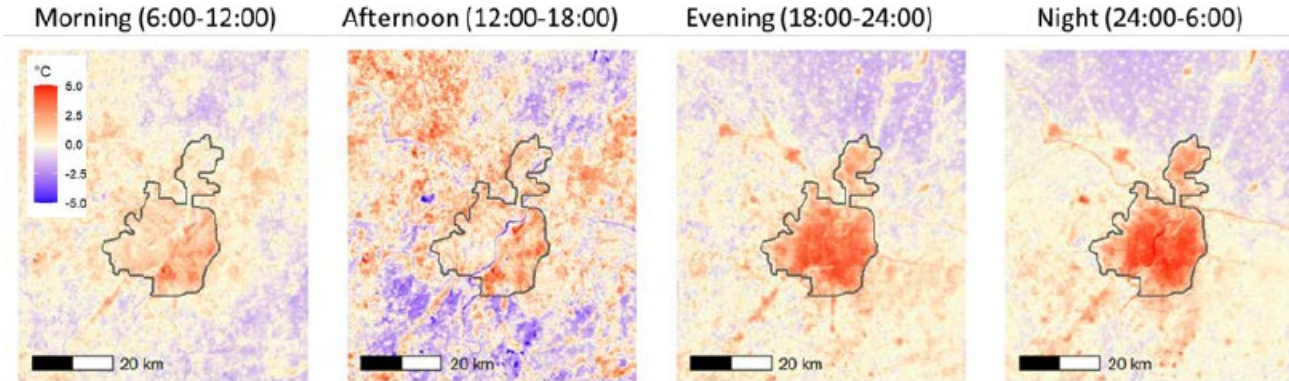
(4.8) Test early warning signals



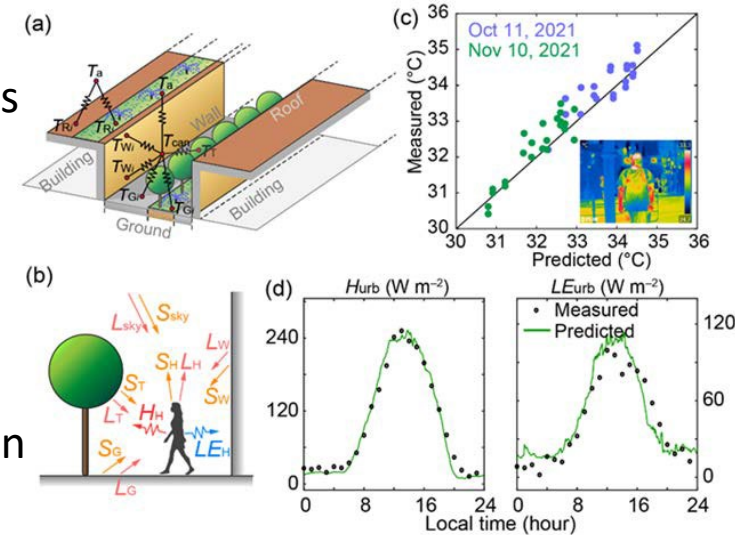
**Objective 1:** Develop time series maps of local climate zones and urban green and blue spaces using multi-source, multi-resolution remote sensing data.



**Objective 2:** Map daily and seasonal patterns of urban land surface temperatures by fusing high spatial resolution and high temporal resolution sources of thermal data.



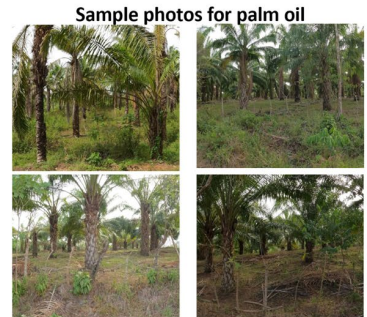
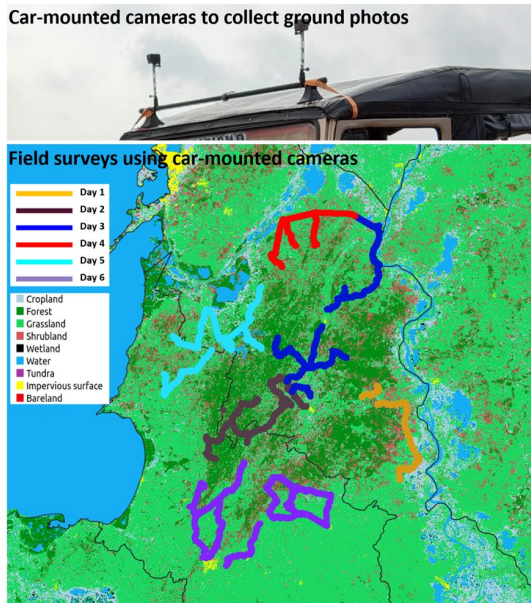
**Objective 3:** Generate high-resolution predictions of moist heat stress by integrating data from objectives 1 and 2 with ground measurements using numerical weather modeling (ASLUM v3 urban climate model) & ML



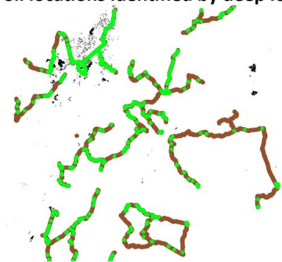
For more information contact: Michael C. Wimberly ([mcwimberly@ou.edu](mailto:mcwimberly@ou.edu)), Chengbin Deng ([cdeng@ou.edu](mailto:cdeng@ou.edu)), Chenghao Wang ([chenghao.wang@ou.edu](mailto:chenghao.wang@ou.edu))



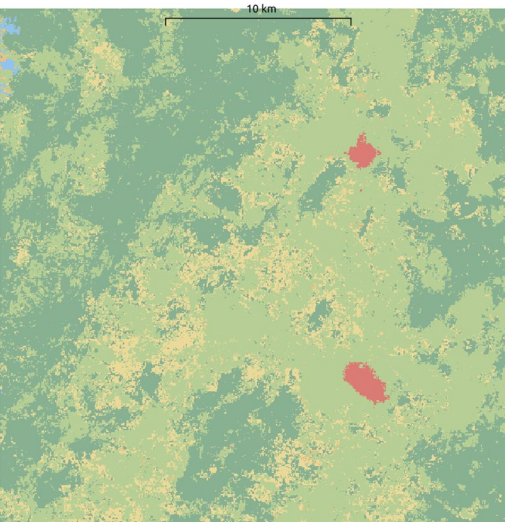
## 1. Remote sensing mapping of LCLUC



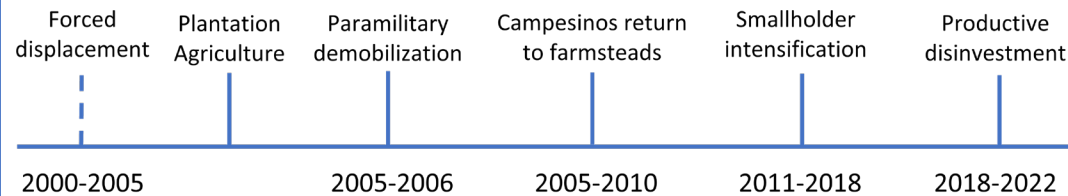
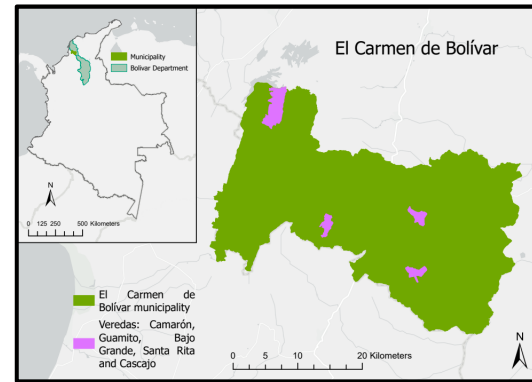
Palm oil locations identified by deep learning



**Objective 1:** Identify patterns of LCLUC at three distinct time periods in the specified locations using satellite remote sensing data and analytics.



- Cropland
- Forest
- Grassland
- Shrubland
- Wetland
- Water
- Tundra
- ImperviousSurface
- Bareland
- Snow&Ice

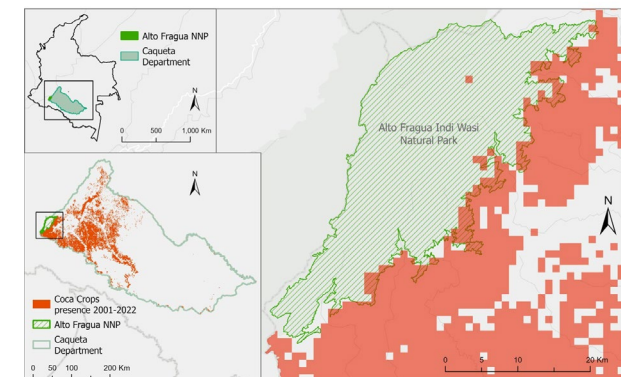


## 2. Participatory Mapping in 3 Veredas in Montes de María

**Objective 2:** Determine how the socio-political/economic drivers of conflict shape and are shaped by LCLUC over time and across study regions.

**Objective 3:** Assess how LCLUC-conflict dynamics impacted LCLUC-peacebuilding dynamics, and with what implications for long-term peacebuilding and LCLUC.

Coca crops expanding into National Natural Parks in Colombia  
The case of Alto Fragua Indi Wasi Natural Park  
Coca crops presence 2001-2022



## 3. Illicit Economies and LCLUC in Caquetá



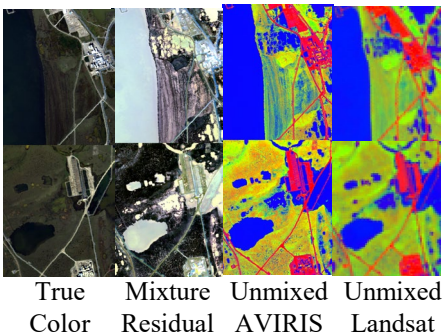


Dan Sousa

# Mapping Arctic Disturbances

*A Multi-Sensor Remote Sensing Analysis of Oil and Gas Impacts*

1. Determine **timescales of oil/gas expansion** from past and prospective infrastructure development around Prudhoe Bay, Alaska
2. Develop a **mixture modeling** approach to monitor and track sub-pixel scale LCLUC changes and disturbance associated with oil and gas exploration in Prudhoe Bay, Alaska
3. Evaluate trends in land cover changes and their **impact on communities** in Alaska
4. Forecast vulnerability due to **future planned oil and gas expansion** around Prudhoe Bay



**New AVIRIS-3!**  
**Summer 2023**  
**(ABOVE)**

*Undergraduate Mentoring*

**Jet Propulsion Laboratory**  
 California Institute of Technology

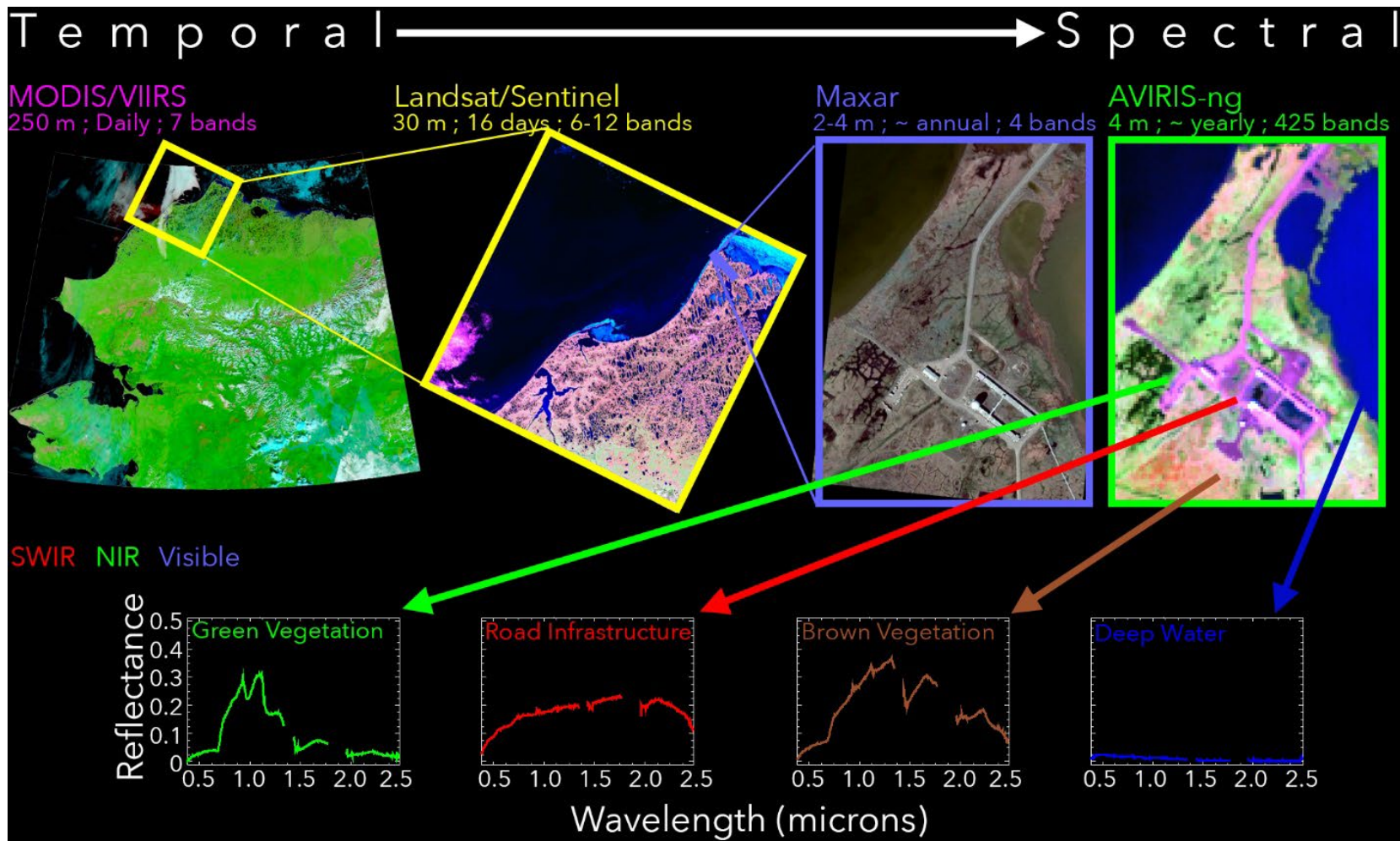
**San Diego State University**

**Identified disturbances**

**Characterized spectral diversity**

**Quantified effect of spatial and spectral resolution**

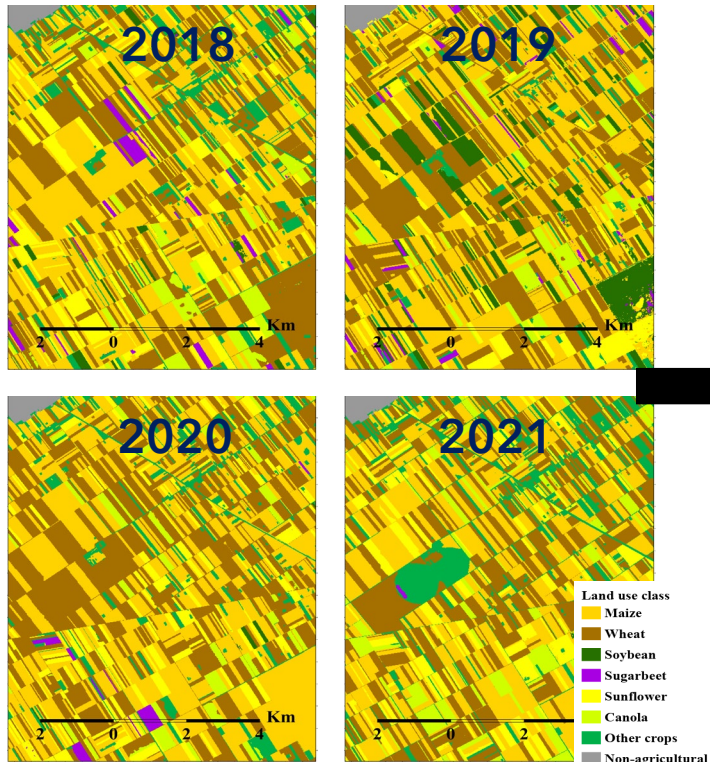
**Implications for SBG and other future spaceborne imaging spectroscopy missions**



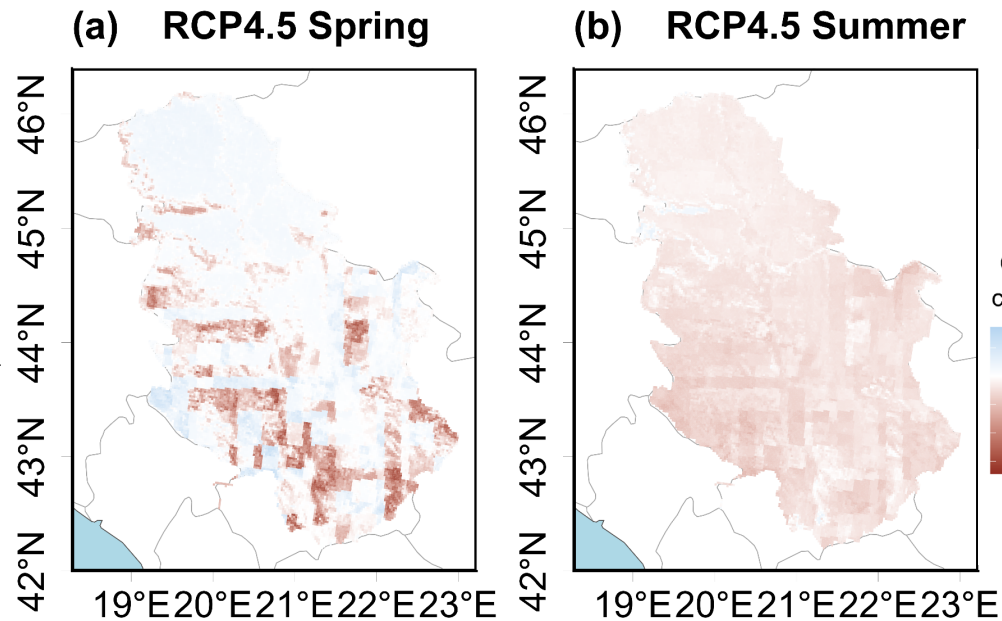


- The Danube River Basin is experiencing warmer growing seasons and irregular precipitation patterns, leading to more frequent droughts and decreased water availability.
- Crop rotations in Serbia are complex, and irrigation is sparse. As summers become hotter and drier...
- Will crop choices change? Will irrigation adoption increase? How will this affect the regional water balance?

**Multi-year crop classification**  
LSTM and domain adaptation

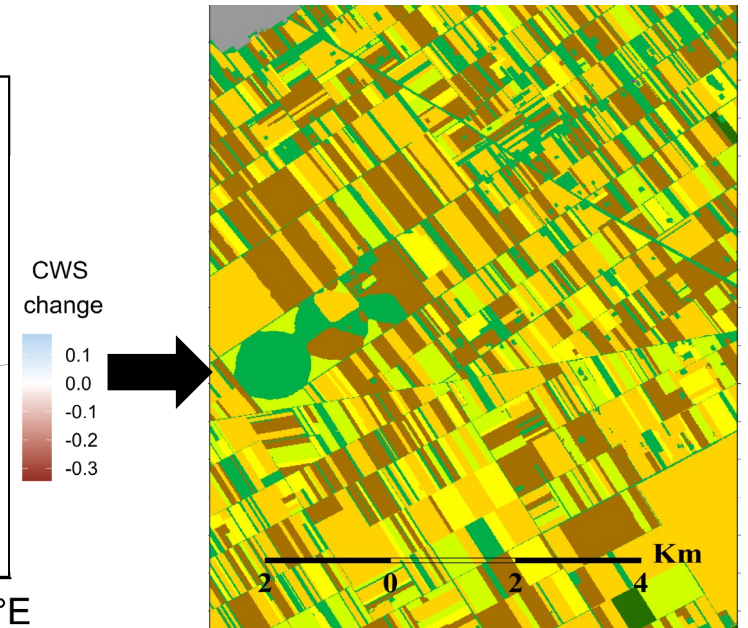


**Hydrological modeling**  
Historical and future water balance



Increasing crop water stress (2041-2070)

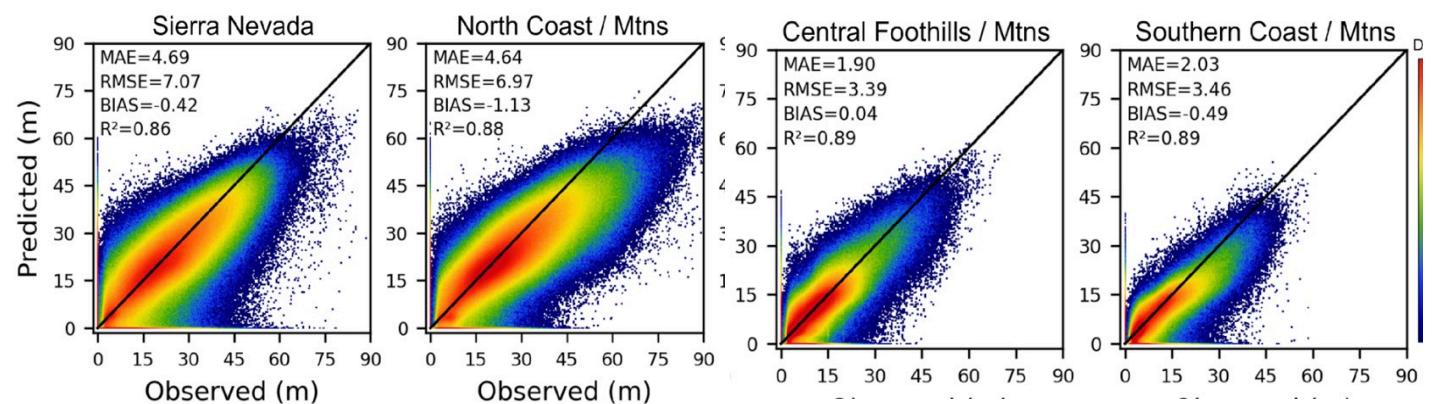
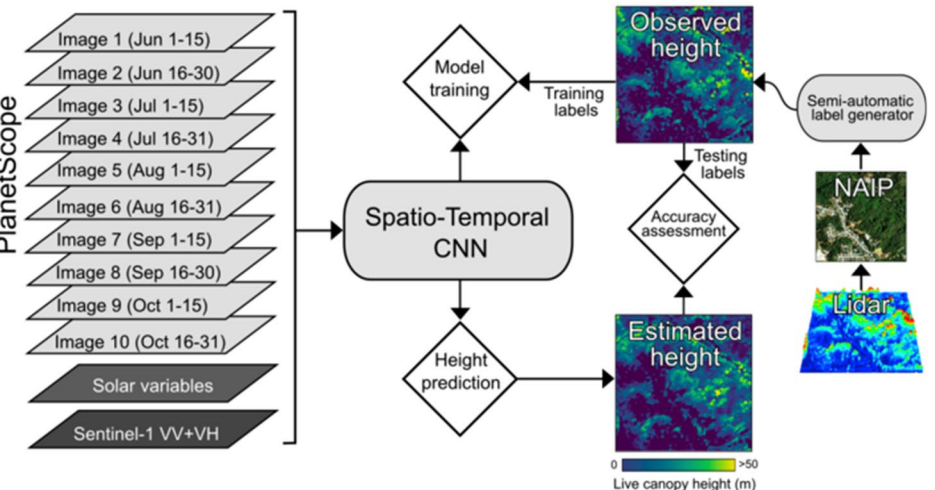
**Agricultural Land use change**  
Crop choice + irrigation adoption



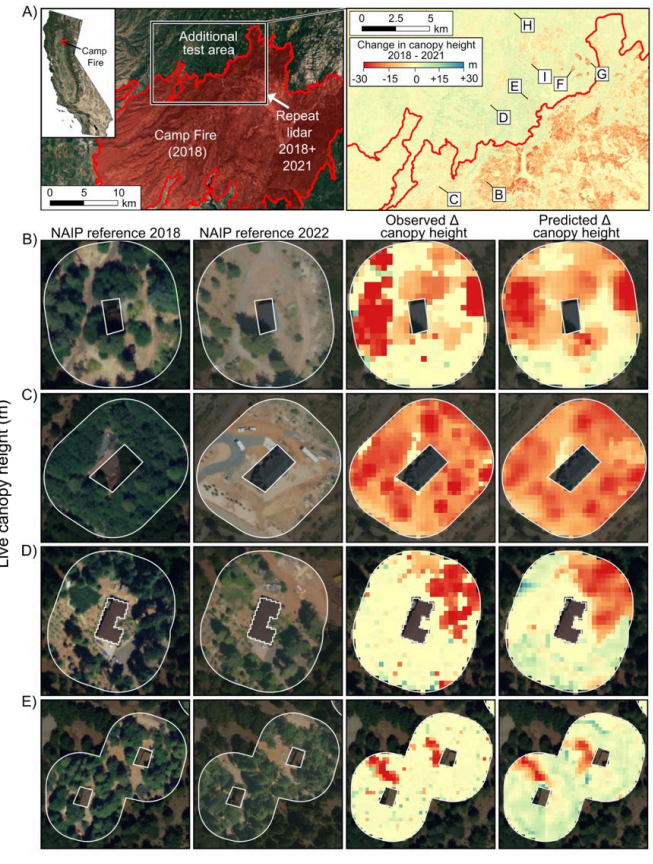
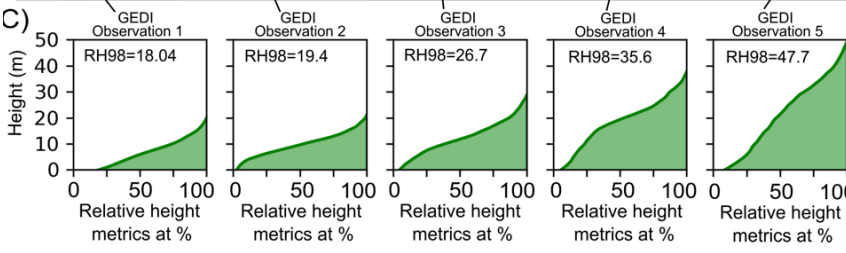
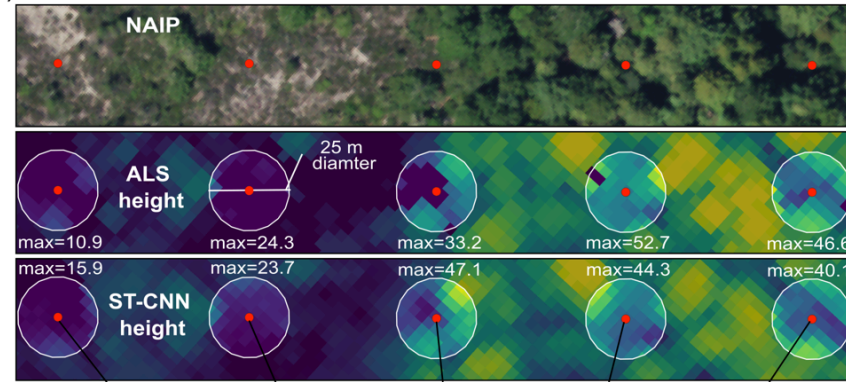
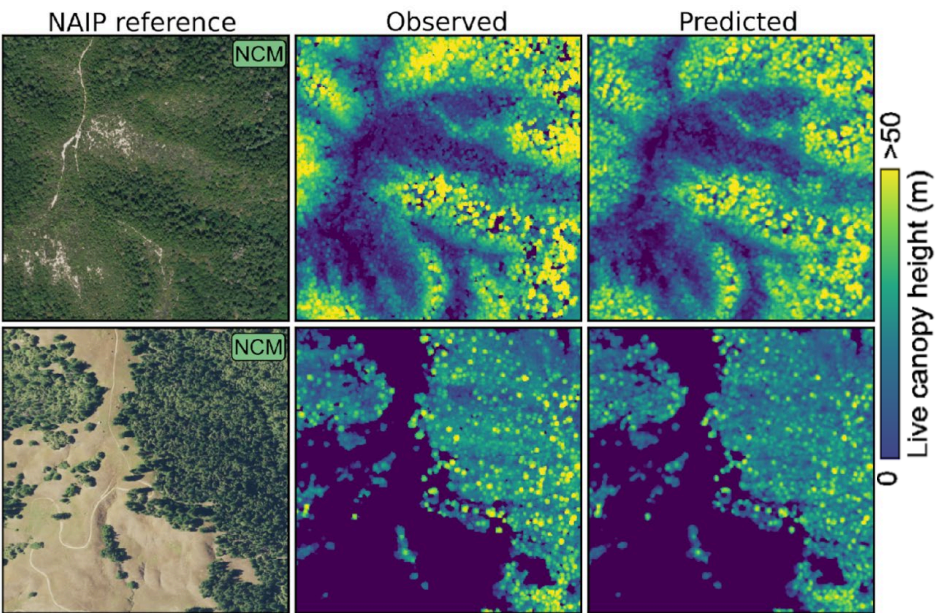
Climate change adaptation decision-making



Monitoring fuel structure is critical for assessing WUI fire hazard and informing fuel management.



The ST-CNN deep learning model, driven by PlanetScope imagery stacks and Sentinel-1 data, provides a scalable approach to quantify live woody plant height at a canopy scale.





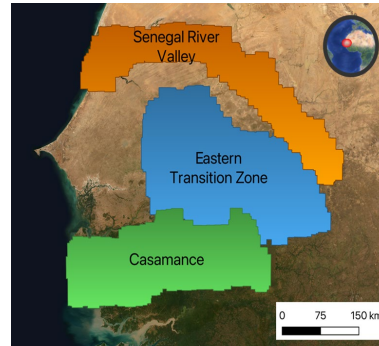


PI: Chris Neigh  
NASA-GSFC

# Deep Learning Approaches for Monitoring Land Cover Land Use Trends in Senegal with VHR Optical Imagery and Data Fusion

## Background and Objectives

West Africa is a hotspot of land cover change that is not sufficiently documented due to extreme changes between wet and dry seasons and the inability of moderate-resolution sensors to detect sub-hectare changes. We look to overcome these limitations using a multi-sensor data fusion approach, utilizing Deep Learning Convolutional Neural Networks (CNNs) with thousands of 2 m resolution Worldview-2,-3 images, SAR (Sentinel-1), and HLS time series data.



1. Quantify changes in the extent and intensity of irrigated rice and dryland agriculture.
2. Test CNNs on VHR data for extracting croplands and individual trees at regional scales.
3. Assess agroforestry and reforestation in degraded fields using time-series SAR and VHR.

## Co-Investigators

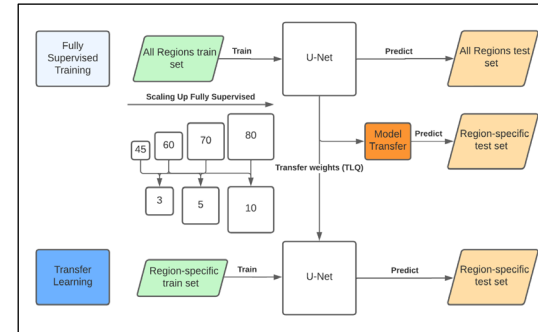
- Konrad Wessels: George Mason University
- Mark Carroll: NASA Goddard Space Flight Center
- Nathan Thomas: Edge Hill University
- Molly Brown: University of Maryland College Park

## Collaborators

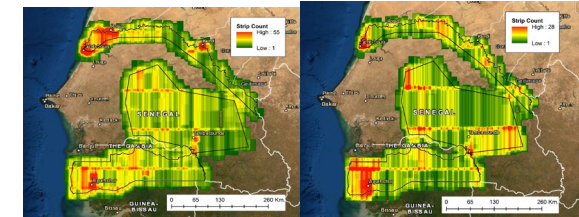
- \*Margaret Wooten: NASA Goddard Space Flight Center/SSAI
- Jordan Caraballo-Vega: NASA Goddard Space Flight Center
- Min Tri Le: George Mason University
- William Wagner: NASA Goddard Space Flight Center/SSAI
- Aziz Diouf: Centre de Suivi Ecologique
- Modou Mbaye: Institut Sénégalais de Recherches Agricoles
- Babacar Ndaou: Centre de Suivi Ecologique
- Woubet Alemu: NASA GSFC/University of Maryland College Park
- Pete Bunting: Aberystwyth University
- Gray Tappan: USGS
- Renaud Mathieu: International Rice Research Institute



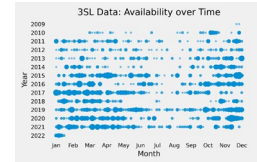
## Methods and Data



Overview of CNN scaling-up experimentation workflow



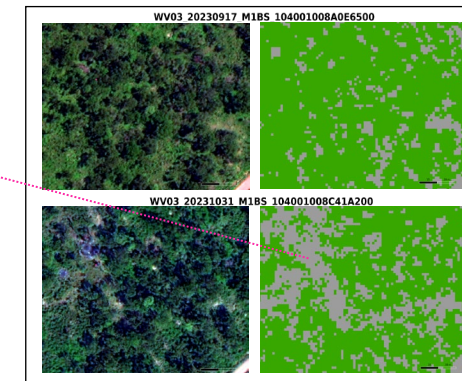
WorldView data availability for mapping change across two time periods for Senegal study sites



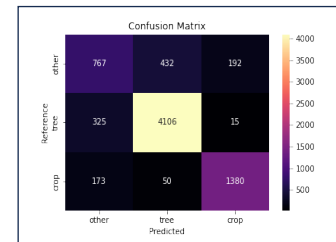
## Results



A man stands with his donkey and recently harvested lumber from the site shown on the image to the right. October 16, 2023.



WorldView imagery and corresponding landcover model outputs show a small clearing of a forested area in the Casamance between September 17 and October 31, 2023. © Maxar 2023



	Overall	2010-2015	2016-2021	ETZ	CAS
<b>Accuracy:</b>	84.1%	82.6%	85.1%	73.7%	86.1%
<b>F1-Score:</b>	83.8%	82.0%	85.0%	73.5%	86.0%
<b>Precision:</b>	83.6%	81.7%	85.0%	74.3%	85.9%
<b>Recall:</b>	84.1%	82.6%	85.1%	73.7%	86.1%

Latest results from external cross-validation of landcover model outputs





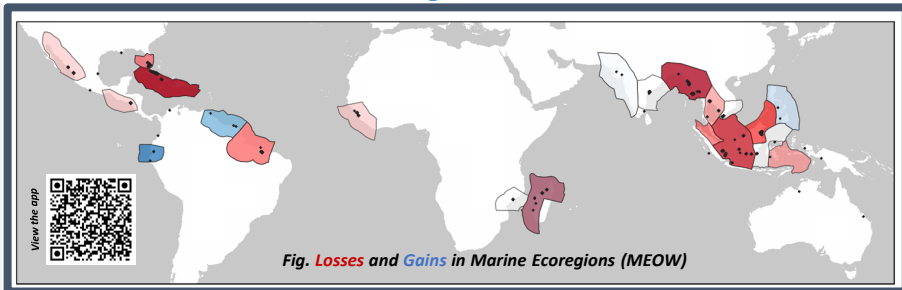
Cheryl Doughty

# Global Hotspots of Change in Mangrove Forests

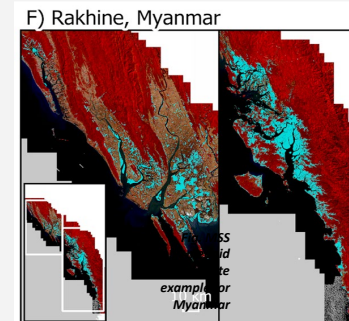
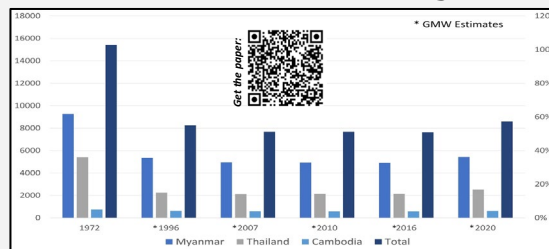
Mangrove forests have lost between 35% and 50% of their extent over the last century. National rates of loss reach 8% in some mangrove-holding countries. Yet, these estimates are highly uncertain due to a disparate collection of published data, with inconsistent methodologies, quality and accuracy. Therefore there is a critical need for systematic and consistent estimates of historic and contemporary global mangrove land cover and land use change.

Marc Simard (PI), David Lagomasino, Kyle Cavanaugh, Lola Fatoyinbo, Nathan Thomas, Daniel Friess, Peter Bunting, Richard Lucas, Priscilla Baltezar, Abigail Barenblitt, Kinsey Blumenthal, Anthony Campbell, Isamar Cortez, Cheryl Doughty, Adriana Parra Ruiz, Paulo Murillo-Sandoval, Atticus Stovall

**Mangrove degradation and regeneration in change hotspots quantified with Landsat from 1984 - 2020**



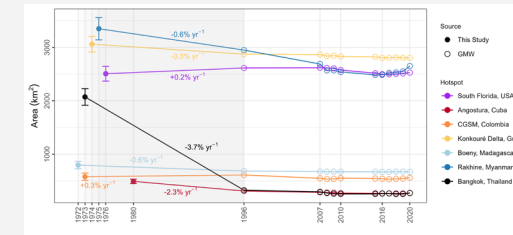
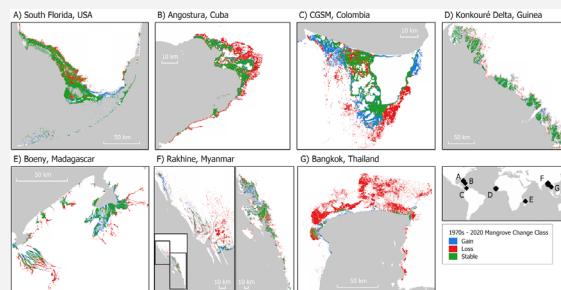
## A regional map of mangrove extent for Myanmar, Thailand, & Cambodia shows losses of 44% by 1996



## Direct anthropogenic drivers identified with Very-High Resolution Imagery

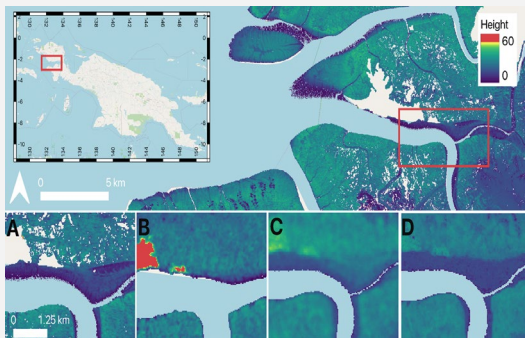


**Mangrove baselines extended to the 1970's with Landsat MSS reveal nuanced changes in global hotspots**

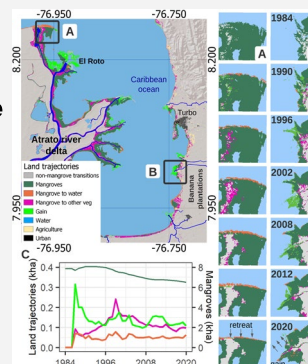


Multi-Source Land Imaging (MuSLI) for Mangrove Hotspots

## A Global Map of Mangrove Canopy Height with a Spatial Resolution of 12-meters



**Mangroves Cover Change Trajectories 1984-2020: The Gradual Decrease of Mangroves in Colombia**



## Published papers

- Mo, Y., Simard, M. and Hall, J.W., 2023. Tropical cyclone risk to global mangrove ecosystems: potential future regional shifts. *Frontiers in Ecology and the Environment*, 21(6), pp.269-274.
- Baltezar, P., Murillo-Sandoval, P., Doughty, C., Lagomasino, D., Tieng, T., Cavanaugh, K., Simard, M. and Fatoyinbo, T., 2023. A Regional Map of Mangrove Extent for Myanmar, Thailand, and Cambodia Shows Losses of 44% by 1996. *Frontiers in Marine Science*, 10, p.1127720.
- Murillo-Sandoval, P.J., Fatoyinbo, L. and Simard, M., 2022. Mangroves cover change trajectories 1984-2020: The gradual decrease of mangroves in Colombia. *Frontiers in Marine Science*, 9, p.892946.
- Castellanos-Galindo, G.A., Casella, E., Tavera, H., Zapata Padilla, L.A. and Simard, M., 2021. Structural characteristics of the tallest mangrove forests of the American continent: a comparison of ground-based, drone and radar measurements. *Frontiers in Forests and Global Change*, 4, p.732468.
- Lagomasino, D., T. Fatoyinbo, S. Lee, E. Feliciano, C. Trettin, A. Shapiro, and M. M. Mangora. 2019. Measuring mangrove carbon loss and gain in deltas. *Environmental Research Letters* 14:025002.

## Acknowledgements

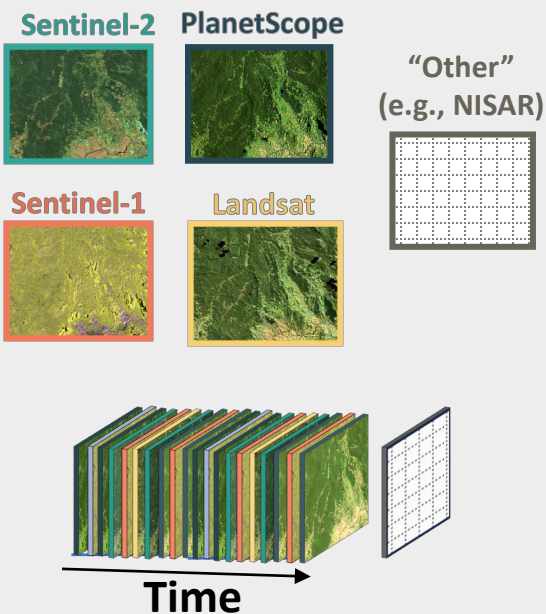
This work was partly performed by the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration (NASA). All investigators are supported by the Land Cover and Land Use Program.



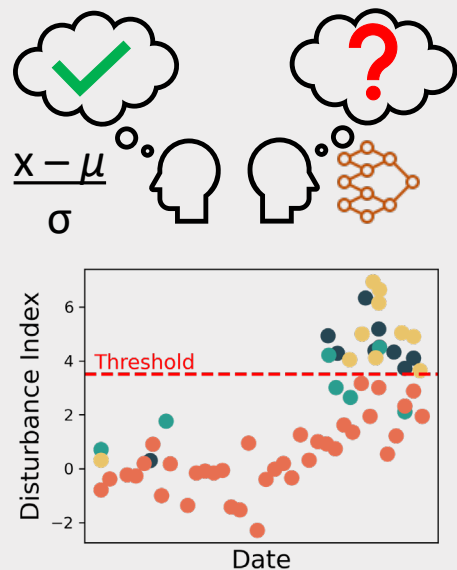


## The Disturbance Index Alert System (DIAS) <sup>2</sup>

### 1. Sensor-agnostic time series monitoring

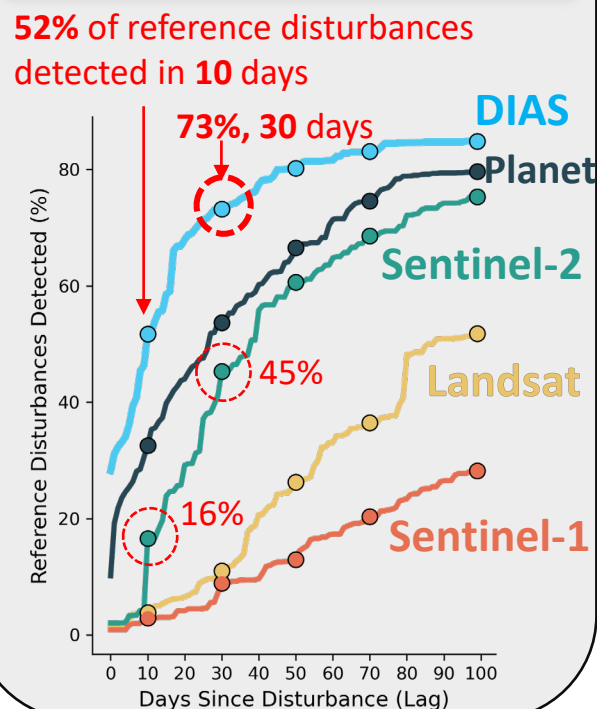


### 2. Simple data fusion and change detection method

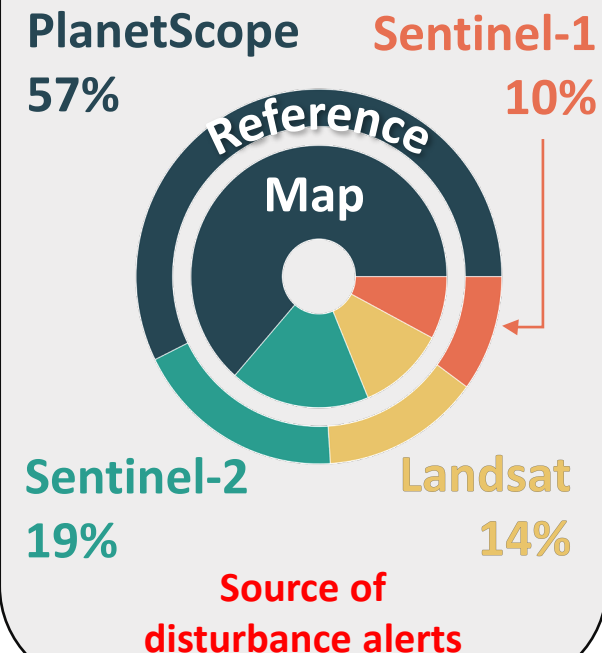


Multi-sensor disturbance index identifies pixel-level changes

### 3. Optimized for rapid disturbance detection



### 4. All input data are used to flag change

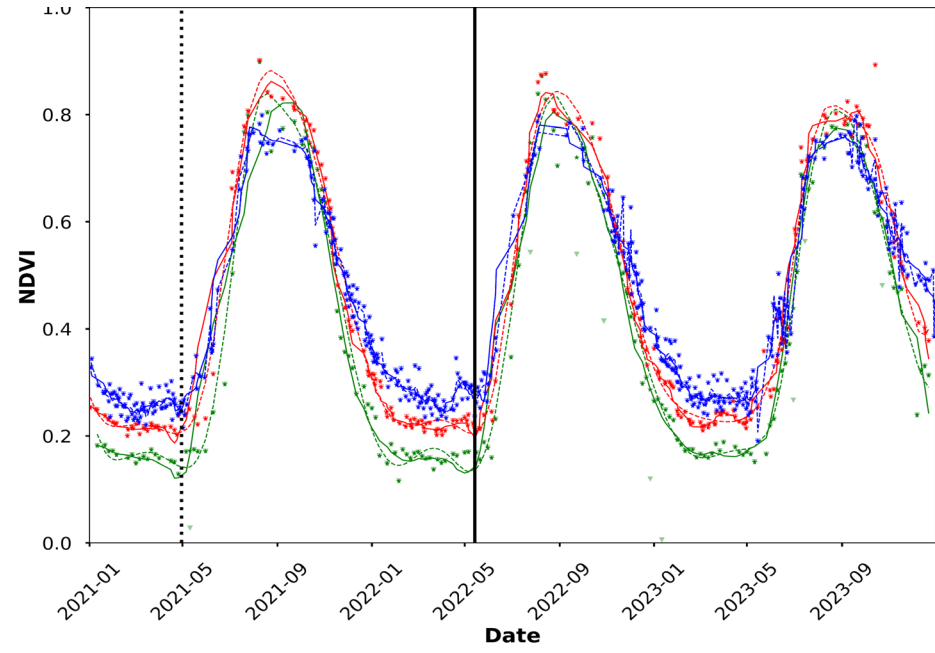
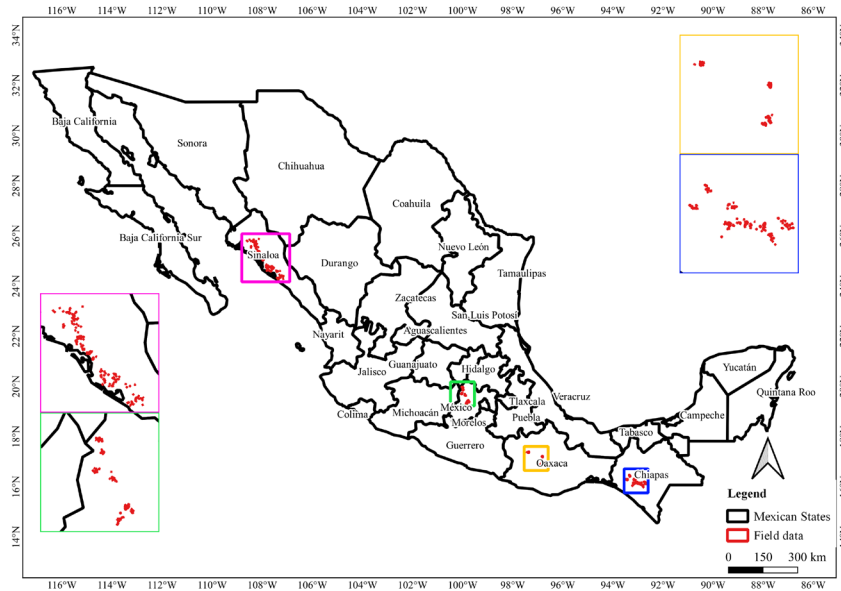


<sup>1</sup> US Forest Service Rocky Mountain Research Station (RMRS-FIA)

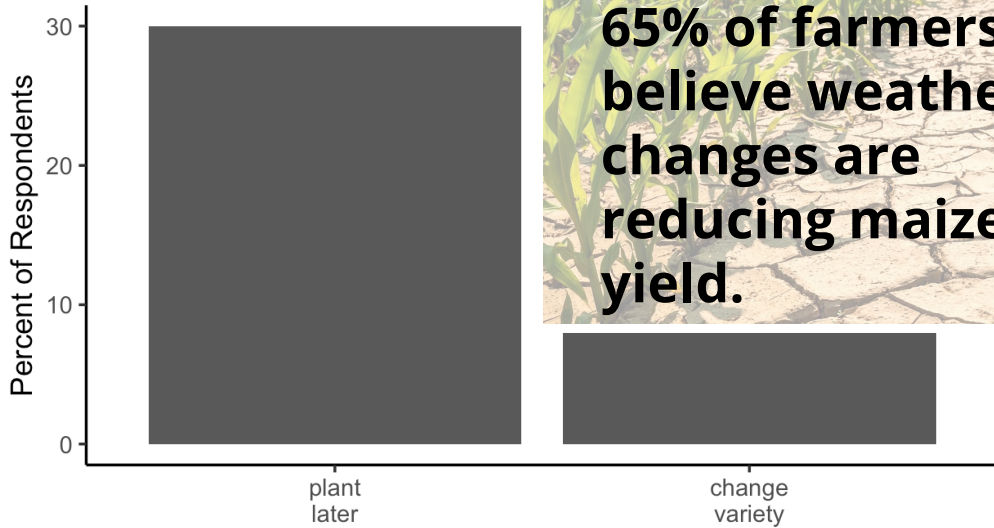
<sup>2</sup> Bullock et al. [Manuscript in preparation]

\* Contact: [eric.bullock@usda.gov](mailto:eric.bullock@usda.gov) | NASA Grant 80HQTR21T0020 (PI: Healey)



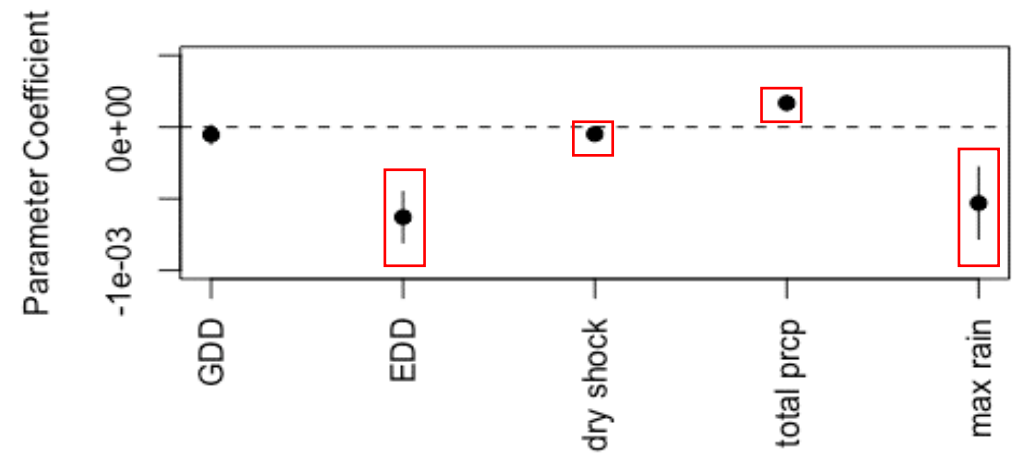


Adaptation actions actual



**65% of farmers believe weather changes are reducing maize yield.**

Impact on Maize Yield







# Nicholas Cuba

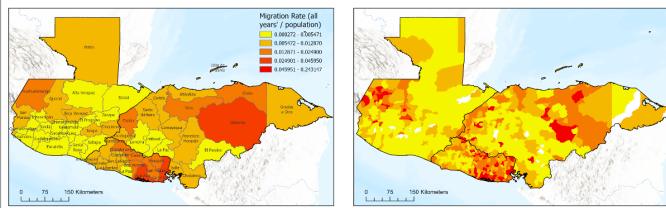
## Mapping the spectral, thermal, and fine-scale textural characteristics of croplands in Central America and variation with rates of outmigration (2012-2018)

**ABSTRACT:** Migration from the Guatemala, El Salvador, and Honduras to the USA has increased substantially in the last decade. As in many parts of the world, traditional and common livelihoods based on agriculture have become less viable in these countries due to factors such as extreme weather events, or climate change, changes in resource access, and pollution. Earth Observation data, considered in conjunction with administrative and survey information, can help to better understand the drivers of international immigration as well as the counter-effects to land systems after outflows of population and in-flows of capital in the form of remittances.

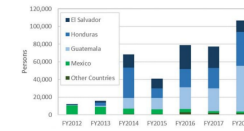
**Objective 1.** Derive agricultural LCLUC metrics related to landscape composition and configuration, and evaluate their spatial and temporal differentiation in the NT in relation to outmigration

**Objective 2.** Identify factors that drive changes to either agricultural LCLUC or outmigration within target communities and evaluate their strength and significance

**Objective 3.** Scale up driver-informed models of migration-related LCLUC to predict and monitor ongoing changes to NT land systems



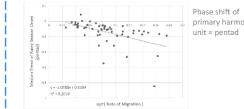
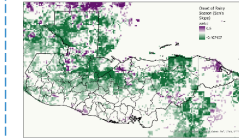
U.S. Customs and Border Patrol records the hometown of each migrant apprehended at the U.S. Southern Border. These data are aggregated at the departmental (left) *municipio* (right) scales and normalized by estimates of population derived from remotely sensed data (WorldPop) to show spatial variability in migration rates.



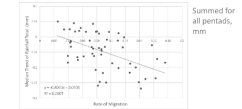
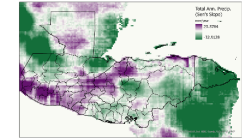
### CLIMATIC VARIABLES AND MIGRATION

Long term trends (1981-2018) in variables derived from data from UCSB's Climate Hazards Center (CHIRPS pentad, CHIRTS daily) varied significantly with migration rate at the Departmental scale, although there are significant spatial and national differences. Variables were derived from seasonal harmonic, and threshold-based deterministic models of precipitation and temperature. Shown below are maps of per-pixel Sen slopes for each variable over the total period (1981-2018 for precipitation data, 1983-2016 for temperature).

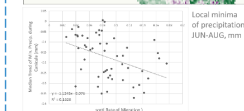
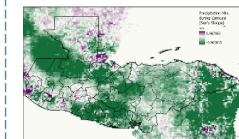
#### ONSET OF RAINY SEASON



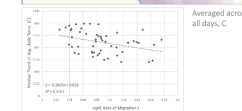
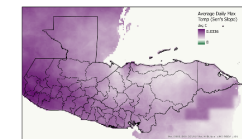
#### TOTAL ANNUAL PRECIPITATION



#### PRECIPITATION MINIMUM DURING CANICULA



#### AVERAGE DAILY MAXIMUM TEMPERATURE



### MAPPING LOW INTENSITY, SMALLHOLDER AGRICULTURE

MIXED COVER AND SLOPED TERRAIN IN SMALLHOLDER CORN/TIPICOS – EXAMPLES FROM ALL THREE COUNTRIES

High-resolution imagery (2022) show a patchwork of managed land in an upland area of western Honduras (Copan, inset).

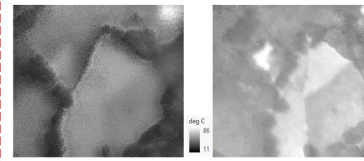
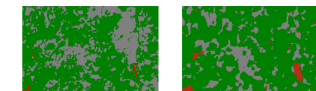


Photos: Across the region, small-holder agriculture LC is characterized by a mix of materials and vegetation types.

A year 2016 random forest classification of Sentinel-2 spectral, derived temporal, and other topographical data captures this land cover relatively well. This output relied on median spectral and phenological inputs from around the growing/rainy season.



Comparable products such as ESA WorldCover (left) and WRI Dynamic World (right), both 2020 classify these crops as grass and miss many patches. There are pastures and areas of grass in this region, but poor infrastructure and capital limit its extent.



TIR measurements from UAS suggest that afternoon observations may be useful for resolving crops, new plantings, and pasture (Camotan, Guatemala)

Crops:  
mean: 35.5 C  
s.d.: 0.6  
New planting:  
mean: 41.0 C  
s.d.: 0.6  
Pasture:  
mean: 37.7 C  
s.d.: 0.5

N=50 points selected within each cover type  
Image height = 120m



### SMALLHOLDER AGRICULTURE ALONGSIDE PASTURE

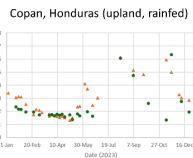
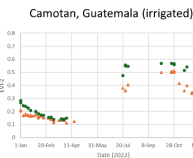
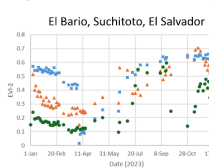


LEFT: Plot size on the order of 60x100m are typical in El Barrio, Suchitoto, El Salvador. Infrastructure and rainfall allow even small producers to grow sugarcane.



RIGHT: This relatively large plot (~400m square) near Copan, Honduras, is municipally owned with small portions (sub-hectare) allotted to individuals. This orthoimage, from data collected 3-4 weeks after planting, shows some variation in crop growth and abundant visible soil.

BELOW: Smallholders offer grow sugarcane on annual cycles that allow for straightforward classification on the basis of high VI throughout the dry season.

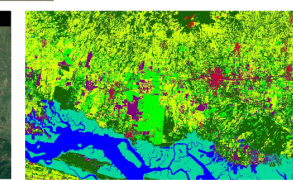
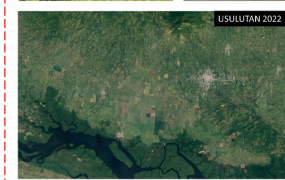
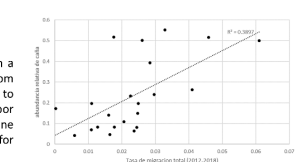


### SMALLHOLDER AGRICULTURE ALONGSIDE EXTENSIVE SUGARCANE TRANSITION FROM CORN/TIPICOS TO SUGAR CANE – USULUTAN, EL SALVADOR



LEFT: In eastern El Salvador there has been a decades-long pattern of transition away from cultivation of corn/beans/squash and cotton to sugarcane production. The conditions of labor and local environmental impacts of sugarcane cultivation have been cited as reasons for migration.

ABOVE: Derivation of a relative abundance index that describes the rate of sugarcane AND large-area bare soil as a portion of all croplands correlates significantly with outmigration rate at the *municipio* scale in the region. (N=36 *municipios* from the departments Usulután, San Miguel and San Vicente)



yellow = granos basicos  
light green = caña  
dark green = forest  
teal = mangroves  
blue = agua  
purple = soil  
red = area urbana

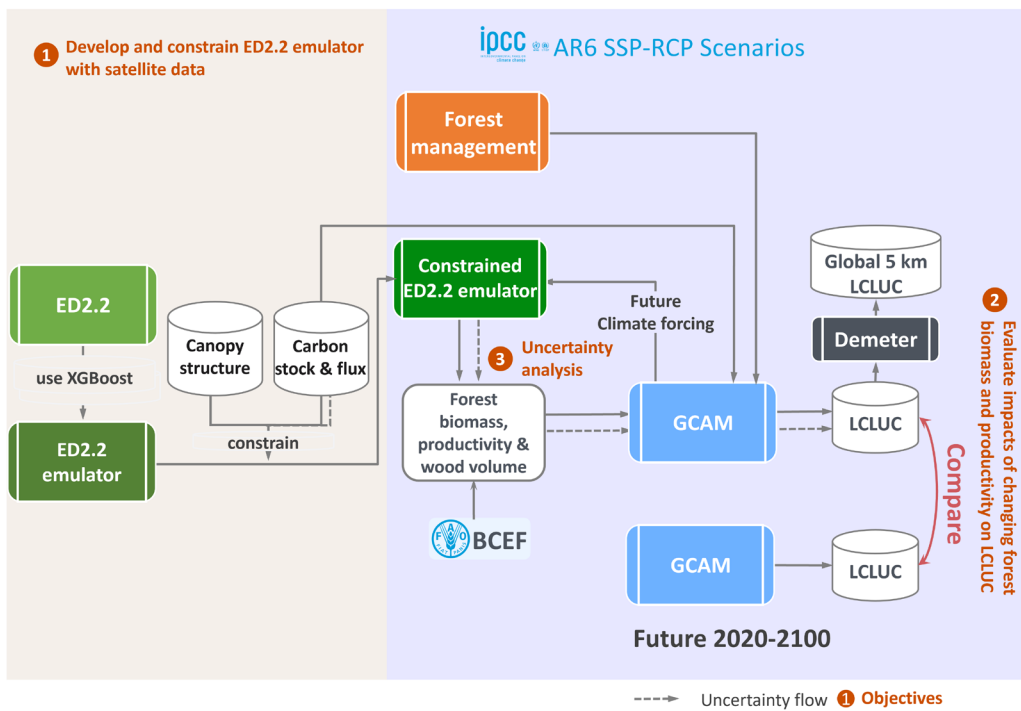
LEFT: Random forest classifications were produced for year 2020 using median composite Sentinel-2 reflectance from both the dry (JAN-MAR) and the wet (JUN-AUG) season, along with slope and elevation data.

Output is shown at left, alongside a 2022 basemap. Sugarcane production characterized by irrigation and a growing season often in excess of 12 months. As a consequence, fields may exhibit high greenness during the dry season or bare soil during the wet season if recently harvested. Patch size of bare soil was used to threshold outputs and attribute large patches to sugarcane production land use.



## Motivation and research questions

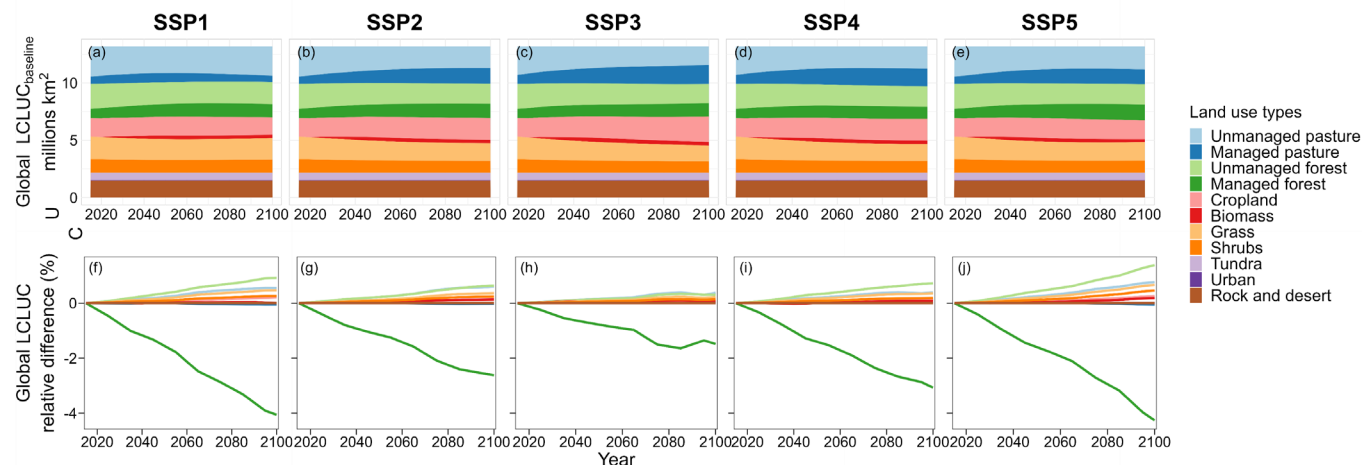
- Land cover and land use change (LCLUC) is one key interface between human and Earth systems, and has crucial impacts on carbon and water cycles, and biodiversity.
- Despite its importance, the changes in forest biomass and productivity are commonly ignored in the future LCLUC projections.
- Both climate change and forest management practice can significantly impact forest productivity.
- What is the impact of climate-induced and forest management-induced changes in forest productivity on LCLUC across the five Shared Socioeconomic Pathways (SSPs) throughout the 21st century?



**Fig. 1** Schematic diagram of the workflow of this project.

## Current progress

- Forest management induced-forest productivity can significantly influence LCLUC, especially for the managed forest and natural lands.



**Fig. 2** Global LCLUC under SSP1-SSP5 from 2015 to 2100. (a-e) global LCLUC without considering forest management change induced forest productivity change. (f-j) The relative difference of global LCLUC between with and without consideration forest management change induced forest productivity change.



## INTRODUCTION

Cover crops can significantly benefit soil conservation, nutrient management, weed control, climate change adaptation, and agroecosystem mitigation. Huge efforts have been made at both federal and state governments to provide financial and technical support to farmers for cover cropping in the U.S. Midwest.

However, knowledge of cover cropping variations and impacts of government policies remains very limited. Accurate and efficient monitoring of cover cropping is essential for understanding cover cropping adoption status, accessing cover cropping benefits, and evaluating the outcomes of cover cropping conservation programs.

While field-level cover cropping information is typically obtained from field investigations, which are time-consuming, labor-intensive, and costly. Remote sensing has the potential to provide timely and cost-effective solutions for large-scale and field-level cover cropping detection but remains at the early stages.

## OBJECTIVE

To fill the gaps in using remote sensing to quantify cover crop adoption at field scales across large spatial and temporal extents, this project proposes to integrate knowledge in remote sensing, large-scale computation, plant phenology, and artificial intelligence, for the development of cover crop quantification framework.

## METHOD

### Extracting cover crop features

Remote sensing NDVI time series for each satellite pixel are decomposed into soil (sNDVI), cover crop (cNDVI), and cash crop components (mNDVI), thus observed NDVI data at crop fields can be written as:

$$NDVI = sNDVI + cNDVI + mNDVI \quad (1)$$

where  $sNDVI = \min\{NDVI_d, d \in T_1\}$  and  $mNDVI_d = \frac{\max(NDVI) - sNDVI}{1 + \exp(a - b \cdot d)}$ ,  $d \in T_2$ .  $T_1$  is the non-growing season and  $T_2$  is the peak-growing season. The  $a$  and  $b$  are detected emerging day and the maximum growth rate, respectively. The cover crop feature ( $cSign$ ) can be defined by:

$$cSign = \sum_{i=P_1}^{P_2} cNDVI, d \in T_3 \quad (2)$$

where  $T_3$  is the growing season,  $P_1$  and  $P_2$  are detected cover crop emerged and terminated dates.

## Modeling cover crop feature thresholds

Cover crop growth varies dynamically across different regions and periods, which leads to dynamic cover crop features. The environmental factors are involved to predict the cover crop feature thresholds ( $cT$ ):

$$cT = F(\text{environmental variables}), d \in T_3 \quad (3)$$

The method can consider the influence of environmental factors on the cover crop mapping, which enables the capacity of the invention to be applied at large-scale and long-term with relatively high accuracy.

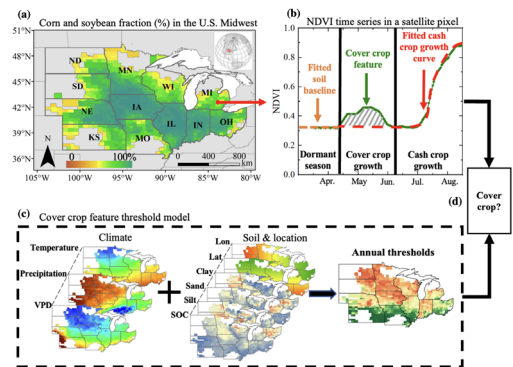


Figure 1. Conceptual framework for quantifying cover crop adoption in the U.S. Midwest using multi-source satellite data.

## RESULTS

### Satellite-based cover crop detection

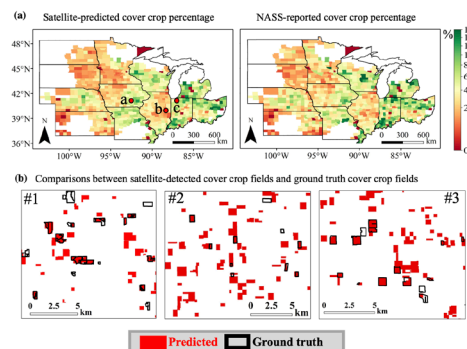


Figure 2. (a) Satellite-based prediction of cover crops across the Midwestern counties in 2017. (b) Field-level comparison of satellite-detected cover crop fields and ground truth data.

## Cover crop trends and their attribution

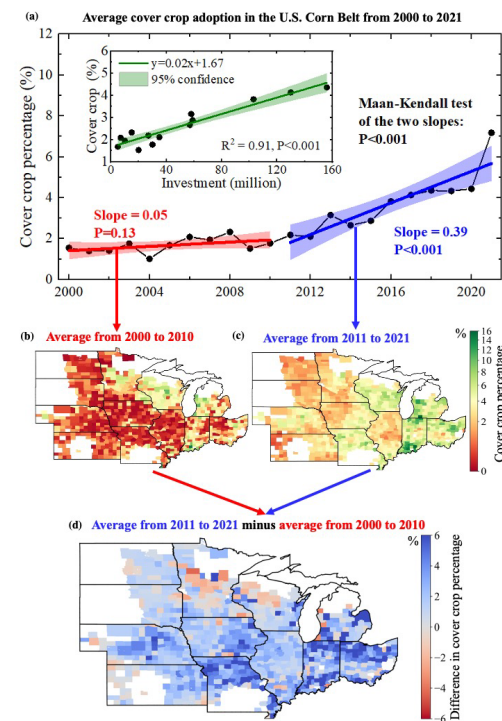


Figure 3. Cover crop adoption in the U.S. Midwest from 2000 to 2021 derived from STAIR fusion NDVI time series.

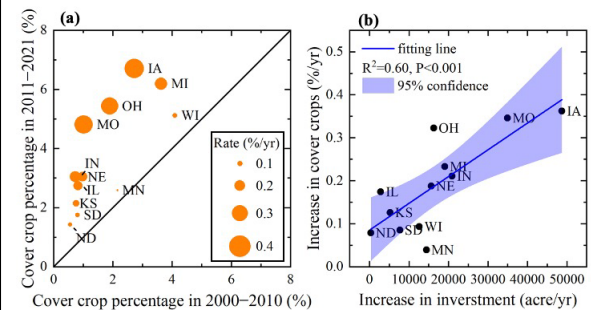


Figure 4. State-level cover crop adoption changes and their relationships to the investment in promoting cover crop adoptions.

## Dynamic vs fixed thresholds

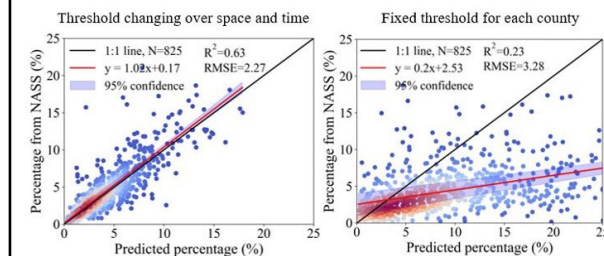


Figure 5. Performance of dynamic and fixed thresholds for predicting cover crop percentages of each county in the U.S. Midwest in 2017.

## CONCLUSION

- (1) High-frequency and 30-m satellite NDVI time series are useful for determining field-level cover crop practice.
- (2) Dynamic cover crop feature-threshold framework is relatively accurate and robust for field-level cover crop quantification.
- (3) The increasing trend of cover crop adoption is highly correlated to the funding for cover crop incentive programs.
- (4) This project could offer a low-touch and reliable solution to gather historical and current cover crop adoption information needed for many

## REFERENCE

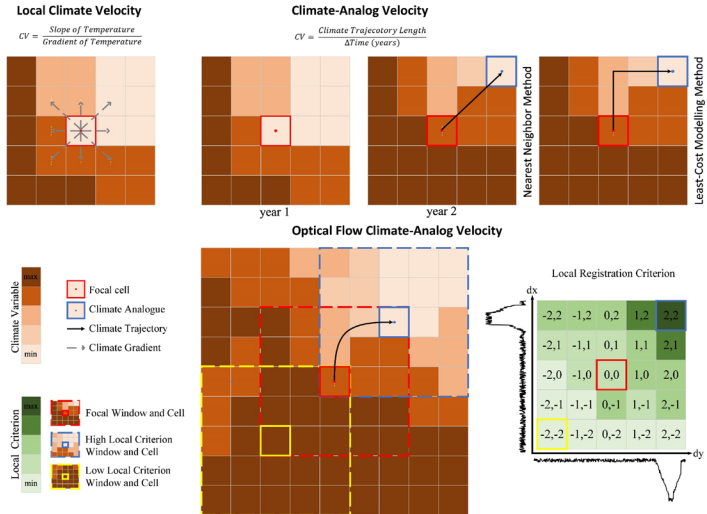
Zhou et. al (2022). Recent rapid increase of cover crop adoption across the US Midwest detected by fusing multi-source satellite data. *Geophysical Research Letters*, 49(22).

## ACKNOWLEDGEMENTS

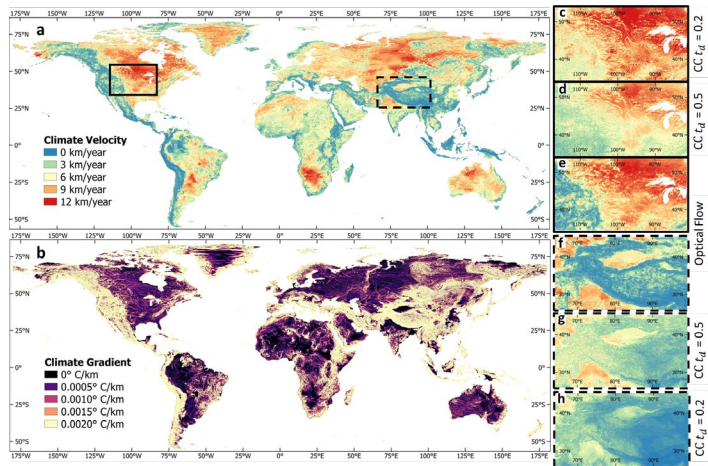
This work was primarily supported by USDA, the National Institute of Food and Agriculture (NIFA), the US Department of Energy's Advanced Research Projects Agency-Energy (ARPA-E) SMARTFARM (MBC Lab and SYMFONI) project, and the NASA FINESST fellowship.



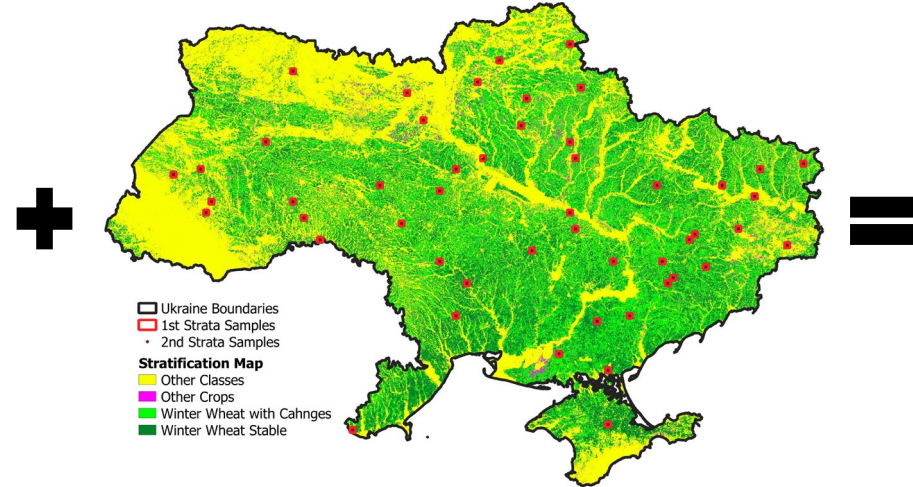
Optical Flow Climate Velocity Technique



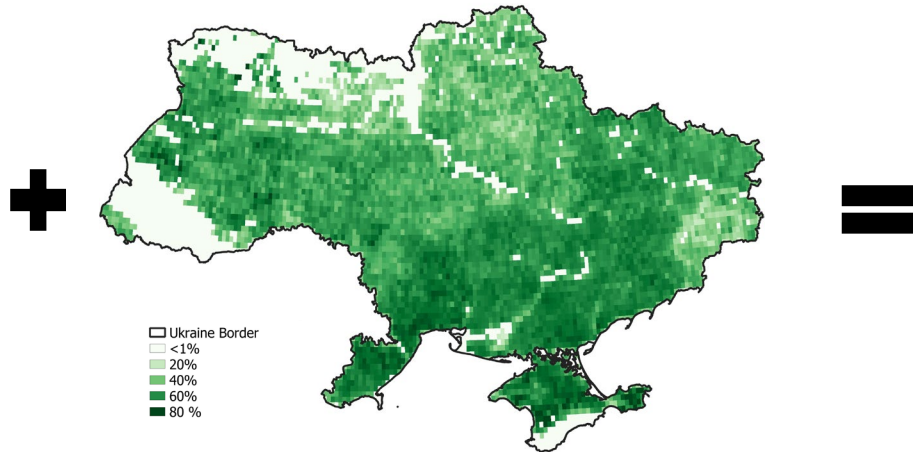
Climate Velocity Flow



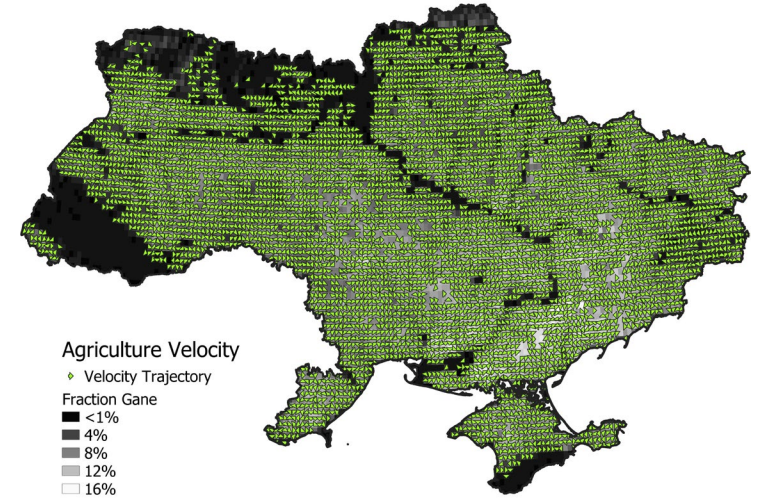
2 Stage Stratification for Area Estimation



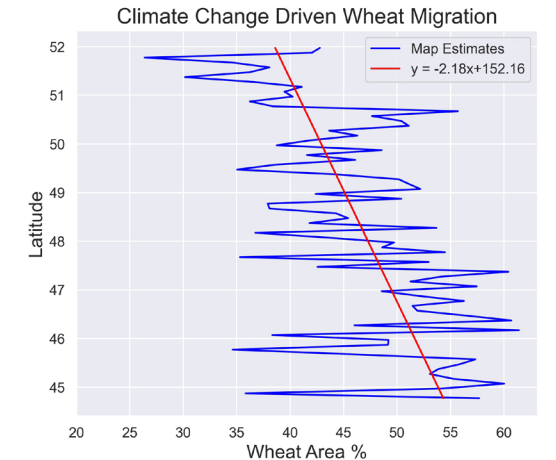
Winter Wheat Fraction over Cropland



Agriculture velocity Flow



Expansion of Winter Wheat Codirectional with Climate Change







Kyra Adams<sup>1</sup>, Bhuvan Varugu<sup>1</sup>, Latha Baskaran<sup>1</sup>, Matthew Bonnema<sup>1</sup>, Jeffrey Nittrouer<sup>2</sup>, Raphael Savelli<sup>1</sup>, Dimitris Menemenlis<sup>1</sup>, Christine Lee<sup>1</sup>

<sup>1</sup>NASA Jet Propulsion Laboratory, California Institute of Technology <sup>2</sup>Texas Tech University

# Integrated ecosystem evolution in response to dam disruptions

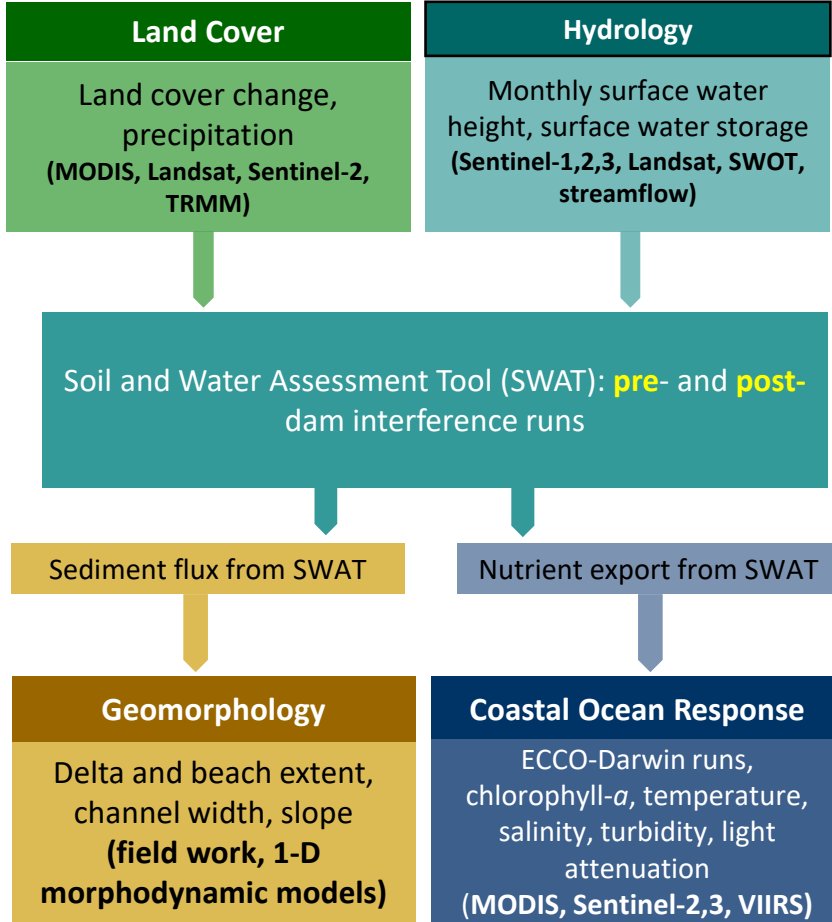
## Introduction



**Top:** Amazon river tributaries, Xingu river basin (yellow), and location of the Belo Monte Dam (red). **Bottom:** Confluence of Xingu tributary with Amazon main river, 2021-08-04 from Sentinel-2. There is a stark water color and sediment concentration difference.

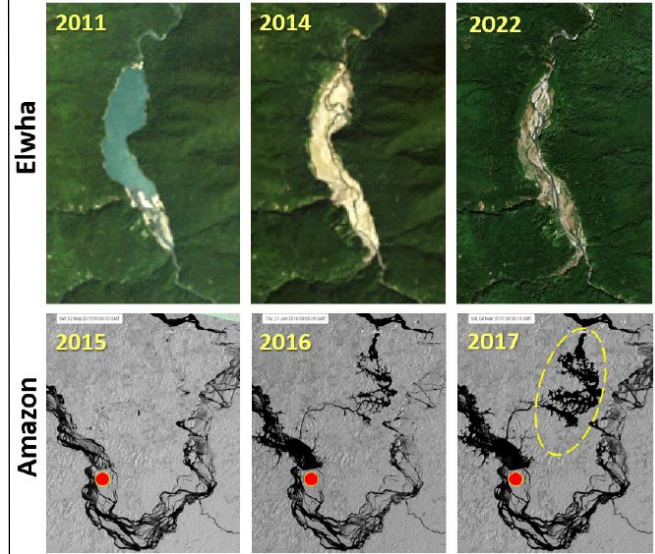
- Dams are a major anthropogenic control on watershed hydrodynamics and geomorphology and, consequently, on freshwater, particle, and nutrient exports across the land-ocean continuum.
- However, dam disruptions have often been assessed within independent disciplines: land cover change, hydrology, or sedimentology / geomorphology.
- The world has shown divergent patterns regarding dams, with the US increasing the rate of dam removal while other regions such as South America and Southeast Asia increasing dam building.
- Within this work, we employ an interdisciplinary approach to understand the interlinkages between terrestrial, deltaic, and oceanic processes for two major dam systems: the Elwha dam in Washington, US (removal) and Belo Monte in Brazil (building).

## Methods



Linkages between watershed land cover, hydrologic flux, and sediment flux will be established using the SWAT model leveraging in-situ and satellite datasets. Model outputs will be used to inform the ECCO-Darwin model to understand nearshore ocean responses driven by the watershed changes. Further, geomorphologic characteristics will be quantified.

## Expected Results



**Top:** Changes to Lake Mills near Glines Canyon reservoirs over time. The lake has been filled with sediment. **Bottom:** Sentinel-1 images of Belo Monte Dam (red) and the filling of Main Reservoir by water (yellow circle)

We expect changes landcover and hydrologic changes to be detectable and quantifiable with satellite, which will inform the SWAT model of the changing watershed characteristics.



A. Amazon delta Aug. 2017 (before Belo Monte dam completion) and B. Amazon delta Aug. 2022 (after completion). C. Difference between 2017 and 2022. Red are areas where delta expanded and blue are areas where delta receded.

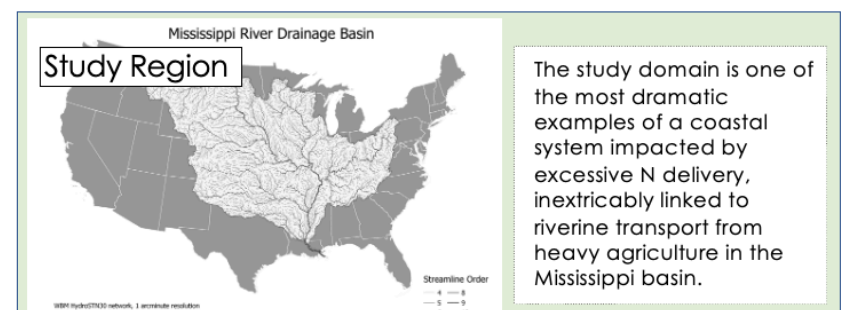
Currently, we are working to characterize delta accretion and erosional patterns for the Amazon river mouth during the Belo Monte dam construction years, to quantify the relative influence Xingu river basin may have on the nearshore ecosystem of Brazil.



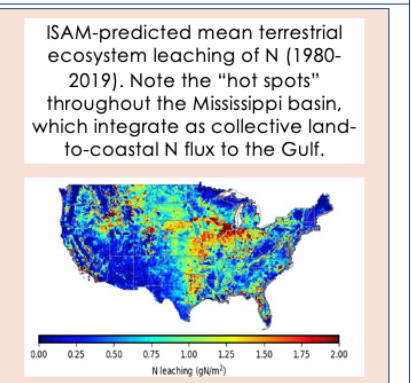
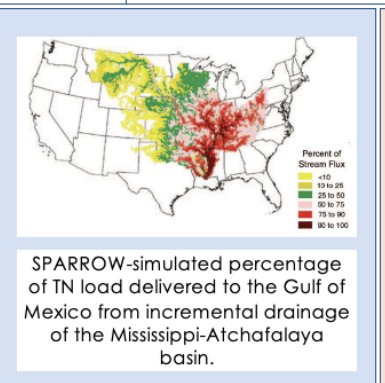
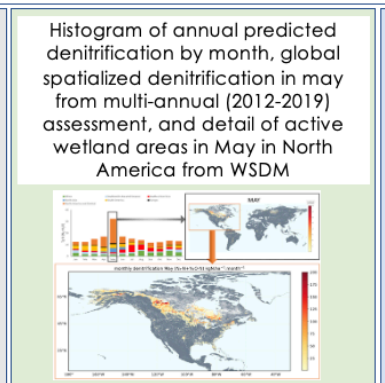
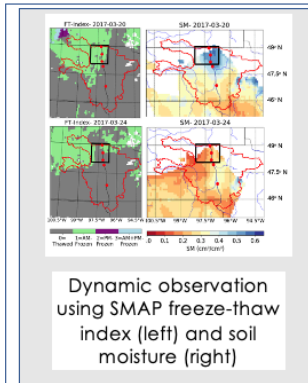
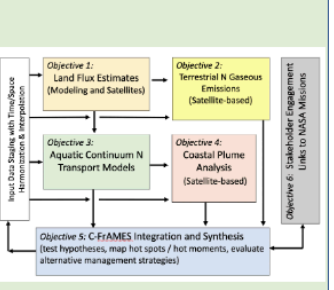


## Aims of This Study

- Analyze short-term variations in N cycle in relation to short-term wetting/drying, heatwaves, drought, extreme precipitation/flooding, and rapid freeze/thaw
- Link remote sensing, geospatial data, and in-situ analysis to established models to detect, geo-position, and analyze short-term variations in the N cycle
- Develop environmental surveillance system to monitor dynamics of near-contemporary N cycle across the Mississippi River Basin/Gulf of Mexico land-to-ocean continuum from 2010 to present



We develop an observation and modeling system to quantify N dynamics; uncovering N cycle sensitivities to (i) the driving variables, (ii) resulting land-to-atmosphere and land-to-water fluxes, and (iii) environmental impacts. This sets the stage for improved environmental surveillance and better-informed management decisions to be explored with stakeholders

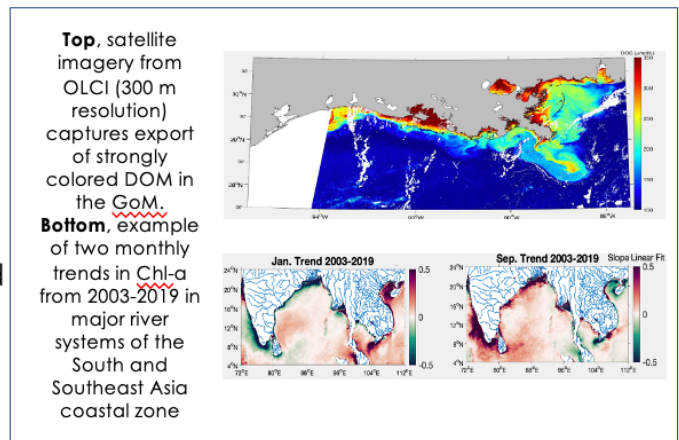


## Six Technical Objectives

1. Integrate land-based remote sensing with models of hydrologic state and dynamics, nutrient loading, mobilization, and sequestration under climate extremes
2. Apply estimation techniques (modeling, remote sensing, and in situ data integration) for land-to-atmosphere gaseous losses and analyze the impact of climate variability
3. Create aquatic transport and processing model estimates of N flux, representing the behavior of both engineered and natural instream systems
4. Carry out and validate remotely sensed inland and coastal river plume analysis
5. Reconfigure existing technical integration frameworks to create C-FrAMES, uniting results and workflows described under Objectives 1-4 and focusing on climate events
6. Engage stakeholders including through NASA mission early adopters

## Hypothesis tested

The fluxes of reactive N from the Mississippi River drainage basin to the Gulf of Mexico over the recent past are determined by the conjunction of nature-based and human-engineered infrastructures associated with a relatively small fraction of the total land mass drained by the river







Juan L. Torres-Pérez

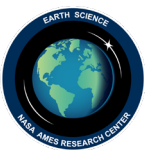
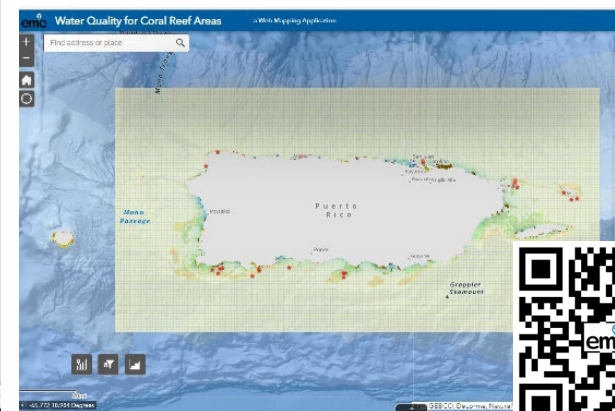
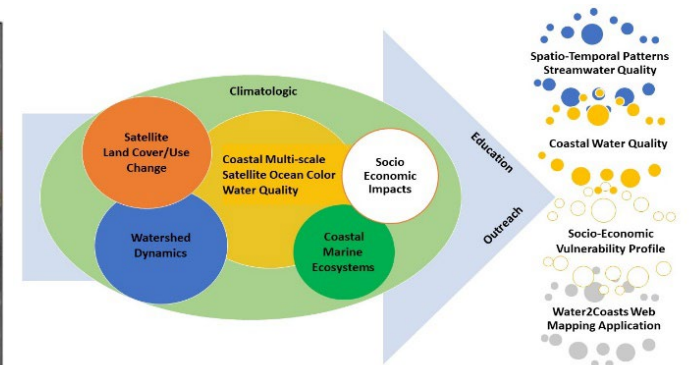
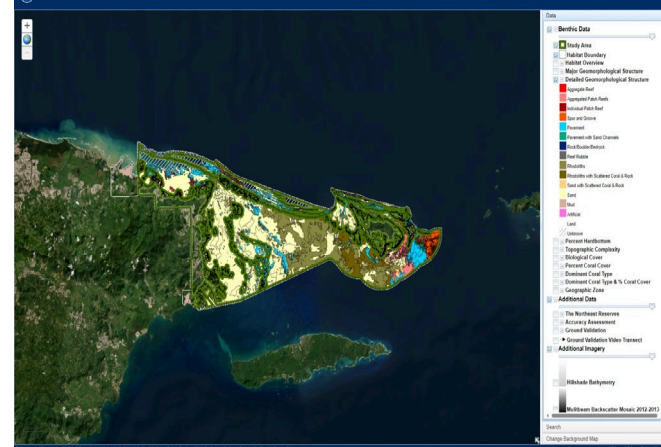
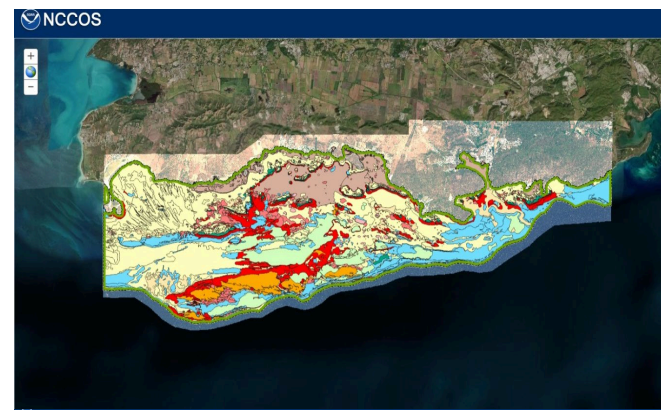
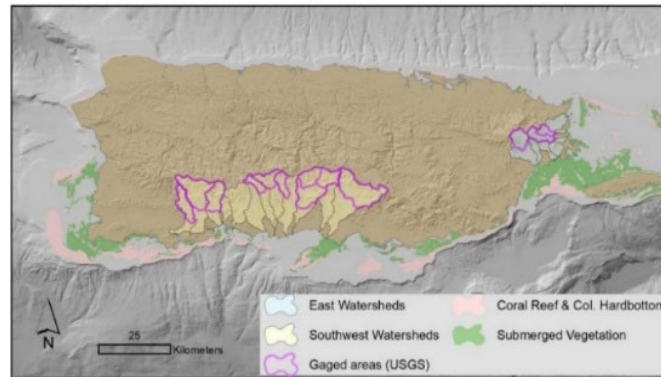
# Watersheds, Water quality, and Coastal Communities in Puerto Rico (Water2Coasts): An interdisciplinary island landscape to coastal ocean assessment with socioeconomic implications

## Objectives:

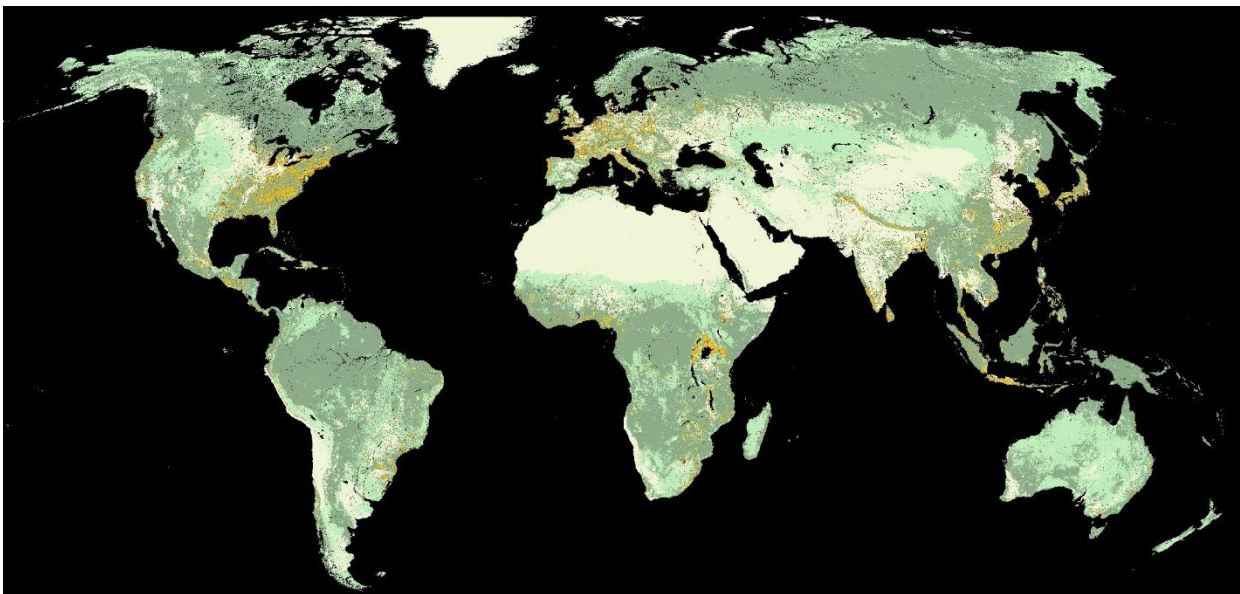
**Objective 1 – Watershed Dynamics:** Use field data and hydrological-LBSP modeling to characterize spatio-temporal patterns of riverine discharge and water quality considering land cover/land use, location of point sources of pollution, available precipitation climatologies, and socio-economic factors.

**Objective 2 – Coastal Water Quality:** Use current and legacy satellite water quality products (chlorophyll-a [Chl-a], colored dissolved organic matter [CDOM], total suspended sediments [TSS], vertical attenuation coefficients [ $Kd_{490}$  and  $Kd_{PAR}$ ]), and field bio-optical data to characterize patterns and constituents of riverine plumes in coastal areas with CMEs of ecological importance.

**Objective 3 – Socio-economic Impacts:** Analyze spatial measures of the socioeconomic vulnerability profile for PR to assess differential impacts on these contrasting coastal communities in southern and eastern PR, and test for spatial associations among socio-economic vulnerability, water quality variables, *Sargassum* accumulation, and ecosystems.

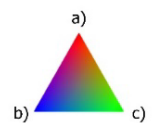
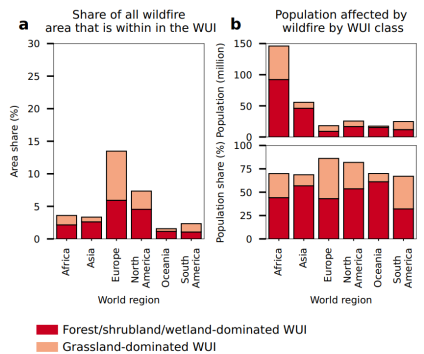
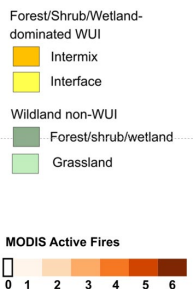
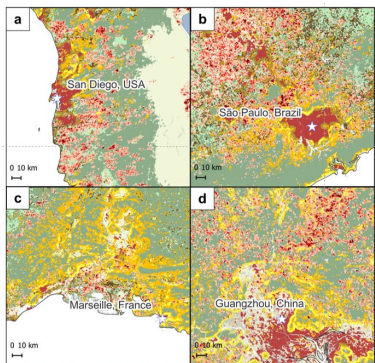
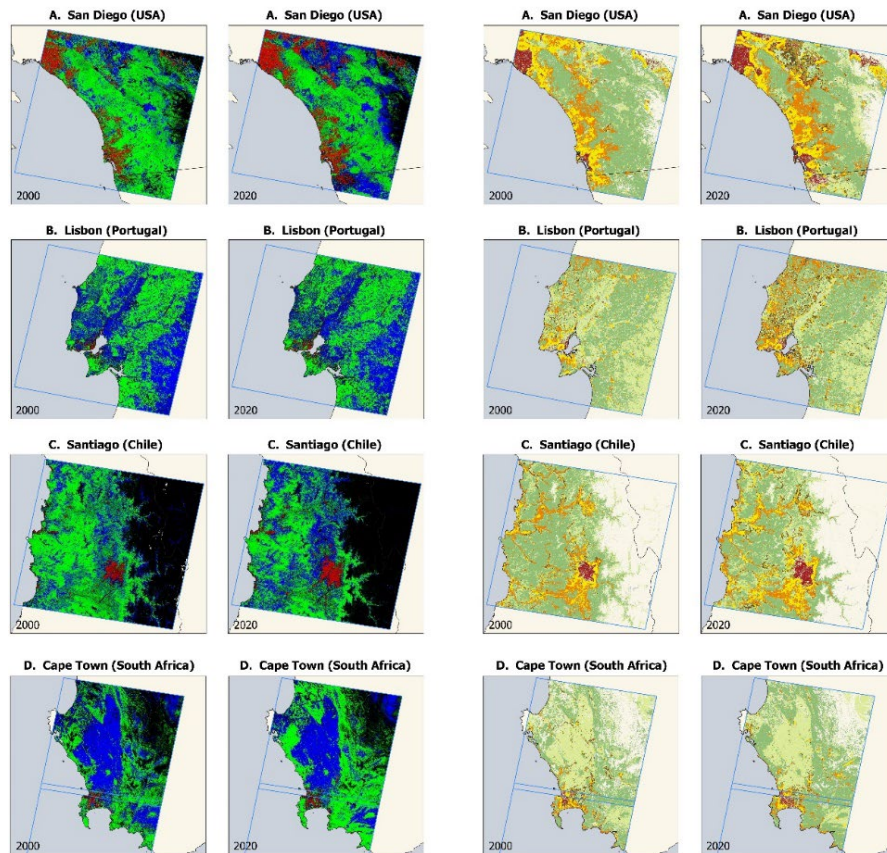






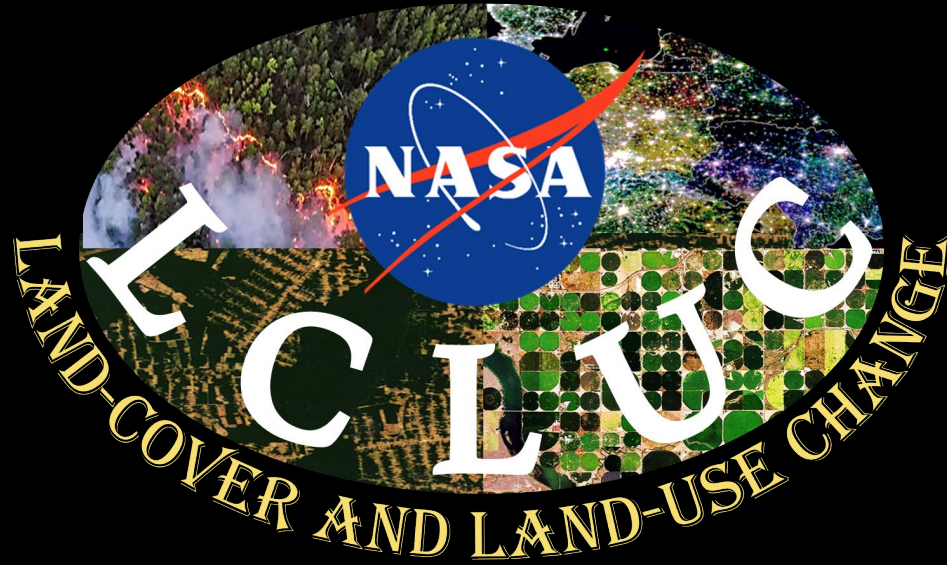
Spectral Unmixing

WUI Mapping





**LCLUC Science Team Meeting April 2-4, 2024**



**Poster Lightning Introductions**

**Thank You**



**LCLUC Science Team Meeting April 2-4, 2024**



**Poster Session : 5:30 to 7:30**

**Gaithersburg Marriott Washingtonian Center  
(Salon A and D)**