Response to comments

Paper #: essd-2023-320
Title: GLC_FCS30D: The first global 30-m land-cover dynamic monitoring product with a fine classification system from 1985 to 2022 using dense time-series Landsat imagery and continuous change-detection method
Journal: Earth System Science Data

Reviewer #1

This paper greatly attempts to map the annual global land cover change using all Landsat observations and the CCD approach. The paper is well written with clear logic, while some issues need to be clarified for publication as a scientific data paper.

Great thanks for the positive comments. The manuscript has been greatly improved based on your and another reviewers' comments and suggestions.

1. The CCDC approach is very sensitive to the parameters adopted, which may identify pseudo changes. This may directly relate to the derived temporal stable regions, and further impact the results of global changed areas (as well as the statistics). As a scientific data paper, this part should be enhanced with quantitative analysis, especially the uncertainty of change detection across different cover types.

Great thanks for the comment. Yes, we agree that the CCDC algorithm was sensitive to the parameter settings, thus the sensitive analysis between three sensitive parameters (minObservations, chiSquareProbability and minNumOfYearScaler) with the land-cover change detection accuracy (omission error and commission error) were supplemented, and the results showed that there was a correlation between the omission error and commission error with the variability of the parameter's values.

In specific, the descriptions of sensitive analysis and how to determine the values of the sensitive parameters have been added in the Section 3.2 as:

Next, the CCD was also a multi-parameter change detection model and demonstrated to be sensitive to the parameter settings (Xiao et al., 2023; Zhu and Woodcock, 2014b). The CCDC algorithm on the Google Earth Engine platform (ee.Algorithms.TemporalSegmentation.Ccdc) contained three key adjustable parameters: minObservations, chiSquareProbability and minNumOfYearScaler. Zhu et al. (2019) analyzed the relationships between the omission error and commission error of land-cover changes with the variability of three parameters in the United States, and found their values affected the change detection accuracy. In this study, we also investigated the sensitivity between parameter settings with the change detection accuracies in Figure S1 (seen the Supplement material) using the time-series points from LCMAP_Val and LUCAS datasets after partly sampling. Notably, the sensitivity analysis was implemented in two large-areas for ensure the feasibility of optimal parameters, that is, which will be suitable for other areas in land-cover change detection. The results also showed the CCD is a parameter-sensitive algorithm and the optimal parameter values were 5, 0.95 and 2-year for minObservations, chiSquareProbability and minNumOfYearScaler.

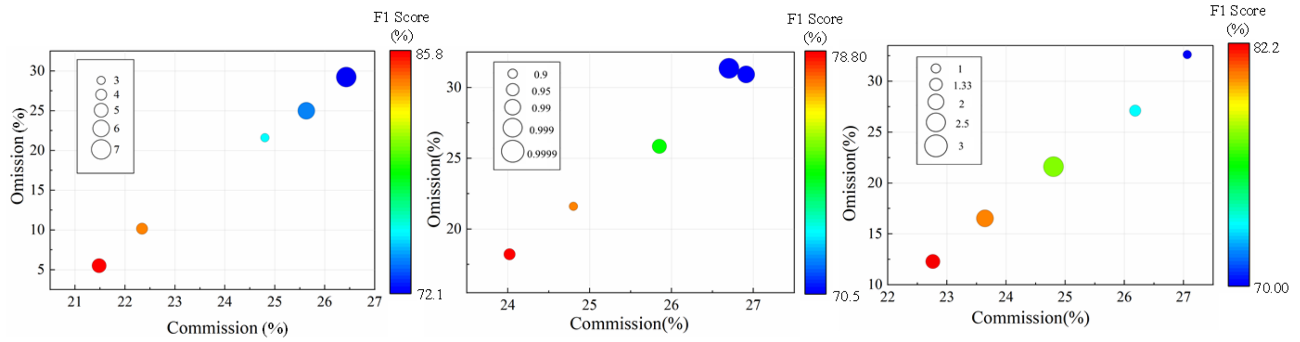

Figure S1. The sensitive analysis between the omission error and commission error with the minObservations, chiSquareProbability and minNumOfYearScaler using the time-series points from LCMAP_Val and LUCAS datasets after partly sampling.

Xiao, Y., Wang, Q., Tong, X., and Atkinson, P. M.: Thirty-meter map of young forest age in China, Earth Syst. Sci. Data, 15, 3365-3386, https://doi.org/10.5194/essd-15-3365-2023, 2023.

Zhu, Z., Zhang, J., Yang, Z., Aljaddani, A. H., Cohen, W. B., Qiu, S., and Zhou, C.: Continuous monitoring of land disturbance based on Landsat time series, Remote Sensing of Environment, https://doi.org/10.1016/j.rse.2019.03.009, 2019.

Meanwhile, using the values were 5, 0.95 and 2 years for minObservations, chiSquareProbability and minNumOfYearScaler, we also analyzed the uncertainty of the CCD algorithm at various land-cover change types based on the random sampling land-cover changed points from NLCD products over the United States in Table S1.

Table S1. The uncertainty analysis of CCD algorithm for different land-cover change types using the random sampling land-cover changed points from NLCD products over the United States.

	To cropland	To forest	To shrubland	To grassland	To water	To bareland	To impervious surface
P.A. (±SE)	70.00(0.55)	45.64(0.49)	42.02(0.89)	66.13(0.33)	77.05(0.54)	42.86(1.32)	70.65(0.42)
U.A. (±SE)	46.10(0.48)	64.66(0.56)	23.81(0.56)	43.94(0.28)	58.02(0.55)	35.29(1.16)	57.33(0.42)

It should be noted that the wetland was independently generated, and the permanent snow ice and tundra were sparse distributed on the United States, the uncertainty analysis of CCD for these three classes were excluded.

2. As a global land cover change dataset, the accuracy assessment regarding those changed pixels should be significantly improved. The confusion matrix just shows the accuracy in 2020, while those changes in different years with field samples

Great thanks for the comment. Yes, we completely agree that the accuracy analyzing for those changed pixels should be taken care. However, collecting a time-series global validation datasets are greatly difficult and challenging, and **there is currently no public long time-series validation datasets**.

In this revision, the time-series LCMAP_Val and LUCAS validation points are further used to calculate the accuracy metrics of changed and unchanged pixels. It should be noted that 'changed' and 'unchanged' referred to the work of Stehman et al. (2021) in validating the LCMAP annual land cover products during 1985-2017. The specific analysis about land-cover changed pixels are added as:

Section 3.4 Accuracy assessment

Lastly, to quality the performance of land-cover changed pixels, we obtained the proposal of Stehman et al. (2021) in assessing the LCMAP annual land-cover products 1985-2017, that is, the validation pixels were grouped into "changed" and "unchanged" categories and the corresponding confusion matrix were calculated. Meanwhile, to minimize the imbalance in the sample size of "change" and "no-change" samples, the metrics of F1 score was supplemented as:

$$F1 = \frac{P.A. \times U.A.}{P.A. + U.A.} \times 2 \times 100\% \qquad (5)$$

Section 4.3 Accuracy assessment based on two third-party regional validation datasets

Table 4 further analyzed the confusion matrix of land-cover changed and unchanged pixels in GLC_FCS30D using LCMAP_Val dataset. It should be noted that the land-cover changed samples in the LCMAP_Val was still sparse, that is, the size of changed samples cannot support the land-cover change analysis over specific land-cover changes. Similarly, Stehman et al. (2021) also grouped the land-cover types into 'No change' and 'change' types for analyzing the land-cover changes. In this study, using the 'changed' and 'unchanged' validation points in LCMAP_Val, the O.A. of the GLC_FCS30D reached the 90.49±0.45%. In particular, the unchanged land-cover pixels played a dominant role and reached the high P.A. of 92.84% and U.A. of 96.28%. In contrast, the P.A. and U.A. of concerned land-cover changed pixels were 72.26±2.04% and 56.62±2.00%, and its F1 score was 63.49%.

Table 4. The confusion matrix of changed and unchanged pixels in GLC_FCS30D dataset using LCMAP_Val datasets.

	Unchanged	Changed	Total	P.A. (SE)	F1
Unchanged	82.21	6.34	88.55	92.84(0.42)	94.53
Changed	3.18	8.27	11.45	**72.26(2.04)**	63.49
Total	85.39	14.61			
U.A. (SE)	96.28(0.32)	**56.62(2.00)**			
O.A. (SE)			90.49(0.45)		

Table 7 presented the confusion matrix of changed and unchanged pixels using the LUCAS validation datasets. The overall accuracy of the GLC_FCS30D reached 90.36±0.38%, the P.A. and U.A. of the changed pixels were 52.86±2.04% and 73.31±2.00%, and the corresponding F1 score was 61.43%. In contrast, the unchanged land-cover pixels reached the high P.A. and U.A., and both two metrics exceeded 90%. Thus, the changed land-cover pixels were more difficult to capture comparing with these unchanged areas. Similarly, Stehman et al. (2021) also found that the accuracy metrics of changed pixels were greatly lower than that of unchanged pixel.

Table 7. The confusion matrix of changed and unchanged pixels in GLC_FCS30D using time-series LUCAS datasets across the Europe Union.

	Unchanged	Changed	Total	P.A. (SE)	F1
Unchanged	82.69	2.79	85.48	96.73	94.49

Changed	6.84	7.68	14.52	52.86	61.43
Total	89.53	10.47			
U.A. (SE)	92.36(0.36)	73.31(1.74)			
O.A. (SE)			90.36(0.38)		

Stehman, S. V., Pengra, B. W., Horton, J. A., and Wellington, D. F.: Validation of the U.S. Geological Survey's Land Change Monitoring, Assessment and Projection (LCMAP) Collection 1.0 annual land cover products 1985–2017, Remote Sensing of Environment, 265, 112646, https://doi.org/10.1016/j.rse.2021.112646, 2021.

Meanwhile, we also highlighted the necessity of strengthening the accuracy analysis for land-cover changed pixels in our future works in Section 4.5 as:

The time-series accuracy variability is only analyzed in two regions, so its performance in more complex areas (such as Africa and Asia) needs to be further investigated. Thus, future work would be paid on collecting long-term time-series validation data sets for more regions, and on building a long time-series global validation dataset, and then analyzed the accuracy metrics of the land-cover changed pixels for all land-cover types.

As well as global product comparison (e.g., ESACCI and MODIS) should be given and discussed.

Based on your suggestion, the comparisons with ESACCI and MCD12Q1 have been added in two typical areas in Section 4.4 as:

4.4 The comparisons with other global land-cover dynamic products

Figure 12 gave the qualitative comparisons between our GLC_FCS30D and two widely used land-cover dynamic datasets (CCI_LC and MCD12Q1) during 2001-2020 in the Indo-China Peninsula, in which experienced evident land-cover changes in forest deforestation and urban expansion. In terms of the urban expansion, three datasets revealed the quick urbanization in the mega-city of Bangkok, and the CCI_LC under-estimated the impervious surface areas in 2001 comparing with two other datasets. Meanwhile, the GLC_FCS30D also captured more spatial details (such as: rural building and road networks) than CCI_LC and MCD12Q1 because of its high spatial resolution of 30 m.

As the most significant deforestation, the CCI_LC showed the worst performance because 1) it under-estimated the forest covers in the 2001 (the rectangle region 1), that is, some forests were wrongly labeled as the croplands; 2) some deforested forests cannot be captured during the period of 2001-2020 in rectangle region 2 (R2), and their deforested forest area was less than that of GLC_FCS30D and MCD12Q1; and 3) there was obvious misclassification problem between forest and wetland in 2000 (the rectangle region 3, R3). Then, the MCD12Q1 also suffered the omission error for forest in rectangle region 1, namely, the captured forest area in 2000 was lower than their actual areas in natural-color imagery. As for the evident deforestation in the region 2, we can find that almost all forest pixels changed to the other land-cover types (savanna and grassland), which was obviously deviated from the actual situation, thus, MCD12Q1 over-estimated the forest deforestation. Meanwhile, the time-series MCD12Q1 showed various land-cover distributions in the R3, which indicated that the MCD12Q1 performed lower mapping accuracy and temporal stability for these wetland areas. In comparison, the GLC_FCS30D achieved the best performance in capturing the spatial distribution of forest in 2000, forest deforestation during 2001-2020, and wetland stability.

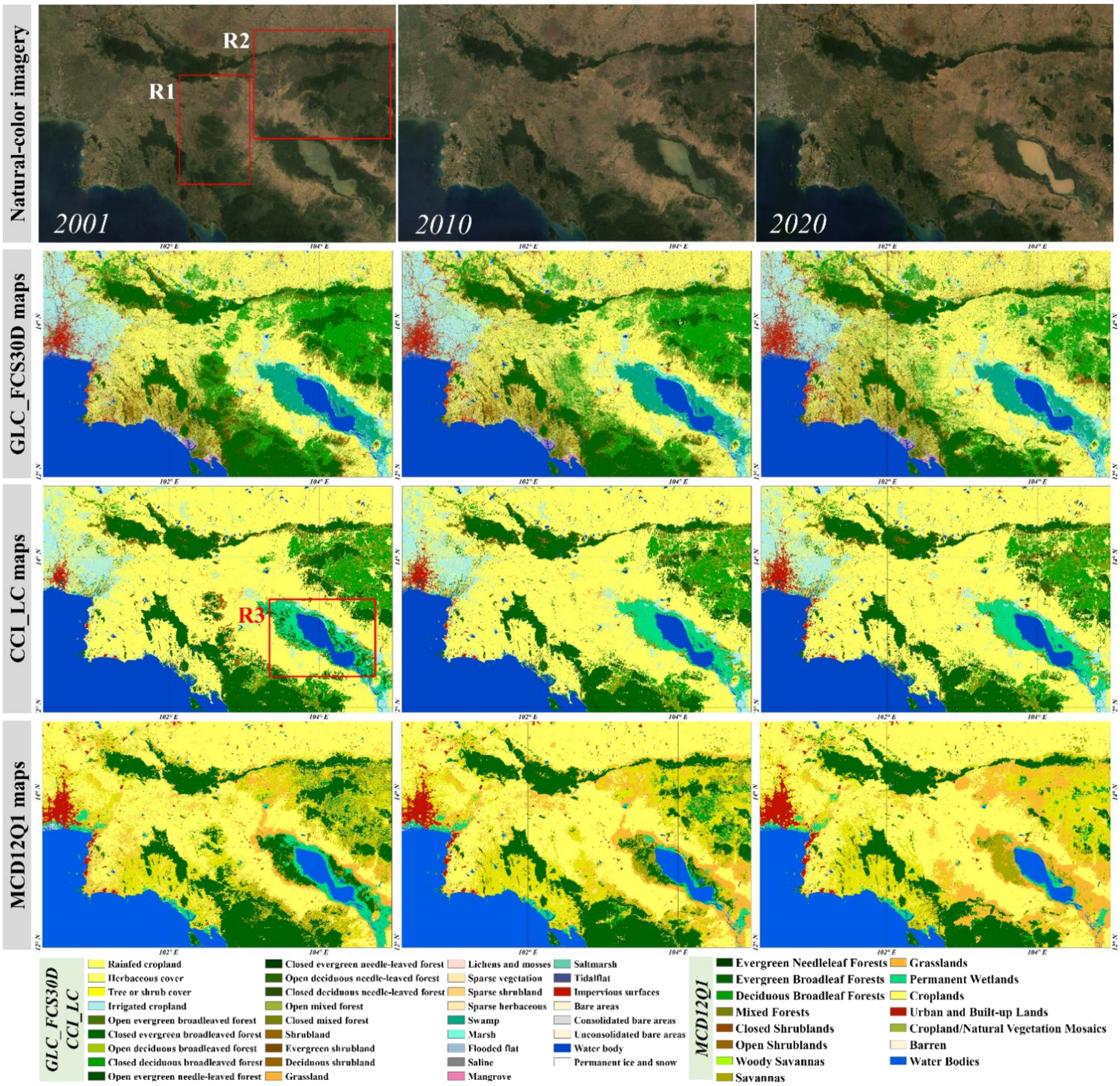

Figure 12. The comparisons between GLC_FCS30D with CCI_LC and MCD12Q1 land-cover dynamic products in Indo-China Peninsula during 2001-2020. The natural-color imagery are composited from the time-series Landsat imagery.

Figure 13 showed another comparison example about three datasets in Paraguay, South America, and the most evident land-cover change was the deforestation and cropland incensement according to the time-series natural-color Landsat imagery. In terms of the spatial distribution, the consistency between GLC_FCS30D and CCI_LC was higher, while the MCD12Q1 was obviously different from the other two datasets. A large amount of deciduous broadleaved forests were labeled as the savanna and woody savanna, and most croplands were identified as the grasslands in the MCD12Q1, which mainly because of the difference of classification system. Then, as for the land-cover change areas, the GLC_FCS30D performed the highest accuracy and captured the richer spatial details. For example, the deforestation intensity during 2010-2020 was significantly greater than that during 2001-2010, and the GLC_FCS30D also revealed the regular deforestation caused by human factors.

In contrast, the CCI_LC and MCD12Q1 failed to capture the deforestation during 2010 and 2020, and the small and fragmented changes (caused by human activities) also cannot be captured.

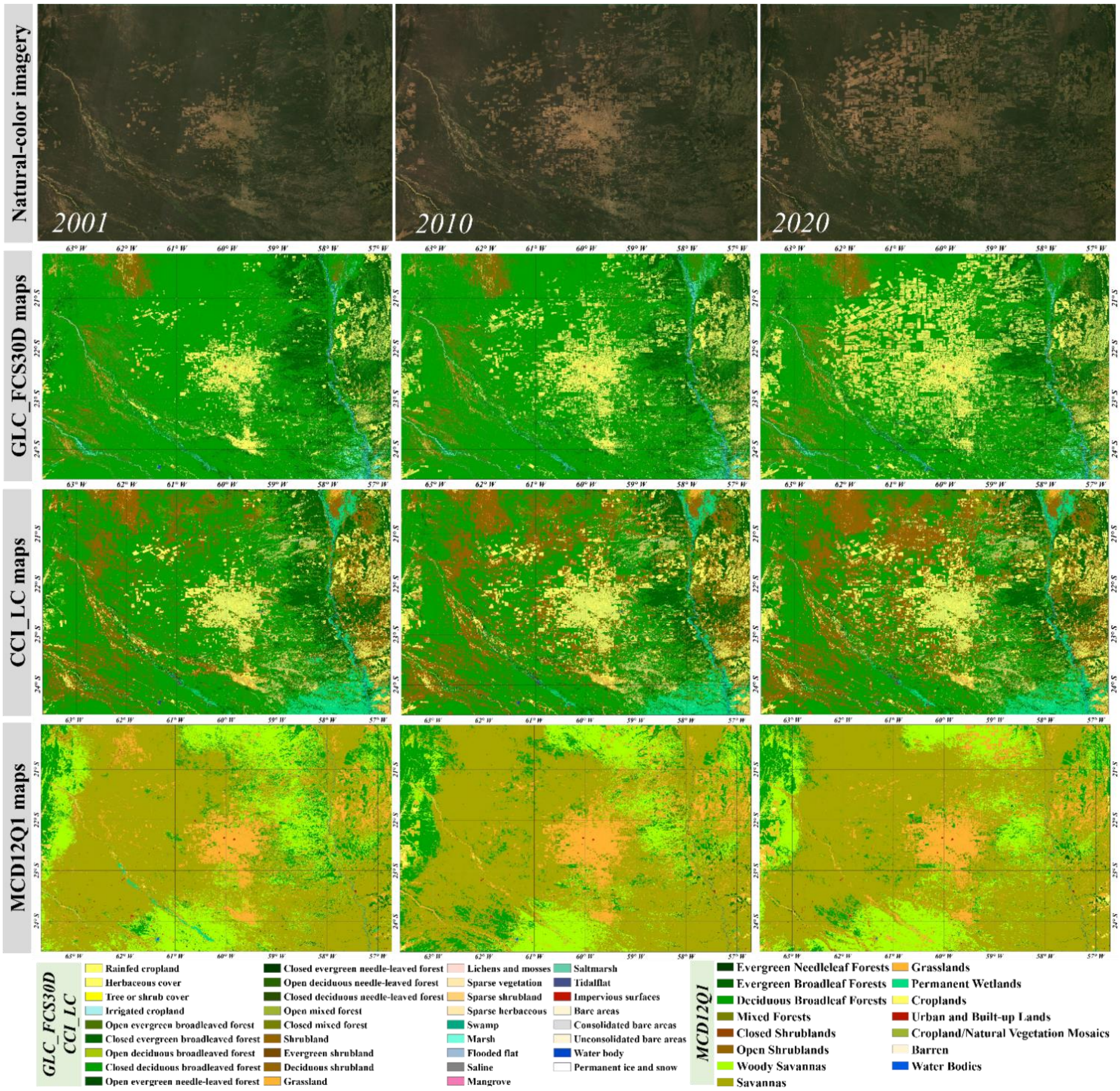

Figure 13. The comparisons between GLC_FCS30D with two time-series land-cover dynamic datasets in Paraguay, South America, during 2001-2020.