

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

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RESEARCH QUESTIONS

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- ▶ develop a phenological classification toolset?
- ▶ 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
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 - ▶ Classified red, yellow, and green areas

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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
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

SOY AND ITS EFFECTS

- ▶ Soy production highly mechanized
- ▶ Over 99 percent of Argentine soy is genetically modified
 - ▶ Resistance to glyphosate = heavy pesticide use
- ▶ Capital requirements cut out small producers

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Must be able to classify crops by type

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 - ▶ Normalized Difference Vegetation Index (NDVI)

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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?

VEGETATION INDICIES

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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
- ▶ Composite 16-day NDVI imagery at 250-meter resolution

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TIME SERIES IMAGES

Time Series Image (TSI)

- ▶ Each band is a 16-day VI composite
- ▶ Bands are sequential composites
- ▶ Contains enough bands to cover an entire growing season

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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?

PHENOLOGICAL CLASSIFICATION

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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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- ▶ A TSI pixel shows VI values over time
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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

TSF Equation 1

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

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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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

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	10.8	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

RESULTS AND DISCUSSION

CONCLUSION