use and track land management (Domke et al. 2021; Hoover et al. 2020). FIA is a field survey of forest plots and reports information on the status and trends of forests in the United States. A subset of plots is measured every year with revisit intervals of 5 to 10 years depending on the state (Burrill et al. 2021; Hoover et al. 2020). The NLCD provides updated datasets continuously every about three years, which was generated by change detection algorithms for only a time period and has a certain amount of commission errors (Jin et al. 2013a). Additionally, the annual global forest maps have been published by JAXA over the years of 2007-2010 and 2015-2018, which are generated using PALSAR and PALSAR-2 images at 25-m and 50-m spatial resolutions (Shimada et al. 2014). The main characteristics of these high-spatial-resolution forest maps covering the CONUS are summarized in Table 1. It remains untested about their application potential for the annual management of forest resources. It is noticed that the high-spatial-resolution forest maps are relatively few for the years after 2010.

Due to the differences in forest definitions, satellite data, in-situ training data, and mapping algorithms, the previous forest maps have large discrepancies on forest area estimates (Qin et al. 2017; Sexton et al. 2016; Smith et al. 2018). The major challenge of the optical remote sensing approach is to collect good-quality observation data without cloud cover (Reiche et al. 2015). The PALSAR-based forest maps often have commission errors caused by buildings, rocks, and high biomass crops (Qin et al. 2017). The combination of the optical and microwave data could take advantage of the optical remote sensing sensors that capture the light and forest canopy interaction and microwave sensors that capture the microwave and forest structure (tree trunk and branch) interaction without cloud contamination. Additionally, an assessment study suggested that the complementarity of optical and SAR datasets improved the discriminative properties for forest mapping compared to the individual dataset (Lehmann et al. 2015). For example, uncertainties of Landsat-based forest maps could be caused by the re-planted areas with small- or medium-size trees or regions with some vegetation types like highland scrub. These regions could be identified correctly by PALSAR data (Lehmann et al. 2015). Improved fForest mappings have been reportedgenerated in a number of studies by using integrated PALSAR and Landsat data in tropical regions (Lehmann et al. 2015; Reiche et al. 2015; Thapa et al. 2014), and PALSAR and MODIS data in monsoon Asia and several sample regions of the word (Qin et al. 2016b; Zhang et al. 2019). However, it remains unclear about the potential to improve the annual forest monitoring in the CONUS To date, no study has by combininged PALSAR and Landsat images during 2015-2017 to map annual forest distributions in the CONUS.

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products to identify those forest pixels that geographically correspond to the ICESat-1 samples and gather their information on the attributes of forest canopy height and canopy coverage. In this process, all the forest products have been resampled into 70-m to match the footprint size of ICESat-1. Then, the distributions of forest pixels were analyzed with the canopy height and canopy coverage for individual forest maps by using 1-D histogram and 2-D histogram graphs.

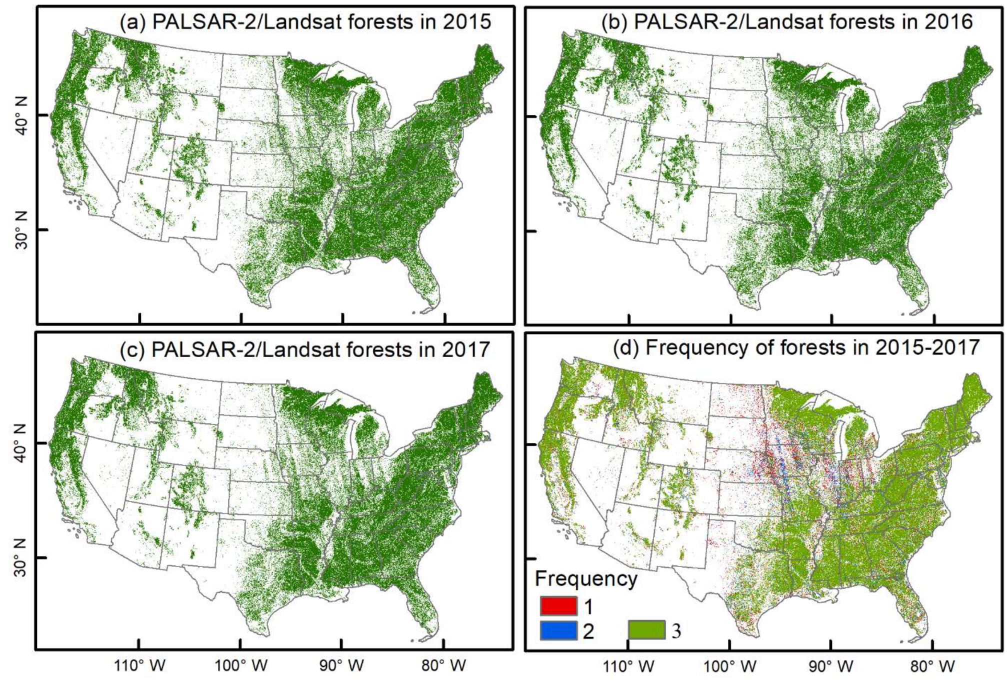
Secondly, we compared our PL-based forest maps with the selected five forest datasets in terms of forest areas at state and CONUS scales. All the forest maps were re-projected into equal-area projection before the forest areas were calculated from individual maps. The linear regression approach was used to show the relationships in forest areas between these forest datasets at the state level. The forest area estimates at the national level were directly compared among them.

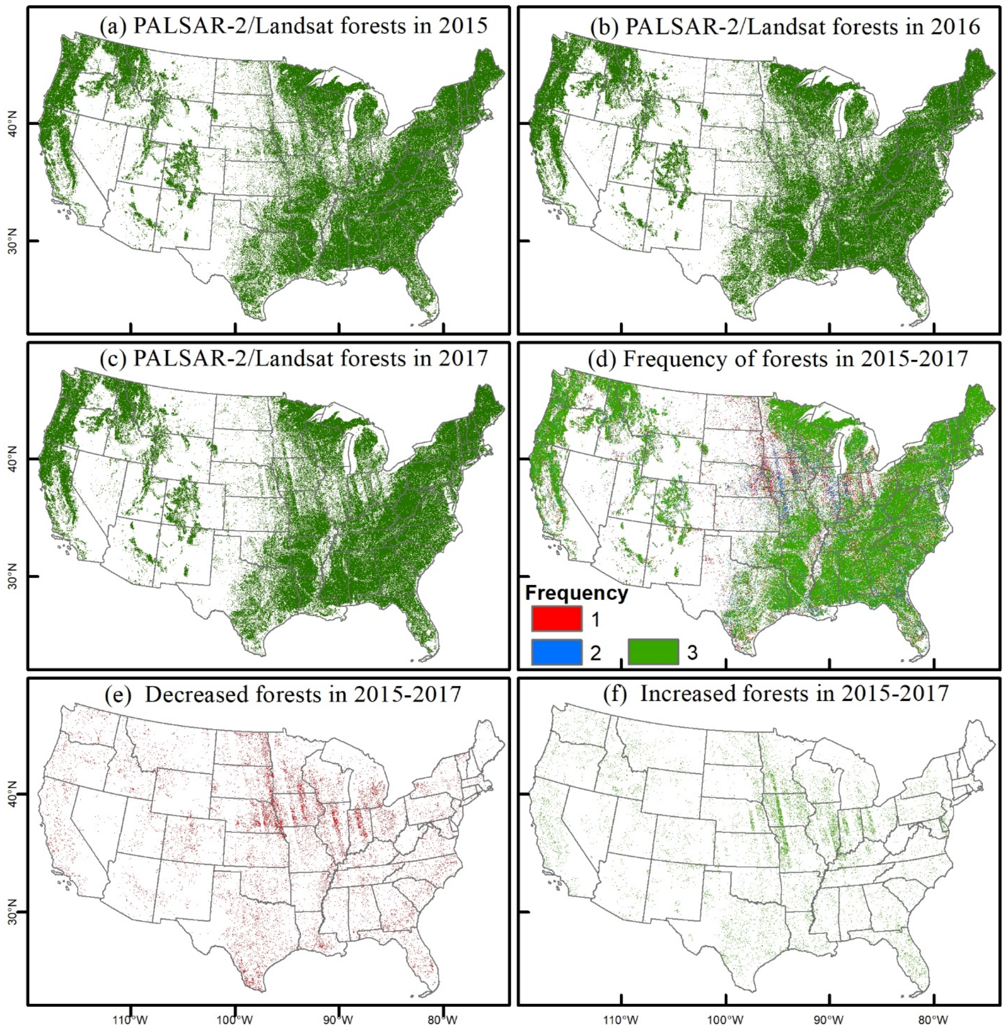
3 Results

3.1 Annual forest and evergreen forest maps in 2015-2017

The PALSAR-2/Landsat forest maps showed the annual forest distribution in CONUS during 2015 to 2017 (Fig.7a, b, c). At the pixel level, we calculated the frequency of individual pixels covered by forest in 2015-2017(Fig.7d). 79% of the forest pixels have consistent forest cover during 2015 to 2017 with a frequency of three, which is much larger than the proportions of forest pixels with one year (11%) or two years (10%) forest cover. The forest dynamics during 2015 to 2017 were shown in Fig.7e, f. It suggested that more forest decrease than forest increase, especially for the central regions.

Based on the third-party validation samples (Fig.4), the accuracies of the PALSAR-2/Landsat forests were high and varied slightly for the years of 2015 to 2017, the overall accuracies of ~93%, the user's accuracies of 87.6% to 95.8%, and producer's accuracies of 90.6% to 91.9% (Table 2). The forest map in 2016 had slightly higher accuracy than 2015 and 2017, which was expected because the temporal and logical consistency check was implemented on the resultant map of 2016 to reduce the noise or misclassification in the F/NF sequence of 2015 to 2017 (see Section 2.7).


(a) PALSAR-2/Landsat forests in 2015
(b) PALSAR-2/Landsat forests in 2016
(c) PALSAR-2/Landsat forests in 2017
(d) Frequency of forests in 2015-2017
Frequency
1
2
3
40° N
30° N
110° W
100° W
90° W
80° W



(a) PALSAR-2/Landsat forests in 2015
(b) PALSAR-2/Landsat forests in 2016
(c) PALSAR-2/Landsat forests in 2017
(d) Frequency of forests in 2015-2017
Frequency
1
2
3
(e) Decreased forests in 2015-2017
(f) Increased forests in 2015-2017
40°N
30°N
110°W
100°W
90°W
80°W

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