Cropping intensity and seasonality parameters across Asia extracted by multi-temporal SPOT vegetation data

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Abstract

Detailed analyses are presented of cropping intensity (CI) and crop-seasonality parameters, such as the start and end of a season, the length of a season, and the seasonal amplitude for the period 1999–2010 across Mainland Asia. The analyses used fitted Normalized Difference Vegetation Index (NDVI) time-series data derived from SPOT VEGETATION 10-day synthesis (VGT S10) instruments. Savitzky-Golay noise filtering was applied to the NDVI time series, and the results of an automated extraction procedure were compared with the results of other research analyses. The results indicated that: 1) the projected spatial distribution of CI agreed with other analyses; 2) detected double-cropping regions generally extend over large areas equipped for irrigation; 3) the developed extracting algorithm was capable of estimating CI within Mainland Asia; 4) measured spatial variation at the start of a season adequately represented the crop calendar for each grid and region; 5) low standard deviations (SD) for the start of seasons and seasonal amplitude of NDVI across the period 1999–2010 were closely related to the presence of irrigated cropland, and SD values were relatively high for arid, rainfed zones; 6) there were large elements of uncertainty in estimations of cropping-seasonality parameters caused by (i) cloud contamination of images, (ii) the single setting of the smoothing filter and determinations of seasons’ starts/ends, and (iii) spatial and temporal resolution of satellite data. Detailed analyses of crop seasonality will contribute to progress across a range of agricultural concerns, including local and large-scale food security and the management of complex agricultural systems.

Key words: Asia, Crop seasonality parameters, Cropping intensity, Inter-annual variation, SPOT VEGETATION.

1. Introduction

A comprehensive understanding of cropping intensity and crop-seasonality parameters, such as the start of seasons, the length of growing seasons, seasonal amplitude, and maximum cropping indices, and their interannual variations is essential for progress in investigations of land use, land-cover monitoring, food- and water-resource management, methane emission estimations, human activities, and climate change.

Cropping intensity (CI), which is defined as the number of crops harvested per year, differs widely from region to region in both space and time (Siebert et al., 2010), reflecting differences in water demands, soil conditions, biogeochemical cycles, natural resources, and agricultural production (Monfreda et al., 2008; Portmann et al., 2010). Moreover, unsustainable agricultural land-use practices can cause considerable adverse effects on the ecological environment and on food production in many parts of the world (Yan et al., 2014). Therefore, sufficient knowledge about the extent and dimension of CI is critical in order to ensure food security in agro-ecosystems. Studies that take a CI approach have traditionally used local statistical data focusing on a single year (e.g., George and Samuel, 2003). Siebert et al. (2010) reported a global-scale analysis of CI, cropland extent, crop duration, and fallow land using the MIRCA2000 data set obtained from Portmann et al. (2010). The average CI across the total global extent of cropland was 0.82, rising to 1.13 when fallow lands were excluded. Zhang et al. (2013) demonstrated that increased cropland area and CI due to climatic warming could increase food production to some extent in Tibet’s Autonomous Region.

Sakamoto et al. (2005) developed a paddy seasonality-detection method using the MODIS 500-m time-series data. Yan et al. (2014) indicated that the proportion of cropland cultivated with multiple crops reached 34% in China, and that MODIS 500-m time-series data have the capability and potential to delineate the dynamics of double- and triple-cropping practices. Moreover, NOAA AVHRR time-series data have been used to identify the extent of double-cropping agriculture in Asia (Canisius et al., 2007), and MODIS data have been used to estimate vegetation seasonality as follows: 1) on a global scale (Zhang et al., 2006), 2) for China (Li et al., 2014; Yan et al., 2014), 3) for South and Southeast Asia (Gray et al., 2014; Xiao et al., 2006), and 4) for India (Biradar and Xiao, 2011). However, previous research related to large-scale estimation of CI and crop-seasonality parameters is scant in relation to agricultural extensification studies. Thus, existing approaches may not be sufficient for detailed evaluations of integrated crop management, water management, irrigation-water requirements, and crop-growth models. As a first step towards an inclusive assessment of the rapidly increasing food demand and human food security associated with human population growth in the near future, an accurate CI analysis for Asia is required in a timely manner.

Drawing from the above insights, the present study aims to provide a novel analysis of complex crop cycles in Mainland Asia...
based on fitted NDVI time-series data obtained from SPOT vegetation (VGT) (SPOT-VEGETATION PROGRAMME, 2013) for the period 1999–2010. The detailed objectives are as follows: 1) to produce CI maps of Asia, 2) to derive quantitative measures of the magnitude and variation of crop conditions and seasonality parameters, 3) to estimate the accuracy of CI and crop-seasonality parameters through comparisons with other studies, 4) to reveal the relationship between the spatial distribution of CI and regional characteristics related to terrain, climate, water resources, and farming, and 5) to reveal the advantages and limitations of the technique for the present study.

2. Materials and methods

2.1 Study area and the climate

The study area extended from 0°N to 47°N and from 60°E to 150°E in Mainland Asia. Figure 1 presents the spatial distribution of the averaged monthly temperature and cumulative precipitation in the study area obtained from CRU TS3.10 (Harris et al., 2014). Seasonal climatic patterns across the region are driven by monsoonal weather. In South Asia, the northeast monsoon season generally lasts from September to May. During the northeast monsoon season, Northern India and Bangladesh have cooler and lower-precipitation months. Southern India and Southeast Asia experience warmer weather. Average temperatures in most parts of China range from 4°C to 14°C during the dry season (Figs. 1a and 1c). Conversely, due to high temperatures and low-pressure conditions, southwest monsoons enter the Indian Peninsula and Southeast Asian landmass and produce a hotter and wetter climate (Figs. 1b and 1d).

In the present study, agricultural land cover at 1 km resolution was extracted using data obtained from Fritz et al. (2015) (Fig. 2) that has an overall accuracy of 82.4%. Low- (e.g., larger than 10 km) and medium- (e.g., 1–10 km) spatial resolution optical sensors may not be as suitable for accurate CI estimation as high-spatial resolution sensors because the pixel size of remotely sensed data with medium resolution is usually larger than the small parcels of agricultural landscapes and because the mixel problem is omnipresent in crop seasonality analysis. However, it is important to explore opportunities to improve estimates of CI using evenly distributed time-series sensed data and by striving for low costs and low requirements for computational resources. In the present study, VGT 10-day synthesis instruments (VGT S10) were used for calculations of CI and crop-seasonality parameters. VGT S10 data were computed from all satellite passes over a single location across 10-day periods. The quality of these measurements was derived directly from the quality of VGT physical instruments. The VEGETATION sensor on board the SPOT satellite simultaneously registers in four multispectral bands, which have a spatial resolution of about 1 km: blue (430–470 nm), red (610–680 nm), near-infrared (790–890 nm), and short-

**Fig. 1.** Spatial distribution of averaged monthly temperature (°C) and accumulated precipitation (mm) for 2010 obtained from CRU TS3.1. (a) temperature in the period from December to March, (b) temperature in the period from June to September, (c) precipitation in the period from December to March, and (d) precipitation in the period from June to September.
wave infrared (1580–1750 nm).

To compare the CI and crop-seasonality parameter estimates from the present study with those from other data sets, information was used that was provided mainly by the following sources: the MIRCA2000 (Portmann et al., 2010, and FAOSTAT (FAOSTAT, 2014). MIRCA2000 and FAOSTAT are obtained on the basis of multiple remote sensing, statistical data, ground truth, and previous research. The MIRCA2000 provides monthly growing areas for 26 irrigated and rainfed crop classes at a spatial resolution of 5 arc-min. The following information is available in MIRCA2000: maximum monthly cropped area, monthly growing area, cell-specific cropping calendars (start and end of cropping period), and annual harvested areas.

2.2 Data processing and data used

The processing procedures of the seasonality algorithm comprised six steps: 1) the construction of an agricultural land mask; 2) the calculation of NDVI and smoothing of the NDVI time-series data; 3) the identification of seasonality cycles from the fitted NDVI time-series through a temporal profile analysis; 4) the creation of CI and crop-seasonality parameter maps; and 5) an accuracy assessment based on comparisons with other independent data. A conceptual flowchart of the process of calculating the crop-seasonality parameters and CI is presented in Fig. 3.

The seasonality cycles were determined in agricultural masked pixels. Composited VGT surface reflectance data were then used to calculate NDVI time-series data. When the radiometric quality of a pixel was low for all four of the bands (as judged by a status map of S10 instruments), it was excluded from the calculations; excluded pixels were replaced in the land-cover maps by spline interpolation. Subsequently, the NDVI was obtained from the composited S10 instruments as: 

\[ \text{NDVI} = \frac{\text{IR} - \text{R}}{\text{IR} + \text{R}} \]

where IR and R are surface reflectance in near-infrared and red, respectively. It was then possible to create a Non-fitted NDVI time series for the period 1999–2010 for each grid cell containing agricultural data.

The noise contained in the NDVI time-series data often makes it difficult to determine the number of seasons and crop seasonality. The extraction of seasonality parameters requires smooth curves of the NDVI time series in which noise unrelated to crop growth and development has been damped (Chen et al., 2004; Sakamoto et al., 2005). The Savitzky-Golay filtering method (Savitzky and Golay, 1964) based on least-squares local polynomial smoothing functions was used to generate fitted NDVI time-series data; this is a widely used procedure in absorption spectroscopy that is applicable to the filtering and differentiation of reflectance spectra (King et al., 1999). It enables an accurate understanding of CI details and seasonal phenological cycles. In the present study, window size and degree of polynomial were set to 5 and 4, respectively. Detailed explanations of Savitzky-Golay filtering are beyond the scope of the present work; more-technical information on noise reduction is offered by Savitzky and Golay (1964).

2.3 Determining crop-seasonality parameters from the fitted NDVI time series

The following crop-seasonality parameters were determined: 1) start of season, determined as the point in time when the left side of the temporal profile reached the NDVI threshold value (see below); 2) end of season, determined as the point in time when the right side of the profile decreased to the NDVI threshold value; 3) length of season, determined as the duration of time from the start to the end of the season; 4) maximum NDVI for the fitted function during the season \( \langle \text{NDVI}_{\text{max}} \rangle \); and 5) minimum NDVI for the fitted function during the season \( \langle \text{NDVI}_{\text{min}} \rangle \).

To identify crop-seasonality parameters from the fitted NDVI time series, the following discrete procedures were applied to each pixel: 1) \( \text{NDVI}_{\text{max}} \) was identified for the year in question, and

![Fig. 2. Agricultural mask used in the present study obtained from Frits et al. (2015).](image-url)
3. Results and discussion

3.1 Seasonality profile in the NDVI time series

Crop-seasonality parameters obtained from the fitted NDVI time series varied among grids, regions, and crop types. Figure 4 presents NDVI temporal profiles for 10 sites in major grain-growing regions cultivated by single- or double-cropping systems. Each site indicated in Fig. 4 was selected (from the MIRCA2000 data set) with proportions of wheat, corn, and rice to total crop-harvested areas that exceeded 80%.

In the major growing areas of Northern China, corn is the major crop. The sites in Northern China, (a) and (b) in Fig. 4, were identifiable as cornfields. Both sites were cropped once per season, and the starting dates were mid-May and early June. The season lengths were similar at the two sites, but the values of the maximum NDVI, seasonal amplitude of NDVI, and the large seasonal integral were higher at site (b). Sites (c) and (d) on the North China Plain had two crop-growth curves per season, with rotations of winter wheat and corn. The start of the seasons of the first and second crop cycles was similar in sites (c) and (d). A small additional peak in winter wheat NDVI values usually occurred before vernalization. Small NDVI peaks were observed in the December-January period. At the start of the season, plants were in the tillering stage. NDVI values peaked in the heading stage in late July, after which values decreased until the maturity date. The time interval between the end of the season for winter wheat in the first cycle and the start of the season for corn in the second cycle was ~30 days. The season lengths of the two crops were similar,
but the NDVI_max for corn was slightly larger than that for winter wheat.

3.2 Spatial distribution of CI

CI values for Mainland Asia were estimated using fitted NDVI time-series values obtained from VGT (CI_VGT). Figure 5a presents the annual average CI_VGT values for the period 1999–2010; Figure 5b presents CI for the year 2000 calculated from the MIRCA2000 data set (CI_MIRCA = total harvested area / cropland extent). Table 1 presents the CI values (including and excluding fallow land) obtained from FAOSTAT (CI_FAO), MIRCA2000, and VGT. The estimated CI_VGT values clearly portray interregional characteristics and double-cropping zones that differ from CI_MIRCA. Estimates of CI_VGT for nations with breadbasket regions in Asia were generally larger than CI_MIRCA. Differences between CI_VGT and CI_MIRCA were relatively large for China. In arid regions of China, values of CI_VGT were close to 1.0, which was expected because the average temperature in the winter season from October to April was lower than approximately 10°C in these regions, and there was little monthly precipitation. Accordingly, these regions have uni-modal crop-growth curves, and farmers cultivated a single crop every year on the same land. Irrigation provides little supplementation to the water provided by precipitation in these regions because the irrigation infrastructure and water resources are limited in comparison with the Huai River Basin and Southern China; farmers rarely harvest more than one crop a year on lands in these Northern regions. By contrast, double cropping

Fig. 4. NDVI time-series data for the period 1999–2010 for the ten sites ((a) 42:08N, 119:07E, (b) 43:19N, 122:10E, (c) 32:43N, 119:50E, (d) 33:59N, 114:37E).

Fig. 5. Spatial patterns of average cropping intensity in mainland Asia during the period 1999–2010, derived from (a) the fitted NDVI time series of VGT 10-day surface reflectance data at 1-km spatial resolution, and (b) the MIRCA2000 dataset at 5 arc min spatial resolution.
is common in the North China Plain (Fig. 5a), where winter wheat is cultivated in combination with rice or corn. In major parts of the Huai River Basin and the Pearl River Delta, the climate is warm and water resources are adequate, a combination that permits double cropping of paddy rice (Yan et al., 2014). The spatial distribution of CI for both river basins were almost similar to Yan et al. (2014) and Li et al. (2014).

Double-cropping regions of the Indian subcontinent occur mainly on the Indo-Gangetic Plain and in the Ganges Basin, where the area equipped for irrigation accounts for > 75% of the arable land (Siebert et al., 2005). Abundant water resources from the Western and Eastern Indian Himalayas and the Ganges River are available for crops during the dry season. In regard to the spatial pattern, the double-cropped area (CI$_{\text{VGT}}$ ≈ 2.0) shares a larger proportion in the Great Northern Plains of India, which was generally consistent with national maps of multiple-cropped arable lands provided by Biradar and Xiao (2011). Overall, the spatial distribution of CI using VGT S10 in Mainland Asia would faithfully reflect the regional characteristics of crop cultivation, avoiding costly and time-consuming image-processing procedures. The use of VGT S10 data can allow a detailed analysis of the spatial patterns and interannual variability of the crop-phenology metrics across very large geographic areas and without missing data compared to using MODIS and AVHRR. Future objectives of the study include analyzing the root causes of differences in CI$_{\text{FAO}}$, CI$_{\text{MIRCA}}$, and CI$_{\text{VGT}}$, which will be needed to address spatial agreement and temporal variability of crop-seasonality parameters more accurately.

### Table 1. National-level cropping intensities including (CI) and excluding (CI$_{\text{NF}}$) fallow land for the year 2000 (FAOSTAT values of CI$_{\text{NF}}$ for fallow land are from 2001).  

| Nation       | FAOSTAT$^*$ CI | FAOSTAT$^*$ CI$_{\text{NF}}$ | MIRCA2000$^{**}$ CI | MIRCA2000$^{**}$ CI$_{\text{NF}}$ | VGT$^{***}$ CI | VGT$^{***}$ CI$_{\text{NF}}$ |
|--------------|---------------|-------------------------------|---------------------|----------------------------------|----------------|------------------|
| Afghanistan  | 0.41          | 1.22                          | 1.01                | 1.16                             | 0.63           | 1.12             |
| Bangladesh   | 1.68          | 1.76                          | 1.23                | 1.52                             | 1.82           | 1.84             |
| Brunei       | 2.35          | –                             | 1.36                | 1.36                             | 1.25           | 1.25             |
| Bhutan       | 1.27          | –                             | 1.02                | 1.19                             | 1.38           | 1.50             |
| China        | 1.69          | –                             | 1.05                | 1.29                             | 1.57           | 1.62             |
| Hong Kong (China) | 0.42     | –                             | 1.06                | 1.08                             | 0.99           | 1.00             |
| India        | 1.43          | 1.67                          | 1.10                | 1.24                             | 1.45           | 1.49             |
| Japan        | 0.71          | –                             | 1.10                | 1.12                             | 1.06           | 1.07             |
| Kyrgyzstan   | 0.79          | –                             | 1.00                | 1.02                             | 0.97           | 1.02             |
| Cambodia     | 0.61          | –                             | 1.09                | 1.09                             | 1.51           | 1.51             |
| South Korea  | 1.44          | –                             | 1.00                | 1.03                             | 1.13           | 1.14             |
| Lao PDR      | 1.07          | –                             | 1.16                | 1.19                             | 1.60           | 1.60             |
| Sri Lanka    | 1.11          | 1.65                          | 1.25                | 1.29                             | 1.51           | 1.53             |
| Myanmar      | 1.54          | –                             | 1.10                | 1.17                             | 1.49           | 1.50             |
| Malaysia     | 1.14          | –                             | 1.03                | 1.03                             | 1.29           | 1.29             |
| Pakistan     | 1.25          | 1.80                          | 1.01                | 1.46                             | 1.47           | 1.70             |
| Philippines  | 1.81          | –                             | 1.11                | 1.15                             | 1.49           | 1.49             |
| North Korea  | 1.22          | –                             | 1.00                | 1.01                             | 0.99           | 1.00             |
| Singapore    | 0.62          | –                             | 1.78                | 1.80                             | 1.20           | 1.33             |
| Thailand     | 0.95          | 0.97                          | 1.08                | 1.10                             | 1.35           | 1.35             |
| Tajikistan   | 1.55          | 1.60                          | 1.14                | 1.27                             | 0.99           | 1.07             |
| Taiwan       | 1.01          | –                             | 1.26                | 1.36                             | 1.45           | 1.46             |
| Uzbekistan   | 1.38          | –                             | 1.03                | 1.12                             | 1.13           | 1.23             |
| Vietnam      | 1.52          | –                             | 1.10                | 1.16                             | 1.42           | 1.43             |

$^*$ FAOSTAT: faostat.fao.org  
$^{**}$ MIRCA2000: Portmann et al. (2010)  
$^{***}$ SPOT VEGETATION (VGT): SPOT-VEGETATION PROGRAMME (2013)
China Plain started in June (Fig. 6b); this spatial pattern was generally consistent with data obtained from the USDA (2014). Although NDVI values will change according to soil conditions, it was confirmed that noise reduction and the threshold method used in the present study can properly evaluate the start/end of seasons compared to the USDA (2014). Overall, the NDVI threshold methodology adopted for determining the start of the season is rather convincing, but the more acceptable rule in each region and crops is important for the performance improvement of the algorithm used and for incremental knowledge for science of the remote-sensing technique.

**3.4 Interannual variation in start of season and seasonal amplitude**

Figure 7 presents spatial patterns in the standard deviation (SD) for the period 1999–2010 for (a) start of season in the first season (day), (b) start of season in the second season (day), (c) seasonal amplitude of NDVI in the first season (100×NDVI), and (d) seasonal amplitude of NDVI in the second season (100×NDVI).
change, change of irrigated areas, and soil and climate conditions. Additionally, crop-seasonality parameters are closely related to actual crop-growth processes on a pixel-by-pixel basis; these parameters not only correspond directly to actual, ground-based phenological events but also provide indicators of climate variations (Pan et al., 2015).

The Ganges River Basin, which has intensive irrigation agriculture, had lower SDs for the start of seasons and seasonal amplitudes of NDVI. The starts of the seasons in this region were largely invariant. Thus, stable crop production has been implemented in the irrigated lands of India.

Rainfed cropping zones in Southern India, Thailand, Myanmar, Vietnam and inland China also had relatively high SD values. Starts of seasons and crop cycles in these regions are affected by the vagaries of weather conditions, especially during the dry season. Grain-producing regions in Shandong, Henan, and Anhui formed a zone of mixed high and low SD values for the start of the seasons in the first season (Fig. 7a). High SD values may be attributable to differences in the timing of the panicle formation stage for winter wheat, which is dependent on cumulative temperatures during the first vegetative stage. Overall, irrigated areas, estuaries, and river basins would have relatively low SD values for the start of seasons except for irrigated winter wheat zones in China. In addition, irrigated (rainfed) areas would also have relatively low (high) SD values for seasonal amplitude of NDVI due to stable (unstable) production of crops.

3.5 Uncertainties and limitations of the analysis

The main discrepancies between CI values calculated in the present study and those of other studies arose from the following: 1) information loss and noise within remote-sensing images caused by frequent cloud cover, 2) a single setting of the smoothing filter and determination of season start/end, and 3) the spatial and temporal resolution of satellite data.

The VGT S10 instruments contained cloud-contaminated pixels: ~ 24% of all land pixels in Mainland Asia for 1999–2010 were contaminated in this manner. Across tropical and subtropical regions suitable for arable agriculture, NDVI values obtained from red and infrared bands were compromised by noise components mixed into surface radiances for both bands; furthermore, satellite data availability was often impacted by frequent cloud cover. To mitigate this effect, Savitzky-Golay filtering was applied to the temporal NDVI time series for each grid cell. Although it was confirmed that the detection algorithm used in the present study allowed a robust estimation of CI and crop seasonality parameters for areas, as the geographical extent of the study area is vast, the temporal profiles of NDVI also vary greatly across the space. Therefore, a single setting of the Savitzky-Golay filter and the threshold values adopted for determining the start/end of the season may not be valid across the land mass. It is better to divide the area into homogenous zones using time-series principal component analysis and to fit the temporal NDVI profile accordingly.

When VGT data at a spatial resolution of ~1 km were used, an element of uncertainty was introduced by mixed pixels containing more than one land-cover type. Consequently, the classification accuracy for crop fields and the estimation accuracy of CI may have been diminished in regions with mixed land use, complex topography, or crop fields that are much smaller than the pixel dimensions of 1 × 1 km. Li et al., (2014) reported that family-farmed fields have areas of 0.01–2.00 ha in Central and Eastern China; these plots of land are smaller than the resolution of the VGT data. Moreover, temporal resolution of sensed data is also important for the reliable determination of the CI and crop-seasonality parameters.

4. Conclusions

The present study focused on Mainland Asia and found that the cropping intensity represented the regional characteristics well. The procedure outlined in this study will therefore contribute to: 1) effective agricultural land-use management to ensure food security and 2) future research on large-scale land-cover dynamics. The following results were obtained:

1. The application of mapping algorithms produced spatial patterns of cropping intensity and crop seasonality parameters for the period 1999–2010 that were generally consistent with multiple-cropping spatial patterns obtained by other analyses. The procedures in the present study provided substantial detailed information at the 1 km grid cell for cropping intensity and crop-seasonality parameters.

2. The standard deviation (SD) for the period 1999–2010 was calculated for the start of season and seasonal amplitude of NDVI. It was found that the SDs for the start of season and seasonal amplitude of NDVI were relatively high where rainfed crops are cultivated; most of the lower SDs were related to irrigated cropland.

3. The present study identified uncertainties in estimations of cropping intensity and seasonality parameters caused by 1) cloud contamination of images, 2) the single setting of the smoothing filter and the determination of season start/end, and 3) the spatial and temporal resolution of satellite data.

More-detailed spatial and temporal resolution will be crucial for reducing uncertainties in the estimations of crop-growth characteristics and dynamics. The extraction of seasonality parameters through remote sensing provides a powerful tool for evaluating the magnitude and distribution of crop phenologies.

References

AQUASTAT, 2014: FAO’s global water information system. Available at http://www.fao.org/nr/water/aquastat/main/index.stm. (accessed on 20 Nov. 2015).

Biradar, C. M., and Xiao, X., 2011: Quantifying the area and spatial distribution of double- and triple-cropping croplands in India with multi-temporal MODIS imagery in 2005. International Journal of Remote Sensing, 32, 367–386.

Canisius, F., Turrell, H., and Molden, D., 2007: Fourier analysis of historical NOAA time series data to estimate bimodal agriculture. International Journal of Remote Sensing, 28, 5503–5522.

Chen, J., Jönsson, P., Tamura, M., Gu, Z., Matsushita, B., and Eklundh, L., 2004: A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. Remote Sensing of Environment, 91, 332–344.

FAOSTAT, 2014: The food and agriculture organization corpo-
rate statistical database. Available at http://faostat.fao.org/site/567/DesktopDefault.aspx. (accessed on 12 Nov. 2015).

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., Abdel Azziz, S., Cipriani, A., Cumani, R., Cecchi, G., Conchedda, G., Ferreira, S., Gomez, A., Haffani, M., Kayitakire, F., Malanding, J., Mueller, R., Newby, T., Nonguierma, A., Olusegun, A., Ortner, S., Rajak, D. R., Rocha, J., Schepaschenko, D., Schepaschenko, M., Terekhov, A., Tiangwa, A., Vancutsem, C., Vintrou, E., Wenbin, W., van der Velde, M., Dunwoody, A., Kraxner, F., and Obersteiner, M., 2015: Mapping global cropland and field size. Global Change Biology, 21, 1980–1992.

George, C. S. L., and Samuel, P. S. H., 2003: China’s land resources and land-use change: insights from the 1996 land survey. Land Use Policy, 20, 87–107.

Gray, J., Friedl, M., Froliking, S., Ramankutty, N., Nelson, A., Krishna Gumma, M., 2014: Mapping Asian cropping intensity with MODIS. IEEE Journal of selected topics in applied earth observation and remote sensing, 7, 3373–3379.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H., 2014: Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. International Journal of Climatology, 34, 623–642.

King, R. L., Ruffin, C., LaMastus, F. E., and Shaw, D. R., 1999: The analysis of hyperspectral data using Savitzky-Golay filtering-practical issues. Geoscience and Remote Sensing Symposium, IGARSS ‘99 Proceedings. IEEE 1999 International, 1, 398–400.

Li, L., Friedl, M. A., Xin, Q., Gray, J., Pan, Y., and Froliking, S., 2014: Mapping crop cycles in China using MODIS-EVI time series. Remote Sensing, 6, 2473–2493.

Montfreda, C., Ramankutty, N., and Foley, J. A., 2008: Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles, 22, GB1022.

Pan, Z., Huang, J., Zhou, Q., Wang, L., Cheng, Y., Zhang, H., Blackburn, G. A., Yan, J., and Liu, J., 2015: Mapping crop phenology using NDVI time-series derived from HJ-1 A/B data. International Journal of Applied Earth Observation and Geoinformation, 34, 188–197.

Portmann, F. T., Siebert, S., and Döll, P., 2010: MIRCA2000 — Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution dataset for agricultural and hydrological modelling. Global Biogeochemical Cycles, 24, GB1011.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., and Ohno, H., 2005: A Crop Phenology Detection Method Using Time-Series MODIS Data. Remote Sensing of Environment, 96, 366–374.

Savitzky, A., and Golay, M. J. E., 1964: Smoothing and differentiation of data by simplified least squares procedures. Analytical Chemistry, 36, 1627–1639.

Siebert, S., Döll, P., Hoogeveen, J., Faures, J. M., Frenken, K., and Feick, S., 2005: Development and validation of the global map of irrigation areas. Hydrology and Earth System Sciences, 9, 535–547.

Siebert, S., Portmann, F. T., and Döll, P., 2010: Global patterns of cropland use intensity. Remote Sensing, 2, 1625–1643.

SPOT-VEGETATION PROGRAMME, 2013: Available at http://nieuw.vgt.vito.be/. (accessed on 5 Sep 2015).

USDA, 2014: Major World Crop Areas and Climate Profiles (MWCACP). Available at http://www.usda.gov/oce/weather/pubs/Other/MWCACP/. (accessed on 20 Nov 2014).

Zhang, G., Dong, J., Zhou, C., Xu, X., Wang, M., Ouyang, H., and Xiao, X., 2013: Increasing cropping intensity in response to climate warming in Tibetan Plateau, China. Field Crops Research, 142, 36–46.

Zhang, X., Friedl, M. A., and Schaaf, C. B., 2006: Global vegetation phenology from Moderate Resolution Imaging Spectroradiometer (MODIS) – evaluation of global patterns and comparison with in situ measurements. Journal of Geophysical Research, 111, G04017.

Zhu, J., Miller, A. E., Martyn, P., Lindsay, C., Broderston, D., and Heinrichs, T., 2014: AVHRR-derived NDVI metrics product user manual version 1.0. Available at MODIS NDVI products and metrics user manual version 1.0. Available at http://static.gina.alaska.edu/NPS_products/AVHRR-NDVI/AV_HRR Derived_NDVI_Metrics/AVHRR derived_NDVI_metrics_ver1.0.pdf. (accessed on 20 Aug 2015).

Xiao, X., Boles, S., Froliking, S., Li, C., Babu, J. Y., Salas, W., and Moore III, B., 2006: Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sensing of Environment, 100, 95–113.

Yan, H., Xiao, X., Huang, H., Liu, J., Chen, J., and Bai, X., 2014: Multiple cropping intensity in China derived from agrometeorological observations and MODIS data. Chinese Geographical Science, 24, 205–219.