Since the early 1970s, remote sensing studies have tracked the land-cover and land-use changes in the Brazilian Amazon, initially using Landsat data to identify areas of deforestation (Skole & Tucker, 1993). The iconic images of development in the state of Rondonia, off of highway BR364, showed the dramatic impact of deforestation. Recently, the Brazilian Instituto Nacional de Pesquisas Espaciais (INPE; National Institute for Space Research) has used Landsat sensors for monitoring deforestation and detecting fires for the purpose of enforcing environmental regulations (Instituto Nacional de Pesquisas Espaciais, 2006). As conversion from natural vegetation and pasture to row crops has become increasingly widespread, the focus has shifted to documentation of the land cover changes in type localities. For example, Brown et al. (2005) illustrated the large-scale development of soybean agriculture with temporal "snap-shots" of Vilhena, Rondônia with Landsat data in 1996 and 2001. Morton et al. (2006) document widespread, regional changes in land cover. This new focus on cropland detection is particularly important due to the large spatial scale of individual farms (i.e. a single farm of row-crop agriculture typically occupies more than 2000 ha) and regional agricultural intensification (Mueller, 2003).

Remotely-sensed green leaf phenology is one metric for distinguishing the type of land-cover and land-use change and is suitable for agricultural applications. Croplands present a more complex phenology than natural land cover due to their many peaks resulting from multiple crops planted sequentially within a growing season. Additionally, the uniform cover of green leaves in an agricultural field creates very high observed greenness, especially as compared to the bare soils left after harvest. This large dynamic range of cropland green vegetation through time depends highly on natural factors (e.g. magnitude and temporal variability of precipitation in the region), as well as, management decisions (e.g. time of planting, crop variety).

Phenology studies often utilize a curve-fitting algorithm for the observed data sets. A curve-fit simplifies parameterization necessary for identification of metrics such as start of season. Previous studies (e.g. Bradley et al., 2007; Zhang et al., 2003) have identified land cover based on specific properties of the observed green leaf phenology, such as start of season, dry season minimums, and amplitude of maximums. The simplest method for creating a smoothed time series is to use a multi-point smoothing function which may not remove high frequency noise. Other curve-fitting methods, (e.g. Bradley et al., 2007) rely on a harmonic curve-fit to the annual average phenology in order to characterize inter-annual variability of a time series. A sigmod curve-fitting algorithm can be applied to a time series of a single year (Fisher et al., 2006; Zhang et al., 2003) but utilizes *a priori* knowledge of the system's seasonality in order to detect the phenological peaks (i.e. the algorithm must be informed with expectation for when to find the phenological peak) (Fisher et al., 2006; Jönsson & Eklundh, 2004; Zhang et al., 2003).

All of these methods have proven powerful in the systems they have been tested in but will fail in the case of row-crop agriculture in Mato Grosso for three reasons: 1) they fail to remove high frequency noise caused by the long rainy season. A multi-point smoothing function maintains sensitivity to high frequency noise observed during the rainy season which poses problems when trying to detect the maximums defining the cropping system. Using such a smoothing procedure would require a finely-tuned crop detection algorithm that would have to be adjusted for the strong precipitation gradients in the region. 2) They cannot capture the inherent variability in the system. Using an average annual phenology to identify land cover (Bradley et al., 2007) does not work because it does not examine each year separately, a problem since observed annual phenology is not a function of the previous year. In this human environment, the change in phenology from year to year (e.g. when converting from natural vegetation to cropland or intensifying from single crops to double crops) can be tremendous, rendering the average annual phenology of the time series meaningless. The traditional Fourier transform expects periodicity whereas the change in crop behavior from single to double cropping systems in addition to management coupled with climate makes the time-series signal non-stationary, which is better handled by the wavelet transform (Sakamoto et al., 2005). 3) The stochastic nature of rainfall and the influence of human management affect the timing and spatial patterns of phenology peaks that make it difficult to precisely predict the timing. This system fails the criteria of *a priori* knowledge regarding the timing of phenology peaks necessary for some curve-fitting algorithms, such as the sigmod (Fisher et al., 2006; Zhang et al., 2003).

We look to the wavelet-based curve-fitting methodology (Wavelet based Filter for determining Crop Phenology, WFCP) presented by Sakamoto et al. (2005) in order to remove high frequency noise while remaining sensitive to annual changes in phenology. This is a necessary step in accepting WFCP as a generalized methodology. The true utility of such a method comes in being able to apply it to various study areas without sacrificing performance or requiring many changes. Our case study presents a robust test for the wavelet methodology—an area with high variability in phenology patterns with additional noise cause by the tropical rainy season. We are interested in the application of the WFCP in the southwestern Brazilian Amazon because of its curve-fitting capabilities for cropland phenology, as well as, the potential for it to be rapid and highly automated.

We implement a wavelet transform for time-series analysis to study these highly dynamic systems. Wavelet analysis provides an efficient method for extracting relevant information from large data sets such as hyperspectral image cubes, sea surface temperature, vegetated land-cover and seismological signals (e.g., Gendrin et al., 2006; Li & Kafatos, 2000; Mallat, 1998; Percival et al., 2004; Sakamoto et al., 2005, 2006; Torrence & Compo, 1998).

In agricultural applications, a wavelet-smoothed time series can be used to identify the start of growing season and the time of harvest with low error (11 to 14 days, respectively; Sakamoto et al., 2005). Wavelet analysis is capable of handling the range of agricultural patterns that occur through time as well as the spatial heterogeneity of fields that result from precipitation and management decisions because the transform is localized in time and frequency. Using a wavelet analysis for a study area in the Amazon is highly desirable because it removes the high