Mapping Asian Cropping Intensity With MODIS

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Abstract—Agricultural systems are geographically extensive, have profound significance to society, and affect regional energy, climate, and water cycles. Since most suitable lands worldwide have been cultivated, there is a growing pressure to increase yields on existing agricultural lands. In tropical and subtropical regions, multicropping is widely used to increase food production, but regional-to-global information related to multicropping practices is poor. The high temporal resolution and moderate spatial resolution of the MODIS sensors provide an ideal source of information for characterizing cropping practices over large areas. Relative to studies that document agricultural extensification, however, systematic assessment of agricultural intensification via multicropping has received relatively little attention. The goal of this work was to help close this information gap by developing methods that use multitemporal remote sensing to map multicropping systems in Asia. Image time-series analysis is especially challenging in this part of the world because atmospheric conditions including clouds and aerosols lead to high frequencies of missing or low-quality observations, especially during the Asian Monsoon. The methodology that we developed builds upon the algorithm used to produce the MODIS Land Cover Dynamics product (MCD12Q2), but uses an improved methodology optimized for crops. We assessed our results at the aggregate scale using state, district, and provincial level inventory statistics reporting total cropped and harvested areas, and at the field scale using survey results for 191 field sites in Bangladesh. While the algorithm highlighted the dominant continental-scale patterns in agricultural practices throughout Asia, and produced reasonable estimates of state and provincial level total harvested areas, field-scale assessment revealed significant challenges in mapping high cropping intensity due to abundant missing data.

Index Terms—Agriculture, remote sensing, time series.

I. INTRODUCTION

ASIA IS HOME to the most intensively farmed croplands on Earth. One-third of global croplands are in Asia, and they account for over half of the world's cereal production, over 45% of total agricultural water withdrawals, and over 70% of the total area equipped for irrigation [1]. Growing demand

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is increasing pressure on Asian croplands to produce more food, but there is a little room for expansion. Nearly 95% of South Asian land suitable for rain-fed agriculture was under cultivation in 1992 [2], and future production increases will overwhelmingly come from agricultural intensification. Agricultural intensification, in a general sense, is the increased use of fertilizer, irrigation, and multicropping practices to increase yields without extending agricultural areas [3], [4]. Intensification is imminent throughout Asia because there is a growing demand for agricultural products and a little room for expansion, but there are serious concerns about the environmental impacts. For instance, significant increases in irrigation are necessary to close existing yield gaps [5], but in areas already suffering from groundwater depletion due to increased withdrawals [6], [7]. Thus, ensuring that intensification does not threaten future water and food security depends on understanding the spatiotemporal dynamics of changing Asian agricultural practices.

There is a long history of remote sensing-based efforts to characterize cropland extent and agricultural practices. Indeed, operational monitoring of agriculture motivated much of the earliest work in remote sensing (e.g., the LACIE and AgRISTARS programs funded by NASA in the 1970s and 1980s [8]–[10]). At the global scale, the MODIS Land Cover Product (MCD12Q1; [11], [12]) provides maps of agriculture and agricultural mosaics at an annual time step and 500-m spatial resolution from 2001 to present. Mapping specific crop rotations, cropping intensity, and irrigation, however, has proven much more challenging using remotely sensed imagery alone. While abundant examples of local- to regional-scale efforts for particular crops and discrete time periods exist (e.g., [13]–[15]), there are a few large-scale results that could be used to identify change over time. For instance, the monthly irrigated and rain-fed crop areas (MIRCA2000; [16]) and the global map of irrigated areas and rain-fed crop areas (GMIA/GMRCA; [17], [18]) provide global maps of irrigation status, cropping intensity, and crop rotations. While extremely valuable, these datasets only provide a "snapshot" in time, and therefore cannot identify change. Further, crop types and cropping cycles are difficult to characterize based on remote sensing alone and ancillary data are often used. For instance, MIRCA2000 used inventory statistics for 402 global administrative areas [19] in combination with various remote sensing-based products [20]–[22]. These census and inventory data have coarse spatial resolution as they are aggregated to political boundaries, report different variables collected with diverse methodologies, and are often unreliable. Thus, while datasets of this type are essential for ensuring sustainable agricultural practices, there is a clear need for improvements that reduce spatial uncertainty, and are capable of identifying changing agricultural practices.

We sought to address these shortcomings and generate Asia-wide maps of multicropping intensity (defined here as the annual cropping frequency) from time series of MODIS spectral vegetation indices (SVIs). Though moderate in spatial resolution, the MODIS sensors provide the temporal sampling frequency required for this type of work. While multicropping represents only one facet of agricultural intensification, it is of critical importance for modeling efforts and is relatively understudied compared to mapping cropland and irrigation extent. Accurate mapping of multicropping practices would complement existing indicators of intensification, providing a fuller understanding necessary to respond to challenges of sustainability and increased production demands. Improved remote sensing methods were developed to address existing methodological limitations, and used to map cropping intensity across most of Asia for the period 2009–2012. Results were assessed at the field- and aggregated provincial-, district-, and state-scales.

II. DATA AND METHODS

Our approach to mapping multicropping intensity throughout Asia refines and extends established remote sensing-based methods for extracting land surface phenology from time series of SVI. Specifically, we refine the time-series segmentation procedure used to generate the MODIS Land Cover Dynamics product (MCD12Q2; [23], [24]) to accommodate more than two cropping cycles per year, to avoid problems caused by crop cycles crossing arbitrary calendar boundaries, and to be more robust against missing data. In contrast to the MCD12Q2 product, however, we make no attempt to extract phenophase transition dates from the time series, but instead focus on counting the total number of cycles in a given time frame.

Time series of enhanced vegetation index (EVI: $2.5 \times [\rho_{nir} - \rho_{red}]/[1 + \rho_{nir} + 6 \times \rho_{red} + 7.5 \times \rho_{blue}]$, where ρ indicates reflectances in the specified wavelengths) were constructed from Collection 5 MODIS Nadir BRDF-Adjusted Reflectances (NBAR) along with their associated quality control (QC) data (MCD43A4 and MCD43A2) [25]. We distinguish this index from EVI calculated using reflectances not corrected for BRDF effects by denoting it as "NBAR-EVI." NBAR-EVI time series had 8-day temporal resolution (resulting from the staggered 16-day compositing procedure), 500-m ground resolution, and were assembled for years 2009–2012 for 40 MODIS tiles encompassing most of Asia. We also assembled MODIS data for the time period 2008–2009 over Bangladesh for field-scale assessment. Individual NBAR-EVI weights were determined as the inverse of one plus the cumulative red, blue, nir band BRDF_Albedo_Band_Quality Science Data Set in MCD43A2 (weight range: 0.1–1, worst to best). Analyses were restricted to areas identified as agriculture and agriculture/natural mosaic in the International Geosphere-Biosphere Project (IGBP) classification scheme in the 2010 MODIS Land Cover Product (MCD12Q1, Type 1).

Fig. 1 graphically depicts our time-series segmentation procedure. The method is based on the MCD12Q2 approach [23] which takes place where the linear slope over a moving-window changes sign to indicate change points between ascending (greening) and descending (browning) phases. However, where
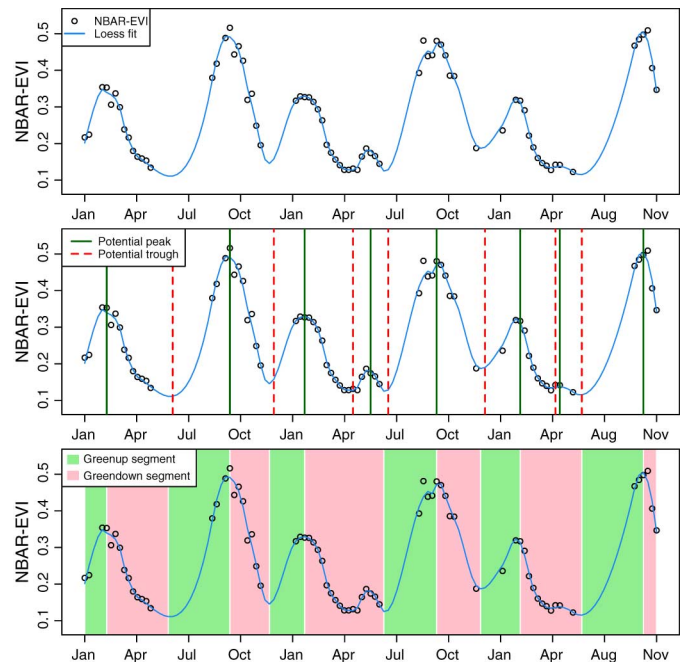

Fig. 1. Overview of the segmentation process as applied to a 3-year, single-pixel time series of NBAR-EVI values. First, a smoothing spline is applied to the raw NBAR-EVI values (symbol size corresponds to fitting weight), then potential peaks/troughs are identified, and finally screened by heuristics to determine final segments.

the MCD12Q2 algorithm utilized a moving-window mean smoothing filter on a gap-filled data, we interpolate and smooth at once using a Loess filter that preliminary testing indicated better preserved temporal NBAR-EVI trajectories and can interpolate long runs of missing data. We produced continuous daily NBAR-EVI series using weighted Loess filtering with the span parameter set to use 33% of the data at once. Moving window size selection is subjective, and in this case, exploratory analysis indicated that 10 days yielded optimal results. Therefore, slopes were calculated on 10-day moving windows on the smoothed time series and days where the slope changed sign flagged as potential change points.

Heuristic filtering is necessary to eliminate spuriously identified vegetation cycles. First, we screened change points by eliminating peaks that were lower than 45% of the time series maximum. For instance, Fig. 1 depicts two potential peak points that were eliminated on the basis of this thresholding procedure. Since some potential peaks may be high enough to clear the global maximum threshold heuristic, but do not have a corresponding trough point that covers a realistic amount of NBAR-EVI amplitude, further filtering was necessary. Thus, we then eliminated segments which did not cover an amplitude of at least 35% of the time-series maximum amplitude (i.e., two peaks separated by a shallow trough). Selecting these parameter values is a subjective process and our selection was guided by visual interpretation of agricultural time series throughout the region. We took the total number of valid peaks in the time series to represent the cropping intensity for that pixel, and recorded the totals for the years 2008–2009 and 2009–2012.

We assessed our results at two spatial scales. First, we assessed district-, provincial-, and state-scale (hereafter
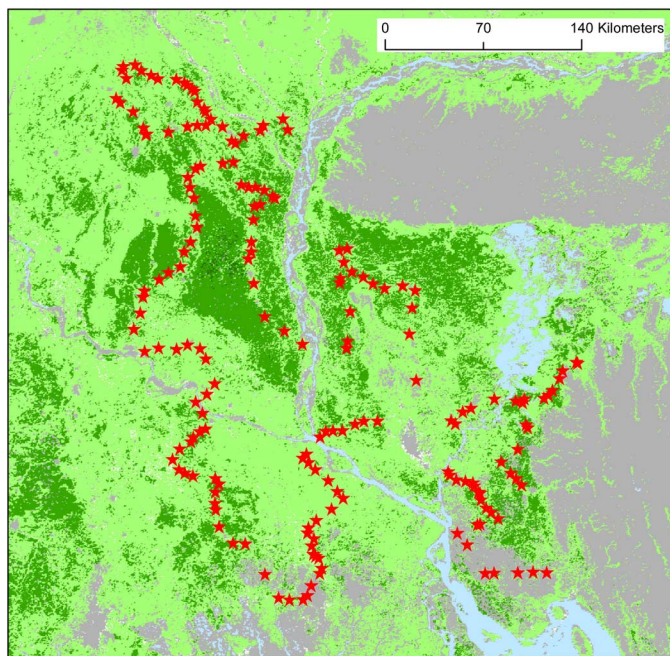
Fig. 2. Location of 191 field validation samples (stars) throughout Bangladesh. Extent is indicated on map in Fig. 3 with which this map shares a legend.

collectively referred to as the "state-scale") total cropped area (Bangladesh and India), and total harvested area (Bangladesh, China, and India) using national-scale inventory statistics. Annual state-scale statistics were averaged over the study period for assessment. In multicropped regions, total harvested area exceeds the amount of land under cultivation (total cropped area). Subpixel land cover heterogeneity was accounted for by computing multiple regression models predicting inventory total cropped area (A_{inv}) with state-scale aggregated agriculture and agriculture/natural mosaic areas (A_{ag} and A_{mosaic}) from the MODIS Land Cover product: $A_{inv} = \beta_0 + \beta_1 A_{ag} + \beta_2 A_{mosaic}$, where β_1 and β_2 are the subpixel calibration coefficients for MODIS Land Cover agricultural and agriculture/natural mosaic areas. Independent models were fit for India and Bangladesh, and the mean model used for China which lacked total cropped area statistics. We then conducted a pixel-scale assessment utilizing field survey data. Survey results recording the total number of cropping cycles in 2008 and 2009, crop types, crop calendars, irrigation status, and GPS locations for 191 fields in an intensively cropped region of Bangladesh (see Fig. 2) were used to assess pixel-level results [26]. The survey was conducted from August 4 to 18, 2010 and concerned the farming practices of the preceding 2 years. Fields in the survey had uniform crop types and management practices at the 500×500 m scale.

III. RESULTS

Results showing average cropping intensity from 2009 to 2012 highlight geographic patterns in agricultural practices across Asia (Fig. 3). In particular, the intensely cropped areas of the Indo-Gangetic plain, Northeast China, and the Mekong Delta [27] show high levels of multicropping. However, in the

western portions of the Sichuan Basin, where extensive terraced rice cultivation exists, frequent missing data prevented reliable retrievals.

Multiple regression model results indicated that the mean subpixel fraction of agriculture in pixels classified as agriculture and agriculture/natural mosaic were 82% and 34%, respectively. While errors in the MCD12Q1 Land Cover product contribute to uncertainty in the areal estimates ([12] calculated producer's accuracies of 84% and 61%, and user's accuracies of 93% and 28% for agriculture and mosaic classes, respectively), there was high correlation between actual and predicted state-scale total cropped area [$R^2 = 94\%$, $p < 0.05$, Fig. 4(a)]. We then used the coefficients and the RS-mapped multicropping areas to predict the total harvested area at the state-scale. We find that we are able to explain 89% of the variability in reported total harvested area across all three countries [$p < 0.05$, Fig. 4(b)]. Residual standard errors are 11 000 and 15 600 km^2 for total cropped and total harvested area, respectively. While large in an absolute sense, these errors represent proportional errors of 5% and 6% in the largest province. The pattern in Fig. 4(b) is largely driven by differences in state areas. State-level comparisons of the ratio of total to net cropped areas from inventory data and remote sensing results indicate low correlation ($R = 0.35$) and considerable underestimates of total cropped area from remote sensing, particularly for Bangladesh.

The class-specific user's and producer's accuracies for the MCD2Q1 product are 83% and 93%, respectively, for class 12 "croplands" and 61% and 28% for class 14 "cropland/natural vegetation mosaic" [12].

Field scale assessment highlights the outstanding challenges in mapping cropping intensity at the pixel scale. The overall classification accuracy was only 11%, and only 25% of fields having two and four total cycles from 2008 to 2009 were correctly identified as such (Table I). Multicropping in general was better mapped, with 22.7% of all fields having four or six total cycles in 2008–2009 mapped as having four or five cropping cycles. However, none of the fields having six total cycles were correctly mapped. In fact, half of those fields were mapped as only having two cropping cycles, and the other half were mapped as having three or four. The peak and amplitude ratio thresholds were implemented to reduce the detection of false cropping cycles due to noise in the time series. However, these heuristics may also limit algorithm accuracy by eliminating true vegetation cycles. To test this effect, we again classified cropping cycles for each of the 191 assessment fields, but without the 35% amplitude threshold. Overall classification accuracy increased to 28% and multicropping accuracy increased to 73% (Table II). While 75% of fields having four cropping cycles were correctly classified, we still failed to map any triple cropping (six total cycles 2008–2009). These results indicate that the algorithm is overall quite conservative, tending to under predict the actual number of cropping cycles at the pixel scale.

IV. DISCUSSION

These results indicate that while our algorithm is capable of capturing large-scale variations in cropping practices across Asia, there are outstanding challenges to mapping
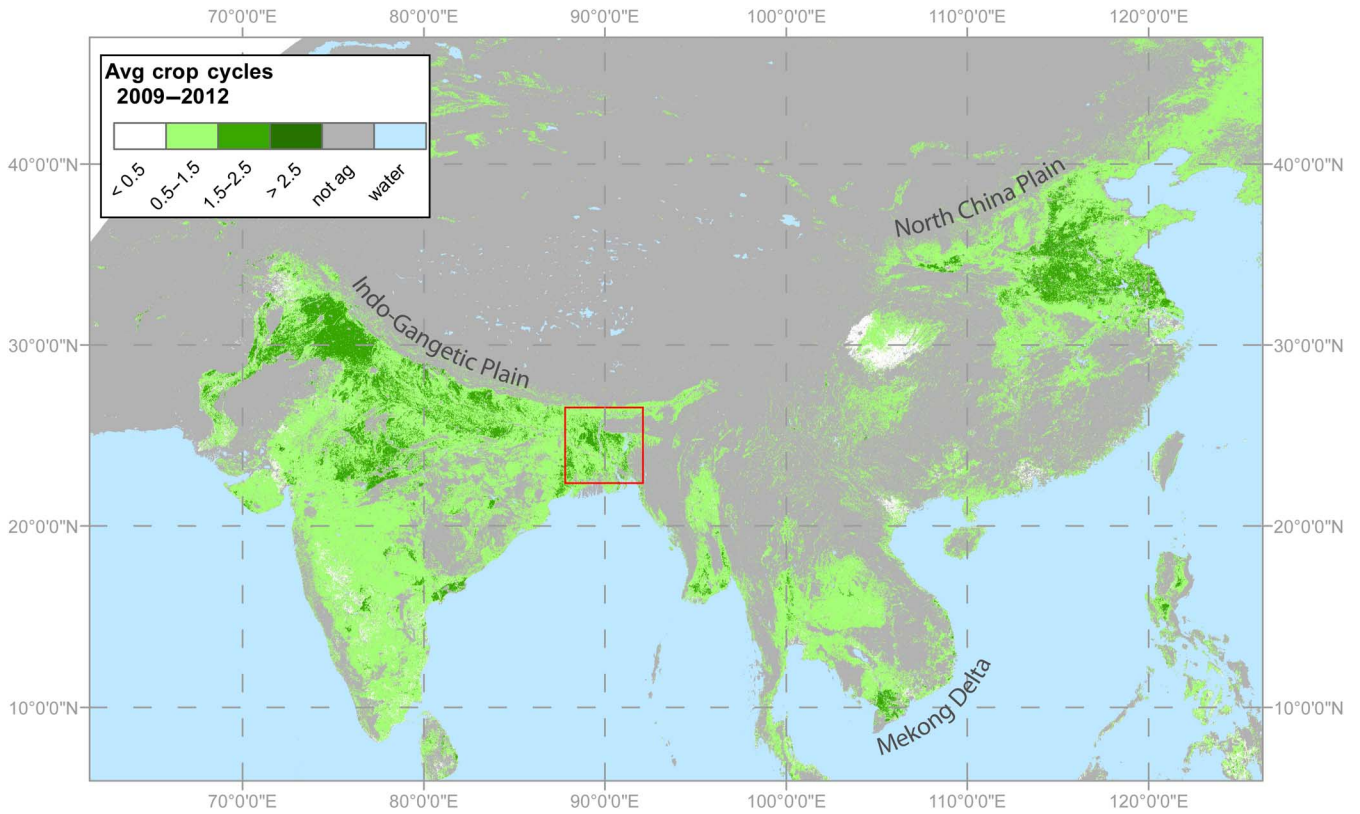
Fig. 3. Mean cropping intensity (average cycles per year) over mainland Asia for the time period 2009–2012. Box indicates the extent of map in Fig. 2.
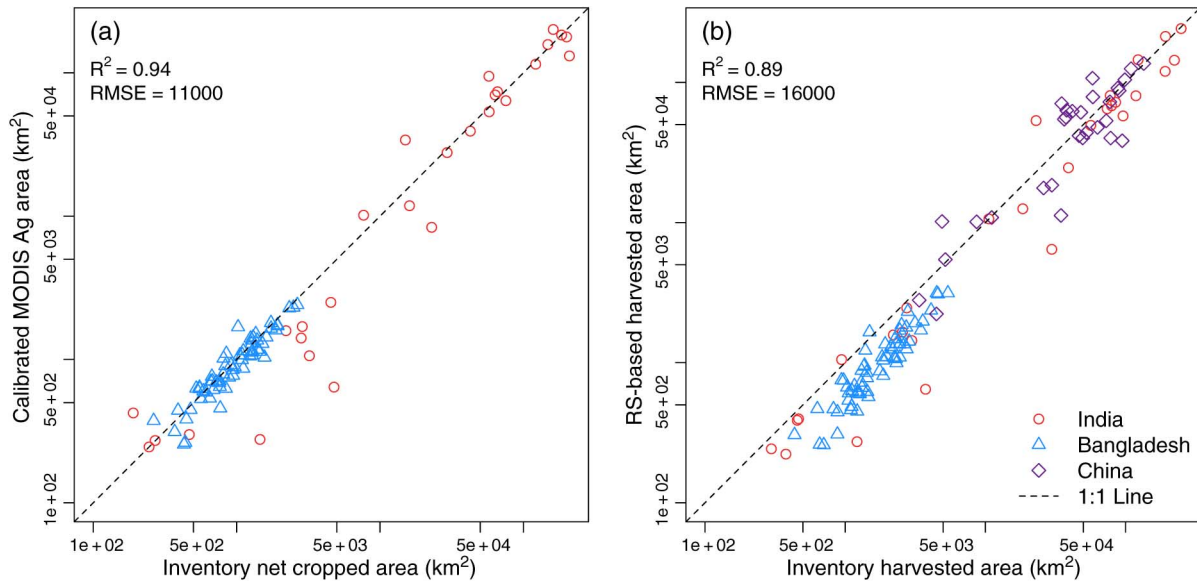

Fig. 4. (a) Census-based total cropped area versus MCD12Q1 calibrated agricultural areas for all districts and states in Bangladesh and India with total cropped greater than 100 km^2. (b) As (a), but for total harvested area and including results for China.

cropping intensity at the pixel scale. Even when heuristic filtering is relaxed, there is considerable difficulty in detecting more than two cropping cycles per year. Analyzing time series over field assessment sites indicates that the primary cause for missed crop cycle detections is abundant missing data, primarily related to the Asian monsoon when MODIS may not obtain a cloud-free observation for many weeks at a time (Fig. 5). Underestimates of total cropped areas resulting from missing

data in MODIS are also common to other studies [14]. Reference [15] showed stronger correlations with inventory data, but did not account for subpixel heterogeneity in MODIS Land Cover as we did. Persistent data gaps mean that entire cropping cycles may be missing from the remote sensing record. For example, Fig. 6 shows the time series and segmentation or a field in Bangladesh that reported triple cropping in 2008 and 2009. Here, the data do not suggest more than two cycles,

TABLE I
CONFUSION MATRIX FOR FIELD-BASED ASSESSMENT

	0	1	2	3	4	5	6	T
0	0	0	2	0	0	0	0	2
1	0	0	0	0	0	0	0	0
2	0	0	2	2	4	0	0	8
3	0	0	0	0	0	0	0	0
4	0	0	28	25	18	0	0	71
5	0	0	0	0	0	0	0	0
6	0	2	68	17	23	0	0	110
T	0	2	100	44	45	0	0	191

Rows are instances of an actual cropping class (1–6), and columns are instances of a predicted class. "T" are row/column totals. For instance, out of 110 field recorded instances of six crops in 2 years, our algorithm predicts 23 as having only four crops.

TABLE II
AS TABLE I, BUT WITHOUT AMPLITUDE RATIO HEURISTICS

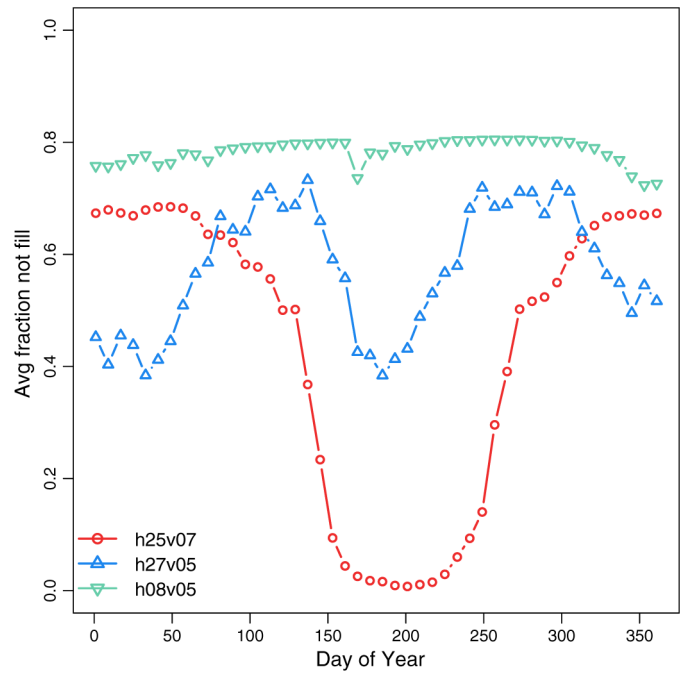|	0	1	2	3	4	5	6	T
0	0	0	0	0	2	0	0	2
1	0	0	0	0	0	0	0	0
2	0	0	1	1	6	0	0	8
3	0	0	0	0	0	0	0	0
4	0	0	8	9	53	1	0	71
5	0	0	0	0	0	0	0	0
6	0	0	13	19	73	5	0	110
T	0	0	22	29	134	6	0	191

Fig. 5. Average fraction of non-missing data in MCD43A4 product from 2001–2012 for tiles in India (h25v07), China (h25v07), and for comparison, over the arid Southwest, United States (h08v05).
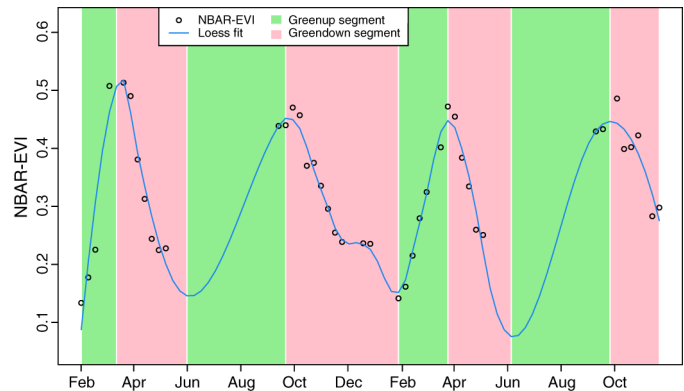

Fig. 6. Example time series and segmentation for a field in Bangladesh that reported three cropping cycles in 2008 and 2009.

but an additional harvest may have occurred during the long period of missing data from May to July (a time period corresponding to the "Aus" cropping season). Thus, future improvements in mapping cropping intensity in Asia will only be realized with methodologies which reduce the missing data problem through incorporation of ancillary and alternative remote sensing data sources such as moderate resolution geostationary satellites (e.g., SEVIRI [28], [29]), microwave sensors (e.g., SeaWinds [30]), and subnational-scale inventory data. In a multisensor fusion context, higher resolution multispectral sensors may provide additional and complementary information, even without benefit of high temporal resolution (e.g., pan-sharpening coarser resolution data).

Interpretation of pixel-scale results is further complicated by the fact that substantial subpixel heterogeneity in land use and cropping practices exists throughout this region. Thus, MODIS reflectance time series may represent the composite response of natural and cultivated vegetation, and multiple independent crops. This is a particular challenge when cultivated and natural vegetation cycles are out of phase (resulting in two detected cycles when only one was cultivated), and when cropping practices are diverse and field sizes are small compared to MODIS pixels. In some cases, crop cycles overlap in the same field. For example, in Northeast China it is common practice for maize to be planted between rows of winter wheat such that the maize has already emerged when the wheat harvest occurs. This results in a shallow NBAR-EVI trough following the wheat harvest because rather than returning to a fallow state, the field contains juvenile maize plants. Relaxing heuristic thresholds may help this problem to some extent, but at the cost of robustness against noise. This may be a viable solution if agricultural areas can be identified *a priori*, because greater than one cycle per year in nonagricultural areas could be suppressed. However, this makes it impossible to use this valuable information to inform the classification of agricultural areas themselves.

V. CONCLUSION

We developed and demonstrated a methodology for mapping cropping intensity, defined here as the number of cropping cycles in a specified time period, and applied it across Asia. State-scale aggregated total cropped and total harvested areas were well correlated with national inventory statistics once MODIS subpixel heterogeneity was accounted for. Field scale assessment highlighted the difficulty in accurately determining cropping intensity, particularly in fields with three cycles per year. We find that field scale results are quite sensitive to the

amplitude threshold heuristic, and that eliminating or reducing this parameter can improve results, but at the expense of robustness against missing data. In general, the algorithm described here produces conservative estimates of pixel-level cropping intensity. Long periods of missing data associated with the Asian monsoon are implicated as the main cause for cropping intensity under estimates because entire crop cycles may be missed due to persistent cloud cover. Therefore, the most promising path toward improving cropping intensity estimates from time series of remotely sensed images is to ameliorate the missing data problem using multisensor fusion with other remote sensing data sources such as microwave and geostationary sensors. Despite these challenges, we show that time series of MODIS NBAR-EVI and a straight-forward time-series segmentation algorithm are capable of highlighting the dominant continental-scale patterns of agricultural practices throughout Asia, and producing reasonable estimates of state and provincial level total cropped and total harvested areas.

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