Large-scale forest conservation and restoration programs significantly contributed to land surface greening in China

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Abstract

China has implemented a portfolio of large-scale forest conservation and restoration programs (FCRPs) to advance the sustainable management of forests. However, the contributions of these programs to forest recovery and land surface greening were generally evaluated on a local scale, which hindered the systematic planning of FCRPs. In this study, we analyzed the spatiotemporal patterns of tree cover (TC) change before and after the intensification of FCRPs using the Mann-Kendall test and the Theil–Sen slope estimator. With the improved phenology-based residual trend analysis (P-RESTREND) method, we derived the spatiotemporal patterns of human-induced tree cover (TC_H) change on the national scale. Then, we calculated the effectiveness index of FCRPs at the provincial level, based on which the effectiveness levels for the 31 provinces of mainland China were classified. Our study showed that the area of forested lands with a significant greening trend was almost five times larger in the post-intensification phase (1999–2015) than in the pre-intensification phase of FCRPs (1982–1998). More than 29.9% of the forested lands were significantly improved in TC by human activities in the post-intensification phase. Provinces with high effectiveness levels were generally distributed in humid areas, whereas the majority of provinces with low and moderately low effectiveness levels were spread in arid and semi-arid regions. We concluded that the implementation of FCRPs had contributed greatly to the land surface greening in China. Moreover, the effectiveness of FCRPs in forest recovery was heterogeneous at the provincial level and was driven by multiple natural and socioeconomic factors.

1. Introduction

Forests cover 31% of the world’s total land, but deforestation and forest degradation are occurring at alarming rates (FAO, & UNEP 2020). In response, many global initiatives have been launched to conserve and restore forests, such as the New York Declaration on Forests and the Bonn Challenge. Several large-scale forest conservation and restoration programs (FCRPs) have also been implemented over recent decades to protect existing forests and reverse forest degradation in China (Zhao et al 2020). The performance of these FCRPs is closely related to China’s progress towards achieving the Sustainable Development Goals (SDGs) and attaining an ecological civilization (Wu et al 2019a).

The FCRPs are generally nationwide sustainability initiatives with an extensive coverage (Lù et al 2015). However, the evaluations of their effectiveness were separately conducted in typical areas (Tong et al 2018, Niu et al 2019, Kong et al 2020, Wang et al 2020). In most cases, these regional studies revealed that the FCRPs were effective in increasing forest cover and contributed greatly to a greener China (Tong et al 2018, Niu et al 2019). On the other hand, afforestation in arid and semi-arid areas was often condemned for
a low survival rate of seedlings and severe damage to native vegetation (Cao 2011). Due to the inconsistent study periods and incompatible evaluation methods, policymakers were not well informed of the outcomes of these FCRPs at the national level, and thus found it difficult to identify the priority areas for forest protection and restoration (Gutiérrez Rodríguez et al 2016, Viña et al 2016).

The performance of FCRPs can be assessed in a variety of ways, among which the residual trend analysis (RESTREND) based on satellite data has been favored by many studies for its robustness and applicability to large-scale evaluations (Evans and Geerken 2004). Since vegetation is affected by both human activities and climate, the key step of RESTREND is to build a vegetation-climate model of the growing season for estimating the climatic component of vegetation. However, the growing seasons were generally determined based on a priori knowledge, which ignored their spatiotemporal variations and introduced various uncertainties (Chen et al 2018). Moreover, without validation by statistical or in situ data of FCRPs, most evaluations arbitrarily equated human-induced vegetation changes derived from RESTREND with their impacts on forest recovery. Therefore, the performance of FCRPs in forest recovery has not been well-informed at the national level.

In this study, based on long-term tree cover (TC) time series, we aimed to address two questions: What are the spatiotemporal patterns of forest recovery in China before and after the intensification of FCRPs? How effective are FCRPs in contributing to land surface greening at the provincial level? This national-scale assessment of FCRPs would unveil China’s progress towards sustainable forest management and commitment to achieving the forest targets of SDGs (Zhang et al 2021). It would also facilitate the systematic restoration planning and identification of priority areas for FCRPs in the future (Ding and Yao 2021).

2. Data and methods

2.1. Remote sensing data

The remote sensing products used in this study include TC time series, NDVI time series and land cover data. The yearly TC maps from 1982 to 2015 were derived from MEaSUREs vegetation continuous fields product (VCF5KYR) with a spatial resolution of 5600 m (Song et al 2018). The TC for each year was mapped at the time of local peak growing season (POS), representing the percent of pixels covered by the vertical projection of tree crowns and ranging from 0 to 100%. Since the VCF5KYR data for the years 1994 and 2000 were not produced, we linearly interpolated these missing TC layers with the antecedent and subsequent annual TC maps on a per pixel basis (Ma et al 2015). Pixels with average TC values above zero during the 34 years were flagged as forested lands, whereas pixels with average TC values of zero were considered treeless areas. The GIMMS NDV1g time series 1982–2015, at approximately 8 km spatial and biweekly temporal resolution, were used to extract phenological metrics of vegetation growing season at the pixel level (Pinzon and Tucker 2014). Pixels with annual mean NDVI values below 0.1 were interpreted as nonvegetated areas and were excluded in phenology retrieval (Wang et al 2019). The annual land cover maps from 1992 to 2015, generated by the European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover (LC) project at 300 m spatial resolution, were downloaded from the CCI-LC database (http://maps.elie.ucl.ac.be/CCI/viewer/index.html). The evergreen forest classes for each year were extracted from the land cover maps.

2.2. Climate data

The monthly mean temperature and monthly total precipitation data for China from 1982 to 2015 were obtained from Peng et al (2019). The climate dataset, with a spatial resolution of approximately 1 km, was generated using the delta spatial downscaling procedure and was validated by observations from 496 national weather stations across China. The monthly solar radiation data from 1982 to 2015, at a ∼4 km spatial resolution, were attained from TerraClimate (Abatzoglou et al 2018). These climate data were resampled to adhere to the spatial resolution of TC layers.

2.3. Statistical data of FCRPs

We collected the annual statistical data on financial investment and coverage area of major FCRPs during 1982–2015 from Bryan et al (2018). The seven major FCRPs implemented in China include the Three-North Shelterbelt Development Program, the Shelterbelt Development Program—Five Regions, the Natural Forest Conservation Program, the Grain for Green Program, the Central Government Forest Ecosystem Compensation Fund Program, the Beijing-Tianjin Sand Source Control Project and the Rocky Desertification Comprehensive Treatment Program in Karst Area. In terms of investment and implementation area, these FCRPs embrace all the large-scale sustainability programs aiming at protecting and restoring forests in China (Bryan et al 2018). The targeted provinces of the seven major FCRPs are illustrated in figure S1 (available online at stacks.iop.org/ERL/17/024023/mmedia). We conducted a range of piecewise regressions between cumulative coverage area of the FCRPs and year using different break values (Toms and Lenesperance 2003). The residual standard error of the two-segment piecewise regression became minimal, which was equal to 4.263, when the year 1999 was chosen as the break point (figure 1(b); Crawley 2007). Therefore, we separated the study period into the pre-intensification
phase (1982–1998) and post-intensification phase (1999–2015) of FCRPs (figure 1(a)). The TC trends in the pre- and post-intensification phases of FCRPs were detected by the Mann–Kendall test and pixels with significant TC trends at the 95% confidence level were identified (Mann 1945). The Theil–Sen slopes for these pixels were estimated, representing the magnitudes of TC trends (Sen 1968). The mean TC change on the national scale during the two stages was analyzed using linear regressions (Zhao et al 2020).

2.4. Extraction of growing season metrics
The biweekly NDVI time series were fitted on a year-by-year basis using the seven parameter double logistic function (Gonsamo et al 2013):

\[ f(x) = \alpha_1 + \frac{\alpha_2}{1 + e^{-\beta_1(x-\beta_2)}} - \frac{\alpha_3}{1 + e^{-\beta_2(x-\beta_2)}} \]  

where \( f(x) \) represents the observed NDVI value at a day of year \( x \). The NDVI values were fitted to the non-linear regression with starting estimates of the seven parameters and a maximum of 2000 iterations. Then the start of growing season (SOS) and POS on a per-pixel basis were calculated from the fitted parameters (Gonsamo et al 2013):

\[ \text{SOS} = \beta_1 - \frac{4.562}{2\beta_1} \]  

\[ \text{POS} = -1.317(-\beta_1 - \beta_2) \]
where $\beta_1$ is the midpoint of spring greenup transition, $\partial_1$ represents the slope coefficient of the transition. To reduce uncertainties, SOS values earlier than the 50th day of the year or later than the 180th day of the year were flagged as outliers (Zhou et al. 2016). Missing values of SOS and POS might occur for some pixels due to the data gaps of NDVI time series and the convergence failure of the fitting function, especially for evergreen forests with weak seasonal signals (D’Odorico et al. 2015). The pixel-based linear interpolations across SOS or POS layers were conducted to replace outliers and to compute values for the gaps. Afterwards, the remaining gaps were filled with the mean value of SOS or POS of evergreen forests in the corresponding year.

2.5. Phenology-based residual trend analysis
The mean temperature, cumulative precipitation and total solar radiation during the period from SOS to POS were calculated on a per-pixel basis for each year. Then we built a pixel-based TC-climate regression model in the pre-intensification phase of FCRPs. It was assumed that human activities such as the implementation of FCRPs had little impact on TC and the variation of TC was only driven by climate during the period (Tong et al. 2017; Zhao et al. 2020). The regression model can be expressed as follows:

$$TC_{POS} = a \times T_{SOS-POS} + b \times P_{SOS-POS} + c \times R_{SOS-POS} + d$$

(4)

where $TC_{POS}$ represents the TC at the time of POS, $T_{SOS-POS}$, $P_{SOS-POS}$ and $R_{SOS-POS}$ are the mean temperature, cumulative precipitation and total solar radiation from SOS to POS, respectively, $a$, $b$ and $c$ are the regression coefficients of these predictors, $d$ represents the intercept. The statistical significance of the regression model was tested by the F test on a per-pixel basis. We concede that more climate variables, as well as CO$_2$ concentration and nitrogen deposition, may also affect the TC dynamics (Piao et al. 2015), but the grid data for these variables are currently unavailable. Following the methods of Liu et al. (2018), Tong et al. (2017) and Zhao et al. (2020), only the main climate variables, that is, mean temperature, cumulative precipitation and total solar radiation from SOS to POS are used to build the TC-climate model in this study.

The performance of the pixel-based TC-climate regression model was evaluated by comparing the satellite-observed and model-simulated TC in 1999. Based on the TC-climate model, the model-simulated TC in 1999 was calculated using the climate layers of the year. The validation statistics, including root mean squared error (RMSE), coefficient of determination ($R^2$) and frequency distribution of their differences, were calculated. We compared the observed and simulated TC in 1999 to validate the model because the FCRPs had little impact on forests in the initial year of the post-intensification phase (figure 1). The data in the pre-intensification phase of FCRPs are not suitable for evaluating the performance of the TC-climate regression model because the model is built based on these data. It is also inaccurate to validate the model using the data after 2000 because the satellite-observed TC is affected not only by climate but the intensification of FCRPs.

In the post-intensification phase of FCRPs, the TC change was affected by both climate and human activities, such as the implementation of FCRPs. Based on the TC-climate regression model, the climate-induced TC ($TC_c$) for each year was predicted by the variables of $T_{SOS-POS}$, $P_{SOS-POS}$ and $R_{SOS-POS}$. For pixels with significant TC-climate models at the 95% confidence level (figure S2), the human-induced TC ($TC_{fcrp}$) was estimated as the residual between the observed TC and $TC_c$, that is, $TC_{fcrp} = TC - TC_c$. For pixels with insignificant TC-climate models, we assumed that the TC was totally induced by human activities, that was, $TC_{fcrp} = TC$ (Zhao et al. 2020). The $TC_{fcrp}$ trends represented the impacts of human activities on TC during the post-intensification phase of FCRPs (Evans and Geerken 2004).

2.6. Quantifying the effectiveness of FCRPs
We calculated the number of pixels with a significant increasing trend in $TC_{fcrp}$ ($N_{fcrp, in}$) and the cumulative area of FCRPs ($A_{fcrp}$) in the post-intensification phase for the 31 provinces of mainland China. Then, we performed correlation analysis between $A_{fcrp}$ and $N_{fcrp, in}$ to demonstrate the cause-and-effect relationship between the implementation of FCRPs and the increasing trend of $TC_{fcrp}$ during the post-intensification phase of FCRPs.

We also calculated the effectiveness index (EI) of FCRPs at the provincial level. The metric was developed by Tong et al. (2017) to quantify the effectiveness of ecological restoration programs, which was formulated as follows:

$$EI_i = \frac{S_i}{R_{tch,sit,i}}$$

(5)

where $S_i$ represents the implementation intensity of FCRPs in province $i$, which is the ratio of the financial investment to the coverage area of FCRPs in the post-intensification phase of FCRPs after normalization (ranging from 0 to 1), $R_{tch,sit,i}$ refers to the ratio of pixels with a significant increasing trend in $TC_{fcrp}$ for province $i$. A low EI value indicates high effectiveness of FCRPs in forest recovery, whereas a high EI value indicates low effectiveness. Based on the size and distribution of the EI values, we classified the 31 provinces of mainland China into four effectiveness types: high (EI ranging from 0 to 0.2, roughly equivalent to the range between the minimum value and the lower quartile), moderately high (EI ranging from 0.2 to 0.3, roughly equivalent to the range between the lower quartile and the median), moderately low (EI
Figure 2. The spatiotemporal patterns of TC change in the pre-intensification phase (a) and post-intensification phase (b) of China’s FCRPs.

ranging from 0.3 to 1, roughly equivalent to the range between the median and the upper quartile), and low (EI above 1, roughly equivalent to the range between the upper quartile and the maximum value).

3. Results

3.1. TC change in the pre- and post-intensification phases of FCRPs

During the pre-intensification phase of FCRPs, up to 89.6% of the forested lands in China presented no significant trend. Approximately 6.4% of the forested lands showed a significant greening trend, primarily distributed in the southeast coastal provinces, as well as the Hebei-Beijing-Liaoning belt. TC loss occurred in around 4% of the forested lands, mainly in Northeast China. The TC also showed a significant decreasing trend in local areas of Guangdong, Shaanxi, Hubei, etc (figure 2(a)). On the national scale, the mean TC presented an insignificant upward trend of 0.03% per year ($p = 0.607$) during the period (figure 3).

During the post-intensification phase of FCRPs, more than 30.4% of the forested lands in China showed a significant greening trend, extensively distributed in the Qinling Mountains, the Daba Mountains, the Yangtze River basin, the Loess Plateau, Northeast China and areas around Beijing. Only 1.5%
of the forested lands presented a significant browning trend and were dotted in local areas. The remaining 68.1% of the forested lands showed no significant trend during the period (figure 2(b)). On the national scale, the mean TC increased significantly by 0.339% per year ($p < 0.001$) (figure 3).

### 3.2. Performance of the TC-climate regression model

The pixel-level validation based on 171,959 paired values showed that the model-simulated TC in 1999 was consistent with the satellite-observed TC of the year, with a RMSE of 7.233 and an $R^2$ of 0.882 (figure 4). The differences between the satellite-observed and model-simulated TC in 1999 were within the range of -5%--5% for 68.6% of the pixels (117,904 out of 171,959 pixels). Moreover, pixels with the TC difference in the range of -10%--10% accounted for 85.8% (147,614 out of 171,959 pixels) (figure 5). These statistics indicated that the pixel-based TC-climate regression model was reliable for predicting the annual $T_{C}$ in the post-intensification phase of FCRPs.

### 3.3. Anthropogenic TC change in the post-intensification phase of FCRPs

More than 29.9% of the forested lands were significantly improved in TC by human activities during the post-intensification phase of FCRPs. The magnitudes of the $T_{C}$ greening trends were particularly high in the Qinling Mountains, the Daba Mountains, the Loess Plateau, areas surrounding Beijing as well as the middle and lower reaches of the Yangtze River. Only 1.8% of the forested lands showed a significant negative trend in $T_{C}$. Approximately 68.3% of the forested lands were not significantly affected in tree canopy by human activities (figure 6). On the national scale, the mean $T_{C}$ increased significantly by 0.347% per year ($p < 0.001$) during the period.

The anthropogenic TC variations were highly heterogeneous at the provincial level. The ratio of pixels with a significant increasing trend in $T_{C}$ ranged from 0.6% (Shanghai) to 67.8% (Shaanxi), whereas the ratio of pixels with a significant decreasing trend ranged from 0% (Tianjin) to 10.8% (Shanghai) (table S1).

### 3.4. Effectiveness of FCRPs in forest recovery at the provincial level

There existed a significant cause-and-effect relationship between the implementation of FCRPs and the increasing trend of $T_{C}$ at the provincial level (figure 7). The number of pixels with a significant increasing trend in $T_{C}$ was correlated significantly and positively with the cumulative area of FCRPs ($R^2 = 0.411$, $p < 0.001$).

The effectiveness of FCRPs varied considerably among the provinces with EI values ranging from 0 to 18.336 (table S2). Provinces with a high effectiveness level were generally distributed in the humid areas, such as Zhejiang, Fujian, Guangdong, Guangxi in the southeastern coast. The majority of provinces...
with low and moderately low effectiveness levels were spread across the arid and semi-arid regions (figures 8 and S3). The economically developed provinces, such as Jiangsu, Beijing, Tianjin, and Shanghai, were actually low in the effectiveness of FCRPs (figure 8).

4. Discussion

4.1. Human-induced forest greening in the post-intensification phase of FCRPs

Our study revealed the spatiotemporal patterns of TC change closely resembled that of TC_H change in the post-intensification phases of FCRPs, indicating human activities were the dominant drivers of forest dynamics during the period (Wu et al. 2019b). Previous studies revealed that the TC increasing trend for areas with planted forest fraction (PFF) ≥ 10% was 29% greater than that for areas with PFF < 10% in China (Chen et al. 2019). Our study illustrated that the Qinling Mountains and the Daba Mountains exhibited prominent gains in both TC and TC_H, which was in line with the previous evaluation at the national level (Viña et al. 2016). These areas were the hotspots of timber extraction activities in the pre-intensification phase. The recently logged areas normally responded dramatically to the implementation of FCRPs and exhibited noticeable forest gains (Viña et al. 2016). This also accounted for the significant forest greening trends in Northeast China during the post-intensification phases of FCRPs.

4.2. Controversy over the anthropogenic forest greening in China

We found that the implementation of FCRPs had caused a widespread forest greening trend in China, which was consistent with previous studies (Chen et al. 2019). However, the expansion of forested lands through afforestation in arid and semi-arid regions was generally attained at the expense of the limited water resources, which eventually lead to a decline in the forest quality (Li et al. 2021). A community-level study conducted in Yunnan revealed that the forest quality, including structure, diversity, biomass, and soil fertility, was not improved by the implementation of the Grain for Green Program (Li et al. 2020). The conversion from croplands to forests generally resulted in a fragmented landscape of forest patches, which contributed less to the expansion of core forests than natural forest protection (Wang et al. 2020). Monocultures were often favored by reforestation programs over protecting and restoring native forests (Hua et al. 2016). Due to the improper implementation of FCRPs, native forests actually suffered a net loss in some regions, though the gross TC showed an apparent greening trend there (Hua et al. 2018). In the context of climate change, more severe disturbances and changing conditions would weaken the capacity of these monocultures to sequester carbon over the long term (Seddon et al. 2019). Therefore, the implementation of FCRPs must be tailored to local conditions to achieve higher quality of plantations, especially in...
Figure 5. The spatial pattern (a) and frequency distribution (b) of the differences between the satellite-observed and model-simulated TC in 1999.

4.3. Heterogeneous effectiveness of FCRPs in forest recovery

Our study revealed that the effectiveness of FCRPs in forest recovery varied geographically at the provincial level, which was consistent with Lü et al (2015). This is because multiple biophysical and socioeconomic factors drive the effectiveness of FCRPs, and these factors are locally specific and temporally dynamic (Li et al 2017). In general, the effectiveness level of FCRPs at the provincial level decreased gradually from southeast to northwest and was consistent with the variation in precipitation gradient, indicating that precipitation was probably one of the key natural drivers (figures 8 and S3). Previous studies confirmed that drought could offset the effectiveness of FCRPs in vegetation recovery (Wu et al 2014). Overall, the impact of climate change on TC was milder and weaker than that of human activities in the post-intensification phase of FCRPs. The TCtrend analysis in this study showed that only 9.9% of the forested lands were positively affected...
by climate, much less than that positively affected by human activities (29.9%). Besides, an equal proportion (9.9%) of the forested lands was negatively influenced by climate during the period, mainly spread across Northeast and Southwest China (figure S4). Soil water deficit in arid and semi-arid regions often resulted in the mortality of plantation seedlings or stunted 'little old man trees', that was, 30-year-old plantation trees with only 20% of their normal height, which remarkably diminished the effectiveness of FCRPs in forest recovery (McVicar et al. 2007). Though the number of pixels with a significant increasing trend in TC$_H$ correlated significantly with the cumulative area of FCRPs at the provincial level.
Figure 8. The effectiveness levels of China's FCRPs in forest recovery at the provincial level.

level, the $R^2$ value was less than 0.5 (figure 7). Apart from the limited data ($n = 31$) used in the analysis, the high mortality of plantations due to the inadaptability to local conditions was probably to blame. Socioeconomic factors also gave rise to the heterogeneous effectiveness of FCRPs. Our study also revealed that the developed provinces, Beijing, Tianjin, Jiangsu and Shanghai, were in the category of low effectiveness level. These provinces were characterized by high population pressure and developed off-farm economy, both of which had negative impacts on the effectiveness of FCRPs in vegetation restoration (Lü et al 2015, Li et al 2017).

4.4. The P-RESTREND method for assessing anthropogenic vegetation dynamics

The P-RESTREND method integrates the retrieval of growing season metrics into RESTREND, which proves to be robust for evaluating anthropogenic vegetation degradation and restoration. Chen et al (2018) applied the P-RESTREND method in detecting human-induced land degradation and found it performed better than the traditional RESTREND technique. In this study, we used the P-RESTREND method to evaluate the impact of FCRPs in restoring forests. The validation showed that the TC-climate regression model was reliable for estimating the annual TC in the post-intensification phase of FCRPs (figures 4 and 5). The derived spatiotemporal patterns of anthropogenic TC change were consistent with the distribution map of planted forests (Peng et al 2014). Furthermore, there existed a significant correlation between the human-induced forest greening trend and the cumulative area of FCRPs at the provincial level (figure 7).

However, we used three principal climate variables in the P-RESTREND method so that we were unable to remove the effects of other secondary environmental factors on TC, which would overestimate the magnitude of annual TC$_{H}$. Moreover, we separated the study period into the pre- and post-intensification phases of FCRPs based on the change of coverage area of the FCRPs at the national level, which, to a certain degree, neglected the local circumstances of their implementations. The forest greening trends occurring in the Hebei-Beijing-Liaoning belt and the southeast coastal provinces in the pre-intensification phase were probably induced by both climate change and earlier FCRPs. Under the assumption that the TC trends were completely triggered by climate change in the pre-intensification phase, the annual TC$_{H}$ values for these regions were underestimated in the post-intensification phase. In addition, we quantified the effectiveness of FCRPs in forest recovery without taking forest quality into account. Forest quality is actually as important as forest cover for indicating the performance of FCRPs and deserves more attention in subsequent studies (Li et al 2020).

5. Conclusions

Based on remote sensing and statistical data, we used the P-RESTREND method to evaluate the effectiveness of FCRPs in forest recovery on the national scale. We found that the area of forested lands with a significant greening trend was almost five times larger in the post-intensification phase than in the pre-intensification phase of FCRPs. Approximately one third of the forested lands in China were significantly
improved in TC by human activities during the post-
intensification phase. The effectiveness of FCRPs in
forest recovery was heterogeneous at the provincial
level, which was affected by multiple natural and
socioeconomic factors. Provinces with a high effect-
iveness level were generally distributed across humid
areas, whereas the majority of provinces with low and
moderately low effectiveness levels were located in
arid and semi-arid regions. Provinces characterized
by high population pressure and a developed eco-
nomy were actually low in the effectiveness of FCRPs.
The P-RESTREND method, which integrated the
retirement of growing season metrics into RESTREND,
proved to be robust for evaluating anthropogenic
vegetation degradation and restoration. The policy-
driven land surface greening would accelerate China’s
growth towards achieving the SDGs targets concern-
ing sustainable forest management.

Data availability statement

The data that support the findings of this study are
available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing interests.

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