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Estimating litter carbon stocks on forest land in the United States

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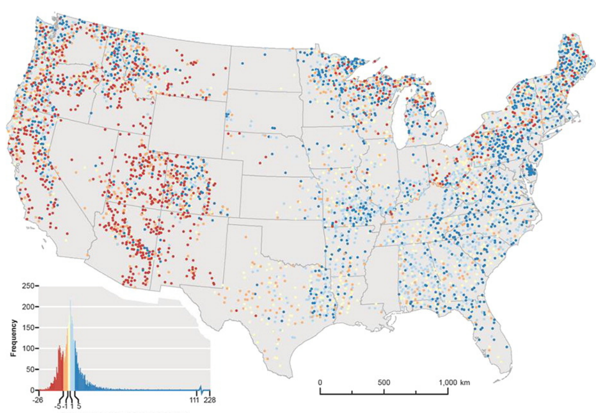
HIGHLIGHTS

- Litter carbon in forests is a relatively small but important part of carbon budgets.
- The US has been overestimating the contribution of litter carbon in forests.
- IPCC default values for temperate forests may lead to overestimates in litter carbon.
- In situ measurements of litter in forests of the US have improved model predictions.

GRAPHICAL ABSTRACT



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ABSTRACT

Forest ecosystems are the largest terrestrial carbon sink on earth, with more than half of their net primary production moving to the soil via the decomposition of litter biomass. Therefore, changes in the litter carbon (C) pool have important implications for global carbon budgets and carbon emissions reduction targets and negotiations. Litter accounts for an estimated 5% of all forest ecosystem carbon stocks worldwide. Given the cost and time required to measure litter attributes, many of the signatory nations to the United Nations Framework Convention on Climate Change report estimates of litter carbon stocks and stock changes using default values from the Intergovernmental Panel on Climate Change or country-specific models. In the United States, the country-specific model used to predict litter C stocks is sensitive to attributes on each plot in the national forest inventory, but these predictions are not associated with the litter samples collected over the last decade in the national forest inventory. Here we present, for the first time, estimates of litter carbon obtained using more than 5000 field measurements from the national forest inventory of the United States. The field-based estimates mark a 44% reduction (2081 ± 77 Tg) in litter carbon stocks nationally when compared to country-specific model predictions reported in previous United Framework Convention on Climate Change submissions. Our work suggests that Intergovernmental Panel on Climate Change defaults and country-specific models used to estimate litter carbon in temperate forest ecosystems may grossly overestimate the contribution of this pool in national carbon budgets.

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1. Introduction

The Intergovernmental Panel on Climate Change recognizes litter carbon (C) as one of five C pools in forest ecosystems included in the Agriculture, Forestry and Other Land Use sector of annual national greenhouse gas inventories (IPCC, 2006). In the United States (US), the national forest inventory (NFI) conducted by the US Department of Agriculture, Forest Service, Forest Inventory and Analysis program is used to compile annual estimates of forest C stocks and stock changes for the national greenhouse gas inventory (US EPA, 2015). For more than a decade, tree- and site-level variables related to each forest ecosystem C pool have been measured in the NFI (O'Neill et al., 2005a; Woodall and Monleon, 2008, and Domke et al., 2013). In recent years, estimation approaches have been developed that rely directly on measurements from the forest ecosystem attributes of interest (US EPA, 2015), reducing the uncertainty associated with the estimates of C stocks and stock changes in the national greenhouse gas inventory and improving their sensitivity to natural and anthropogenic disturbances.

The US uses a stock-difference C accounting approach (IPCC, 2006) in United Nations Framework Convention on Climate Change reporting, requiring estimates of litter C stocks, defined in this study as the pool of organic C above the mineral soil (i.e., litter (Oi), fulvic (Oe), and humic layers (Oa)) including woody fragments with large-end diameters of up to 7.5 cm (Woodall et al., 2012), on every NFI plot across space and time. Before extensive field data were collected on non-live tree attributes, the Forest Service estimated litter C with a country-specific model developed with data obtained from the literature using geographic region (a proxy for climate), forest stand age (an indication of time since disturbance), and species composition (an indication of the source and character of organic matter) as predictor variables (Smith and Heath, 2002). Significantly, this model has served as a primary source of information used in Intergovernmental Panel on Climate Change guidance for temperate forest ecosystems in nations lacking litter C estimates in their NFIs (IPCC, 2006 and US EPA, 2014).

Globally, the litter C pool accounts for an estimated 5% (43 Pg) of all forest ecosystem C stocks (Pan et al., 2011). In contrast, the country-specific model (Smith and Heath, 2002) used in the 1990–2012 US national greenhouse gas inventory predicted litter C at 11.7% (5056 Tg) of total forest C stocks (43,126 Tg), with an estimated net annual increase of 14 Tg C yr^{-1} over the last 5 years (US EPA, 2014). Although the US' country-specific model uses NFI plot attributes to estimate litter C stocks, these predictions are not associated with the litter samples collected over the last decade by the Forest Inventory and Analysis program (O'Neill et al., 2005b and Woodall et al., 2012). General comparisons of the country-specific model predictions to the NFI estimates suggest that the country-specific model does not accurately characterize the litter C in forests of the US.

Developing data-driven models to characterize the litter C pool is challenging as it can be highly variable (Böttcher and Springob, 2001; Schulp et al., 2008 and Woodall et al., 2012) with large differences between forest types on the same soils (Ladegaard-Pedersen et al., 2005) and variations in thickness across short distances (Smit, 1999). This pool's vulnerability to disturbance, particularly wildfire (Stinson et al., 2011), also contributes to the variability (Pan et al., 2011). There are few NFIs with observations of litter C with which to build models and evaluate litter C predictions at regional or national scales (Kurz and Apps, 2006 and Keith et al., 2009).

The Forest Service has been measuring litter attributes, including C content and bulk density, on a subset of the NFI plots since 2001 (O'Neill et al., 2005b and Woodall et al., 2012). Here, we show how these data support a new approach to litter C estimation. Specifically, we: 1) demonstrate the inadequacies of the country-specific model currently used relative to estimates of litter C stocks obtained from the NFI; 2) develop a new modeling framework based on litter measurements in the NFI and stand, site, and climatic variables; and 3) use the new modeling framework to estimate litter C in the 2015 US national greenhouse gas inventory.

2. Methods

In this study, we used observations of litter variables – total C (organic and inorganic) concentration in percent of the litter sample, oven-dry sample weight of the litter material, and the per-unit-area estimate of medium and large fine woody debris – to estimate C from the annual NFI (2001 — 2012). The sample included 4553 inventory plots and 5263 unique forest conditions (i.e., domains mapped on each plot using land use, forest type, stand size, ownership, tree density, stand origin, and/or disturbance history — there may be multiple conditions on a single inventory plot), hereafter referred to as plots (Bechtold and Patterson, 2005) in the conterminous US (Fig. 1a). The annual NFI includes a nationally consistent sampling frame and plot design so the methodologies established for replacing the country-specific model predictions of litter C stocks could be applied nationally to enable stock-difference C accounting. Note that litter samples from Mississippi, Oklahoma, and Wyoming were not available at the time of this study (Fig. 1a).

2.1. Plot design and sampling

The Forest Inventory and Analysis program employs a multi-phase inventory, with each phase contributing to the subsequent phase. First, current aerial photography (e.g., National Agriculture Imagery Program, USDA Farm Services Agency, 2008) is used in a prefield process to examine all sampling points (i.e., plot locations) to determine whether a forested condition exists at each point. Next, each sample point is assigned to a stratum using satellite imagery or thematic products (e.g., National Land Cover Database, Jin et al., 2013) obtained from satellites. A stratum is a defined geographic area (e.g., state or estimation unit) that includes plots with similar attributes; in many regions strata are defined by predicted percent canopy cover. Base intensity permanent ground plots are distributed approximately every 2428 ha across the 48 conterminous states of the US in four geographic regions (Fig. 1). Each permanent ground plot comprises a series of smaller fixed-radius (7.32 m) plots (i.e., subplots) spaced 36.6 m apart in a triangular arrangement with one subplot in the center (Fig. 2). Tree- and site-level attributes – such as diameter at breast height (dbh) and tree height – are measured at regular temporal intervals on plots that have at least one forested condition (i.e., there may be multiple condition plots) defined in the prefield process (USDA Forest Service, 2014a). Litter samples are collected along with other non-standing tree ecosystem attributes (e.g., downed dead wood) on every 16th base intensity plot distributed approximately every 38,848 ha (Bechtold and Patterson, 2005). Although sample intensity was 1/16th of the base plot intensity during this study's time period (2001–2012), there may be opportunities to increase the sample intensity in future NFIs.

Litter variables are sampled as a complete unit on plots adjacent to subplots 2, 3, and 4 using a circular sampling frame that is 30.48 cm in diameter (Fig. 2; USDA Forest Service, 2011). At each sample point, the entire litter thickness (i.e., duff and litter layers) is measured to the nearest 0.25 cm at points in each cardinal direction within the sampling frame to the point where mineral soil (A horizon) begins (O'Neill et al., 2005b). The entire litter layer (excluding live vegetation, woody debris > 0.64 cm in diameter, rocks, cones, and bark) within the confines of the sampling frame is removed for lab analysis. Litter samples are analyzed for bulk density, water content, total C, and total N (O'Neill et al., 2005b) and the laboratory results are managed as part of the Soils Lab Table (SOILS_LAB) in the publicly available Forest Inventory and Analysis database (USDA Forest Service, 2014b and Woodall et al., 2010).

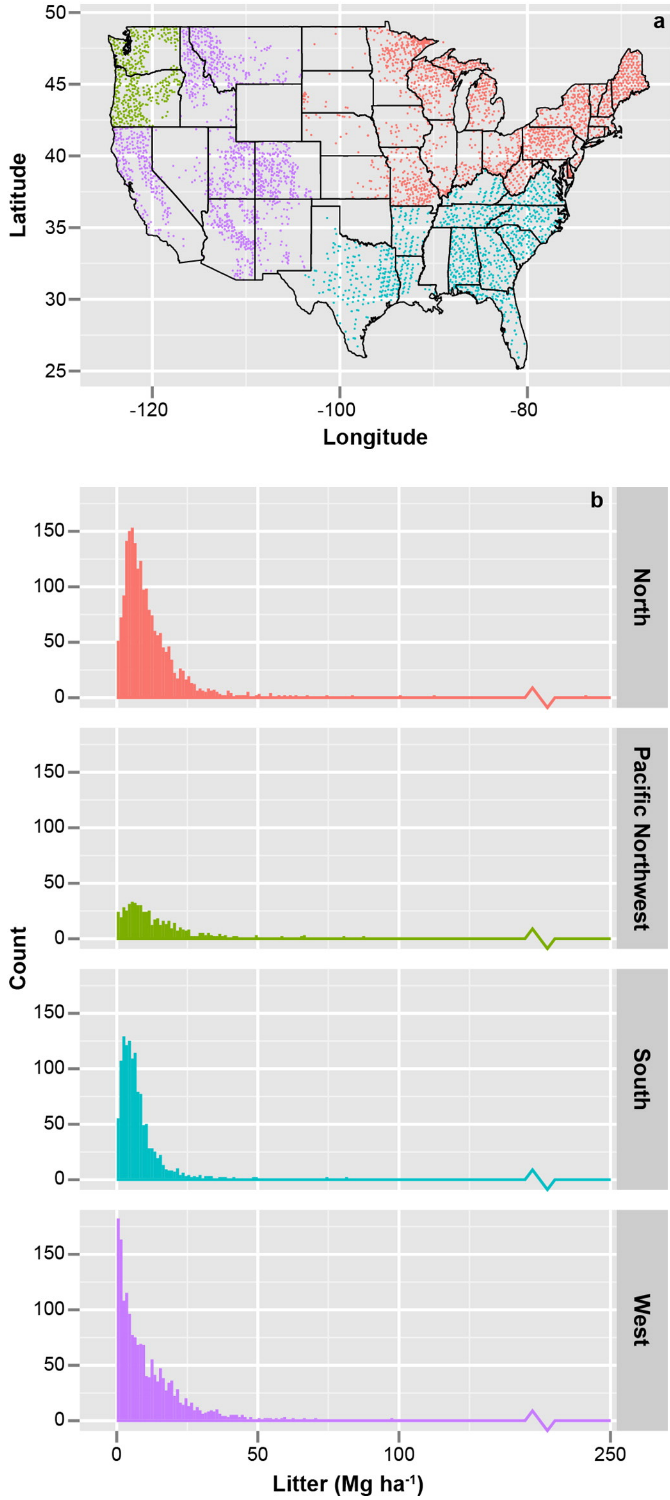

Fig. 1. Distributions of NFI plots by region in the conterminous US that have at least one forested condition and include measurements of litter attributes ($n = 4553$). Note that plot locations are approximate.

Estimates of litter (Mg C ha^{-1}) obtained directly from the NFI observations, F_{NFI}, were calculated as:

$$F_{NFI} = C\left(\frac{SW_{OD}}{A}\right) + FWD \tag{1}$$

where C was the total C (organic and inorganic) concentration in percent of the litter sample, SW_{OD} was the oven-dry sample weight of the litter material collected from the sampling frame, A was the area ($\pi \cdot 15.24$ cm^2) of the sampling frame, and FWD was the per-unit-area estimate (Mg C ha^{-1}) of medium and large fine woody debris with large-end diameter ≤ 7.50 cm (Woodall and Monleon, 2008).

The country-specific model (Smith and Heath, 2002) included two basic components, net accumulation and decay. The assumption was that net accumulation of litter C mass increased with stand age. The model passes through the origin, represents continuous net accumulation with stand age, and the rate of accumulation decreases so that the line approaches an asymptote. The country-specific predictions of litter C, F_{CS}, included medium and large fine woody fragments and were calculated as:

$$F_{CS} = \frac{C_A Age}{C_B + Age} + \overline{D}_A e^{-\left(\frac{Age}{\overline{D}_B}\right)} \tag{2}$$

where C_A and C_B were region- and forest type-specific coefficients describing net litter C accumulation based on the assumption that litter C mass increased with *Age*, which was stand age in years, $\overline{D}_A$ was the mean litter C mass of mature forests, $\overline{D}_B$ was the mean residence time of litter C mass, and e was the exponential function.

2.2. Country-specific model evaluation

Before evaluating an alternative approach for estimating litter C in the national greenhouse gas inventory, the country-specific model predictions currently used in the national greenhouse gas inventory (F_{CS}) were compared with estimates from the NFI (F_{NFI}) using two approaches. First, two one-sided tests of equivalence (Wellek, 2003 and Robinson and Froese, 2004) were used to compare F_{CS} and F_{NFI} by forest type and region. We used a conservative region of indifference (i.e., tolerance interval ± 25% of the standard deviation) for the equivalence test, although any region may be specified for comparison. Under the two one-sided tests, when using a nominal $\alpha = 0.05$, equivalence is demonstrated if the 90% confidence limit of the absolute value of the mean of the differences between estimates fall within the tolerance interval. Confidence intervals (t-based) for the mean were calculated following standard parametric procedures.

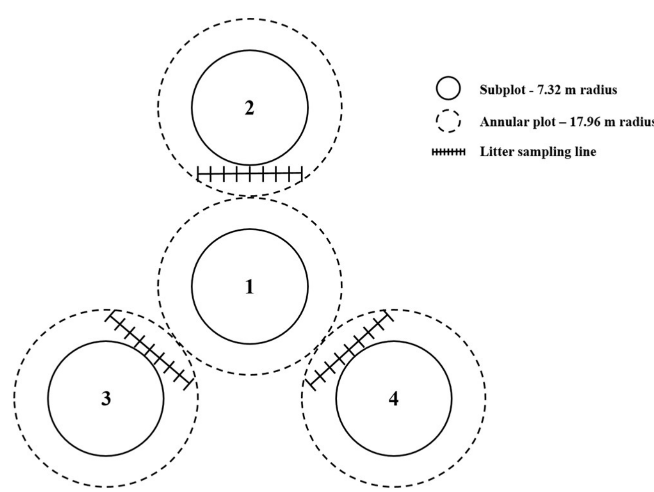

Fig. 2. Forest inventory and analysis plot diagram. Each permanent ground plot comprises a series of smaller fixed-radius (7.32 m) plots (i.e., subplots) spaced 36.6 m apart in a triangular arrangement with one subplot in the center. Litter variables are sampled as a complete unit on plots adjacent to subplots 2, 3, and 4 using a circular sampling frame that is 30.48 cm in diameter. Litter samples are collected at every other plot remeasurement at a new location along the litter sampling line.

Next, region- and forest type-specific predictions of litter C were compared with estimates from the NFI using a metric known as modeling efficiency (Nash and Sutcliffe, 1970 and Vanclay and Skovsgaard, 1997):

$$EF = 1 - \frac{\sum (F_{NFI} - F_{CS})^2}{\sum (F_{NFI} - \overline{F}_{NFI})^2} \tag{3}$$

where F_{CS} and F_{NFI} have previously been defined and $\overline{F}_{NFI}$ is the mean estimated litter C stock per unit area by region and forest type. Differences between F_{CS} and F_{NFI} were also mapped to visually evaluate geographic trends in litter C across the US.

2.3. Model development

Despite the considerable investment in sampling thousands of NFI plots for litter attributes across the US, more than 96% of sample points lack empirical estimates of litter C based on NFI measurements. Ignoring the sample points that lacked litter C measurements was not an option given the relatively small sample size and the fact that the litter C sample in the NFI did not extend across the entire United Nations Framework Convention on Climate Change reporting period. As an alternative, replacing F_{CS} predictions with estimates from the NFI using imputation procedures was investigated during initial data exploration. The imputation approaches included: 1) replacing F_{CS} on plots without F_{NFI} with the mean from the same stratum to which a plot with no F_{NFI} was assigned; 2) replacing F_{CS} on plots without F_{NFI} with the stratum mean and a number represented the uncertainty in the stratum sample mean and observed variability around this mean; 3) replacing F_{CS} on plots without F_{NFI} randomly selected from F_{NFI} ($k = 1, 3, 5, 10, 20$) most similar (based on proxies for soil forming factors and other site characteristics from the NFI) to plots lacking an F_{NFI} for each region; and 4) replacing F_{CS} on plots without F_{NFI} with the mean of F_{NFI} ($k = 1, 3, 5, 10, 20$) most similar (based on proxies for soil forming factors and other site characteristics from the NFI) to plots lacking a F_{NFI} for each region. However, the relatively small number of F_{NFI} estimates in the NFI and the lack of empirical estimates on most NFI plots returned the same F_{NFI} estimate many times in the database used to compile estimates for the national greenhouse gas inventory, resulting in bias and artificial reductions in variance in all the aforementioned approaches evaluated. Several parametric and nonparametric regression approaches were evaluated to predict litter C for all NFI plots lacking observations. The first phase of model selection was to partition the NFI data that included litter observations into training and testing groups and then evaluate the predictions against the observations — both graphically and using root mean square error and modeling efficiency. In addition, the regression approaches needed to easily accept a variety of data types, tolerate missing observations, capture the range of variability of litter C observations, be adapted to accommodate data limitations, and incorporate new information as it becomes available. Given all of these criteria, a nonparametric modeling approach was selected for further evaluation.

Random Forests is a machine learning tool that uses bootstrap aggregating (i.e., bagging) to develop models to improve prediction (Breiman, 2001). Random Forests also relies on random variable selection to develop a forest of uncorrelated regression trees. These trees recognize the relationship between a dependent variable (y), in this case litter C stocks, and a set of predictor variables (X). The learning algorithms use recursive partitioning to split the data based on the predictors to create homogenous groupings of the dependent variable. The recursive partitioning continues until either the subset of y at each node is the same value or further splitting adds no value. A random subset of predictors (selected without replacement) is used to determine the split for each node. Bootstrap resampling is used to develop B replicates of each regression tree, Θ. Each b bootstrap sample is selected by sampling n observation from (y, X) with replacement to create (yb, Xb). Approximately two-thirds of the original estimates are in the bootstrap sample (in bag) and one third is out of bag denoted by the superscript b and $-b$ respectively. Θb is then developed for each b bootstrap sample. The random forest is the ensemble ($\Theta 1$, $\Theta 2$, $\Theta 3$, …, ΘB).

Many predictors were evaluated using random forests' variable selection and Spearman's rank correlation coefficient. These included attributes measured on base intensity plots in the NFI as well as auxiliary information that directly or indirectly related to soil forming factors. The attributes included in the variable selection (both continuous and categorical variables) obtained from the NFI included: latitude, longitude, elevation, slope, aspect, forest type group, water code, stand age, physiographic class, site index, stand origin, natural disturbance code, treatment (silvicultural) code, basal area, stand density index, relative density, years since disturbance, and aboveground live tree C. United States Geological Survey digital elevation products (Danielson and Gesch, 2011) and 30-year climate norms from 1981 to 2010 (PRISM, 2012) were also included in the variable selection process. Digital elevation data were used only when NFI data were not available. Climate norms included mean annual maximum temperature, mean annual precipitation, and two variables obtained from climate norms: degree days above 5 °C, and degree days above 5 °C during the growing season (Rehfeldt, 2006). A ratio of precipitation to potential evapotranspiration was also included as a growing season moisture index (Akin, 1991).

Due to regional differences in sampling protocols during periodic Forest Inventory and Analysis inventories (pre-1999) many of the predictors included in the variable selection process were not available across the entire United Framework Convention on Climate Change reporting period. To avoid problems with data limitations and model overfitting, the list of variables were pruned using training and testing groups to reduce the random forests to the minimum number of relevant predictors (including both continuous and categorical variables) without substantial loss in explanatory power or increase in root mean square error. The random forests models were trained using 70% of the NFI dataset ($n = 3684$) and tested using the remaining data ($n = 1579$). This process was repeated multiple times, splitting the data randomly each time. The general form of the final random forests models were:

$$F_{RF} = f(elev, lon, above, gmi, fortypgrp, ppt, t\max, lat) \tag{4}$$

where $elev$ = elevation, lon = longitude, $above$ = aboveground live tree carbon (trees ≥ 2.54 cm dbh), gmi = the ratio of precipitation to potential evapotranspiration, $fortypgrp$ = forest type group, ppt = mean annual precipitation, $t\max$ = mean annual maximum temperature, and lat = latitude. The random forests model predictions, F_{RF}, were then summed with a number, u, to represent the uncertainty in the predictions resulting from the sample-based estimates of the model parameters and observed residual variability around the predictions. For each replacement, u was independently and randomly generated from a $N(0,\sigma)$ distribution with σ incorporating the variability from both sources. Each model prediction was replaced independently m times and m separate estimates were combined following Rubin (1987):

$$\overline{F}_{RF} = \frac{1}{m}\sum_{k=1} F_{RF}^{k} \tag{5}$$

where $\overline{F}_{RF}$ is the estimate of the mean for the kth completion of the data set. In this study, $m = 1000$, which is markedly larger than the $m = 2$–10 recommended by Rubin (1987) but given the small number of plots that included litter attributes in the NFI ($n = 5263$) relative to all base intensity plots lacking litter attributes it was deemed necessary (Bodner, 2008). The predictions, $\overline{F}_{RF}$, from the test groups were compared to F_{NFI} estimates graphically and using the root mean square error, two one-sided tests, and modeling efficiency. All analyses were conducted using *R* statistical software, version 2.15.2 (R Development Core Team, 2014). Specifically, the 'randomForests' package (Liaw and Wiener, 2002) was used to develop the random forests model, the 'equivalence' package (Robinson, 2014) was used for model comparisons, and the 'ggplot2' package (Wickham, 2009) was used to develop figures.

3. Results

Estimates of litter stocks, F_{NFI}, obtained from measurements of litter attributes and estimates of *FWD* in the NFI ranged from 0.0004 to 238.71 Mg C ha^{-1}, with an estimated mean of 9.99 ± 0.14 Mg C ha^{-1} (mean ± standard error) (Table 1). The wide range of litter C stocks observed was not indicative of the distribution of litter estimates from the NFI (Fig. 1b) but rather a single plot with the maximum estimated number of *FWD* pieces allowed ($n = 999$) which resulted in an estimated 227.94 Mg C ha^{-1} from *FWD* alone. In most regions and forest types, *FWD* represented a relatively small proportion of total litter C stocks (Table 1). Mixed hardwood stands in the North and South had the largest ratio (0.40) of *FWD* to litter material in stocked forests while conifer-dominated stands generally had a smaller proportion of *FWD*. That said, conifer-dominated stands generally had the highest mean estimated litter C stocks across the US (Table 1).

Regionally, forests in the Pacific Northwest had the highest estimated mean litter C stocks at 13.91 ± 3.48 Mg C ha^{-1} and also the highest estimated mean aboveground live tree C stocks (85.23 ± 21.35 Mg C ha^{-1}). Southern forests had the lowest estimated mean litter C stocks at 7.04 ± 0.78 Mg C ha^{-1} and the lowest estimated mean aboveground live tree C stocks (33.07 ± 3.01 Mg C ha^{-1}). Both hardwood (i.e., aspen-birch and maple-beech-birch) and softwood (spruce-fir and pine) forests in the Northern US had high mean estimated litter C stocks relative to the aboveground live tree C stocks seen in other regions. In the West, mixed conifers and pine forests had the highest mean estimated litter C, 15.55 ± 0.45 and 12.08 ± 0.57 Mg C ha^{-1}, respectively.

3.1. Model comparisons

3.1.1. Country-specific predictions vs. NFI estimates

In general, the country-specific model predictions (F_{CS}) showed a substantial upward bias resulting in statistically significant differences from NFI estimates (F_{NFI}) in nearly every region and forest type (Fig. 3, Table 1). The country-specific model predictions of litter C stocks (per-unit-area) were, on average, more than 87% (8.77 ± 0.19 Mg C ha^{-1}) larger than NFI estimates. In nearly all cases, the estimated means, $\overline{F}_{NFI}$, were better predictors of litter C stocks by region and forest type than the country-specific model with an overall modeling efficiency = −1.63 and a root mean square error = 16.12 Mg C ha^{-1}. While country-specific model predictions for mixed hardwood forests in the North and mixed conifer-hardwood and mixed hardwood forests in the South were statistically equivalent to NFI estimates (Table 2), only the F_{CS} for mixed hardwood forests in the North was a marginally better predictor (modeling efficiency = 0.06) than the estimated mean, $\overline{F}_{NFI}$ for that region and forest type (Table 2).

The range of F_{CS} was relatively narrow (2.23–72.18 Mg C ha^{-1}) compared to the broad range of F_{NFI} (0.0004–238.71 Mg C ha^{-1}) resulting in poor model fits and large differences by forest type group and region (Fig. 3). The largest differences in litter C stocks, excluding the redwood/sequoia forest type which only had 2 observations for comparison, were in the Western US (Table 2) where F_{CS} in the pinyon–juniper, hardwood, and nonstocked forest types were 4.3 (16.15 Mg C ha^{-1}), 3.6 (20.48 Mg C ha^{-1}), and 3.5 (12.03 Mg C ha^{-1}) times larger than NFI estimates, respectively. The nonstocked forest types in the Pacific Northwest and South were more than 2 times (10.58 and 2.74 Mg C ha^{-1}, respectively) smaller than NFI estimates of litter C stocks (Table 1).

3.1.2. Random forests predictions vs. NFI estimates

The relationships between the dependent variable, litter C stocks, and the 7 continuous predictor variables identified by random forests variable importance were evaluated using Spearman's rank correlation to identify potential relationships. Aboveground live tree C was positively correlated (0.38) with litter C stocks as were *gmi* (0.36), *lat* (0.32), *ppt* (0.18), *elev* (0.06), and *lon* (0.06) while *t*max was negatively correlated (−0.36). The random forests model with error term (Eq. (5)) had an overall modeling efficiency = 0.25 and a root mean square error = 8.83 Mg C ha^{-1}. Mean differences between F_{NFI} and $\overline{F}_{RF}$ ranged from −1.28 Mg C ha^{-1} in the spruce/fir/hemlock forests of the Pacific Northwest to 3.63 Mg C ha^{-1} in nonstocked stands in the same region, although

Table 1
Summary statistics (mean and standard deviation (SD)) of country-specific litter predictions (F_{CS}), litter estimates (F_{NFI}), aboveground live tree C (*AGLTC*) stocks and estimated fine woody debris and litter material (all in Mg C ha^{-1}) from observations obtained from the Forest Inventory and Analysis database by region and forest type group.

			$\overline{F}_{CS}$		$\overline{F}_{NFI}$		Fine woody debris			Litter material			AGLTC	
Region	Forest type	*n*	Mean	SD	Mean	SD	Mean	Min	Max	Mean	Min	Max	Mean	SD
All regions	All forest types	5263	18.77	11.88	9.99	9.94	2.19	0.00	227.94	8.01	0.00	111.59	47.23	47.87
North	Aspen/birch	216	8.64	1.67	12.28	9.83	3.25	0.00	37.45	9.20	0.07	62.74	31.49	21.05
	Mixed conifer/hardwood	58	26.91	5.21	9.77	7.38	1.99	0.00	7.36	7.78	0.31	32.38	52.51	29.07
	Mixed hardwood	858	7.66	1.91	8.75	8.77	2.51	0.00	82.30	6.29	0.07	111.59	56.88	35.00
	Nonstock	20	4.80	0.00	5.44	9.50	0.83	0.00	4.45	4.35	0.08	17.85	0.67	0.86
	Northern hardwood	466	26.56	4.13	12.98	13.59	3.67	0.00	227.94	9.36	0.09	73.67	63.27	35.85
	Pine	129	12.88	1.77	14.20	9.98	2.74	0.00	45.18	11.53	0.17	56.84	47.71	30.22
	Spruce/fir	178	31.40	7.45	13.07	10.01	2.39	0.00	19.64	10.74	0.04	54.03	31.35	22.51
PNW	Douglas-fir/hemlock	182	32.34	13.38	14.77	12.49	3.12	0.00	15.88	13.14	0.55	86.10	136.59	112.29
	Hardwood	51	8.48	3.09	9.75	10.99	2.04	0.00	6.32	8.67	0.33	64.96	83.73	91.30
	Nonstock	7	7.50	0.79	18.08	23.30	16.01	0.13	37.98	11.22	0.06	27.12	0.89	1.12
	Spruce/fir/hemlock	19	37.12	8.23	13.04	9.18	1.75	0.24	4.58	12.21	1.76	31.07	119.72	138.82
South	Mixed conifer/hardwood	112	9.34	2.17	8.49	9.39	2.36	0.00	73.14	6.13	0.17	27.56	43.97	30.02
	Mixed hardwood	651	6.06	2.16	6.73	6.04	1.93	0.00	34.31	4.82	0.06	48.86	46.17	39.18
	Nonstock	20	2.70	0.00	5.17	5.26	0.85	0.00	9.21	4.59	0.29	29.92	1.04	2.00
	Pine	421	9.64	2.63	7.48	6.21	1.47	0.00	16.48	6.03	0.02	74.07	41.46	33.40
West	Hardwood	378	28.41	4.04	7.86	7.94	1.46	0.00	15.91	6.73	0.00	65.44	32.48	39.76
	Mixed conifer	627	37.19	3.95	15.55	11.38	2.14	0.00	36.47	13.82	0.03	68.77	53.11	49.35
	Nonstock	77	17.30	0.00	4.98	6.30	1.26	0.00	9.63	3.84	0.02	31.18	1.55	3.10
	Pine	331	23.12	3.30	12.08	10.41	1.54	0.00	10.44	10.85	0.15	96.37	37.90	28.82
	Pinyon/juniper	460	21.10	0.00	4.95	6.01	1.21	0.00	14.59	3.85	0.00	33.01	13.02	10.77
	Redwood/sequoia	2	60.37	2.11	8.99	9.33	0.78	0.78	0.78	8.60	1.61	15.59	301.08	3.48

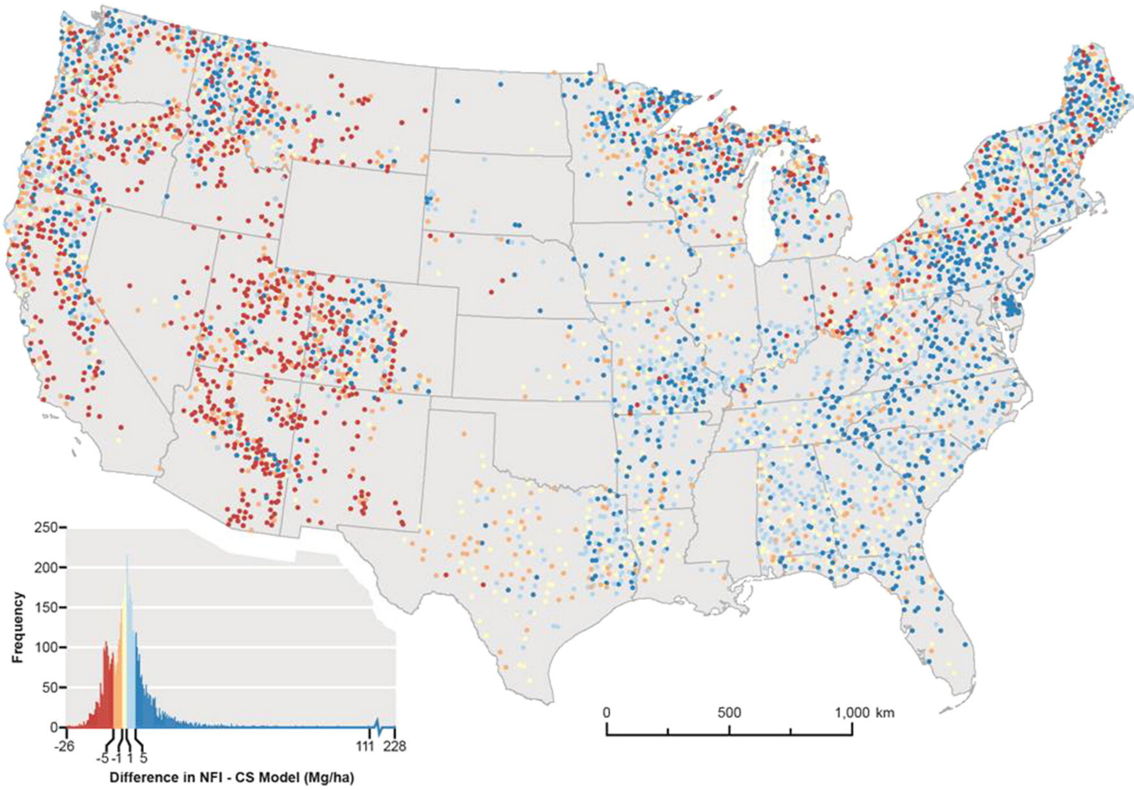

Fig. 3. Differences between estimates of litter C stocks (Mg ha^{-1}) from the national forest inventory (NFI) and country-specific (CS) model predictions previously used in National Greenhouse Gas Inventory reports. Only NFI plots which include measurements of litter attributes in the conterminous US are displayed.

both types had a relatively small number of plots for comparison ($n = 19$ and 7, respectively). In general, the random forests model slightly overpredicted litter C stocks relative to NFI estimates in most regions and forest types, although most of the overpredictions were not statistically significant (Table 2, Fig. 4). In the nonstocked forest type across all regions, the $\overline{F}_{RF}$ was statistically significantly different than F_{NFI}. Otherwise, significant differences were only observed in regions and forest types with a relatively small number of samples for model fitting and comparison.

3.1.3. Country-specific predictions vs. random forests predictions

The country-specific model was previously used to predict litter C stocks for all sample points included in the estimation of litter C in the national greenhouse gas inventory report (US EPA, 2014). To evaluate

Table 2
Equivalence test results of litter C stocks (Mg C ha^{-1}) by region and forest type group. Mean = mean difference, SE = standard error of the mean difference, and TOST is two-one-sided test results where NE = not equivalent and E = equivalent where the absolute value of the mean of the differences is ±25% of the standard deviation.

		$F_{NFI}-F_{CS}$			$F_{NFI}-\overline{F}_{RF}$			$F_{CS}-\overline{F}_{RF}$		
Region	Forest type group	Mean	SE	TOST	Mean	SE	TOST	Mean	SE	TOST
All regions	All forest type groups	−8.77	0.19	NE	−0.11	0.06	E	8.67	0.16	NE
North	Aspen/birch	3.65	0.67	NE	0.01	0.30	E	−3.64	0.41	NE
	Mixed conifer/hardwood	−17.14	1.02	NE	−0.48	0.42	NE	16.66	0.91	NE
	Mixed hardwood	1.09	0.30	E	−0.15	0.13	E	−1.24	0.20	NE
	Nonstocked	0.37	1.18	NE	−0.64	0.55	NE	−1.02	0.75	NE
	Northern hardwood	−13.58	0.64	NE	−0.09	0.32	E	13.49	0.36	NE
	Pine	1.32	0.84	NE	0.25	0.38	E	−1.07	0.54	NE
	Spruce/fir	−18.33	0.95	NE	−0.22	0.33	E	18.11	0.73	NE
PNW	Douglas-fir/hemlock	−17.57	1.19	NE	−0.02	0.38	E	17.55	1.00	NE
	Hardwood	1.27	1.63	NE	−0.35	0.72	NE	−1.62	1.00	NE
	Nonstocked	10.58	8.84	NE	3.63	4.90	NE	−6.95	4.01	NE
	Spruce/fir/hemlock	−24.08	2.72	NE	−1.28	0.98	NE	22.80	2.08	NE
South	Mixed conifer/hardwood	−0.85	0.89	E	0.39	0.44	E	1.24	0.50	NE
	Mixed hardwood	0.67	0.24	E	−0.14	0.10	E	−0.81	0.17	E
	Nonstocked	2.74	2.12	NE	−0.13	0.81	NE	−2.87	1.47	NE
	Pine	−2.16	0.30	NE	−0.20	0.13	E	1.96	0.21	NE
West	Hardwood	−20.55	0.45	NE	−0.14	0.16	E	20.41	0.36	NE
	Mixed conifer	−21.64	0.46	NE	−0.03	0.20	E	21.61	0.32	NE
	Nonstocked	−12.32	0.72	NE	−0.34	0.33	NE	11.97	0.47	NE
	Pine	−11.04	0.58	NE	−0.15	0.26	E	10.90	0.38	NE
	Pinyon/juniper	−16.15	0.28	NE	−0.09	0.13	E	16.07	0.18	NE
	Redwood/sequoia	−51.38	8.09	NE	−0.37	3.66	NE	51.02	4.43	NE

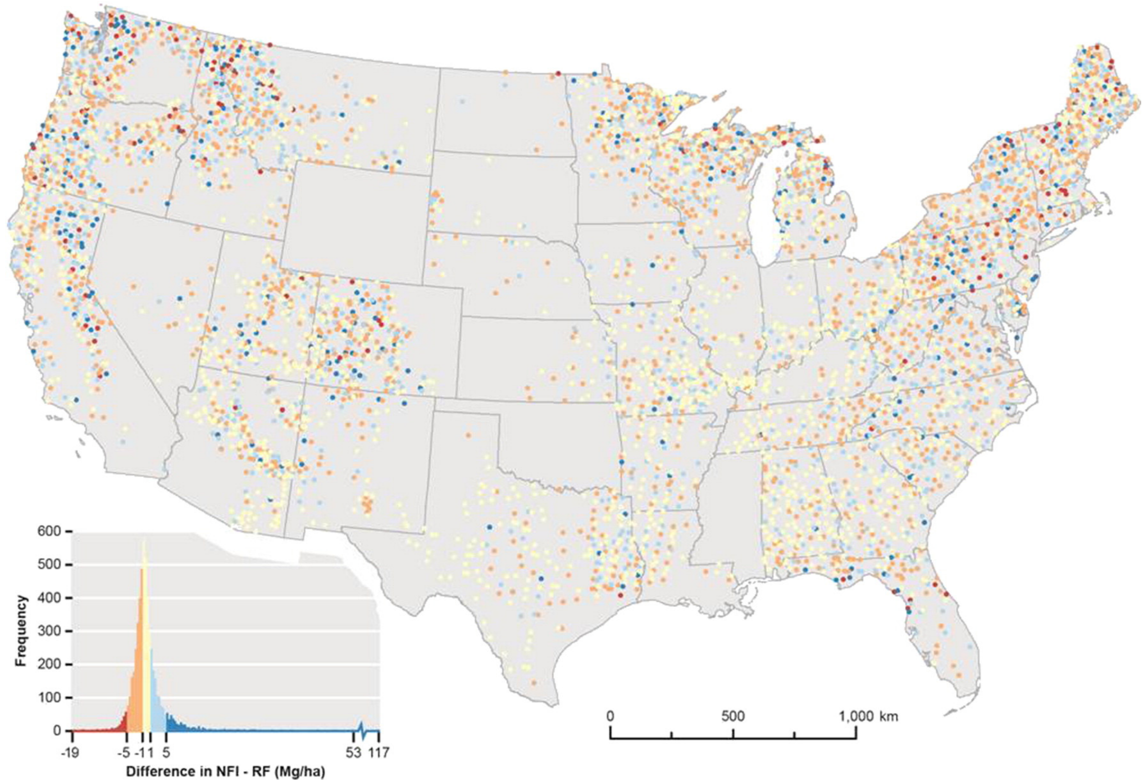

Fig. 4. Differences between estimates of litter C stocks (Mg ha^{-1}) from the national forest inventory (NFI) and random forests (RF) model predictions used in the 2015 National Greenhouse Gas Inventory report. Only NFI plots which include measurements of litter attributes in the conterminous US are displayed.

the implications of replacing F_{CS} with $\overline{F}_{RF}$ in the national greenhouse gas inventory report, we first compared the litter C stock predictions and then expanded the per-unit-area predictions to the population to assess potential changes in litter C stocks by region.

Across all regions and forest types the differences between F_{CS} and $\overline{F}_{RF}$ were statistically significant (Table 2). The differences were consistent with those observed between F_{NFI} and F_{CS} given that the majority of the region and forest type $\overline{F}_{RF}$ predictions were statistically equivalent

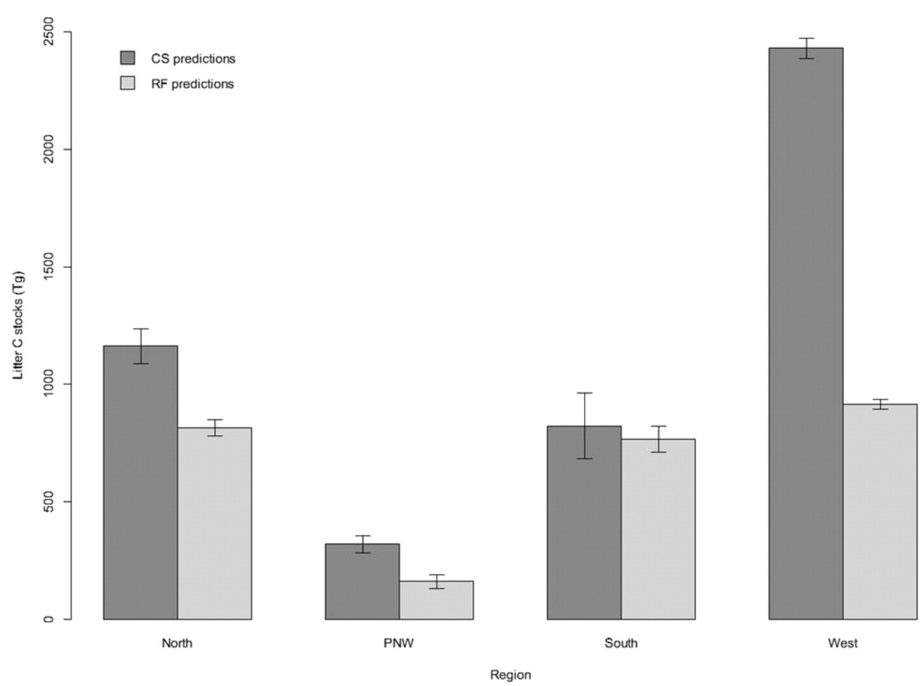

Fig. 5. Population estimates of litter C stocks (with standard errors) by major US region (see Fig. 1) obtained from random forests (RF) predictions and country-specific (CS) model predictions. Only NFI plots from the conterminous US were used to compile regional estimates.

to F_{NFI}. The largest mean differences ($F_{CS} - \overline{F}_{RF}$) were in the Western US (17.52 Mg C ha^{-1}) followed by the Pacific Northwest (16.94 Mg C ha^{-1}), North (4.50 Mg C ha^{-1}), and South (0.40 Mg C ha^{-1}).

The trends observed in litter C stock predictions carried through to the population predictions for each region (Fig. 5). Overall, the F_{CS} resulted in population estimates that were more than 44% (2081 ± 77 Tg) larger than population estimates obtained from $\overline{F}_{RF}$. The largest differences were in the West where F_{CS} predictions resulted in population estimates 62% (1517 ± 86 Tg) greater than predictions obtained using $\overline{F}_{RF}$. In the Pacific Northwest, F_{CS} resulted in population estimates that were 49% (158 ± 22 Tg) larger than estimates obtained from $\overline{F}_{RF}$ and in the North and South, F_{CS} predictions resulted in population estimates that were 30% (349 ± 39 Tg) and 7% (56 ± 5 Tg) larger, respectively (Fig. 5).

4. Discussion

The development of litter C estimates to satisfy national C monitoring efforts can be challenging given the variability associated with this C pool (Yanai et al., 2000; Böttcher and Springob, 2001; Schulp et al., 2008 and Woodall et al., 2012). Litter C stocks can exhibit large differences in development between forest types on the same soils (Ladegaard-Pedersen et al., 2005) and depths at short distances (Smit, 1999) in combination with a high vulnerability to disturbance, particularly wildfire (Stinson et al., 2011). This variability complicates not only the inventories of litter attributes but also the prediction of litter C stocks in NFIs lacking litter measurements and reporting instruments (e.g., national greenhouse gas inventory report) that require estimates that extend beyond the longitudinal time series available for estimation. In general, the Intergovernmental Panel on Climate Change guidelines for national greenhouse gas inventories suggest that countries use estimation methods consistent with their resources, and when properly implemented, they should provide unbiased estimates of emissions and sinks (IPCC, 2006).

In the US, the country-specific model has been used to predict litter C stocks and stock changes in the Forest Inventory and Analysis program and national greenhouse gas inventory report for more than a decade and was developed using an extensive list of published estimates prior to the start of litter sampling in the NFI. This approach may be characterized as an Intergovernmental Panel on Climate Change Tier 2 estimation method since it relies on activity data specific to the US by major forest type and includes other important country-specific variables (e.g., stand age) that may influence the accumulation and decomposition of litter biomass but does not directly rely on litter attributes from an inventory system (IPCC, 2006). When the country-specific model was developed, there were no NFI data available to evaluate the accuracy and precision of the model predictions and since it relied on the available information published on litter C in the US, the model predictions were assumed to be accurate. In fact, F_{CS} from this study are well within the simulated confidence bounds for the default litter C stocks specified in the Intergovernmental Panel on Climate Change guidelines, although this may be due in large part because the country-specific model developed by Smith and Heath (2002) was one of sources used to inform the Intergovernmental Panel on Climate Change defaults (IPCC, 2006).

With an extensive sample of litter C stocks across a national plot network on forest land in the US (US Forest Service, 2014b) it is now possible to evaluate the country-specific model predictions. It is not surprising that the country-specific model did not fit the NFI data well, given the high variability observed in litter C stock estimates in this study and the literature (Webster and Oliver, 1990; Smit, 1999; Yanai et al., 2000; Böttcher and Springob, 2001; Smith and Heath, 2002 and Schulp et al., 2008) and the fact the country-specific model was developed prior to initiation of litter sampling in the NFI. In general, the country-specific model produced predictions with a substantial positive bias resulting in statistically significant differences between F_{NFI} and F_{CS} in nearly every region and forest type. The large differences between F_{NFI} estimates and F_{CS} predictions can be attributed to several factors. First, the published estimates used to develop the country-specific model predictions, while extensive ($n = 582$), did not capture the range of variability in litter C stock estimates observed in the NFI. Second, the mean litter C for "mature" forests was used to develop the model coefficients, where forest stands were defined as mature when "the age was greater than 90 percent of the minimum age set for mature litter or sites where the researchers described the stand as mature" (Smith and Heath, 2002). The model was then used for all age classes and when a given forest type reached the "mature" threshold (identified by stand age), the model predictions reached an asymptote intended to represent litter C at an approximately steady state. While Smith and Heath (2002) acknowledge this simplification, it restricted the range of variability in model predictions and perhaps led to the upward-bias documented in nearly all forest types and regions. Third, mean C content estimates from the literature were used by broad forest type and region in the country-specific model whereas plot-specific C content measurements were used to obtain estimates of litter C from the NFI. Finally, given the high variability observed in the NFI litter C estimates, the country-specific model did not include important interactions between the variables included in the model as well as other variables (e.g., temperature, precipitation, biomass) that may directly and indirectly influence litter biomass accumulation and decomposition (Parton et al., 2007 and García-Palacios et al., 2013). Models of litter C that are sensitive to climate variables, physiographic factors and vegetation type are consistent with our understanding of soil formation (Jenny, 1941 and Simonson, 1959), forest growth and productivity (e.g., Weiskittel et al., 2011 and Sabatia and Burkhart, 2014), and woody debris decomposition (e.g., Russell et al., 2014).

Given the large investment in sampling litter attributes, it is now possible to transition from the Intergovernmental Panel on Climate Change Tier 2 estimation method which resulted in biased estimates of litter C stocks to a Tier 3 approach which builds on the ecological relationships identified in litter accumulation and decomposition studies (Wardle et al., 2004 and Parton et al., 2007) as well as the availability of litter C estimates in the NFI. Several alternative approaches were evaluated to replace county-specific model predictions for sample points used in the estimation of litter C stocks and stock change in the US national greenhouse gas inventory. Ultimately a modeling framework using random forests was implemented which allowed selecting from a large suite of biotic and abiotic variables with potentially complex interactions and develop a model that fit the NFI data reasonably well (when compared to the country-specific model). There are several advantages to this modeling framework over the country-specific model. First and foremost, it was fit using estimates of litter C stocks obtained directly from litter samples in the NFI. This improved both the accuracy and precision of the model predictions used to compile estimates for the national greenhouse gas inventory. Second, the random forests modeling framework included site-, stand-, and region-specific variables that make the model more sensitive to changes in forest ecosystems. This is particularly important for stock change estimates in the national greenhouse gas inventory where changes in litter inputs are driven, in large part, by changes in aboveground biomass (i.e., aboveground live tree C stocks) (Grigal and McColl, 1975 and Vogt et al., 1986). Likewise, the accumulation and decay of litter material is driven largely by temperature and/or precipitation (Meentemeyer, 1978; Berg et al., 1993; Wardle et al., 2004 and Parton et al., 2007) and, to a lesser extent, by litter composition (i.e., forest type) and soil organisms (Lavelle et al., 1993; Hattenschwiler et al., 2005 and García-Palacios et al., 2013). Third, the random forests modeling framework includes the uncertainty in the predictions resulting from the sample-based estimates of the model parameters and observed residual variability around those predictions and accounts for the large data gap that exists between the subset of NFI plots that include litter measurements and the sample points used to compile estimates from the national greenhouse gas inventory. Fourth, the modeling framework is easily adapted to accommodate data limitations over the national greenhouse gas inventory reporting period and updated as new information becomes available. This is particularly important as new litter samples and remeasurements of litter attributes become available in the NFI. The modeling framework can incorporate this new information on an annual basis to produce the most up-to-date estimates across the entire reporting period from 1990 to the present. These updates will be documented in the "Recalculations" section of United Nations Framework Convention on Climate Change reports to ensure transparency. Further, estimates from different reporting years should not be compared due to potential changes in methodology. Only estimates in a given reporting year should be compared. Although it requires additional investment to annually incorporate new measurements of litter to increase the transparency and reduce the uncertainty associated with the estimation of C litter stocks the cost may be worth the reward given the dynamics and importance of the litter C pool to global C monitoring efforts.

5. Conclusions

As we learn more about the ecological processes driving C accumulation, sequestration, and emissions in forest ecosystems, we are not only able to improve upon our estimates of forest C stocks and stock changes but also better quantify the uncertainty associated with our estimates. Thanks to a large investment in the comprehensive annual inventory of forests in the US we were able to develop a new modeling framework for the prediction of litter C stocks and stock changes that is site-specific and sensitive not only to changes in vegetation but also to major drivers of litter accumulation and decomposition in forest ecosystems, temperature and precipitation. The transition from the country-specific model to the random forests modeling framework resulted in significant artificial reductions (i.e., decreases resulting from a change in methodology rather than a biological change in litter) in C stock predictions across all regions and forest types and thus, a decrease in litter C stock estimates at the national scale. Under the Tier 2 approach, litter C stocks represented an estimated 11.7% of all forest ecosystem C in the US. The Tier 3 approach that was developed using NFI measurements of litter C accounts for uncertainty in the predictions, is sensitive to changes in forest biomass and climate, and reduces the contribution of litter C stocks to ca. 7.0% (2831 Tg) of total forest C stocks (40,177 Tg) nationally (EPA, 2015), much closer to the global estimate of 5% reported by Pan et al. (2011) — with an estimated net annual increase of 3.0–3.1 Tg C yr^{-1} over the last 5 years. We note that most estimates of litter C stocks and stock changes compiled by other nations were developed in much the same way as the country-specific model or are based on Intergovernmental Panel on Climate Change defaults (IPCC, 2006) which were developed, in part, using the country-specific model described in this study. If the trends observed here hold true for temperate forest ecosystems in other nations, the Intergovernmental Panel on Climate Change default values for the litter C pool would lead to substantial overestimates of litter C stocks and stock changes in nations' C budgets. This is a concern as nations look to these budgets to inform post-2020 C emission reduction targets and negotiate future commitments.

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