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Remote sensing-based global crop monitoring: experiences with China's CropWatch system

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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. China's global crop-monitoring system (CropWatch) uses remote sensing data combined with selected field data to determine key crop production indicators: crop acreage, yield and production, crop condition, cropping intensity, crop-planting proportion, total food availability, and the status and severity of droughts. Results are combined to analyze the balance between supply and demand for various food crops and if needed provide early warning about possible food shortages. CropWatch data processing is highly automated and the resulting products provide new kinds of inputs for food security assessments. This paper presents a comprehensive overview of CropWatch as a remote sensing-based system, describing its structure, components, and monitoring approaches. The paper also presents examples of monitoring results and discusses the strengths and limitations of the CropWatch approach, as well as a comparison with other global crop-monitoring systems.

Keywords: CropWatch; crop monitoring; remote sensing; crop production

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1. Introduction

Disruptions in food supply have a marked effect on the well-being of populations and countries. Climate change-related extreme weather events, competition for water resources, energy needs, and a growing population are increasing the risk of food shortages (FAO 2007). To ensure national food security, timely, reliable, and objective predictions of crop conditions and production, both within countries and globally, are needed to plan crop imports, exports, and prices (Li et al. 2007). Brown (2005) also describes the urgent need for a comprehensive, systematic, and accurate global agricultural monitoring system.

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 employ crop-monitoring systems to monitor their own countries' or regional and global crop production. In the United States, the U.S. Department of Agriculture (USDA) Foreign Agricultural Service (FAS) (http://www.fas.usda.gov/default.asp) provides crop monitoring as part of its Global Agricultural Monitoring (GLAM) program (Becker-Reshef et al. 2010). The European Commission operates its AGRI4CAST program implemented by the

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European Commission Joint Research Center under the Monitoring Agricultural Resources (MARS) program (Supit, Hooijer, van Diepen 1994; Vossen and Rijks 1995; Genovese 2001; Genovese, Fritz, and Bettio 2006; Duveiller, López-Lozano, and Baruth 2013), while the FAO established the Global Information and Early-Warning System (GIEWS) (http://www.fao.org/giews/english/index.htm), which focuses on food and agriculture at the global scale. India, Canada, and Brazil operate a Crop Acreage and Production Estimation (CAPE; SAC 1995), the Crop Condition Assessment Program (CCAP; Reichert and Cassiy 2002), and the Geosafras program (Fontana et al. 2006), respectively.

China's global crop monitoring began in 1998 with the development of the China CropWatch System. CropWatch is designed specifically to use remote sensing data to assess national and global crop production and related indicators. 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 reliance on ground assessments and field monitoring. Currently in its 15th year of operation, CropWatch provides production estimates for wheat, maize, rice, and soybean and covers most of the prominent food-producing countries in the world (Wu 2000).

CropWatch results have been calibrated and verified, and its methods and models have been presented and discussed in many publications (Fang et al. 1997; Wu 2000; Jiang et al. 2002; Fan et al. 2003; Zhang et al. 2003, 2004; Meng, Li, and Wu 2004; Wu et al. 2004a; Wu, Meng, and Li 2010a; Wu,Tian, and Li 2004b; Wu and Li 2004, 2012; Zeng et al. 2004; Mu, Yan, and Wu 2005; Xu et al. 2008; Du et al. 2009a, 2009b; Jia et al. 2010, 2011; Li et al. 2011). What has not been presented – and what this paper sets out to do – is a comprehensive overview of CropWatch as a remote sensing-based system, describing its structure, components, and monitoring approaches. The paper also presents examples of monitoring results and discusses the strengths and limitations of the CropWatch approach, as well as comparison with other existing systems.

2. CropWatch structure and methodology

2.1. Overview

CropWatch uses high- (30 m and above) and low-resolution (250–1000 m) remote sensing data, combined with selected field data, to calculate and present various crop-monitoring indicators. After pre-processing of acquired remote sensing data, system components carry out crop condition monitoring, drought monitoring, crop acreage monitoring, crop yield prediction, food production estimation, and cropping intensity monitoring (Figure 1). Information on crop acreage and crop yield predictions is combined to estimate crop production. Next, the available information on crop condition, droughts, production, and cropping intensity is combined to determine the balance in supply and demand for food and, if necessary, provide early warning of risks to the food supply. Drought monitoring, food production monitoring, and early warning are provided only for China, whereas crop condition monitoring, crop acreage estimation, and estimates of crop yield and production are performed at the global scale. The crop acreage estimation is implemented only for 6 countries (United States, Argentina, Brazil, France, Germany, and Ukraine), while

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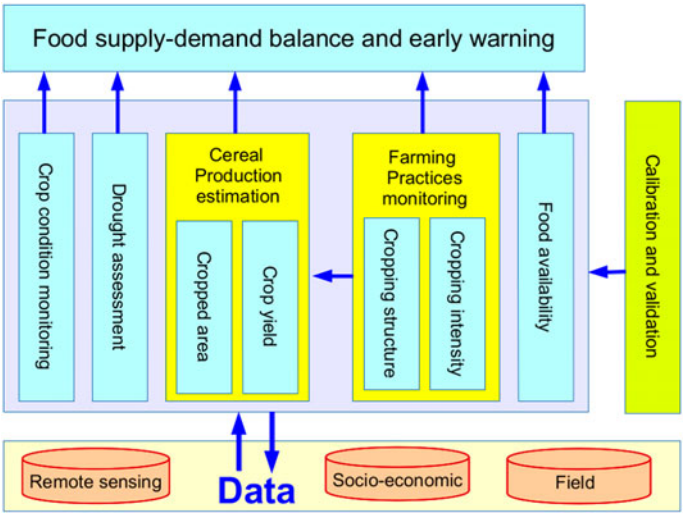

Figure 1. CropWatch components and structure (modified from Wu et al. 2010b).

the other global monitoring indicators are computed for all the 31 major food-producing countries.

The following sections provide more detail on the system's remote sensing inputs, components, model calibration and validation, and data management.

2.2. *Pre-processing of remote sensing data*

CropWatch uses remote sensing data from various sources. As necessary, data is acquired from satellites, downloaded, and, if needed, immediately pre-processed using internationally established methods (Table 1). Data is stored in a central database where it can be automatically accessed by the various CropWatch components.

Data quality is one of primary factors that influence the accuracy of derived crop information on condition, yield, acreage, etc. While the initial objective of data pre-processing is to provide consistent data-sets (both temporally and spatially) for crop monitoring, techniques will also be developed for removing noise and improving data quality.

2.3. *Monitoring crop condition*

Information about the condition of crops in early crop-growing stages (before harvest) can help indicate potential food surpluses and shortages and support related decision-making (Meng and Wu 2008). CropWatch crop condition monitoring is based on a multi-year comparison of the Normalized Difference Vegetation Index (NDVI) (Rao, Ayyangar, and Rao 1982; Wu 2000; Meng et al. 2007) and combines both current crop condition monitoring and a monitoring of the crop growth (Meng, Wu, and Li 2008; Wu, Meng, and Li 2010a). For current crop condition monitoring, two NDVI images representing comparable periods from the current and previous

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Table 1. CropWatch remote sensing data and data pre-processing procedures.

Target area	Data Source	Spatial Resolution	Pre-processing	Data Products	Usage*
China	FY-3a MERSI	250 m/1000 m	Geometric correction, calibrating DN images to TOA reflectance, atmospheric correction, cloud identification, and masking	NDVI, LST, bands reflectance	1, 2, 6
	TERRA/AQUA MODIS	250 m/1000 m	Geographic correction; radiation calibration; image resizing; mosaic, cloud identification; and atmospheric correction	NDVI, albedo, LST	1, 2, 3, 4, 5, 6
	ENVISat ASAR	30 m	Geometric correction, radiance calibration, and speckle reduction	Backscattering coefficient, texture	3
	Radarsat-1	30 m	Geometric correction, radiance calibration, and speckle reduction	Backscattering coefficient, texture	3
Global	Landsat TM/ ETM	30 m	Geometric correction, calibrating DN images to TOA reflectance, atmospheric correction, cloud identification, and masking	bands reflectance	3, 5
	HJ-1 CCD	30 m	Geometric correction, calibrating DN images to TOA reflectance, atmospheric correction, cloud identification, and masking	bands reflectance	2, 3, 5
	IRS P6 AWIFS	56 m	Geometric correction, calibrating DN images to TOA reflectance, atmospheric correction, cloud identification, and masking (Johnson 2008)	bands reflectance	3, 5, 6
	TERRA/AQUA MODIS	1000 m	Download (http://reverb.echo.nasa.gov), mosaic, re-project	NDVI, FPAR, LST	1, 3, 4
	NOAA AVHRR	1000 m	Cloud identification and masking; calibration; atmospheric correction; retrieving LST from thermal bands; and geometric correction	NDVI, NDVI, LST	1, 2, 4, 5, 6

*1: crop condition monitoring, 2: drought monitoring, 3: crop acreage estimation, 4: crop yield estimation, 5: grain production estimation, 6: cropping-index monitoring.
Note: DN = digital number; FPAR = fraction of photosynthetically active radiation; NDVI = normalized difference vegetation index; LST = land surface temperature; TOA = top of atmosphere.

years are compared to identify areas where crop conditions are poorer, better, or similar (Wu 2000; Esquerdo, Zullo, and Antunes 2011).

Monitoring of crop growth is also based on NDVI images, but this time, a time series of NDVI images across the growing season is used to develop crop-growth profiles, based on the statistical average of the NDVI (weighted for the percentage of farmland) in a region or country compared to those from previous years (Meng, Wu, and Li 2008; Wu, Meng, and Li 2010a). The process uses counties as the basic unit for the extraction and reconstruction of crop-growing profiles, as an analysis on a larger scale would be more likely to incorporate incorrect information as a result of the spatial heterogeneity of crop patterns. To remove the noise from the NDVI time-series caused by clouds and atmospheric conditions, harmonic analysis (HANTS) (Roerink and Menenti 2000) and S-G methods (Savitzky and Golay, 1964) are used. Selected descriptors including peak value, average value, and rate of increase are extracted to provide a quantitative evaluation of crop condition (Brown et al. 1982). The crop profile method has been extended to a new method of non-parametric crop forecasting, which compares minimum, average, and maximum crop-growing profiles of the last five years to evaluate the current crop conditions, with similar crop-growing profiles interpreted to indicate similar crop conditions (Gommes 2007).

After removing data from non-farmland areas (using cropland masks), the crop condition results of both assessments – the current crop condition and crop growth – are combined with information about phenophase, agro-meteorological conditions, and variations in crop proportion for a comprehensive analysis and assessment of crop condition. The crop condition monitoring of China is based on county datasets, and that of other countries depends on the farmland area of the country. For major producers such as United State and India, the monitoring is implemented based on province or state data, while for other countries, the monitoring is implemented directly at nation scale.

The inter-annual variabilities of phenology and crop rotation are a main source of uncertainty. The result is that the crop condition variation information is mixed with variation in crop phenophase and crop types. Introduction of explicit crop phenophase and crop type information will help to solve or at least alleviate the problem.

2.4. Monitoring agricultural droughts

Agricultural drought – a natural disaster that occurs when water supply is insufficient to satisfy the demand from crops – is recognized as the biggest natural threat to food security (Wang, Lou, and Wang 2007). The drought evaluation model of CropWatch uses different indicators for different zones and times of the year, based on a zonal map for agricultural drought monitoring that takes topography, climate, soil type, and crop-planting patterns into account (Mu et al. 2005, Mu 2006). Used indicators include the crop vegetation health index (VHI, Kogan 1998), temperature condition index (TCI), and vegetation condition index (VCI, Kogan 1995), which all are calculated based on remote sensing-derived NDVI, land surface temperature (LST), and soil-moisture data. A look-up table (LUT) was built for selecting the best indicator for different regions in different months. This LUT can be calibrated and updated as necessary. The model predicts and estimates the severity of drought for China and generates maps to illustrate the degree and status of droughts.

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During a drought, maps can be released every ten days to inform decision makers about the drought's severity and likely impacts.

The drought model is particularly useful at the national scale. It relies on data series covering several years and performs better where phenology and rotation remain stable over time. This situation cannot be taken for granted, all the more so, since climate change scenarios predict an increase of the frequency of droughts in the future. This is why the drought model needs improving to better apprehend spatial inhomogeneity; this will be achieved by combining data from different sensors and satellites (multi-resource, high resolution).

2.5. Estimating crop acreage

Total crop production depends on both crop yield and the total area where the crop is grown. To estimate crop acreage, CropWatch combines remote-sensing-based estimate of the crop-planting proportion (cropped area to arable land) with a crop type proportion (specific type area (like wheat) to cropped area). This crop planting and type proportion (CPTP) method combines satellite data with sampled field data (Wu and Li 2004, 2012).

For China, the planting proportion is estimated based on an unsupervised classification of high-resolution satellite images from Landsat TM, IRS P6 AWIFS, and HJ-1 CCD, with an accuracy above 95% (Li and Wu 2004). The crop-type proportion for China, however, is not based on remote sensing but estimated by combining GPS, video, and GIS data (collectively referred to as GVG) from field transects (Wu and Li 2004). The specifically developed GVG instrument collects thousands of field photos that are used to estimate the proportion of different crop types with an accuracy above 98% (Wu, Tian, and Li 2004b; Wu and Li 2012). The GVG instrument also provides data on the relative contributions of all food crops to the planted area, which is cropping structure, a fundamental variable for food production estimation. Because the planting proportion and crop-type proportion are estimated at late stages of crop-growing season, we assume the all existing crops at that stage will survive to the time of harvest. The acreage of a specific crop can then be computed by multiplying farmland acreage, planting proportion, and crop-type proportion of the crop.

Crop acreage estimation outside China – to estimate crop acreage for wheat, soybean, maize and rice – relies on various techniques to identify crops based on remote sensing data sources (described in Jia et al. 2010, 2011; Li et al. 2011).

To further reduce reliance on field data, a new technique is currently under development to use indicators from satellite data. The crop identification method would also be suitable for global crop acreage estimation. The method uses multifrequency SAR data to classify crops, and has been shown to be effective for different agricultural landscapes with accuracies above 90% for most major crops (Chen et al. 2007; Karjalainen, Kaartinen, and Hyyppä 2008; Jia et al. 2011).

2.6. Estimating crop yield and production

Global and national crop yields for rice, wheat, soybean, and maize are estimated using three separate methods, the results of which are integrated to reduce uncertainty. The first method uses an agro-meteorological yield model that accounts

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for yield trend (influenced by agricultural technology and field management) and meteorological yield (sensitive to changes in weather conditions during the growing season; Meng et al. 2004). The second method is an analysis of remote sensing-based yield indicators. The yield estimation model for this method was developed by identifying relevant remote sensing indicators and their relationship with yield through a regression analysis (Li, Steven, and Clark 1990; Benedetti and Rossini 1993).The third method is a recently developed crop biomass and harvest index method (Du et al. 2009a; Meng, Du, and Wu 2013), which estimates crop biomass based on the crop's photosynthesis and water stress during the growing season, and then estimates the harvest index of crops from their growth parameters (Du et al. 2009b). This new model is independent of statistical data and, after calibration with field observed crop biomass and harvest index, can be applied to different regions across the globe.

Once established, crop yield information is combined with crop acreage estimates to determine crop production. Crop production estimates are made one month before harvest and revised immediately after harvest.

2.7. Estimating food availability

Because information about total food availability is more useful for assessing potential food shortages than production information on main crops only, CropWatch specifically monitors China's national production of food crops such as wheat, rice, maize, oat, sorghum, barley, and potato, covering both summer- and autumn-harvested food crops. Food production is calculated using Equation (1):

$$Gp_T = Gp_L * (1 + V_A) * (1 + V_y) \tag{1}$$

in which Gp_T is the food production of the current year, Gp_L is the food production of the previous year, V_A is the variation in the area cultivated with food crops, and V_y is the variation in yield. The variation in food crop-growing area can be determined with Equation (2):

$$(1 + V_A) = (1 + V_c) * (1 + V_g) \tag{2}$$

where Vc is the variation in total crop-planting proportion and Vg is the variation in percentages of food crops proportion.

Unlike cereal crop production estimates, which are based on the current year's estimated crop yield and acreage, total food production estimates use information about last year's food production and combine it with an assessment of the change in average yield and planting area between the two years (Equation 1). The variation in yield (an average for all crops) is calculated using remote sensing NDVI data for the two years, using highly accurate models to predict yield based on the remote sensing-based parameters (Doraiswamy and Cook 1995). Variation in acreage is estimated using both field survey (Wu et al. 2004) and remote-sensing data, as described in Equation 2.

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2.8. Estimating cropping intensity

Cropping intensity is the ratio of total crop acreage of all planting seasons in a year to the total area of arable land, an indication of the extent to which the food-producing potential of an area is realized. CropWatch estimates the cropping intensity using a NDVI time-series from meso- or low-resolution satellite images (Fan and Wu 2004, Meng et al. 2011). After using a HANTS algorithm to reconstruct the NDVI profile for each pixel (Zhang et al. 2004), 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 number of peaks per pixel is then converted to cropping intensity, with values of 1, 2, and 3 to illustrate areas with one, two, or three crop seasons respectively (Fan and Wu 2004). Results are reported at regional, provincial, and national scales.

2.9. Monitoring the food supply–demand balance and providing early warning

Using CropWatch outputs, a separate model combines the various CropWatch monitoring indicators with statistical information to analyze the food supply-demand balance for China. Balancing food supply and demand is a key element of macro-economic adjustment of the food market, and CropWatch can indicate areas in China where food production is greater than, nearly equal to, or less than the demand. By using remote-sensing-derived data on food production, which can be acquired in a spatially distributed manner (Zeng et al. 2004), CropWatch has been able to improve the capacity on early warning of food supply and demand imbalances.

CropWatch food supply early warning is currently only carried out for China, but the intent is to move toward a continuously updated outlook on global food demand and supply.

2.10. Calibration and validation

Calibration and validation are critical for accurate and credible remote sensing products (Justice and Townshend 1994), and CropWatch models are all individually calibrated and validated at the time of development. Calibration and validation is done for different agricultural systems and regions in China, based on information from 15 experimental sites across the country. Results indicate the accuracy is 80% for crop condition monitoring, 95% for crop acreage estimation of major crops, 94% for crop yield prediction, 82% for drought monitoring, 92% for food production estimation, and 90% for cropping intensity monitoring (Li and Wu 2004; Zhang et al. 2004; Li 2008; Wu et al. 2012).

Validation of CropWatch on a global scale is currently (2012–2014) being implemented within the framework of the Group on Earth Observations (GEO) and Joint Experiment for Crop Assessment and Monitoring (JECAM), comparing CropWatch and other existing systems for calibration and validation. Plans are also to collect additional data through a literature review (especially on crop yield and production) for model calibration and to validate CropWatch results outside China.

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2.11. Data management

The CropWatch operational system consists of its monitoring algorithms and models, a graphic interface, a database, and a batching process to access and process the files. The system is highly systematized and acquired data – including remote sensing, meteorological, spatial, statistical, and validation data – is automatically processed, stored, and managed by the database, with general system operation supported by just three full-time staff. The database is developed with Oracle database and ArcSDE as the spatial data management engine. The monitoring technologies of CropWatch were developed into softwares with Graphical User Interface (GUI) through the Interactive Developing Language (IDL) tools from ITT Corporation.

3. Results

By relying primarily on remote sensing data, CropWatch is able to generate several crop-monitoring indicators that previously were not easily available on a regional or global scale. Examples are estimates of global crop production, crop conditions on a regional scale, regional drought monitoring, regional crop-planting proportions and crop acreage, and China's cropping intensity index.

3.1. Global crop production estimates

As part of its global crop monitoring, CropWatch tracks the production of wheat, rice, maize, and soybean in 31 major food-producing countries. According to CropWatch results, in 2012, these target countries contributed about 85.94% of the global wheat production, 82.3% of the global rice production, 77.5% of the global maize production, and 92.7% of the global soybean production.

Figure 2 shows CropWatch results for global crop production in 2012, compared to 2011, for wheat, rice, maize, and soybean. Global wheat production was 561.68 million tons, a decrease of 3.25% compared to the previous year. The results specifically show a decrease in the production of wheat in Australia, Pakistan, Turkey, United Kingdom, Germany, Russia, Ukraine, Kazakhstan, Spain, Romania, Poland, and Belarus, while production increased in other wheat-producing countries. According to the CropWatch data, global maize production was 731.21 million tons, 0.37% below the previous year. Maize production decreased in the United States, Argentina, France, Italy, Romania, Hungary, Spain, and India, but increased in other major producing countries. Global rice production was 49.78 million tons, 1.07% lower than the previous year, with rice production decreasing in India, Bangladesh, Vietnam, and Burma and increasing in the other major rice-producing countries. Finally, global production of soybean was 22.57 million tons, a reduction of 8.22% compared to previous year.

3.2. Crop condition on a country scale

As an example of crop condition monitoring, Figure 3 shows CropWatch results for crop condition in Romania in 2012.

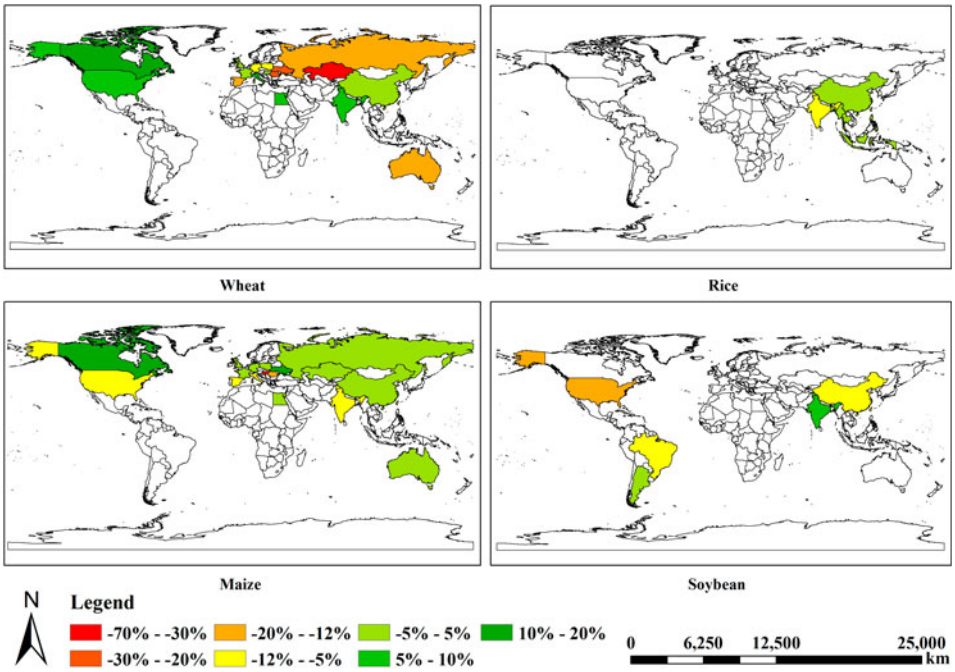

Figure 2. CropWatch estimates of global crop production of wheat, rice, maize, and soybean in 2012, compared to 2011.
Note: Only target countries are shown; white areas are non-target countries for a particular crop.
Source: CropWatch bulletin in 2011 and 2012.

Figure 3a shows the spatial heterogeneity of crop condition. The cyan and blue areas on the crop condition map indicate that compared to the five-year average, crop conditions across the country have deteriorated. Figure 3b shows the temporal variation (trend) in crop condition. The crop growth profiles confirm the poor crop condition and show that in 2012, the crop NDVI profile is much below both the five-year average and the 2011 profiles, indicating a relatively poor crop condition for the period. The poor crop condition in August is the result of the continuous drought that started in June (MARS bulletin, 2012).

Because Romania is a relatively small country, a profile can be generated as a single curve for the entire country. For larger countries such as the United States or India that cover different climate zones, separate curves are generated for different areas.

3.3. Regional drought monitoring – Monitoring China's severe 2009 drought

In the spring of 2009, China experienced a severe drought. Figure 4 illustrates the development of the drought from late January to late February, using TERRA MODIS satellite data.

The drought mainly occurred across northern China, where normally at that time of year winter, wheat is growing. In the period between January 20 and February 16,

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Figure 3. Crop condition map (a) and crop-growing profile (b) for Romania, August, 2012.
Source: CropWatch bulletin in August 2012.

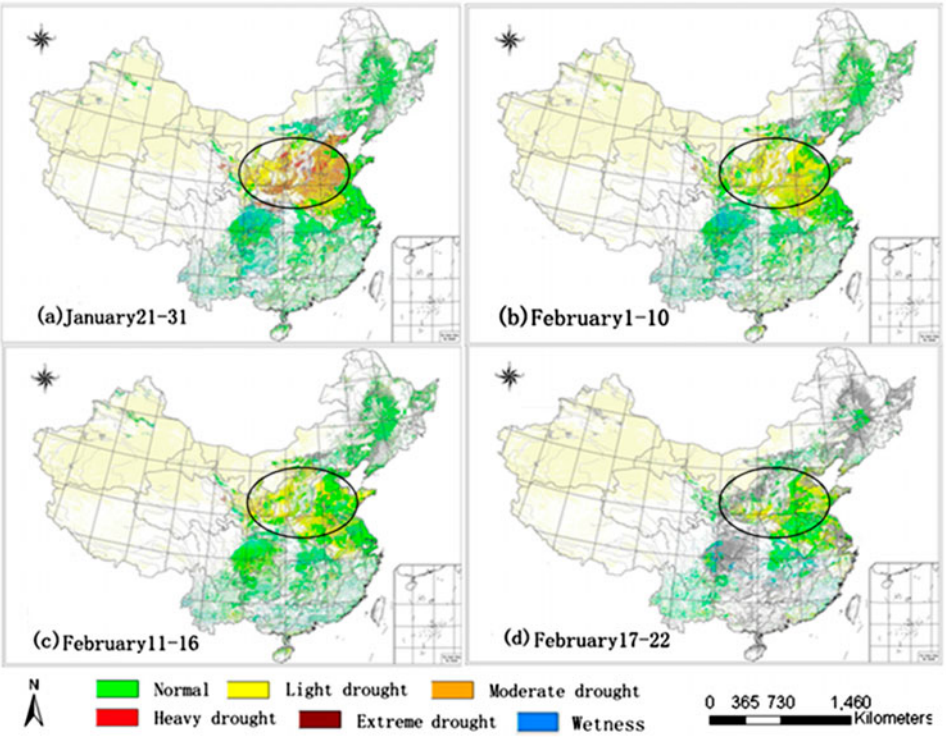

Figure 4. CropWatch drought maps for China in 2009, (a) January 21–31, (b) February 1–10, (c) February 11–16, and (d) February 17–22.
Source: CropWatch bulletin in 2009.

the drought had two key characteristics. The first was its relatively large extension throughout North China Plain (circled area). Across five provinces, the drought area on average (temporal average) involved 45% of the cultivated land (the highest percentage of drought area per cultivated land was 89% at the end of January). The second characteristic of the drought was its severity. In particular at the end of January (Figure 4a), a large number of areas are experiencing 'moderate drought' or 'heavy drought.' In February, both the extent of the drought and its levels decrease, toward a level rated mainly as 'light' and 'moderate drought' (Figure 4b, c, d).

According to meteorological data, the number of consecutive days without precipitation in the north, northwest, and central areas in that period from winter to early February was up to 80 days, and in some areas even as high as one hundred days, clearly constituting a drought. As the maps show, starting around February 16, the extent and severity of the drought decreased, with the affected areas decreasing from the highest value of 89% to as low as 29%. Meteorological information also confirms this change and showed precipitation in the north in late February (especially after February 25) effectively counterbalanced the effects of the drought. By analyzing the CropWatch data, decision makers were able to assess the severity of the drought and take appropriate measures.

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3.4. Crop acreage and crop-planting proportions

As a result of free data access to satellite image distribution centers, it is now possible for CropWatch to use HJ-1 satellite data to cover the entire planting area for major food crops in China. Figure 5 shows areas in China with and without crops planted for the summer harvest season in winter-wheat-planting areas of China in 2010 estimated using an unsupervised classification method for HJ-1 CCD data. Based on the classification results, the crop-planting proportion (CPP) can be estimated as the proportion of cropped arable land to total arable land.

Figure 6 presents results of the CropWatch assessment of crop type proportions by transect sampling, GVG, and a visual interpretation of crop type proportion in collected pictures (Wu and Li 2012). The map shows the proportion of winter wheat in 363 winter-wheat-planting counties in 2010. Winter-wheat acreage can be calculated by multiplying CPP and the proportion of winter wheat of the cropped land area for different counties and combining these numbers to arrive at a provincial or national total, using the information from Figures 5 and 6.

Table 2 shows the 2010 crop type proportion of the autumn cropping season for major crop-producing provinces in China. Using the GVG system, results not only include the planting proportion of crops such as maize and soybean, but also those of cash crops such as cotton and tobacco. As a result, the ratios of food crops to total crops or food crops to cash crops can be generated. The results from GVG present cropping structure in the autumn cropping season, which is essential in agricultural decision-making.

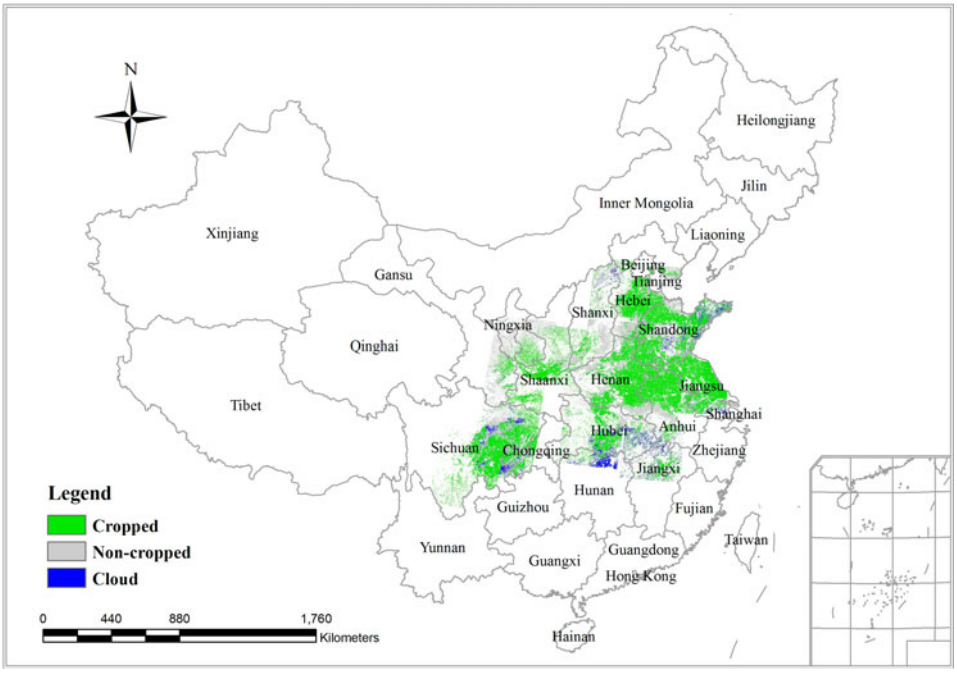

Figure 5. Map of cropped farmland in north China in 2010.
Source: CropWatch data in 2010.

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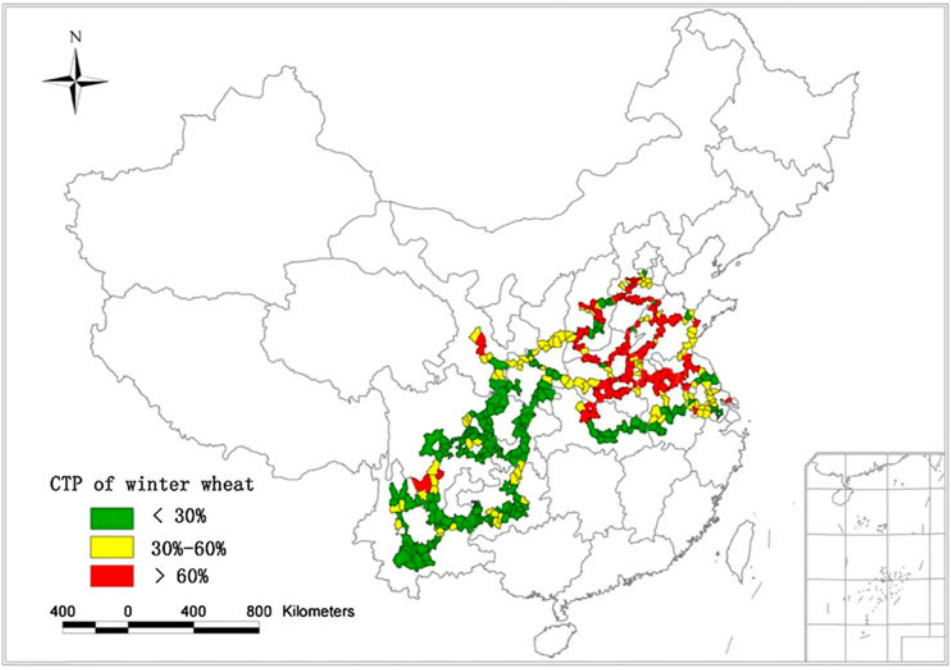

Figure 6. Crop type proportion of winter wheat in the major wheat-producing regions in China, 2010. (Adapted from Wu and Li, 2012.)

3.5. Cropping intensity monitoring in China

Figure 7 shows the spatial distribution of China's 2012 cropping intensity index.

The average cropping intensity index of 2012 is 173.75%, a 0.31% increase compared to 2011. The primary reason for the increase is a new subsidy policy that has provided an incentive for farmers. The map illustrates that the triple-cropping area accounts for 11.74% of total farmland in China, while double-cropping and single-cropping areas account for 50.27% and 37.99%, respectively.

3.6. Information dissemination

For seven months during the growing season from April to October, three full-time operators each month use two weeks to process data and generate the various output maps, such as those presented in the previous sections. After a final check by supervisors, results are immediately released and shared electronically with relevant government agencies. In addition, information is released in a monthly bulletin which is available in print and online (http://www.cropwatch.com.cn), in both English and Chinese. While most information is made available in near real-time, crop production information for China is only published three months after the bulletin is released to avoid unnecessary fluctuations in food prices. Crop production estimates for major crops are acquired a month before harvest and revised a month later. In the event of natural disasters that may affect crop production, crop-monitoring indicators are prepared more frequently and also released immediately. The crop yield, acreage, and production data from CropWatch are also actively shared with the GEO Agriculture

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Table 2. Proportion of major crops of autumn cropping season in major crop-producing provinces in China, 2010 (percentages,%).

Province	Spring wheat	Single rice	Late rice	Spring maize	Summer maize	Durra	Soybean	Potato	Sweet potato	Pesnut	Rapeseed	Sunflower	Cotton	Tobacoo	Vegetable and fruit	Others	Grain proportion
Hebei					63.97		2.21	1.36		6.21			14.16		7.46	4.63	67.54
Shanxi					57.72		4.55	11.49		2.76	1.13	8.63	1.37		6.21	6.14	73.76
Inner Mongolia	11.13			38.82		2.35	15.51	11.33				5.16		0.15	0.38	15.17	79.14
Liaoning		18.76		69.73			6.61			2.78					1.52	0.6	95.1
Jilin		19.06		70.68			7.36			0.15		0.52			0.82	1.41	97.1
Heilongjiang	0.93	26.75		34.59			32.73			0.33	0.15	0.73		0.52	1.01	2.26	95
Jiangsu		68.13			13.23		9.17			1.11			2.15		4.03	2.18	90.53
Zhejiang		24.13	57.45				3.65	0.21							9.25	5.31	85.44
Anhui		32.45	16.12		24.59		19.63			1.33			1.27		1.68	3.93	92.79
Fujian		13.05	17.86												34.62	34.47	30.91
Jiangxi		10.69	48.69							5.03				1.46	12.43	21.7	59.38
Shandong					66.58		7.03	1.11		10.93			3.53		9.12	1.7	74.72
Henan		12.76			60.93		10.36			5.88			3.94		4.15	1.98	84.05
Hubei		50.83	11.42		6.43		1.41			1.55			11.69		5.64	11.03	70.09
Hunan		17.42	71.53		2.73								6.88		1.02	0.42	91.68
Chongqing		44.92			23.53					1.61				1.01	8.15	20.78	68.45
Sichuan		53.52			27.19					1.69				0.32	5.78	11.5	80.71
Guizhou		43.14			49.18									1.01	3.69	2.98	92.32
Yunnan		33.37			38.02		1.45	0.89	0.53					15.13	7.43	3.18	74.26
Shaanxi	3.63	2.99			28.01		2.86	3.52	1.23			2.37			5.33	50.06	42.24
Gansu	11.86	0.7		25.93	0.21		0.73	2.96				0.78	2.83		7.46	46.54	42.39
Ningxia	6.13	9.13		31.03			0.26	5.56				0.93			13.87	33.09	52.11

Source: CropWatch data in 2010.

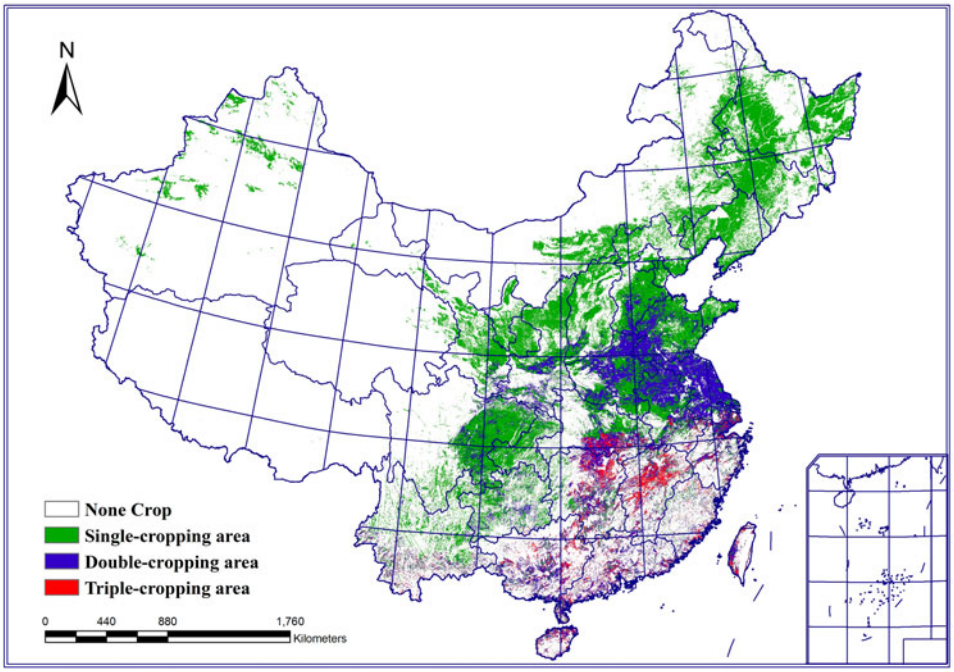

Figure 7. Cropping intensity in China, 2012. Green areas indicate areas with single-season cropping, blue with two-season cropping, and red with triple-cropping.
Source: CropWatch bulletin in October, 2012.

Monitoring Community of Practice to increase the transparency of global crop production information.

4. Discussion

CropWatch relies on remote sensing data for its calculation of crop production indicators. Its newly developed models, operational methods, and highly systematized processing, requiring only limited supervision, are combined to deliver an additional set of information about global and regional crop condition and production (Wu, Meng, and Li 2010a; Wu et al. 2010b). The following sections discuss particular strengths and weaknesses of the CropWatch approach and compare the system's results to results from other global crop-monitoring systems.

4.1. Strengths and limitations of using remote sensing data for global crop monitoring

The most significant strength of CropWatch is its ability to provide timely, independent, and reliable crop information for local, regional, and national scales. CropWatch is fully systematized, from data pre-processing to information products dissemination, which reduces labor intensity, and avoids man-made errors. The high level of systemization also allows for the system to be transplanted to users without much technical background on remote sensing technology. Because all remote sensing data is pre-processed, especially atmospheric correction, the consistency of

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interpretation among different remote sensing images is guaranteed, which is essential for crop monitoring. As a result of its systematization, CropWatch monitoring approaches have also been successfully implemented for other purposes, such as for drought monitoring at both the Information Center of China's Ministry of Water Resources and the National Disaster Relief Center of China, as well as for provincial crop-monitoring systems in the provinces of Anhui, Hubei, Jiangxi, and Shaanxi. In addition, technology and systems for global crop monitoring have been transferred to Chinagrain®web for operation to support key information related to food-futures.

Other strengths of the CropWatch system are its cost-effectiveness and reliance on independent data. By limiting the use of field data, CropWatch does not require the use of expensive field offices, and its data processing and checking require few staff. Results are only based on objective data and not influenced by intentional or unintentional overestimates or underestimates of production. The data is also independent of the information about global crop production that is available from agricultural agencies and food management, statistical analysis, and market departments. As such, CropWatch can act as an independent source of global crop-monitoring information. Ongoing development and recent upgrades to the CropWatch system, such as the development of the biomass harvest index model for yield prediction or the use of remote sensing data to determine crop type proportions, further strengthen the independence of CropWatch monitoring results.

The heterogeneity (both spatially and temporally) of agricultural areas also points to an advantage of using a remote sensing-based system. Remote sensing is the most effective tool for large-area crop monitoring. Unlike other approaches, remote sensing methods act as an independent information source that can reveal the crop condition at a certain stage without knowing the reason. This is a quite different approach from the more traditional, field-based and 'personal' monitoring, but one that is already greatly contributing to our current understandings of global crop production and condition.

Finally, the remote sensing-based outputs on crop condition, drought situation, cropping intensity, food production, crop yield, and crop acreage, that CropWatch can now easily generate, provide new kinds of input for food security assessments.

As described for the individual components, research on new methods and additional calibration and validations continue. For each monitoring component, first research is carried out, to make the theory and methods mature enough, after which the new method is incorporated into the system. When making the monitoring method operational, the heterogeneity of the agricultural landscape, climate, planting practices, and crop proportions, among other aspects, are taken into account. Intensive validation has been done for each monitoring component in CropWatch, including drought monitoring (2006–2013), crop condition monitoring (2005–2011), crop acreage estimation (2002–2013), cropping intensity monitoring (2004–2010), crop yield and production estimation (2003–2013), and food production estimation. The validation of these monitoring themes was implemented at both experimental site (usually 5 km *5 km) and region scales.

Challenges in the use of CropWatch relate mostly to the accuracy for results outside China and to data availability. Extensive validations have been done in China, using experimental sites, but outside China, validation is much harder as the 'actual' crop parameter values for large areas are difficult to acquire. Another major challenge to the expanded use of CropWatch is the uncertainty related to the availability of

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satellite images at the 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.

4.2. CropWatch results compared to other global monitoring systems

CropWatch provides crop-monitoring services independent from those of other key global monitoring systems, such as GIEWS, GLAM, and the EU's JRC's MARS Program. With all systems having different focus areas and using different data sources and models, the availability of multiple estimates on global crop production and other key indicators will increase transparency and enable an enhanced understanding of global crop developments.

Figure 8 compares United States' maize production (Figure 8a) and inter-annual variations (Figure 8b) as reported by USDA (USDA-FAS 2003–2012), FAO (FAOSTAT 2003–2011), and CropWatch.

For 2005–2009, the production numbers reported by CropWatch are higher than those reported by the USDA and FAO, while in 2004 and 2010–2012 they are lower. Reported inter-annual variations are consistent (positive or negative) among the systems for 2005–2012, although differences in variation amplitude are observed. Take the inter-annual change between 2003 and 2004 for example, the reported maize production variations by CropWatch and USDA/FAO are opposite, with FAO and USDA describing an increase and CropWatch a decrease. In 2010, CropWatch shows a much larger inter-annual change than the other two systems. While USDA and FAO only reported a production reduction of 5% in that year, CropWatch reported a much higher reduction.

Another example of how the use of multiple global monitoring systems can enhance transparency and increase insight into a situation: Figures 9, 10, and Figure 11 illustrate USDA FAS and CropWatch results for crop conditions in Russia in the summer of 2010. That summer, Russia – the world's third largest producer of wheat – was experiencing severe weather conditions: Droughts destroyed one-fifth of its wheat production.

Both maps illustrate that crop conditions in 2010 are significantly worse than normal in nearly every major crop-production region in Russia and Kazakhstan (orange and red areas in Figures 9 and 10). The Volga, Ural, and Siberian Districts, all are experiencing worse crop conditions as a result of the drought, and the persistent drought and excessive heat are reducing yield prospects for all crops. The CropWatch data shows that more than one third of cropland in Russia is experiencing crop conditions worse than those in 2009 (orange and red areas in Figure 10); only 5.3% of cropland showed a better condition (green and dark green areas), while the rest maintained a similar condition. The crop-growing profile in Figure 11 also shows that the crop-growing profile for 2010, based on NDVI data, in April and May, is still similar to the five-year average, but that starting in June the profile drops, reflecting a slowdown of crop growth due to the continuous drought. This would indeed predict a decrease in crop yield.

A direct comparison of wheat production estimates for Russia for 2009, 2010, and 2011 from USDA (USDA-FAS 2003–2012), FAO (FAOSTAT 2003–2011), and CropWatch monitoring systems is presented in Table 3.

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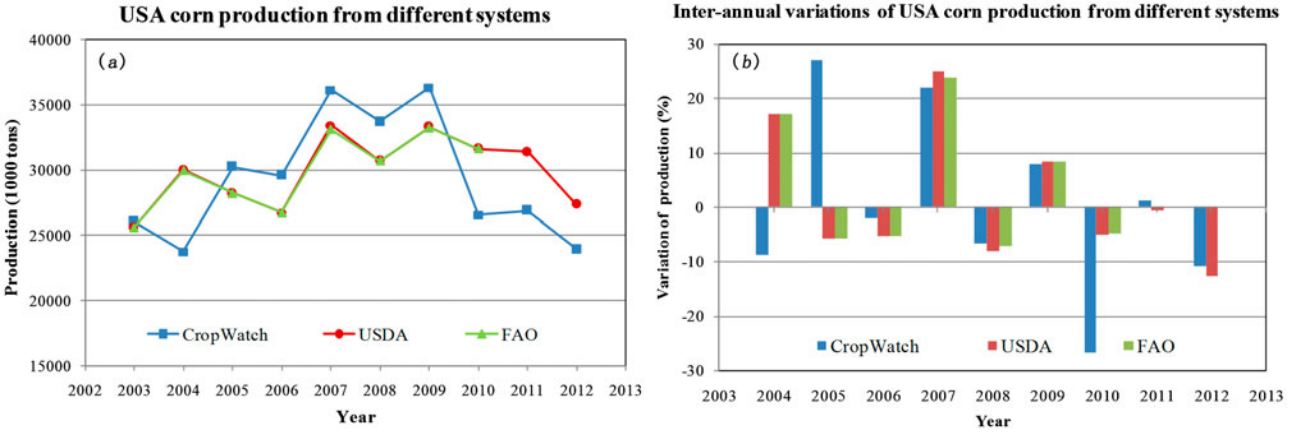

Figure 8. United States' maize production figures (1, 000 ton) (*a*) and maize production inter-annual variation in percentages (*b*).
Source: USDA FAS (www.fas.usgs.gov/wap_arc.asp), FAOSTAT (http://faostat3.fao.org/home/index.html), and CropWatch (CropWatch bulletin).

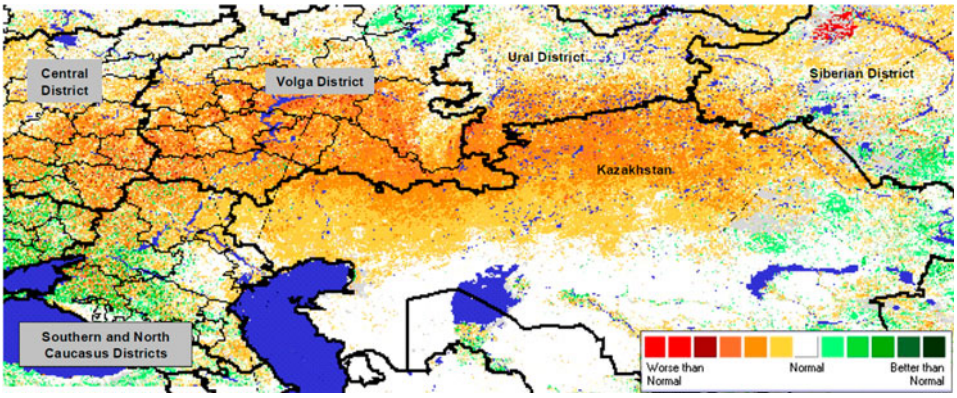

Figure 9. Crop condition monitoring results for Russia by USDA FAS, showing MODIS NDVI data, departure from mean, July 11–27, 2010. (Adapted from USDA FAS, August, 2010).

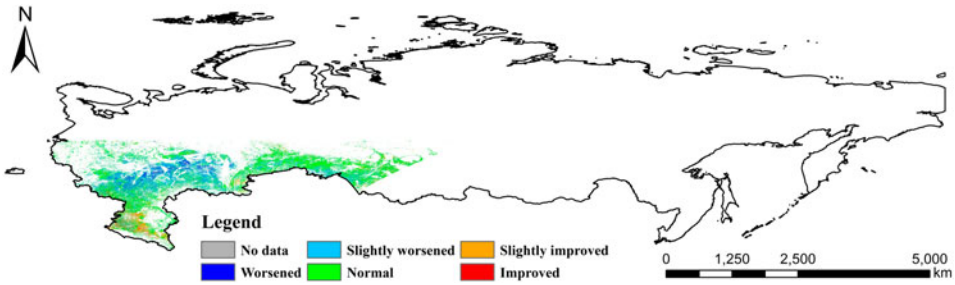

Figure 10. CropWatch crop condition map of Russia for the end of July 2010. The crop condition map shows the condition of the crop compared to previous years.
Source: CropWatch Bulletin in 2010.

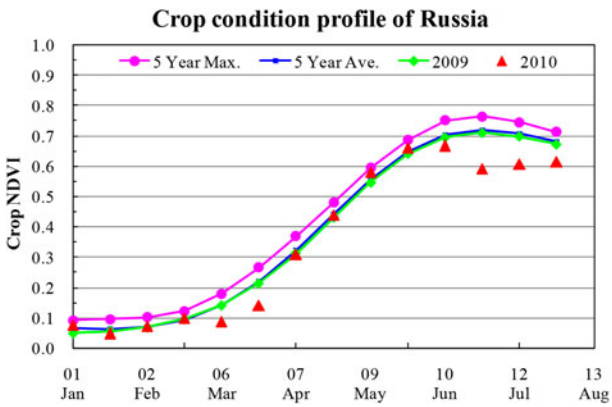

Figure 11. Crop-growing profile chart for Russia from CropWatch in 2010
Source: CropWatch bulletin in 2010.

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Table 3. Comparison of wheat production estimates from different systems; data for Russia, 2009–2011.

	Yield estimate(tons per hectare)			Production estimate(Million tons)		
Year	USDA	CropWatch	FAO	USDA	CropWatch	FAO
2009	2.15	1.54	–	61.7	44.3	61.7
2010	1.59	1.19	–	42.5	31.9	41.5
2011	2.15	1.50	–	56.0	39.0	55.0
Variation (2009–2010)	−26.05%	−22.70%	–	−31.12%	−28.09%	−32.77%
Variation (2010–2011)	37.82%	25.15%	–	34.94%	22.28%	32.5%

– data not available.
Source: World agricultural production report by USDA FAS, FAOSTAT (http://faostat3.fao.org/home/index.html#DOWNLOAD), and CropWatch (CropWatch bulletin.)

All three systems observed a reduction in wheat production for 2010, followed by an increase in 2011. The relative decrease in production between 2009 and 2010 is similar for the three systems (decreases of −31.12%, −28.09%, and −32.77% for USDA, CropWatch and FAO, respectively), but the increase in production between 2010 and 2011 varies (increases of 34.94%, 22.28%, and 32.5% for USDA, CropWatch, and FAO, respectively). Also, the production numbers from FAO and USDA are close, while those from CropWatch are much smaller, which can be explained by the also much lower yield estimate. This is mainly because different systems use different methods in estimating yields.

While CropWatch is able to provide a new and independent source of crop-monitoring information, the system is more limited than other global systems in providing postharvest analysis and supporting decision-making. USDA FAS' Crop Explorer, for example, presents a comprehensive overview of food production for the entire globe as well as for major food-producing countries by integrating remote sensing monitoring with information from local agricultural production reports, providing a complete description of agricultural production for international or local food trade markets. The professional and in-depth postanalysis of its monitoring result is an important reason for the huge number of web visits (more than 70000 in 2008) to the Crop Explorer site (http://www.pecad.fas.usda.gov/cropexplorer). The postharvest analysis of CropWatch needs to be enhanced for providing further value-added information services.

5. Conclusion and outlook

China's CropWatch, currently in its 15th year of operation, provides independent, remote sensing-based information on global crop condition and crop yield and production. In addition, the system provides information on droughts, cropping intensity, and early warning for food supply and demand balance in China. By almost exclusively relying on remote sensing and statistical data, CropWatch provides information that previously was not available on this large scale in a timely manner in China. CropWatch-systematized processing has reduced the uncertainty in the results, as well as labor intensity and cost. In addition, CropWatch adds to the global base of

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agricultural information a new set of crop data independent of field reports. Several of CropWatch monitoring models ensure the independency of the monitoring result.

Looking forward, CropWatch will continue to upgrade its system and work to strengthen analysis of repercussions of the food production. In particular, the expected availability of crop-monitoring data from new high-resolution sensors will be important for the development of CropWatch. As the use of the CropWatch system and data analysis is being transferred to various users, research will focus on exploring the suitability, capacity, and potential of the new data becoming available and determining appropriate methods for their use, to achieve a higher accuracy in crop estimations. As more data can be accessed and acquired free of charge, costs of large-scale crop monitoring are going down and it will become more affordable for systems to use satellite data and use it more frequently and from multiple sources, allowing for more real-time data to be processed. New methodologies will likely need to be developed and tested to include this new data into the system.

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