

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

September 17, 2014

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# RESEARCH QUESTIONS

Can I...

- ▶ develop a phenological classification toolset?
- ▶ extract crop signatures from Kansas data?
- ▶ classify an Argentina study area with the Kansas signatures?

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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 <i>Ley de Bosques</i> (2007)	573,296
<i>Ley de Bosques</i> to OTBN (2009)	473,001
OTBN to 2011	459,108
<b>Total</b>	<b>1,505,405</b>

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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

## SOY AND ITS EFFECTS

- ▶ Soy production highly mechanized
- ▶ 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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## 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
- ▶ Composite 16-day NDVI imagery at 250-meter resolution

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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)

# PHENOLOGICAL CLASSIFICATION

## Question

How does one determine a crop's VI values?

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How does one determine a crop's VI values?

## Answer

Existing approaches require training sites.

# PHENOLOGICAL CLASSIFICATION

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What if you don't have training sites?

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Sounds a lot like hyperspectral remote sensing...

# TIME SERIES IMAGES

## Idea

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



## TIME SERIES IMAGES

Graphics/transformations.pdf

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 Equation 1

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

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

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

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

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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)

<b>Crop</b>	<b>Planting Date Range</b>
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

Graphics/pellegrini75to14\_landscape.pdf

## DEPARTMENT OF PELLEGRINI

### 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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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

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

# 1. REPROJECTION

- ▶ Land Processes Distributed Active Archive Center's (LPDAAC) MODIS Reprojection Tool

## 2. BUILDING THE 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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## 3. EXTRACT CROP SIGNATURES

### 3.1 Identify pure pixels (e.g. non-mixels)

- ▶ Intersected MODIS pixel grid with vectorized CDL
- ▶ Selected all features  $\geq 53,000 \text{ m}^2$  in area

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Now we have crop signatures!

# FITTING SIGNATURES

## 4, 6. Fit Kansas signatures to <insert study area here> TSI using TSF method

- ▶ Not using the TSF's wavelet filtering
- ▶ PCLT to fit reference signatures to a TSI using TSF equations
  - ▶ Creates a RMSE raster for each signature
  - ▶ *xscale* and *yscale* bounds: 0.6 to 1.4
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Brute force through different threshold combinations, classifying and assessing the accuracy to find the best result.

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## RESULTS AND DISCUSSION

# RESULTS

- ▶ Summer 2014 Pellegrini ground truth
- ▶ Pellegrini agricultural practices
- ▶ Kansas crop signatures
- ▶ Kansas classification
- ▶ Pellegrini classification

## PELLEGRINI GROUND TRUTH

- ▶ 378 of 400 sample points were identified
- ▶ Many additional fields were collected

Graphics/collecteddata.pdf

# PELLEGRINI GROUND TRUTH

## Summer 2014 Pellegrini Land Cover Classes

Cover Type	Hectares	Sample Points
Forested	389,541	247
Other	42,229	22
Corn	41,488	36
Pasture	35,057	37
Soy	27,498	24
Poroto	9,539	7
Nothing	3,057	3
Sorghum	1,646	2
Unknown	92,248	17
Omitted	52,052	5
<b>Total</b>	<b>694,346</b>	<b>400</b>

## Key Dates for Pellegrini Summer Crops

Crop	Ideal Planting Range	Harvesting Begins
Soy	15 December to 15 January	1 May
Corn	15 January to 15 February	1 June
Sorghum	15 January to 15 February	1 June
Poroto	15 January to 20 February	10 May



## KANSAS CROP SIGNATURES

Graphics/KSclustered.pdf

# KANSAS CROP SIGNATURES

~~plots/allsigKS.pg~~

**Crop Signatures Extracted from the Kansas TSI Crop  
Clusters**

# CONCLUSION