September 2017

NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) @ 30-m for Europe, Middle-east, Russia, Central Asia: Cropland Extent Product (GFSAD30EUCEARUMECE)

Algorithm Theoretical Basis Document (ATBD)

Document History

Document Version	Publication Date	Description
1.0	September, 2017	Original
1.1		Modification made according to USGS reviewer's comments

Contents

I. Members of the team

Global Food Security-support Analysis Data 30-m (GFSAD30) Cropland Extent-Product of Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEARUMECE) was produced by the following team members. Their specific role is mentioned.

Ms. Aparna R. Phalke, PhD student at the University of Wisconsin, Madison. She along with her PhD advisor Dr. Mutlu Ozdogan led the GFSAD30EUCEARUMECE cropland extent product generation effort. Ms. Phalke was instrumental in design, coding, computing, analyzing, and synthesis of the Landsat derived nominal 30-m GFSAD30EUCEARUMECE cropland extent product of the Europe, Middle-east, Russia and Central Asia for the nominal year 2015. She was also instrumental in writing the manuscripts, ATBD's, and User documentations.

Dr. Mutlu Ozdogan, Professor at the University of Wisconsin, Madison and Co- Investigator of the GFSAD30 project. He along with his PhD student Ms. Aparna Phalke generated GFSAD30EUCEARUMECE cropland extent product. Dr. Ozdogan was instrumental in developing conceptual framework of GFSAD30EUCEARUMECE cropland extent product. He made significant contribution in writing the manuscripts, ATBD's, User documentations, and providing scientific guidance on the GFSAD30 project.

Dr. Prasad S. Thenkabail, Research Geographer, United States Geological Survey, is the Principal Investigator of the GFSAD30 project. Dr. Thenkabail was instrumental in developing conceptual framework of the GFSAD30 project. He provided constant guidance to the project team, conducted regular project meetings and workshops, and made significant contribution in writing the manuscripts, ATBD's, User documentations, and providing scientific guidance on the GFSAD30 project.

Dr. Russell G. Congalton, Professor at the University of New Hampshire, led the independent accuracy assessment of the entire GFSAD30 project including GFSAD30EUCEARUMECE 30-m cropland extent product.

Ms. Kamini Yadav, PhD student at the University of New Hampshire was a lead member of the independent accuracy assessment team led by Dr. Russell G. Congalton.

Mr. Richard Massey, PhD student at the Northern Arizona University, shared his expertise in cloud computing and coding.

Dr. Pardhasaradhi Teluguntla, Research Scientist, Bay Area Environmental Research Institute (BAERI) at United States Geological Survey (USGS), joined in the intellectual discussions, provided insights and shared his expertise in documentation.

Mr. Justin Poehnelt, former member of the GFSAD30 team, helped initial conceptualization and development of the croplands.org website.

Ms. Corryn L. Smith, former member of the GFSAD30 team, helped in releasing the GFSAD30EUCEARUMECE cropland extent product on croplands.org website.

II. Historical Context and Background Information

Monitoring global croplands is imperative for ensuring sustainable water and food security to the people of the world in the twenty-first century. However, the currently available cropland products suffer from major limitations such as: (1) The absence of precise spatial location of the cropped areas; (2) The coarse resolution of the map products with significant uncertainties in areas, locations, and detail; (3) The uncertainties in differentiating irrigated areas from rainfed areas; (4) The absence of crop types and cropping intensities; and/or (5) The absence of a dedicated Internet data portal for the dissemination of cropland products. Therefore, our project aims to close these gaps through a Global Food Security Support-Analysis Data @ 30-m (GFSAD30) product. This algorithm theoretical basis document (ATBD) provides a detailed account of the GFSAD30 cropland extent product for Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEARUMECE, Table 1). The document is organized into four broad sections. Section 1 introduces the rationale of generating the product. Section 2 provides an overview and the technical background information and algorithms employed in the generation of the product. Section 3 presents and discusses the results. Section 4 describes the validation activities of the product.

Table 1. Basic information of the Global food security support-analysis data @ 30-m cropland extent product for the Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEARUMECE).

Product Name	Short Name	Spatial Resolution	Temporal Resolution
GFSAD 30-m Cropland Extent-Product of Europe, Middle-east, Russia and Central Asia	GFSAD30EUCEA-RUMECE	30-m	nominal 2015

III. Rationale for Development of the Algorithms

Mapping the precise location of croplands enables the extent and area of agricultural lands to be more effectively captured, which is of great importance for managing food production systems and to study their inter-relationships with water, geo-political, socio-economic, health, environmental, and ecological issues (Thenkabail et al., 2010). Further, accurate development of all higher-level cropland products such as crop watering method (irrigated or rainfed), cropping intensities (e.g., single, double, or continuous cropping), crop type mapping, cropland fallow, as well as assessment of cropland productivity (i.e., productivity per unit of land), and crop water productivity (i.e., productivity per unit of water) are all highly dependent on availability of precise and accurate cropland extent maps. Uncertainties associated with cropland extent maps effect the quality of all higher-level cropland products reliant on an accurate base map. However, precise and accurate cropland extent maps are currently nonexistent at the continental scale at a high spatial resolution (30-m or better). This lack of crop extent maps is particularly true for complex, small-holder dominant agricultural systems. By mapping croplands at a high-resolution at the continental scale, the GFSAD30 project has resolved many of the shortcomings and uncertainties of other cropland mapping efforts.

The two most common methods for land-cover mapping over large areas using remote-sensing images are manual classification based on visual interpretation and digital per-pixel classification. The former approach delivers products of high quality, such as the European CORINE Land Cover maps (Büttner, 2014). Although the human capacity for interpreting images is remarkable, visual interpretation is subjective (Lillesand et al., 2014), time-consuming, and expensive. Digital per-pixel classification has been applied for land-cover mapping since the advent of remote sensing and is still widely used in operational programs, such as the 2005 North American Land Cover Database at 250-m spatial resolution (Latifovic, 2010). Pixel-based classifications such as maximum likelihood classifier (MLC), neural network classification (NN), decision trees, Random Forests (RF), and Support Vector Machines are powerful, and fast classifiers that help differentiate distinct patterns of landscape.
Both supervised and unsupervised classification approaches are adopted in pixel-based classifiers. However, per-pixel classification includes several limitations. For example, the pixel's square shape is arbitrary in relation to patchy or continuous land features of interest, and there is significant spectral contamination among neighboring pixels. As a result, per-pixel classification often leads to noisy classification outputs – the well-known "salt-and-pepper" effect. There are other limitations of pixel-based: 1. they fail to fully capture the spatial information of high resolution imagery such as from Landsat 30-m imagery, and 2. they often, classify same field (e.g., a corn field) into different classes as a result of within field variability. This may often result in a field with a single crop (e.g., corn) classified as different crops.

We used the supervised pixel-based random forest (RF) classifier (Pelletier et al., 2016, Tian et al., 2016, Shi and Yang, 2015, Huang et al., 2010). A description of how to classify cropland extent of Europe, Middle-east, Russia and Central Asia is provided in section 2.3 and its sub-sections (see overview of the methodology in Figure 1).

IV. Algorithm Description

An overview of the algorithm description provided in Figure 1. The methodology used in this project (Figure 1) is briefly described in this paragraph to provide an overview and presented in detail in sub-sequent sections of this ATBD document. The process (Figure 1) involved combining 2014 to 2016, 16-day time-series Landsat-7 and Landsat-8 30-m data along with SRTM 30-m data. The process included several well-designed steps (Figure 1). First, the data pre-processing for cloud and snow masking performed on Google Earth Engine (GEE). Second, seasonal mosaics were created for six seasons in the study area: Season 1 (January-February), Season 2(March-April), Season 3 (May-June), Season 4 (July-August), Season 5 (September-October) and Season 6 (November-December). Such a seasonal mosaic aided in achieving cloud free clear images of the continent. Each seasonal mosaic contained 56 bands as listed in Table 5. Third, reference data generated throughout Europe, Middle-east, Russia and Central Asia to train the RF classifier. There are total of 54435 reference samples for this purpose (Table 2). Fourth, the results of the pixel-based RF algorithms, post-processed with Kernel filter to obtain the composite cropland extent product for Europe, Middle-east, Russia and Central Asia. Fifth, the composite cropland extent product of Europe, Middle-east, Russia and Central Asia evaluated for accuracy using 8968 test samples. The process was iterated until adequate accuracies were attained. Independent team from University of New Hampshire performed accuracy assessment of the developed cropland extent product independently. In this process, the validation data was only available to the accuracy assessment team and was hidden from the production team. As a result, there were complete independent accuracies. Finally, the GFSAD30EUCEARUMECE product was available on croplands.org.

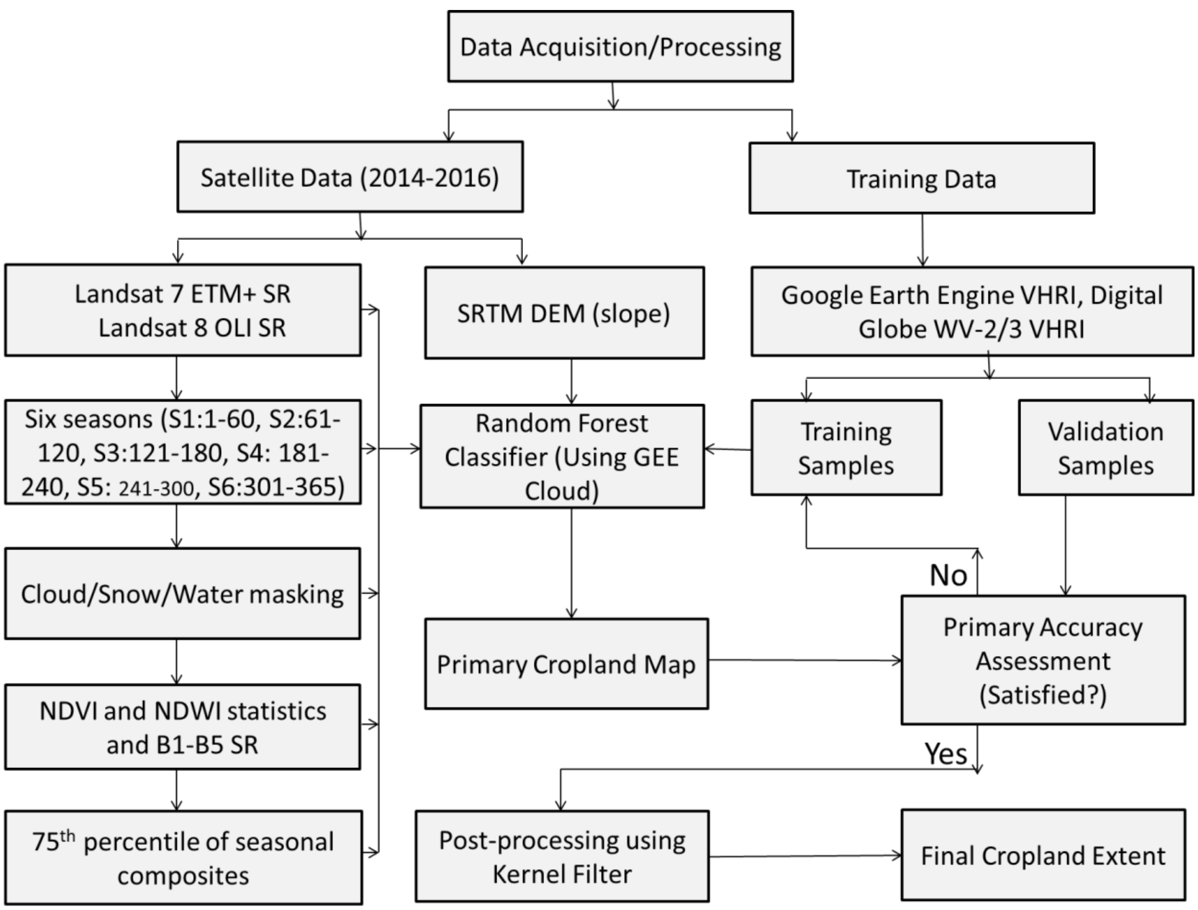

Figure 1. Flowchart of mapping methods for Landsat derived cropland extent-product of Europe, Middle-east, Russia and Central Asia for the nominal year 2015.

a. Input data

1. Reference Croplands Samples

Reference data are required for both training/testing the machine learning algorithms (see section 2) as well as for validating the final products. Over 120,000 reference samples, spread across the world, were collected for this project and can be found at the following web site: https://croplands.org/app/data/search . Of these there were over 9000 samples for Europe, Middle-east, Russia and Central Asia.

Reference training/testing data collected in the following two sources. First, we generated random samples by interpreting sub-meter to 5-meter very high spatial resolution imagery (VHRI) throughout Europe, Middle-east, Central Asia and Russia available to us from the National Geospatial Agency (NGA) and Google Earth high resolution imageries. Second, ancillary data sources such as ‘Land Use and Coverage Area Frame Survey’ (LU-CAS) by Eurostat. We collected 54435 reference and 8968 validation samples (Table 2). The reference samples used to “train” the Random Forest algorithm to separate croplands from non-croplands. This required us to keep adding training samples until an optimal classification result ob- tained (see section 2). The whole set of reference data including primary and secondary data were made available, at the following web site: https://croplands.org/app/data/search.

Zones	Training samples		Validation samples	
	Cropland	Non-cropland	Cropland	Non-cropland
1	3430	1795	36	59
2	4065	1962	202	249
3	5563	663	217	290
4	7464	3493	201	325
5	2253	2677	12	462
6	4017	4283	55	176
7	1255	2945	2	370
8	2732	3482	60	711
9	148	483	15	1373
10	432	114	200	370
11	160	668	24	1232
12	2	349	0	2327
Total	54435		8968	

Table 2. Reference samples over Europe, Middle-east, Russia and Central Asia for the nominal year 2015

2. Satellite Imagery: Landsat-7 and Landsat-8

To incorporate crop dynamics across the entire study area which extensively covers Europe, Middle-east, Russia and Central Asia was stratified into twelve zones based on expert knowledge, agro-ecological characteristics and administrative boundaries (Figure 2).

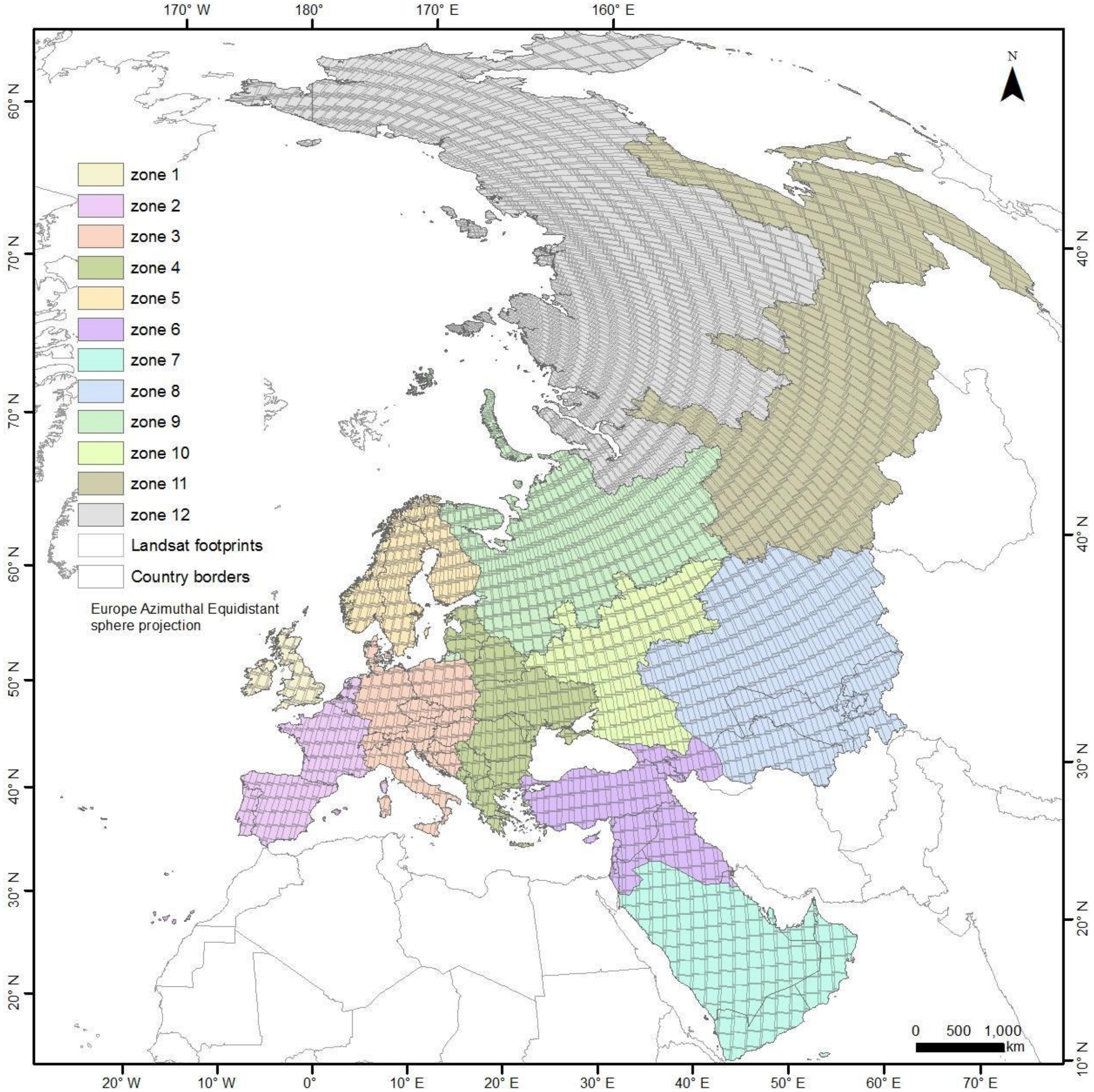

Figure 2. Stratification of the Europe, Middle-east, Russia and Central Asia into twelve distinct zones based on agro-ecological characteristics and administrative boundaries. The figure also shows the Landsat data tiles distribution across study area. The Random Forest (RF) supervised machine-learning algorithm used for classification of croplands and non-croplands in each of the twelve zones.

Landsat-8 and Landsat-7 time-series multispectral images at the resolution of 30-meter (Irons et al., 2012; Roy et al., 2014) for the time period of 2014 to 2016 were used as primary data aiming to provide seamless 30-meter data for the entire study area. We processed approximately 160,000 Landsat images with 3351 Landsat tiles spread across study area for 2014 to 2016 time period (Table 3 and Table 4).

Sensor	Time-period	Bands	Resolution	Type	Data Source
Landsat-7 ETM+	Jan 2014-Dec 2016	B1 (Blue) B2 (Green) B3 (Red) B4 (Near Infrared) B5 (Shortwave Infrared 1) B7 (Shortwave Infrared 2) NDVI NDWI	30m 30m 30m 30m 30m 30m 30m 30m	SR*	USGS
Landsat-8 OLI	Jan 2014-Dec 2016	B2 (Blue) B3 (Green) B4 (Red) B5 (Near Infrared) B6 (Shortwave Infrared 1) B7 (Shortwave Infrared 2) NDVI NDWI	30m 30m 30m 30m 30m 30m 30m 30m	SR	USGS
Shuttle Radar Topography Mission(SRTM)		Slope	30m		USGS

Note: *SR is the surface reflectance product of the Landsat data and data accessed through Google Earth Engine (GEE)

Table 3. Characteristics of input multi-temporal Landsat data and slope band

Zones	Landsat tiles	Number of Landsat satellite images sensor-wise					
		LE7	LC8	LE7	LC8	LE7	LC8
z1	57	488	713	530	717	535	698
z2	135	1844	2112	1859	2217	1832	2191
z3	151	2208	2514	2223	2600	2272	2539
z4	167	2154	2668	2478	2666	2575	2575
z5	168	996	1866	1481	1806	1663	1816
z6	139	2359	2866	2574	2729	2389	2771
z7	152	1868	3305	2977	3137	2942	3282
z8	290	3274	5299	4737	5004	4434	5088
z9	430	892	2054	1460	1959	1530	3006
z10	183	1499	2330	2000	2198	1697	2212
z11	513	2401	3656	3274	3905	3218	5372
z12	966	18	44	28	124	21	4987
		2014		2015		2016	

Table 4. Number of Landsat scenes in the study area with two Landsat sensors (ETM+ and OLI) for 2014 to 2016 in each zone.

In addition to remotely sensed inputs, we used 'slope' derived from the Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) (http://www2.jpl.nasa.gov/srtm/). Topographic features play an important role in mapping croplands because most of the world's cultivated areas occur on gradual slopes and medium elevations (Jarvis et al., 2008). In order to ensure cloud-free or near-cloud-free wall-to-all coverage, bi - monthly composites, depending on the cloudiness of the countries\regions, were composed. 30-m mega-file data-cubes (MFDC's) were created as per the following steps leading to 56-band MFDC for Europe, Middle-east, Russia and Central Asia.

Systematic detail of MFDC composition is given in table 4 described as below:
The goal of the time-composites was to achieve cloud-free or near cloud-free time wall-to-wall composites over the entire study area. The process involved collecting all the Landsat images over study area and composing bands by taking 75th percentile value of each pixel of each band. The band stack, and time-periods divided into seasons led to formation of MFDC (Table 5). All compositions were performed on the Google Earth Engine (GEE) a cloud-based geospatial platform for planetary-scale data analysis (Gorelick et al, 2017).

Study area	Europe, Middle-east, Russia and Central Asia
Number of seasons	Six seasons: (Season 1: January-February, Season 2: March-April, Season 3: May-June, Season 4: July-August, Season 5: September-October and Season 6: November-December)
Number of input bands in mega-file data cubes (MFDC)	56 bands: 1. Six seasons per year NDVI and NDWI bands i.e. NDVI (18 Bands), NDWI (18 bands) 2. Slope (1 band) (derived from SRTM DEM) 3. Standard Deviation of NDVI, Range of NDVI and Minimum of NDVI of overall composite (3 bands) 4. Landsat SR B1, B2, B3, B4, B5 and B7 maximum and minimum 75th percentile of overall composite (12 bands) 5. NDVI and NDWI max and min 75th percentile of overall composite (4 bands)

Table 5. Data cube of 30-m for the entire study area composited using time-series Landsat data for time-period 2014 to 2016 and slope derived from STRM elevation data.

b. Theoretical description

1. Definition of Croplands

For our Global Food Security-Support Analysis Data project at 30-m (GFSAD30) cropland extent map for Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEARUMECE), cropland extent was defined as: “lands cultivated with plants harvested for food, feed, and fiber, including both seasonal crops (e.g., wheat, rice, corn, soybeans, cotton) and continuous plantations (e.g., coffee, tea, rubber, cocoa, oil palms). Cropland fallow are lands uncultivated during a season or a year but are farmlands and are equipped for cultivation, including plantations (e.g., orchards, vineyards, coffee, tea, rubber” (Teluguntla et al., 2015). Cropland extent includes all planted crops and fallow lands. Non-croplands include all other land cover classes other than croplands and cropland fallow (Figure 3).

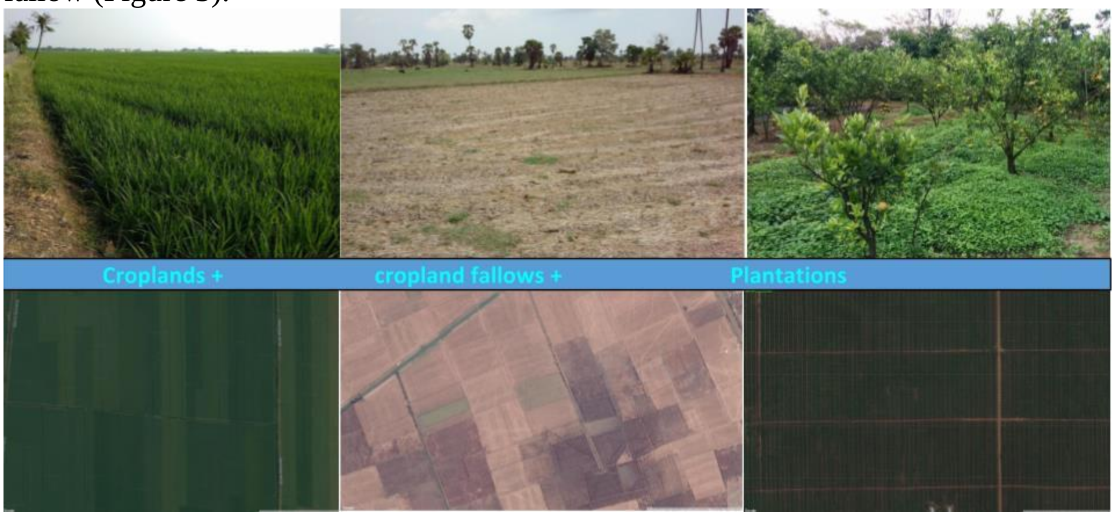

Figure 3. Illustration of definition of cropland mapping. Croplands included: (a) standing crop, (b) cropland fallows, and (c) permanent plantation crops.

2. Algorithms

The study used pixel-based supervised random forest machine learning algorithm to create the cropland extent product. Classification algorithm described in detail below. Study area stratified into twelve separate zones (Figure 2) to facilitate the optimal classification.

c. Practical description

1. Random Forest (RF) Algorithm

The Random Forest classifier is more robust, relatively faster in speed of classification, and easier to implement than many other classifiers (Pelletier et al., 2016). The Random Forests classifier uses bootstrap aggregating (bagging) to form an ensemble of decision trees (Pelletier et al., 2016) by searching random subspaces from the given data (features) and the best splitting of the nodes by minimizing the correlation between the trees.
All supervised pixel-based classifications such as the Random Forest are heavily dependent on the input training samples selected. In order to discriminate croplands under various environments and conditions, the sample size of the initial training dataset needs to be large, especially in complex regions. All samples were selected to represent a 90-m x 90-m polygon. To achieve required quality of cropland extent map, an iterative sample selection procedure was implemented with the following steps for training the Random Forest (RF) machine learning algorithm is described below (also see logical flow in Figure 1):

1. Build the Random Forest classifier on Google Earth Engine (GEE) cloud computing environment using existing training samples for each of the twelve zones (e.g., Figure 2). Initially we began with a small number of

samples and slowly increased the sample size until we reached a high degree of accuracy and the accuracy plateaued at certain sample size;
2. Classify the 30-m seasonal mosaics (Table 4) for each of the twelve zones (Figure 2) using the Random Forest algorithm in GEE cloud;
3. Visual assessment of classification results compared with existing reference maps as well as sub-meter to 5-m very high spatial resolution imagery (VHRI). The process was iterated until sufficient correspondence was achieved;
4. Added 'crop' and ‘non-crop’ samples in areas that were not covered using reference data obtained from the sub-meter to 5-m very high spatial imagery from Google Earth Imagery. For locations where interpretations were challenging (fallow-land or abandoned fields), historical Landsat Images and ground data were also used.
5. Loop step 1-4 by progressively increasing the training dataset until classification becomes stable.

The number of iterations required for the training sample selection is a function of the complexity of the area. In this situation, the iterative selection was looped 4~5 times to improve the classification results.

2. Programming and codes

The pixel-based supervised machine-learning algorithm (RF) coded on Google Earth Engine (GEE) using Python Scripts using Application Programming Interface (API). The codes are made available in a zip file and are available for download along with this ATBD.

3. Results

The machine learning algorithm (RF), discussed in previous sections, were trained to separate croplands versus non-croplands for each of the twelve zones (Figure 2) based on the previously described reference data. The random forest classifier then run on the Google Earth Engine (GEE) cloud computing environment using the Landsat based data-cube (Table 5) for each of the twelve zones to separate croplands versus non-croplands. The process was iterated and knowledge in the algorithms tweaked several times, before producing the final, accurate results of croplands versus non-croplands. This process resulted in the global food security-support analysis data @ 30-m cropland extent for Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEARUMECE) product (Figure 4). This product is publically available through the Land Processes Distributed Active Archive Center (LP DAAC). The same dataset is also available for visualization at https://croplands.org/app/map. Full resolution of 30-m cropland extent can be visualized in croplands.org by zooming-in to specific areas as illustrated in Figure 5. For any area in Europe, Middle-east, Russia and Central Asia, croplands can be visualized by zooming into specific areas in croplands.org. The background sub-meter to 5-m imagery, available for the continent on the Google Earth, helps evaluate the quality of the cropland extent product (“zoom in” and “toggle” cropland “on” and “off” to see the sub-meter to 5-m imagery in the background.

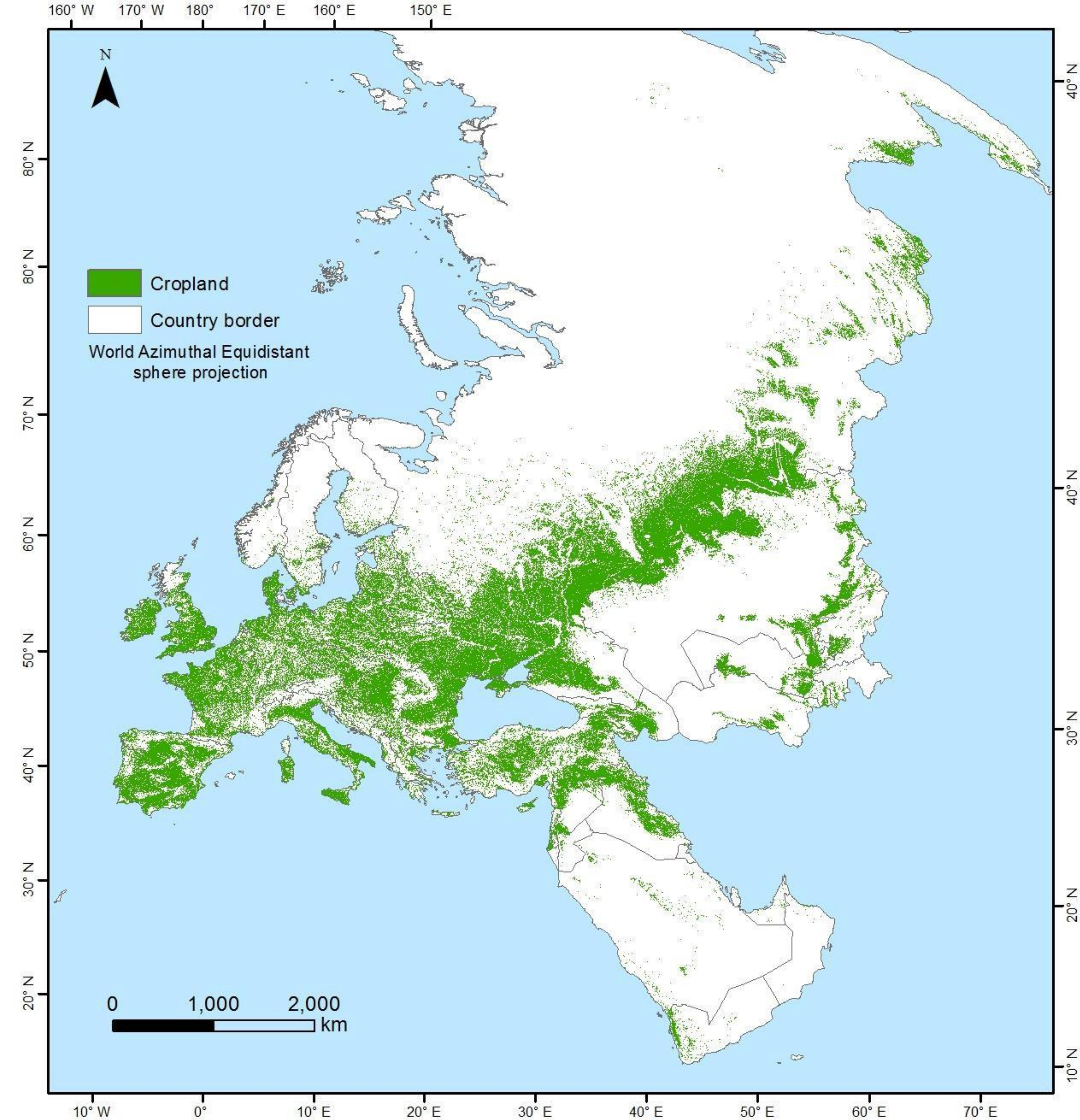

Figure 4. Cropland extent-product at 30-m for Europe, Middle-east, Russia and Central Asia (GFSAD30EUCEA-RUMECE). This product is made available for visualization @: croplands.org. The data is downloadable from LP DAAC.

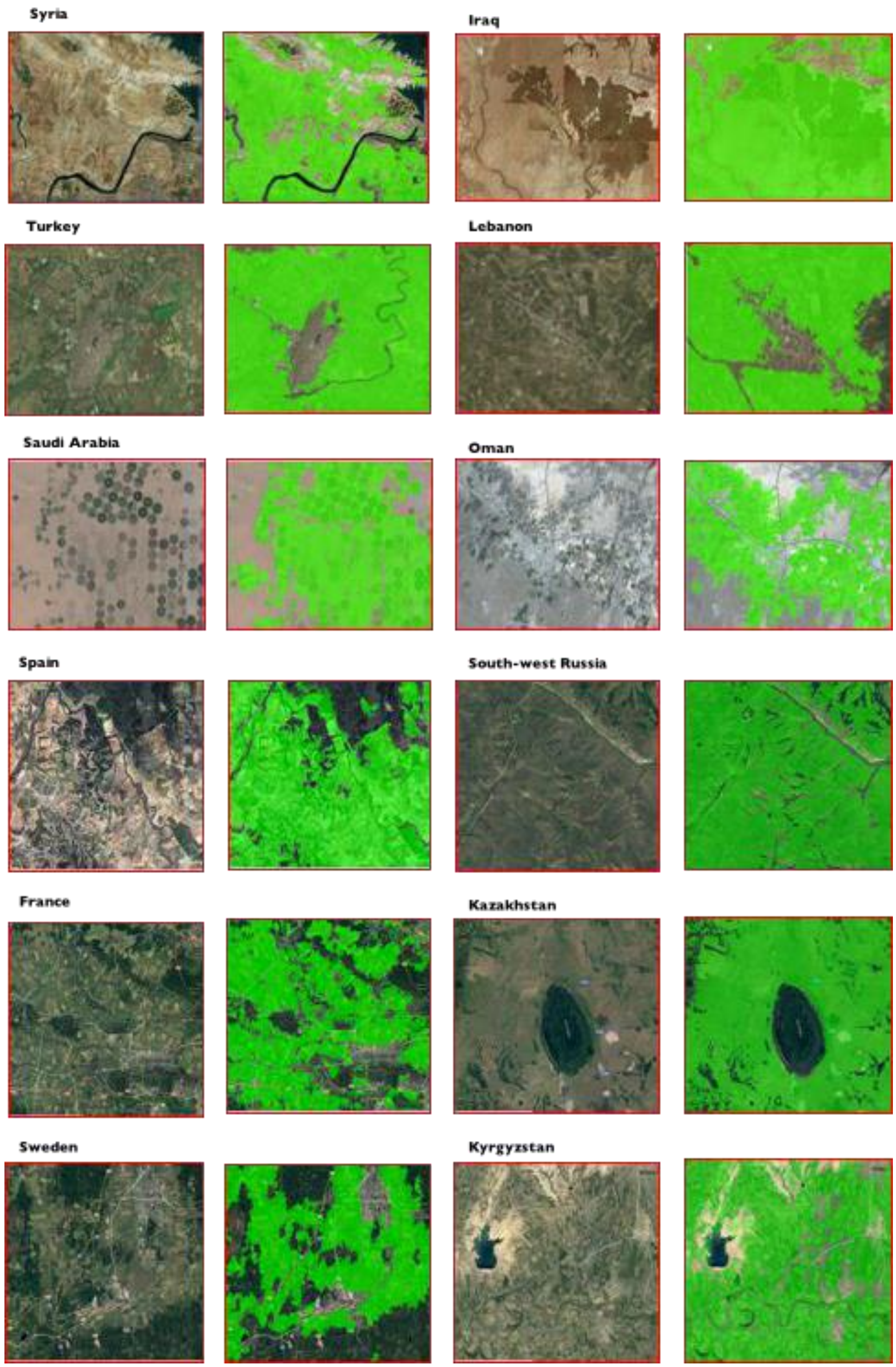

Figure 5. Visual interpretation of cropland extent product at 30-m for Europe, Middle-east, Russia and Central Asia. Green color represents the cropland mask and background is the natural color composite high resolution satellite image.

4. Cropland areas of Europe, Middle-east, Russia and Central Asia

Country-wise cropland areas calculated based 30-m crop extent maps from this study are summarized here. Table 4 and Table 5 show a country-by-country cropland area statistics of all countries generated from this study and compared with several other sources such as the national census data based MIRCA2000 (Stefan Siebert and Portmann, personal communication; Portmann, 2010) which were also updated in the year 2015, The Food and Agricultural Organization (FAO) of United Nation's compiled statistics, MODIS 500-m derived cropland areas from GRIPC (Salmon et al., 2015), and GIAM-GMRCA (Thenkabail et al., 2009 and Biradar et al., 2009) derived cropland areas. Overall as per GFSAD30EUCEARUMECE estimates, total net cropland of Europe, Middle-east, Russia and Central Asia is 279.1 Mha, 70 Mha, 155.8 Mha and 76.9 Mha respectively.

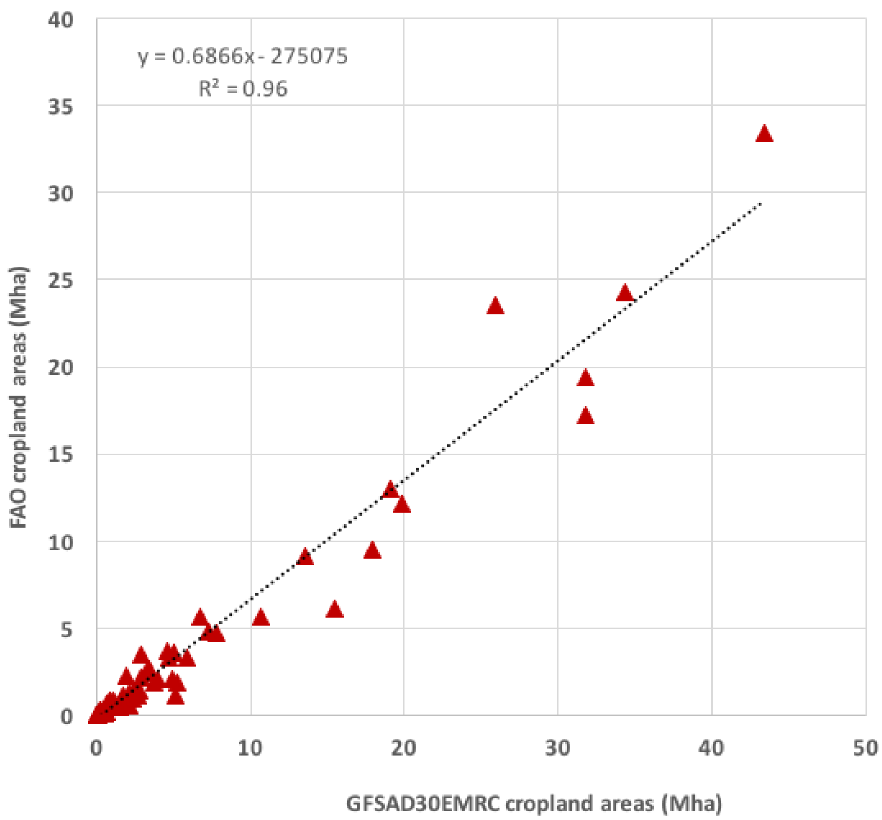

Figure 6. Scatter plot of country wise areas estimated by GFSAD30EUCEARUMECE and FAO.

On average, the GFSAD30EUCEARUMECE had much higher estimates; higher by about 2-30% relative to statistical data from MIRCA and FAO (Table 5 and 6). There are several reasons for these significant differences in areas between GFSAD30EUCEARUMECE when compared with MIRCA and FAO estimates. These include:

(i) The ability of the higher spatial resolution 30-m derived croplands GFSAD30EUCEARUMECE map to capture fragmented croplands;

(ii) The ability of the 30-m derived croplands GFSAD30EUCEARUMECE map to account for actual areas when compared with sub-pixel areas of lower resolution imagery derived cropland products (e.g., GRIPC, GLC);

(iii) Differences in how cropland data are gathered\estimated\calculated. The 30-m derived cropland GFSAD30EUCEARUMECE map provides objective estimates relative to how other statistical data were obtained. Statistical data of countries are reported by countries based on a wide range of methods, techniques, and data used. For example, FAO compiles the statistics reported by individual countries, which are based on national censuses, agricultural samples, questionnaire-based surveys with major agricultural producers, and independent evaluations (FAO, 2006 and The World Bank, 2010). Since each country has its own data collection mechanism, differences in data gathering, resource limitations, and lack of objectivity in many countries (due to resource limitations) results in data quality issues;

(iv) Definition issues. Not every country adheres to same definitions of croplands. Our study used the TNCA definition to include planted crops along with croplands left fallow as well as permanent crops such as plantations (e.g., olive, fruit trees, vineyards, coffee and tea plantations, oil palm plantations etc). Many countries use similar definitions while others use different definitions (e.g., leaving out cropland fallow).

(v) Uncertainties inherent in all estimates. One can expect uncertainties in cropland areas maps (e,g., Figure 6) or areas estimated from different sources (e.g., Table 6 and Table 7) as a result of definitions, data used, methods adopted, and reporting mechanisms (e.g., FAO mostly reports official areas reported by the Countries). GFSAD30EUCEARUMECE uncertainties are gauged by the error matrices. In GFSAD30EUCEARUMECE uncertainties in cropland estimates mainly arose from three sources: (a) aquaculture, (b) green houses, and (c) managed grasslands.

Region Name	Country Name	Land Area[1]	GFSAD30[2]	MIRCA2014[3]	FAO-Agricultural land (without pasture)[4]	GIAM-GMRCA[5]	GRIPC2005[6]
Name	Name	Ha	Ha	Ha	Ha	Ha	Ha
Europe	Ukraine	57,971,910	43,375,936	34,483,060	33,392,284	31,285,731	50,085,213
Europe	Turkey	76,899,209	34,314,153	23,230,840	24,280,464	12,356,748	20,189,904
Europe	France	54,805,243	31,795,512	19,627,780	19,403,358	20,048,339	40,252,787
Europe	Spain	49,873,874	31,786,945	18,748,612	17,216,960	18,813,770	20,624,711
Europe	Germany	34,888,430	19,863,347	12,328,316	12,141,034	11,196,575	22,101,291
Europe	Poland	30,413,208	19,057,505	14,485,510	12,943,557	14,775,550	21,809,121
Europe	Italy	29,403,805	17,934,740	9,559,511	9,485,256	9,265,975	17,265,516
Europe	United Kingdom	24,196,927	15,461,875	6,566,839	6,098,400	5,985,362	9,888,546
Europe	Romania	22,998,299	13,617,454	10,163,640	9,155,071	9,938,493	16,732,340
Europe	Belarus	20,288,636	10,655,942	6,266,646	5,659,718	11,052,202	12,705,839
Europe	Hungary	9,050,078	7,294,849	4,883,556	4,776,758	4,600,188	7,743,140
Europe	Bulgaria	10,863,931	5,838,245	3,675,656	3,309,740	4,718,322	7,872,550
Europe	Portugal	9,141,439	5,229,711	2,704,046	1,904,628	3,115,042	2,264,433
Europe	Ireland	6,889,803	5,148,229	1,150,309	1,093,329	630,766	527,115
Europe	Serbia	8,745,675	5,083,568	3,434,899	3,594,105	3,119,543	0
Europe	Azerbaijan	8,258,681	4,947,772	2,518,816	2,102,594	2,234,411	4,033,759
Europe	Czech Republic	7,721,311	4,740,783	3,154,321	3,255,552	3,586,245	4,986,646
Europe	Greece	12,891,509	4,636,262	3,814,012	3,697,749	3,665,237	4,918,732
Europe	Lithuania	6,268,065	3,991,855	3,002,289	2,081,286	2,708,784	5,592,286
Europe	Sweden	41,053,333	3,449,715	2,600,998	2,641,782	1,124,739	2,101,480
Europe	Denmark	4,241,546	3,259,391	2,603,932	2,436,450	1,681,824	3,416,587
Europe	Moldova	3,287,234	2,863,151	2,171,410	2,118,504	1,827,082	3,161,580
Europe	Austria	8,250,000	2,745,656	1,470,858	1,438,272	1,938,650	2,727,139
Europe	Latvia	6,213,559	2,663,665	1,907,594	1,173,120	2,053,248	2,760,286
Europe	Slovakia	4,812,968	2,466,820	1,544,638	1,405,040	1,800,719	2,542,400
Europe	Croatia	5,603,448	2,347,095	1,594,850	956,800	1,586,883	3,062,561
Europe	Netherlands	3,375,000	2,234,414	1,040,835	1,090,773	1,434,345	2,321,567
Europe	Georgia	6,947,368	2,185,454	1,195,715	566,808	925,416	2,797,931
Europe	Finland	30,210,526	1,944,280	2,256,339	2,261,560	846,455	693,120
Europe	Bosnia & Herzegovina	5,103,118	1,776,082	1,084,319	1,098,048	1,314,387	2,863,715
Europe	Belgium	3,031,111	1,676,417	3,230,784	862,048	1,426,221	2,046,939
Europe	Armenia	2,847,403	1,492,498	661,526	510,414	522,285	1,264,396
Europe	Estonia	4,231,818	1,408,622	842,763	604,219	1,077,199	1,277,601
Europe	Switzerland	4,002,625	1,357,409	465,170	430,050	720,372	1,339,537
Europe	Norway	30,727,273	830,916	691,298	839,592	487,408	267,885
Europe	Albania	2,736,364	703,638	801,083	698,320	1,088,326	1,868,466
Europe	Slovenia	2,017,241	674,902	200,578	200,772	542,659	705,434
Europe	Cyprus	925,926	513,145	171,943	120,750	156,041	253,336
Europe	Montenegro	1,345,550	218,299	381,028	189,152	374,691	0
Europe	Luxembourg	258,893	137,439	61,665	64,059	111,041	177,984
Europe	Liechtenstein	14,778	5,467	4,031	3,228	4,839	5,527
Europe	San Marino	5,988	5,198	1,959	1,000	3,162	4,697
Europe	Andorra	46,997	1,196	1,123	1,008	5,776	3,975

1= total land area is land area excluding area under inland water bodies
2=current study
3=Monthly irrigated and rainfed crop areas (MIRCA) around the year derived by Portman et al.
4=FAO Agricultural land area excluding pasture based on FAO2013 statistics consider nominal 2015
http://www.fao.org/faostat/en/#data/QC
5= global croplands derived from Global Irrigated Area Mapping (GIAM) and Global Map of Rainfed Cropland Areas (GMRCA) by Thenkabail et al.,2009 and Biradar et al., 2009
6= Global rain-fed, irrigated, and paddy croplands (GRIPC) derived by Solomon et al.,2015

Table 6. Net cropland areas (NCAs) derived based on 30-m GFSAD30 cropland product and comparison with other cropland products for Europe.

Region Name	Country Name	Land Area[1]	GFSAD30[2]	MIRCA2014[3]	FAO-Agricultural land (without pasture)[4]	GIAM-GMRCA[5]	GRIPC2005[6]
Name	Name	Ha	Ha	Ha	Ha	Ha	Ha
Middle east	Syria	18,372,523	6,752,220	4,741,506	5,660,556	1,446,239	2,886,777
Middle east	Saudi Arabia	214,913,259	2,920,610	3,260,511	3,468,700	742,196	289,239
Middle east	Yemen	52,819,820	2,480,329	1,655,154	1,454,024	297,998	341,428
Middle east	Macedonia	2,519,900	864,548	646,760	454,837	865,762	1,742,628
Middle east	Israel	2,170,124	606,876	424,611	382,836	201,470	511,835
Middle east	Jordan	8,913,043	491,087	406,142	282,900	148,266	354,583
Middle east	United Arab Emirates	8,367,647	247,015	394,786	264,016	93,810	7,751
Middle east	Lebanon	1,022,288	240,023	338,571	288,272	151,455	219,125
Middle east	Oman	31,118,644	177,808	126,395	135,864	84,302	30,843
Middle east	West Bank	565,500	116,826	0	0	65,748	0
Middle east	Kuwait	1,776,471	40,747	16,713	14,949	37,333	1,434
Middle east	Qatar	1,160,714	26,897	12,520	15,015	38,509	361
Middle east	Gaza Strip	36,500	22,774	0	0	6,601	11,248
Middle east	Bahrain	77,670	6,099	8,224	3,896	0	89
Russia	Russia	1,633,037,879	155,799,806	127,482,904	123,516,453	128,675,415	235,890,486
West Asia	Iran	162,802,013	33,063,882	16,644,983	18,969,365	8,133,031	7,358,862
West Asia	Iraq	43,532,338	12,451,749	6,647,068	4,751,250	3,576,735	2,543,489
West Asia	Afghanistan	65,249,570	8,499,171	9,480,926	7,923,190	3,756,220	909,683
Central Asia	Kazakhstan	270,051,813	25,885,023	23,102,226	23,558,240	38,950,704	36,389,615
Central Asia	Uzbekistan	42,573,482	7,789,426	6,051,359	4,663,925	6,423,474	5,861,982
Central Asia	Turkmenistan	46,988,473	3,729,913	2,605,478	1,923,990	2,065,350	1,694,870
Central Asia	Kyrgyzstan	19,164,260	2,159,334	2,094,460	1,348,359	2,691,843	2,580,683
Central Asia	Tajikistan	14,011,799	1,135,755	1,363,955	874,000	1,573,635	1,531,621

1= total land area is land area excluding area under inland water bodies
2=current study
3=Monthly irrigated and rainfed crop areas (MIRCA) around the year derived by Portman et al.
4=FAO Agricultural land area excluding pasture based on FAO2013 statistics consider nominal 2015 http://www.fao.org/faostat/en/#data/QC
5= global croplands derived from Global Irrigated Area Mapping (GIAM) and Global Map of Rainfed Cropland Areas (GMRCA) by Thenkabail et al.,2009 and Biradar et al., 2009
6= Global rain-fed, irrigated, and paddy croplands (GRIPC) derived by Solomon et al.,2015

Table 7. Net cropland areas (NCAs) derived based on 30-m GFSAD30 cropland product and comparison with other cropland products for Middle-east, Russia and Central Asia.

V. Calibration Needs/Validation Activities

An independent accuracy assessment for the 12 regions and study area as a whole, were performed by our assessment team at the University of New Hampshire. For this assessment, 3000 reference samples that were collected independently of any reference training and testing samples used by the mapping team. Error matrices were generated for each of the twelve zones separately and for the entire study area providing producer's, user's, and overall accuracies (Story and Congalton, 1986, Congalton, 2015).

For the entire study area, the weighted overall accuracy was 93.8% with producer's accuracy of 86.5% and user's accuracy of 85.7% (Table 7). When considering all twelve zones, the overall accuracies ranged between 76-100%, producer's accuracies ranged between 64-92%, and user's accuracies ranged between 54-95% (Table 7). These results clearly imply the high level of confidence in differentiating croplands from non-croplands for Europe, Middle-east, Russia and Central Asia.
High producer's accuracies across zones suggest than few croplands were omitted during the mapping process. On the other hand, high user's accuracies across zones suggest than croplands were rarely mapped (or committed) in error. The machine learning algorithms (RF) was optimized to map the maximum extent of croplands. To some extent, this decision increases commission errors. In summary, producer's accuracy 86.5% and user's accuracy 85.7% with overall accuracy 91% for entire study area error matrix clearly indicates that croplands have been mapped with high accuracy (Table 8)

Zone 1, % of TCA*=3.5%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	156	15	171	91.2%
	No-Crop	13	66	79	83.5%
	Total	169	81	250	
	Producer Accuracy	92.3%	81.5%		**88.8%**

Zone 2, % of TCA*=12.5%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	129	24	153	84.3%
	No-Crop	28	69	97	71.1%
	Total	157	93	250	
	Producer Accuracy	82.2%	74.2%		**79.2%**

Zone 3, % of TCA*=14.4%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	144	12	156	92.3%
	No-Crop	20	74	94	78.8%
	Total	164	86	250	
	Producer Accuracy	87.8%	86.1%		**87.2%**

Zone 4, % of TCA*=16.5%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	145	11	156	93%
	No-Crop	21	73	94	77.7%
	Total	166	84	250	
	Producer Accuracy	87.4%	87.0%		**87.2%**

Zone 5, % of TCA*=1.2%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	18	1	19	94.7%
	No-Crop	2	229	231	99.1%
	Total	20	230	250	
	Producer Accuracy	90%	99.6%		**98.8%**

Zone 6, % of TCA*=1%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	87	22	109	79.8%
	No-Crop	10	131	141	92.9%
	Total	97	153	250	
	Producer Accuracy	89.7%	85.6%		**87.2%**

Zone 7, % of TCA*=1%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	8	0	8	100%
	No-Crop	1	241	242	99.6%
	Total	9	241	250	
	Producer Accuracy	88.9%	100%		**99.6%**

Zone 8, % of TCA*=13.2%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	36	11	47	76.6%
	No-Crop	4	199	203	98%
	Total	40	210	250	
	Producer Accuracy	90%	94.8%		**94%**

Zone 9, % of TCA*=2.4%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	7	6	13	53.9%
	No-Crop	4	233	237	98.3%
	Total	11	239	250	
	Producer Accuracy	63.6%	97.5%		**96%**

Zone 10, % of TCA*=17.2%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	106	35	141	75.2%
	No-Crop	25	84	109	77.1%
	Total	131	119	250	
	Producer Accuracy	80.9%	70.6%		**76%**

Zone 11, % of TCA*=7.2%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	21	6	27	77.8%
	No-Crop	5	217	222	97.8%
	Total	26	223	249	
	Producer Accuracy	80.8%	97.3%		**95.6%**

Zone 12, % of TCA*=0.02%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	0	0	0	NA
	No-Crop	0	250	250	100%
	Total	0	250	250	
	Producer Accuracy	NA	100%		**100%**

All zones, % of TCA*=16.5%		Reference Data			
		Crop	No-Crop	Total	User Accuracy
Map Data	Crop	857	143	1,000	85.7%
	No-Crop	134	1,866	2,000	93.3%
	Total	991	2,009	3,000	
	Producer Accuracy	86.5%	92.9%		**90.8%**
	Weighted Accuracy**				**93.8%**

Note: *TCA (Total Croplands Area) = 582 Mha

** The all-zones Weighted Accuracy is weighted by proportion of croplands in each zone

Table 8. Independent Accuracy Assessment of 30-m Cropland Extent Map for Europe, Middle-east, Russia and Central Asia. Accuracies were assessed for each of the 12 zones as well as for the entire study area.

VI. Constraints and Limitations

GFSAD30EUCEARUMECE product mapped the croplands of Europe, Middle-east, Russia and Central Asia@ nominal 30-m, which is the best-known resolution for cropland mapping over such large areas with 3130 Mha lands covering two largest continents of the globe. It also has high levels of accuracies with weighted overall accuracies of 93.8%, Producer's accuracy of 86.5% and user's accuracy of 85.7%.

A producer's accuracy of 86.5% for the cropland class means an error of omission of 13.5%. This means 13.5% of the continental croplands were missing in the product. User's accuracy 85.7% for the cropland class for the continent means there is an error of commission of 14.3%. This means, 14.3% of non-croplands are mapped as croplands. We tweaked the machine learning algorithms (section IV) to maximize capturing as much croplands as feasible automatically. In this process, some non-croplands get mapped as croplands as well. This is a preferred solution in order not to miss croplands or only to miss them minimally. As a compromise mapping some non-croplands as croplands becomes unavoidable.

There are numerous issues that cause uncertainties and limitations in cropland extent product. Some of these issues are discussed here. First, temporal coverage. 16-day Landsat coverage put together, there is substantial temporal coverage. Yet, we were only able to achieve seasonal cloud-free or near cloud-free mosaics of the entire study area. This is not surprising given the such a large area involved and frequent cloud (e.g., frequent clouds over the United Kingdom, Ireland, Sweden, Norway etc.) or dust across the study area. As a result, if we were to have daily coverage over an area (e.g., like MODIS) then it becomes feasible to have more frequent (e.g., monthly or bi-monthly composites) temporal coverage of the study area that will help advance cropland mapping at improved accuracies. Second, there is a need for greater understanding of the Landsat-7 and Landsat-8 data on how well they are correlated and in efforts to achieve better harmonization of data from two different sensors. Third, is the limitation of the reference training and validation data. In this project, we already have large training and validation data compared to any previous work as described in various previous sections. Nevertheless, much wider and extensive field visits to different parts of the study area will be helpful in better understanding of the issues involved and as a result better mapping. For example, slash and burn croplands in the rainforests or agro-forest driven croplands, helps us in better define, understand, and map croplands. These and a better understanding of croplands through field visits as well as understanding of host of other issues (e.g., various types of irrigated and rainfed croplands, croplands in desert margins, various types and ages of cropland fallows) all will help improve cropland mapping. Greatest difficulties in cropland mapping in Middle-east were in desert margins (e.g., Iraq where rainfed agriculture in limited to a very short season when anything will grow), rainforests (e.g., slash and burn agriculture), cropland fallows (e.g., whether a fallow is 1 year or 5-year or permanent). These and numerous other issues (e.g., implementing machine learning algorithms and uncertainties inherent in them) will continue to be there in cropland mapping over such large areas as Europe, Middle-east, Russia and Central Asia. Nevertheless, advances made in this study is significant, especially in developing a nominal 30-m cropland extent of the study area at very good accuracies.

VII. Publications

The following publications are related to the development of the above croplands products:

1. Peer-reviewed publications within GFSAD project

Congalton, R.G., Gu, J., Yadav, K., Thenkabail, P.S., and Ozdogan, M. 2014. Global Land Cover Mapping: A Review and Uncertainty Analysis. Remote Sensing Open Access Journal. Remote Sens. 2014, 6, 12070-12093; http://dx.doi.org/10.3390/rs61212070.

Congalton, R.G, 2015. Assessing Positional and Thematic Accuracies of Maps Generated from Remotely Sensed Data. Chapter 29, In Thenkabail, P.S., (Editor-in-Chief), 2015. "Remote Sensing Handbook" Volume I: Volume I: Data Characterization, Classification, and Accuracies: Advances of Last 50 Years and a Vision for the Future. Taylor and Francis Inc.\CRC Press, Boca Raton, London, New York. Pp. 900+. In Thenkabail, P.S., (Editor-in-Chief), 2015. "Remote Sensing Handbook" Volume I: **): Remotely Sensed Data Characterization, Classification, and Accuracies**. Taylor and Francis Inc.\CRC Press, Boca Raton, London, New York. ISBN 9781482217865 - CAT# K22125. Print ISBN: 978-1-4822-1786-5; eBook ISBN: 978-1-4822-1787-2. Pp. 678.

Gumma, M.K., Thenkabail, P.S.,Teluguntla, P., Rao, M.N., Mohammed, I.A., and Whitbread, A.M. 2016. Mapping rice-fallow cropland areas for short-season grain legumes intensification in South Asia using MODIS 250 m time-series data. International Journal of Digital Earth, http://dx.doi.org/10.1080/17538947.2016.1168489

Massey, R., Sankey, T.T., Congalton, R.G., Yadav, K., Thenkabail, P.S., Ozdogan, M., Sánchez Meador, A.J. 2017. MODIS phenology-derived, multi-year distribution of conterminous U.S. crop types, Remote Sensing of Environment, Volume 198, 1 September 2017, Pages 490-503, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2017.06.033.

Phalke, A. R., Ozdogan, M., Thenkabail, P. S., Congalton, R. G., Yadav, K., & Massey, R. et al. (2017). A Nominal 30-m Cropland Extent and Areas of Europe, Middle-east, Russia and Central Asia for the Year 2015 by Landsat Data using Random Forest Algorithms on Google Earth Engine Cloud. (in preparation).

Teluguntla, P., Thenkabail, P.S., Xiong, J., Gumma, M.K., Congalton, R.G., Oliphant, A., Poehnelt, J., Yadav, K., Rao, M., and Massey, R. 2017. Spectral matching techniques (SMTs) and automated cropland classification algorithms (ACCAs) for mapping croplands of Australia using MODIS 250-m time-series (2000–2015) data, International Journal of Digital Earth.
DOI:10.1080/17538947.2016.1267269.IP-074181, http://dx.doi.org/10.1080/17538947.2016.1267269.

Teluguntla, P., Thenkabail, P., Xiong, J., Gumma, M.K., Giri, C., Milesi, C., Ozdogan, M., Congalton, R., Yadav, K., 2015. CHAPTER 6 - Global Food Security Support Analysis Data at Nominal 1 km (GFSAD1km) Derived from Remote Sensing in Support of Food Security in the Twenty-First Century: Current Achievements and Future Possibilities, in: Thenkabail, P.S. (Ed.), Remote Sensing Handbook (Volume II): Land Resources Monitoring, Modeling, and Mapping with Remote Sensing. CRC Press, Boca Raton, London, New York., pp. 131–160. Link.

Xiong, J., Thenkabail, P.S., Tilton, J.C., Gumma, M.K., Teluguntla, P., Oliphant, A., Congalton, R.G., Yadav, K. 2017. A Nominal 30-m Cropland Extent and Areas of Continental Africa for the Year 2015 by Integrating Sentinel-2 and Landsat-8 Data using Random Forest, Support Vector Machines and Hierarchical Segmentation Algorithms on Google Earth Engine Cloud. Remote Sensing Open Access Journal (in review).

Xiong, J., Thenkabail, P.S., Gumma, M.K., Teluguntla, P., Poehnelt, J., Congalton, R.G., Yadav, K., Thau, D. 2017. Automated cropland mapping of continental Africa using Google Earth Engine cloud computing, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 126, April 2017, Pages 225-244, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2017.01.019.

2. Web sites and Data portals:

http://croplands.org (30-m global croplands visualization tool)
http://geography.wr.usgs.gov/science/croplands/index.html (GFSAD30 web portal and dissemination)
http://geography.wr.usgs.gov/science/croplands/products.html#LPDAAC (dissemination on LP DAAC)
http://geography.wr.usgs.gov/science/croplands/products.html (global croplands on Google Earth Engine)
croplands.org (crowdsourcing global croplands data)

3. Other relevant past publications prior to GFSAD project

Biggs, T., Thenkabail, P.S., Krishna, M., GangadharaRao Rao, P., and Turral, H., 2006. Vegetation phenology and irrigated area mapping using combined MODIS time-series, ground surveys, and agricultural census data in Krishna River Basin, India. International Journal of Remote Sensing. 27(19):4245-4266.

Biradar, C.M., Thenkabail, P.S., Noojipady, P., Yuanjie, L., Dheeravath, V., Velpuri, M., Turral, H., Gumma, M.K., Reddy, O.G.P., Xueliang, L. C., Schull, M.A., Alankara, R.D., Gunasinghe, S., Mohideen, S., Xiao, X. 2009. A global map of rainfed cropland areas (GMRCA) at the end of last millennium using remote sensing. International Journal of Applied Earth Observation and Geoinformation. 11(2). 114-129. doi:10.1016/j.jag.2008.11.002. January, 2009.

Dheeravath, V., Thenkabail, P.S., Chandrakantha, G, Noojipady, P., Biradar, C.B., Turral. H., Gumma, M.1, Reddy, G.P.O., Velpuri, M. 2010. Irrigated areas of India derived using MODIS 500m data for years 2001-2003. ISPRS Journal of Photogrammetry and Remote Sensing. http://dx.doi.org/10.1016/j.isprsjprs.2009.08.004. 65(1): 42-59.

Thenkabail, P.S. 2012. Special Issue Foreword. Global Croplands special issue for the August 2012 special issue for Photogrammetric Engineering and Remote Sensing. PE&RS. 78(8): 787- 788.Thenkabail, P.S. 2012. Guest Editor for Global Croplands Special Issue. Photogrammetric Engineering and Remote Sensing. PE&RS. 78(8).

Thenkabail, P.S., Biradar C.M., Noojipady, P., Cai, X.L., Dheeravath, V., Li, Y.J., Velpuri, M., Gumma, M., Pandey, S. 2007a. Sub-pixel irrigated area calculation methods. Sensors Journal (special issue: Remote Sensing of Natural Resources and the Environment (Remote Sensing SensorsEdited by Assefa M. Melesse). 7:2519-2538. http://www.mdpi.org/sensors/papers/s7112519.pdf.

Thenkabail, P.S., Biradar C.M., Noojipady, P., Dheeravath, V., Li, Y.J., Velpuri, M., Gumma, M., Reddy, G.P.O., Turral, H., Cai, X. L., Vithanage, J., Schull, M., and Dutta, R. 2009a. Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium. International Journal of Remote Sensing. 30(14): 3679-3733. July, 20, 2009.

Thenkabail, P.S., Biradar, C.M., Turral, H., Noojipady, P., Li, Y.J., Vithanage, J., Dheeravath, V., Velpuri, M., Schull M., Cai, X. L., Dutta, R. 2006. An Irrigated Area Map of the World (1999) derived from Remote Sensing. Research Report # 105. International Water Management Institute. Pp. 74. Also, see under documents in: http://www.iwmigiam.org.

Thenkabail, P. S.; Dheeravath, V.; Biradar, C. M.; Gangalakunta, O. P.; Noojipady, P.; Gurappa, C.; Velpuri, M.; Gumma, M.; Li, Y. 2009b. Irrigated Area Maps and Statistics of India Using Remote Sensing and National Statistics. Journal Remote Sensing. 1:50-67. http://www.mdpi.com/2072-4292/1/2/50.

Thenkabail, P.S., GangadharaRao, P., Biggs, T., Krishna, M., and Turral, H., 2007b. Spectral Matching Techniques to Determine Historical Land use/Land cover (LULC) and Irrigated Areas using Time-series AVHRR

Pathfinder Datasets in the Krishna River Basin, India. Photogrammetric Engineering and Remote Sensing. 73(9): 1029-1040. (Second Place Recipients of the 2008 John I. Davidson ASPRS President's Award for Practical papers).

Thenkabail, P.S., Hanjra, M.A., Dheeravath, V., Gumma, M.K. 2010. A Holistic View of Global Croplands and Their Water Use for Ensuring Global Food Security in the 21st Century through Advanced Remote Sensing and Non-remote Sensing Approaches. Remote Sensing open access journal. 2(1):211-261. doi:10.3390/rs2010211. http://www.mdpi.com/2072-4292/2/1/211

Thenkabail P.S., Knox J.W., Ozdogan, M., Gumma, M.K., Congalton, R.G., Wu, Z., Milesi, C., Finkral, A., Marshall, M., Mariotto, I., You, S. Giri, C. and Nagler, P. 2012. Assessing future risks to agricultural productivity, water resources and food security: how can remote sensing help? Photogrammetric Engineering and Remote Sensing, August 2012 Special Issue on Global Croplands: Highlight Article. 78(8): 773-782.

Thenkabail, P.S., Schull, M., Turral, H. 2005. Ganges and Indus River Basin Land Use/Land Cover (LULC) and Irrigated Area Mapping using Continuous Streams of MODIS Data. Remote Sensing of Environment. Remote Sensing of Environment, 95(3): 317-341.

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