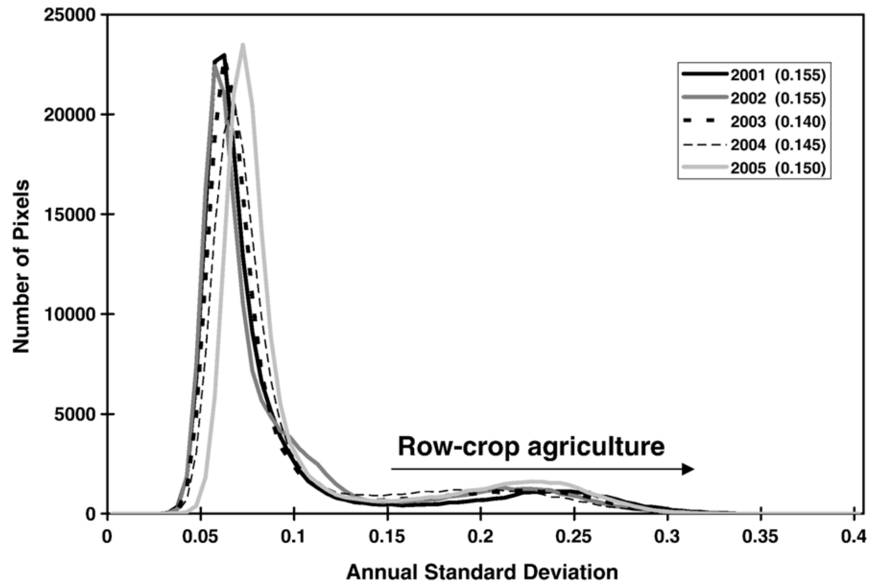

Fig. 5. This histogram show how the high standard deviation separates areas of row-crop agriculture from other land cover classes through the entire study scene. Row-crop agriculture was identified as areas that have an annual standard deviation greater than the local minimum (~0.15) identified specifically for that year. The actual standard deviation used for each year is printed in the legend.

in $s(t)$. This formulation (Eq. (3)) can be used to reconstruct a signal (Gendrin et al., 2006).

The wavelet-created time series W is a summation of wavelets over a number of different widths,

$$W = \sum_{i=1}^{x} W(a,b)_i \tag{3}$$

where $W(a, b)_i$ is the wavelet transform created in Eq. (1). Wavelet transforms of decreasing width are summed from $\boldsymbol{i}$ to $\boldsymbol{x}$, where $\boldsymbol{x}$ is the number wavelet transforms necessary to achieve the user defined number of coefficients retained from the input data. The width of a wavelet transform has half the width of the previous wavelet. It is the sum of the wavelets (W in Eq. (3)) that is referred from here on as the wavelet-smoothed time series.

The wavelet filtering begins by applying a smoothing function on the one-dimensional time series that is evenly-spaced, to avoid aliasing effects, after cloud-removal and interpolation of missing values. First, a discrete wavelet transform removes the residual high frequency noise. The smoothed EVI time series is then reconstructed with an inverse discrete wavelet transform.

Applying the wavelet to an EVI time series requires selecting parameters of mother wavelet, order, and power that define the wavelet behavior. We used the Coiflet mother wavelet with order 4 because the wavelet shape is as similar as possible to the peaks in agricultural phenology we are detecting. (See Sakamoto et al., 2005 for performance comparison of mother wavelets). Order is a measure of the wavelet's smoothness, where a higher order produces a smoother wavelet (Burke, 1994).

The wavelet requires a power threshold that corresponds to the number of coefficients determining how much of the input EVI time series is retained during the wavelet transform. A higher power or a greater number of coefficients retains more of the original data by forming a narrower wavelet that includes more fine-scale features but may also retain more noise. A lower power, or fewer coefficients, retains less high frequency data by applying a wider wavelet. A low power wavelet may capture trends through the entire time series but may loose phenological detail during a single year.

We conducted error analysis cropping patterns detected with the 70%, 80%, 85%, 90% (both 0.3 and 0.4 EVI detection thresholds; see Section 2.6 for further discussion of this threshold) and 95% (0.4 threshold) power wavelets. A random point generator selected 122 verification points within the row-crop agricultural zone. Reference data on cropping patterns for a given year in a given pixel were generated from the input EVI time series with bad pixels removed. These reference data are used to verify the cropping patterns detected from each wavelet-smoothed time series and the results tabulated to calculate overall accuracy and K_{hat}. Each point has five years worth of data and each year was treated individually, essentially multiplying the number of verification points by the number of years, giving a total of 610 verification points.

Table 1
The effects of wavelet power on accuracy are reported using overall accuracy and K_{hat} by comparing wavelet-detected cropping patterns to reference patterns generated by the user from the input EVI time series

Wavelet power (%)	Overall Accuracy	K_{hat}
70	81.0%	70.3%
80	83.4%	74.2%
85	90.0%	84.1%
90	87.2%	80.4%
90 (0.4 threshold)	88.5%	92.1%
95 (0.4 threshold)	44.8%	25.6%

Overall accuracy is the percent of points accurately identified in a class out of the total number of points sampled. K_{hat} values incorporate misclassifications while assessing classification accuracy.