# Agricultural Classification of Multi-Temporal MODIS Imagery in Northwest Argentina Using Kansas Crop Phenologies

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background.pdf

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# RESEARCH QUESTIONS

Can I…

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- extract crop signatures from Kansas data?
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# OUTLINE

1. Background
2. Study Areas
3. Data and Methods
4. Results and Discussion
5. Conclusion

# BACKGROUND

# DEFORESTATION IN ARGENTINA

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- 1998 to 2002: 940,000 ha deforested
- *Ley de Bosques* passed in November 2007
  - Classified red, yellow, and green areas through the *Ordenamiento Territorial de los Bosques Nativos* (Land Management Order for Native Forests, OTBN) passed in 2009

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# DEFORESTATION IN ARGENTINA

**Deforestation in Argentina, 2006 to 2011**

| Time Period | Hectares Deforested |
|---|---:|
| 2006 to *Ley de Bosques* (2007) | 573,296 |
| *Ley de Bosques* to OTBN (2009) | 473,001 |
| OTBN to 2011 | 459,108 |
| **Total** | 1,505,405 |

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- Deforestation has remained extremely high
- Questions the effectiveness of the *Ley de Bosques*

# SOY AND ITS EFFECTS

- Argentina's soybean cultivation has continually increased
  - 5 million ha in 1993 to 19 million ha in 2011

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- Over 99 percent of Argentine soy is genetically modified
  - Resistance to glyphosate = heavy pesticide use
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### Questions

- What if two crops have similar VI values on a single date?
- How does one determine a crop's VI values?

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# VEGETATION INDICIES

## Question

What if two crops have similar VI values on a single date?

## Answer

Use imagery from multiple dates.

# TIME SERIES IMAGES

NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Sensor

- Terra and Aqua satellites
- Each images the Earth once per day
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# TIME SERIES IMAGES

## Key Points

- A TSI pixel shows VI values over time
- Each crop's phenology exhibits a unique temporal signature

# CROP TEMPORAL SIGNATURES

Graphics/wardlowCropSignatures.png

(From Wardlow and Egbert 2005)

**Question**

How does one determine a crop's VI values?

# PHENOLOGICAL CLASSIFICATION

## Question

How does one determine a crop's VI values?

## Answer

Existing approaches require training sites.

# PHENOLOGICAL CLASSIFICATION

**Problem**

What if you don't have training sites?

# TIME SERIES IMAGES

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Sounds a lot like hyperspectral remote sensing...

## TIME SERIES IMAGES

**Idea**

Could we use a hyperspectal-like method to fit known crop signatures to unknown pixels?

# TIME SERIES IMAGES

Graphics/transformations.pdf

# TSF METHOD

Two-Step Filter (TSF) method from Sakamoto et al. (2010)

- Two steps: (1) wavelet smoothing and (2) curve fitting
- Curve fitting can fit reference signature to unknown pixels

# TSF METHOD

## TSF Equation 1

$$RMSE = \left[\frac{1}{365/s} \sum_{x=j(0),j(1)\ldots}^{n} \left(f(x) - g(x)\right)^2\right]^{\frac{1}{2}}$$

where

- $n$ is the number of dates in the TSI
- $f(x)$ is the temporal signature for a given pixel in a dataset
- $x$ is the DOY, as defined by $j(y)$

### TSF Equation 2

$$g(x) = yscale \times \ h\left(xscale \times (x + tshift)\right)$$

where

- *yscale* and *xscale* are coefficients controlling the vertical and horizontal scaling of a reference signature $h(x)$
- *tshift* is a constant representing the horizontal shift, in days, of $h(x)$
- $x$ is the DOY

# TSF METHOD

Graphics/transformations.pdf

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## TSF Equation 1

$$RMSE = \left[\frac{1}{365/s} \sum_{x = j(0), j(1)\ldots}^{n} \left(f(x) - g(x)\right)^2\right]^{\frac{1}{2}}$$

Minimizing Equation 1 with appropriate constraints on *yscale*, *xscale*, and *tshift* will find the fit of a a reference signature to a pixel.

# PHENOLOGICAL CLASSIFICATION

**Problem**

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# PHENOLOGICAL CLASSIFICATION

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What if you don't have training sites?

## Answer

The TSF equations allow the classification of unknown pixels using a library of crop signatures.

# STUDY AREAS

# KANSAS STUDY AREA

- 2012 Kansas top crops:
  - Winter wheat
  - Corn
  - Soy
- Ground truth:
  USDA Cropland Data Layer

Graphics/KSstudysite.pdf

# KANSAS STUDY AREA

**Kansas Study Site Planting Dates**
**(adapted from Shroyer et al. 1996)**

| Crop | Planting Date Range |
|---|---:|
| Wheat | 25 September to 20 October |
| Corn | 1 April to 10 May |
| Sorghum | 15 May to 20 June |
| Soybeans | 5 May to 10 June |

Graphics/argentinaOverview_landscape.pdf

# DEPARTMENT OF PELLEGRINI

Graphics/pellegrini75to14_landscape.pdf

## Deforestation in Pellegrini, 2001 to 2011

| Time Period | Hectares Cleared | Percent of Land Area | Hectares per Year |
|---|---|---|---|
| 2001 to 2005 | 5,968 | 0.9 | 1,492 |
| 2006 to 2011 | 75,249 | 10.9 | 15,050 |

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Annual rate of clearing increased over 1000%!

Top crops in Pellegrini, 2001 to 2005

- Soy
- Corn
- Winter Wheat

(From Volante et al. 2005)

# DATA AND METHODS

# DATASETS

- 250-meter MODIS 16-day composite VI imagery
- 30-meter 2012 USDA Cropland Data Layer
- 30-meter Landsat 8 OLI satellite imagery
- Pellegrini boundary shapefile

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# DATASETS

- 2014 Pellegrini Land Cover vector dataset

# PELLEGRINI DATA COLLECTION

- Data collection in Pellegrini 12 March to 3 April
  - 400 random sample points
    - Direct observation
    - Interviews with farmers
    - Satellite image interpretation
  - Agricultural practices and planting/harvesting dates

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# PROCESSING WORKFLOW

1. Reproject the MODIS composite VIs
2. Assemble composite VIs into TSIs
3. Extract crop signatures from the Kansas TSI
   - 3.1 Identify pure pixels (e.g. non-mixels)
   - 3.2 Use the CDL to isolate each crop
   - 3.3 Identify phenological groups using k-means clustering
   - 3.4 Extract pixel values for each group and average
4. Fit the Kansas signatures to the Kansas TSI using the TSF method
5. Classify the Kansas RMSE rasters and assess accuracy
6. Fit the Kansas signatures to the Argentina TSI
7. Classify the Argentina RMSE rasters and assess accuracy

# REPROJECTION

1. Reproject the MODIS composite VIs
    - Land Processes Distributed Active Archive Center's (LPDAAC) MODIS Reprojection Tool

# BUILDING THE TSIs

2. Assemble composite VIs into TSIs
   - Python command line tool (PCLT) to stack composites
   - Kansas TSI covered 2012 DOY 97 to 2012 DOY 273
   - Argentina TSI covered 2014 DOY -13 to 2014 DOY 161
     - Aqua DOY 105 composite used in place of DOY 113 composite
     - DOY 129 interpolated from DOY 105 and DOY 145 composites

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# RESULTS AND DISCUSSION

# CONCLUSION