Time series analysis of satellite data reveals continuous deforestation of New England since the 1980s

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Abstract
Land cover and land change were monitored continuously between 1985 and 2011 at 30 m resolution across New England in the Northeastern United States in support of modeling the terrestrial carbon budget. It was found that the forest area has been decreasing throughout the study period in each state of the region since the 1980s. A total of 386 657 ± 98 137 ha (95% confidence interval) of forest has been converted to other land covers since 1985. Mainly driven by low density residential development, the deforestation accelerated in the mid-1990s until 2007 when it plateaued as a result of declining new residential construction and in turn, the financial crisis of 2007–08. The area of forest harvest, estimated at 226 519 ± 66 682 ha, was mapped separately and excluded from the deforestation estimate, while the area of forest expansion on non-forested lands was found to not be significantly different from zero. New England is often held as a principal example of a forest transition with historical widespread deforestation followed by recovery of forestlands as farming activities diminished, but the results of this study support the notion of a reversal of the forest transition as the region again is experiencing widespread deforestation. All available Landsat imagery acquired after 1985 for the study area were collected and used in the analysis. Areas of land cover and land change were estimated from a random sample of reference observations stratified by a twelve-class land change map encompassing the entire study area and period. The statistical analysis revealed that the net change in forest area and the associated modeled impact on the terrestrial carbon balance would have been considerably different if the results of the map were used without inferring the area of forest change by analysis of a reference sample.

1. Introduction

Trees in a forest sequester carbon as they grow, which is released when the forest is logged through decaying or burning of the logged wood. With the concentration of carbon dioxide in the atmosphere increasing, the mapping and monitoring of change in forest area have become a field of intensive research (Kennedy et al 2007, Kuemmerle et al 2009, Olofsson et al 2011, Zhu et al 2012, Hansen et al 2013, Pelletier and Goetz 2015) and the focus of international frameworks (UN-REDD 2008, Penman et al 2014). Much of the reported deforestation is occurring in the tropics while, according to the Global Forest Resources Assessments of the United Nations, the forest area of countries in Western Europe and North America are stable or even increasing—in certain cases by as much as 20%–30% since 1990 (FAO 2010). While these numbers depend on the definition of forest, it is well established that many Western countries have experienced a forest transition (Mather 2001) with an increase in forest area following economic development despite a growing population (Kauppi et al 2006). It has been suggested that if the same development could take place in the developing world, if a global forest transition could be achieved, it would not only end a long era of net deforestation, but would also lead to significant carbon sequestration in terrestrial ecosystems (Meyfroidt and Lambin 2011). While economic and technological development could slow/ reverse the trend of deforestation, and while the historical deforestation undoubtedly has been
Table 1. Area estimates with 95% confidence intervals and margin of errors (ratio of confidence interval to area estimate expressed as percentages). The mapped areas are the size of the strata, and map bias the difference between mapped and estimated areas. All areas are presented in hectares.

| Stratum                          | Area ± 95% CI | MoE   | Mapped area | Map bias |
|----------------------------------|--------------|-------|-------------|----------|
| High/medium density residential  | 163 548 ± 45 972 | 28%   | 350 213     | 186 665  |
| Low density residential          | 1104 941 ± 154 389 | 14%   | 968 118     | −136 823 |
| Herbaceous/Agriculture           | 910 208 ± 102 449 | 11%   | 766 515     | −143 693 |
| Forest                           | 7435 877 ± 209 652 | 3%    | 7607 907    | 172 030  |
| Wetland                          | 307 649 ± 86 683  | 28%   | 305 848     | −1800    |
| Water                            | 415 040 ± 32 830  | 8%    | 389 401     | −25 639  |
| Forest → High/medium density residential | 60 571 ± 36 333  | 60%   | 66 381      | 5809     |
| Forest → Low density residential | 210 973 ± 81 000 | 38%   | 58 423      | −152 550 |
| Forest → Other land covers       | 122 345 ± 53 550 | 44%   | 71 017      | −51 327  |
| Herbaceous/Agriculture → Forest  | 15 699 ± 25 210  | 161%  | 16 516      | 616      |
| Other land covers → Forest       | 9734 ± 9563     | 98%   | 67 109      | 57 376   |
| Forest → Forest                   | 226 519 ± 66 682 | 29%   | 378 749     | 152 230  |

reversed in many parts of the world, the claim of increasing forest area in the Western countries has not been thoroughly investigated.

The six-state region of New England in the northeastern United States experienced a forest transition when the deforestation trend that commenced with European settlement in the 17th century was reversed around 1850 as agricultural activity slowed and industrialization increased (Foster 1992, Foster and O’Keefe 2000). The forest area of New England continued to increase until the 1970s (Foster and Aber 2004) after which the exact nature of the forest change dynamics remains uncertain: Jeon et al (2014) found that New England (Maine excluded) had lost about 121 000 ± 83 000 ha (error-adjusted area estimate with 95% confidence interval) of forest between 1990 and 2005—a loss not reflected in the Forest Inventory and Analysis (FIA) of the USDA US Forest Service which instead showed that the forest area remained stable from 1985 to 1998. Forest loss was evident in the FIA data from 1998 to 2005, similar to the findings of Jeon et al (2014) although the FIA loss estimates were less. Evidence of forest loss was also provided by Drummond and Loveland (2010) who estimated the net forest loss in three ecoregions in the Northeastern United States at 725 000 ± 253 000 ha or 3.4% ± 1.2% of the area between 1973 and 2000 (error-adjusted area estimates with 85% confidence intervals). These estimates represent a larger area than the study area of both Jeon et al (2014) and this study, and includes all of Maine and large parts of New York and New Jersey, but even if just considering the Northeastern Coastal Zone ecoregion (most of Connecticut and Massachusetts, and a small part of New Hampshire) the net forest loss was estimated at 137 000 ± 22 000 ha from 1973 to 2000 or 3.7% ± 0.6% relative to the total area of the ecoregion (Drummond and Loveland 2010). Cunningham et al (2015) studied the loss of undeveloped land (forest, woodlands and agriculture) in Eastern Massachusetts during the housing bubble in 2000–2006 and the subsequent ‘bust’ in 2006–2013. While a smaller areas was studied and areas of change were not adjusted for classification errors and uncertainty was not quantified, the authors concluded that the rate of development has remained high since 2000 although decreasing from 598 ha yr⁻¹ 2000–2006 to 486 ha yr⁻¹ 2006–2013.

Thus, there is mounting evidence that New England has experienced a net loss of forest since the 1970s/80s but the exact nature and trajectory remain uncertain. The field of environmental remote sensing has seen important advancements in the last few years following free data policies (Woodcock et al 2008, ESA 2013), including: (1) production of global high resolution forest change maps (Hansen et al 2013, Kim et al 2014); (2) the development of time series analysis methods for monitoring change (Kennedy et al 2010, Zhu et al 2012, Kennedy et al 2014); and (3) increased development and use of statistical inference for area estimation (McRoberts 2011, Olofsson et al 2013, Stehman 2014). In this letter we report on a more complete and detailed analysis of land change in New England than has been done to date. The study is based on an analysis of a time series of satellite data from the Landsat satellite systems for continuous monitoring of land cover across New England. The analysis includes identification of land change and subsequent mapping of the pre- and post-disturbance land covers. Unbiased estimates of rates of land cover change were inferred from a sample of reference observations stratified by a map of land cover and land cover change (see table 1). the remotely sensed products.

2. Material and methods

2.1. Mapping

The study area is in the Northeastern United States and includes the states of Connecticut, Rhode Island, Massachusetts, New Hampshire, Vermont and Maine (figure 1). Only the southwestern part of Maine (about 30% of the state) was mapped and a small sliver of Northwestern Vermont was outside the coverage of
the satellite data that was processed for this study. The part of Maine that was not included in the study area is less populated and it is assumed that the mapped part, which includes the Portland Metropolitan area, exhibits higher rates of residential development that the rest of the state.

Land change was mapped by applying the Continuous Change Detection and Classification (CCDC) algorithm to pixel-level time series of Landsat data (Zhu et al. 2012, Zhu and Woodcock 2014). CCDC is a break detection method for finding structural change in time series by monitoring for change in forecast residuals. CCDC uses initial time series observations as a training period to form simple statistical models for each of the Landsat optical bands that can predict the expected surface reflectance for a given date. The predicted reflectance is compared to the subsequent observations in the time series, and when the average difference across the optical bands between predicted and observed reflectance differs by two times the root mean square error of the model multiple consecutive times, the algorithm concludes that a change has occurred on the land surface. When change has been detected, the algorithm breaks the prediction and starts a new model that progresses until a new change is detected. Time series prediction model attributes, including the model coefficients and root mean square error, for each time series segment (i.e. the stable periods between abrupt change events) were input to a random forests classifier (Breiman 2001) together with training data to perform a supervised land cover classification for each segment for every pixel. This approach to land cover classification allows for continuous monitoring of land change and for

Figure 1. The final stratification of the study area and the stratified random sample used for statistical inference of area.
construction of a land cover map for any time step or a change map for any time interval during the study period.

2.2. Estimation of area
It was assumed that the mapped areas of land cover and land change were biased because of classification errors and were therefore estimated from a sample of reference observations. For this purpose, a random sample stratified from the map was selected. The stratification is shown in figure 1; it contains six stable strata and six change strata between 1986 and 2011. The total sample size was determined using equation (5.25) in Cochran (1977) with a target standard error for the Forest-to-low-density-residential stratum of 0.25% of the total population and by assuming one error of omission per 100 sample units. For twelve strata, this gave a sample size of 1386. These were allocated following ‘good practices’ for estimation of the area of change such that 50 units each were selected from the change strata and 100 each from the stable strata except the Forest stratum from which 500 units were selected (Olofsson et al 2014). An additional 50 units were allocated to the Unclassified stratum which includes areas that did not have enough usable observations to run CCDC or that experienced a change too late in the time series to initialize a new segment for a land cover prediction. The intent of including this class in the stratification was to assign a land cover class to these unclassified pixels. Pixels without enough usable observations dominated this class and include coastal shores with noisy signals due to changes in the tide or bright mountain surfaces that saturate Landsat’s detectors. This process yielded a total sample of 1350 units.

The sample units were carefully examined using time series of Landsat data visualized in a custom plugin to the QGIS software (Holden 2015) and very high resolution images in Google Earth with three interpreters examining each sample unit independently and providing reference labels. The interpreters did not know which stratum they were in when they provided the reference labels as we believe this would have biased the interpretation. The reference labels provided were Forest, Wetland, Water, High and Low density residential and Herbaceous/Agriculture, and these were provided at the start and end of the study period. In case of transition, the timing was noted. A group was convened to make a decisive interpretation for each sample unit where there was disagreement among interpreters or if they indicated a low confidence in the assigned label. An error matrix of estimated area proportions was created by cross-tabulating the map and reference labels, and area estimates with confidence intervals were constructed for each stratum using stratified estimation (Olofsson et al 2013).

These estimators pertain to the full stratification in time and space and are not directly applicable to different subregions and time intervals of the study domain. As we are interested in the temporal development of land cover for subregions such as individual states, it was assumed that the bias in the area of mapped land covers were uniformly distributed in time and space. This assumption implies that if, for example, the mapped area of deforestation was \( x \) ha and the unbiased estimate was \( \hat{y} \) ha for the full stratification, and the mapped area for Massachusetts 1990–1995 was \( y \) ha, it was assumed that an unbiased estimate of \( y \) was \( \hat{y} = \hat{y} \frac{y}{x} \).

3. Results and discussion
The analysis revealed that the forest area of New England has been decreasing throughout the entire study period. The estimated areas of land cover and land cover change are presented in table 1: a total of 386 657 ± 98 137 ha of forest were converted to other land covers since 1986—this estimate contains only areas that experienced land use change and does not include the 226 519 ± 66 682 ha of disturbed forest that remained forest after disturbance. The primary driver of the New England deforestation is residential development: more than half of the deforestation was attributed to development of residential areas of low density with another 15% being attributed to development of high density residential areas, which includes industrial and commercial development. The remaining 31%, classified as being converted to other land covers, includes post-disturbance land covers that are not forest or urban development such as golf courses, landfills, recreational parks, agricultural development, etc. The accuracy of the map was 84% and provided an essential component in the estimation of the area of land cover and land cover change: applying equation (4.2) in Cochran (1977) for estimating the size of a simple random sample required to achieve the precision of the estimate of the area of forest converted to low density residential that was achieved in this study (81 000 ha or 0.74% of the map area), yielded a sample size of about 6000 units.

Of importance is the lack of forest expansion to counter the deforestation: two strata were constructed to capture reversion of agricultural lands and other land covers to forest but neither of the area estimates of these strata was significantly different from zero (table 1). This implies that the land change process that was driving the forest transition of New England—reversion of agricultural lands and pastures back to forest—ceased prior to the mid-1980s, seemingly because there are less agricultural lands with potential to revert. When combined with a recent renaissance of small scale farming in New England and programs in place aiming at preserving and even growing the farming industry (Donahue et al 2014), the result suggests
that there is little or no prospect for a continuation of the New England forest transition or a reversal of the observed deforestation trend. This prediction is further reinforced by the fact that forest is mainly being converted to land covers that are harder and less likely to revert back to forest than agricultural lands. The lack of forest expansion also impacts the terrestrial carbon dynamics; while the new forest added as a result of the New England forest transition is still growing and sequesters carbon, the lack of forest expansion in combination with a permanent conversion of forest lands will deplete much of New England’s land use-related carbon sink. This result was confirmed by Jeon et al. (2016) who found the sink to have decreased from 2 Tg of carbon per year in 1980 to 0.2 Tg in 2005, and while economic recessions may slow the deforestation (Cunningham et al. 2015) there is little prospect of a reversal of the trend suggesting that the depletion of the land use-related carbon sink will continue and eventually turn the sink to a source. When this will happen—or if it already happened—remains to be investigated.

Further evidence of the observed change being driven by residential development is provided in figure 2 which shows the relationship between the annual estimated rate of deforestation attributed to residential development and the rate of percentage homeownership for the northeast census region (US Census Bureau 2015). The time series of annual conversion of forest to residential land is noisy because of classification errors and the series was filtered using a Savitzky–Golay filter to facilitate the comparison to the homeownership information. The filtered time series and the homeowner time series are well correlated ($R^2 = 86\%$) and the bust of the housing bubble around 2006 is clearly evident with a marked drop in both homeownership and forest conversion. It is also an indication that the remotely sensed rate of forest conversion is capturing the economic dynamics in the region and that future studies could relate these changes in land cover to socio-economic drivers that cause them. The forest conversion rate in figure 2 represents the entire the study area whereas figure 3 shows the accumulated amount of forest lost to residential development per state. The conversion rates are expressed as a percentage of the forest area in 1986 to facilitate comparison: the states of Connecticut, Rhode Island and Maine exhibit considerably higher rates that accelerated in the late 1990s with 3% to 4% of the forest area converted by 2010. Note that only the southeastern, more populous part of Maine is included in the study area and that deforestation expressed as a percentage of forest area is likely to be considerably less for the whole state.

While the housing bust following the acceleration in development in many states after 2005 is evident in figure 3, it is noteworthy that this does not flatten the accumulation, but merely slows it down. This is even more evident in figure 4 which shows the forest area of the whole study area from 1986 to 2010. The time series shown in blue is the net of all forest change including the forest gain classes which are associated with high uncertainty. The carbon emissions from fossil fuel combustion increased steadily for all states in the study area from 1990 to 2008 and after a decrease following the economic recession they are again increasing (EPA 2015). The land use-related carbon sink had decreased to just above zero in 2005 (Jeon et al. 2016) and with continued deforestation it is bound to turn to a source of carbon and will thus be adding to the region’s increasing and already high carbon emissions.

Figure 4 also includes a comparison to the forest area as inferred from the national forest inventory of the United States (the FIA Program of the USDA US Forest Service). Comparing FIA data with remote sensing-based estimates of land change should be done with care as different definitions, objectives and sampling designs will yield different area estimates that are
not easily comparable (Jenkins and Riemann 2002, Drummond and Loveland 2010). But the question of how well the national forest inventory captures the observed land use patterns is interesting and deserves investigating. As evident in figure 4 the FIA data exhibits a slight decline in forest area until 2005 after which it plummets by about 100 000 ha in one year. Further comparisons are presented in figure 5 where the change rates for each state are expressed as percentages of the forest area in 1986. The story is similar in all states with a continuous loss of forest of about 1.5%–2.5% (the reason for the loss being less than that in figure 3 is that the net change in forest area includes forest expansion); Vermont is the exception where the forest loss rate was close to zero, and the rate for Maine only includes the more populous part—the state-wide rate is probably much less. This is reflected in the FIA data which represents the entire state of Maine. For many of the other states, the FIA data exhibits a high variance, especially after 2005 with substantial gains in forest area in Connecticut, Rhode Island and Massachusetts (and in Vermont and New Hampshire although a large drop occurs after 2010). This could potentially be a consequence of measuring only 3/5 of the sample of FIA plots in 2005 (personal communication with staff at FIA, USDA Forest Service).

Finally, this study highlights the importance of constructing unbiased estimators of area from a sample of reference observations rather than just ‘believing the map’. If counting the pixels of the land cover
categories in the map without making statistical inference of area from the reference sample, the area of net forest change would have been associated with a severe upward bias of about +320 000 ha (i.e. a deforestation rate of about 120 000 ha—75% less than the unbiased estimate). The story of this paper and the impact on the terrestrial carbon balance associated with the forest change would have been considerably different if good practices for estimation of the area of land change had not been followed (Olofsson et al 2014).

4. Conclusions

Using a dense time series of Landsat data and statistical inference of area from stratified sample of reference observations it was found that New England has experienced continuous deforestation over the last 30 years totaling a loss of almost half a million hectares of forest. The rates of forest expansion on previously non-forested lands were found to not be significantly different from zero. The deforestation, driven mainly by residential development, has thus reversed the forest transition of New England and is likely to turn the land use-related carbon sink created by the forest transition to a source of carbon. The temporal trajectory of the deforestation is related to economic activity and accelerated during the 1990s but plateaued in 2007 following the 2007–08 financial crisis. While the national forest inventory provides evidence of a reduction in forestlands, it does not capture these dynamics. The results highlight the importance of continuous monitoring and targeted sampling of land cover change as the bias in the land change map would have hidden the true magnitude and pattern of the deforestation of New England.

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