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A model for estimating windbreak carbon within COMET-Farm^{TM}

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Abstract Agroforestry as a land management practice presents a method for partially offsetting greenhouse gas emissions from agricultural land. Of all agroforestry practices in the United States, windbreaks in particular are used throughout the United States providing a useful starting point for deriving a modelling system which could quantify the amount of carbon sequestered on U.S. agricultural land and provide for broad usability. We present our first approximation to this end by presenting a model that estimates current and future stocks within multiple carbon pools of windbreak systems such as live trees, the O horizon, downed woody debris and standing dead trees. In this article, we describe each modelled process driving carbon fluxes within carbon pools including novel windbreak tree growth and mortality models. Our model is generalized by region and species group allowing us to run scenarios for any common tree species in any location within the contiguous United States. Integrated into the agricultural greenhouse gas accounting tool, COMET-Farm^{TM}, the windbreak component gives landowners and land managers power to view agroforestry systems in the same context as agricultural operations and provides an alternative to intensive biomass inventories.

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Introduction

Carbon sequestration through agroforestry has been identified as an important climate change mitigation method (Smith et al. 2007), however no complete inventory of agroforestry systems exists in the United States, and the potential role of U.S. agroforestry in greenhouse gas mitigation has not been quantified. Though the term "agroforestry" is not widely used within U.S. agricultural industries, five major classes of agroforestry systems are documented by the Natural Resources Conservation Service (NRCS) and are widely used by producers, including windbreaks, farm woodlots, silvopasture, riparian buffers and alley cropping. Assistance by the NRCS has been provided to establish agroforestry plantings on hundreds of thousands of acres of cropland and grassland in the United States (NRCS Air Quality Office—personal communication). There is growing recognition of the need to address this knowledge gap, evidenced by a June, 2014 workshop organized by the North American Agroforestry Center around this topic (Schoeneberger et al. in prep).

We developed biomass carbon accumulation models for use in an inventory in U.S. agroforestry systems, and also to be used within the agroforestry module of the online, web-based COMET-Farm™ greenhouse gas accounting tool (available online at: http://cometfarm.nrel.colostate.edu) to aid decision makers in assessing the greenhouse gas consequences of adding, renewing, modifying, or removing agroforestry systems.

In this paper we describe a modelling framework that incorporates a set of species- and region-specific growth models to account for tree carbon sequestration, paired with models to describe tree death and carbon cycling. We focus on windbreak systems given their prevalence throughout the U.S. (Montagnini and Nair 2004) and their importance within U.S. Department of Agriculture Conservation Planning (USDA 2015) as a means for reducing soil erosion and improving crop yields. Since using off-the-shelf forest-based models is unsuitable for agroforestry systems (CAST 2011), our framework blends models that were fit using actual windbreak data and, where appropriate, forest-based models.

Model overview

Our biomass and growth modelling system, subsequently referred to as the windbreak carbon model (WCM), annually tracks the carbon mass from living and dead vegetation in windbreak systems on an individual tree basis. WCM was designed to maximize utility and as such generalizes windbreaks by their respective land resource region (LRR; NRCS 2006), and each windbreak species by its species group. The LRR scheme used is modified from NRCS (2006) by splitting 5 land resource regions in 2 to reduce climate variability within the regions, delineating 25 rather than 20 LRRs identified by NRCS (2006) (Fig. 1; Supplementary Table 1). Climatic variability is a source of error in ecosystem models, and to minimize climate contributions to model error terms we examined mean annual temperature and precipitation at the Major Land Resource Areas (MLRA) level within the LRR. We split LRRs into smaller land areas along MLRA boundaries in the LRRs where mean annual temperature varied by more than 2 °C or total precipitation by more than 10 cm. Species groups are a classification schema pooling individual species into 10 species groups using taxonomic relationships and wood specific gravity to aid in generalized allometric models (Jenkins et al. 2003). We performed all analyses and modeling in R (R Core Development Team 2014) using the package 'quantreg' (Koenker 2015).

Carbon pools

In each annual time step, WCM computes the mass of carbon, or stock, within each pool. Five carbon pools are tracked: overstory live trees representing the aboveground and belowground stock of woody perennial plants with a diameter at breast height (dbh) of at least 2.5 cm; the understory constituting above- and belowground stock of herbaceous vegetation, shrubs, and trees with a dbh less than 2.5 cm; standing dead trees which represent aboveground and belowground stock from recent mortality of trees not yet fallen over; downed woody debris, fallen woody material with a diameter at least 7.6 cm; and the O soil horizon, comprising the materials above mineral soil (Fig. 2). Pools were delineated to be compatible with both USDA and EPA protocols for greenhouse gas

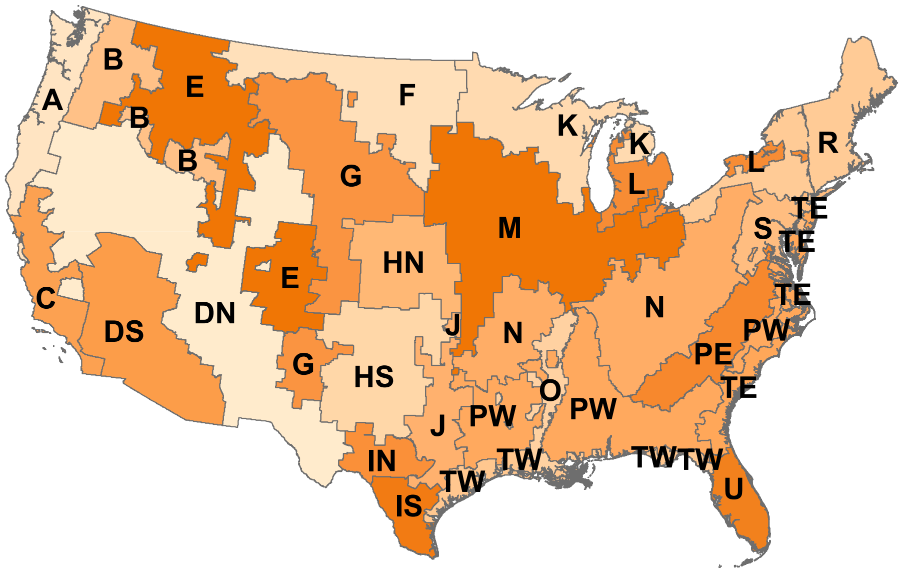

Fig. 1 Map of land resource regions, labeled by *alphabetical code*, within the contiguous United States (adapted from USDA 2006)

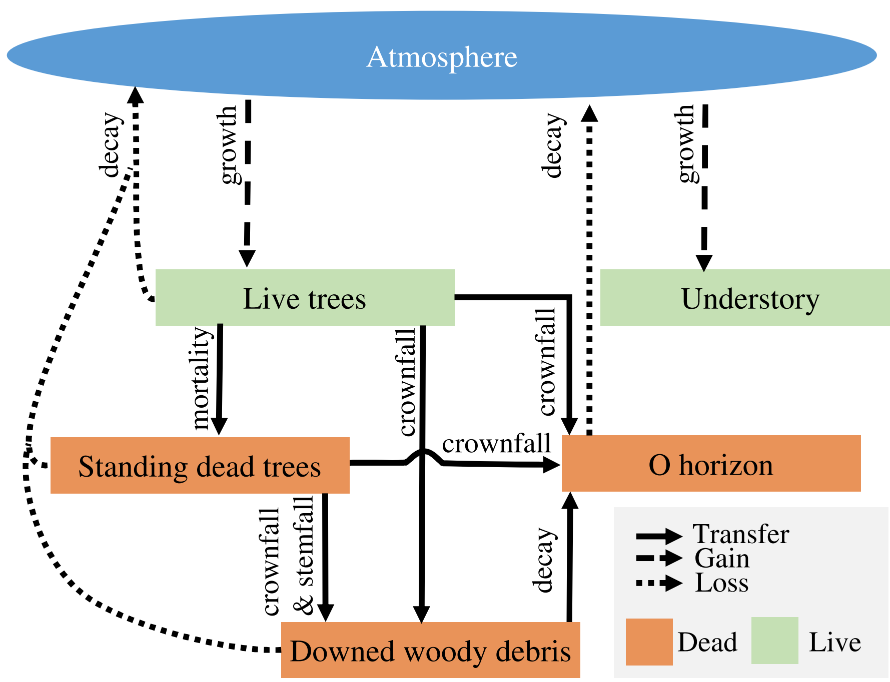

Fig. 2 Carbon pools (*boxes*) and ecological processes (*arrows*) tracked in the windbreak carbon model

inventories (Hoover et al. 2014; US Environmental Protection Agency 2014).

Each pool is also broken into components and components into sub-components where the added specificity is required to model processes. Overstory live trees and standing dead tree pools are divided into coarse root, stem and tree crown components. We further subdivide the crown component into foliage and four diameter size classes of branchwood: less than 0.6 cm, between 0.6 and 2.5 cm, 2.5–7.6 cm and greater than 7.6 cm. The O horizon comprises the duff and litter components, of which litter is further subdivided into foliage fall and branch fall from the three smaller branchwood diameter size classes. The understory pool consists of three components: trees less than 2.5 cm dbh, with sub-components akin to live overstory trees, shrubs and herbaceous vegetation. The downed woody debris pool is solely the fall of branches or main stems over 7.6 cm in diameter.

Modeled processes

Tree growth

In WCM, the tree growth process determines how much belowground and aboveground carbon stock accrues over time. The growth models behind the tree growth process were developed specifically for windbreak trees using preexisting datasets and in such a way as to negate detailed inputs regarding site conditions or stand level characteristics such as tree stocking rates; instead each growth model requires just species group and LRR as inputs. We trained a range of growth models from a forest inventory database, tested the resulting estimates of carbon stock on a windbreak inventory database, and selected the models best representing windbreak growth to compile a set of growth models.

Training growth models

As comprehensive studies or inventories of windbreak growth are lacking, we used data from the national forest inventory of the U.S. conducted by the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) Program. FIA plots are systematically distributed approximately every 2428 hectares across the 48 conterminous states. Each plot which contains a forest land use is comprised of a series of smaller plots (i.e., subplots) where tree- and site-level attributes—such as diameter at breast height and tree height—are measured at regular temporal intervals (Bechtold and Patterson 2005), and this information is populated into a database (Woodall et al. 2011). Of the entire FIA database, we selected those tree records that had been remeasured, c. 2,000,000 trees. The information from the revisited plots included dbh measured at each visit, species, state and county location.

We used quantile regression to estimate parameters relating 5-year periodic annual increment (PAI), the change in dbh over 5 years of growth, to dbh using FIA data. Whereas ordinary least squares regression describes the conditional mean response of the dependent variable, quantile regression describes the response of a conditional percentile of the distribution of the dependent variable (Cade and Noon 2003). Quantile regression can be used to fit linear functions on any desired conditional quantiles, denoted as τ, which can range from 0 to 1. The advantage of this method of linear regression is that we could fit parameters to a range of responses of PAI to dbh. After assigning species group by species and LRR by state and county, we estimated parameters for each τ of PAI, from 0.01 to 0.99, in intervals of 0.01, for each species group in each LRR, using the model form:

$$\ln(\mathrm{PAI}) = \beta_0 + \beta_1 \ln(\mathrm{dbn}) + \beta_2 \mathrm{dbh}^2 \tag{1}$$

where PAI is the positive change in dbh observed in the FIA database, in Δ cm year^{-1}, normalized over 5 years, and dbh (cm) is the initial measurement. Dbh was chosen as a predictor due to its ease of measurement and the model form used (Eq. 1) has been successfully applied to a range of trees globally (Assmann 1970; Wykoff 1990; Huber and Sterba 2009). The quadratic term in the equation is zero, or negative and small in magnitude. In the latter case, this term characterizes decline in growth at older tree ages potentially associated with physiological changes at the tree level and reductions in nutrient availability within older stands (Ryan et al. 1997).

Testing and selection of growth models

The next step was to identify what degree of tree growth observed from FIA best described growth in windbreaks. We used the USDA Natural Resources Conservation Service's Ecological Site Inventory (ESI) database to test each parameterization of the growth model for each species group and LRR combination. The ESI includes a series of observations of windbreaks across the U.S; while FIA was designed to capture trends over time, ESI was designed to aid in site descriptions and provide a baseline inventory for management decision-making. As a result, the ESI database captured a snapshot of conditions for c. 9800 windbreak rows. As windbreak rows tend to be relatively homogeneous, each windbreak row record has associated tree measurements such as total tree age, species, and dbh.

To test the fitted parameters for each τ, we compared the dbh observed in the ESI dataset against dbh predicted from Eq. 1. We assumed that it took 5 years for any tree to reach 2.5 cm dbh (e.g. Lukaszkiewicz and Kosmala 2008). We acknowledge this is a potentially confounding issue, as sapling growth can vary by region, species, site index (Nigh and Everett 2007). Lacking continental-scale data on windbreak sampling tree growth, we proceeded with this assumption in the hopes that it may be improved in the future. Then in an iterative process, we solved for PAI starting from 5 years of age, added the estimated value to dbh starting from 2.5 cm, and then solved for PAI again forming an array of dbh on tree age. Diameter at breast height values between each 5 years of age were linearly interpolated. We formally examined the fit of parameters for each τ, for each species group in each LRR, using a pair of fit statistics:

$$\text{Mean Bias} = \frac{1}{n}\sum_{i=1}^{n}\left|\left(Y_i - \hat{Y}_i\right)\right| \quad (2)$$

$$\text{Mean Percent Error} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(Y_i - \hat{Y}_i\right)}{Y_i} \quad (3)$$

where n is the number of observations, Y_i is is the observed value and $\hat{Y}_i$ is the actual value. For each species group in each LRR, we desired to choose the parameters (1) that would minimize mean bias and mean percent error, (2) on the condition that the quadratic term in Eq. 1 was positive rather than zero or negative. By repeating this process over each species group in each LRR, we were able to quantitatively judge 99 equations describing the whole spectrum of tree growth observed in FIA as applied to windbreaks. The selected parameters for the best judged τ were incorporated into WCM to describe the relationship of tree age to dbh.

We repeated this process of training on FIA records and testing on ESI records for all species groups pooled across LRRs as well. Where the data limited our ability to fit models for a given species group and LRR, the nationally pooled parameter fitting ensured full coverage over the contiguous U.S. Fit statistics of the selected growth models are provided in Supplementary Table 2.

Allocating carbon stock among tree components

Aboveground and belowground tree carbon stock at each year of growth were estimated using the predicted dbh and the allometric equations for each species group as reported by Jenkins et al. (2003). The allometric equations were designed to produce biomass estimates for trees in forests; however, open-grown trees, such as in windbreaks, generally have a greater proportion of biomass in the crown than in forest-grown trees (Zhou et al. 2007). Using the dbh-based correction factors supplied by Zhou et al. (2014) for green ash (*Fraxinus pennsylvanica* Marsh.) and eastern redcedar (*Juniperus virginiana* L.), for hardwood and softwood species respectively, we were able to adjust relative proportion of biomass in stems downward and crowns upward. Using these two sources of equations, we were to divide aboveground biomass stock into the crown, stem, and coarse root components appropriately. Subsequently, we converted biomass to carbon stock using a factor of 2:1 (IPCC 2003). We then subdivided crown carbon stock within crown subcomponents using allometric equations from various studies mapped to each species group (Table 1).

Tree mortality

We determined the proportion of trees in the live overstory that move to the standing dead pool annually. In forest systems, mortality is typically modeled as a function of stand density (e.g. Ryan et al. 1997; Rebain 2010); this basic tenet, known as self-thinning, holds that stands, at full-stocking, obey a maximum density for a given average size of the individual tree. However, application of a density-driven algorithm for our model is tenuous given the unique open-grown environment of windbreaks. Instead, we used an age-driven approach knowing that studies of tree demography have shown a relationship of tree age with risk of mortality (Harcombe 1987).

Tree survival regression

To determine rates of mortality as a function of tree age, we regressed percent survival on total age (i.e.,

Table 1 Mapping of species groups to species and sources of crown subcomponent proportioning

Species group	Species mapping and equation source
Aspen, alder, cottonwood, willow	Quaking aspen, Loomis and Roussopolous (1978)
Cedar, larch[a]	Western red-cedar, Western larch, Brown and Johnston (1976)
Douglas-fir	Douglas-fir, Brown and Johnston (1976)
Hard maple, oak, hickory, beech	Northern red oak, Loomis and Blank (1981)
Juniper, oak, mesquite	One-seed juniper, Grier et al. (1992)
Mixed hardwood	Northern red oak, Loomis and Blank (1981)
Pine	Ponderosa pine, Brown and Johnston (1976)
Soft maple, birch	Northern red oak, Loomis and Blank (1981)
Spruce	Engelmann spruce, Brown and Johnston (1976)
True fir, hemlock[a]	Subalpine fir, Western hemlock, Brown and Johnston (1976)

[a] Species group split by genus

years since seedling establishment), recorded in each windbreak row in the ESI dataset. These regressions for survivorship were fit with a negative logarithmic curve; mortality is greatest immediately after tree establishment and gradually decreases over time. This is the most typical pattern observed in tree populations, especially in even-aged systems (Goff and West 1975; Harcombe 1987). The survivorship curves were fit on the equation:

$$\text{Survival}_t = exp(4.60517 + \beta_1 t) \quad (4)$$

where survival_t is percent of trees surviving at age t. In an initial attempt, a survivorship curve was fit for each species group, but small sample sizes and lack of observations at older ages was limiting though the results hinted that hardwoods generally had lower survivorship rates than softwoods. Thus, survivorship curves were fit on all hardwoods species and on all softwood species separately, yielding two solutions (Table 2). Our results predicted that a population of hardwoods and softwoods would have a half-life, defined as $\log_{10}(0.5)/\beta_1$, at 44 and 65 years of age and a mean life, defined as $-1/\beta_2$, at 63 and 94 years of age for hardwood and softwood species, respectively.

Carbon cycling

In addition to estimating individual tree growth, WCM also addresses carbon turnover within broader windbreak systems. Datasets describing carbon cycling within agroforestry systems are virtually nonexistent, thus we largely adapted carbon dynamics models from the Forest Vegetation Simulator (FVS) and the associated Fire and Fuels Extension model (FVS-FFE) (Rebain 2010). FVS is a growth-and-yield forest model which predicts tree growth and mortality at the stand scale; FVS-FFE tracks the decay and movement of biomass across carbon pools given the growth and death predicted by FVS. We broke down carbon cycling into five processes, as follows.

Live crown breakage

Annually, all trees, regardless of species group or LRR, shed 1 % of each crown sub-component to the respective subcomponent of either the litter component or downed woody debris pool. This process, as taken from FVS-FFE, represents background fall from physical forces such as wind or snow. Crown stock

Table 2 Summary of windbreak tree survivorship regressions

Species class	β_0	β_1	SEM	P	R^2	n
Hardwood	4.6052	−0.0159	0.0004	<0.0001	0.21	7019
Softwood	4.6052	−0.0106	0.0004	<0.0001	0.20	2758

was not discounted as it was assumed new growth within each year replaces stock lost through breakage.

Live foliage fall

A portion of the crown was deposited from the live tree overstory to the foliage fall subcomponent in the O horizon annually. The stock of foliage fall added to the litter was determined by:

$$Foliagefall = \left(\frac{Foliagemass}{Standingspan}\right) \tag{5}$$

where *standingspan* is the portion of foliage shed annually by a species group. Values for standing span were generalized by species group from species-specific values presented by FVS-FFE and are not parameterized by LRR (Table 3). Foliage stock is not discounted and assumed to be replaced by new growth within each year.

Standing deadfall

For a period after mortality occurs, standing dead stock falls at a linear rate to the litter and downed woody debris components. The equation to determine crown fall of standing dead trees is similar to Eq. 4, where the stock fallen is the quotient of available standing stock and the standing span. We generalized standing span by LRR and by species group using species-specific values within FVS-FFE (Supplementary Table 3). For this and other modeled processes that are parameterized by LRR and adapted from FVS-FFE, parameters were selected from geographic variants of FVS-FFE that had the most overlap by geographic area with each LRR. In addition to crown fall, the stems of standing dead trees fall over a period determined by their dbh at year of death. The stem fall rate was set to 0.01 for stems over 82 cm; for stems under 82 cm, the equation to determine the stem fall rate, regardless of species group or LRR, was:

$$Stemfallrate = 0.064311 - 0.00066\ \mathrm{dbh} \tag{6}$$

Table 3 Standing span of foliage generalized to species group

Species group	Standing span (years)
All hardwoods	1
Cedar, larch (*Cupressaceae*)[a]	5
Cedar, larch (*Larix*)[a]	1
Douglas-fir	5
Juniper, oak, mesquite (*Juniperus*)[a]	4
Pine	4
Spruce	6
True fir, hemlock (*Abies*)[a]	7
True fir, hemlock (*Tsuga*)[a]	4

[a] Species groups split by genus

Standing dead stem decay

Annually, a portion of stock in the standing dead tree pool was lost through decay. The rate of decay, adopted from FVS-FFE is determined by Eq. 6 and applied to all species groups in each LRR.

$$Stemdecayrate = \frac{0.2}{13.85 + .488\ \mathrm{dbh}} \tag{7}$$

Downed woody debris, litter and duff decay

We initialized O horizon carbon pools at zero as they are relatively insignificant during windbreak establishment (Schoeneberger 2009). Following deposition to the O horizon, the model simulates effects of decay within the DWD and O horizon pools. The model assumes that the stock of each year's additions to the forest floor pool carbon are initially reduced by 26 % to approximate the effects of decay on O horizon chemical composition. This change in carbon to biomass ratio, taken from Smith and Heath (2002), generalized across all O horizon material and all states of decay. Following the authors' guidance, we did not alter downed woody debris percent carbon. The following exponential decay function determined the stock of each sub-component remaining at year's end:

$$\mathrm{Stock}_{t+1} = \mathrm{Stock}_t \times (1 - r)^t \tag{8}$$

where t is year, and r is a decay rate. Decay rates were adapted from FVS-FFE. Decay for branch fall were LRR specific (Supplementary Table 4), and foliage fall and duff decay rates were set at 0.65 and 0.002 respectively for all LRRs. Of the stock lost through decay, 2 % was added to the duff subcomponent, as in FVS-FFE.

Understory growth

The understory pool consists of sapling trees, shrubs and herbaceous vegetation. Unlike other processes in

WCM, the growth of the two latter components are not modeled dynamically. Instead, we followed suggestions from Hoover et al. (2014) and adapted lookup values for aboveground shrub and herbaceous vegetation carbon stock from FVS-FFE. These values, multiplied by 1.11 to account for belowground carbon stock (Hoover et al. 2014), represent maximal carbon stock. As windbreaks are typically planted in areas that may have been cultivated or otherwise cleared (Schoeneberger 2009), we assume shrub and herbaceous vegetation are initially zero and accrue mass linearly for 2 and 20 years, respectively, to reach maximal carbon stock. The tables used for these two understory components are provided in Supplementary Tables 5 and 6.

Model evaluation

Implementation

The WCM is fully usable by the general public through use of the agroforestry module of COMET-Farm™. Through the user interface, users can select the location of an agroforestry practice, and enter in their tree population by species, number of trees by dbh class and species. The agroforestry module runs the WCM and reports the aggregate carbon stock in each pool for the current year and for the next 50 years in 10-year intervals, limited to reporting up to 100 years of age. Analogous to the region and forest type specific look-up tables for estimating *forest* carbon stocks in the U.S. (Smith et al. 2006), WCM provides to landowners and land managers a "ball-park" estimate to serve as an alternative where resource-intensive methods to characterize carbon stocks and changes are prohibitive.[1]

To demonstrate the application of our model, we have selected a hypothetical windbreak consisting of 100 hemlock (*Tsuga*) trees in the eastern Pacific Northwest (LRR B). In this scenario, living tree carbon stock rises over time, eventually sequestering over 150 Mg of carbon in 100 years with the stem comprising about half of the total living tree carbon stock (Fig. 3a, b). Concurrent with the increase in overstory live tree stock, the standing dead stock rises; the dead standing stems, having longer standing spans than the crown components, comprise about 60 % of that pool's carbon stock (Fig. 3c, d). In this example, the other pools together sum together to 5 % of the live tree overstory by the hundredth year of growth (Fig. 3e). Initially, the understory comprises a majority of the other pools and is overtaken by the O horizon by the 25th year. Fifty years later, the downed woody debris pool contains a significant portion of the other pools' stock as standing dead stock begins to fall and accumulate (Fig. 3f). In total, the model predicts an average rate of sequestration of 1.5 Mg C year^{-1} for this scenario (Fig. 3g) with about 85 % of total carbon stock in the live tree overstory (Fig. 3h).

Validation

To ensure that our model provides sensible and reliable results, we tested the two processes developed specifically for WCM as well as the adjustment of crown sub-components for open-grown trees. In validating the growth equation, we used a dataset of 18 ponderosa pine (*Pinus ponderosa* Douglas ex. Lawson) windbreak trees in Montana and Nebraska (Ballesteros 2015). The author measured dbh and age of each tree and destructively sampled and weighed each tree. The trees ranged in dbh from 15 to 41 cm, from 15 to 54 years of age, and from 19 to 464 kg of carbon, assuming 50 % carbon by mass (IPCC 2003). In WCM, the respective species group is pine and the LRR is G. Based on the observed tree ages, we found our model over predicted dbh, especially at older ages, averaging a bias of 8.5 cm dbh (Fig. 4a). Not surprisingly, this led to a significant overestimation of carbon stock of 128 kg on average. Holding dbh constant in order to evaluate our carbon stock by dbh relationship, we found much greater agreement, with only a slight underestimation bias of 10 kg of carbon stock (Fig. 4b). Taken together our evaluation suggests that the largest source of error is our growth equation. As small as the validation set was, new sources of data should be incorporated into future refinements of our model.

Given that the relationship between age and survival percentage was weak (Table 2), we found it

[1] Supplementing the interactive agroforestry module, estimated carbon stocks for each LRR and species group from establishment through 100 years of growth as well as the selected growth equations are available to view within the Help page on the COMET-Farm™ website, accessible at: http://cometfarm.nrel.colostate.edu.

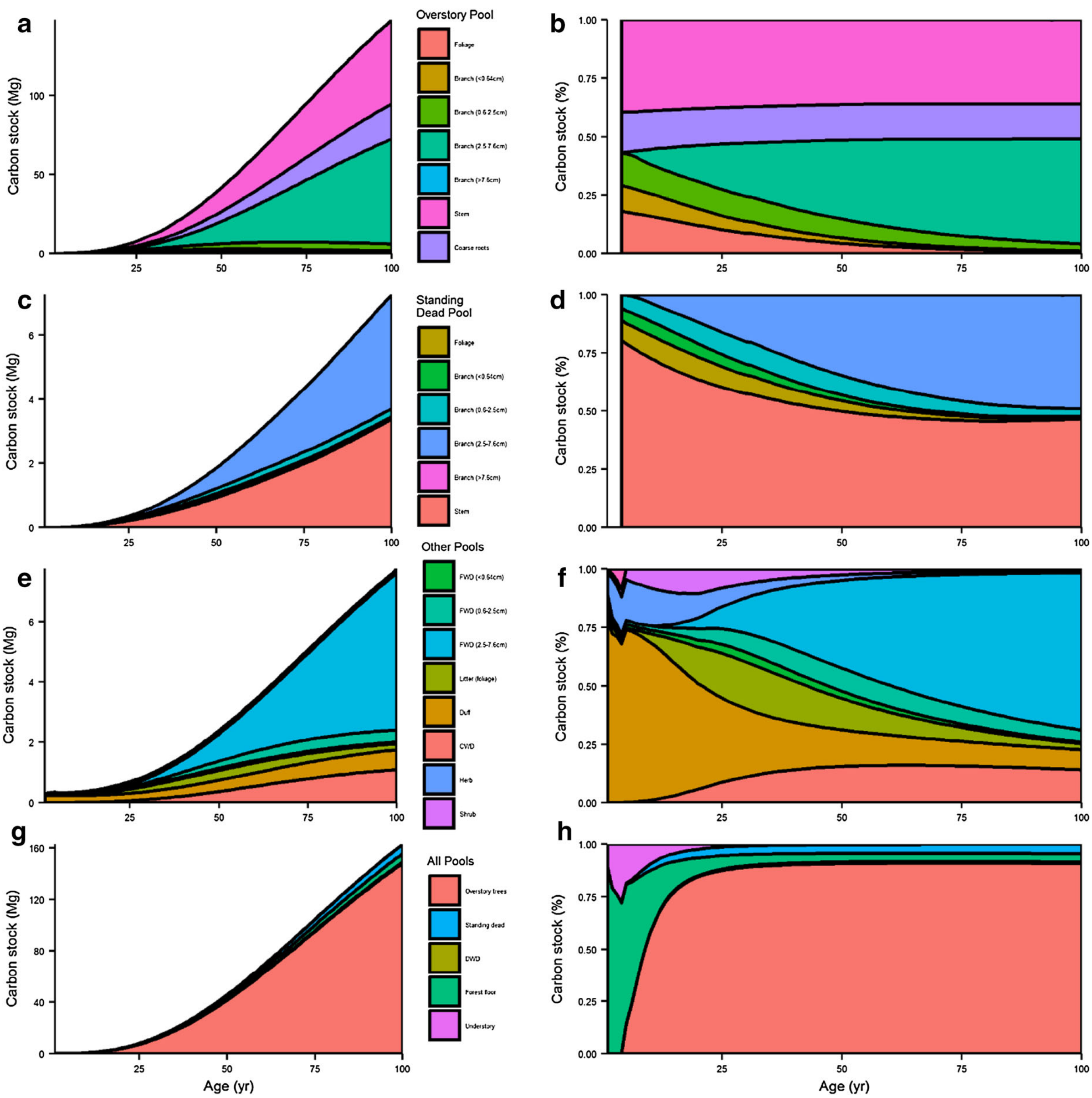

Fig. 3 Overstory, standing dead and other pools, and aggregated across carbon pools by totaled stock (*left hand* **a**, **c**, **e**, **g**, respectively) and by proportion (*right side* **b**, **d**, **f**, **h**, respectively) estimated for 100 hemlock trees within the true fir, hemlock species group in land resource *region B*. *Legends* correspond to each figure in its row

necessary to evaluate our survival curve regressions. Unfortunately, data on windbreak tree survival over a wide range of ages are sparse and we instead compared our survival curves to studies of tree survival in forests and urban settings. In the Great Lakes region, (Hett and Loucks 1976) identified greater mortality rates in forest plots than in windbreaks for both eastern hemlock [*Tsuga canadensis* (L.) Carr.] and balsam fir [*Abies balsamea* (L.) Mill] forests, while Roman and Scatena (2011) also found greater mortality rates in street tree plantings of field maple (*Acer campestre* L.) (Fig. 5). Our survivorship curves may be slightly higher because observations of mortality at older tree ages were few; 75 % of the surveyed windbreak rows in the ESI dataset were less than 25 years old.

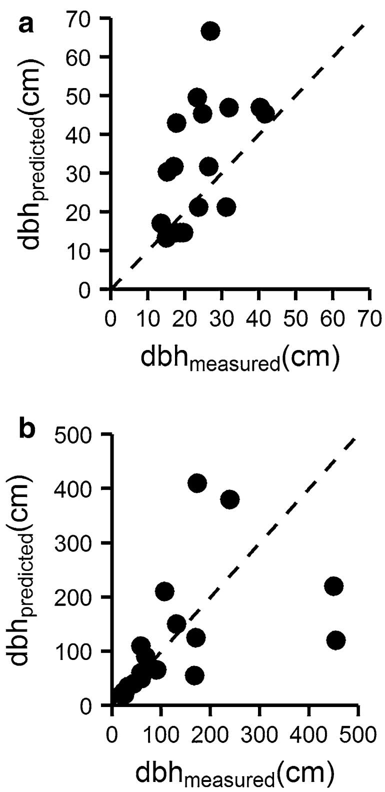

Fig. 4 Predicted dbh as a function of age plotted against observed dbh (**a**) and predicted above-ground carbon stock plotted against measured carbon stock (**b**); predictions from the windbreak carbon model and measurements from Ballesteros (2015)

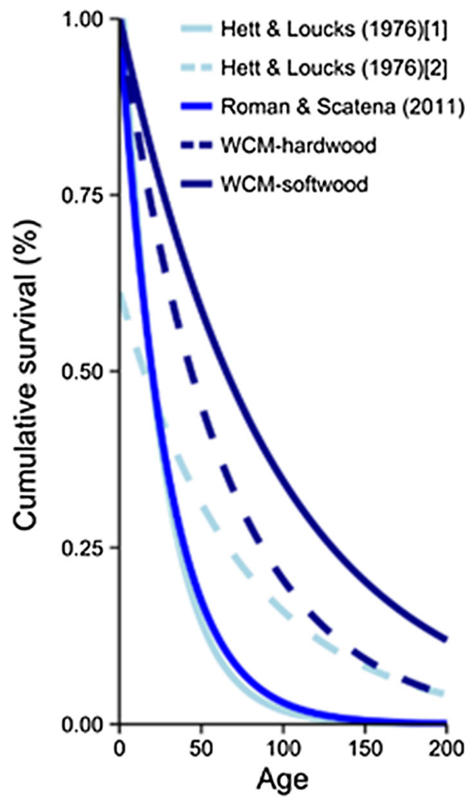

Fig. 5 Survivorship curves generated for the windbreak carbon model (WCM) displayed among that of urban street trees (Roman and Scatena 2011), eastern hemlock forest trees (Hett and Loucks 1976)[1] and balsam fir forest trees (Hett and Loucks)[2]

Assumptions and limitations

In order to distill dynamics occurring in windbreak systems into a model with few inputs, we accounted only for tree size, measured by dbh, to determine tree growth, as measured by PAI. Alternatively, we could have used site-level information recorded in ESI and FIA such as stand density, slope, aspect, latitude, and elevation to help explain tree growth, as has been demonstrated by Wykoff (1990) and Uzoh and Oliver (2006), however some or all of these data are impractical to either surmise or ask a landowner to characterize and enter in online carbon modeling tools like COMET-Farm™. Regarding tree survivorship, we used a simplified model to explain cumulative survivorship as a function of tree age. In fact, only a small portion of variability in survival was explained for both hardwoods and softwoods. Harcombe (1987) suggested tree size may be a better predictor of mortality, but on inspection we found equally poor predictive power by dbh alone or dbh and age together (results not shown). It is probable that the variability seen in the ESI dataset was driven by unaccounted interactions between site-specific factors such as microclimates, soil characteristics and management activities such as irrigation or fertilization. Understanding the tradeoff between ease of use and accuracy, we settled for accepting greater uncertainty in exchange for greater simplicity.

It is important to note we did not explicitly account for inter-tree competition in our growth model. To informally test this assumption, we explored dbh to age relationships across tree sizes and tree spacing densities using the ESI dataset and found no signal to suggest density was a primary influence on cumulative growth (results not shown). In windbreak systems, the linear spatial arrangement results in forest edge-like growing conditions and as a result, competitive factors such as shading and resource competition may be weaker than in forested environments (Schoeneberger 2009; Zhou et al. 2014), We interpret this to suggest it may be appropriate to extend our windbreak model to other agroforestry practices where inter-tree competition is likely to be low and to extending our model to agroforestry practices with high tree densities where inter-tree competition may influence growth rates.

Another potentially important factor in this model is the assumed time to reach a dbh of 2.5 cm. Biomass accumulation increases rapidly until canopy closure, hence the predicted biomass accumulation rate in the first two decades after establishment is sensitive to our assumed time. This effect becomes less significant as the windbreak system matures. We intend to improve the model as regionally and species-specific data on open-grown seedling growth become available.

Finally, in development of our growth process model, although the FIA dataset was comprehensive and provided a sufficient sample size to train growth equations on each species group and LRR, the ESI dataset was limited to only 13 of the 25 LRRs. To address the gap, we use our national, LRR non-specific growth equations. We acknowledge that accuracy will be improved by accounting for regional variation, and we are examining ways to expand on the ESI dataset to take into account variations in the LRRs not represented in the original dataset.

Conclusion

We have assembled a generalized model to describe the carbon dynamics occurring within windbreak systems. We presented our methods to estimate tree growth and survival, directly addressing concerns that forest-based models may not accurately capture the distinct growing conditions in open-grown, agroforestry systems. By driving the model at the LRR and species group level, we reflect the coarse-scale factors that influence growth and carbon dynamics. The use of LRRs provides wall-to-wall coverage of the contiguous U.S. and, with the use of species groups, the carbon dynamics in virtually every common species can be predicted. This incentivizes adoption of a nationally consistent approach for both measurement and reporting. We refrained from including fine-scale factors that are burdensome and difficult for the layperson using COMET-Farm™ to collect and may only marginally improve performance due to inherently high within-site and across-site variability in woody ecosystems (Jenkins et al. 2003).

As noted by Schoeneberger (2009) and Hoover et al. (2014), carbon accounting in agroforestry systems should also consider soil organic matter and harvested wood products. Future modeling efforts, including ours, could leverage existing models or datasets to account for the aforementioned issues. Further revisions to WCM will allow COMET-Farm™ users to select discrete disturbance or management events and estimate how a particular event would affect the immediate and legacy effects on carbon pools. In addition, relevant research will be incorporated as it becomes available. We know the potential exists. For example, Lister et al. (2012) have demonstrated the feasibility of adapting FIA to inventory trees outside of forests. Efforts such as these would greatly improve growth and carbon estimation methods for all agroforestry systems and aid in validation.

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References

Assmann E (1970) Tree growth and form. In: Davis P (ed) The principles of forest yield study, 1st edn. Pergamon Press, New York, pp 39–81

Ballesteros W (2015) Carbon storage potential of windbreaks on agricultural lands. Dissertation, University of Nebraska

Bechtold WA, Patterson PL (2005) The enhanced forest inventory and analysis program-national sampling design and estimation procedures. General technical report SRS-GTR-80 US Department of Agriculture, Forest Service, Southern Research Station, Asheville, NC

Brown JK, Johnston CM (1976) Debris prediction system. Report RWU-2104 US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory, Missoula, MT

Cade BS, Noon BR (2003) A gentle introduction to quantile regression for ecologists. Front Ecol Environ 1(8):412–420. doi:10.2307/3868138

CAST (2011) Carbon sequestration and greenhouse gas fluxes in agriculture: challenges and opportunities. Task Force Report No 142 Council for Agricultural and Science Technology, Ames, Iowa

Goff FG, West D (1975) Canopy-understory interaction effects on forest population structure. For Sci 21(2):98–108

Grier GC, Elliott KJ, McCullough DG (1992) Biomass distribution and productivity of Pinus edulis-Juniperus monosperma woodlands of north-central Arizona. For Ecol Manag 50:331–350

Harcombe PA (1987) Tree life tables: simple birth, growth, and death data encapsulate life histories and ecological roles. Bioscience 37(8):557–568

Hett JM, Loucks OM (1976) Age structure models of balsam fir and eastern hemlock. J Ecol 64(3):1029–1044. doi:10.2307/2258822

Hoover C, Birsdey R, Goines B, Lahm P, Marland G, Nowak D, Prisley S, Reinhardt E, Skog K, Skole D, Smith J, Tretting C, Woodall C (2014) Quantifying greenhouse gas sources and sinks in managed forest systems In: Eve M, Pape D, Flugge M, Steele R, Man D, Riley-Gilbert M, Biggar S (eds) Quantifying greenhouse gas fluxes in agriculture and forestry: methods for entity-scale inventory. Technical Bulletin 1939 US Department of Agriculture, Office of the Chief Economist, Washington, DC, pp 6001–6113

Huber M, Sterba H (2009) Development of species composition in long term simulations with an individual-tree growth simulator. J For Sci 55(5):194–200

IPCC (2003) Good practice guidance for land use, land-use change and forestry. Insititute for Global Environmental Strategies, Kanagawa

Jenkins JC, Chojnacky DC, Heath LS, Birdsey RA (2003) National-scale biomass estimators for United States tree species. For Sci 49(1):12–35

Koenker R (2015) Quantreg: quantile regression. R package version 5.24. https://cran.r-project.org/web/packages/quantreg/index.html. Accessed 01 Dec 2015

Lister AJ, Scott CT, Rasmussen S (2012) Inventory methods for trees in nonforest areas in the Great Plain states. Environ Monit Assess 184:24655–24674

Loomis RM, Blank RW (1981) Estimating northern red oak crown component weights in the northeastern United States. Research paper NC-RP-194 US Department of Agriculture, Forest Service, North Central Research Station, St. Paul, MN

Loomis RM, Roussopolous PJ (1978) Estimating aspen crown fuels in north-eastern Minnesota. Research paper NC-RP-156 US Department of Agriculture, Forest Service, North Central Research Station, St. Paul, MN

Lukaszkiewicz J, Kosmala M (2008) Determining the age of streetside trees with diameter at breast height-based multifactorial model. Arboric Urban For 34(3):137–143

Montagnini F, Nair PKR (2004) Carbon sequestration: an underexploited envionmental benefit of agroforestry systems. Agrofor Ecosyst 61:281–295

Nigh GD, Everett R (2007) Years-to-stump-height and years-to-breast-height models for interior Douglas-fir, western larch, and ponderosa pine. Northwest Sci 81(4):293–304. doi:10.3955/0029-344X-814293

NRCS (2006) Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin. Agricultural Handbook 296, US Department of Agriculture, Natural Resource Conservation Service Service, US Government Printing Office, Washington, DC

R Core Development Team (2014) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria

Rebain S (2010) The fire and fuels extension to the forest vegetation simulator: updated model documentation. Internal Report, US Department of Agriculture, Forest Service, Forest Management Service Center, Fort Collins, CO

Roman LA, Scatena FN (2011) Street tree survival rates: meta-analysis of previous studies and application to a field survey in Philadelphia, PA, USA. Urban For Urban Green 10(4):269–274. doi:10.1016/jufug201105008

Ryan M, Binkley D, Fownes J (1997) Age-related decline in forest productivity: pattern and process. Adv Ecol Res 27:213–262

Schoeneberger MM (2009) Agroforestry: working trees for sequestering carbon on agricultural lands. Agrofor Syst 75:27–37. doi:10.1007/s10457-008-9123-8

Schoeneberger MM, Patel-Weyand T, Bentrup G (in prep) Agroforestry and climate change: reducing threats and enhancing resiliency in agricultural landscapes. General technical report WO-GTR US Department of Agriculture, Forest Service, National Headquarters, Washington DC

Smith JE, Heath LS (2002) A model of forest floor carbon mass for United States forest types. Research paper NE-RP-722 US Department of Agriculture, Forest Service, Northeastern Research Station, Newtown Square, PA

Smith JE, Heath LS, Skog KE, Birdsey RA (2006) Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States. General technical report NE-GTR-343 US Department of Agriculture, Forest Service, Northeastern Research Station, Newtown Square, PA

Smith P, Martino D, Cai C, Gwary D, Janzen H, Kumar P, McCarl B, Ogle S, O'Mara F, Rice C, Scholes B, Sirotenko O (2007) Agriculture. In: Metz B, Davidson OR, Bosch PR, Dave R, Meyer LA (eds) Contribution of working group III to the fourth assessment report of the intergovernmental panel on climate change, 2007. Cambridge University Press, Cambridge

US Environmental Protection Agency (2014) Ch 6 Land use, land use change, and forestry. In: Inventory of US greenhouse gas emissions and sinks: 1990–2013. National Center for Environmental Publications, Washington

USDA (2006) Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin. USDA Handbook 296, U.S. Department of Agriculture

USDA (2015) National Agroforestry Center. U.S. Department of Agriculture. http://www.nrcs.usda.gov/wps/portal/nrcs/main/national/nac/. Accessed 23 June 2016

Uzoh F, Oliver W (2006) Individual tree height increment model for managed even-aged stands of ponderosa pine throughout the western United States using linear mixed effects. For Ecol Manag 221:147–154

Woodall CW, Heath LS, Domke GM, Nichols MC (2011) Methods and equations for estimating aboveground volume, biomass, and carbon for trees in the U.S. forest inventory, 2010. General technical report NRS-GTR-88 US Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA

Wykoff WR (1990) A basal area increment model for individual conifers in the northern Rocky Mountains. For Sci 36(4):1077–1104

Zhou X, Brandle JR, Schoeneberger MM, Awada T (2007) Developing above-ground woody biomass equations for open-grown, multiple-stemmed tree species: shelterbelt-grown Russian-olive. Ecol Model 202:311–323. doi:10.1016/jecolmodel200610024

Zhou X, Schoeneberger MM, Brandle JR, Awada TN, Chu J, Martin DL, Li J, Li Y, Mize CW (2014) Analyzing the uncertainties in the use of forest-derived biomass equations for open-grown trees in agricultural land. For Sci 60:1–18