Dear Editor and Reviewers,

Thank you very much for taking time out of your busy schedule to improve our manuscript. We have carefully considered your comments and revised the paper accordingly. The revised parts are marked in yellow. The main correction in the paper and the responses to the reviewers' comments are as flowing:

Response to referee #1:

This study developed a 30 m young forest age map in China using Landsat images covering the period of 1990 to 2020. I found this study quite interesting and I like this idea. The approach used was straightforward and well validated. I have two major suggestions. First, a substantial amount of the contents in sections 4.3&4.4 are discussion. Suggest to reorganize these parts. Second, it's good to see the sensitivity test in this study (the analysis of key parameters in section 4.2). This help strengthen the validity of the parameters used, but this is always tricky for spatial data. My concern is that China's forests are greatly varied and how to validate that the five areas chose are representative?

Response:

Thank you very much for your positive comments and constructive suggestions. We have carefully considered your comments and have responded as follows.

First, Sections 4.3&4.4 in this manuscript have been moved to Sections 5.1&5.2.

"5 Discussion
5.1 Spatial distribution of young forests in China
5.2 Average age of young forests in different provinces
5.3 …"

Second, in the original version, we selected five areas to confirm the threshold of key parameters for estimating forest age using the CCDC algorithm. These five regions come from the east (Area 1 and Area 5), southwest (Area 2), central (Area 3), and northeast (Area 4) of China, and the forests in these areas account for the main part of forests in China. As you said, however, it is possible that these five areas do not completely represent the forest characteristics of the entire China. To this end, **we added other three test areas in the new version**, they are distributed in the northwest (Area 6), north (Area 7), and south (Area 8) of China. These eight test areas come from seven major geographical regions of China, which have different geographical and vegetation growth conditions that cannot be ignored in forest age mapping. In addition, these eight areas also represent different forest protection policies and forestry uses. For example, the forests in the Three-North Shelter Forest Region are mainly protected, while there are a large number of plantation forests for timber production in southern China. The corresponding figures and texts have been modified as follows.

"4.2 Analysis of key parameters in CCDC

The sensitivity of the model to breakpoint detection affects directly the accuracy of stand age mapping, and the two parameters chiSquareProbability and minObservations play important roles in the model. To determine the optimal parameters, we selected eight regions in China (Figure 1) for testing. These eight regions are all sized 0.5°×0.5° and distributed in the east (Area 1 and Area 5), southwest (Area 2), central (Area 3), northeast (Area 4), northwest (Area 6), north (Area 7), and south (Area 8) regions of China. In this research, the value of the chiSquareProbability parameter was increased from 0.50 to 0.99, while minObservations was increased from 2 to 20."

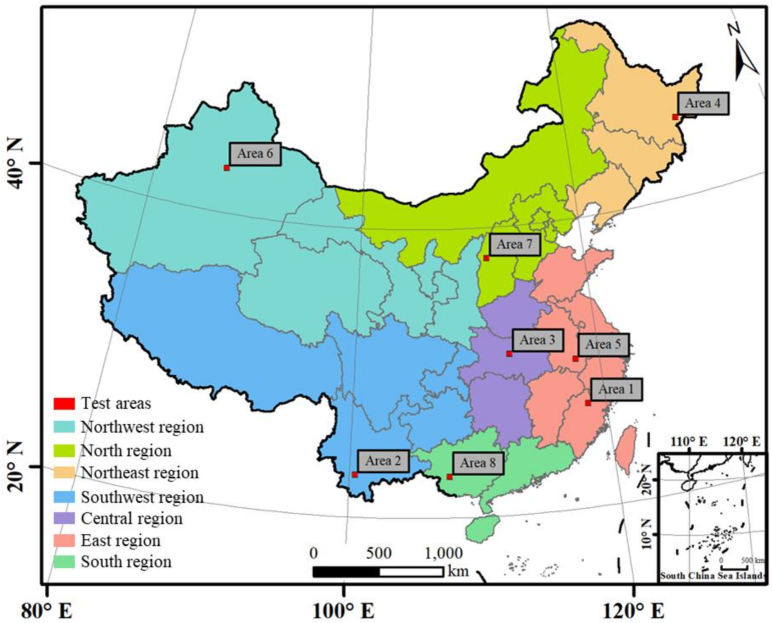

***Figure 1**. Spatial distribution of the eight test areas for analyzing the influence of key parameters.*

"4.2.1 Analysis of chiSquareProbability

Figure 2(a) shows that the OA of stand age mapping in the eight areas varies with the choice of different chiSquareProbability values. The largest OAs of the other four areas except Area 3 and Area 8 occur when the chiSquareProbability value is around 0.98, whereas the largest OAs of Area 3 and Area 8 occur when the chiSquareProbability value is 0.82 and 0.80, respectively. The OAs of Area 3 and Area 8 reach the largest value earlier, as the forest land in these two areas are disturbed more frequently."

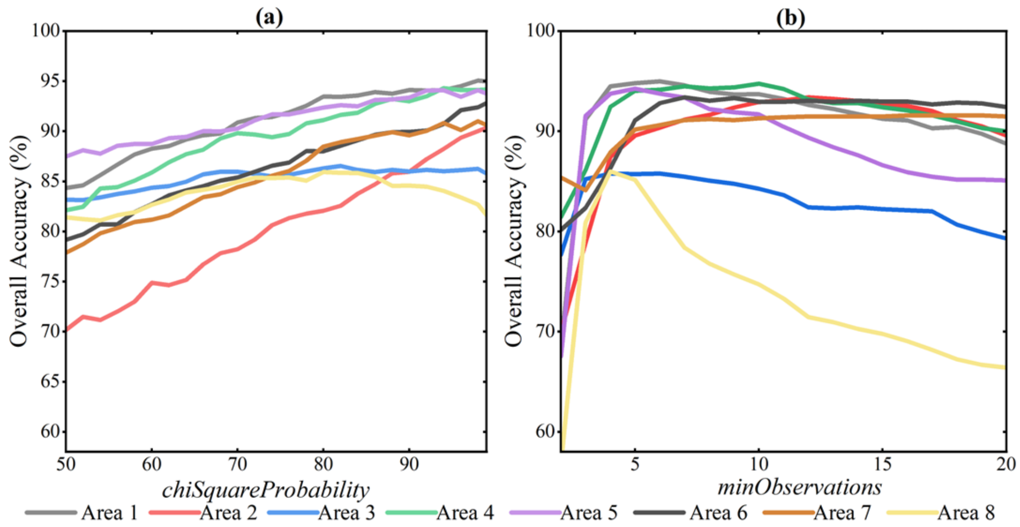

***Figure 2**. OA of forest age under different values of (a) chiSquareProbability and (b) minObservations in eight regions.*

"Figure 3 shows the model performance when different chiSquareProbability values were used. Specifically, columns 1, 2, and 3 show the stand age maps of the eight regions when the parameter chiSquareProbability values are 0.50, 0.74 and 0.99, respectively. As the value of the parameter chiSquareProbability increases, the area of regrowth detected by the CCDC algorithm decreases. When the value was 0.50, the stand age map for each region contains a large number of misclassified regrowth areas. These misclassified regrowth areas are due mainly to the small values of chiSquareProbability, which make the model extremely sensitive to breakpoint detection.

Generally, there is a close relationship between forest restoration and forest loss. For this reason, FLH was added to the fourth column for convenient visual comparison. The color of the FLH indicates the year of forest loss. As the earliest available year for FLH is 2000, the fourth column of Figure 3 shows only the years of forest loss after 2000. The fifth column of Figure 3 shows the corresponding fine spatial resolution Google Earth maps (GEMs). Clear traces of forest disturbance can be observed in the eight regions from the GEMs. These areas are more consistent with the dark red areas in the third column of the stand age maps."

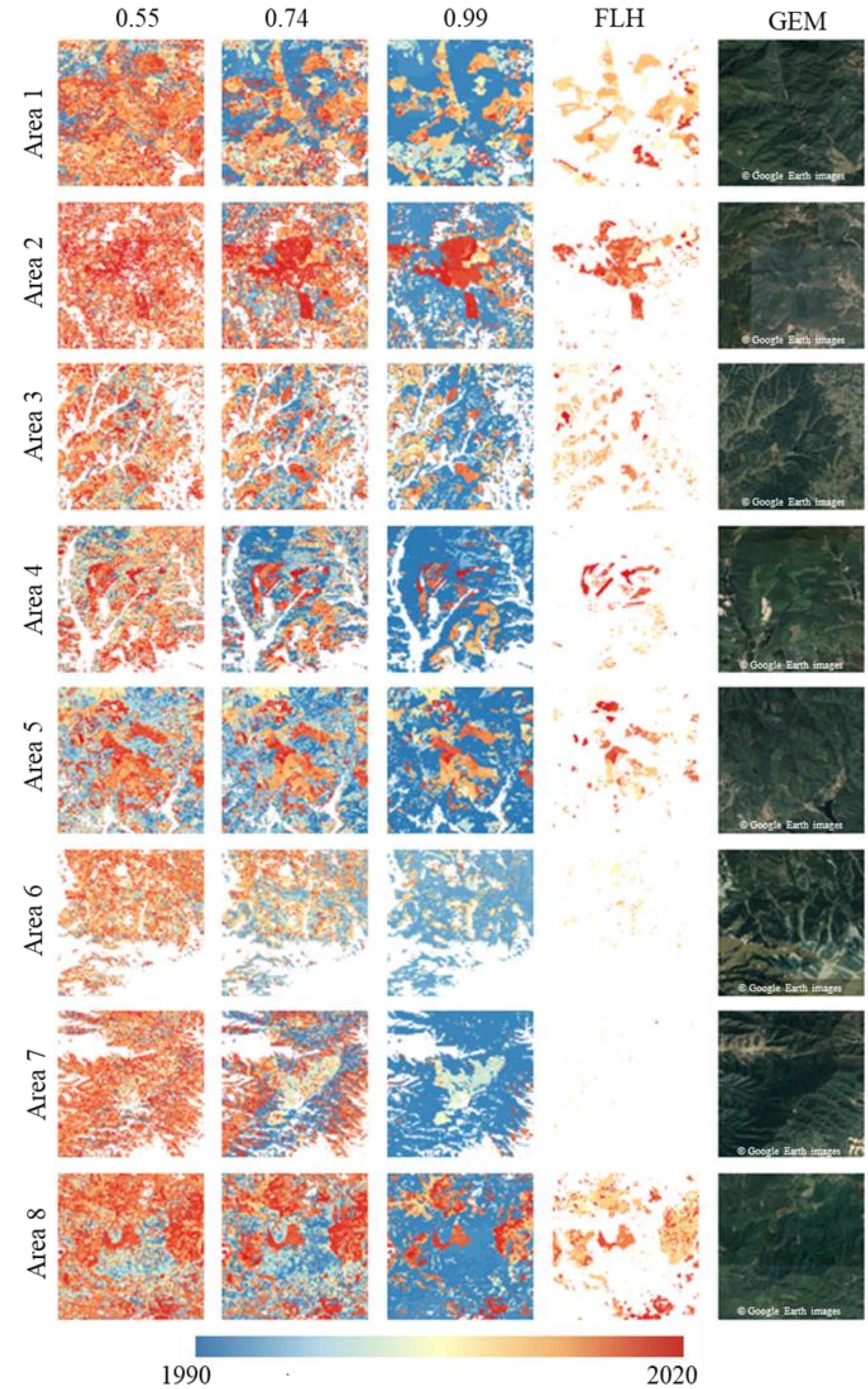

Figure 3. Stand age maps of the eight regions (marked in Figure 1) under different values of chiSquareProbability (0.55, 0.74, and 0.99).

"4.2.2 Analysis of minObservations

Figure 2(b) shows that the OA of stand age in the eight regions varied with minObservations. The OAs of stand age in the eight areas show a trend of initially increasing and then decreasing. This means that when the minObservations value is smaller, the CCDC model can detect more breakpoints while producing more misclassified regrowth values. When the minObservations value exceeds the optimal threshold, the model presents incorrect detection results. When the parameter is less than six, the OAs of the eight regions increase rapidly. When the parameter is *greater than 12, the OAs of each region enter a stage of rapid decay. The largest OAs for both Area 1 (94.98%) and Area 3 (85.78%) occur when the values of minObservations are equal to six. The OAs of Area 8, Area 5, and Area 6 reach the maximum value when minObservations is four, five, and seven, respectively. While Area 4, Area 2, and Area 7 reach the maximum OA (94.75%, 93.37%, and 91.58%, respectively) when the values of minObservations are 10, 12, and 16, respectively."*

"5.3 Effect of input features on the model
… Figure 4 shows the OAs of the eight regions with the input of different features. Using the original Landsat bands as the input to the model can achieve the greatest mapping accuracy. Except for the spectral feature, whose performance is relatively stable in the eight regions, the performance of the other features in the eight regions is quite different."

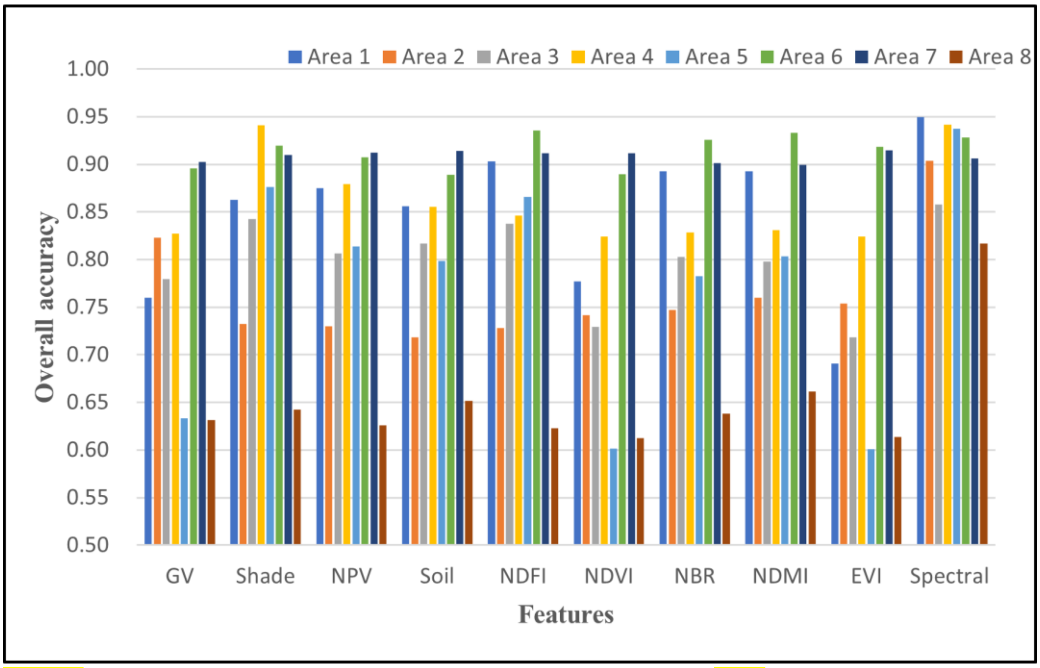

Figure 4. OA of the CCDC-based method with different input features in eight regions.

Other minor suggestions:

1. In Table1, the author listed all the gridded data used. I think the forest definitions might differ between these datasets. Have you consider the definition differences and how you deal with this issue? Does it affect the results?

   Response:
   We totally understand the reviewer's concern. The definition of forest is not uniform across these datasets. However, it will not affect the validation samples generation and its quality, because we only sampled from the consensus area (described detailly in Section 3.3). In other words, the undefined areas of forests due to different definitions will not be considered to generate regrowth samples.

2. Line205, 'too large' -> 'too high'. Same to Line206, because sensitivity should be described by high/low.

Response:
We thank the reviewer for pointing out this issue. The statement of 'too large' has been modified accordingly.

"For example, if the sensitivity is too high, then slow forest degradation (owing to insect pests and selective logging, etc.) will also be detected as breakpoints. Because there is no land cover type change in this process, a high sensitivity will lead to an underestimation of forest age…"

3. For figure5, why the second column forest grids were all classified as UF? For 2015, forest was identified in the second column of the 2nd and 3rd rows of the both datasets. Seems these two grids are also regrowth forests according to the classifier defined. Also, there is a typo of 'includiing', which shoud be 'including'.

Response:
Thank you so much for your careful check. These two grids you mentioned belong to the regrowth forest, so we modified Figure 5. Also, the spelling mistakes were corrected accordingly.

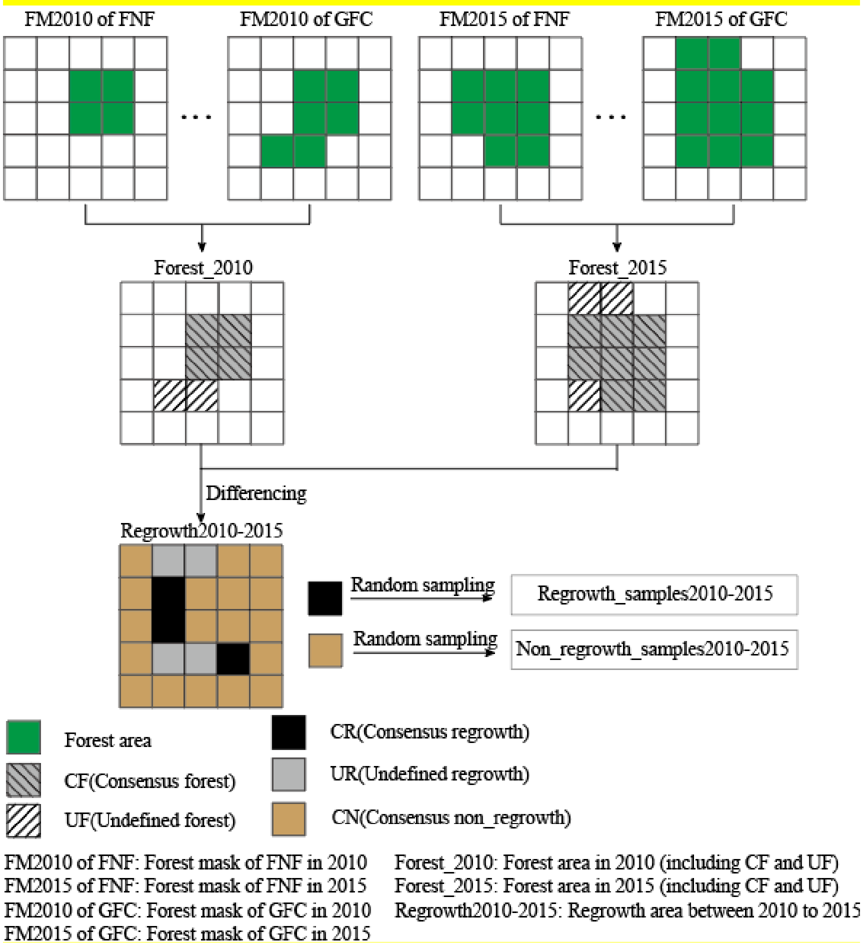

Figure 5. Validation samples generated using LULC products.

4. Line272, I am not very clear how the validation sample sets were generated.

Could you provide more information here?

Response:
Thank you for pointing out this issue. The validation sample were generated by auxiliary datasets (Table 1). First, we confirmed the area of consense regrowth (CR) and consense non-regrowth (CN) with four periods (such as 2000–2005, 2005–2010, 2010–2015 and 2015–2020). Second, regrowth samples and non-regrowth samples were randomly generated from CR and CN of each period, respectively. As a result, we obtained 2618 regrowth samples and 21007 non-regrowth samples.

"(3) Random sampling and confusion matrix calculation. Stratified random sampling was used to generate validation sample sets. First, we confirmed the area of consense regrowth (CR) and consense non-regrowth (CN) with four periods (i.e., 2000–2005, 2005–2010, 2010–2015, and 2015–2020). Second, about 1000 regrowth samples and 5000 non-regrowth samples were randomly generated from CR and CN of each period. Considering the possibility of regrowth events occurring in each period within the same pixel, only the regrowth samples in the most recent period were retained for the regrowth samples in the four periods. As a result, 2,618 regrowth samples (red dots in Figure 6) and 21,007 non-regrowth samples (blue dots in Figure 6) were obtained."

5. Line289, 'smaller'->'lower'

   Response:
   We thank the reviewer for pointing out this issue. The word 'smaller' have been replaced by 'lower'.

   "The provinces with relatively weak classification performance were Gansu, Jiangxi, Shaanxi and Beijing (in order), and the OAs of these four provinces were lower than 60%."

6. Line308-309, better rephrase this sentence: "more ... than ...". It is not appropriate to compare these two since your data only limited to young forests, while MPI-BGC covers all ages.

   Response:
   We gratefully appreciate your valuable suggestion. We have rewritten this part according to your suggestion.

   "...depict the age of these forests. The forest age map produced in this research presents clear information at the 30 m spatial resolution, which is helpful for monitoring small-scale deforestation activities and estimating land-atmosphere carbon fluxes."

7. Line318, why randomly selected samples but not all the regrowth data?

   Response:
   Thank you so much for your careful check. We only randomly selected 10000 samples to calculate Pearson's product-moment correlation coefficient, because 10000 samples can basically reflect the relationship between two data. However, using all the regrowth data is time-consuming and we should consider the limits of GEE's computing power.

8. Lines 403-404, This may not be the case. For example, it could be the reason that the forestation areas remained the same but the forest establishment (tree survival rate) was lower in recent decade. To make this claim, you need to refer to the data of forestry yearbook.

   Response:
   We gratefully appreciate for your valuable comment. Indeed, the lower rate of tree survival after 2000 also could be the reason. So we referred to the 5th, 6th, 7th, and 8th national forest inventory data and found that the area of net gain planted forest is 102,520, 65,924, 84,311, and 76,416 km^2 during 1994-1998, 1999-2003, 2004-2008, and 2009-2013, respectively. It means that there was less planted forest after 1999, which may be the reason. According to this, we rephrased the sentences of Lines 403-404.

   "We referred to the 5th, 6th, 7th, and 8th national forest inventory data and found that the area of net gain planted forest is 102,520, 65,924, 84,311, and 76,416 km^2 during 1994-1998, 1999-2003, 2004-2008, and 2009-2013, respectively (Liu et al., 2021). It means that there was less planted forest after 1999, which is consistent with our findings. Another reason may be that the country's early policies (specifically, the Returning Farmland to Forest Program and the Afforestation Program) were implemented effectively, and by 2000 many areas suitable for afforestation had been occupied."

9. Line426-428, Yes, this is reasonable. Suggest to use eucalyptus, which has been widely planted in Guangxi and Guangdong, as an example. Eucalyptus is a fast growing species and is generally harvested in 5-10 years.

   Response:
   We thank the reviewer for the nice suggestion. We have re-written this part according to the reviewer's suggestions.

   "On the other hand, a large number of eucalyptus plantations were distributed in southern China, leading to young forest regrowth in the south."

Response to CC2:

High-resolution forest age mapping is an important part of carbon cycle research and is one of the most significant research points. Based on the CCDC algorithm, this study maps the age of young forests in China with a resolution of 30 meters. This product are valuable for the calculation of the carbon cycle and carbon budget. As a user, I am very interested in your dataset, but I found some limitations in this dataset which may hinder its further applications.

First, it is found that there are serious spatial discontinuity in this dataset, such as the following regions: R1 (121-122 °E, 50-51 °N), R2 (123-125 °E, 51-52 °N), R3 (117-119 °E, 29-30 °N), R4 (119-120 °E, 28-29 °N).

Second, the forest age mapping was carried out based on the CCDC algorithm, but it has been demonstrated that the CCDC algorithm had several limitations. (1) It did not consider the spatial differences between pixels (Ye et. al., 2023). (2) It did not consider the varied temporal consistency of the Landsat time series (Zhu et. al., 2020). (3) Large inconsistency of disturbance maps existed between the adjacent Landsat path overlap and non-overlap regions (Qiu et. al., 2022 Characterization of land disturbances based on Landsat time series). Why not use a better version of the CCDC-family algorithms such as COLD (Zhu et. al., 2020), Bi-CCD (Zheng et. al., 2021), S-CCD (Ye et. al., 2021), NRT-MONITOR (Shang et. al., 2022), OB-COLD (Ye et. al., 2023)?

Last, it was reported that young forests under 31 years old account for 19% of China's total forest (Lines 400-401, page 16), which is quite different from the results of the ninth forest inventory in China. These differences should be clearly explained.

Response:

We thank you for using our dataset and giving the above positive comments and nice suggestions. We have carefully considered your comments and have responded as follows.

First, this issue is mainly about the set of values for years larger than 31. Specifically, by classifying the pixels with values >31 into one category and then displaying forest age, the problem of spatial discontinuity you mentioned can be resolved. We have resolved this issue and shared a new version of the dataset, which is openly available at https://doi.org/10.6084/m9.figshare.21627023.v7.

"6 Data availability

The produced 30 m map of young forest age across China in this research is openly available at https://doi.org/10.6084/m9.figshare.21627023.v7 (Xiao, 2022). The Landsat data and the auxiliary data are from public data archive and user team of GEE (https://code.earthengine.google.com/)."

Second, as you mentioned, there are some CCDC-family algorithms, which may be more suitable for turbulence monitoring and/or classification of land cover. We use CCDC to track the breakpoints of Landsats time series, for the three main reasons: (1)

CCDC is the classical algorithm in turbulence detection. We considered using it to estimate the age of forest and the results in this paper already demonstrated that it is an acceptable choice; (2) other CCDC-family algorithms might be sensitive to detect breakpoints. In future research, we will examine whether the use of other versions will necessarily further increase the accuracy; (3) GEE cloud platform provided the basic CCDC in its official algorithm libraries, which is more suitable for large-scale mapping than other CCDC-family algorithms currently.

Third, the differences you mentioned may come from three parts: (1) Differences in statistical time. The ninth national forest inventory (NFI) of China is covering the period 2014–2018, however, our dataset is covering the period 1990–2020; (2) Differences in the methods of forest age statistics. The NFI classified the forest into five forest classes (such as young, mid-aged, near-mature, mature, and over-mature forests), and the age range of each class is vary with tree types. For example, the natural Pinus massoniana Lamb less than 20 years old belongs to the young stage, while the natural Abies fabri less than 40 years old also belongs to the young forest. However, we definite the 1-31-year-old forests as young forests; (3) Mapping error. As mentioned in Section 5.4 of the manuscript, there are still uncertainties in estimating the age of forests.

Response to referee #2:

In this manuscript a continuous change detection and classification (CCDC)-based method for large-scale forest age mapping is proposed, and used to estimate young forest ages across China in 2020 at a spatial resolution of 30 m. This is of interest to the scientific community. The reliability and applicability of the proposed CCDC-based forest age mapping method has been validated by comparing the forest age map with 20 Hansen’s forest change dataset, Max Planck Institute for Biogeochemistry (MPI-BGC) 1 km global forest age datasets and field measurements. This study would be very helpful to reduce the uncertainties in the research of forest carbon cycle. It only needs a minor revisions as follows:

1) Line 518: “of should be” should be replaced with “should be”.

Response:

Thank you very much for your positive comments and suggestions to improve our manuscript. We have carefully considered your comments and revised the paper accordingly. We have modified the sentence in Line 518.

Thank you again for your work on our paper. We look forward to hearing from you in due course.

With best wishes

The authors