

## Response to comments

**Paper #:** *essd-2017-74*

**Title:** *Gross and net land cover changes based on plant functional types derived from the annual ESA CCI land cover maps*

**Journal:** *Earth System Science Data*

### **Reviewer #1:**

#### **General Comments:**

##### **Comment #1**

The discussion paper presents an interesting dataset (PFT annual maps at  $0.5 \times 0.5$  deg resolution derived from Global Land Cover annual maps) which should be made publically available as it is the core dataset of this study. The paper focuses mainly on the comparison of estimates of areas, gross and net changes of different plant functional types (maps of PFTs derived from the ESA CCI LC product) with 3 other sources : Hurtt et al. (2011), Hansen et al. (2013) and Houghton and Nassikas (2017). This comparison is useful for understanding the range of discrepancies between such datasets.

The datasets and the results of the comparison are clearly expressed and well presented. However the discussion should be complemented with further issues which can explain part of the discrepancies between the CCI LC derived PFT dataset and independent datasets (see section ‘Comparison with other datasets’ in Specific Comments for detailed information on such issues).

##### **Response #1**

We thank the reviewer for the comments and suggestions. Please see the detailed point-by-point responses below.

#### **Specific Comments:**

##### **Comment #2**

Title: I suggest to revise the title in order to relate better to the content of paper, e.g. : ”Gross and net land cover changes of the main plant functional types derived from the annual ESA CCI land cover maps (1992-2015)”

##### **Response #2**

Revised as suggested.

##### **Comment #3**

Access to the core dataset of this study:

In abstract: “The annual ESA CCI land cover products can be downloaded from <http://maps.elie.ucl.ac.be/CCI/viewer/download.php>” This paper is focused on the derivation of PFT change estimates from the ESA CCI LC product. (“our analyses are based on the PFT maps that have been translated from the ESA CCI LC maps, rather than the original LC classes”). Only one “example of LC map and PFT map in 2000 used in this study” is made available (“can be downloaded from doi: <https://doi.org/10.5281/zenodo.834229>”)

I consider that it would be more appropriate and pertinent for this paper to provide access to the full derived dataset (PFT annual maps at  $0.5 \times 0.5$ deg resolution) as main product of this study - in complement to the ESA CCI LC product which is already available through ESA and UCL web sites.

##### **Response #3**

We will upload the full derived dataset (annual PFT maps at  $0.5^\circ \times 0.5^\circ$  resolution) to the data repository website and give a doi in the revised manuscript.

#### Comment #4

Use of FAO data:

FAO data are referred a few times in the paper, e.g. in Introduction: “Global net LULCC carbon emissions (ELUC) are estimated to be  $1.1 \pm 0.4$  Pg C yr<sup>-1</sup> during the past decade (2006-2015) by the bookkeeping model of Houghton and Nassikas (2017) based on the national land cover data from Food and Agriculture Organization (FAO)” It would be useful to indicate if it refers to FAO FRA 2015 data or the FAO STAT along the paper.

When referring to FAO FRA 2015 estimates, Keenan et al (2015) reference should be added because its reports the main findings of the FRA-2015. Moreover Keenan et al (2015) is used as key reference by the global environmental scientific community (see manuscript in-press with BioScience available: <http://scientistwarning.forestry.oregonstate.edu/>)

Keenan R J et al (2015) Dynamics of global forest area: results from the FAO Global Forest Resources Assessment 2015. *Forest Ecology and Management* 352:9–20

#### Response #4

The national forest area data from Houghton and Nassikas (2017) are based on FAO FRA data. As suggested, we will note it in Introduction and Methods and add Keenan et al. (2015) as a reference accordingly. We will also add Keenan et al. (2015) in Discussion (see **Response #6**).

**P2L8:** “Global net LULCC carbon emissions (E<sub>LUC</sub>) are estimated to be  $1.1 \pm 0.4$  Pg C yr<sup>-1</sup> during the past decade (2006-2015) by the bookkeeping model of Houghton and Nassikas (2017) based on the national land cover data from Food and Agriculture Organization Forest Resources Assessment (FAO FRA) (FAO, 2015; Keenan et al., 2015).”

**P5L2:** “The national forest areas from Houghton and Nassikas (2017) are based on FAO Forest Resources Assessment (FRA) data (FAO, 2015; also see Keenan et al. (2015) for the main findings of FAO FRA 2015).”

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#### Comment #5

Description of the ESA CCI land cover products (section 2.1) and their accuracies:

The reference to Yang et al 2017 (*ISPRS Journal of Photogrammetry and Remote Sensing* 125 (2017) 156–173) should be added e.g. in introduction and / or section 2.1. Yang et al 2017 reports the “Accuracy assessment of seven global land cover datasets over China” including two maps from previous version of CCI LC dataset (epochs 200 and 2010)

“The accuracy of ESA CCI LC products was evaluated at global scale. An object -based validation database of 2600 Primary Sampling Units was built by a panel of international experts to specifically assess the accuracy of both the LC classes and change (ESA, 2017).” The estimates of accuracy of the ESA CCI LC products should be provided here, based on published results in ESA (2017) report. It should also be clearly mentioned that accuracy of changes was not evaluated / quantified.

#### Response #5

We will cite the reference by Yang et al. (2017) in **Section 2.1** and add sentences about the accuracy of ESA CCI LC products on **P4L4:** “The accuracy of ESA CCI LC products was evaluated at global scale according to international standards, using an independent validation dataset to produce confusion matrix and derive overall accuracy figure. An object-based validation database of 2600 Primary Sampling Units was built by a panel of international experts to specifically assess the accuracy of both the LC classes and changes (ESA, 2017). Research is currently ongoing to find how addressing the new challenges underlying this database, i.e. following a per-object approach and interpreting not a unique land cover class but a distribution of land cover classes within a Primary Sampling Unit. The uniqueness of these two concepts in the framework of global land cover validation results that more time is needed to derive reliable figures about LC classes and LC changes accuracy. It will also prevent from any comparison with previous validation figures.

In this respect, for the sake of comparison, the accuracy of the ESA CCI LC product from 2010 was assessed using the GlobCover 2009 validation database (Bontemps et al. 2010). Using all the points

interpreted as “certain” by the experts, whether “homogeneous” (i.e. made of a single LC class) or “heterogeneous” (i.e. made of several or mosaic LC classes), the overall accuracy was found to be 71.5%. Accounting only the “homogeneous” and “certain” points, the overall accuracy raised to 75.4% (ESA, 2017). The highest user accuracy values were found for the classes of rainfed cropland, irrigated cropland, broadleaved evergreen forest, urban areas, bare areas, water bodies and permanent snow and ice. Conversely, mosaic classes of natural vegetation were associated with the lowest user accuracy values, as well as the three classes of lichens and mosses, sparse vegetation and flooded forest with fresh water.

The overall accuracy of the ESA CCI LC products was also assessed by independent studies over specific regions (e.g. Tsendbazar et al. (2015) over Africa and Yang et al. (2017) over China), which can give valuable insights for specific applications.”

However, as we described on **P3L9**: “The objectives of this study are to document the major gross and net changes and transitions in PFT maps derived from annual ESA CCI LC products and to evaluate whether they can be used in LSMs.”, we only focus on the translated PFT maps for the use of LSMs rather than the original ESA land cover classes. So, we didn’t expand the accuracy assessment in this study.

#### **Reference:**

*Bontemps, S., Defourny, P., Van Bogaert, E., Kalogirou, V. and Arino, O., GlobCover 2009 - Products Description and Validation Report (2010). Available at: [http://due.esrin.esa.int/page\\_globcover.php](http://due.esrin.esa.int/page_globcover.php)*  
*Tsendbazar N.E., de Bruin S., Fritz S. and Herold M. 2017. Spatial Accuracy Assessment and Integration of Global Land Cover Datasets, Remote Sensing, 2015, 7(12), 15804-15821; doi:10.3390/rs71215804*

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#### **Comment #6**

Comparison with other datasets (section 2.4 and discussion section):

Keenan et al (2015) compares the findings of FRA 2015 with other remote sensing studies. It provides some explanation and discussion on the issue raised by the author: “land use data are not necessarily the same as land cover, and the exact definitions and categorization of forest (cropland and grassland) are different for each dataset”.

The discussion on differences in area and area changes (section 4.1. and 4.2) is interesting and covering a number of important issues, but it should be complemented by at least two further issues: A main difference between FAO FRA-2015 dataset and Hansen et al (2013) product is that FAO reports a land use definition when Hansen reports a Tree cover percentages. A major impact of such differences in definition is related to Oil Palm plantations. Oil Palm plantations are not reported as forests by FAO (considered as agricultural use) when they are mapped as dense Tree Cover by Hansen. This difference has major impacts on estimates of LC changes for countries like Indonesia. It would be useful to pay attention to this specific vegetation type and to mention the Land Cover class under which are mapped Oil Palm plantations in CCI LC product (regional class ‘Tree or Scrub Cover’ under ‘Cropland’ first level class) and to mention to which PFT it has been attributed (Forest or croplands).

#### **Response #6**

We will cite Keenan et al. (2015) when discussing the differences between remote sensing data and FAO FRA data on **P10L15** “Furthermore, in the definition of forest by FAO, natural disturbance suppressing forests do not change the land remaining a forest, but from satellite, they are not detected as forest cover. Keenan et al. (2015) also compared the forest area from FAO FRA 2015 with remote sensing data and attributed their differences to five factors, the major one of which is the different definitions of “forest”.” and **P12L10** “For example, a forest cleared for wood harvest is not taken as a forest loss because new secondary forest will be planted on this land, thus no change in land use (Keenan et al., 2015). However, remote sensing can easily detect such land cover change and treat it as forest loss.”

We agree that different definitions of oil palm plantation in different datasets is important for the forest/cropland area difference in S.E. Asia. As suggested, we will add discussion on **P10L24**: “The attribution of oil palm plantations is an important factor for the differences in area changes between

different datasets, especially in Indonesia. Oil palm is taken as cropland rather than forest in the FAO definitions (FAOSTAT, 2015) but detected as tree covers from the remote sensing (Tropek et al., 2014; Carlson et al., 2012, 2013; Koh et al., 2011; Hansen et al., 2013), including in the CCI LC products. This partly explains that the larger cropland increase in LUH2v2h (Hurttt et al., 2011) and larger forest decrease in Houghton and Nassikas (2017) than those in ESA CCI PFTs and Hansen et al. (2013) in Indonesia (Figure 4).”.

#### **Reference:**

- Tropek, R., Sedláček, O., Beck, J., Keil, P., Musilová, Z., Šimová, I. and Storch, D.: Comment on “High-resolution global maps of 21st-century forest cover change”;, *Science*, 344(6187), 981, doi:10.1126/science.1248753, 2014.
- Carlson, K. M., Curran, L. M., Ratnasari, D., Pittman, A. M., Soares-Filho, B. S., Asner, G. P., Trigg, S. N., Gaveau, D. A., Lawrence, D. and Rodrigues, H. O.: Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia, *Proc. Natl. Acad. Sci. USA*, 109(19), 7559–7564, doi:10.1073/pnas.1200452109, 2012.
- Carlson, K. M., Curran, L. M., Asner, G. P., Pittman, A. M., Trigg, S. N. and Adeney, J. M.: Carbon emissions from forest conversion by Kalimantan oil palm plantations, *Nat. Clim. Chang.*, 3(3), 283–287, doi:10.1038/Nclimate1702, 2013.
- Koh, L. P., Miettinen, J., Liew, S. C. and Ghazoul, J.: Remotely sensed evidence of tropical peatland conversion to oil palm, *Proc. Natl. Acad. Sci.*, 108(12), 5127–5132, doi:10.1073/pnas.1018776108, 2011.
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#### **Comment #7**

It is also known in the remote sensing community that it is difficult to map and estimate forest areas in the dry tropics with medium resolution satellite (Landsat type), in particular when tree cover is below 40%. Consequently it is at least as challenging or more difficult to map such forests from coarser resolution imagery or to estimate accurately area changes from medium or coarse resolution data. This is illustrated, reported or discussed in a number of papers including Hansen et al (2013) and Achard et al (2014) and more recently in Bastin et al (2017) and Gross et al (2017). This can explain partly why the estimate of forest area derived from the CCI LC product is lower than national estimates derived from the FAO FRA dataset.

Achard F et al (2014) Determination of tropical deforestation rates and related carbon losses from 1990 to 2010 *Global Change Biology* (2014) 20, 2540–2554

Gross D et al (2017) Uncertainties in tree cover maps of Sub-Saharan Africa and their implications for measuring progress towards CBD Aichi Targets. *Remote Sens Ecol Conserv.* doi:10.1002/rse2.52

The remote sensing community, in particular scientists dealing with monitoring of REDD+ activities, has produced technical guidelines or scientific papers which report that it is more efficient and accurate to produce area estimates by combining a sample of reference dataset (sample of reference plots) with a wall to wall map, than by using only a wall to wall map. This is particularly valid for estimating Land Cover changes which are usually considered as ‘rare’ events. See GOFC-GOLD 2015, GFOI 2016, Olofsson et, 2014; Sannier et al 2016

GOFC-GOLD, 2015, A Sourcebook of Methods and Procedures for Monitoring and Reporting Anthropogenic Greenhouse Gas Emissions and Removals Associated with Deforestation, Gains and Losses of Carbon Stocks in Forests Remaining Forests, and Forestation (GOFC-GOLD Land Cover Project Office, Wageningen University, The Netherlands).

GFOI 2016, Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative, Edition 2.0, FAO, Rome

Olofsson P et al 2014, Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment* 148 (2014) 42–57

Sannier C et al 2016 Suitability of Global Forest Change data to report forest cover estimates at national level in Gabon. *Remote Sensing of Environment*, 173, 326-338

#### **Response #7**

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We thank the reviewer for this useful information. As suggested, we will add sentences to discuss the forest estimate in the arid region on **P10L11**: “In the drylands like tropical Africa, it is difficult to map and estimate forest area using medium (e.g. Landsat, Hansen et al., 2013) or coarse resolution satellite data (e.g. ESA CCI LC) (Bastin et al., 2017; Achard et al., 2014; Gross et al., 2017), in particular when tree cover is below 30% (Achard et al., 2014). Bastin et al. (2017) recently reported a forest estimate in drylands using very high spatial resolution satellite imagery, which is 40-47% more than previous forest assessments. The difficulty of detecting forest in these sparse tree cover regions could partly be responsible for the lower forest area from ESA CCI PFT maps than those from Hansen et al. (2013) and Houghton and Nassikas (2017) in tropical Africa (Figure 1).”

We will also add some discussion on the joint use of different datasets on **P12L18**: “In addition, instead of using a single dataset, combining a sample of several datasets is reported to be considerably more efficient and accurate to estimate land cover area and change (Olofsson et al., 2014; Sannier et al., 2016) and has been adopted as technical guidelines (GOFC-GOLD, 2015; GFOI, 2016) in the remote sensing community, especially for the forest monitoring in reduce emissions from deforestation and forest degradation in developing countries (REDD+) programme.”

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#### **Comment #8**

Figures to be improved

Figure 3 is much too small to see the changes

Figures 4 to 6 would also benefit to be displayed over a larger area.

#### **Response #8**

We will enlarge these figures in the revised manuscript and also upload the high-resolution figures separately.

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