New indicators for global crop monitoring in CropWatch - case study in North China Plain

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Abstract: CropWatch is a monitoring system developed and operated by the Institute of Remote Sensing and Digital Earth (Chinese Academy of Sciences) to provide global-scale crop information. Now in its 15th year of operation, CropWatch was modified several times to be a timely, comprehensive and independent global agricultural monitoring system using advanced remote sensing technology. Currently CropWatch is being upgraded with new indicators based on new sensors, especially those on board of China Environmental Satellite (HJ-1 CCD), the Medium Resolution Spectral Imager (MERSI) on Chinese meteorological satellite (FY-3A) and cloud classification products of FY-2. With new satellite data, CropWatch will generate new indicators such as fallow land ratio (FLR), crop condition for irrigated (CCI) and non-irrigated (CCNI) areas separately, photosynthetically active radiation (PAR), radiation use efficiency for the photosynthetically active radiation (RUE_PAR) and cropping index (CI) with crop rotation information (CRI). In this paper, the methods for monitoring the new indicators are applied to the North China Plain which is one of the major grain producing areas in China. This paper shows the preliminary results of the new indicators and methods; they still need to be thoroughly validated before being incorporated into the operational CropWatch system. In the future, the new and improved indicators will help us to better understand the global situation of food security.

Keywords: remote sensing, crop monitoring, crop forecasting, CropWatch, global crop outlook

1. Introduction
Monitoring the production of main agricultural crops is important to predict and prepare for disruptions in food supply and fluctuations in global crop market prices. Timely, reliable and objective predictions of crop condition and production are needed to implement national and global food security plans, as well as crop import, export and pricing policies [1]. Several countries and organizations, including the United States, the European Commission, the Food and Agriculture Organization of the United Nations (FAO), China, Brazil, Canada, and India currently operate crop monitoring systems to monitor their domestic or regional and global crop production. China’s global crop monitoring began in 1998 with the development of CropWatch. CropWatch is designed specifically to use remote sensing data to assess national and global crop production. While all global crop monitoring systems rely on remote sensing data to a certain extent, CropWatch is unique in that it has significantly reduced the need for visual assessments, field monitoring, and expert reviews. During

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its 15 years operation, CropWatch was modified several times to be a timely, comprehensive and independent global agricultural monitoring system using advanced monitoring technology. It provides production estimates for wheat, maize, rice, and soybean and covers most of the major grain-producing countries in the world [2].

In the last few years, many new sensors have been deployed, including Chinese sensors such as the China Environmental Satellite (HJ-1 CCD) and the Medium Resolution Spectral Imager (MERSI) on the FY-3A satellite. In combination with Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership (NPP) satellite, they will provide more opportunities for improved crop monitoring, especially at global scale. Currently CropWatch is being upgraded with new indicators based on new Chinese sensors.

With new satellite data, CropWatch will generate new indicators such as fallow land ratio (FLR), crop condition for irrigated (CCAI) and non-irrigated (CCAN) areas separately, photosynthetically active radiation (PAR), radiation use efficiency for the photosynthetically active radiation (RUE\textsubscript{PAR}) and crop rotation information (CRI). Fallow land ratio, irrigated and non-irrigated crop condition are good indicators for crop/grain growing condition. Indicators of crop rotation and cropping index represent land use intensity, which are good predictors for annual crop output. Photosynthetically active radiation (PAR) is an essential factor to determine the growth and productivity of plants. Radiation use efficiency for the photosynthetically active radiation (RUE\textsubscript{PAR}) is an important variable for estimating the net primary productivity (NPP), which is widely used in assessing crop yield [3]. Land surface temperature can potentially be used both as a measure of heat and drought impact [4][5]. Accumulated land surface temperature was used as the major factor to estimate RUE\textsubscript{PAR}. With the incorporation of the new and improved indicators, the CropWatch system can provide reliable information on grain production and the global situation of food security.

In this paper, the methods for monitoring those new indicators are presented and applied to the study area North China Plain which is one of the major grain producing areas in China. This work is the first step of incorporating the new indicators into CropWatch system; collection of additional field data, calibration and verification will be carried out in the future.

2. Material and methods

2.1. Site Description

This paper focuses on the North China Plain (NCP), which extends from 32°00' N to 40°24' N and 112°48' E to 122°45' E. The study area covers about 310,000 km\textsuperscript{2}. Seven provinces/mega-cities are situated in the Plain (Beijing, Tianjin, part of Hebei, Shandong, Henan, Anhui and Jiangsu province). NCP is affected by very diverse climatic conditions, from cold arid steppe climate to humid warm temperate with hot summer. Farming practices and rainfed climatic production potential vary accordingly. The climate is continental in the whole area. Refer to table 1 for details. Most part of the region belongs to the warm temperate climate zone. The mean annual precipitation ranges between 480 and 1050mm; it is concentrated between June and September, during the summer monsoon. The study area is characterized by the cultivation of wheat, maize, rice, cotton, groundnut, soybean and vegetables in farms subdivided into very small parcels belonging to various families.

Table 1. Some climatic features of the NCP area. The data in the table stem from the FAO/DWD New_LocClim database and software [6].

| Items               | Anhui    | Beijing  | Hebei    | Henan    | Shandong  | Tianjin  |
|---------------------|----------|----------|----------|----------|-----------|----------|
| Longitude(DD.dd)    | 117.28   | 116.40   | 114.47   | 113.75   | 117.02    | 117.20   |
| Latitude(DD.dd)     | 31.86    | 39.30    | 38.04    | 34.77    | 36.67     | 39.08    |
### Table: Climate Information

| Altitude (m) | Köppen climate class | Köppen Climate description | Budyko radiation dryness | Budko runoff (%) | Gorczynski Continentality | Miami model rainfed NPP (g (DM)/m²/year) |
|-------------|----------------------|----------------------------|--------------------------|-----------------|---------------------------|----------------------------------------|
| 20          | Cfa                  | Humid warm temperate with hot summer | 1.251                    | 22.8            | 62.7                      | 1428                                   |
| 20          | Dwa                  | Snow climate with winter hot | 1.865                    | 11.7            | 60.0                      | 990                                    |
| 60          | BSK                  | Cold steppe climate         | 2.164                    | 8.9             | 59.9                      | 887                                    |
| 100         | Cwa                  | Warm temperate with dry and hot summer | 1.894                   | 11.5            | 61.0                      | 1045                                   |
| 20          | Cwa                  | Warm temperate with dry and hot summer | 1.773                   | 13.0            | 61.0                      | 1081                                   |
| 0           | Bsk                  | Cold steppe climate         | 2.213                    | 8.2             | 68.1                      | 862                                    |

2.2. Remote sensing data

Both high- and low-resolution remote sensing data, combined with selected field data, were used to calculate and present the new indicators for crop monitoring over the study area. Multi-temporal China Environment Satellite (HJ-1) CCD images were acquired to map fallow and cropped area in NCP. The HJ-1 CCD image processing, which included geo-correction, radiance calibration and atmospheric correction, was carried out using the ENVI 4.8 software.

Time series of 16-day composite MODIS 250 m NDVI data (MOD/MYD13Q1 V005), 8-day composite MODIS surface reflectance product (MOD09A1, V005) and 8-day composite MODIS land surface temperature product (MYD11A2 V005) were acquired during 2010 and 2011 from the next generation metadata and service discovery tools Reverb (http://reverb.echo.nasa.gov). Five tiles (h26v04, h26v05, h27v04, h27v05 and h28v05) were used.

The data from Chinese geostationary meteorological satellite (FY-2) were acquired to generate remote sensing derived PAR.

2.3. Methodology

CropWatch system components carry out crop condition monitoring, drought monitoring, crop area monitoring, crop yield prediction, food production estimation, and cropping index monitoring mainly based on remote sensing data. The new indicators that will be incorporated to upgrade the CropWatch system are described below.

#### 2.3.1. Fallow land monitoring

The land-use map [7] of year 2010 at 1:100,000 scale derived from HJ-1 CCD images was used to extract cropped and fallow areas. NDVI was calculated for each HJ-1 CCD image and multi-temporal NDVI was obtained. Three key periods for cropped and fallow area mapping are identified (named Time a, Time b and Time c). NDVI at these three periods was used after clouds were masked out. Images of difference between NDVI images at Time a and Time b and difference between NDVI images at Time b and Time c were derived. The pixels with a value below 0.2 in two NDVI difference images were classified as fallow land. The cropped and fallow land distribution map was then resampled to generate the ratio of fallow land (Rf) map with 250m resolution.

#### 2.3.2. Discrimination of irrigated and non-irrigated area

Ozdogan and Gutman [8] define irrigated land as agricultural areas that receive full or partial application of water to the soil to offset periods of rainfall shortfalls under dry-land conditions, excluding irrigated pastures, paddy fields, and other semi aquatic crops. However, paddy fields also...
depend on irrigation during the growing period. Therefore, both irrigated dry-land and paddy fields are counted as irrigated areas in this paper.

Indices including NDVI [9], Enhanced Vegetation Index (EVI; [10]), Land Surface Water Index (LSWI; [11]), and Green index (GI; [12]) were calculated and compared. In order to calculate the indices, surface reflectance values from the red (620-670 nm), green (545-565 nm), blue (459-479 nm), NIR (841-876 nm), SWIR (1230-1250 nm) bands were used.

After masking out cloud and snow cover, we reconstructed the time series of NDVI, EVI, LSWI and GI with S-G filter [13]. GI shows the largest sensitivity to irrigation presence during peak crop growth [8]. We used time series of GI and a CART algorithm (http://edoc.hu-berlin.de/master/timofeev-roman-2004-12-20/PDF/timofeev.pdf) to separate irrigated and non-irrigated areas under dry-land condition.

For paddy field identification, the method proposed by Xiao [14][15] was modified and used. Land Surface Water Index (LSWI), NDVI and EVI were used. Xiao defined a pixel as paddy fields when $\text{LSWI} + \text{threshold} \geq \text{NDVI}$, or $\text{LSWI} + \text{threshold} \geq \text{EVI}$, and $\text{EVI} \geq 0.5 \times \text{NDVI}$, where the threshold was set to 0.05 [14][15]. We found the result has higher accuracy when the threshold is set to 0.1.

2.3.3. PAR estimation
PAR was simulated according to the relationship of PAR and solar radiation which can be expressed as follows,

$$\text{PAR} = \eta \times \text{Rs}$$

where $\text{Rs}$ is incoming shortwave solar radiation, and $\eta$ is the radiation proportionality factor.

The ratio of PAR to solar radiation can be estimated based on Dong’s method [16]. Meanwhile, solar radiation can be modeled by the relationship between sunshine duration and solar radiation [17].

The regional data of sunshine duration interpolated from weather station measurements cannot provide accurate spatial distribution due to the elevation and weather condition. We propose a method to simulate regional sunshine duration from the Fengyun (FY-2D) cloud classification product. FY-2D classifies clouds into seven categories, namely Clear Sky, Mixed Pixels, Altostratus (or Nimbostratus), Cirrostratus, Cirrus densus, Cumulonimbus and Stratocumulus (or altocumulus). Each class is associated with a value (named sunshine factor, SF) that represents the influence of clouds on sunshine hours. For our study, the SF for each aforementioned class was $1$, $0.5$, $0.6$, $0.8$, $0.6$, $0.2$ and $0.4$, respectively. Daily sunshine duration can be estimated by accumulation of hourly sunshine factor during the day.

2.3.4. Radiation use efficiency estimation
Radiation use efficiency for the photosynthetically active radiation (RUE$_{\text{PAR}}$) is known to change dramatically across seasons and between vegetation types [18] and can be affected by different conditions in temperature, water and leaf phenology [19]. Land surface temperature accumulation (LSTA) is an essential factor for crop growth, which is used as one of the factors to RUE$_{\text{PAR}}$ in this paper. Also, Normalized difference water index (NDWI) calculated by shortwave infrared reflectance (SWIR) and near infrared reflectance (NIR) is used as the drought impact factor to modify RUE$_{\text{PAR}}$.

By incorporating NDWI and LSTA, RUE$_{\text{PAR}}$ can be estimated as follows:

$$\varepsilon = \varepsilon_{\text{max}} \times \text{scaledNDWI} \times \text{scaledLSTA}$$

where $\varepsilon_{\text{max}}$ is the maximum radiation use efficiency for the photosynthetically active radiation, which was collected from literature according to the landuse type; $\text{scaledLSTA}$ and $\text{scaledNDWI}$ can be calculated according to the following equations:

$$\text{scaledLSTA} = \frac{\text{LSTA} - \text{LSTA}_{\text{min}}}{\text{LSTA}_{\text{max}} - \text{LSTA}_{\text{min}}}$$
$$\text{scaledNDWI} = \text{NDWI} + 1$$
where $LST_{\text{min}}$ and $LST_{\text{max}}$ can be obtained from statistics of the last ten years of $LSTA$ data.

### 2.3.5 Cropping index and crop rotation

The cropping index is the ratio of total crop area of all planting seasons in a year to the total area of arable land, an indication of the extent to which the grain-producing potential of an area is realized. CropWatch estimates cropping indices using a time-series of NDVI derived from meso- or low-resolution satellite images \[20\] \[21\]. In this paper, the method proposed by Fan and Wu \[20\] was modified. S-G filter \[13\] was applied to NDVI time-series derived from MODIS with 250m resolution to reconstruct the NDVI profile for each pixel.

Several descriptors including the number of peaks, range of each peak and peak values were extracted from the reconstructed NDVI profile. The descriptors were then used to estimate the cropping index of each pixel. The number of peaks in the NDVI profiles can be counted, with each peak (if above a certain value and at least two months from a previous peak) representing a crop-growing season. The model can generate a cropping-index per pixel, with cropping index values of 1, 2, and 3 to illustrate areas with a single, two, or three crop seasons respectively. Results are reported at regional, provincial, and national scales.

Combining the information on cropping index and crop phenology, a decision tree algorithm was applied to the time series of vegetation indices (NDVI & EVI) to separate areas with different crop rotations. Training data were selected according to images with 30m resolution (HJ-1 CCD or Landsat EMT+).

### 3. Results

Maps of cropped and fallow land of the study area in 2010 and 2011 were generated using the method described in section 2.3.1. Fallow areas were found distributed throughout the study area. A total of 14.7% and 14.3% of the arable lands over the study area were left fallow during the summer season in 2010 and 2011, respectively, but were very unevenly distributed. Most of fallow lands were located in the north of the study region during the summer season, specifically in Hebei and Shandong provinces. The percentage of fallow areas was larger than 15% for Hebei and Shandong provinces because some of fields in two provinces were kept for cotton planting during the autumn season.

![Figure 1](image-url). The spatial distribution of irrigated areas in 2010 in North China Plain
For the autumn season, almost all the farmland was planted with crops. Only 3.9% and 3.4% of the land were kept fallow in 2010 and 2011, respectively. Most of the fallow lands were located near the boundary of the study area.

Using time-series GI data and the CART algorithm, the irrigated land of NCP was separated from non-irrigated land. Also, the paddy fields were identified with the method described in section 2.3.2. The distribution maps of paddy fields and irrigated dry-land were then merged to generate the irrigated farmlands in NCP (shown in figure 1 for 2010). Based on a comparison with the global maps of FAO and IWMI, the main irrigated areas and non-irrigated areas in NCP have been effectively separated, which confirms the validity of the methodology.

Daily PAR for the years 2010 and 2011 was derived according to the method described in section 2.3.3. Monthly or seasonally PAR was then estimated by accumulation of daily PAR. The validation of estimated PAR will be discussed in the future and compared with ground data. Based on the relationship between primary crop production and PAR, the spatial variation of crop growth condition can be simulated accurately in the study area.

Spatially distributed RUE_PAR over the North China Plain was generated for each cropping season in 2010 and 2011 considering the influence of LSTA and NDWI. The RUE_PAR map shows detailed spatial distribution information and reflects the difference of diverse environmental conditions, especially low temperature and drought impact. This result mainly relies on remote sensing data: it can eliminate short-term fluctuations in solar radiation and other environmental variables by the accumulation of land surface temperature during a long-term period.

Figure 2a shows the spatial distribution of NCP’s cropping index in 2010 at pixel scale. Most areas in Henan and Jiangsu province were double cropped. Single cropping farmlands are mainly located in north of Shandong province and Hebei province. Classification results of crop rotation over North China Plain are shown in Figure 2b. According to the map of crop rotation, rice was mainly planted in...
Anhui and Jiangsu Provinces. In the center of the study area, crops were mainly rotated between winter wheat and maize. Cotton was planted in the south of Hebei province.

Cropping index and crop rotation information are commonly used as indicators of the intensity of farmland use or the extent to which the grain producing potential of an area is used.

4. Discussion and conclusion
CropWatch is specialized in using remote sensing data for crop monitoring. CropWatch is capable of providing timely, independent and reliable crop information for regional, national and global scales. The models, operational methods and principles of CropWatch components were thoroughly validated before being incorporated into the system. For each monitoring component, research is first carried out, to make the theory and methods operational. The heterogeneity of the agricultural landscape, climate, planting practices, and cropping patterns, among other aspects, are taken into account.

In this paper, some new indicators including fallow land ratio (FLR), crop condition anomaly in irrigated (CCAI) and non-irrigated (CCAN) areas separately, photosynthetically active radiation (PAR), land surface temperature accumulation (LSTA) and cropping index (CI) with crop rotation information (CRI) were proposed and estimated over NCP. We intend to absorb the new indicators into the CropWatch system to project food production. Ongoing developments and recent upgrades to the CropWatch system, such as the development of the biomass harvest index model for yield prediction or the new indicators proposed in this paper further strengthen the independence of CropWatch monitoring results.

The first challenge related to the new indicators is the lack of ground data. Take the irrigation identification results as an example: the large irrigation district in Haihe basin was used as the training area for separating irrigated and non-irrigated farmland based on the hypothesis that farmlands within the large irrigation district are almost all irrigated. So far, the results were only compared with the Global Map of Irrigation Areas (GMIA, [22]) and Global Irrigated Area Map (GIAM, [23]). Extensive validations should be done over the study area using experimental sites. Unfortunately, validation is more difficult outside China as the “actual” crop variables for large areas are hard to acquire. With international cooperation under the JECAM program, ground data should be collected both in China and abroad for the verification of methods in this paper.

The second challenge to the expanded use of CropWatch is the uncertain availability of satellite images at necessary spatial, temporal and spectral resolutions. Weather conditions, as well as other factors such as conflicts in satellite programming, can lead to the absence of remote sensing images in certain regions at certain periods. Budget limitations will likely further intensify this issue of data availability. To what extent we should use Chinese satellite data and to what extent we use other data from non-national sources is also a problem that needs to be solved.

In the future, after comprehensive validation of the methods proposed in this paper, the CropWatch system will provide more reliable, objective information on crop production and food security. CropWatch monitoring results will further improve our current understanding of global dynamics of food production and trade.

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