Reviewer #3:

General Comments:

Comment #1

This manuscript integrated CCDC time series change detection method and CART model to map and identify forest disturbance type at a global scale. I have a few concerns on the validity and robustness of the proposed method.

Response #1

Thanks for your recognition and constructive suggestions, which make our manuscript stronger. In this version, we have further revised the manuscript and addressed all your concerns. Please see the detailed point-by-point responses below.

Comment #2

The detection of disturbed forest pixels solely depends on CCDC model. What's the accuracy of change detection? I wonder whether the change detection error and/or modelling uncertainty of CCDC will affect the subsequence disturbance type mapping? CCDC assumes NDVI of all the forest pixels can be quantified by a linear trend term and a harmonic seasonality term (Eq. 1). In fact, not all the pixels will perfectly fit into this assumed model, which would consequently affect the fitting performance of CCDC and therefore the subsequent disturbance mapping. (**Revised**)

Response #2

Thanks for your constructive comments. We acknowledge the uncertainty of CCDC in change detection. To alleviate this issue, we did not solely rely on the feature indicators of CCDC before model training, but instead supplemented many other datasets such as forest fire distribution, land use types, forest changes, plantations, etc. This study has minimized the interference caused by CCDC fitting uncertainty as much as possible. We have added as much detailed information as possible in the manuscript (Page 7, Line 151-154; Page 4, Line 87-92; Table 2).

"In fact, not all the pixels will perfectly fit into this assumed model, which would consequently affect the fitting performance of CCDC and therefore the subsequent disturbance mapping. To address this issue, we also added feature indicators such as DP and LUC (Table 2) before machine learning training and classification to improve the robustness of the classification model."

"Utilizing multi-temporal Landsat data in 2000-2020 and ancillary datasets (Section 2.2.5), we constructed a comprehensive feature set comprising 18 disturbance indicators (Table 2). These features were systematically derived from both temporal and spatial dimensions, including: Overall characteristics of forest disturbance (OC), pre-disturbance forest conditions (PDC), post-disturbance recovery patterns (PDP), disturbance potential metrics (DP), land use/cover features (LUC), spatial contextual attributes (SC)."

Table 2 Global Forest Disturbance Characteristics Indicator

Indicator type	Forest disturbance characteristic indicators		
OC	Disturbance frequency	Average disturbance period	Number of segments
PDC	Linear intercept before disturbance	Internal fluctuations before disturbance	Interannual trend before disturbance
PDP	Linear intercept after disturbance	Internal fluctuations after disturbance	Interannual trend after disturbance
DP	Forest fire area	Plantation area	Intensity of population
LUC	2020 Land Use /Cover	Forest cover in 2000	Forest cover in 2020
SC	Longitude	Latitude	Disturbance partition

Comment #3

Besides, in addition to CCDC, there are many change detection models available, such as BEAST, BFAST, and Landtrendr. Why did the author go with CCDC? Will applying different model end up with the same change detection outcomes? (**Explained**)

Response #3

Thanks for your comments. All of these models are capable of detecting changes, and each algorithm has its specific advantages. Based on our work requirements, we need to be able to achieve rapid high-resolution forest change detection results on a global scale. It is important to note that these models generally exhibit very slow computational speeds when processing long-time-series, high-resolution remote sensing imagery at the global level. In contrast, a global fitted dataset based on the CCDC algorithm has already been generated, which significantly reduces both time and computational resources. Therefore, we selected the CCDC model. We believe that other models could also yield satisfactory results, however, the associated time costs are difficult to estimate.

Comment #4

It seems that the authors only considered and mapped abrupt forest loss, while graduate forest changes (e.g., forest degradation) and forest gain (e.g., natural regrowth and afforestation) were only mapped. (**Revised**)

Response #4

Thanks for your comments. This GFD map only includes abrupt forest disturbance types. For gradual weak disturbances, we propose these types in the forest disturbance classification framework, such as degradation caused by drought, pests and diseases, etc. This will be an independent topic for further research. We have added corresponding explanations in the manuscript (Page 9, Line 190-195).

"For the forest weak disturbance types caused by drought disturbance (16) and pest disturbance (17), their sample point selection needs to refer to high-resolution long-term remote sensing images. Meanwhile, weak disturbances in forest cover are highly time-bound. For example, the decline in vegetation index caused by a period of drought will quickly recover due to an increase in precipitation. At the global scale, it is currently limited by the availability of remote sensing images. We are unable to select relevant sample points through Landsat imagery. Therefore, this study did not consider these two weak disturbance types of drought disturbance and pest disturbance. This will be an independent topic for further research."

Comment #5

Line 80: "CRAT" should be "CART" (**Revised**)

Response #5

Thanks for your suggestion. We have revised the expression here (Page 13, Line 93-95):

"Our classification approach employed a decision tree-based machine learning algorithm (CART), with accuracy metrics quantitatively assessed using independent test sample points (Fig. 1)."

Comment #6

5. Does the undisturbed area indicate no change has occurred in the pixel? What's the omission rate (or under-detection rate) of CCDC? (**Revised**)

Response #6

Thanks for your comments. Undisturbed areas refer to pixels that have not undergone significant change, no abrupt forest loss or other major disturbances. The CCDC model's inherent uncertainty can also lead to a certain rate of omission errors. To mitigate this uncertainty, we incorporated multiple auxiliary datasets to reduce its impact, such as the Hansen et al. forest change dataset, among others. We have added corresponding explanations in the manuscript (Page 7, Line 151-154).

"In fact, not all the pixels will perfectly fit into this assumed model, which would consequently affect the fitting performance of CCDC and therefore the subsequent disturbance mapping. To

address this issue, we also added feature indicators such as DP and LUC (Table 2) before machine learning training and classification to improve the robustness of the classification model."

Comment #7

How does the proposed algorithm perform in Landsat images with dense and consistent cloud coverage (e.g., in tropical area)? (**Revised**)

Response #7

Thanks for your comments. Our algorithm performs reasonably well in Landsat imagery with dense and consistent cloud cover, such as in tropical regions, though its efficacy is inherently dependent on image quality. In these areas, the predominant disturbance types, such as shifting cultivation and deforestation, exhibit lower identification accuracy compared to other disturbance categories, which is likely attributable to persistent cloud contamination. Nevertheless, our model still achieves an accuracy of nearly 80% or higher (Page 13, Line 179-183) in these challenging cloud conditions.

"Forestry replanting shows strong(93.07% ±0.40%, 90.92% ±0.45%), while shifting cultivation achieves moderate performance and slightly more variable accuracy (84.03% ±0.87%, 84.56% ±0.86%). Deforestation of natural forests exhibits the lowest user's accuracy (74.33% ±1.85%), suggesting significant confusion with other disturbance types, despite its relatively higher producer's accuracy (85.01% ±1.62%)."
