The return of China’s forests: Three decades of forest transition revealed by satellites

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Abstract

A large-scale greening and forest expansion has been observed in China over the past decades, which has accelerated since around 2010. This has been inferred by the use of satellite data, however with too coarse spatial resolution to reveal spatial details about China's forest transition. By using three decades of dense satellite observations at a 30-m spatial resolution, we reveal here the complex spatio-temporal patterns of individual forest stands forming the forest return history of southern China. We calculate forest age, forest densification rates, and annual landscape fragmentation, and show that the observed forest area surge around 2010 is a result of trees planted after 2000 that formed dense forests about a decade later. We document that old forests in the 1980s were mostly fragmented into scattered patches located on mountain tops, but forests rapidly expanded downhill by 729,540 km² from 1986–2018, connecting forest patches and creating buffer zones that alleviated the clear-cut and logging pressure from old forests. This process decreased forest fragmentation and sextupled core forest areas. Our study contests several widely accepted assumptions that negatively relate humans actions with forest dynamics, and provides a detailed documentation of forest densification and expansion for a country that had been largely deforested three decades ago.

Introduction

Three decades ago, Southern China was almost entirely deforested (1), but the region now hosts one of the largest tropical and subtropical forest fraction in the world (2). This implies that only fractions of primary forest are left, and that the vast majority of current forest areas are secondary forests, most of them being planted. A similar forest transition, from deforestation to reforestation, was observed in Europe and USA already in the 19th and 20th centuries (3–5), and has recently been documented for Vietnam and China starting in the 1980s (2, 6, 7). What makes the transition starting in the 80’s particularly interesting from a monitoring perspective is that the entire period has been recorded by satellites, starting with deforested landscapes in the early 1980s until today with large parts of the region covered by dense forests. Forestation measures in China intensified after the year 2000, with several large-scale tree plantation programs being initialized (8–9), either as monoculture plantations or as semi-natural forests with a more heterogenous species composition. Several studies have reported a dramatic increase in greenness in the recent decade, which has often been interpreted as either climate driven or intensified plantation efforts (10), both in area and density. However, the spatial resolution of the imagery used in these studies was too coarse to attribute the greening to either densification of existing forests or forest expansion. Therefore, it remains largely unclear if increased plantation activities alone could have caused this phenomenon (11), when new forest stands were added to the landscape, and whether these new forests are fragmented patches or form larger forest stands.

Satellite instruments, providing coarse spatial resolution satellite images since the early 1980s, have documented the extensive greening of the region, characterizing the transition of a landscape dominated by grass- and croplands into tree cover (2, 10). This transition happened progressively over the past decades, supposedly by successively creating fractions of forests, however impossible to identify from
the use of coarse resolution satellite data. While upscaling from field plots and stand growth modeling provide an overall indication of forest ages for a region as a whole (12–13), this kind of information is often not sufficiently detailed to pinpoint spatial nuances and differences in forestation. It does also not support an in-depth understanding of the history and future potential of forest expansion and densification for areas dominated by mosaics of planted forests. This is because a majority of the tree planting activities in China have been conducted by individual farmers who have replaced their croplands with forests, and this forest patchwork is then managed at the level of individual fields (14). This landscape heterogeneity is intensified by large differences in elevation and slope within small areas, which is typical for karst areas dominating Southern China (9).

Over the past decade, forest stands began converging into larger areas of closed canopies (8), but the age structure of the forests remains undocumented because the areas appear as homogeneous forests seen from space. Consequently, information on forest growth, coverage, age, and growth saturation are mostly based on models, coarse spatial resolution satellite data sources, or upscaled from field plots, which includes considerable uncertainty (12, 15). This is problematic, because information on forest age, growth rate, and whether a given forest is a monocultural plantation or a semi-natural forest with heterogenous species composition, are crucial information for estimates of the potential biodiversity and ecosystem services of the forests, including time-averaged carbon stocks and carbon sequestration potentials (16). This challenge is not only the case for southern China, but applies to all areas of heterogeneous landscapes and where forest management such as tree plantations, shifting cultivation, forestry, and restoration happens at small scale. Hence, large regions where forests are locally managed are labeled as forestation areas and merged into broad forest age groups, often neglecting the complexity of very heterogeneous forest structures, amplified by regular harvest and replanting.

To give clear and reliable accounts on forest expansion, densification, age, and consequently on carbon stocks and sequestration potentials in managed forest areas, more detailed monitoring techniques are needed. Medium resolution images (30 m) are available over several decades via the Landsat program, but the temporal depth of these data has rarely been applied to estimate the age of individual forest stands in highly heterogeneous plantation landscapes (17), and plantations characterized by successive planting and harvesting are generally challenging to map (18, 19). This study attempts to overcome this by making use of the long time series of Landsat images to quantify forest area, age, and fragmentation changes in southern China between 1986 and 2018 at 30-m spatial resolution to resolve the complex spatio-temporal patterns of forestation in southern China. We train a machine-learning model and create annual forest probability (fp) maps as a proxy for forest density (8). These maps are used to analyze the age of forests, their growth rate (densification), as well as the annual degree of forest fragmentation, defined here as the relationship between core and non-core forests (20). Generally, emerging forests are detectable at forest probabilities above around 20%. An area is considered as dense forest if the predicted probability surpasses and remains above a certain threshold (50%) until 2018 (Fig. 1a). This generally excludes short-rotation plantations, but includes plantations and forestry where tree stands are allowed to age and create dense canopy covers. We define forest age as the number of years a forest has been in a dense state, and the growth or densification rate is calculated as the mean annual change in forest
probability between early stage forests (fp = 20%) until the forest is dense (fp = 50) (Fig. 1a). Thus, age refers to the number of years a forest has been in a dense state (fp > = 50%). Using these data, we reconstructed the forestation history of southern China (Fig. 1b), offering another level of details in our understanding of the underlying mechanisms of the recent pronounced increase in greening and how this relates to forest expansion and densification.

Results

Forests expansion in Southern China

We observe a continued strong forest expansion (dense forest area) during 1986–2018, with two pronounced peaks in the mid-1990s and around 2010 (Fig. 2a). A gain in forest is here reported when a 30x30 m area exceeds the dense forest stage. We find that the forest extent increased from 249,414 km\(^2\) in 1986 to 491,496 km\(^2\) in 2003 and 978,954 km\(^2\) in 2018, which means the area fraction of Southern China covered by forest increased from 9–35%. We did not observe large contractions or losses of forests, defined as areas where the forest probability falls below 50%. However, the first large forest expansion in the mid-1990s was followed by minor (dense) forest contractions. A similar contraction after the second forest expansion period around 2010 has not yet been observed (Fig. 2a).

Only Minor Forest Areas Are Older Than The Satellite Records

We then studied the age of the dense forests by counting how many years each forest has been in a dense state (fp > = 50%) until 2018. We found that only 225,890 km\(^2\) (23%) of the current forest area contains forests older than our 33-year time series, that were present in 1986 and have not been cut until 2018. Only 10,326 km\(^2\) of these ‘old’ forests (fp > = 50% in 1986) have been lost over the past three decades. A total of 32% of the current forests have reached their dense forest stage during the past 10 years (Fig. 2b). A closer look at the age distribution shows a clear spatial diffusion process where new dense forests often expand from remnants of older forests that existed in 1986 (Fig. 2f).

Accelerated Densification Rate Of Recent Forests

For all dense forests, we calculated how fast they reached their dense state. This period is the number of years it takes for a forest to go from fp = 20% to fp = 50%, and the densification rate is the mean annual probability increment with the unit probability % per year. We did not calculate the continued densification rate for dense forests (fp > 50%). The densification rates of different forest age groups (years after reaching a dense state) (Fig. 2c) can be grouped in two different classes: forests that reached a dense state more than 10–11 years ago have a homogeneously slow densification rate, and forests that reached the dense state in the past decade have an almost doubled densification rate, that means they reach the dense state much faster.
The densification rate and period depend on management-related factors including species selection and planting densities, but also on growing conditions, such as soil and climate. We assume that management and climate vary over space and time, while site conditions are static. In the following, we investigate which of these conditions could have caused the high densification rates of recent dense forests.

Climate conditions, reflected here by rainfall and temperature (21), started being more favorable around 2010–2013, which could contribute to the shorter densification period of recent forests (Fig. 3a and 2c). We further investigated the elevation reflecting site conditions for different forest age groups (Fig. 3b). We find that there is a clear pattern showing that forests that reached the dense state more than 10–15 years ago were located at higher elevation areas, indicating a progressive forest expansion from mountains into valleys, where we find today the younger dense forests (Fig. 5). Although growing conditions in lower elevation areas may be more favorable, our results demonstrate comparable densification rates of recent forests between mountain (Fig. 4a) and valley areas (Fig. 4b).

Our data show that forests that reached the dense stage during the past 10 years are likely the result from plantation programs starting around 2000. When entering a dense stage, they become clearly visible in satellite images and then their densification rate can be tracked back in time. Although forest expansion rates have recently declined just as swiftly as they increased around 15 years ago (Fig. 2a), younger dense forests reached their dense state almost twice as fast as older dense forests did (Fig. 2c), independent of terrain (Fig. 4a,b), signifying that forests planted after 2000 have a different species composition as previous forests. This is supported by Fig. 4c, showing that the densification rates of forests that reached a dense state more than 11 years ago were relatively normally distributed across the populations, while there was a clear shift towards fast growing forests for forests that reached a dense state less than 10 years ago (left skewed distribution), irrespective of elevation (Fig. 4ab). High densification rates typically suggest fast growing plantations, which often have a low diversity.

**Continued Growth Of Dense Forests**

We visually studied the continued probability increment of forests after they reached a dense state, that is after the fp exceeded 50% (Fig. 3c). Here we find that even earlier formed forests (> 33 years) progressively increased in density over the full period. We also find that the increasing forest probability values converge across dense forest age groups towards the end of the time series, and almost approaches forest probabilities of dense forests that formed more than 33 years ago. This implies that the continued probability increment of forests that reached a dense state in recent years is faster than it was the case for forests that reached a dense state in earlier years, and the same is observed for the densification rate. The increased probability increment during 1995 and 2005 may be due to favorable climate conditions (Fig. 3a).

This pattern is also reflected in the biomass accumulation of forests, which was obtained by using the ESA CCI Globbiomass dataset (22). The data show that biomass density increases with forest age (years
after reaching a dense state) up to about 15 years back from 2018 (Fig. 6a). The older dense forests (16–32 years by 2018) have similar levels of biomass and only forests that formed before our time series (33+ years), which includes old forests, had notably higher values. The similar levels of biomass are supported by the forest probability (Fig. 6b), which shows that all forests from 1987–2008 reach similar forest probability levels towards 2018.

Reversed Fragmentation

Next, we go beyond analyzing the forest transition and study the spatial distribution of forest expansion and how it contributes to large coherent forest areas and increased landscape connectivity. Forest fragmentation is typically seen as ecosystem degradation process (23, 24), but the reverse case, increased landscape connectivity via restoration, has rarely been shown. Here, we study the connectivity of the forest patches by dividing them into core and non-core forests (only dense forests). Core-forests is defined as minimum 9 dense forest grids in a 3 by 3 square at a 30 m resolution, implying a minimum size of 9 ha for a core forest. Non-core forests are edges of core forests, as well as island forests (isolated 30x30 m grids) in a non-forest matrix. Individual plantations are typically first seen as islands of non-core forest, which, if not regularly harvested and more trees are planted at the edges of the plantation areas, progressively expand into larger core-forest areas.

Our data show that forests in 1986 were mostly scattered patches; core forests covered 93,197 km$^2$ but 63% of the forests were non-core forests (Fig. 6c). Out of these non-core forests, 36,003 km$^2$ were unconnected islands (30x30 m), the other non-core forests were bridges and edges. Connected core forests started increasing in the mid-1990s, but increased massively in the past decade (much more than non-core forests) with a total increase of 517% (482,092 km$^2$). These numbers imply that 84% of the core forests in 2018 are new (i.e. less than three decades). Interestingly, forests which were younger than 10 years in 2018 are rarely core forests (Fig. 6d). In 2018, 403,664 km$^2$ (41% of the forests) are non-core forests, which are forests with reduced ecological importance. These may be recently converted farmlands, or the result of patch-wise forest harvest activities through selective logging or small-scale forestry, but also edges of core forests contribute to this class. Figure 7 illustrates the distribution of existing and new core forests as well as non-core forests for southern China, and a close-up example illustrating the progressive forestation of an area between 1986–2018.

Discussion

This study has developed a dataset and method for tracking individual forests at annual scale, which allows us to study the forestation history of southern China. The difference to previous maps is that we provide forest age at a high spatial resolution (12, 13, 25), which better captures the patchwork from different forest planting programs and individual farmer’s land management decisions in the complex karst landscapes. We track the evolution of dense forest areas over time and document how they have quadrupled over three decades, confirming the massive forest expansion found in previous studies (8, 15,
Here we go beyond the reporting of forest area (27) and show that also core forests have sextupled over recent decades.

We found two distinctive waves of dense forest cover increase: one in the 1990s, likely the result from the earlier “greening the barren mountain” program aiming to recover forest mountain tops. Interestingly, this wave of increase was followed by a wave of forest loss. The second wave of forest cover increase manifested as dense forest around 2010, being the driver of the pronounced increase in greening observed in other studies (8, 10, 11). This second wave is the result of forest expansions resulting from plantation activities starting around 2000, which reached a dense state around 2010. The densification rate of the second wave, that is the growing speed before a forest reaches a dense state, is a magnitude higher than densification rates of the first wave, and it is relatively homogeneous over the years. These insights contradict previous assumptions that the greening starting around 2010 is attributable to intensified forestation measures or changed policies that took place around 2010 (7, 10), but is the result of previous forest expansion measures which become visible from satellite imagery approximately a decade after plantation. The question if forest expansion or densification caused the pronounced greening after 2010 cannot be answered with one or the other. The forests have been planted, and thus expanded in the early 2000s, after which they densified over approximately one decade, becoming visible in satellite observations once reaching a dense state. After becoming visible, it was then possible to track back the temporal evolution of the forests, here termed densification rate of emerging forests. Moreover, after a longer dry period in the 2000s, climate conditions were more favorable over the past decade, likely contributing to the increased densification rate.

Our study shakes several widely accepted assumptions represented by an expectation of a uni-directional interaction between humans and forest resources. First, previous studies have shown that human influence have increasingly caused a removal of forests, leaving forests to steep terrain and mountain tops in large parts of the world (28, 29); here the opposite is observed to be the case with forests expanding progressively down the mountains into valleys and flat areas. Second, it has also been shown that small forest areas and remnants of old forests are increasingly lost (30); here we show that new forests expand around ‘old’ forests (here defined as dense forests that formed before 1986) and only small areas of ‘old’ forests are lost over three decades. On the contrary, we observe increased densification of ‘old’ forests, likely because new forests serve as buffer zones around ‘old’ forests serving as a primary source for logging, thereby alleviating the pressure from woody resource exploitation in ‘old’ forests. Moreover, with millions of people migration from the rural areas into cities, the human pressure is strongly declining (10). Third, several studies find globally increasing forest fragmentation (23, 24), destroying habitats and biodiversity; here, the opposite is the case, and we show that forest expansion connects previously disconnected patches leading to a massive increase in core forests.

Nevertheless, China’s ‘new’ forests are the result of human management, and the homogeneous growing speed is an indication for a low woody plant diversity. For being a stable carbon sink, biodiversity should be kept high and harvest low (31). Also the forest transition in Europe generated a forest landscape with a relatively low diversity, which becomes problematic in times of climate change (32, 33), where droughts
and insects threaten forest stands. The coming years will show how sustainable, resistant and resilient China’s new forests are.

**Methods**

**Concept**

This study aims at creating temporally stable long time series of forest dynamics in China using the entire Landsat archive. We use a Random Forest regression model with two classes, validated with field plots and sub-meter GF-2 satellite data to estimate the “forest probability” (fp): a high probability implies the area comes close to the training data of the dense forest class, a low probability implies it comes close to the training data of the non-forest class. If an area crosses an uniform probability threshold (fp 50%), it can be considered as forest (termed here “dense state”), if it remains above this threshold until 2018, the number of years after crossing the threshold until 2018 are the forest age; the speed in probability increase per year before crossing the threshold is the densification rate (Fig. 1).

**Landsat data**

We make use of the entire Landsat 5/7/8 archive available in Google Earth Engine ranging from 1986 to 2020, which provides atmospherically corrected surface reflectance images. For each image, we used the quality assurance band to identify and remove the bad-quality observations caused by clouds and snow/ice. Previous studies have shown that the temporal depth of the archive is sufficient for time series analyses over this period (34), but southern China is a very cloudy region, and we had to form annual median images and in addition use a 3-year moving median to reduce noise (8), which shortened the study period to 1986–2018. In addition to the 6 bands, we calculated two widely used vegetation indices (NDVI and NBR) for each year. The annual composites were then downloaded.

**Modeling forest probability**

A total of 15,991 training pixels (30 x 30 m) were selected in dense forests and 158,728 pixels in non-forest areas across southern China. To identify dense forests, we made use of national forest inventory data from 2014–2018, 10,000 + high resolution satellite images from GF-1 (2 m resolution) and GF-2 (80 cm resolution) images, and the time slide function Google Earth to ensure that forests in the training samples existed as dense forest over the full period. Training samples were distributed over the full time range of Landsat images, making sure that the model performs robustly over the different Landsat sensors. We then trained a Random Forest model using all Landsat bands, NDVI and NBR, and an SRTM elevation model to predict the probability for each 30 x 30 m pixel if it belongs to the forest class (fp = 100%) or the non-forest class (fp = 0%). The accuracy on the validation set (25% of the data not used for training) was 98% (Kappa 93%); the true positive rate was 90.4%, the true negative rate 8.6%; the false negative rate 0.6% and the false positive rate 0.4%. The model was applied on each year predicting the forest probability for each 30 x 30 m pixel. Previous work has shown that this forest probability is highly correlated with tree cover, and annual probability maps can be used to track the densification of forests.
over time (8). The forest probability ranges from 0 to 100%, and we defined that a pixel with a probability larger or equal to 50% can be considered as “dense forest”, following Tong et al., 2020. Pixels with a forest probability between 20 and 50% were considered as emerging forest, and their increase in probability per year was defined as densification rate in % yr\(^{-1}\).

**Deriving Forest Age And Densification Rate**

Our method is very sensitive to noise and disturbances, for example, the densification rate calculation requires a continuous increase without drop, and the forest age calculation requires the probability to remain above 50% for all years after the threshold has been reached. It was thus necessary to remove short term drops resulting from noise, data quality and small disturbances from the time series, but keep large disturbances, such as harvest that have a footprint of several years. We thus applied a polynomial fitting to the forest probability time series, in addition to the annual median and 3-year moving median that was applied on the raw Landsat time series.

After a pixel has crossed the 50% forest probability threshold and it is classified as forest, it must remain above this threshold. We then count the number of years after it crossed the 50% forest probability threshold until 2018, which we define as forest age. We estimate the “plantation year” as the year when a pixel crosses 20% forest probability, and remains above this threshold, continuously increasing up to 50%. Note that the term “plantation year” may be misleading, as it can also imply that a forest recovers from a natural or anthropogenic disturbance, such as drought or harvest, and the crossing of a forest probability threshold implies that certain tree structures are visible, which is not the case directly after a plantation. The speed an emerging forest grows between the 20 and 50% thresholds is the densification rate, the unit is the probability change per year.

Our definition of forest age is derived from the year a forest stand reaches a dense stage. A forest that meets our definition has on average already accumulated around 60(± 37) Mg biomass per hectare (Fig. 6a), according to biomass map from ref 25. This does not exclude that the real plantation year is earlier. In other words, a forest with an age of 5 years in 2018 could have been planted 20 years ago but only reached a dense state 5 years prior to 2018 due to unfavorable growing conditions. Although we do estimate the “plantation year” using a low threshold value, the confidence in the date when reaching a dense state is much higher, as lower probability values may be noisy and clear dates are difficult to determine. These definitions imply that areas we map as forest are closed canopy forests, and newly planted or recently harvested forests are mostly not included. Forest plantations which are regularly harvested, such as Eucalyptus and rubber, are typically not included, as they do not reach or maintain high probability values. While this approach has a high reliability on the mapped forests, it may underestimates the actual extend by excluding young forests.

**Forest Fragmentation**
We used MSPA, a morphological segmentation approach, on the binary annual forest/no-forest maps (20). The method segments forest pixels into two major classes: core forest and non-core forest. Core forests require to be surrounded by at least 30 m of forests from all sides, the remaining pixels are non-core forests. These non-core forests can be divided in many subclasses, such as island, bridge, edge (20). The ecological meaning of both classes varies with a large range of interpretations. The method has been successfully applied to study forestation programs in China, however at a 250 m resolution (38).

Declarations

Data availability

The data produced in this study will be made available upon acceptance of the manuscript.

Code availability

The codes for this study will be made available upon acceptance of the manuscript.

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Competing interests: The authors declare no competing interests.

References


Figures
**Figure 1**

**Schematic overview of definitions and study area.** *a,* The figure exemplifies our definitions of forest, non-forest, forest age and densification rate. Forest probability is the output from a Random Forest model and shows how likely an area resembles a dense forest. We set a threshold of 50% to define an area as dense forest, and the number of years from the year the threshold is crossed until 2018 as the forest age. Note that the area must remain above 50% until 2018 to qualify as forest. The years before the threshold is crossed are used to calculate the densification rate. It is defined as the mean probability change per year in the period where an area is between a probability of 20% and 50%. If the area falls below 20% the count is reset. *b,* The study area covers the southern provinces in China.
Figure 2

Forest gain, loss, age, and densification rate over 1986-2018. 

**Figure 2**

**Forest gain, loss, age, and densification rate over 1986-2018.**

- **a.** Dense forest expansion and contraction per year. 
- **b.** Forest age*, reflecting the number of years after a forest area reaches a dense state. 
- **c.** Mean densification rates** (the unit is probability in % per year) of different forest age* groups. 
- **d.** The forest age* of the entire region in 2018. 
- **e.** Same for densification rate*. 
- **f-g.** Close-ups on forest age* in 2018 and densification rate* for a selected area. 

* = years after reaching a dense state  
** = before reaching a dense state
Figure 3

Growing conditions and densification of forests. a, The PDSI (Palmer drought severity index) uses rainfall and temperature data to estimate positive and negative climate conditions. b, The distribution of forest age* from 2018 is shown along the elevation gradient (SRTM; 90 m). The color shadings reflect the 5, 10, 25, 75, 90, 95th percentiles, the line is the median. c, Continued annual probability of dense forests that have surpassed the 50% probability threshold is shown for different age classes. The age class are derived from the year a line crossed a probability of 50%, which is here the starting year. The upper line starting at around 70% fp are all forests older than 1986. * = years after reaching a dense state.

Figure 4

Densification rate**, forest age* and elevation. a, Number of Landsat grids (30x30 m) having a certain densification rate** (rounded to full numbers) for forests with an age* of 1-10 years growing above 500 m elevation. b, Same but for forests below 500 m elevation. c, Distribution of densification rates** for forests with an age* of at least 11 years. * = years after reaching a dense state. ** = before reaching a dense state.
Figure 5

Examples of forest age and densification rate. a, This example shows that only dense forest remnants on mountain tops were left in 1986 (forest age 33+ years), and forests progressively expanded down the hills. b, Similar as (a), but here the areas closer to the settlement are still deforested in 2018. c, A previously entirely deforested area has partly been forested mostly with species having a very high densification rate. Slower growing species have been planted in the western part of the image. Maps
Figure 6

Biomass and forest fragmentation related to forest age*. **B**iomass from ESA CCI Globbiomass and associated standard deviations for different forest age* groups from 2019. **a,** Average forest probability for different forest ages from 2019. **c,** Forests split in core (grey) and non-core forests (black) and the annual distribution of both classes. **d,** The ratio between core and non-core forests for different forest ages*. * = years after reaching a dense state.
Figure 7

**Forest fragmentation from 1986-2018.** The map shows the distribution of new and existing core forests, as well as non-core forests. The close up figures show how core and non-core forests changed for an example area for three selected years. A core forest is defined as an area that is surrounded by at least 30 m of forest (19).