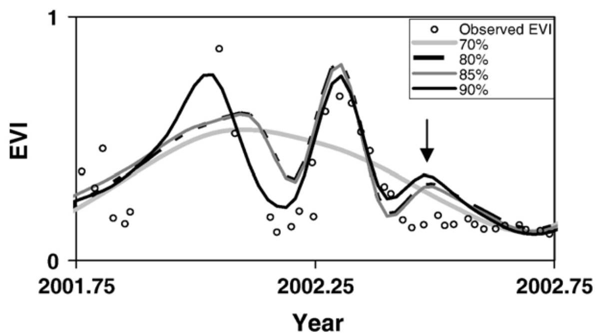

Fig. 6. Comparison of 70% power (9 coefficients), 80% power (15 coefficients), 85% power (19 coefficients) and 90% power (27 coefficients) wavelet-smoothed time series shows how wavelet power determines the amount of detail retained. Circles represent the EVI time series with cloud-contaminated values removed. Using a higher power may fit maxima in the data better but can also create false peaks, indicated here with an arrow. False peaks are removed from crop detection by an EVI threshold of 0.4.

This error analysis shows high overall accuracies and K_{hat} values for all wavelet powers except the 95% power wavelet (Table 1). From these results we conclude the 90% power wavelet-smoothed time series best captures cropping patterns and will be the focus of our further analysis. We employed the 90% power wavelet (27 coefficients) which minimized RMS error and had the lowest omission and commission errors in detecting cropping patterns. Qualitatively, we observed thousands of pixels where the strong overall performance of the 90% wavelet was apparent when compared to the other wavelet powers. Fig. 6 provides one such example. In areas of single crops, the 90% power wavelet captures the overall data trend well, getting closest to the high observed EVI values and the low values while reducing false detections of peaks. The agricultural system gets more complex where there are double crops. Resonance in the wavelet may create false peaks but they do not go above our threshold of 0.4 EVI. Throughout the time series, RMS error is low, on the order of magnitude of 0.1 for the 90% power wavelet-smoothed time series.

The power threshold is a variant on the method of Sakamoto et al. (2005) where multiple frequency thresholds defined the length of plausible growing seasons to remove noise with the wavelet. We chose to use the power variable to remove high frequency noise as it required no assumption of length of growing season. This gives more flexibility in fitting both very narrow peaks, as is often the case in both wide peaks found in single crops and very narrow peaks found in double cropping systems.

Application of the wavelet filter can create distortion around the edges of the EVI time series (Sakamoto et al., 2005). To avoid this problem, we augmented the input EVI time series to allow for spin-up, or conditioning of the wavelet. Conditioning the wavelet is a necessary step shown by Sakamoto et al. (2005). For our application, we augmented the one-dimensional EVI time series by replicating the first and last year worth of data ten times at the beginning and end, respectively, of the time series. After applying the wavelet transform, the extra years of data were removed from the wavelet-smoothed time series.

2.6. Phenology and land cover/land use

The cropping patterns, or the numbers of crops grown each year, were detected from the wavelet-smoothed EVI time series. Each crop is characterized by one maximum in the wavelet-smoothed EVI time series. To determine if a cropland pixel had a single or double cropping pattern, we detected the number of local maximums in one growing year of the wavelet-smoothed EVI time series. We defined a local maximum as having a higher EVI than the two points before and two points after that point. The wavelet-smoothed EVI time series divided into five growing years from August through July for 2000–2005 and are identified by their harvest year: 2001, 2002, 2003, 2004, and 2005.

Wavelets are very sensitive to small maximums in portions of the time series where EVI range is low. The wavelet response to these small local maximums slightly amplifies small real peaks, thereby creating false peaks in phenology. From farm histories, we know that the EVI for crops generally exceeds 0.4. We removed false detections by using a threshold of 0.4 EVI for the 90% power wavelet to minimize false detections to remove these minor false peaks from being detected as phenological peaks of cropland. In some areas we detect two or three real phenological maximums in the EVI time series. In such cases, the first maximum is minor and is likely caused by the early green-up of volunteer crops, weeds or other green cover at the beginning of the rainy season before crops are planted. The second and third maximums, where present, correspond to single and double crops. The early weedy growth or volunteer crops may be distinguished from crops as they do not exceed the 0.4 EVI threshold that prevents us from detecting early green-ups as crops. Utilizing this threshold works with the assumption that every area of row crops has a strong crop phenology (i.e. peaks above 0.4 EVI) but it may exclude very small, real, phenological maximums such as the case of a failing crop that did not exceed the threshold.

With these detection criteria, we can identify the cropping patterns and change in cropping patterns that characterize the intensification and extensification of cropland, as first shown by Sakamoto et al. (2006). For verification of the cropping patterns, we used the observed EVI time series with bad pixels removed. A random point generator selected 122 verification points within the cropland areas. For each point, there are five growing seasons (August–July) in the time series. Each growing season was treated individually, essentially multiplying

Table 2
Total area in row-crop agriculture * is reported here in square kilometers by harvest year

Year	Area (km^2)
2001	6255
2002	6799
2003	7543
2004	8532
2005	9535

* The area of row-crop agriculture was measured by the number or pixels having one or more crops in a year of the 90% wavelet-smoothed time series.