2020 forest age map for China with 30 m resolution

Anonymous Referee #1

Dear Editor and Reviewer:

On behalf of my co-authors, we thank you very much for giving us an opportunity to revise our manuscript, and we also appreciate reviewers very much for their positive and constructive comments and suggestions on our manuscript entitled "2020 forest age map for China with 30 m resolution" (Manuscript Number: essd-2023-385).

We revised the manuscript according to these comments and suggestions. All changes were marked in highlight text in the revised manuscript. The line numbers in the response are the corresponding line numbers in the revised version.

Once again, thank you very much for your comments and suggestions. Once again, thank you very much for your comments and suggestions.

Reply:

Line20 and Line25: MLA is an abbreviation for machine learning algorithms. We have re standardized the abbreviations.

Line50, Line54-56, and Line57: The sentence is not clear, and it has been adjusted.

Line77-78: The sentence has been adjusted according to your kind advices and detailed suggestions.

Line92: We have corrected this space.

Line99: We have corrected the citation of references.

Line220-222: The sentence is not clear, and it has been adjusted.

Line239: We have corrected these mistakes.

Line258: We adjusted Figure 3 to the same page as its title

Line278: The meaning of the headings is not clear, and the new explanation has been given.

Figure 5. (a) Boxplot of forest age of China grouped by provinces (b) Violin plot of the forest age grouped by vegetation divisions.

Line282: The mistake has been corrected according to your kind advices and detailed suggestions.

Line289: Thank you very much for your professional advice, we have re-adjusted the horizontal and vertical coordinates of the Figure 6.

Line303: We adjusted Table 3 to the same page as its title.

Line303: The brackets in Table 3 have been corrected.

Line371: We have re-adjusted the horizontal and vertical coordinates of the Figure 8(b).

2020 forest age map for China with 30 m resolution

Anonymous Referee #2

Dear Editor and Reviewer:

Thank you for your constructive comments and suggestions on our manuscript entitled "2020 forest age map for China with 30 m resolution" (Manuscript Number: essd-2023-385). We appreciate the time and effort you have invested in reviewing our work. We agree with your assessment of deficiencies in the introduction, method, and discussion sections, and we have addressed these issues comprehensively in the revised version. In the revised manuscript, we have offered a more detailed explanation of the algorithm and its combination with machine learning, addressing any specific concerns you have raised. Also, we have carried out a comprehensive check on the structure and language of the full text. All changes were marked in highlight text in the revised manuscript. Please find our responses to your comments below:

Reply:

1. The introduction should highlight the innovation, why is it LandTendr algorithm instead of CCDC and other algorithms?

Reply: Thanks to the reviewer for pointing this out, we strengthened the innovation of this study in the introduction and added a review of the LandTendr algorithm in predicting the age of forests in the introduction. Please see below or check in Line 70-79.

Disturbance detection approaches, capable of identifying the time of the most recent stand-replacing disturbance, have proven accurate in forest age estimation (Li et al. 2024), which mainly include Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr) (Kennedy et al. 2010), Continuous Change Detection and Classification (CCDC) (Zhu and Woodcock 2014), the Vegetation Change Tracker (VCT) (Huang et al. 2010), Breaks for Additive Season and Trend (BFAST) (Verbesselt et al. 2010a; Verbesselt et al. 2010b). Among these algorithms, LandTrendr has been recognized for its efficiency in detecting forest disturbances such as fire, deforestation, and urban expansion (de Jong et al. 2021; Rodman et al. 2021). For instance, Li et al (2024) mapped planted forest age using LandTrendr algorithm, demonstrating its efficiency and reliable for forest age mapping. However, these approaches are limited to obtaining forest age in areas with disturbance recorded by remote sensing, thus restricting a comprehensive understanding of forest age structures. Consequently, it is necessary to develop a framework that can provide comprehensive forest age information on a large scale.

2. Line 86: Why is China divided into these eight vegetation regions?

Reply: Given this topographic, climatic and vegetation species diversity, China harbors eight main vegetation regions (Wu 1980; Zhang ,2007). The age distribution characteristics of different vegetation types vary (Harms et al.2001; Chen et al.2007; Magnani et al.2001; Li et al.2007). Therefore, we have established age models for each vegetation region. The application of eight vegetation regions division is widely applied in the ecological field and generating remote sensing products at national scale (Sun, Sang, and Axmacher 2020; He et al. 2017; Wang et al. 2021; Liu et al. 2022). For the division basis of eight vegetation regions, we have added literature citations in Line 96.

3. Line 104: Why is there a distinction between planted forest and natural forest, what is the purpose of the authors, respectively, and what is the difference between planted forest and natural forest in algorithm.

Reply:

The effects of natural and planted forests on forest age are different. Therefore, we took forest origin (plantation forest and natural forest) as the influence factor of forest age, processed it into dummy variable for quantification, and participated in the machine learning modeling of forest age model.

Different forest origins may lead to different forest age distributions and changes.

Natural and planted forests have distinct age distributions. Natural forests have a complex stand age distribution, with different tree species and heights having different ages, forming a complex canopy structure and species diversity. Planted forests have a simple age distribution, with mostly the same tree species and height, and lower ages, because planted forests are mainly for meeting human economic needs, so they are harvested when the trees reach a certain growth period, making it difficult to form long-lived trees (Guo et al. 2014; Jiao et al. 2003).

4. Line 118: the resolution of Climate data (30 arc-second) is not consistent with it in Table 1.

Reply: 30 arc-seconds is approximately equal to 1 kilometer. The mistake has been corrected according to your detailed professional suggestion in Line 146.

5. Line 123: Why the PC1 gives annual trends in temperature and precipitation, PC2 gives seasonal variations in temperature and precipitation, and PC3 gives precipitation and temperature extremes?

Reply: We apologize for the omission of the PCA principal component analysis results in the Supplementary section, and have already been supplemented. Please check the supplementary Table 1.

Supplementary Table1 shows the factor score coefficient matrix of the first three components PC1, PC2, PC3, we find that:

(1) PC1 is related to BIO1, BIO2, BIO5, BIO6, BIO9, BIO10, BIO12 and BIO18， which represent annual trends in temperature and precipitation.

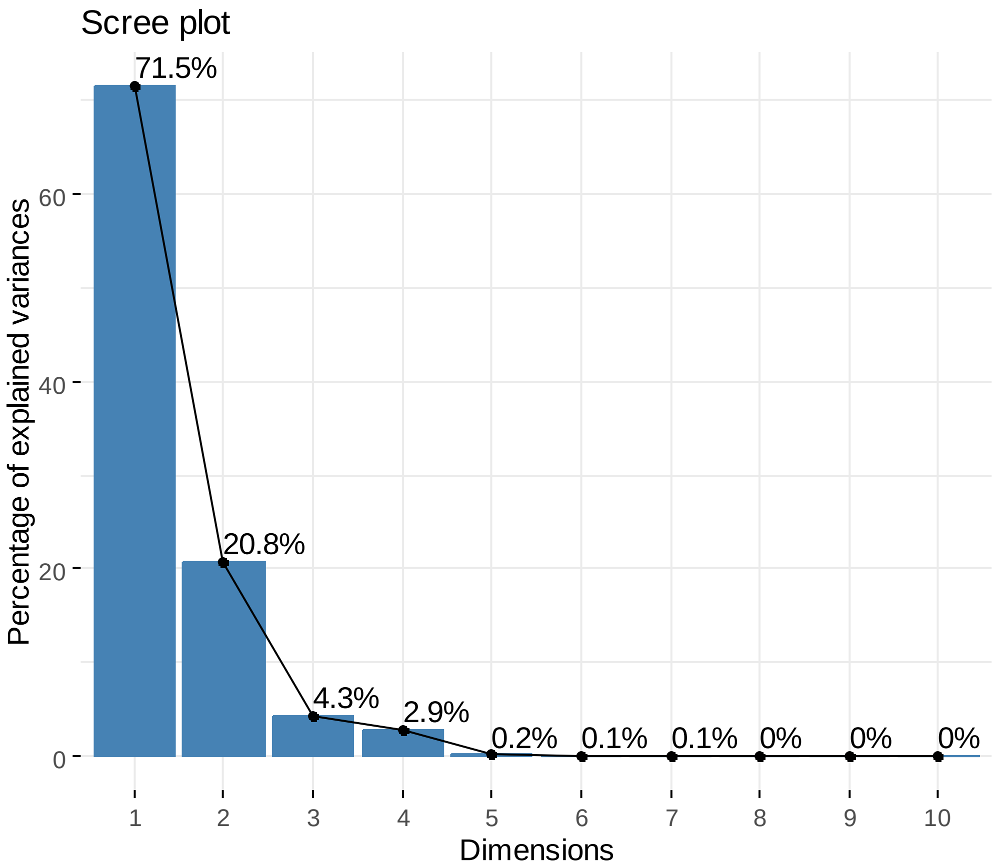
(2) PC2 is related to BIO3, BIO4, BIO7, BIO11 and BIO15. These factors mainly reflect seasonal variations in temperature and precipitation

(3) PC3 is related to BIO8, BIO13, BIO14, BIO16, BIO17, and BIO19, and these factors reflect precipitation and temperature extremes.

Therefore, the PC1 gives annual trends in temperature and precipitation, PC2 gives seasonal variations in temperature and precipitation, and PC3 gives precipitation and temperature extremes.

Supplementary Table1 Principal component analysis of 19 bioclimatic variables

Variables	Describe	Principal Component		
		PC1	PC2	PC3
BIO1	Annual Mean Temperature	0.272	0.112	0.224
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	-0.205	0.177	-0.145
BIO3	Isothermality (BIO2/BIO7) (×100)	-0.129	0.403	-0.123
BIO4	Temperature Seasonality (standard deviation ×100)	0.039	-0.476	0.128
BIO5	Max Temperature of Warmest Month	0.266	-0.093	0.261
BIO6	Min Temperature of Coldest Month	0.262	0.181	0.200
BIO7	Temperature Annual Range (BIO5-BIO6)	-0.059	-0.447	0.041
BIO8	Mean Temperature of Wettest Quarter	0.221	0.029	0.447
BIO9	Mean Temperature of Driest Quarter	0.253	0.220	0.097
BIO10	Mean Temperature of Warmest Quarter	0.272	-0.069	0.264
BIO11	Mean Temperature of Coldest Quarter	0.243	0.253	0.168
BIO12	Annual Precipitation	0.272	-0.013	-0.271
BIO13	Precipitation of Wettest Month	0.256	0.077	-0.266
BIO14	Precipitation of Driest Month	0.255	-0.147	-0.257
BIO15	Precipitation Seasonality (Coefficient of Variation)	-0.198	0.286	0.066
BIO16	Precipitation of Wettest Quarter	0.255	0.110	-0.269
BIO17	Precipitation of Driest Quarter	0.248	-0.165	-0.275
BIO18	Precipitation of Warmest Quarter	0.211	0.210	-0.162
BIO19	Precipitation of Coldest Quarter	0.250	-0.124	-0.303



Supplementary Figure1 Scree plot of 19 bioclimatic variables

6. Line 146: The algorithm description and detail of forest age in changed area and forest age in unchanged area is missing.

Reply: Thank you very much for your professional advice, we have adjusted a clear description of the overall algorithm design and objectives. In addition, we have described how the two methods will be integrated in conjunction with each other. Please check below (Line 211-217).

Given the extensive forest coverage in China, it is challenging to handle such large forest area for ML and the LandTrendr algorithm to estimate forest age, even with our vegetation zoning efforts. To enhance the efficiency of forest age estimation and conserve computational resources, we have divided China into 1°×1° grids (see Supplementary Figure 2), limiting ML and LandTrendr algorithms to estimate forest age within each grid. Subsequently, we merge the predictive results from each grid using the Mosaic New Raster tool in ArcGIS Pro 3.0 to obtain nationwide forest age map. Finally, the forest age map estimated through LandTrendr algorithm is applied to update the ML-based results to produce China's forest age data.

7. Line 235: which is the year of China's forest age map? Is it 2020? Use LandTrendr to look back at the age of forests during 1985-2020, but why not

present the age change in the <u>results</u>. Please refer to Xiao, 2023 and Huang, 2023 for details

Reply: We appreciate the reviewer's insightful suggestion. After sorting out the whole method part, we present the corresponding age detected by LandTrendr in Figure 4b, and made description about this result. Please see below or check in Line 260-265.

Based on the optimal MLAs and the LandTrendr change detection algorithm, we have obtained forest age data for China as shown in Figure 4. Figure 4a presents the nationwide distribution of forest age as estimated by MLAs, whereas Figure 4b displays the age distribution from 1985 and 2020 as determined through change detection. The results reveal that reforestation activities from 1985 and 2020 are primarily situated in the southern, southeastern, and northern China, aligning with the findings from Xiao et al (2023). Furthermore, estimates derived from MLAs indicate that old-growth forests are primarily located in the northeast and southwest regions of China.

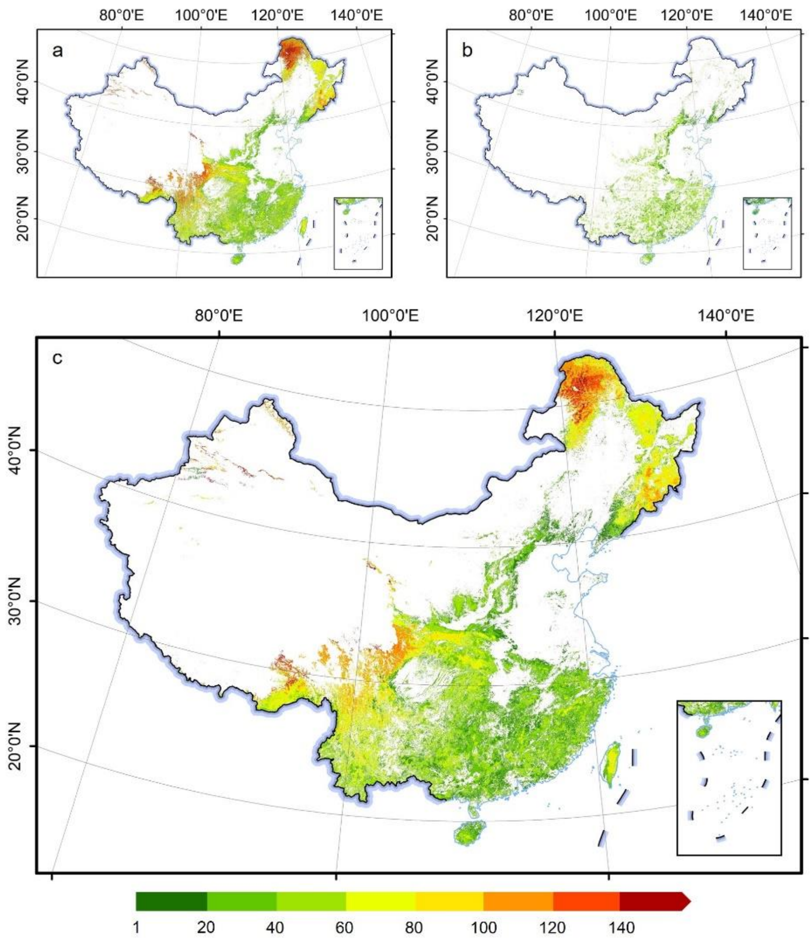


Figure 4. Forest age estimated from LandTrendr (a), MLA (b), and final China's forest age distribution (c) with 30 m resolution.

8. The discussion part of this paper is a little limited, which is all about input data constraints, having no limitations of the algorithm. whether forest age estimation should be combined with forest restoration and other conditions, and whether the parameters of LandTrendr algorithm will affect the detection results.

Reply： We agreed with the reviewer's comments and added the method limitations to the discussion section, including the current limitations of machine learning and limitations specific to the change detection algorithm. Please see below or check in Line 388-400.

Regarding to methods, we combined MLA and disturbance detection approach to derive forest age, for MLA, overfitting is a common challenge, where a model learns the training data too well and fails to generalize to unseen data (Belgiu and Drăguţ 2016). The results presented in Supplementary Table 5 suggest that the constructed forest age models exhibit a certain degree of overfitting, which can cause some errors for forest age estimation. Addressing the issue of overfitting, data augmentation and exploring new deep learning algorithms may be promising directions for further investigation. For LandTrendr approach, it is affected by different parameters such as input bands, vegetation parameters (NBR index), climates, vegetation, terrain and atmospheric conditions (Banskota et al. 2014; Hermosilla et al, 2015; Hua et al, 2021; Huang et al, 2023; Yang et al, 2018). China's unprecedented development has led to extensive land cover changes, making it one of the most intensively managed forest regions globally (Tong et al., 2020). This has resulted in significant forest fragmentation, posing challenges in using NBR and other indices for change detection (Li et al 2024), and creating uncertainty in forest age identification. Furthermore, while the LandTrendr algorithm effectively captures sharp disturbances like fires, clearcutting, and reforestation, it falls short in detecting subtle changes such as silviculture and thinning (Huang et al. 2023; Zhu 2017), This limitation may lead to the omission of young trees and an overestimation of forest age.

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