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

2016 Environ. Res. Lett. 11 064002

(http://iopscience.iop.org/1748-9326/11/6/064002)

Environmental Research Letters

OPEN ACCESS

RECEIVED
11 February 2016

REVISED
29 April 2016

ACCEPTED FOR PUBLICATION
12 May 2016

PUBLISHED
26 May 2016

LETTER

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

Pontus Olofsson, Christopher E Holden, Eric L Bullock and Curtis E Woodcock

Department of Earth and Environment, Boston University, 685 Commonwealth Ave., Boston, MA 02215, USA

E-mail: olofsson@bu.edu

Keywords: land cover, land change, deforestation, time series, Landsat, area estimation, New England

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 residental	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	122 343 ± 53 350	44%	71 017	−51 327
Herbaceous/Agriculture → Forest	15 699 ± 25 210	161%	16 316	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 Costal 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} 2006–2103.

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 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

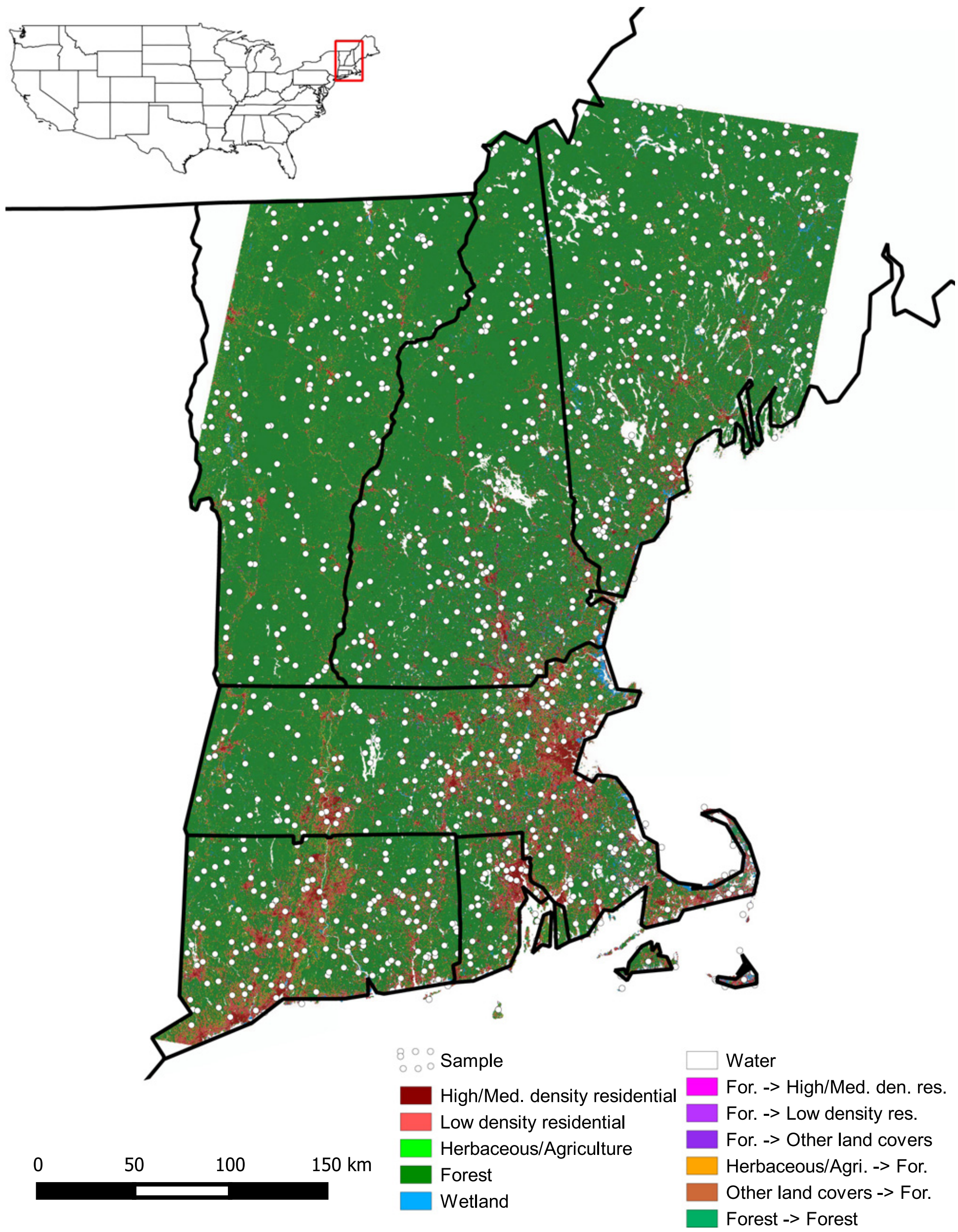

Figure 1. The final stratification of the study area and the stratified random sample used for statistical inference of area.

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 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 $\hat{x}$ 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 $\hat{y} = y\frac{x}{\hat{x}}$.

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

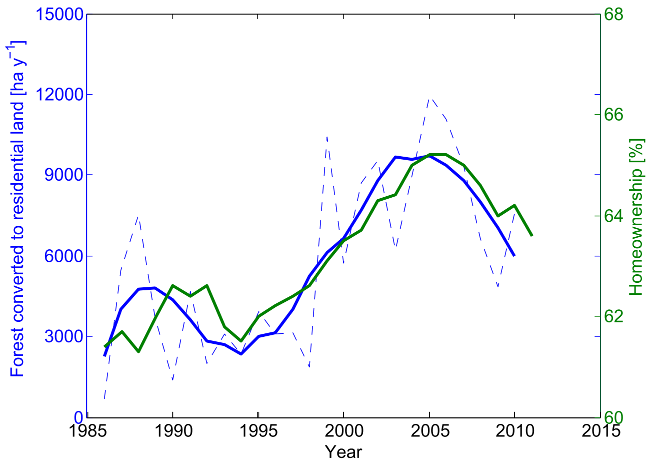

Figure 2. Annual rates of homeownership in percent and deforestation attributed to residential development in hectares. The dashed line shows the annual time series of forest conversion which was filtered (solid blue line) using a Savitzky–Golay filter to reduce noise.

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 south-eastern, 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

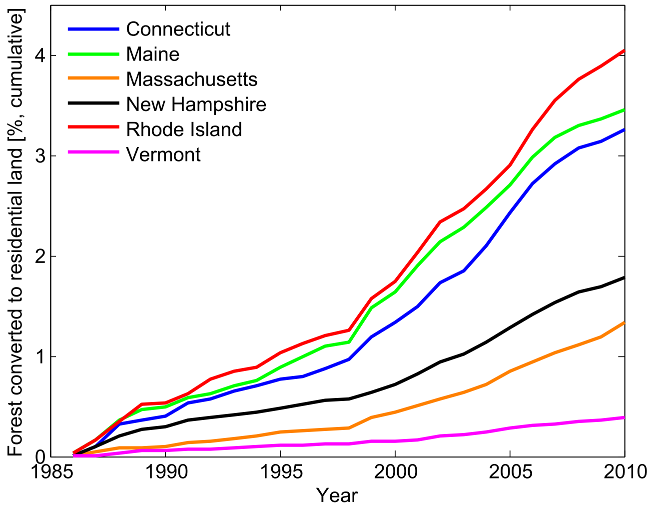

Figure 3. Accumulated deforestation attributed to residential development expressed as a percentage of the forest area in 1986 for each state in the study area.

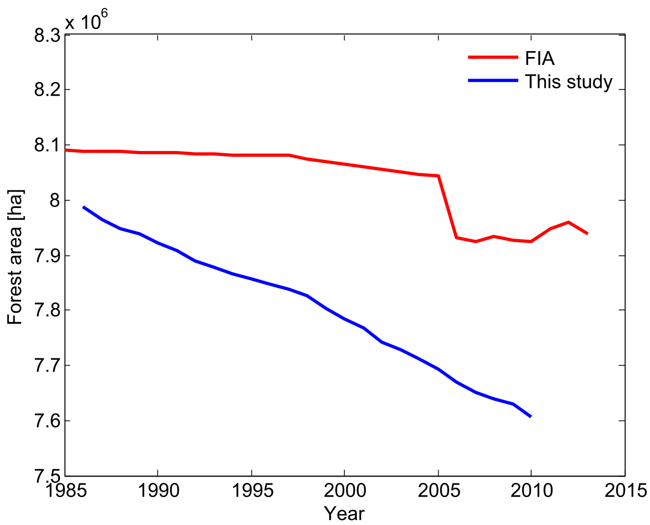

Figure 4. Estimated forest area for the study area according to the data in this study in blue and as inferred from the FIA data in red. The FIA estimate of the forest area of Maine was multiplied by 0.3 as only 30% of state was included in this study, which may explain the offset between the two estimates. Of primary importance here are the trends through time, not the overall total.

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

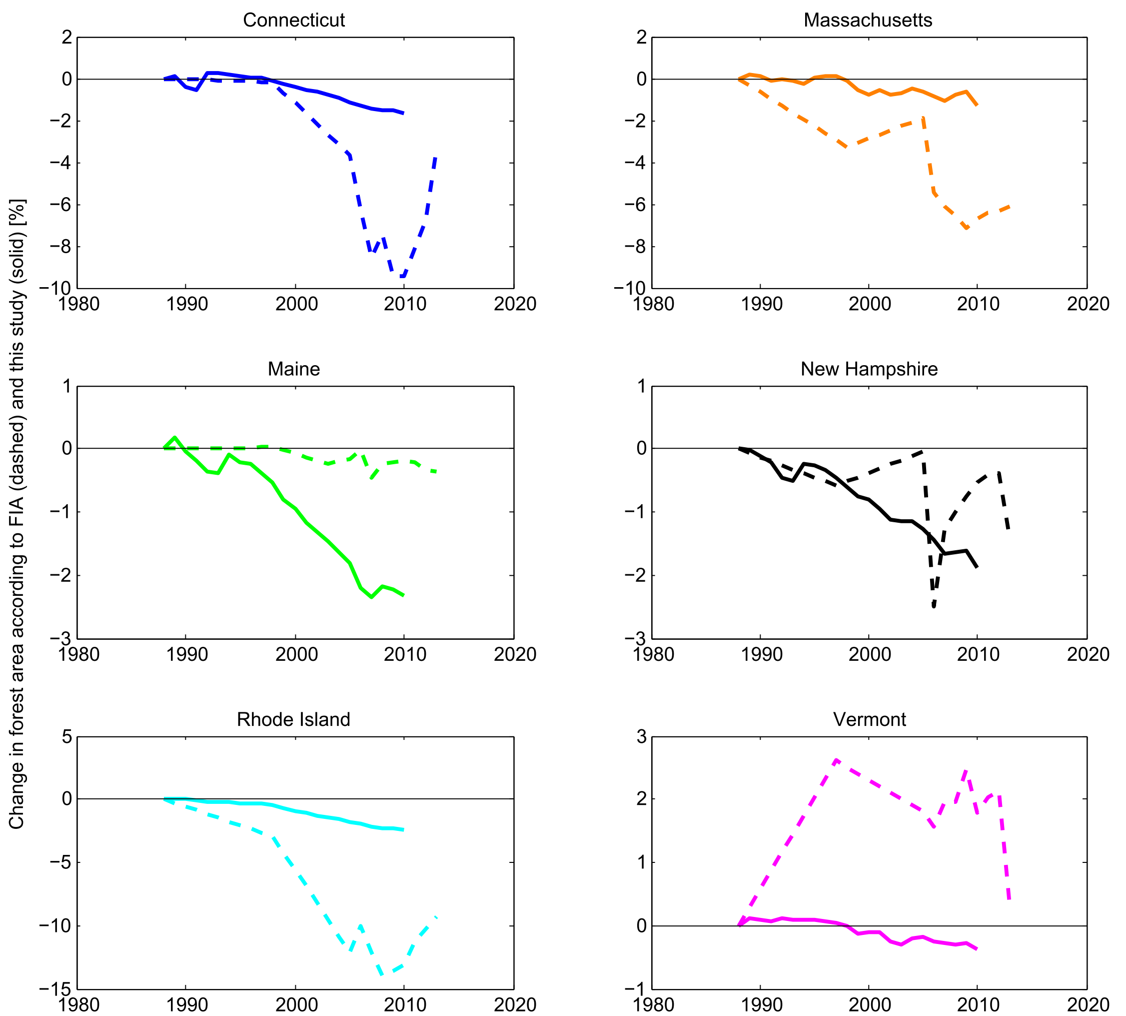

Figure 5. Forest loss as percentages of the forest area in 1986 based on FIA data (dashed) and the results of this study (solid).

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.

Acknowledgments

This research was financed by the National Aeronautics and Space Administration Interdisciplinary Science Program (NASA IDS grant number NNX12AM82G) and the USGS Landsat Science

Team Program for Better Use of the Landsat Temporal Domain Monitoring Land Cover Type, Condition, and Change (grant number G11PS00422).

References

Breiman L 2001 Random forests *Mach. Learn.* **45** 5–32

Cochran W G 1977 *Sampling Techniques* (New York: Wiley)

Cunningham S, Rogan J, Martin D, DeLauer V, McCauley S and Shatz A 2015 Mapping land development through periods of economic bubble and bust in Massachusetts using Landsat time series data *GISci. Remote Sens.* **52** 397–415

Donahue B, Burke J, Anderson M, Beal A, Kelly T, Lapping M and Berli L 2014 *A New England Food Vision* (Durham, NH: Food Solutions New England, University of New Hampshire)

Drummond M A and Loveland T R 2010 Land-use pressure and a transition to forest-cover loss in the eastern United States *Bioscience* **60** 286–98

EPA 2015 *Inventory of US Greenhouse Gas Emissions and Sinks 1990–2013* (Washington, DC: U.S. Environmental Protection Agency)

ESA 2013 Free access to Copernicus Sentinel satellite data (http://esa.int/Our_Activities/Observing_the_Earth/Copernicus/Free_access_to_Copernicus_Sentinel_satellite_data) (accessed 3 October 2015)

FAO 2010 Global forest resources assessment 2010 *FAO Forestry Paper* 163

Foster D R 1992 Land-use history (1730–1990) and vegetation dynamics in central New England, USA *Ecology* **80** 753–72

Foster D R and Aber J D 2004 *Forests in Time: The Environmental Consequences of 1000 Years of Change in New England* (New Haven, CT: Yale University Press)

Foster D R and O'Keefe J F 2000 *New England Forests Through Time : Insights from the Harvard Forest Dioramas* (Cambridge, MA: Harvard University Forest)

Hansen M C, Potapov P V, Moore R, Hancher M, Turubanova S A, Tyukavina A and Townshend J R G 2013 High-resolution global maps of 21st-century forest cover change *Science* **342** 850–3

Holden C E 2015 Yet Another Time Series Model (YATSM). Zenodo (doi:10.5281/zenodo.17129) (https://github.com/ceholden/yatsm)

Jenkins J C and Riemann R 2002 What does nonforest land contribute to the global carbon balance? *Proc. Third Annual Forest Inventory and Analysis Symposium; Gen. Tech. Rep.* NC-230 ed R E McRoberts *et al* (St Paul, MN: U.S. Department of Agriculture, Forest Service, North Central Research Station) pp 173–9

Jeon S B, Olofsson P, Houghton R A, Feng Z, Xiaoyuan Y and Woodcock C E 2016 The effect of historical land use and recent deforestation on the terrestrial carbon budget of New England *Forest Ecology and Management* submitted

Jeon S B, Olofsson P and Woodcock C E 2014 Land use change in New England: a reversal of the forest transition *J. Land Use Sci.* **9** 105–30

Kauppi P E, Ausubel J H, Fang J, Mather A S, Sedjo R A and Waggoner P E 2006 Returning forests analyzed with the forest identity *Proc. Natl Acad. Sci. USA* **103** 17574–9

Kennedy R E *et al* 2014 Bringing an ecological view of change to Landsat-based remote sensing *Frontiers Ecol. Environ.* **12** 339–46

Kennedy R E, Cohen W B and Schroeder T A 2007 Trajectory-based change detection for automated characterization of forest disturbance dynamics *Remote Sens. Environ.* **110** 370–86

Kennedy R E, Yang Z and Cohen W B 2010 Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—temporal segmentation algorithms *Remote Sens. Environ.* **114** 2897–910

Kim D, Sexton J O, Noojipady P, Huang C, Anand A, Channan S and Townshend J R G 2014 Global, Landsat-based forest-cover change from 1990 to 2000 *Remote Sens. Environ.* **155** 178–93

Kuemmerle T, Chaskovskyy O, Knorn J, Kruhlov I, Radeloff V C and Hostert P 2009 Forest cover change and illegal logging in the Ukrainian Carpathians in the transition period from 1988 to 2007 *Remote Sens. Environ.* **113** 1194–207

Mather A S 2001 The transition from deforestation to reforestation in Europe *Agricultural Technologies and Tropical Deforestation* ed A Angelsen and D Kaimowitz (Wallingford: CABI) pp 35–52

McRoberts R E 2011 Satellite image-based maps: scientific inference or pretty pictures? *Remote Sens. Environ.* **115** 715–24

Meyfroidt P and Lambin E F 2011 Global forest transition: prospects for an end to deforestation *Annu. Rev. Environ. Resour.* **36** 343–71

Olofsson P, Foody G M, Herold M, Stehman S V, Woodcock C E and Wulder M A 2014 Good practices for estimating area and assessing accuracy of land change *Remote Sens. Environ.* **148** 42–57

Olofsson P, Foody G M, Stehman S V and Woodcock C E 2013 Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation *Remote Sens. Environ.* **129** 122–31

Olofsson P, Kuemmerle T, Griffiths P, Knorn J, Baccini A, Gancz V and Woodcock C E 2011 Carbon implications of forest restitution in post-socialist Romania *Environ. Res. Lett.* **6** 45202

Pelletier J and Goetz S J 2015 Baseline data on forest loss and associated uncertainty: advances in national forest monitoring *Environ. Res. Lett.* **10** 021001

Penman J, Baltuck M, Green C, Olofsson P, Raison J and Woodcock C E 2014 *Integrating Remote-Sensing and Ground-Based Observations for Estimation of Emissions and Removals of Greenhouse Gases in Forests: Methods and Guidance from the Global Forest Observations Initiative* 1st edn (Geneva: Group on Earth Observation)

Stehman S V 2014 Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes *Int. J. Remote Sens.* **35** 4923–39

UN-REDD 2008 *UN Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries* (*UN-REDD*) FAO, UNDP, UNEP Framework Document, United Nations

US Census Bureau 2015 Housing Vacancies and Homeownership (http://census.gov/housing/hvs/index.html) (accessed 5 June 2015)

Woodcock C E, Allen R, Anderson M, Belward A, Bindschadler R and Cohen W B 2008 Free access to landsat imagery *Science* **320** 1011–2

Zhu Z and Woodcock C E 2014 Continuous change detection and classification of land cover using all available Landsat data *Remote Sens. Environ.* **144** 152–71

Zhu Z, Woodcock C E and Olofsson P 2012 Continuous monitoring of forest disturbance using all available Landsat imagery *Remote Sens. Environ.* **122** 75–91