Allometric Equations for Estimating Above-Ground Biomass Carbon sequestration in Five Tree Species grown in an Intercropping Agroforestry System in Southern Ontario, Canada

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Abstract

Allometric equations were developed for estimating above-ground biomass carbon (AGBC) sequestration in five tree species grown in a tree-based intercropping system at the University of Guelph Agroforestry Research Station (GARS), Guelph, Ontario, Canada. A total of 66 representative trees from five species: Red Oak (*Quercus rubra*) [n = 12], Black Walnut (*Juglans nigra*) [n = 16], Black Locust (*Robinia pseudoacacia*) [n = 10], White Ash (*Fraxinus americana*) [n = 15], Norway Spruce (*Picea abies*) [n = 13] were selected, harvested and their aboveground biomass and C content were quantified. Three commonly used allometric models were used to develop predictive equations. Regression models were developed and parameterized for each tree species and the best are presented based on information criteria (AIC, AICc, and BIC), mean absolute percentage error (MAPE), over/under estimation (MOUE), root mean square error (RMSE), R^2, and regression coefficients (a, b) of the observed/predicted (OP) linear regression analysis. All equations with diameter at breast height (D) only and D and tree height (H) as the predictor variables fitted the AGBC data well, with $R^2 > 97\%$ and RMSE < 40. However, a power model using D as the only predictor is recommended as the best model for Black Walnut, Black Locust, White Ash, and Norway Spruce. The models presented are the best fitted allometric equations for the indicated species and are recommended for these species, growing on similar soils under the same temperate conditions at densities of < 100 trees per hectare.

1. INTRODUCTION

The integration of agroforestry systems into climate change strategies is a promising approach to address environmental and societal challenges while promoting sustainable development. The sequestration of carbon in aboveground biomass (AGBC) through woody cropping systems in Canada is seen as a capable land-use strategy to achieve the country's climate change mitigation goals, as stated in the United Nations Framework Convention on Climate Change (UNFCCC) (Environment and Climate Change Canada [ECCC], 2020). Agroforestry systems can also benefit growers economically by providing valuable feedstock (Bazrgar et al., 2022) to support green technologies in Canada. Understanding the contribution of agroforestry systems to off-set GHG emissions requires accurate quantification of AGBC at the individual tree species level (Altanzagas et al., 2019), especially since the growth and biomass of trees grown under agroforestry cropping systems can vary significantly depending on species and agroclimatic conditions (Jassal et al., 2013; Fortier et al., 2010; Pinno et al., 2010; Truax et al., 2021). It is therefore critical to understand the long-term biomass accumulation of promising tree species under agroforestry land-use systems in different regions of Canada and their adaptability to diverse agroclimatic conditions. This understanding is essential for assessing biomass productivity at a system level and to monitor carbon stocks on a spatial and temporal scale across the country (Cooper, 1983; Specht and West, Chambers et al., 2001 2003; Kebede and Soromessa, 2018).

There are currently no predictive models available to estimate the above ground biomass for tree species under tree-based intercropping systems on marginal lands in southern Ontario, Canada. Regression models are commonly used and cost-effective methods for predicting aboveground biomass and carbon stocks in various woody crop production systems (Ravindranath and Ostwald, 2008; Youkhana et al., 2017), and many researchers have employed resultant allometric equations for biomass estimation due to their accuracy and efficiency (Rathore et al., 2021; Lambert et al., 2005). These equations primarily utilize tree growth characteristics such as diameter at breast height (DBH), height, and collar diameter as regressors (Guiabao, 2016; Naik et al., 2019). This study aimed to evaluate species-specific nonlinear regression equations for predicting carbon sequestration in aboveground biomass of five common tree species suitable for use in an intercropping agroforestry land-use systems in southern Ontario, Canada.

2. MATERIALS AND METHODS

2.1. Site Descriptions

The study was conducted in a 30-ha tree-based intercropping system established in 1987 at the University of Guelph Agroforestry Research Station (GARS), Guelph, Ontario, Canada (latitude 43^0 32’ 28” N, 80^0 12’ 32” W) (Fig. 1). The average annual precipitation at GARS is 904 mm of which 338 mm is received during the growing season (May to September) of 144 frost-free days. A 30-hectare tree based intercropping system site was established in 1987 at GARS. Most of the land at GARS is Class 3–4 agricultural land, based on the Canadian Land Inventory (CLI) classification, and soils are classified as Gray Brown Luvisols, with fine sandy loam texture (Bazrgar et al., 2022). The tree density is 111 trees ha^{-1} with a within row spacing of 6 m and between row spacing of 6 and 15 m. The tree row width is 2 m, where no crops are grown. Tree alleys are intercropped with a crop rotation of corn (*Zea mays*), and soybean (*Glycine max*).

2.2. Aboveground Biomass Sampling and Carbon Quantification

Tree harvest occurred during the winter of 2020 using a commercial harvester. Representative trees (n = 66) of Red Oak (*Quercus rubra*) [n = 12], Black Walnut (*Juglans nigra*) [n = 16], Black Locust (*Robinia pseudoacacia*) [n = 10], White Ash (*Fraxinus americana*) [n = 15], Norway Spruce (*Picea abies*) [n = 13] were selected. Trunk, branches, and leaves (for Norway spruce) for each tree were separated and weighed in the field using a compact truck loader, Kubota CTL Model SVL75-2, and a Digital Crane Hanging Scale, Vevor with a 1000 kg capacity, following the protocols of Zhou et al. (2011), Battulga et al. (2013), and Bazrgar et al. (2020). The moisture content (MC) at the time of harvest for each component of a tree was quantified using sub-samples and MC (%) was used to convert whole-tree green weights to oven-dry weights. C concentration for each separated component in each tree sample was quantified using the combustion method (LECO CR412) (Table 1), and actual C content in AGB was calculated using (*i*):

AGBC = AGB×(MCC/100) [*i*]

Where AGBC refers to aboveground biomass carbon (kg C), AGB refers to aboveground dry biomass (kg) and MCC refers to the mean carbon concentration (%) in the tree.

Table 1
Mean carbon concentration (%) of studied agroforestry tree species

Poplar clones	Carbon Concentration
Norway Spruce	47.23 (± 0.66)
Black Walnut	47.13 (± 1.61)
Red Oak	47.79 (± 0.58)
Black Locust	47.53 (± 0.56)
White Ash	47.41 (± 0.33)

2.3. Developing Regression Equations

In order to develop allometric equations, three commonly used non-linear regression models were evaluated for estimating the AGBC of trees (Table 2). The measured tree data were divided into two portions, the first of which was used for model fitting (Training set) and the second of which was used for model validation (Test set). Tree height (H, in m) and diameter at breast height (D, in cm) were used as regressors. The predicted C sequestration in AGB was calculated by multiplying the predicted AGB by the respective C concentration in AGB associated with each species.

Models were fitted to the data of H, D and AGBC using SAS 9.4 (SAS Institute Inc. Cary, NC), and parameterization in each model was done separately for each species using the Iterative Optimization Method (Cooper et al. 2005, Chen et al. 2012, Bazrgar et al., 2022). In this method, starter values are repeatedly entered to estimate the best model parameters through the least squares method.

Final values for parameters were estimated based on statistical significance, the model R^2 and the Root Mean Square Error (RMSE) of non-linear regression analysis. The model R^2 (pseudo R^2 for non-linear regression) was calculated based on the below (*ii*):

$PseudoR2 = Residualsumofsquare/Totalsumofsquare$ [*ii*]

The best-fitted equation for each tree species was selected using standard criteria as follows:

(1) The scatter plot of observed and predicted AGBC values (OP) were plotted against the 1:1 line using the test set of the tree data (Pineiro et al., 2008; Bazrgar et al, 2022). Post analysis of the OP linear regression was conducted using SAS 9.4 and goodness of fit was evaluated based on: a) RMSE, which indicates the bias in the model (deviation of the actual slope value from the 1:1 line) (Savage, 1993), b) the Coefficient of Determination (adjusted-R^2), which is a measure of the proportion of the variance in observed values explained by the predicted values, and 3) the OP linear regression coefficients (significance of slope = 1 and intercept = 0).

(2) Mean absolute percentage error (MAPE) given below (*iii*):

$$MAPE = 1/n \sum_{i=1}^{n} \left| \frac{Observedi - Predictedi}{Observedi} \right| \times 100 \ [iii]$$

(3) Over/under estimation (MOUE) (%) was also calculated based on the formula below (iv) and used to evaluate the predictive equations.

$$MOUE = \frac{Meanobserved - Meanpredicted}{Meanobserved} \times 100 \ [iv]$$

(4) Fit statistics of nonlinear regression analysis including Akaike information criteria (AIC), AICc (Akaike's Corrected Information Criterion), and BIC (Bayesian Information Criterion).

Table 2
Allometric models used to develop predictive equations for C sequestration in aboveground biomass in five tree species under a tree based intercropping system in southern Ontario, Canada.

Eq. No.	Allometric Models	References
1	$AGBC = aD^b$	Altanzagas et al., 2019; Xue, et al., 2016; Dong et al., 2015; Batulga et al. 2013; Hosoda et al., 2010
2	$AGBC = a(D^2H)^b$	
3	$AGBC = aD^bH^c$	

2.4. Statistical Analysis

All regression analyses were carried out using SAS 9.4 applying the NLIN, NLMIXED and REG procedure to perform statistical analyses and model fitting and evaluation. All linear and non-linear assumptions including normality of the standardized residuals and variance homogeneity were verified with plots of standardized residuals for all equations using SAS 9.4.

3. RESULTS

3.1. Model parameterization

Three commonly used allometric models (Table 2) were used to develop predictive equations for C sequestration. Regression models were developed and parameterized for each tree species and the best of them were used as candidate models for predicting AGBC. Table 3 shows the parameters developed for the regression equations using diameter (D) at breast height and height (H) data. The results indicated that all equations with D only and D and H as the predictor variables fitted the AGBC data well, with an $R^2 > 97\%$ and RMSE < 40.

3.2. Model validation - Predicted versus observed regression of fitted models

Results of the validation of allometric equations (goodness of fit) for each tree species using the observed/predicted (OP) linear regression are presented in Table 4. For this purpose, the scatter plot of observed and predicted AGBC values (OP) was plotted against the 1:1 line using the test portion of the tree data (Pineiro et al., 2008). The best fitted models for each tree species were selected based on RMSE, R^2, and regression coefficients (a = 0, b = 1) values associated with each equation for each tree species (Table 4, Fig. 2).

The results indicated that for red oak, Eqs. 1 and 2 showed acceptable prediction of AGBC and could be considered as candidate models (b ± SE = 1.08 ± 0.078, and 0.92 ± 0.074, respectively). For black walnut, all equations predicted acceptable values based on the evaluation statistics; however, Eq. 1 had the lowest RMSE (16.9 Kg C $tree^{-1}$) and could be the best candidate for predicting AGBC. Eq. 2 gave an acceptable prediction of AGBC in Norway spruce based on the OP analysis. The coefficient of linear regression in this equation was the closest to 1 (b ± SE = 0.97 ± 0.053). However, the RMSE (4.7 Kg C $tree^{-1}$) was lowest in Eq. 1 suggesting that both Equations 1, and 2 were candidate equations for Norway spruce. OP analysis was not able to validate the best model for black Locust (Fig. 2); however, Eq. 1 had the highest R^2 (0.93), lowest RMSE (17.6 Kg C $tree^{-1}$), and the closest coefficient of regression to 1 (b ± SE = 0.79 ± 0.125). Therefore, Eq. 1 could be considered the best candidate based on the OP analysis results. All equations predicted AGBC satisfactorily in white ash based on the OP analysis; however, for this species the R^2 for the OP linear regression was lower than other spices (0.64, 0.65, 0.65, for Eq. 1, 2, and 3, respectively). The R^2 values associated with all three predictive equations for white ash were higher than 0.60, which can be accepted given the statistically significant ($p > 0.0311, 0.0281, 0.0278$, for Eq. 1, 2, and 3, respectively). All equations had similar RMSE, although Eq. 1 showed the closest coefficient regression to 1 (b ± SE = 0.94 ± 0.32).

Table 3

Estimated parameters of the studied non-linear regression equations for modeling the above-ground biomass C in five tree species in an intercropping system in southern Ontario, Canada using diameter (D) at breast height and height (H) data.

Eq. No.	Equation	Parameter	Red Oak	Black Walnut	Norway Spruce	Black Locust	White Ash
1	$AGBC = aD^b$	a ± SE	0.032 ± 0.0114	0.013 ± 0.0161	0.016 ± 0.0114	0.013 ±0.0347	0.023 ±0.0209
		b ± SE	2.599 ± 0.1944	2.842 ± 0.3716	2.790 ± 0.1944	2.676 ±0.7683	2.613 ±0.2573
		RMSE*	29.40	18.81	23.15	19.09	39.68
		R^2	0.988	0.977	0.988	0.967	0.991
2	$AGBC = a(D^2H)^b$	a ± SE	0.008 ± 0.0067	0.0093 ± 0.0115	0.046 ± 0.0506	0.000039 ±0.00029	0.037 ±0.0278
		b ± SE	1.086 ± 0.0845	1.052 ± 0.1278	0.883 ± 0.1171	1.577 ±0.7963	0.895 ±0.0771
		RMSE*	30.3	18.2	15.6	24.7	31.6
		R^2	0.984	0.982	0.984	0.937	0.994
3	$AGBC = aD^bH^c$	a ± SE	0.033 ± 0.0339	0.0086 ± 0.0124	0.039 ± 0.0376	0.246 ±1.254	0.034 ±0.0343
		b ± SE	3.607 ± 0.9081	1.948 ± 0.707	2.431 ± 0.4732	3.269 ±1.1911	1.910 ±1.9104
		c ± SE	_1.376 ± 1.4499	1.284 ± 1.0399	0.114 ± 0.4225	_1.924 ±2.9554	0.767 ±0.767
		RMSE*	37.6	18.5	18.7	23.1	31.4
		R^2	0.989	0.982	0.991	0.973	0.994

Table 4

Evaluation statistics (Adjusted R^2, root mean square error (RMSE) and parameter estimations [interception (a), coefficient of regression (b)] of the observed/predicted (OP) linear regression in five tree species in an agroforestry intercropping system in southern Ontario, Canada, using diameter (D) at breast height and height (H) data.

Equation No.	Equation	Tree species	R^2	RMSE	CV	a ± SE	b ± SE
1	$AGBC = aD^b$	Red Oak	0.985	12.5	10.1	1.70 ± 10.35	1.08 ± 0.078
		Black Walnut	0.988	16.9	13.5	0.63 ± 8.94	1.03 ± 0.052
		Norway Spruce	0.998	4.7	5.2	8.96 ± 2.72	0.76 ± 0.018
		Black Locust	0.930	17.6	22.0	6.98 ± 13.99	0.79 ± 0.125
		White Ash	0.638	51.8	37.5	7.14 ± 48.22	0.94 ± 0.32
2	$AGBC = a(D^2H)^b$	Red Oak	0.981	13.9	11.3	11.48 ± 10.90	0.92 ± 0.074
		Black Walnut	0.984	19.4	15.4	2.98 ± 10.17	1.03 ± 0.059
		Norway Spruce	0.988	10.9	12.1	-11.41 ± 7.17	0.97 ± 0.053
		Black Locust	0.896	21.6	26.9	24.66 ± 14.57	0.69 ± 0.134
		White Ash	0.652	50.8	36.8	13.19 ± 45.07	0.88 ± 0.289
3	$AGBC = aD^bH^c$	Red Oak	0.986	11.8	9.6	10.26 ± 9.30	1.39 ± 0.094
		Black Walnut	0.983	20.1	16.0	3.61 ± 10.54	1.03 ± 0.061
		Norway Spruce	0.996	6.1	6.8	-0.72 ± 3.74	0.84 ± 0.026
		Black Locust	0.863	24.7	30.9	3.72 ± 20.76	0.78 ± 0.179
		White Ash	0.653	50.7	36.7	12.01 ± 45.29	0.89 ± 0.291

3.3. Model validation – Information criteria, mean absolute percentage error (MAPE) and over/under estimation (MOUE)

Information criteria such as AIC, AICc, and BIC are important measures for selecting non-linear models because they provide a quantitative measure of how well a particular model fits the data while considering model complexity. These criteria help to strike a balance between model fit and model complexity, allowing for the selection of the most appropriate non-linear model. Therefore, this study deployed these criteria for further validation of the selected model. The lower fit statistic values indicate a better-fit model (Tables 5 and 6).

Results showed that for red Oak, information criteria statistics, similar to the MAPE (10%) and MOUE (1.8%) support the results of OP analysis and indicated Eq. 2 as the best fitted model for predicting AGBC for this species under agroforestry systems. For black walnut, AIC, AICc, and BIC were lowest in Eq. 2 (84.2, 89, and 84.8, respectively), but were not considerably lower than the Eq. 1 fit statistics (86.4, 91.2, 87 respectively) (Table 5). MAPE (11.6%) and MOUE (3.6%) were also the least in Eq. 1for black walnut. Findings from this study indicated that Eq. 1 showed the lowest AIC, AICc, BIC and MAPE (18.8%) for Norway spruce. However, the MOUE suggested Eq. 2 (-15.6%) as the best equation for this species. For black locust, supporting the results from OP analysis, information criteria suggested Eq. 1 as the best predictor model for AGBC. Prediction with Eq. 1 also had the lowest MAPE (32.6%) for this species; however, the lowest MOUE (-1%) was associated with Eq. 2 for this species. For white ash, the results showed that Eq. 2 had the lowest AIC, AICc, and BIC (71, 77, 71.3, respectively), which were not extensively different from the Eq. 1 statistics (73.8, 79.8, 74.1, respectively). MAPE (25.91 Kg C $tree^{-1}$) and MOUE (-0.71 Kg C $tree^{-1}$) were both lowest in Eq. 1.

Table 5
Fit statistics of nonlinear regression analysis including Akaike information criteria (AIC), AICc (Akaike's Corrected Information Criterion), and BIC (Bayesian Information Criterion) and best selected equations (bold values) based on the lowest fit statistics values for five tree species under agroforestry intercropping systems in southern Ontario, Canada.

	Red Oak			**Black Walnut**			**Norway Spruce**			**Black Locust**			**White Ash**		
Fit Statistics	Eq. No.1	Eq. No.2	Eq. No.3	Eq. No.1	Eq. No.2	Eq. No.3	Eq. No.1	Eq. No.2	Eq. No.3	Eq. No.1	Eq. No.2	Eq. No.3	Eq. No.1	Eq. No.2	Eq. No.3
AIC	94.2	**49.4**	95.1	86.4	**84.2**	86.1	**59.5**	63.5	61.4	**47.4**	48.7	48.4	73.8	**71.0**	72.9
AICC	99.0	**89.4**	105.1	91.2	**89.0**	96.1	**67.5**	71.5	81.4	**71.4**	72.7	88.4	79.8	**77.0**	86.3
BIC	94.8	**47.9**	95.9	87.0	**84.8**	86.9	**59.3**	63.4	61.1	**46.3**	47.5	46.8	74.1	**71.3**	73.3

Table 6
Mean absolute percentage error (MAPE), mean observed and predicted C sequestration in aboveground biomass, and mean over/under estimation in percent (MOUE) of three predictive equations in five tree species under tree based intercropping systems in southern Ontario, Canada.

Tree species	EqNo.	Equation	MAPE	Mean observed (Kg C tree^{-1})	Mean predicted (Kg C tree^{-1})	MOUE[1] (%)
Red Oak	1	AGBC = aD^b	11.0	123.1	112.4	8.7
	2	AGBC = $a(D^2H)^b$	10.0	123.1	120.8	1.8
	3	AGBC = aD^bH^c	34.6	123.1	81.3	33.9
Black Walnut	1	AGBC = aD^b	11.6	125.6	121.1	3.6
	2	AGBC = $a(D^2H)^b$	12.3	125.6	119.3	5.1
	3	AGBC = aD^bH^c	12.4	125.6	118.6	5.6
Norway Spruce	1	AGBC = aD^b	18.8	90.2	109.2	-21.1
	2	AGBC = $a(D^2H)^b$	21.0	90.2	104.2	-15.6
	3	AGBC = aD^bH^c	19.3	90.2	108.7	-20.5
Black Locust	1	AGBC = aD^b	32.6	80.1	92.1	-14.9
	2	AGBC = $a(D^2H)^b$	41.9	80.1	80.9	-1.0
	3	AGBC = aD^bH^c	33.1	80.1	98.1	-22.5
White Ash	1	AGBC = aD^b	25.9	138.0	139.0	-0.7
	2	AGBC = $a(D^2H)^b$	31.9	138.0	141.4	-2.4
	3	AGBC = aD^bH^c	31.4	138.0	141.1	-2.2

4. DISCUSSION

4.1. Selecting the best-fit model

All of the evaluation statistics (OP analysis, MAPE and MOUE and information criteria statistics) confirmed that Eq. 2 (Table 7) was the best-fit model for predicting AGBC in red oak grown under an intercropping scenario. For black walnut, OP analysis supported the results from MAPE and MOUE and suggested Eq. 1 (Table 7) as the best fitted equation. Fit statistics were lowest in Eq. 2, but they are not considerably less than Eq. 1 fit statistics. Therefore, we selected Eq. 1 as the best-fit equation for black walnut, intercropped. For Norway spruce, OP analysis indicated both Equations 1 and 2 were the best candidate equations. Therefore, we recommend Eq. 1 (Table 7) as the best predictor of AGBC for Norway Spruce, grown in an intercropped scenario. Findings from this study also suggested Eq. 1 as the best predictor model for AGBC for black locust cultivated under an intercropping agroforestry scenario based on the results from the OP analysis, information criteria and MAPE. For white ash, notwithstanding the fact that fit statistics were lowest in Eq. 2, the current study suggests that Eq. 1 (Table 7) is the best-fit model for this species when intercropped, due to the indicated results from OP analysis, MOUE and MAPE.

For most of the tested tree species (red oak excepted) the power function using D as the only predictor was sufficient to provide the best model. Other studies have also indicated that the power equation is easy to fit to biomass data, requires only basic system inventory data to apply in practice, and usually provides reasonably accurate predictions (Ter-Mikaelian and Korzukhin 1997; Jenkins et al. 2003; Wang 2006; Sierra et al. 2007; Basuki et al. 2009). However, the results of this study demonstrate that adding tree height or height classes as an additional predictor into biomass equations can significantly improve the model fitting and performance for red oak.

5. CONCLUSION

This study parameterized, evaluated, and suggested species-specific nonlinear regression equations for predicting carbon sequestration in aboveground biomass of five common tree species grown in an intercropping scenario in southern Ontario, Canada. The suggested models were selected based on OP analysis, information criteria, MAPE and MOUE statistics. Many scientists have recommended linear regressing OP values for evaluating quantitative models and post analyzing the regression coefficients (Monte et al., 1996; Loehle, 1997; Kobayashi and Salam, 2000; Knightes and Cyterski, 2005; Pineiro et al., 2008, Altanzagas et al., 2019, Bazrgar et al., 2022). Information criteria are also crucial in selecting non-linear models due to their ease of assessing the fit of the model to the data, penalize model complexity, striking a balance between fit and complexity, and facilitating model comparison.

Different regression models were found as best fits for AGBC sequestration in five tree species under an intercropping system. Results indicate that all equations with D only and D and H as the predictor variables fitted the AGBC data well, with $R^2 > 97\%$ and RMSE < 40. However, a power function using D as the only predictor was selected as the best model for black walnut, black locust, white ash, and Norway spruce.

The selected models are presented in presented in Table 7. The listed equations in this table for the respective tree species are the best fitted allometric equations that should be used for open-grown and low tress density (< 100 trees per hectare) land-use systems.

Table 7
Best fitted selected allometric equation for predicting aboveground biomass C in five tree species under an intercropping agroforestry system in southern Ontario, Canada

Tree Species	Best allometric equation
Red Oak	$0.00776(D^2H)^{1.0856}$
Black Walnut	$0.0126D^{2.8417}$
Norway Spruce	$0.03674D^{2.5355}$
Black Locust	$0.0132D^{2.6762}$
White Ash	$0.0231D^{2.6126}$

Declarations

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Figures

Figure 1

University of Guelph Agroforestry Research Station (tree-based intercropping system), Guelph, Ontario, Canada.

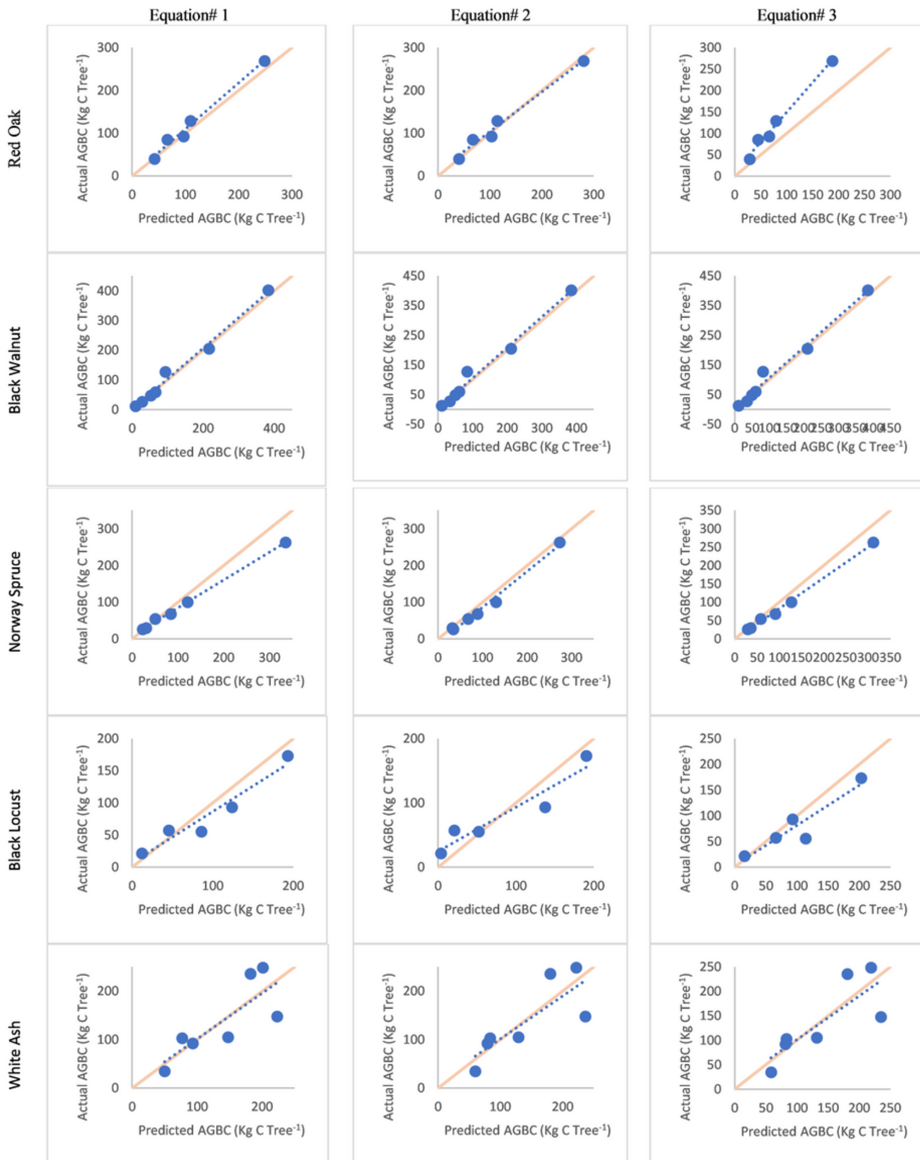

Figure 2

Comparison of predicted C sequestration by studies equations nos. 1-3 in five tree species under tree-based intercropping systems and observed C sequestration in aboveground biomass in southern Ontario, Canada. (Blue line: linear regression of predicted and observed data, Red line: 1:1 line).