COMPARING AND SYNTHESIZING DIFFERENT GLOBAL AGRICULTURAL LAND DATASETS FOR CROP ALLOCATION MODELING

Liangzhi You*[,1] ,Stanley Wood[2], Kate Sebastian[3]

[1] International Food Policy Research Institute, 2003 K Street, NW, Washington, DC 20006, USA – Phone: (202) 862-8168 Email:l.you@cgiar.org
[2] International Food Policy Research Institute, 2003 K Street, NW, Washington, DC 20006, USA- Phone: (202) 862-8122, Email: s.wood@cgiar.org
[3] International Food Policy Research Institute, 2003 K Street, NW, Washington, DC 20006, USA

KEY WORDS: Cultivated land, Land cover, Remote sensing, crop, Food security

ABSTRACT

Cultivated land has been feeding the world for thousands of years. Only in the last few decades, remote sensing is used to assess and monitor the extent and status of cultivated land. One of the greatest challenges when working with existing land cover datasets is the lack of consistent and reliable data on the location and area intensity of cultivation. By most counts land cover datasets identify cultivated areas as those that encompass cropland and highly managed pasture. Extensive pasture and grazing lands are difficult to distinguish from natural grasslands and thus are usually not identified separately. A number of coarse resolution (1km) global land cover datasets exist but the accuracy and extent of the areas classified as cultivated vary widely. These datasets include: IFPRI's (International Food Policy Research Institute) extent of cultivated area, which was derived from the Global Land Cover Characterization Database (GLCCD) and is based on 1992/93 AVHRR satellite data; GLC2000 which was derived from 2000 SPOT satellite data; Boston University's Global Land Cover dataset based on 2000 MODIS data. Each of these datasets includes classes related to cultivated areas but each were derived using different criteria, thresholds, etc… and none of them stands out as fully encompassing the areas across the globe that are characterized by cultivation particularly those characterized by a mosaic of cultivation and other natural land covers. It is thus a challenge for individuals and organizations working with these datasets to find a reliable 'picture' of cultivation in one dataset.

A preliminary analysis of these datasets performed for the Millennium Assessment (MA) found that the MODIS dataset was severely lacking in its representation of cropland and cropland mosaics. It reported a mere 12.6% of global land cover designated as cropland or cropland mosaic compared to 18.3% for GLC2000 and 27.3% from IFPRI. The regions with the most severe deficits were Latin America and Sub-Saharan Africa which is not surprising since these are areas where mosaic classes are most prevalent in the other datasets. The goal of this paper is to derive an integrated cultivated area dataset based by merging the existing crop land surfaces. We first describe the three global cultivated land datasets, and compare their disagreements. Using actual crop census data as a benchmark, we assessed the difference and accuracy of these three cultivated land surfaces. We then proposed a method to exploit the synergy of existing datasets. Finally we apply our method to develop a new synthesized global cultivated land product and a corresponding confidence estimate of the new cultivated land dataset. This new cultivated land has been used in our spatial allocation model (SPAM).

1. 1. INTRODUCTION

Food security remains a challenge in many developing countries, in particular Sub-Sahara Africa and South Asia. Accurate spatial information of cropland is particularly important for crop monitoring and food security. The satellite derived land cover datasets have been widely used in this purpose. For example, The Famine Early Warning Systems Network (FEWS NET, funded by USAID) has been using satellite data to provide timely and rigorous early warning and vulnerability information on emerging and evolving food security issues. Global crop land cover also provides vital baseline information of agriculture production in many spatial explicit models and in applications such as United Nations' Millennium Ecosystem Assessment (2005), the Global Environmental Outlook (GEO, 2007). However, there is significant disagreements and high uncertainty among different land over datasets (Fritz and See, 2005; Giri et al. 2005; Jung et al., 2006). The uncertainty and inconsistency is particularly high for cultivated land (cropland and managed pasture), comparing to other natural vegetations such as tree covers (Wood, Sebastian and Scherr, 2000). One of the greatest challenges when working with existing land cover datasets is the lack of consistent and reliable data on the location and area intensity of cultivation. By most counts land cover datasets identify cultivated areas as those that encompass cropland and highly managed pasture. Extensive pasture and grazing lands are difficult to distinguish from natural grasslands and thus are usually not identified separately. A number of coarse resolution (1km) global land cover datasets exist but the accuracy and extent of the areas classified as cultivated vary widely. These datasets include: IFPRI's (International Food Policy Research Institute) extent of cultivated area, which was derived from the Global Land Cover Characterization Database (GLCCD) and is based on 1992/93 NOAA-AVHRR (National Ocean and Atmosphere Agency, Advanced Very High Resolution Radiometer) satellite data; GLC2000 which was derived from 2000 SPOT-VEGATATION ( )satellite data; Boston University's Global Land Cover dataset based on 2000 MODIS (MODerate resolution Imaging Spectroradiometer) data. Each of these datasets includes classes related to cultivated areas but each were derived using different criteria, thresholds, etc… and none of them stands out as fully encompassing the areas across the globe that are characterized by cultivation particularly those characterized by a mosaic of cultivation and other natural land covers. It is thus a challenge for individuals and organizations working with these datasets to find a reliable 'picture' of cultivation in one dataset.

A preliminary analysis of these datasets performed for the Millennium Assessment (MA) found that the MODIS dataset was severely lacking in its representation of cropland and cropland mosaics. It reported a mere 12.6% of global land cover designated as cropland or cropland mosaic compared to 18.3% for GLC2000 and 27.3% from IFPRI. The regions with the most severe deficits were Latin America and Sub-Saharan Africa which is not surprising since these are areas where mosaic classes are most prevalent in the other datasets. The goal of this paper is to derive an integrated cultivated area dataset based by merging the existing crop land surfaces. We first describe the three global cultivated land datasets, and compare their disagreements. Using actual crop census data as a benchmark, we assessed the difference and accuracy of these three cultivated land surfaces. We then proposed a method to exploit the synergy of existing datasets. Finally we apply our method to develop a new synthesized global cultivated land product and a corresponding confidence estimate of the new cultivated land dataset. This new cultivated land has been used in our spatial allocation model (SPAM).

2. OVERVIEW OF CURRENT GLOBAL CROPLAND DATASETS

The cropland is generally derived from global land cover product. Mapping global land cover is a quite challenging and involves inter-disciplinary contributions from satellite technology, image processing, computer science, and photogrammetry. Here we used three high-resolution global land cover datasets: NOAA-AVHRR (Hansen at al., 2000; Loveland et al., 2000), TERRA-MODIS (Friedl et al., 2002), and SPOT-VEGETATION (JRC, 2003). The differences among these land cover datasets are related sensor capabilities of different satellites, raw data processing, acquisition years, classification system (land cover legend), classification procedure (supervised vs. unsupervised), and t validation of the final product (Jung et al., 2006). These differences lead to the different uncertainty and different accuracy in cropland estimate among the three land cover products.

Here we're mainly interested in accurately estimation of cultivated land, and therefore we are only extracting those land cover classes related to cultivated land. The following sections would describe the above-mentioned three land cover products in general, and how we estimated cultivated land in particular.

1) IFPRI cropland extent from NOAA-AVHRR

Global 1-km resolution AVHRR satellite imagery is consolidated into monthly global composites from the period of April 1992 to March 1993. The global land cover characteristics database was produced by the Earth Resource Observation System (EROS) Data Center of the U.S> Geological Survey and the University of Nebraska- Lincoln (USDS EDC 1999; Leveland et al. 2000). The dataset identifies approximately 200 seasonal land cover regions (SLCRs) per continent to capture both spatial and seasonal variations in vegetation cover. All these SLCRs were assigned manually into one of the 94 classes of the Olsen' Global Ecosystem Legend by local experts using ancillary data such as land use, elevation, ecoregion maps, or other image data.

To better capture crop land, IFPRI reassessed the cropland-related classed in consultation with EDC. For example, an area interpreted as containing more than 60 percent forest and classified as, "deciduous borad-leaaf forest" cover using the IGBP classification scheme might contain an agricultural subcomponent, e.g., its detailed classification might describe it as "deciduous broad forest with cropland". The reassessment aimed to identify all such occurrences of agriculture, even when they occurred as minor cover components. This reassessment resulted in three primary agricultural cover categories based on ranges of agricultural area intensity (30-40, 40-60, and > 60 percent agricultural), and two indeterminate categories in which agriculture might feasibly occur but whose area intensity lay below the SLCR threshold of 30 percent (Wood, Sebastian and Scherr 2000). Table 1 show these class description. This is referred in this paper as IFPRI agricultural land data.

[Table 1 here]

2) Crop land from TERRA-MODIS

The MODIS land cover product from Boston University (MOD12Q1 V004) is based on data from the Moderate Resolution Imaging Spectoradiometer instrument on the NASA Terra Platform during October 2000 to October 2001. It provides a suite of land cover classifications with the primary classification in the International Geosphere-Biosphere Programme (IGBP) scheme (Running, et al., 1994, Belward, et al., 1995). The classification was produced using a supervised approach. Training sites where developed by analyzing high resolution (e.g., Landsat TM) imagery in conjunction with ancillary data (Muchoney et al., 1999). The classification was produced using a decision tree classification algorithm (C4.5 [Quinlan 1993]) in conjunction with a technique for improving classification accuracies that has received considerable attention in the machine learning and statistics communities known as boosting [Freund 1995]. MODIS uses all 17 classes of IGBP, and there are two classed related to agricultural land: croplands (Class 12), and cropland/natural vegetation mosaic (Class 14).

3) Cropland from SPT-VEGETATION

The Global Land Cover 2000 (GLC2000) was created using daily 1km SPOT4-VEGETATION data from November 1999 to December 2000. It following a bottom up approach in which over 30 research teams around the world contributed to 19 regional windows, where local experts were responsible for the classification and mapping. The individual groups could freely choose their methodology except that they follow Land Cover Classfication System developed by FAO (Di Gregorio and Jansen 2000; Fritz et al. 2003). The global product has 22 land cover classes, in which there are 3 explicit crop land classes: Cultivated and managed areas (Class 15), Cropland / Tree Cover / Other natural vegetation (Class 16), and Cropland / Shrub or Grass Cover (Class 17).

Our main concern here is agricultural land, and we pull all the agriculture-related classes in all the above three products together. This is shown in Table 2. It also includes the implied cropland weights, which indicate the percentage of actual agricultural area within the pixel. For example, Cultivated and managed areas in GLC2000 has a weight of 50~100 percent. This means any pixel which has over 50% of cultivated area is classified as "Cultivated and managed areas" in GLC 2000. In consultation with the land cover experts who produced these land cover products, we also put the so-called "suggested weight" in Table 2. These are the actual weights suggested to estimate the actual agricultural land in a pixel.

[Table 2 here]

3. COMPARISON OF CROPLAND DATASETS AND CROP STATISTICS

Characterizing cropland is difficulty, in particular for moderate-resolution sensors. First, all the above three products are continental/global products, and cropland were only two or three of the several land cover categories under consideration. These sensors are not fine-tuned for detecting cropland (than say natural land covers such as trees). Second, cropland in many parts of the world, particularly in Africa and Latin America, is of low intensity and part of a heterogeneous landscape. Therefore, land cover classification datasets in 1-km resolution (where most of cultivated plots are far less than 1.0km^2) are unable to depict agriculture land (Ramankutty, 2004). Third, constant clouds during crop growing season in humid zones such as West, Central Africa may prevent the satellites from taking sufficient images. This would in turn lead to difficulty in characterizing cultivated lands.

[Table 3 here]

There is wide difference among these three land cover datasets. Table 3 shows the regional comparison of cropland-related land cover classes for the above three datasets. Here we only showed 4 land cover classes (which all of the three have in common): cropland,, cropland mosaic, forest, grassland, savanna, shrub land. We included the last two classes because agricultural land exists in some of them. Globally, IFPRI agricultural extent identifies 12.4% of cropland, 14.9% of cropland mosaic, the highest among the three datasets. GLC 2000 classifies only 5.1%, and MODIS – Boston University only 2.4% of global land area as cropland mosaic. Presumably, some of these cropland mosaic pixels are included in the forest or grassland, woody savanna, shrub land classes. The differences in the regions are even larger. For example, GLC 2000 classifies 12.6% of land area as cropland while only 4.6% by MODIS-Boston University.

While there is no census data on cropland area on pixel level, FAOSTAT provides the crop land area by countries. We could estimate the country total cropland by summarizing the cropland of all pixels with a country from satellite land cover data. Since not all pixel area is crop land even it is classified as cropland. We would use the weights given in Table 2 to calculate the minimum and maximum cropland by each country, taking the lower and upper limit of the cropland-related classes as described in Table 2. Using the FAOSTAT statistics as a benchmark, we calculated the multipliers of these estimated minimum and maximum country total crop land. Figure 1 and 2 show the comparison among FAOSTAT statistics and those estimations from the three satellite sources in Asian countries. The estimations (both minimum and maximum cropland) for a few countries, Brunei, Bhutan, Mongolia, Laos, are way off the mark. Most countries, however, are more or less close to actual crop land according to FAOSTAT (multiplier of 1). There are large variations among the countries in Asia. Similar variations exist for the rest of world.

[Figure 1here]

4. A SYNTHESIZED CROPLAND SURFACE

In the past, we may have to choose one land cover product which was considered to be more accurate. Recently, there are a few studies comparing and combining different land cover datasets (Jung et al. 2006, Fritz and See 2008). Following similar line of research, we propose to create a hybrid cropland dataset by land cover data fusion. This would take advantage of the synergy among the three land cover products introduced before. This hybrid cropland is the crop land dataset used for our crop allocation model (You, Wood, and Wood-Sichra 2006).

Since our crop allocation model has a 5-minute resolution, we first convert all the land cover dataset into the same 5-minute resolution grid. Our original land cover datasets are all in 30 second resolution. There are approximately 100 30-second pixels within each our new common 5-minute pixel. We calculate the share of each crop land related class within each 5-minute pixel. There are 5 classes which include crop land in IFPRI cultivated land surfaces, and both GLC2000 and MODIS-BU have 3 cropland-related classes (Table 2). Due to the high heterogeneity of land cover class and limited spatial resolution of land cover dataset, there is always uncertainty on the exact percentage of crop land in all the above cropland-related classes. Even for those classes classified explicitly as crop land, the crop land percentage may vary from 80% to 100% of the pixel area. For those cropland mosaic classes, that percentage varies from as low as 20% to 80%. Table 2 shows the crop land share ranges for different crop land classes. The suggested land crop land shares are the values suggested from the remote sensing experts of these three datasets. Taking these suggested cropland shares, we calculate the crop land shares (or areas if multiplied by the pixel area) of these three land cover datasets for each pixel. Therefore, we would have the three independent crop land areas for each 5-minute pixel from the above three land cover datasets. These would form the basis for us to create a hybrid cropland.

4.1 Definition of consistency index

For each pixel, estimated crop land extent varies among different land cover datasets. To assess the consistency among these different datasets, we define a consistency index (CI). s_i represents the shares of cropland from land cover products *i* (e.g, *i* = GLC2000, MODIS, IFPRI cultivated land), and consistency index (CI) is defined as

$$CI = 1 - \sqrt{\frac{\sum_{i,j=1\&i<j,i\neq j}^{n} \left(s_i - s_j\right)^2}{CN}} \qquad (1.1)$$

where CN = $\frac{n(n-1)}{2}$ is the total number of squaring items in the summation. For *i=2*, then *CN=1* and $CI = 1 - \sqrt{(s_1 - s_2)^2}$. If *i=3*, then *CN=3* and

$$CI = 1 - \sqrt{\frac{1}{3}\left[(s_1 - s_2)^2 + (s_1 - s_3)^2 + (s_2 - s_3)^2\right]}$$

4.2 Hybrid cropland

The purpose of this hybrid cropland is for our crop allocation model. The comparison with actual crop statistics at the aggregate level in Section 3 suggests that all three land cover datasets have a tendency to under-estimate crop land. In our crop allocation model, the current hybrid crop land sets the upper boundary for crop allocation. The model won't work if the aggregate cropland is less than the sum of all crop areas. In this sense, we want more crop land rather than less. In order to facilitate our crop allocation model, our hybrid cropland would focus on median and maximum cropland area, and ignore the minimum estimation.

We calculate three values for each pixel from these three cropland products: median, maximum, and consistency index. These three values per pixel would be our hybrid cropland. The median and maximum are the median and the maximum estimates of the crop land areas among GLC 2000, MODIS and IFPRI cultivated land while the consistency index is the measurement of how consistent these three surfaces are. Table 4 demonstrate the how the three values are estimated using a few sample pixels.

[Table 4 here]

The final hybrid croplands are shown in Figure 3 and Figure 4. Figure 3 shows the maximum of the hybrid cropland while Figure 4 the median. We also mapped the consistency among the three crop land products in Figure 5. As you could see, the variation of consistency is huge. Not surprisingly, the highest inconsistency occurs in Latin America, Africa where smallholders dominate and crop land is usually mixed with other land cover types. In SPAM, we would take account of this uncertainty of crop land estimating in allocating particular crops.

[Figure 3 here]
[Figure 4 here]
[Figure 5 here]

5. CONCLUSION

Different satellite images have different missions and focuses, and classification, training, and validation approaches vary from one to another. So it is not surprising that discrepancy exists among different land cover products. On the other hand, two generic problems exist among all land cover products. First, mapping a continuum landscape with discrete classes is problematic (Foody 2000, Jung et al. 2006). For a mixed class such as crop land and grass land, one may classify it as cropland and the other grassland. There is discrepancy but both are right. This problem is particular serious for cropland and coarse resolution dataset. 1 km is high resolution but majority of crop land in the world is less than $1km^2$. In principle, most cropland is such mixed unit. Another problem is the low separability between crop land and grass land, shrub land, or even trees. For example, many plantain (banana) in East Africa are planted right on the edge of forest. These plantain trees are as high as the nearby trees and satellite signatures could not tell them apart.

In this paper, we showed that the estimation of crop land varies among different land cover products. By comparing these estimations with aggregate country cropland census data, we could see the weakness and strength of individual product in estimating crop land. Then we propose an approach to explore the synergy among different land cover product. By combining the existing three crop land products (IFPRI, MODIS, and GLC 2000), we created a hybrid cropland with a consistency index. We have used such a hybrid cropland in our other research work such as spatial allocation model.

REFERENCES

Belward, A. S., J. E. Estes, and K. D. Kline, The IGBP-DIS Global 1-km Land-Cover Data Set DISCover: A Project Overview, Photogram. Eng. Remote Sens., 65, 1013-1020, 1999.

Di Gregorio, A., L. J. Jansen. 2000. *Land cover classification system (LCCS): classification concepts and user manual*. FAO, Rome.

Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* **80**, 185-201

Friedl MA, DK McIver, JCF Hodges, XY Zhang, D. Muchoney, A. H. Strahler et al., 2002. Global land cover mapping from MODIS: algorithms and early results, *Remote Sensing of Environment* 83 (1-2): 287-302

Fritz, S., E. Bartholome, A. Belward, A. Hartley, H. Stibig, H. Eva et al.. 2003. *Harmonisation, mosaicing and production of the Global Land Cover 2000 database (beta version),* Ispra: European Commission, Joint Research Centre (JRC)

Fritz, S., L. See. 2005. Comparison of land cover maps using fuzzy agreement. *International Journal of Geographic Information Science* 19, 787-807

Fritz, S., L. See. 2008. Identifying and quantifying uncertainty and spatial disagreement in the comparison of global land cover for different applications. *Global Change Biology* 14, 1-19.

Giri C., Z. Zhu, B. Reed. 2005. A comparative analysis of the global land cover 2000 and MODIS. *Remote Sensing of Environment* 94, 123-132

Hansen, M. C., R. Defries, J. Townshend, R. Sohlberg. 2000. Global land cover classification at 1km spatial resolution using a classification tree approach. *International Journal of Remote Sensing* **21**, 1331-1364

JRC. 2003. *Global land cover 2000 database*. European Commission, Joint Research Center.

Jung, M., K. Henkel, M. Herold, G. Churkina. 2006. Exploring synergies of global land cover products for carbon cycle modeling. *Remote Sensing of Environment* 101, 534-553

Loveland, T.R., B. Reed, JF Brown, DO Ohlen, Z. Zhu, L. Yang et al.. 2000. Development of a global land cover characteristics database and IGBP DISCover from 1km AVHRR data. *International Journal of Remote Sensing* **21**, 1303-1330

Millennium Ecosystem Assessment. 2005. *Ecosystem studies: Ecosystem science and management*. Island Press, Washington, DC, ISBN 1-59726-040-1

Muchoney, D., Strahler, A., Hodges, J., and LoCastro, J., 1999, The IGBP DISCover Confidence Sites and the System for Terrestrial Ecosystem Parameterization: Tools for Validating Global Land Cover Data. Photogrammetric Engineering & Remote Sensing, v65 n9, 1999.

Quinlan, J. R., C4.5: *Programs for Machine Learning*, Morgan Kauffman, 1993.

Running, S. W., Loveland, T. R., and Pierce, L. L., 1994, A vegetation classification logic based on remote sensing for use in global scale biogeochemical models, Ambio, 23, 77-81

United Nations Environment Programme (UNEP), 2007, *Global Environment Outlook 4 (GEO-4)*, UNEP, Nairobi.

USGS EDC. 1999. United States Geological Surveys Earth Resources Observation System (EROS) Data Center, *Carbon in live vegetation map*. Sioux Falls, SD: USGS EDC. Unpublished data.

Wood, S., K Sebastian, S. Scherr. 2000. *Pilot analysis of global ecosystems: agroecosystems.* International Food Policy Research Institute and World Resources Institute, Washington, USA.

You, L., S. Wood, U. Wood-Sichra. 2006. Generating global crop distribution maps: from census to grid. Selected paper at IAEA 2006 Conference at Brisbane, Australia.

Agricultural land cover class	SLRC class type
Great than or equal to 60% agriculture	Dominant class is agriculture (cropland; cropland with …; cropland/pasture
40-60% agriculture	Cropland/natural vegetation mosaic (Cropland/glass land; grassland/cropland; etc…)
30-40% agriculture	Dominant class is not agriculture but agriculture is present (… with cropland)
Other vegetated land cover (0-30% agriculture with forest)	Dominant class is forest Agriculture may be present but has not been noted (Forest; Forest with grassland; etc)
Other vegetated land cover (0-30% agriculture with grassland)	Dominant class is grassland Agriculture may be present but has not been noted (grassland; grassland with forest; …)
Sparsely vegetated	Sparsely vegetated areas (Desert; semidesert; tundra; snow and ice)

Source: Wood, Sebastian and Scherr(2000)

Table 1 Agricultural land class description

Land cover data	**cropland class**	**Crop Area**			
		Variable	Minimum (%)	Maximum	Suggested
IFPRI	Cropland & plantation	80-100	80	100	100
	Agriculture with forest & Agriculture with other natural vegetation	60-80	60	80	70
	Cropland/pasture, Agriculture/forest mosaic, agriculture/other mosaic	40-60	40	60	50
	Forest with agriculture, Other vegetation with agriculture	20-40	20	40	30
GLC2000	15: Cultivated and managed areas	50-100	50	100	100
	16 Mosaic: cropland/tree cover/Other natural vegetation	40-60	40	60	50
	17Mosaic: cropland/Shrub and/or grass cover	0-20	0	20	10
MODIS	Cropland	80-100	80	100	100
	Cropland/Natural vegetation mosaic	40-60	40	60	50

Table 2 crop land classes

Region and Land Cover Class	**Land Cover Datasets**		
	IFPRI Ag Extent	**GLC2000**	**MODIS-BU**
	(Share of total land area - percent)		
Global			
Cropland	12.4	13.2	10.2
Cropland mosaic	14.9	5.1	2.4
Forest	24.7	32.2	23.3
Grassland, savanna, shrub land	29.2	32.0	47.9
Asia			
Cropland	25.7	25.1	22.1
Cropland mosaic	17.1	5.5	2.3

Forest	18.0	24.6	24.7
Grassland, savanna, shrub land	22.9	28.5	33.2
Former Soviet Union			
Cropland	11.0	9.0	14.4
Cropland mosaic	12.7	5.1	0.8
Forest	36.9	41.8	25.6
Grassland, savanna, shrub land	23.7	30.5	53.5
Latin America			
Cropland	7.9	12.6	4.6
Cropland mosaic	22.5	10.5	4.0
Forest	41.5	46.0	41.7
Grassland, savanna, shrub land	23.7	27.0	46.0
Northern Africa/Middle East			
Cropland	3.5	4.6	3.6
Cropland mosaic	5.0	1.4	0.2
Forest	1.2	1.5	0.8
Grassland, savanna, shrub land	15.9	16.0	18.8
OECD Countries			
Cropland	14.2	14.3	11.9
Cropland mosaic	11.7	1.2	4.5
Forest	25.8	34.9	24.1
Grassland, savanna, shrub land	36.8	42.6	54.0
Sub-Saharan Africa			
Cropland	7.8	9.8	1.9
Cropland mosaic	17.5	7.1	0.8
Forest	15.1	29.4	14.4
Grassland, savanna, shrub land	40.3	33.8	63.1

Table 3 Regional comparison of primary land cover classes by land cover datasets

Cropland Shares			Hybrid cropland surface		
Landcover 1	Landcover 2	Landcover 3	Median	Maximum	CI
0.00	0.00	1.00	0.00	1.00	0.18
0.00	1.00	1.00	1.00	1.00	0.18
0.00	0.90	1.00	0.90	1.00	0.22
0.00	0.40	1.00	0.40	1.00	0.29
0.96	0.04	0.90	0.90	0.96	0.27
0.50	0.03	0.91	0.50	0.91	0.37
0.00	0.30	0.80	0.30	0.80	0.43
0.27	0.93	0.36	0.36	0.93	0.50
0.50	0.50	0.00	0.50	0.50	0.59
0.00	0.05	0.50	0.05	0.50	0.61
0.50	0.20	0.50	0.50	0.50	0.76
0.00	0.20	0.20	0.20	0.20	0.84
0.10	0.20	0.00	0.10	0.20	0.86
0.45	0.50	0.50	0.50	0.50	0.96
0.20	0.20	0.20	0.20	0.20	1.00

Table 4 Consistency index and hybrid cropland

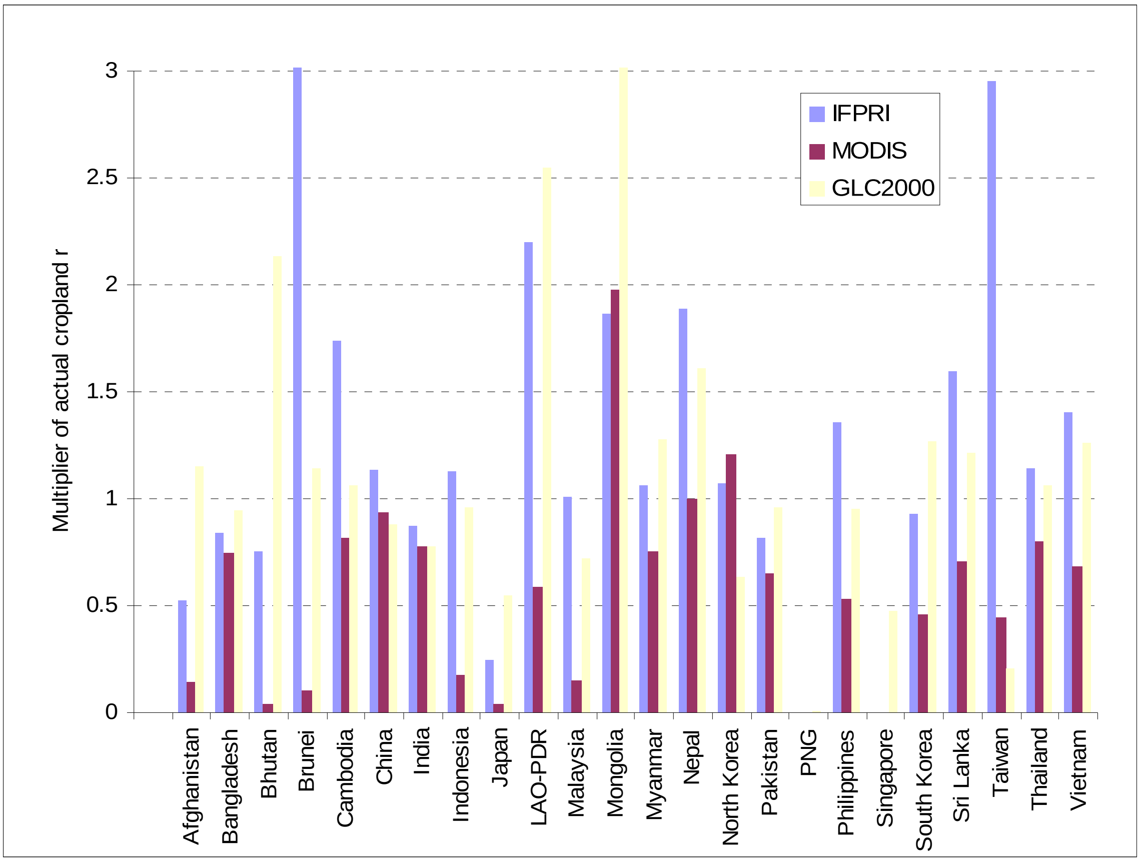

Figure 1 Compare actual crop land in Asian countries to estimated minimum crop land from satellites

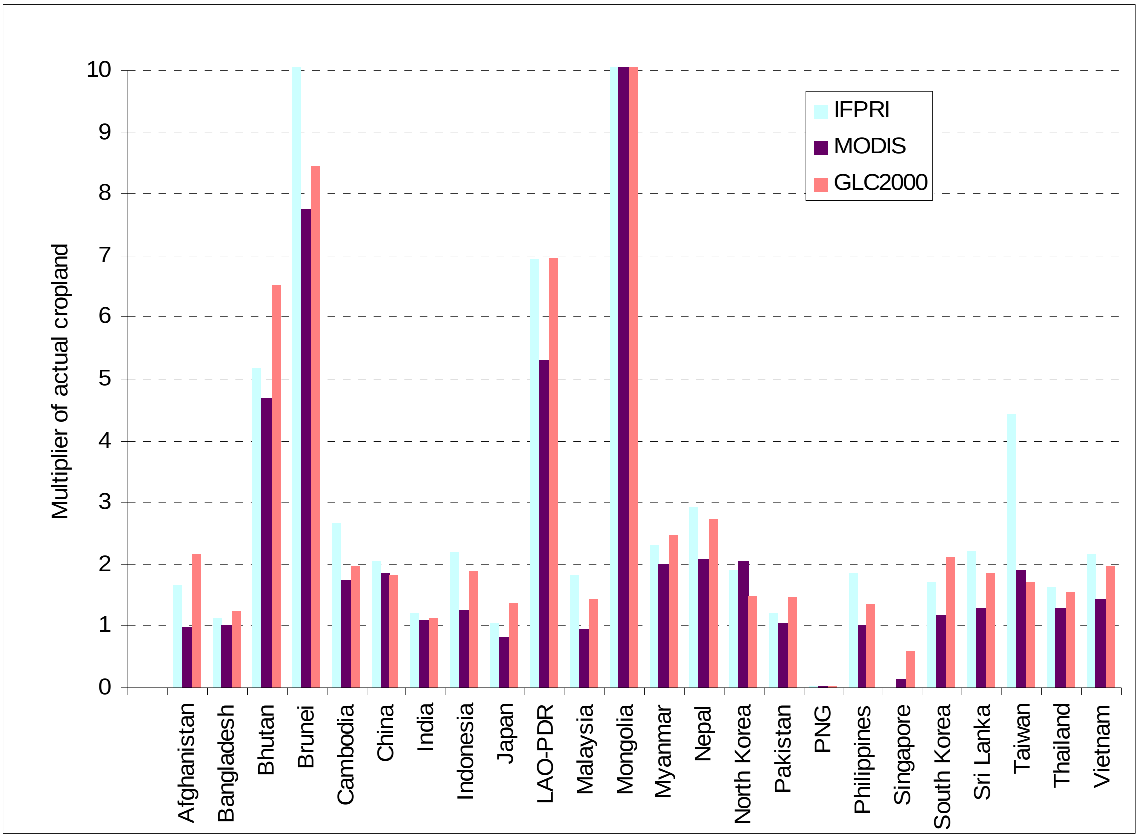

Figure 2 Compare actual crop land by Asian countries to estimated maximum crop land from satellites

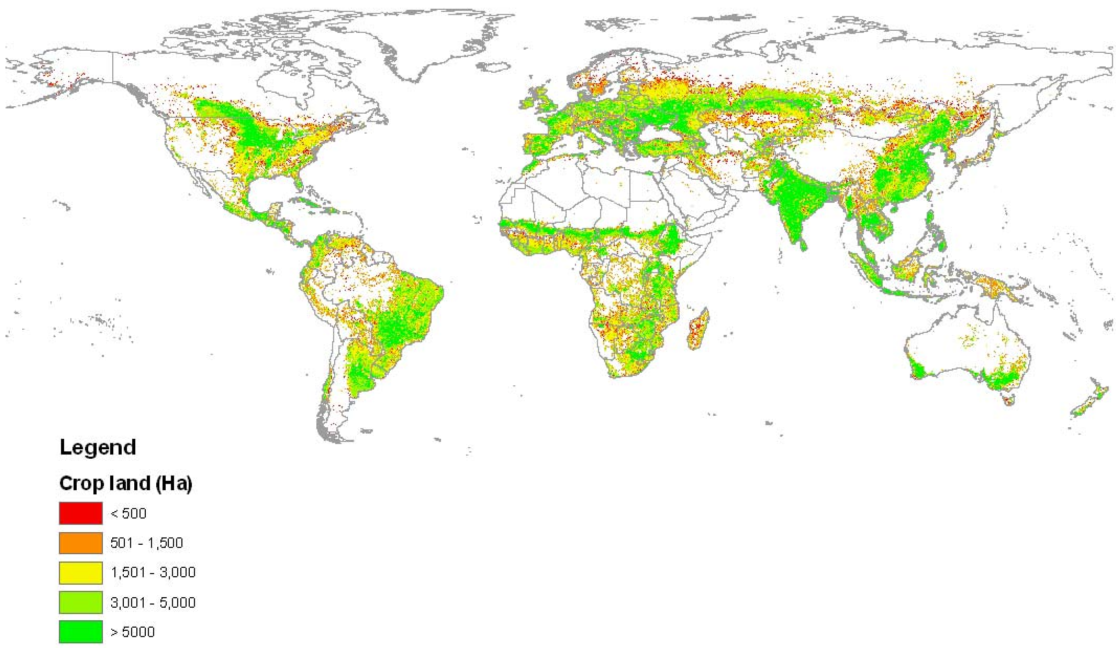

Figure 3 Hybrid cropland - maximum

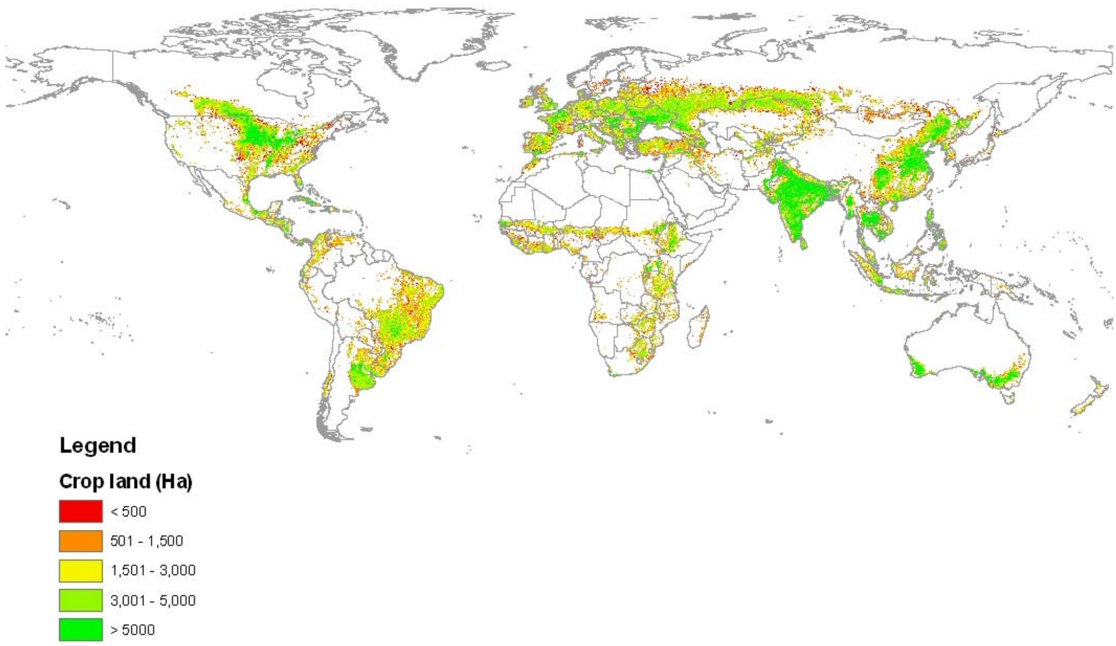

Figure 4 Hybrid cropland – median