National forest carbon harvesting and allocation dataset for the period 2003 to 2018

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Abstract. Forest harvesting is one of the anthropogenic activities that most significantly affect the carbon budget of forests. However, the absence of explicit spatial information on harvested carbon poses a huge challenge in assessing forest harvesting impacts, as well as the forest carbon budget. This study utilized provincial-level statistical data on wood harvest, the tree cover loss (TCL) dataset, and a satellite-based vegetation index to develop a Long-term harvEst and Allocation of Forest Biomass (LEAF) dataset. The aim was to provide the spatial location of forest harvesting with a spatial resolution of 30 m and quantify the post-harvest carbon dynamics. The validations against the surveyed forest harvesting at 133 cities and counties indicated a good performance of the LEAF dataset in capturing the spatial variation of harvested carbon, with a coefficient of determination (R^2) of 0.83 between the identified and surveyed harvested carbon. The linear regression slope was up to 0.99. Averaged from 2003 to 2018, forest harvesting removed 68.3±9.3 Mt C yr^{-1}, of which more than 80% was from selective logging. Of the harvested carbon, 19.6±4.0%, 2.1±1.1%, 32.8±11.8%, 7.0±0.4%, 19.4±0.4%, and 19.1±9.8%~~22%, 45%, 4%, and 29%~~ entered the ~~wood fuel~~fuelwood, ~~wood products,~~ paper ~~products~~and paperboard, wood-based panels, furniture, constructions, and ~~residual~~residues pools, respectively. Direct combustion of fuelwood~~wood fuel~~ was the primary source of carbon emissions after wood harvest. However, carbon can be stored in wood products for a long time, and by 2100, almost ~~90~~40% of the harvested carbon during the study period will still be retained. This dataset is expected to provide a foundation and reference for estimating the forestry and national carbon budgets. The 30 m × 30 m harvested carbon dataset from forests in China can be downloaded at https://doi.org/10.6084/m9.figshare.23641164.v2 (Wang et al., 2023).

1. Introduction

As a critical terrestrial ecosystem type, forests play a pivotal role in regulating the global carbon cycle (Dixon et al., 1994). Over the period 2001 to 2019, global forests sequestrated 2.07 Gt C yr^{-1} from the atmosphere (Harris et al., 2021), contributing more than 70% of the global terrestrial carbon sinks (Friedlingstein et al., 2022). Forests also provide numerous important ecosystem services to society (Costanza et al., 1997), which may substantially impact the forests carbon sink (Lal et al., 2013). One of the most important services is the provision of wood products (Deal and White, 2012), which results in the transference~~transfer~~ of carbon from forest ecosystems into the social system. The carbon harvested from forests is typically transferred into the pools of ~~harvested~~ Harvested ~~wood~~ Wood ~~products~~ Products (HWPs) through their usage~~use~~ of wood for constructions, furniture ~~(i.e., wood products)~~, and fine papers ~~(i.e., paper products)~~, among others. These products are eventually decomposed and emitted into the atmosphere with different turnover times (IPCC, 2014, 2019a). For example, when harvested wood is used to make paper, the carbon within the paper decomposes and returns to the atmosphere within several years (Brunet-Navarro et al., 2017). On the contrary, the harvested carbon entering the wood ~~products~~ used ~~in~~ for constructions has a slow turnover rate and can be stored for many years (Brunet-Navarro et al., 2017). Previous studies have highlighted the large ~~uncertainty~~ uncertainties in estimating carbon emissions of wood post-harvest due to a lack of information about the proportion of wood entering ~~into~~ various wood pools (Skog et al., 2004).

In China, forests are playing an increasingly important role in terrestrial carbon sinks benefiting from long-term afforestation projects (Liu et al., 2014). A recent study based on satellite data revealed that China is one of the few countries experiencing persistent greening over the past decades (Chen et al., 2019; Yuan et al., 2019). Unlike India, where croplands dominate~~s~~ greening, nearly half of China's greening comes from forests (Chen et al., 2019). However, despite these positive trends, China ranks as the second-largest timber consumer and the largest wood importer globally (Research and Market, 2019). In 2017, the consumption of wood in China reached 192.5 million cubic meters, with 43.6% of that consumption being supplied by domestic harvests (Research and Market, 2019). A previous study has highlighted that harvesting is the primary cause of forest disturbance in China, accounting for 85% of the average annual forest loss (Curtis et al., 2018). However, the impacts of forest harvesting on the terrestrial carbon cycle has not been estimated yet due to a lack of available data on harvested carbon. Accurate

60 forest harvesting data are crucial for measuring the national carbon sink-source balance, an important component of national carbon budget analysis related to forest resources and wood utilization (Winjum, et al., 1997).

Although some efforts have been made, there are still large uncertainties in estimating harvested carbon in forest ecosystems (Hurtt et al., 2011, 2020). For example, the Land-Use Harmonization 2

65 (LUH2) dataset provides annual harvested biomass carbon data from primary and secondary forests (Hurtt et al., 2011, 2020). However, the spatial resolution of the LUH2 dataset ($0.25° \times 0.25°$) is too coarse to analyze the dynamics of forest ecosystems at the regional or local scales, and its performance in assessing carbon harvest has not been examined in China. In addition, to our knowledge, no studies have been conducted to quantify the proportion of harvested wood or carbon entering ~~into~~ various wood

70 pools, which is crucial for estimating carbon emissions returning to the atmosphere (Skog et al., 2004; Johnston and Radeloff, 2019). Over the past decades, construction, papermaking, and furniture manufacturing have shown substantial changes in China (Zhang et al., 2019; FAO, 2023), largely influencing the proportion of harvested carbon among various wood pools and the magnitude of emissions.

75 In this study, we developed a Long-term harvEst and Allocation of Forest Biomass (LEAF) dataset to provide: (1) the spatial location of harvested carbon with a high resolution of 30 m; (2) the proportion of harvested carbon allocated into various wood pools; and (3) the lagged carbon emissions of harvested carbon from the aforementioned wood pools. The tree cover loss (TCL) dataset developed by Hansen et al. (2013) and the interannual variation of a satellite-based vegetation index were used to determine the

80 location of harvested carbon, and the provincial statistical biomass storage provided by the China Forestry and Grassland Statistical Yearbook was used to quantify the magnitude of harvested carbon. Post-harvest carbon dynamics were estimated based on a first-order decay (FOD) function according to the post-harvest wood use provided by the statistical data (IPCC, 2014, 2019a).

2. Methods and Materials

85 This study aimed to generate a Long-term harvEst and Allocation of Forest Biomass (LEAF) dataset, which is a component of the Terrestrial Ecosystem Disturbance (TED) dataset, named ~~referred to~~ as TED-LEAF. The LEAF dataset includes the location and magnitude of forest harvesting and the estimates of

post-harvest carbon dynamics. The identification of forest harvesting was based on the detection of changes in multi-temporal vegetation indices. Combined with statistical harvest data, the forest harvesting and other disturbances causing such changes could be separated. Utilizing the classification of HWPs provided by statistical data, we estimated the delayed carbon emissions by 2100 from HWPs based on IPCC methodologies with China-specific activity data.

2.1 Method of calculating harvested carbon

We aimed to identify two types of forest harvesting: clear-cutting and selective logging (Fig. 1). In this study, clear-cutting is the harvesting of an entire stand at once on a scale of 30 m × 30 m, while selective logging is the harvesting of a portion of the stand within that area that is suitable and should be harvested.

For clear-cutting, the location was determined using the TCL dataset produced by Hansen et al. (2013). The TCL dataset indicates stand replacement disturbance or the complete removal of tree cover canopy at a scale of 30 m × 30 m. It has been widely used to identify deforestation globally or in multiple regions (Hansen et al., 2013; Curtis et al., 2018). To calculate the harvested carbon from clear-cutting, it was necessary to determine the above-ground biomass carbon (AGB, t C) storage for each pixel. Only the 9th National Forest Inventory (NFI) provided both provincial forest AGB density (CD, t C ha^{-1}) and forest area (S, ha). Then, we calculated pixel-level (30 m × 30 m) AGB storage for 2014 to 2018 as:

$$AGB_j = CD \times S \times \frac{NDVI_j}{SNDVI} \tag{1}$$

where AGB_j indicates the AGB of the jth forest pixel in a given province and year; $NDVI_j$ denotes the Normalized Difference Vegetation Index (NDVI) of the jth forest pixel in that province for that year; $SNDVI$ is the sum of NDVI of all forest pixels in that province for that year. According to the province-level biomass storage (V, m^3) provided by the 6th to 8th NFIs covering 1998 to 2013 at 5-year intervals, this study used the following method to calculate pixel-level (30 m × 30 m) AGB storage for 2003 to 2013:

$$AGB_j = V \times \frac{NDVI_j}{SNDVI} \times Coef \tag{2}$$

where $Coef$ (t C m^{-3}) is the coefficient that converts biomass storage (V) to biomass carbon (AGB). Combining the provincial forest biomass storage (V_9, m^3) from the 9th NFI, we calculated the provincial $Coef$ (Table ~~S1~~S2) as:

$$Coef = \frac{CD \times S}{V_9} \tag{3}$$

Then, the harvested carbon was calculated for all pixels corresponding to clear-cutting derived from the TCL dataset. The total harvested carbon from clear-cutting (HC_C, t C) in a given province can be calculated by aggregating all pixels occurring tree cover loss.

120   For selective logging, we developed a satellite-based method to identify the location and magnitude of selective logging. The method was based on the principle of multitemporal satellite-based vegetation index analysis and detected the changes of NDVI between two adjacent years. This approach relied on two fundamental assumptions. First, we assumed that NDVI values decreased resulting from selective logging. Therefore, we calculated the NDVI difference ($NDVI_{diff}$) between the current year ($NDVI_t$) and
125   subsequent year ($NDVI_{t+1}$) at all pixels (Eq. (4)) and determined the possible logging locations with decreased $NDVI_{diff}$, where $NDVI_{diff} < 0$ indicated potential selective logging.

$$NDVI_{diff} = NDVI_{t+1} - NDVI_t \tag{4}$$

Second, we assumed that the reductions in NDVI values resulting from selective logging would be more significant compared to the decreases caused by other factors such as droughts, heat-waves, ice
130   storms, and insect outbreaks (Yuan et al., 2014), without considering fires due to their low frequency in China (Curtis et al., 2018). Changes in vegetation coverage caused by logging activities were expected to have a drastic and rapid impact on ecosystems compared to other environmental changes and disturbances. Therefore, the decreased magnitude of NDVI values due to selective logging was assumed to be the largest. Based on this assumption, we can identify ~~potential~~ selective logging areas by focusing
135   on pixels exhibiting larger $NDVI_{diff}$. For a specific province, all pixels with negative $NDVI_{diff}$ values were sorted by ascending order in $NDVI_{diff}$. The pixels at the front of the sorted list had more negative $NDVI_{diff}$ values and a larger likelihood of being logging locations. Thereby, a threshold of $NDVI_{diff}$ ($NDVI_{Th}$) was needed to distinguish selective logging from other disturbed pixels. Selective logging was considered to have occurred only when $NDVI_{diff} < NDVI_{Th}$. Then, the harvested carbon (HC_S, tC) was calculated in all
140   pixels corresponding to selective logging according to Eq. (5):

$$HC_{s\,j} = \frac{NDVI_{diff\,j}}{NDVI_j} \times AGB_j \tag{5}$$

Therefore, the province-level statistical harvested carbon (SHC) was used to determine the $NDVI_{Th}$ of each province, which made the sum of HCc and HCs equal to SHC. Theoretically, the determined $NDVI_{Th}$ should be less than 0. However, in several provinces, when $NDVI_{Th}$ was set to 0, the sum of HC_C and

145 HC$_S$ (identified harvested carbon) was still lower than SHC (e.g., Anhui), implying that the identified

harvested carbon was underestimated. Then we assigned the unidentified harvested carbon (SHC−HC$_C$−

HC$_S$) to pixels where selective logging occurred.

$$HC_{S1\,j} = (SHC - HC_C - HC_S) \times \frac{NDVI_{diff\,j}}{SNDVI_{diff}} \tag{6}$$

where $HC_{S1\,j}$ is the harvested carbon added by the jth pixel where selective logging occurred; $NDVI_{diff\,j}$

150 indicates the $NDVI_{diff}$ of the jth pixel, and $SNDVI_{diff}$ is the sum of $NDVI_{diff}$ of all pixels where selective

logging occurred in that province. This approach increased the harvested carbon for all pixels where

selective logging occurred, so we also examined whether the harvested carbon exceed their AGB at the

pixel scale. If so, we counted these pixels as clear-cutting. To assess the accuracy and validity of the

dataset, we additionally quantified the proportion of pixels with harvested carbon exceeding their AGB

155 compared to the total number of harvested pixels at the province level.

In addition, this study assumed that forest harvesting did not occur in the National Nature Reserves

and high-altitude regions because of high transport costs and harvesting expenses. For the Tibetan Plateau

and Yunnan Province, we assumed no harvesting at elevations higher than 2,500 m. In the other provinces,

harvesting was assumed to be absent at elevations higher than 1,500 m, according to Nabuurs et al.,

160 (2019).
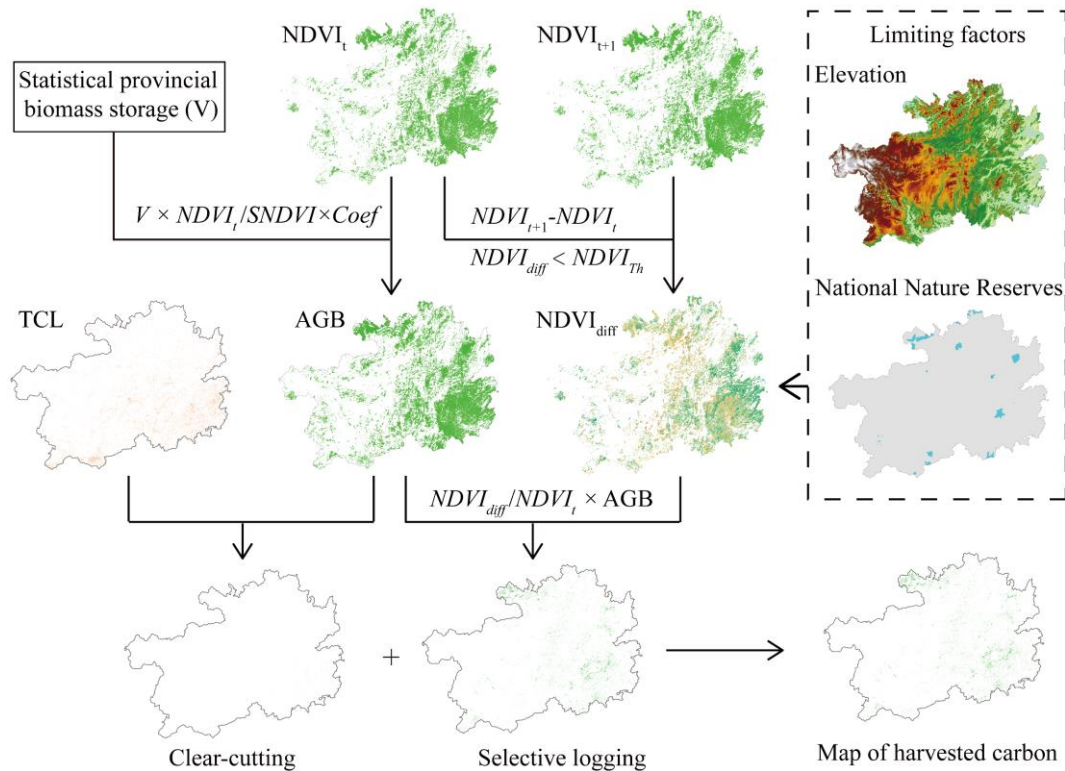
Figure 1: Flowchart for mapping forest carbon harvesting.

2.2 Annual carbon changes from HWPs in-use and end-use

The harvested wood was allocated into ~~four~~ six wood pools (Fig. 2). (1) Fuelwood~~Wood fuel~~ pool, where the wood ~~was~~ is burned ~~for~~ as fuel, resulting in immediate carbon emissions through combustion~~.~~; (2) paper and paperboard pool, including household paper, printing paper, packaging paper, etc.; (3) wood-based panels pool, including fiberboard and particle board made from wood residues (such as barks, branches, sawdust) or small stems bonded with adhesives, are commonly used as decorative panels for various applications like wall cladding and ceiling finishes; (4) furniture pool, referring to wooden household items such as tables, chairs, wood beds, etc.; (5) constructions pool, referring to the structural components used to support buildings, such as beams, columns, and trusses; and (6) residues pool, including leaves, killed understory vegetation, and unutilized wood residues, which are typically left on the logging site or treated as fuel (Lippke et al., 2011; Stockmann et al., 2012), and were assumed as fuel in this study. The wood pools of (2), (3), (4), and (5) belong to HWPs pool~~and (3) wood products pool~~ ~~(i.e., HWPs pools)~~, where the carbon will remain stored until the products are either retired from use or reach the end of their ~~lifespan~~service life (Table S4) and are consequently discarded. Subsequently, these discarded products are then sent directly to ~~either directed to solid waste disposal sites (SWDS)~~landfill, where they decompose~~, or are incinerated~~ (Stockmann et al., 2012; IPCC, 2019a).
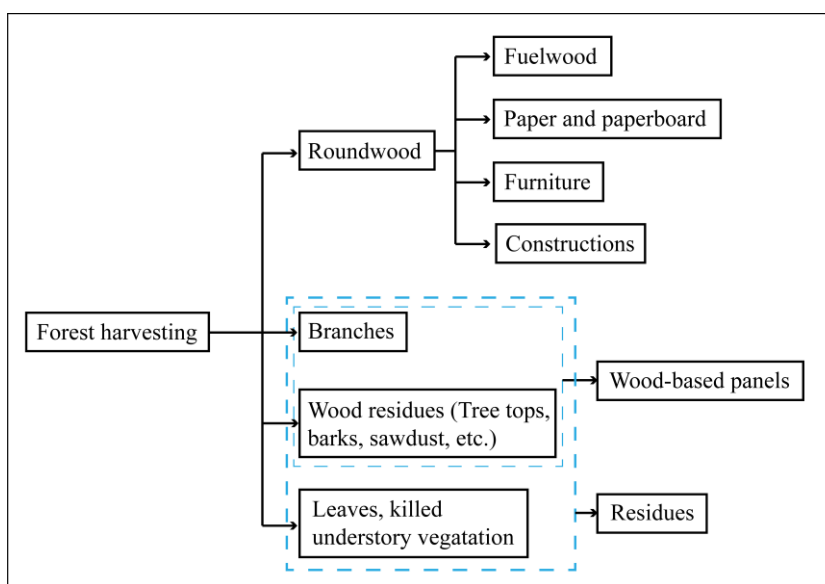
Figure 2: The allocation of post-harvest wood to the six wood pools.

In this study, the volume (m³) of fuelwood, pulpwood (wood for paper and paperboard), wood-based panels, and the sum volume (m³) of wood for furniture and constructions can be obtained directly from the China Forestry Statistical Yearbook. The constructions and furniture pools were allocated as the

percentage of 74.6±6.2% and 25.4±6.2% from their sum, respectively, according to China Timber and Wood Products Distribution Industry Yearbook. The wood in pools (1) to (5) was converted into carbon, with conversion factors listed in Table S3. Then, the carbon entering the residues pool can be calculated by subtracting the carbon in pools (1) to (5) from the total harvested carbon (Sect. 2.3.2). ~~the lifespan of paper products and wood products were assumed to be 5 and 100 years (IPCC, 2019a), respectively, and we calculated the delayed emissions to 2100. Waste incineration is currently more common in developed countries, while in China, landfills remain the primary method of disposal (Cai et al., 2018; IPCC, 2019b). (4) Residual pool, including losses from primary processing during conversion from harvested wood to lumber and discarded poor quality wood, which would be left on site or used as wood fuel (Lippke et al., 2011; Stockmann et al., 2012). It is difficult to obtain the percentage of discarded wood products and residual wood to be decomposed or incinerated. We assumed all of the discarded wood products were deposited to SWDS, which were decomposed, and all of the residual wood was treated as wood fuel for combustion.~~

2.2.1 Annual carbon changes in "HWPs in use"

Carbon stocks and decays from in-use HWPs were calculated using the methodologies for estimating carbon removal from HWPs described in the "2006 IPCC Guidelines for National Greenhouse Gas Inventories" (IPCC, 2006a) and the "2013 Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol" (IPCC, 2014). "Decay" in this paper refers to the discarding of ~~wood and paper product~~HWPs from end uses (and sent to landfill~~SWDS~~), not biological decay. Moreover, here we focused on the carbon fate of wood harvested in China, the imports and exports were not considered. The FOD method (Pingoud and Wagner, 2006) was used to estimate the carbon change in the ~~two~~ HWPs pool ~~of in-use wood products and in-use paper products~~ as:

$$C(i + 1) = e^{-k} \times C(i) + \left[\frac{(1 - e^{-k})}{k}\right] \times Inflow(i) \tag{7}$$

$$\Delta C(i) = C(i + 1) - C(i) \tag{8}$$

where i denotes the year; $C(i)$ is the carbon stock in the HWPs pool at the beginning of year i; and k ($k = ln(2)/HL$) is the decay constant (yr^{-1}). HL is the number of years it takes to lose half of the existing material in the pool, which is a function of the country-specific service life of particular HWPs (HL=*service life* × *ln* (*2*)) (IPCC, 2019b). k for paper and paperboard, wood-based panels, furniture, and constructions ~~paper products and wood products~~ were ~~taken~~ calculated as ~~0.347~~0.333, 0.125, 0.067, and

0.0230.025, respectively, according to the IPCC default values (IPCC, 2014). *Inflow*(i) is the inflow to the HWPs pool during year i, and $\Delta C(i)$ represents the carbon stock change of the HWPs pool during year i. Next, the amount of discarded organic carbon (*DOC*) deposited in the landfillSWDS, as the wood or paper productsHWPs go out of use in year i, was calculated using Eq. (9):

$$DOC_i = Inflow(i) - \Delta C_i \qquad (9)$$

2.2.2 Annual carbon changes in solid waste disposal sites (SWDS)landfill

The *DOC* deposited in SWDS landfill was divided into three parts, (1) *DOC* for aerobic decomposition (DOC_{ar}), producing CO_2 until all available oxygen has been used up; (2) *DOC* for anaerobic decomposition (DOC_{an}), producing both CH_4 and CO_2; (3) *DOC* that will not be decomposed but stored long-term in the landfillSWDS (DOC_{ls}).

The DOC_{ar} was calculated as:

$$DOC_{ar_i} = DOC_i \times f_{ar} \qquad (10)$$

where f_{ar} denotes the proportion of *DOC* undergoing aerobic decomposition. Based on the landfill situation in China, The disposal of waste products in China aligns with the "unmanaged deep" category in the SWDS (Zhang et al., 2019), and the f_{ar} was assumed to be 0.28±0.15 (Table S5). The DOC_{ar_i} undergoes aerobic decomposition and releases as CO_2 in year i:

$$CO_{2\,ar_i} = DOC_{ar_i} \times \frac{44}{12} \qquad (11)$$

The DOC_{an} is calculated with Eq. (12), as:

$$DOC_{an_i} = DOC_i \times (1 - f_{ar}) \times DOC_f \qquad (12)$$

where DOC_f indicates the fraction of *DOC* that can be decomposed under anaerobic conditions (Table S6)., with values of 0.5 and 0.1 for paper products and wood products (IPCC, 2019a), respectively. The annual carbon change of DOC_{an} in the landfillSWDS was calculated according to the FOD method (Pingoud and Wagner, 2006).

$$DOC_{an\,a_i} = DOC_{an_i} + DOC_{an\,a_{i-1}} \times e^{-k} \qquad (13)$$

$$DOC_{an\,decomp_i} = DOC_{an\,a_{i-1}} \times (1 - e^{-k}) \qquad (14)$$

where $DOC_{an\,a_i}$ represents the DOC_{an} accumulated in the landfillSWDS at the end of year i; $DOC_{an\,decomp_i}$ denotes DOC_{an} decomposed in the landfillSWDS in year i; the anaerobic decomposition generally occurs in the following year of deposition. k ($k = ln(2)/HL$) is the decay constant (yr^{-1}), estimated based on

~~Considering~~ the environmental conditions of landfill~~SWDS~~ in China (Table S6).~~, *k* for paper waste and wood waste were taken as 0.05 and 0.025, respectively (IPCC, 2019a).~~ Then, the potentials to generate CH_4 and CO_2 from the anaerobic decomposition of DOC_{an} were:

$$CH_{4_i} = DOC_{an\ decomp_i} \times F \times \frac{16}{12} \times (1 - R_T) \times (1 - OX_T) \tag{15}$$

245
$$CO_{2\ an_i} = \left[DOC_{an\ decomp_i} \times (1 - F)\right] \times \frac{44}{12} \tag{16}$$

where CH_{4_i} and $CO_{2\ an_i}$ are CH_4 and CO_2 produced by anaerobic decomposition in landfill~~SWDS~~ in year *i*. *F* denotes the volume fraction of CH_4 in the generated landfill gas, ~~and the IPCC default~~with a value of 0.5 ± 0.1 (Cai et al., 2018) ~~is encouraged (IPCC, 2019a)~~. R_T and OX_T are ~~We assumed that there was no~~ the recovery rate and oxidation rate of CH_4 in China (Table S5)~~and that the landfill gas will all be~~

250 ~~released into the atmosphere~~. The total CO_2 decomposed from *DOC* in year *i* was the sum of $CO_{2\ ar_i}$ and $CO_{2\ an_i}$. The CH_4 emissions were transformed to CO_2 equivalents (CO_2e) to harmonize calculations of the overall global warming potential (IPCC, 2023).

The DOC_{ls} can be calculated as:

$$DOC_{ls_i} = DOC_i - DOC_{ar_i} - DOC_{an_i} \tag{17}$$

255 Then, the carbon stock in the landfill~~SWDS~~ at the end of year *i* was calculated as:

$$DOC_{s_i} = \sum_0^i DOC_{ls_i} + DOC_{an\ a_i} \tag{18}$$

2.3 Datasets

2.3.1 National Forest Inventories

The ~~National Forest Inventories (~~NFIs~~)~~ provided nine periods of provincial biomass storage for

260 1973-1976, 1977-1981, 1984-1988, 1989-1993, 1994-1998, 1999-2003, 2004-2008, 2009-2013, and 2014-2018 (National Forestry and Grassland Administration, 2019). We used the biomass storage data during the 6th-9th NFIs to generate the distribution of AGB for 2003-2018.

2.3.2 Statistical forest harvesting data

The annual provincial wood output (m^3), extracted from the China Forestry and Grassland Statistical

265 Yearbook, was categorized into two main types: commercial and non-commercial wood. Commercial wood was further divided into ~~simply logs, processed lumber~~roundwood, pulpwood~~lumber for paper~~, and fuel-wood~~, and others, whereas lumber for wood products (such as furniture, construction lumber, etc.)~~

~~was calculated as total commercial wood minus the lumber for paper and fuel~~. Non-commercial wood included the volume of wood ~~timber~~ logged ($\bcancel{T}_{log}F_{log}$) by farmers for burning and for their personal consumption. Commercial wood refers to ~~lumber~~ wood output ($\bcancel{L}_{output}W_{output}$), not the actual logging volume ($\bcancel{L}_{log}W_{log}$). $\bcancel{L}_{log}$ W_{log} refers to the total volume of wood cut from the forest, regardless of whether it was further processed into commercial ~~lumber~~wood. $\bcancel{L}_{output}$ W_{output} refers to the volume of wood that can be used for further production and sale after preliminary processing (such as peeling, sawing, etc.). Meanwhile, this process may eliminate some unusable or poor-quality wood, the $\bcancel{L}_{output}$ W_{output} is generally less than the $\bcancel{L}_{log}W_{log}$. Based on the provincial ~~lumber~~ wood output rates (R, i.e., the ratio of $\bcancel{L}_{output}$ W_{output} to $\bcancel{L}_{log}W_{log}$) provided by China's timber production plan from the National Bureau of Statistics (Table ~~S1~~S2), we calculated the actual annual $\bcancel{L}_{log}$ W_{log} of commercial wood for each province as:

$$\bcancel{L}W_{log} = \frac{\bcancel{L}W_{output}}{R} \tag{19}$$

Then, the total harvested carbon (i.e., the SHC in Sect. 2.1) for a given province was calculated as:

$$SHC = \left(\bcancel{L}W_{log} + \bcancel{T}F_{log}\right) \times Coef \tag{20}$$

2.3.3 Surveyed forest harvesting data

The surveyed forest harvesting data, i.e., the harvested volume at the city and county-level, was retrieved from the official website of each provincial Forestry Bureau. To ensure the effective implementation of the forest harvesting quota system, the provincial Forestry Bureau randomly selects several cities and/or counties, conducting comprehensive field inspections of the annual forest harvesting. The actual annual harvest volume of a specific city or county is determined through comprehensive cross-validation of multiple methods, including declaration and approval records reviewing, on-site measurements, and remote sensing monitoring, etc. These techniques are employed to ensure the accuracy and reliability of the obtained harvest data. There were 133 records nationwide available from 2006 to 2018, concentrated in the provinces of Guizhou, Yunnan, Zhejiang, and Sichuan (Fig. S1).

2.3.4 Forest cover map

The Chinese Forest Cover Dataset, reconstructed by fusing the NFIs and twenty Land Use and Land Cover datasets, was used as the forest cover base map. This forest cover accurately depicts the historical changes in China's forest cover in the period of 1980-2015, with overall accuracy from 76.9% to 99.4%

(Xia et al., 2023).

2.3.5 Satellite-based vegetation index

The NDVI dataset from 2000 to 2020 calculated by Dong et al (2021) was applied to allocate AGB and identify selective logging. This NDVI dataset was calculated using all Landsat5/7/8 remote sensing data for the whole year, the NDVI maxima in each image year were obtained by data pre-processing and data smoothing (Dong et al., 2021).

2.3.6 Mask data

This study used the elevation and National Nature Reserves to exclude the regions where rarely occur harvesting. The elevation dataset was obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/) and the distribution of National Nature Reserves was provided by the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn).

2.4 Accuracy assessment

The surveyed forest harvesting data at city and county-level were employed to validate the accuracy of the LEAF dataset by conducting a comparison with the estimated harvested carbon. The relationships between the estimated harvested carbon and the corresponding surveyed harvested carbon were assessed by linear regression. Then the coefficient of determination (R^2) and slope of linear regression can be calculated, and the closer these two values are to 1, the better the estimates.

3. Results

3.1 Accuracy evaluation of LEAF dataset

Accuracy evaluation of the LEAF dataset generated from this study showed good performance in indicating spatial variations of harvested carbon in China. This study used province-level statistical harvested carbon to determine the threshold for identifying selective logging and used city and county-level surveyed harvested carbon ranging from 2006 to 2018 to examine the performance. The estimated harvested carbon showed high consistency with surveyed harvested carbon, with R^2 of 0.83 and a linear regression slope of 0.99 (Fig. 23).
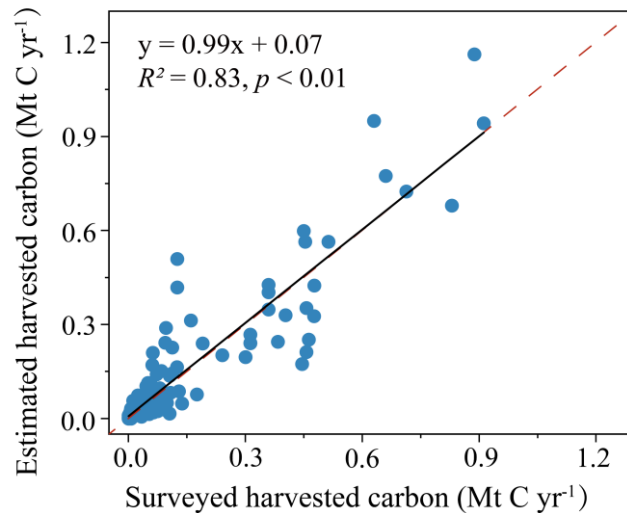
Figure ~~2~~3: Comparison of estimated and surveyed harvested carbon from the official website of each provincial forestry bureau at the city and county levels across all investigated provinces. The solid line indicates the regression lines, and the red dashed line indicates the 1:1 line.

The validation also showed the performance of the LEAF dataset across various provinces and periods. The dataset exhibited excellent skill in simulating the spatial variation of harvested carbon across all surveyed provinces, with R^2 between estimates and surveyed data ranging from 0.24 to 0.96 (Fig. S2). Zhejiang performed the best (Fig. S2e), while Sichuan's performance was relatively low, with R^2 less than 0.5 (Fig. S2c). The LEAF dataset also effectively reproduced the spatial variations of harvested carbon across different periods, with R^2 values ranging from 0.31 to 0.99 (Fig. S3). The estimates for 2013 and 2017 demonstrated superior performance, with both linear regression slopes approximating 1 (Fig. S3c and g). However, except for 2016, estimates from other periods displayed varying degrees of underestimation or overestimation (Fig. S3).

3.2 Spatial and temporal patterns of harvested carbon in China

There was a large heterogeneity in harvested carbon over the regional scale. Harvesting mainly occurred in Eastern and Southern China, and rarely in Northwest China (Fig. ~~3a~~ 4a and b). Guangxi Province recorded the highest harvested carbon, constituting approximately 30% of China's annual total harvested carbon. This volume is 2.5 times larger than that of Fujian, the province with the second highest harvested carbon (Fig. ~~3c~~4c). In terms of harvesting ways, over 80% of the nationwide clear-cutting harvested carbon originated from Guangxi, Guangdong, Fujian, Yunnan, and Jiangxi (Fig. ~~3c~~4c). Forest harvesting in Jiangxi, Guangdong, Yunnan, and Hainan was dominated by clear-cutting, in these provinces, harvested carbon from clear-cutting comprised more than 50% of the total harvested carbon

(Fig. ~~3c~~4c, Fig. ~~4a~~5a). For other provinces, selective logging was the main way of forest harvesting (Fig.

345 ~~4b~~5b).
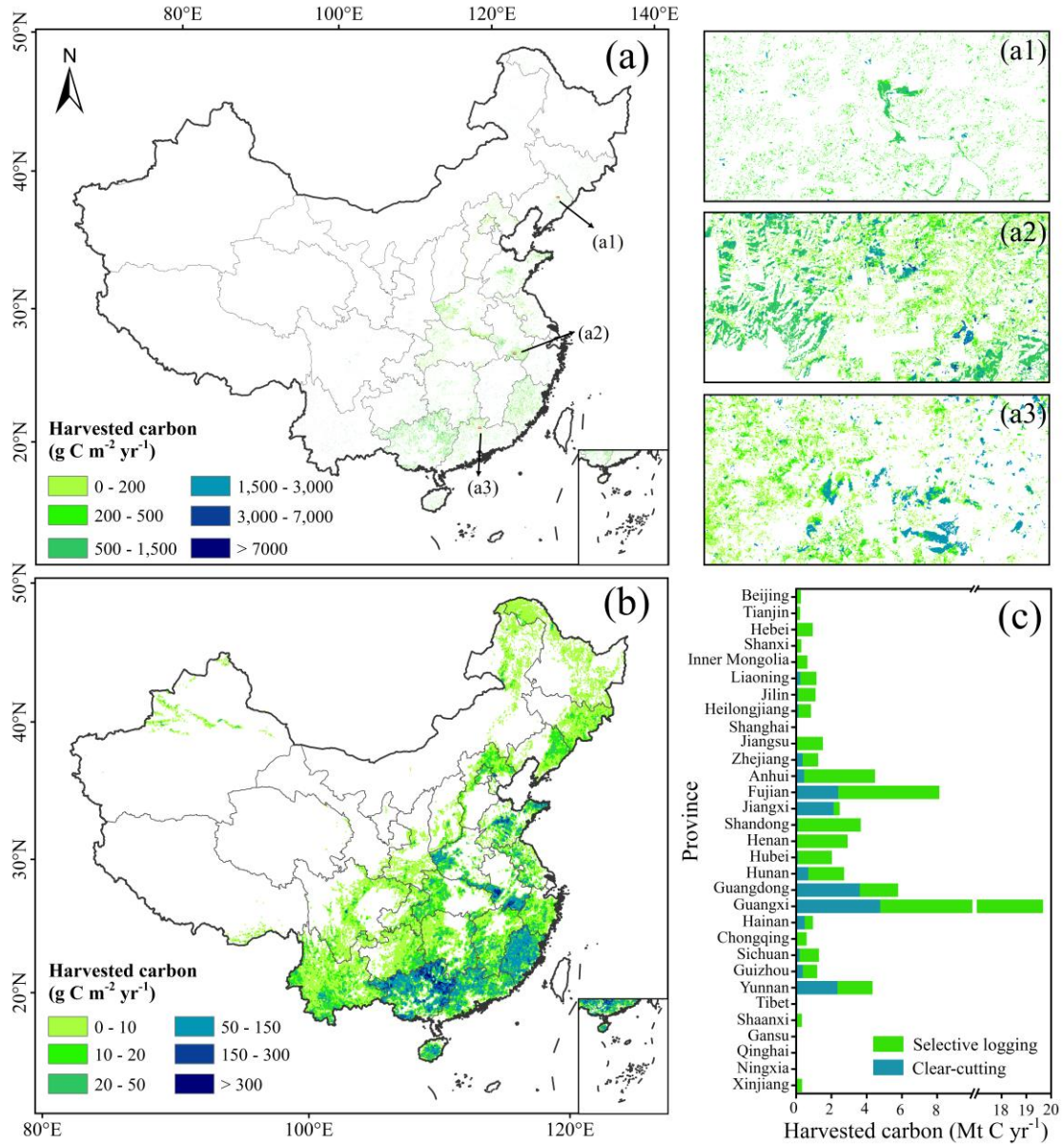
Figure ~~3~~4: Map of forest harvested carbon for China in 2016 at (a) 30 m and (b) 0.1°resolution and the zoomed-in view of the example areas of (a) (a1, a2, and a3), the map at 0.1° was derived from a 30 m data upscaling, and (c) shows the harvested carbon from clear-cutting and selective logging by province

350 in 2016.
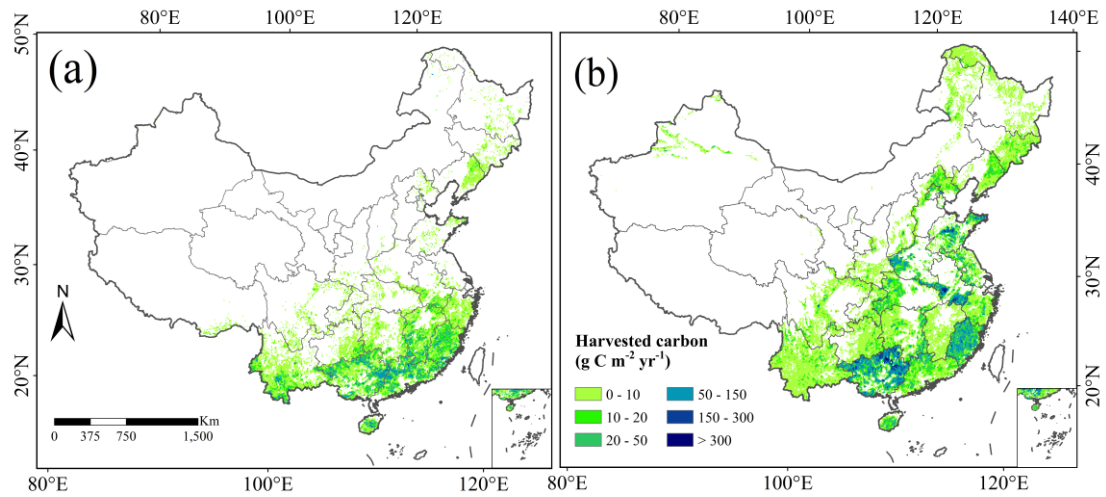
Figure 45: Map of forest harvested carbon from (a) clear-cutting and (b) selective logging for China in 2016 at 0.1°resolution.

China experienced an overall upward trend in forest carbon harvesting, with average harvesting of 68.3$\pm$9.3 Mt C yr^{-1} from 2003 to 2018 (Fig. 56). The most substantial growth in harvested carbon was observed from 2003 to 2008, increasing approximately 1.6 times from 49.8 Mt C yr^{-1} in 2003 to 79.5 Mt C yr^{-1} in 2008 (Fig. 56). Among all surveyed years, the harvested carbon peaked in 2008, primarily driven by an uptick in fuelwood~~wood fuel~~ harvest (Fig. 67). In subsequent years, the harvested carbon generally plateaued, with minor fluctuations. Selective logging was the main way of forest harvesting (Fig. 56). Averaged from 2003 to 2018, there was 55.6$\pm$7.2 Mt C yr^{-1} from selective logging, accounting for around 82% of the total harvested carbon (Fig. 56). Nevertheless, the proportion of harvested carbon from clear-cutting was overall on the rise, reaching its peak in 2012 when it constituted 30% of the total harvested carbon for that year (Fig. 56).
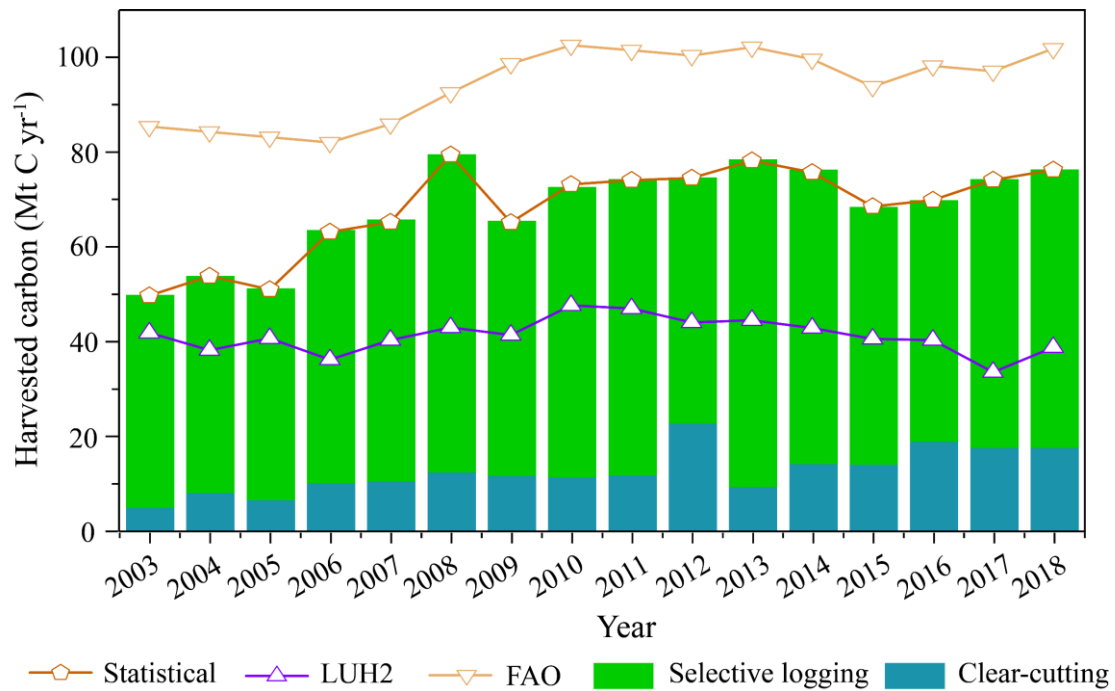
Figure 5̶6: Long-term changes of harvested carbon in China between 2003 and 2018 from statistical, LUH2, FAO, and LEAF datasets.

3.3 Allocation of harvested carbon into the various wood pools

This study also provides the allocation of harvested carbon into the various wood pools with different lifetimes, including fuelwood~~wood fuel~~ pool, paper and paperboard pool, wood-based panels pool, furniture pool, constructions pool, ~~wood products pool, paper products pool,~~ and ~~residual~~ residues pool (Sect. 2.2). Averaged from 2003 to 2018, over the entire China, harvested carbon was allocated into ~~four~~ six pools with 19.6±4.0%, 2.1±1.1%, 32.8±11.8%, 7.0±0.4%, 19.4±0.4%, and 19.1±9.8%, respectively (Fig. 6̶7). ~~Timber~~ Wood for ~~wood products~~HWPs mainly came from Southern China, with Guangxi contributing ~~an average of 16.6%~~ more than 20% of the national ~~timber~~ wood for ~~wood product~~HWPs annually, followed by Fujian (9.6̶7.5%). Meanwhile, Guangxi also contributed up to 42.7̶45.5% of the wood used for paper production (Fig. 7̶8). Over 50% of the wood in Fujian was used for fuelwood~~wood fuel~~, contributing nearly 30% of the national fuelwood~~wood fuel~~. Similar to Fujian, more than 50% of the wood in Yunnan was used for fuelwood~~wood fuel~~, making Yunnan the second-largest province in terms of wood supply for fuelwood~~wood fuel~~ (Fig. 7̶8). From 2003 to 2018, wood harvesting has been increasing, while wood for fuel has been decreasing, with its share decreasing from 3̶129% to 13̶16%. More wood was used ~~to produce wood and paper products~~for HWPs production. The wood residues decreased from 2003 to 2018 (Fig. 7).~~; however, wood in residual pool was also increasing~~
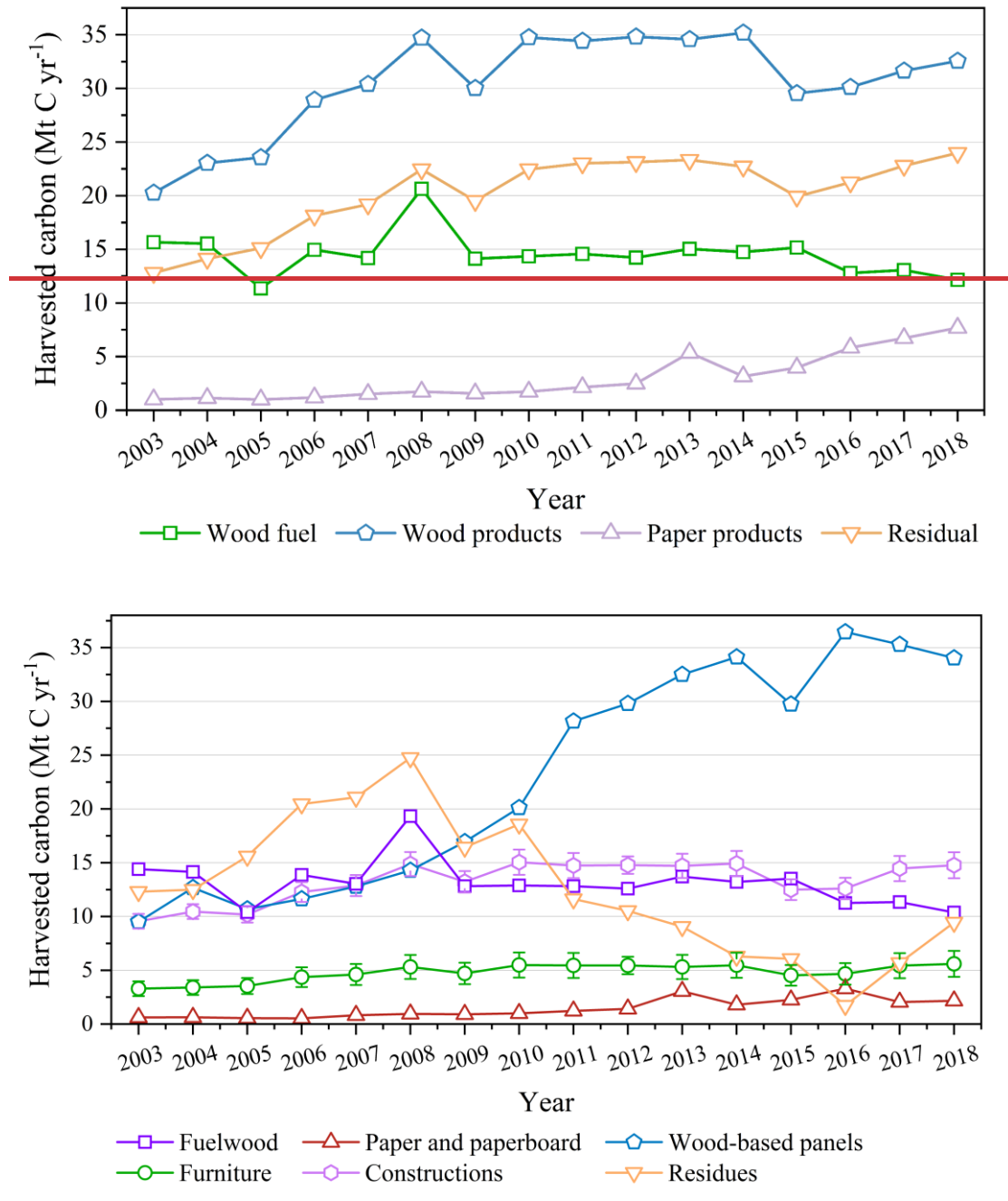
Figure 67: Long-term changes of different pools of harvested carbon from 2003 to 2018 in China.
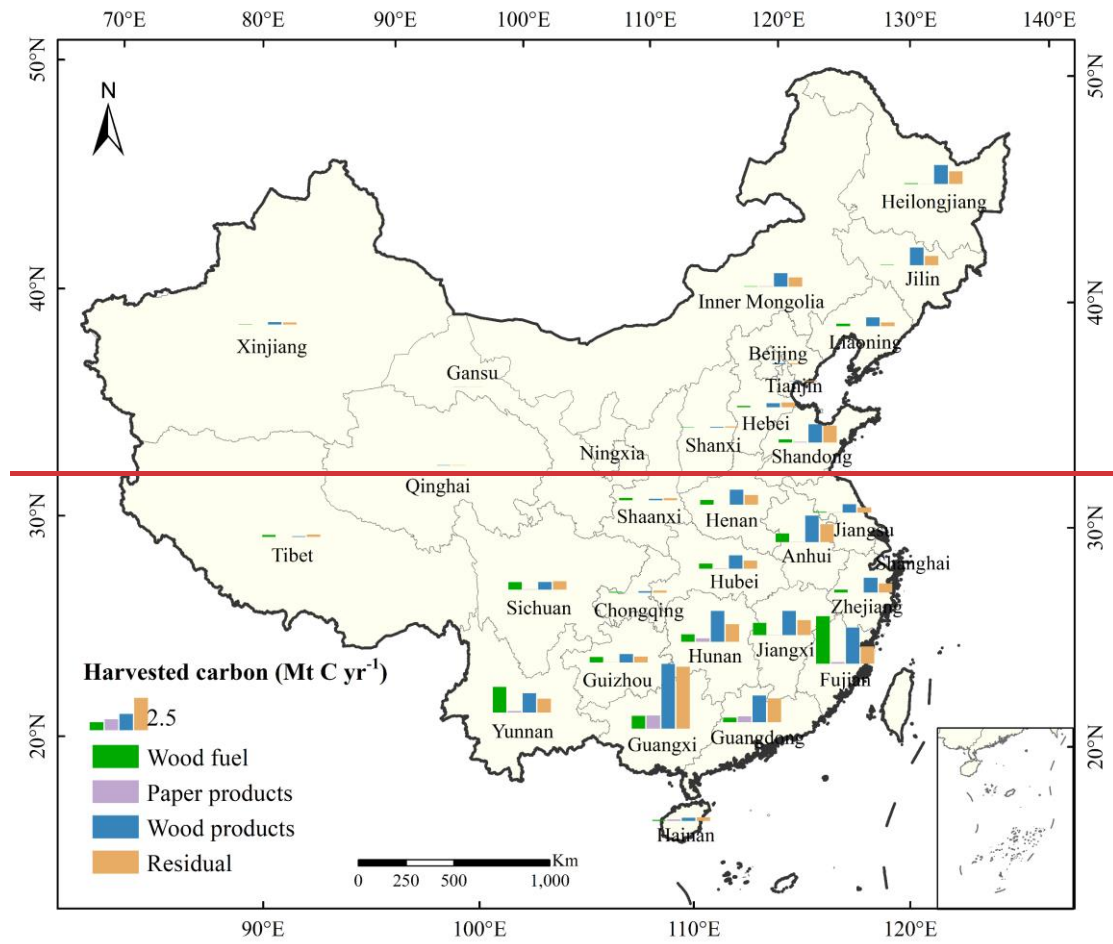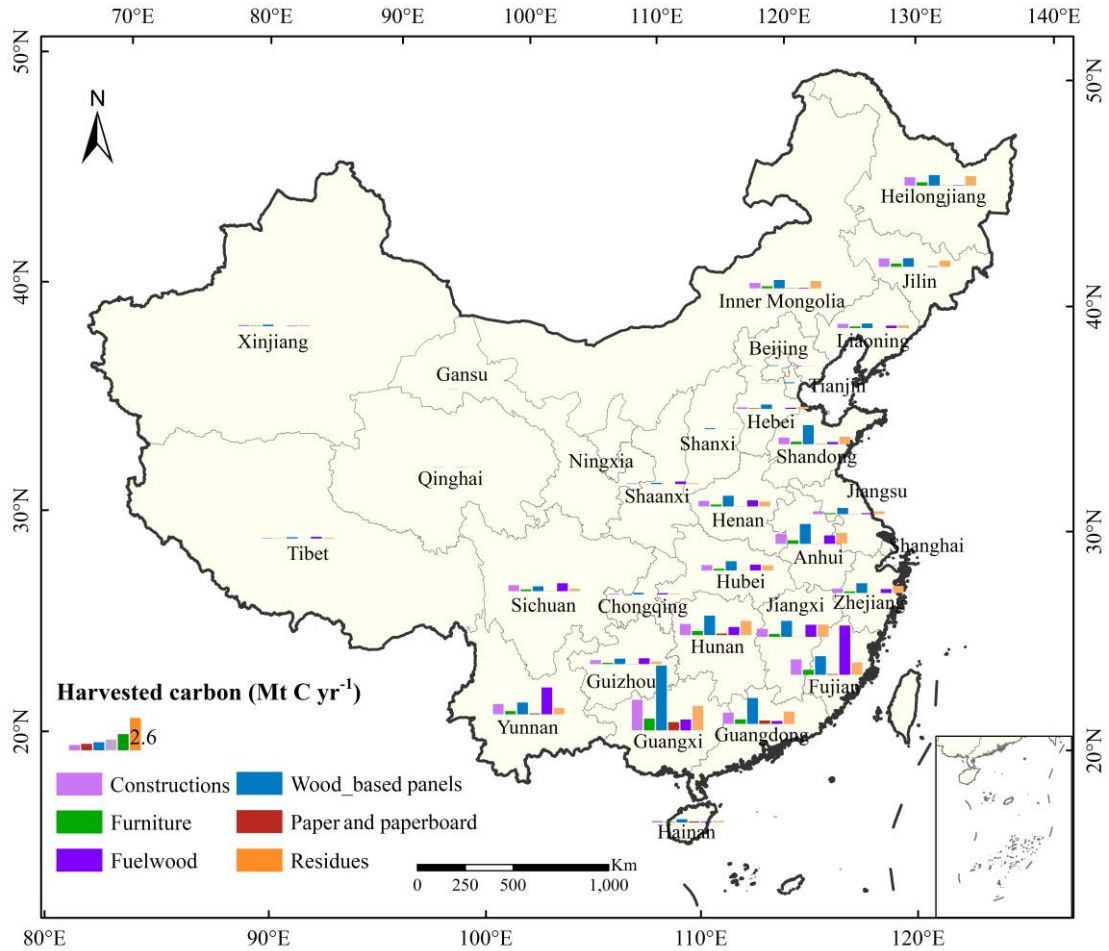
Figure 78: Pools of provincial harvested carbon averaged from 2003 to 2018.

We further quantified the delayed emissions of harvested carbon in various pools. Combustion of fuelwood ~~wood fuel~~ resulted in major carbon emissions, and ~~wood products~~wood-based panels contributed a major share of carbon stock (Fig. 89). Fuelwood~~Wood fuel~~ was typically burned for a short period of time (1 year), resulting in average emissions of ~~55.1~~48.1±7.4 Mt CO_2e yr^{-1} from 2003-2018 (Fig. ~~8a~~9c). Additionally, discarded ~~or retired paper and wood product~~HWPs that enter landfill~~SWDS~~ undergo gradual decomposition, releasing an average of ~~3.9~~3.1±3.0 Mt CO_2e yr^{-1}, 13.3±11.2 Mt CO_2e yr^{-1}, 2.0±1.2 Mt CO_2e yr^{-1}, ~~and~~ 8.93.7±1.7 Mt CO_2e yr^{-1} for paper and paperboard, wood-based panels, furniture, and constructions, respectively, from 2003 to 2100 (Fig. ~~8a~~9d). The total carbon stock sustained an upward trend, peaking at 2141.3±195.7 Mt CO_2e in 2018 (Fig. ~~8b~~9a, b). As products ~~are~~ were discarded and/or retired, the carbon stock in currently used products persistently declines without ongoing wood inputs (Fig. 9a). Furthermore, most of the waste products that enter landfill~~SWDS~~ do not decompose and become a permanent carbon sink (Fig. ~~8b~~9b). About ~~90%~~39.2%±10.3% of harvested

carbon during 2003-2018 will still be stored in the ~~wood products~~HWPs by 2100 (Fig. ~~8b~~9b).
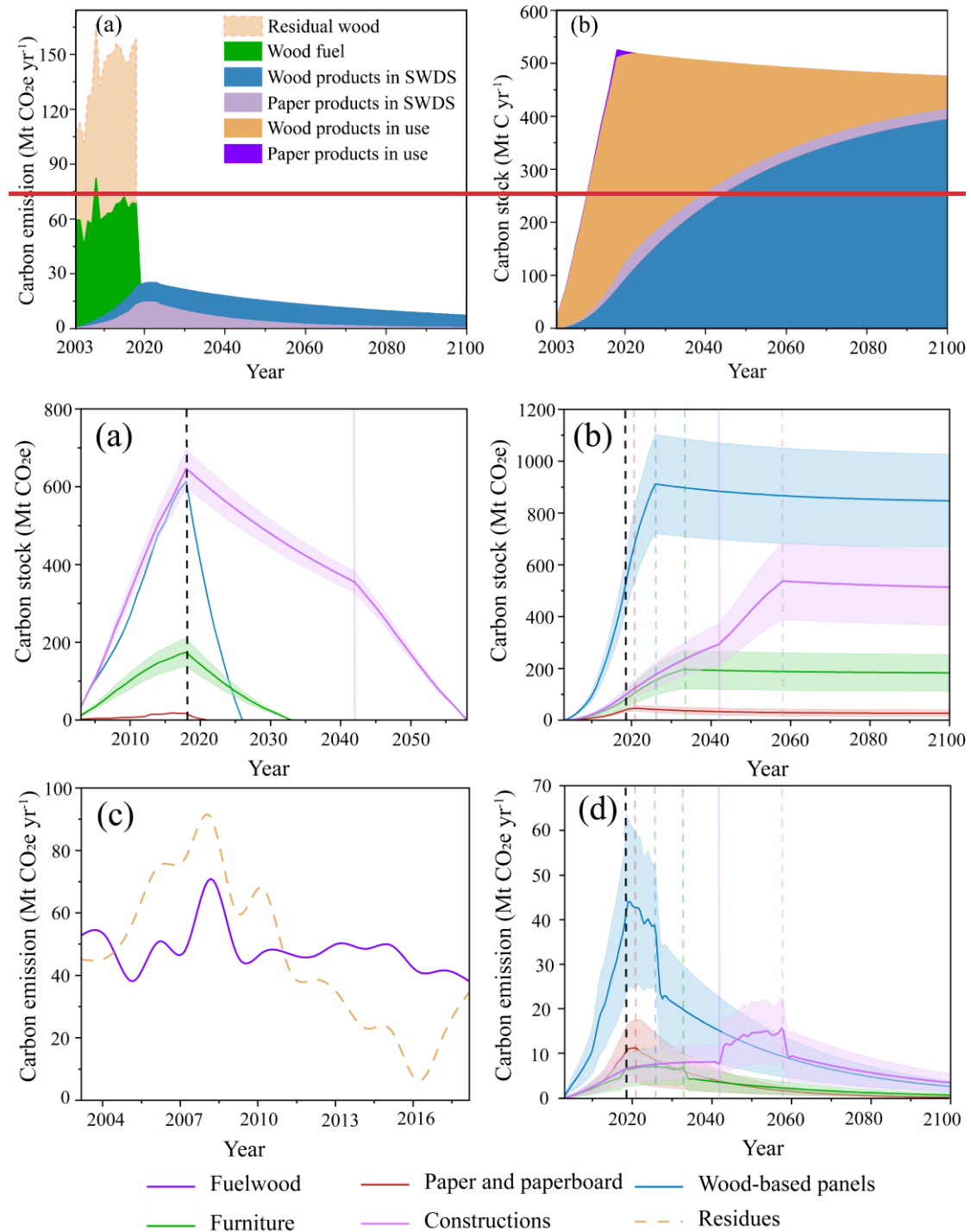
Figure ~~8~~9: The post-harvest carbon dynamics: (a) the accumulated carbon stock of HWPs in-use; (b) the accumulated carbon stock in landfill; (c) annual carbon emissions of fuelwood and residues, since the burning of residues is not a definite fact, we represented it using dashed lines; (d) annual carbon emissions in landfill. The black dashed line indicates the year of 2018, when there is no new wood inflow in the HWPs, the other dashed lines in (b) and (d) indicate the year when the corresponding products were all discarded, and the purple solid line indicates the year when the first construction wood reached its service life. Since paper and paperboard, wood-based panels, and furniture have a service life of less than 16 years, carbon stock of emissions has no sharp changes before and after the year reached service

life. The shaded area represents the variation range.Annual (a) carbon emissions (b) and stock of harvested wood in use and end use.

4. Discussion

4.1 Implications for simulating the carbon sink in China

Forest harvesting is one of the most important human activities determining the terrestrial ecosystem carbon budget (Liu et al., 2011; Pan et al., 2011). Forest harvesting largely decreases the leaf area index, increases litter biomass, and alters stand temperature and moisture, strongly impacting the structure and function of ecosystems (Nepstad et al., 1999; Liu et al., 2011; Jian et al., 2022). Harvesting causes damage to the forest canopy and soils, leading to temporary increases in litter carbon stock. It ultimately results in a net loss of soil carbon due to the damages inflicted on the forest canopy and soil. Following a disturbance, soil carbon loss can exceed carbon gain in above-ground biomass (Kowalski et al., 2004). Pennock and van Kessel (1997) found that soil carbon decreased by 5 to 20 t C ha^{-1} over a 20-year period following clear-cutting, a significant loss compared to the carbon accumulated in a maturing forest's biomass (Pennock and Van Kessel, 1997).

Forest harvesting is a type of human activity that cannot be simulated by ecosystem modeling. Therefore, the development of regional and global datasets is necessary for quantifying the impacts of forest harvesting. The LUH2 dataset is an important source of data for indicating global forest harvesting and has been widely used to simulate the impacts of forest harvesting on the terrestrial carbon sink (Harper et al., 2018; Hurtt et al., 2020; Friedlingstein et al., 2022). However, our results showed that the LUH2 dataset underestimated harvested carbon by about 38.5% on average for China, compared with the statistical data (Fig. 5, Fig. S4). The LUH2 dataset used national wood volume harvest data from the Food and Agriculture Organization (FAO, 2020), which were allocated to the pixels where tree cover lost (Hurtt et al., 2020). Across all of China, the harvested carbon data from the FAO were approximately 40% higher compared to the statistical data averaged from 2003 to 2018., caused by the different statistical methodologies and data sources used in FAO and the China's statistical data. Nevertheless, in LUH2, the wood from agricultural expansion has been subtracted, the remaining national wood was then explicitly harvested (Hurtt et al., 2020). However, according to LUH2, the cropland area has increased by 41 million hectares since 1980 in China, which significantly deviates from the actual situation (i.e., decreased by 14 million hectares) (Yu et al., 2022). Therefore, LUH2 has overestimated wood harvests

due to agricultural expansion, leading underestimated of wood from forest harvesting. And after 2000, the spatial pattern of forest harvesting was constrained using the Landsat forest loss data (i.e., TCL) (Hansen et al., 2013) by verifying if the annualized gridded forest loss derived from the Landsat data matched the forest harvesting information in the LUH2 dataset. However, the TCL dataset only indicates clear-cutting and does not include selective logging. Our result showed that there was a large proportion of selective logging (Fig. 56), indicating that the LUH2 dataset largely underestimates the harvest area.

This study not only represents the temporal and spatial patterns of harvested carbon, but also provides the allocation of harvested carbon among the pools. Unlike harvested crop carbon, which will emit into the atmosphere at a faster rate, harvested forest carbon is stored in various HWPs pools, and emits back into the atmosphere with different lifetimes (Skog, 2008; IPCC, 2019a). As an extension of forest resources, the carbon dynamics of HWPs in use and after use have multiple impacts on national greenhouse gas (GHG) inventories (Johnston and Radeloff, 2019). Clarifying the proportion of post-harvest carbon allocated to different pools is the key to accurately assessing carbon dynamics. In addition, previous studies focused more on the carbon stored in HWPs (Stockmann et al., 2012; Matsumoto et al., 2022; Wei et al., 2023). However, the assessment of the global potential of HWPs as a carbon sink is subject to the balance between carbon inflows and outflows (Johnston and Radeloff, 2019). In particular, waste products emit non-CO_2 GHG such as CH_4, contributing to climate change (Cai et al., 2018). Moreover, the carbon emissions from harvested wood exhibit delayed and long-term effects. Moreover, the carbon emissions from harvested wood exhibit delayed and long-term effects., previous Previous studies rarely provided estimates of future carbon dynamics for HWPs (Heath et al., 2010; Zhang et al., 2019; Wakelin et al., 2020). Tracking the long-term dynamics of carbon and assessing the future climate mitigation potential can provide a better foundation for GHG management in the forestry sector.

4.2 Spatio-temporal changes of harvested carbon and allocation in China

The spatial heterogeneity of forest harvesting is influenced by the distribution of forest resources in China (Fig. 34). Intensive harvesting in Southern China (e.g., Guangxi and Fujian) indicates a demand for specific tree species, such as *Eucalyptus* and *Cunninghamia lanceolata* (Yu et al., 2020). As the total harvesting increased, both clear-cutting and selective logging exhibited a general upward trend (Fig. 56), mirroring the dynamic equilibrium in the allocation of harvesting ways across China's forests. The rate of increase in clear-cutting significantly outpaced that of selective logging (Fig. 56). A growing demand

for ~~timber~~ wood is driving an upward in large-scale forest harvesting. Nevertheless, selective logging has remained the principal way of forest harvesting in China. Moreover, selective logging is a widely employed silvicultural practice that plays a central role in forest management worldwide (Liu et al., 2011). In the United States, the area covered by selective logging is approximately 61% of that occupied by

475   clear-cutting (Masek et al., 2011). In Brazil, selective logging doubles the previous estimates of the total forest degraded by human activities (Asner et al., 2005). Selective logging is a more diffuse disturbance than forest clearance (Fisher et al., 2014) and is mostly invisible to satellites (Asner et al., 2005; Matricardi et al., 2010; Hethcoat et al., 2019). Despite many efforts to address the challenge of estimating selective logging using satellite data through image classification, it is still difficult to monitor low-

480   intensity selective logging due to the coarse resolution of satellite imagery (Asner et al., 2005; Matricardi et al., 2010; Hethcoat et al., 2019). Objective spatially explicit reporting on selective logging is the basis for model-based assessment of the impact of forest harvesting on the carbon budget.

       Forest harvesting in China continued to increase during the study period. However, the wood for fuel declined by nearly 23%, especially the harvesting for burning from farmers, contributing an average

485   of nearly 70% of burned timber annually, decreased by nearly 35% (Fig. S5). This rapid decline in rural areas indicates that China is successful in the rural energy transition, benefiting the mitigation of air pollution and climate change (Chen et al., 2016; Tao et al., 2018). Production of wood and paper products in China was on the rise (Fig. ~~6~~7), constituting a carbon pool that delays carbon release (Fig. ~~8~~9). HWPs in use rarely emit carbon if there was no decay or combustion (e.g., building fire), being a stable carbon

490   sink during their lifespan, especially wood used for construction~~s~~ (Profft et al., 2009; Churkina et al., 2020). Although the CO_2 emitted in landfill~~SWDS~~ is considered carbon neutral (Van Ewijk et al., 2020), CH_4 emissions from landfill~~SWDS~~ are detrimental to climate due to their higher global warming potential (IPCC, 2023). Promoting an increase in carbon storage and a reduction of carbon emissions can be achieved by extending the lifespan and improving the recycling rate of ~~wood product~~HWPs (Brunet-

495   Navarro et al., 2017). However, this approach may not be as effective for paper products, as they often have low or even negative recycling benefits (Van Ewijk et al., 2020). Therefore, recommendations in the wood sector prioritize allocating harvested wood to long-lasting products (Fortin et al., 2012; Smyth et al., 2014) and products with high recycling rates (Brunet-Navarro et al., 2016; Werner et al., 2010). ~~Meanwhile, the increase of wood in the residue pool reflects inefficient processing and poor wood quality.~~

500   Improving the efficiency of wood harvesting and processing processes, as well as enhancing forest

ecological management, is also necessary for the reduction of carbon emissions.

4.3 Uncertainties of the LEAF dataset

Although the LEAF dataset demonstrated a good performance in capturing the spatial variability of harvested carbon in China, several potential uncertainties exist. First, currently, the use of forest wood was majorly extracted from the aboveground components. Typically, roots of logged trees will be disposed by several ways, including decay stimulation, sprout regeneration, combustion, and the production of small boards (Li et al., 2012). There are no detailed information regarding to roots due to large differences over the regions and species. Therefore, this study did not include the root biomass in the entire estimate, which may result in underestimation of HWPs and its subsequent emissions.

FirstSecond, the harvested carbon was found to be underestimated in several provinces over several years. Among the estimates covering a span of 16 years across 31 provinces, approximately 28% of them were underestimated, with the highest frequency of underestimation occurring in southern provinces (Fig. 9a10a). Compared to statistical values, the harvested carbon was underestimated by an average of 0.4-60.4% from 2003 to 2018 across these investigated provinces (Fig. 9b10b). Anhui Province had the highest degree of underestimation, with underestimation occurring in all years (Fig. 910). To avoid this underestimation, we assigned the unidentified harvested carbon to the pixels where selective logging occurred, increasing the harvested carbon of these pixels (Sect. 2.1, Eq. (6)), resulting in an estimation of more harvested carbon than the actual AGB at several pixels. We examined the number of pixels where the harvested carbon exceeded its AGB at the province level. The results showed that the number of pixels where harvested carbon exceeded its AGB was less than 2% of the number of pixels where harvesting occurred for each province annually (Fig, S6).
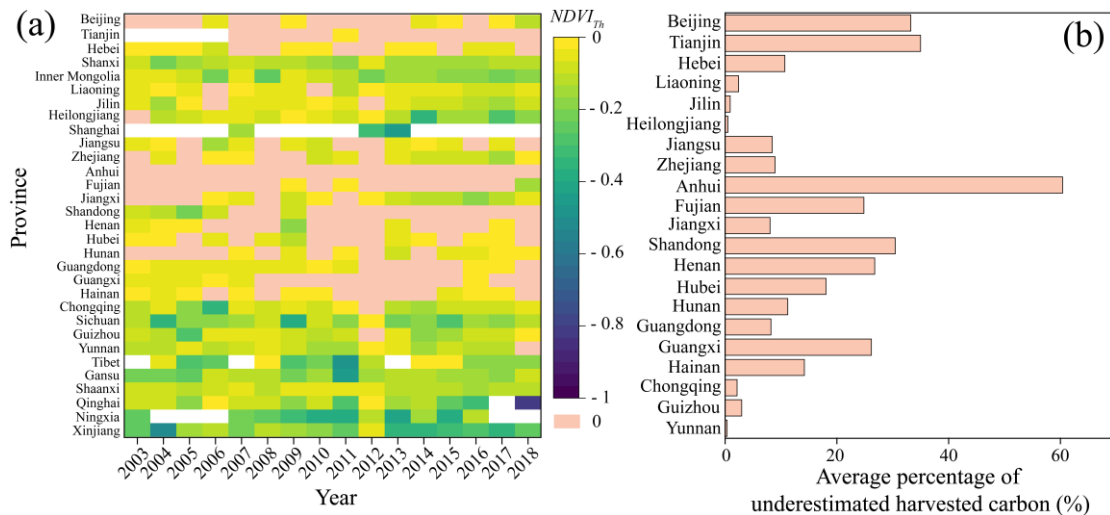
Figure 109: (a) Annual $NDVI_{diff}$ thresholds ($NDVI_{Th}$) for each province. An $NDVI_{Th}$ of 0 indicates that the province's harvested carbon was underestimated that year and a blank $NDVI_{Th}$ denotes that there was no harvesting in that province that year according to the statistics. (b) Average percentage of underestimated harvested carbon in the provinces where underestimation occurred from 2003 to 2018.

The underestimation of harvested carbon is closely related to the accuracy of identifying both selective logging and clear-cutting. AGB is an important potential cause. After forest harvesting, trees regeneration would form new biomass. This study used the national forest inventory datasets to estimate AGB, which were conducted at a five-year interval. With this five-year period, the forest inventory can't include the increased biomass due to trees regeneration, which will lead to an underestimation of AGB. The conversion of biomass storage to AGB (*Coef*) exhibited significant variations among provinces, possibly due to different dominant vegetation types and growing stock levels across provinces. The default biomass conversion and expansion factors (BCEF, equivalent to *Coef* in this study) provided by IPCC also confirmed the significant differences in *Coef* across vegetation types and growing stock levels (IPCC, 2006b). However, compared to IPCC's coarse regional classification, the provincial-level *Coef* we utilized in this study is more detailed. The quality of selective logging identification largely depends on the quality and performance of NDVI. The accuracy is largely impacted by low data quality in cloudy and rainy southern areas. In addition, NDVI is sensitive to green vegetation cover but not dense vegetation (Huete et al., 2002), and begins to saturate over dense vegetation with AGB values higher than 25 t C ha⁻¹ (Chang et al., 2023), contributing to the underestimation of AGB. Overlooking the continued growth ~~of uncut vegetation~~after harvesting within a pixel and the regional-scale climate impacts led to an underestimation of $NDVI_{diff}$. Consequently, the harvested carbon may be underestimated at regional scales, particularly in provinces with substantial forest coverage (e.g., Guangxi). The estimation of clear-

cutting was primarily limited by the performance of the TCL dataset generated by Hansen et al. (2013).

In subtropical and temperate regions, the producer's accuracy and user's accuracy of TCL are both

approximately 80%, indicating that the dataset can identify tree cover loss with relatively high accuracy.

However, there is still a 20% level of uncertainty (Hansen et al., 2013), and further efforts are needed to

550 improve the identification of clear-cutting.

~~Second, the lack of specific information concerning the destiny, utilization, and longevity of~~
~~harvested wood introduced several uncertainties in the allocation and carbon dynamics estimation of~~
~~harvested carbon. It is virtually impossible to trace the trade patterns and lifetimes of wood after it has~~
~~been harvested and sold (Profft et al., 2009).~~ Third, we compared our estimates of carbon stocks of HWPs

555 with previous studies. Zhang et al. (2019) estimated the carbon stock of HWPs to be 1.7 Gt CO2e for the

period of 2003-2016, which is 1.3 times higher than our estimates for the same period (Fig. 8b). Zhang

et al. (2019) used statistical data of HWPs provided by FAO, which has a significant disparity to China's

official figures (Fig. 6). Zhang et al. (2018) estimated carbon stocks of HWPs from 1950 to 2015 using

China's official data, but which also included the imported HWPs. As the China's wood imports are

560 considerable, the estimates of Zhang et al. (2018) for 2003-2015 is nearly 1.8 times of our estimates. This

study aims to quantity the contribution of harvested wood to national CO_2 emission in China; therefore,

we excluded the imported wood according to the IPCC standard. Moreover, these previous estimates

depended on default factors recommend by IPCC inventory method to calculate CO_2 emission and stock

in HWPs, and which showed large differences with specific factors in China used by this study. In

565 addition, this study also provides estimates of stock and CO2 emission dynamics, which is quite

important for understanding its long-term contributions. Nevertheless, ~~Information~~ information on the

end products of harvested wood (i.e., bathroom tissue, tableware, types of furniture, columns, etc.) is

unavailable (Profft et al., 2009), leading to rough estimates of wood destination and product

~~lifetimes~~service life. In this study, all residual wood was assumed to be burned as fuelwood~~wood fuel~~

570 would induce an overestimation of carbon emissions. Meanwhile, this study ignored recycled wood

products, which may extend the carbon storage in products (Brunet-Navarro et al., 2017), causing an

underestimation of carbon stock in products in use. More efforts are needed to track the production and

end use of the harvested wood, as they play a key role in the estimation of the effects on national GHG

inventories (White et al., 2005; Johnston and Radeloff, 2019). ~~Additionally, the decomposition of organic~~

575 ~~matter in SWDS is closely related to the management system and environmental conditions (Ximenes et~~

5. Data availability

580   The 30 m × 30 m Long-term harvEst and Allocation of Forest Biomass (LEAF) dataset is available at https://doi.org/10.6084/m9.figshare.23641164.v2.(Wang et al., 2023).

The file format of the product is GeoTIFF with the spatial reference of WGS84 (EPSG:4326). Each GeoTIFF file represents annual harvested forest carbon (unit: $g\,C\,m^{-2}yr^{-1}$), the absolute harvested carbon per pixel is obtained by multiplying by the corresponding pixel area.

585   **6. Conclusion**

This study produced a Long-term harvEst and Allocation of Forest Biomass (LEAF) dataset, which provides spatial information on forest harvesting at a resolution of 30 m. The validation results demonstrated the accuracy and reliability of the LEAF dataset in capturing the spatial variation of harvested carbon. From 2003 to 2018, harvested carbon showed an increased trend. Additionally, our

590   dataset showed that selective logging resulted in more than 80% of the total harvested carbon. The carbon taken away from forest harvesting was allocated to four wood pools, with the direct combustion of fuelwood~~wood fuel~~ as the primary source of carbon emissions after harvesting. However, it is important to highlight that the carbon stored in wood products has the potential for long-term retention. In summary, the development of the LEAF dataset enhances our understanding of the spatial patterns of forest

595   harvesting and post-harvest carbon dynamics in China. The LEAF dataset generated by this study is an important data source for estimating the carbon budget of forest ecosystems in China, which can also provide essential insights for sustainable forest management and climate change mitigation efforts.

Author contributions

WY and DW designed the research, performed the analysis, and wrote the paper; PR, and XX

600   performed the analysis; ~~NF~~LF, ZQ, and XC edited and revised the manuscript.

Competing interests

The authors declare that they have no conflict of interests.

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