remotely sensed green-leaf phenology. Because of the frequent anomalous observations (noise) in these data from clouds and other instrument and observation effects, we temporally smoothed the time series with a wavelet transform to distinguish true phenological peaks from noise. Croplands were detected from the wavelet-smoothed time series by their characteristically high annual standard deviation of green-leaf phenology, because crops have large annual phenological changes as they go from essentially bare soil to extremely uniform green cover. The results are grouped into classes of cropland with the cropland class divided into subclasses based on single- and double-cropping patterns from the number of phenological peaks in the wavelet-smoothed time series over the growing year. We have named the growing year for the year of harvest (e.g., August 2000–July 2001 would represent the 2001 growing year), which allows us to track the wet season growth peaks. Each year was analyzed independently of its class from the previous year. Galford et al. (Galford et al. 2008) discuss this methodology in detail.

Further phenological analyses of single- and double-cropping patterns were used to determine areas of extensification (new croplands) and double-cropping intensification (a shift from single to double cropping). We used the 2001 growing year as the baseline year for quantifying change. We classed "extensification" as any area that moved from "not cropland" in 2001 to "cropland" in any subsequent year and remained in cropland through 2006. We identified the source ecosystem cleared for the cropland using the potential natural vegetation map, or the extent of natural vegetation were there no land use, of Mello (Mello 2007) to calculate greenhouse gas emissions. Mello (Mello 2007) collected and compiled natural vegetation data from various state-level offices in Mato Grosso using a geographic information system (GIS).

Besides natural vegetation, croplands may also be derived from pastures. We combined our cropland classification scheme, the natural vegetation map (Mello 2007), and pasture maps generated elsewhere but covering almost the same study period (2001–05; Morton et al. 2009; Morton et al. 2006) to determine these land-use transitions. For 2006, new pasture areas were assumed to have a linear relationship based on the 2001–05 period, and their distribution was weighted by biome. Our approach allows us to identify where and when new croplands are developed directly from each natural ecosystem or from pastures. In the case of pastures, we can identify the natural ecosystem from which they have been derived. The pasture dataset is likely an overestimate of planted pasture in the cerrado region, because it includes natural (unmanaged) grasslands that may not be grazed. Despite these caveats, this is the best spatially explicit estimate of pasture lands available to us for the study period. Pasture-to-cropland transitions were identified where new croplands were detected in areas mapped as pasture in the previous growing season.

To create a spatially coherent product, we smoothed the cropping-pattern classes using a 3×3 pixel window to sieve outlying classes, designating them as unclassed (ITT 2008). Unclassed pixels were then clumped (ITT 2008) into the dominant class within the 3×3 pixel window. Cropping-pattern classes from the sieving and clumping procedure were then validated against field data (see section 2.3 for further discussion of validation). After validation, we restricted analysis to Mato Grosso.