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A framework for identifying carbon hotspots and forest management drivers

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ABSTRACT

Spatial analyses of ecosystem system services that are directly relevant to both forest management decision making and conservation in the subtropics are rare. Also, frameworks that identify and map carbon stocks and corresponding forest management drivers using available regional, national, and international-level forest inventory datasets could provide insights into key forest structural characteristics and management practices that are optimal for carbon storage. To address this need we used publicly available USDA Forest Service Forest Inventory and Analysis data and spatial analyses to develop a framework for mapping "carbon hotspots" (i.e. areas of significantly high tree and understory aboveground carbon stocks) across a range of forest types using the state of Florida, USA as an example. We also analyzed influential forest management variables (e.g. forest types, fire, hurricanes, tenure, management activities) using generalized linear mixed modeling to identify drivers associated with these hotspots. Most of the hotspots were located in the northern third of the state some in peri-urban areas, and there were no identifiable hotspots in South Florida. Forest silvicultural treatments (e.g. site preparation, thinning, logging, etc) were not significant predictors of hotspots. Forest types, site quality, and stand age were however significant predictors. Higher site quality and stand age increased the probability of forests being classified as a hotspot. Disturbance type and time since disturbance were not significant predictors in our analyses. This framework can use globally available forest inventory datasets to analyze and map ecosystems service provision areas and bioenergy supplies and identify forest management practices that optimize these services in forests.

1. Introduction

Increased atmospheric carbon dioxide (CO_2) concentrations due to emissions from anthropogenic activities is a concern because of its role in global climate change and its subsequent effects on ecosystem structure, ecological processes, and overall human well-being (McNulty and Aber, 2001). Since forests and soils sequester carbon from the atmosphere and incorporate it in their biomass, forest management is increasingly being used as a CO_2 emission reduction and offset strategy (Canadell and Raupach, 2008; Luyssaert et al., 2008). Additionally, policy instruments and emerging carbon markets are providing incentives to forest landowners for the carbon sequestered in their forests [e.g. Reducing Emissions from Deforestation and Forest Degradation (REDD+; Mackey et al., 2008), European Emissions Trading Scheme (EU ETS; Hepburn, 2007)]. Indeed, landowners could potentially receive monetary payments for the carbon stored in their property and for not emitting it through deforestation and degradation of their forests. Because of this, there is an increasing interest in managing forested landscapes for their carbon sequestration and storage function in addition to the provision of other ecosystem services (Houghton, 2001; Tallis and Polasky, 2009).

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Several forest management factors such as disturbance regimes, stand age, net primary productivity, species diversity, and decomposition dynamics have been described as drivers influencing carbon storage and sequestration (Wardle et al., 2003; Luyssaert et al., 2008). Additionally, net carbon storage and cycling in forest ecosystems depends on land use and forest management practices (Houghton, 2001; Pregitzer and Euskirchen, 2004). Specific forest management practices such as reduced impact logging can also substantially reduce carbon emissions from forest-timber harvesting management operations (Pinard and Cropper, 2000; Putz et al., 2008).

Assessments using existing forest inventory and remote sensing data, as well as spatial statistics, could be used to quantify and map these carbon stocks for different forest types and regions (Tallis and Polasky, 2009; Heath et al., 2011). Other methods and analyses that classify ecosystems, detect and map the occurrence of invasive species, and identify areas of high biological biodiversity are increasingly being used (Mittermeier et al., 1998; Balmford et al., 2002; Drake and Lodge, 2004; Ernst et al., 2006). However, we know of few frameworks that use these approaches combined with existing, yet disparate datasets to spatially analyze carbon storage in warm, temperate and subtropical forests, and to identify their structural, management and ecological drivers.

Effective management of forests for optimal carbon storage requires identification and mapping of ecosystem attributes, including spatially explicit analyses of carbon dynamics and its drivers (Tallis and Polasky, 2009). While Houghton (2001) and Pregitzer and Euskirchen (2004) have analyzed carbon stocks and dynamics at the global scale, Heath et al. (2011) analyzed forest carbon stocks on lands managed by the USDA Forest Service. Regional studies such as those of Brown et al. (1999) and Brown and Schroeder (1999) have analyzed the spatial distribution of forest biomass in the eastern United States (US). Many of these studies use forest inventory data and national-scale biomass estimators for forest-level biomass and carbon stock assessments.

A hotspot analysis is a specific spatial analysis technique that has been used for identifying areas, or "clusters", where high values for a variable of interest occur (Mitchell, 2005). These techniques have previously been used for determining areas of high biological diversity (Mittermeier et al., 1998) and for mapping distinct, localized areas affected by biological invasions (Drake and Lodge, 2004). Several clustering analysis techniques have been developed to identify and map variables of interest and, in general, can be categorized into two groups (O'Sullivan and Unwin, 2002). The first group consists of techniques such as kernel density estimation and quadrant count analysis that measure the variation in the mean value of the variable (Xie and Yan, 2008). The second group utilizes second-order statistics to measure the spatial dependency of the data, and include for example the Moran I and Getis-Ord G^* statistics (Anselin, 1995). Coulston and Ritters (2003) for example used forest fragmentation indicators to study spatial clusters representing extreme indicator values in the southeastern US and identified distinct clusters of fragmented forests. Mola-Yudego and Gritten (2010) used kernel-based hotspot analysis to study forest management conflict clusters based on the number of reported conflicts. Other studies have analyzed social–ecological hotspots (i.e. areas with high human perceived values coinciding with high ecological productivity or biological diversity), areas of high malaria occurrence in Kenya (Ernst et al., 2006), and identified areas for conservation efforts, as well as mapping ecosystem services such as water supply, soil quality, and carbon in South Africa (Alessa et al., 2008; Egoh et al., 2008).

Several other modeling studies have determined that ecological disturbances such as fire, wind, insects, land use change, and timber harvesting are important drivers of carbon stocks and sequestration in forest ecosystems (Cropper and Ewel, 1987; Pregitzer and Euskirchen, 2004; Houghton, 2001; Thornton et al., 2002; Wardle et al., 2003). Long-term carbon storage in a forest ecosystem is highly dependent on disturbances, more so than other factors such as climate and ambient CO_2 concentrations (Chapin et al., 2002) since most disturbances leads to the release of considerable amount of carbon into the atmosphere (Page et al., 2002). Wind damage and hurricanes are another important disturbance in different subtropical forest types (Oswalt and Oswalt, 2008; Thompson et al., 2011) and can have significant impacts on regional carbon balances (Mason, 2002; Lindroth et al., 2009).

Forest types, structure, and age also influence carbon dynamics in forests (Houghton, 2001; Litvak et al., 2003; Pregitzer and Euskirchen, 2004; Kashian et al., 2006). For example, annual wood production and higher carbons stocks may vary between hardwood and softwood forests (Brown et al., 1999). Jonsson and Wardle (2010) found that plant species composition had a significant effect on aboveground C stocks in boreal forests. Forest age has also been documented as a major driver of carbon stock and sequestration (Gower et al., 1996) as shown in a *Pinus elliottii* plantation in Florida, where net ecosystem exchange (NEE) was higher and positive (i.e. carbon sequestration) in younger forests relative to older age ones (Thornton et al., 2002).

Based on this literature, a framework that utilizes existing and accessible biometric and spatial datasets for identifying areas with high carbon storage – and the forest management drivers influencing them – could provide insights into more effective forest management practices, land acquisition options for conservation areas, and decision making regarding the provision of specific ecosystem services. However, this kind of spatially explicit information for landscape-scale ecosystems with a high carbon storage capacity and provision of other ecosystem system services is rare (Balmford et al., 2002). To address this lack of information, we present a framework that used existing forest inventory data, generalized linear mixed models, and spatial statistics to identify carbon hotspots and influencing drivers such as forest management practices (e.g. management goals, age, and treatments), biophysical characteristics (e.g. forest structure and composition), and ecological disturbances (e.g. wind and wildfire) in warm temperate and subtropical forests in the state of Florida, US.

Our specific objective was to develop a framework that mines available and easily accessible USDA Forest Service, Forest Inventory and Analysis (FIA) data to identify areas of high carbon stocks (i.e. carbon storage hotspots) and influential forest management drivers. The FIA data is a national-level inventory that is commonly used for timber volume estimates (Jenkins et al., 2003) and provides other relevant forest management information such as forest biomass and other ecological characteristics (Ney et al., 2002; Woodbury et al., 2007; Chen et al., 2011). For this framework below, we utilize the local Getis-Ord G^* statistic as a local indicator of spatial association that can be statistically tested and used to characterize spatial patterns of forest aboveground carbon and to identify spatial clusters of high (i.e. hotspots) and low (i.e. coldspots) carbon storage values. These hotspots can then be analyzed using plot-level data to determine significant ecological and management drivers affecting such patterns. We hypothesize that carbon hotspots will be located in highly forested, less urbanized northern Florida as compared to the central and the southern parts of the state (Carter and Jokela, 2003). Also these hotspots should be comprised of older, dense, more diverse, privately owned forests with minimal disturbance histories.

A framework such as the one we propose should not only identify forested landscapes at the mesoscale with high carbon storage (i.e. hotspots), but also the forest management related drivers behind them. This type of framework based on publicly available regional, national, and international forest inventory datasets (e.g. United States' Forest Inventory and Analysis, Canada's National Forest Inventory system, European Forest Inventory Database) and multivariate spatial analysis techniques should provide policy makers, private and public forest managers and landowners with useful information for identifying conservation areas and development of forest management practices that optimize carbon storage and other ecosystem services.

2. Methods

2.1. Study area

The State of Florida is characterized by a warm, temperate and warm, humid, subtropical climate as well as a warm humid tropical climate in the extreme southern part of the state. Average annual precipitation is typically 1000–1600 mm and average annual temperature ranges from 16–25 °C (McNab and Avers, 1994). The coastal plains and flatwoods, eastern and western coastal lowlands, and everglades characterize the four USDA Forest Service Ecoregions in the state (Bailey, 1995). There are over 20 forest types found in the state that range from temperate pine and oak lands to tropical hardwoods (Woudenberg et al., 2010).

2.2. Data

We used FIA plot-level, vector digital data in a shape file format from the Florida Geographic Data Library (http://www.fgdl.org). The data included information on land tenure, forest management, stand, and ecological disturbance characteristics for the plots from 2002 to 2007. In addition, the data include carbon pool estimates for: aboveground understory, belowground portion of the understory, dead and downed, standing dead, litter, and soil organic matter for each plot. Smith and Heath (2002, 2008) provide detailed methods used to estimate these different carbon pools.

Since the plot-level vector digital data did not provide tree-level carbon values, we used tree-level data from an additional FIA database available at http://www.fia.fs.fed.us/tools-data/ to calculate tree-level aboveground and belowground carbon for each plot. The FIA database (i.e. FL_TREE) provided tree-level data for all the trees in a plot and on carbon mass per tree in the aboveground portion (i.e. CARBON_AG) of live trees with a diameter at breast height (DBH) >2.5 cm and dead trees >12.5 cm in DBH. Tree-level values were then converted to tons/acre values using the appropriate expansion factors (i.e. TPA_UNADJ) for trees in subplots (Expansion factor of 6.01), and microplots (Expansion factor of 74.96). For each plot, the tree aboveground carbon (tons/acre) value was calculated by summing all the individual tree values on the plot for both live and dead trees. Similarly, for each plot, the tree belowground carbon (tons/acre) was calculated using a similar procedure as tree aboveground carbon. All carbon estimates were converted to Mg C/ha and the aboveground and belowground tree carbon estimates for each plot were merged at the plot-level using the digital shape file as described above. Woudenberg et al. (2010) provide specific field data collection methods and descriptions of plot and tree-level data. Using the carbon pool estimates (Table 1); we developed five carbon pools categories for this analysis: aboveground, belowground, dead, soil organic carbon, and total carbon (Table 2).

The FIA plot-level data categorized plots according to land tenure as: private, state and local government, other governmental, non-governmental conservation and natural resource organizations, and federal lands. For the purpose of our analysis, we categorized land tenure as either public (e.g. state and national forests, conservation forests) or private (e.g. non-industrial private forests, industrial forests, etc). Management treatments on each plot were categorized as: no treatment, cutting, site preparation, artificial regeneration, natural regeneration, and other silvicultural treatment (e.g. fertilization, herbicide application, girdling, and pruning). Management characteristics on plots were analyzed as treated (i.e. plots with any kind of treatment described above) and untreated (i.e. no treatment and natural regeneration).

The various forest types identified in the FIA data were aggregated into six different forest type categories as described in Table 3. Since site quality was defined in the FIA dataset in terms of annual wood volume production (m^3/ha/year), we defined four categories: Site quality 1 (>120 m^3/ha/year), 2 (85–119 m^3/ha/year), 3 (50–84 m^3/ha/year), and 4 (<50 m^3/ha/year). Finally, we analyzed four disturbance types: no disturbance, fire (e.g. ground and crown fire), animal and anthropogenic (e.g. timber harvest, site preparation, etc), and windstorm (e.g. tornadoes, hurricanes, flooding).

A single FIA plot was used to characterize approximately 6000 acres or 24 km^2 and as described by Woudenberg et al. (2010) and McRoberts et al. (2005), plot coordinates are approximate but well within the mesoscale used in our hotspot analyses. We defined mesoscale in this framework as approximately 6400 km^2. To protect landowner privacy, the publicly available FIA dataset provides plot coordinates within 1.6 km of actual field coordinates. Additionally, up to 20 percent of the private plot coordinates are manipulated or "swapped" with other private plots in the same county with similar measured attributes. Manipulating and additionally exchanging plot attributes will influence the spatial characteristics of the data and thus the accuracy of spatially explicit predictive models according to Coulston et al. (2006). However, according to McRoberts et al. (2005) the swapping process used in the FIA data only affects coordinates and all other general plot and tree-level characteristics remain the same. Therefore, plot coordinate manipulation alone by FIA will not affect the state-level and mesoscale analyses used in our framework.

Table 1
Forest carbon pools identified in the USDA Forest Service Forest Inventory and Analysis data and their description.

Carbon pools	Description
Tree aboveground[c]	Carbon in bole, crown, branches, and stump of live trees >2.5 cm and dead trees >12.5 cm (excluding foliage biomass)
Tree belowground[c]	Carbon in coarse roots (>2.5 mm) for live (>12.5 cm) and dead (>12.5 cm) trees
Understory aboveground[a]	Carbon in aboveground portion of seedlings, shrubs, and bushes
Understory belowground[a]	Carbon in belowground portion of seedlings, shrubs, and bushes
Carbon down dead[a]	Carbon in woody material (>7.5 cm) and their stumps and roots >7.5 cm
Carbon litter[b]	Carbon in fine woody debris, fine roots, and organic forest floor above the mineral soil
Soil organic carbon[a]	Soil organic carbon to a depth of 1 m.

[a] Estimated using models as described in Smith and Heath (2008).
[b] Estimated using models as described in Smith and Heath (2002).
[c] Described in Woudenberg et al. (2010).

Table 2
Aggregated forest carbon pools based on combined categories, from Table 1, identified in the USDA Forest Service Forest Inventory and Analysis data.

Carbon pools	Description
Aboveground (Mg C/ha)	Sum of tree aboveground and understory aboveground
Belowground (Mg C/ha)	Sum of tree belowground and understory belowground
Carbon dead (Mg C/ha)	Sum of down dead, and litter aboveground
Soil organic carbon (Mg C/ha)	Soil organic carbon to a depth of 1 m.
Total carbon	Sum of aboveground, belowground, carbon dead, and soil organic carbon

Table 3
Analyzed aggregated forest types for Florida, USA based on USDA Forest Service Forest Inventory and Analysis forest types.

Forest types analyzed	FIA forest types[a]
Longleaf pine	Longleaf pine, longleaf pine/oak
Slash pine	Slash pine, slash pine/hardwood
Other pine hardwood	Loblolly pine, sand pine, pond pine, shortleaf pine, loblolly pine/hardwood, other pine/hardwood
Oak hickory	Post oak/black jack oak, white oak/red oak/hickory, sassafras/persimmon, yellow poplar, southern scrub oak, red maple/oak
Oak gum cypress	Sweetgum/nuttall oak/willow oak, overcup oak/water hickory, bald cypress/water tupelo, sweetbay/swamp tupelo/red maple, bald cypress/pond cypress.
Mixed upland hardwood	Mixed upland hardwood/tropical hardwood/ exotic hardwood

[a] Refer to plants.usda.gov/checklists for scientific names.

2.3. Hotspot analysis

We used the aboveground carbon values in the FIA plot-level data that were only classified as forested ($n = 2160$) to identify spatial clusters (i.e. aggregation of plots with higher or lower values of aboveground carbon stocks). Specifically, this framework used the Getis-Ord G_i^* statistic (Getis and Ord, 1992), which is one of the Local Indicators of Spatial Association (LISA) measures (Mitchell, 2005; Anselin, 1995) to identify clusters of plots with higher or lower carbon values. One advantages of using LISA measures over traditional kernel-based methods is their ability to provide statistical significance to identified clusters. We used the Spatial Statistics extension of the ArcGIS 9.2 software to compute the G_i^* statistics and perform the hotspot analysis. The G_i^* statistic was calculated as the sum of the product of weight and the attribute value (aboveground carbon) of neighbors divided by the sum of the attribute value of all plots in the dataset:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j}{\sum_j x_j} \tag{1}$$

where $G_i^*(d)$ is the statistics calculated for each target plot, d is the distance that defines the neighbors, w_{ij} is spatial weight, x_j is the aboveground carbon value for all plots in the dataset. In our framework, the value of w_{ij} was 1 if a plot is within the defined neighborhood distance or 0 otherwise. Aggregation of plots with a higher G_i^* statistic indicates clusters of higher aboveground carbon values (i.e. hotspots) and lower G_i^* statistic values indicate clusters of lower aboveground carbon values (i.e. coldspots).

A z-score was used to test the statistical significance of a G_i^* statistic and the score provided the probability of observing high or low values of the statistic. The expected value of G_i^* given a random distribution was calculated for each plot in the dataset. The z-score (Equation (2)) was the difference between the calculated G_i^* and the expected $G_i^*[E(G_i^*)]$ divided by the variance of $G_i^*[(\mathrm{Var}G_i^*)]$:

$$Z\left(G_i^*\right) = \frac{G_i^* - E\left(G_i^*\right)}{\sqrt{\left(\mathrm{Var}G_i^*\right)}} \tag{2}$$

$$E\left(G_i^*\right) = \frac{\sum_j w_{ij}(d)}{n-1} \tag{3}$$

where n is the number of plots. A z-score was statistically significant at $p = 0.05$. A high and statistically significant z-score indicates the clustering of high aboveground carbon storage (i.e. hotspot), while a low and statistically significant z-score indicates the clustering of low aboveground carbon storage values (i.e. coldspot).

As described above, plots within a specified and fixed distance are considered neighbors for the calculation of the G_i^* statistic, therefore distance values need to be based on a-priori knowledge of the attribute under consideration or some other quantitative and objective procedures. To this end, we used the spatial autocorrelation tool in ArcGIS to measure the degree of clustering at different distances. Specifically z-scores were calculated by using the average nearest neighbor distance between FIA plots (4.6 km based on $n = 2160$ plots) and then several clustering distances were used (4.6–60 km at 5 km increment) until the z-score was maximized at 45 km (km), indicating the strongest clustering of plots within the distance. Thus, the G_i^* statistic was calculated for each plot by using aboveground carbon values of all the neighbors within a 45 km radius (6358 km^2). The sampling intensity of the FIA is one plot per 24 km^2, so the 45 km distance band used in this framework increases the actual number of neighbor FIA plots (i.e. at least eight plots) used to calculate the G_i^* statistic. Furthermore, according to McRoberts et al. (2005), using FIA plot distances greater than 32 km will have negligible effects on design based estimates of forest characteristics.

2.4. Statistical analyses of drivers

We analyzed tenure (i.e. ownership), forest type, site quality, stand age, and treatments as drivers of forest carbon storage in our model. For our statistical analyses, we checked for homoscedasticity by examining plot of residuals vs predicted values and normality by examining the histogram and QQ plot and with the Shapiro–Wilks and Kolmogorov–Smirnoff statistics. Aboveground carbon, belowground carbon, dead carbon, and soil carbon in both hotspots and coldspots were analyzed for significant differences using a t-test. We identified drivers related to hotspots using a generalized linear mixed model and the PROC GLIMMIX procedure (SAS v 9.2). Hotspots (1) and coldspots (0) were considered as dummy variables. Significant relationships between hotspots and drivers such as ownership, forest types, treatments, site quality, and stand age were tested using a generalized linear mixed model with binary distribution. Multiple comparisons were adjusted using Tukey's test. Similarly, we also related fire and windstorm disturbance and years since disturbance to individual hotspots using the generalized linear mixed model. Forest types and stand age were included as covariates in the model to control for these same variables when relating disturbance to hotspots. Aboveground carbon values between stand age classes, site qualities, and forest types were compared using ANOVA (PROC MIXED SAS 9.2) and multiple comparisons were adjusted using Tukey's test.

Spatial autocorrelation in our hotspot analysis was accounted for by treating residuals as spatially auto-correlated and we therefore analyzed several spatial covariance structures (exponential, power, and spherical) for our residual analyses. We selected the spatial covariance structure for residuals that gave the lowest Akaike Information Criterion (AIC) value in linear mixed model analysis (PROC MIXED procedure; SAS 9.2). In GLIMMIX we looked at the Pearson chi-square to the degrees of freedom ratio and chose the spherical structure since it had the ratio closest to 1. A critical value of $\alpha = 0.05$ was used to determine statistical significance in all analyses.

3. Results

3.1. Hotspot spatial distribution

Our analysis identified hotspots and mapped forested areas in Florida (Fig. 1) with high aboveground carbon (C) storage values.

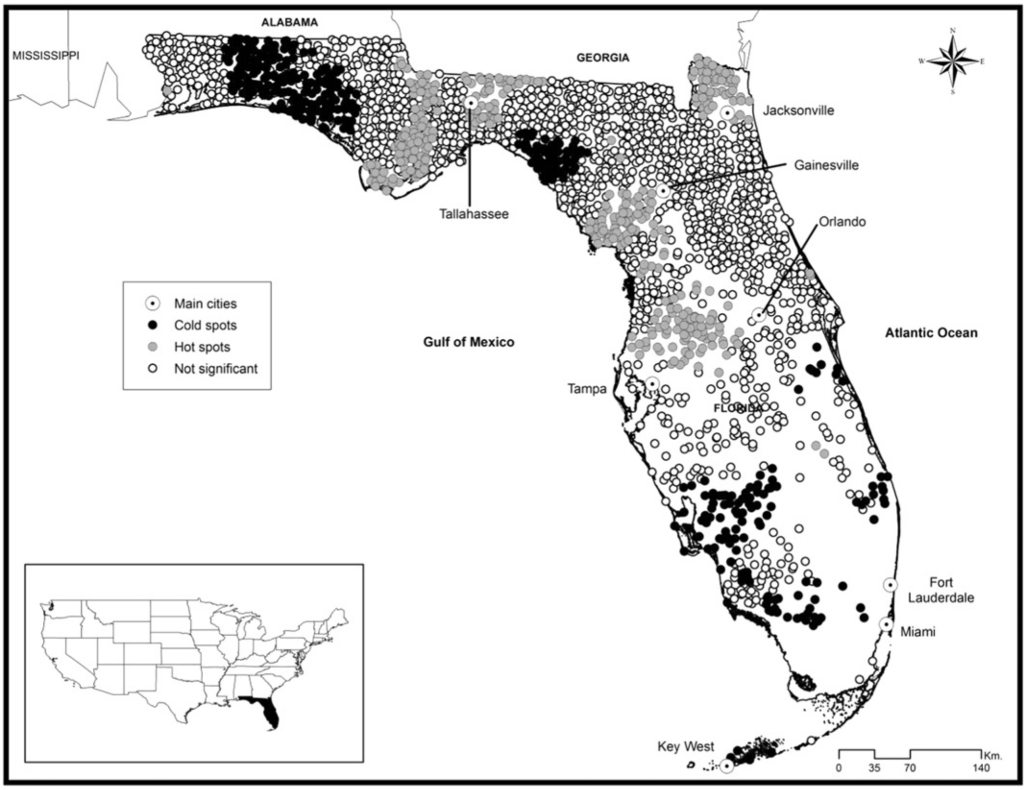

Fig. 1. Map showing aboveground forest carbon storage hotspots (gray circles) and coldspots (dark circles) in Florida, United States based on USDA Forest Service Forest Inventory and Analysis data.

Out of a total 2160 FIA plots analyzed, only 729 plots were identified as being located in either hotspots or coldspots and of these, 49% were considered hotspots and 51% of the plots were coldspots. As hypothesized, most of the carbon storage hotspots were located in northern Florida in the Coastal Plains-Flatwoods and Costal Lowland ecoregions (Bailey, 1995). Overall, the northern part of Florida is more forested, has an important forest industry-based economy, and is less urbanized than the southern part of the state (McNab and Avers, 1994). The C storage hotspots were not typically located near major metropolitan urban areas of South Florida (e.g. Tampa, Orlando, Miami-Fort Lauderdale). However, some hotspots were immediately adjacent to the north Florida cities of Tallahassee and Jacksonville. Additional hotspots were close to the Apalachicola National Forest (northwestern Florida) and around the Nassau Wildlife Management Area (Costal northeastern Florida).

3.2. Hotspot characteristics

Mean aboveground carbon storage for forests classified as hotspots (45.58 Mg C/ha) was significantly greater than mean aboveground carbon storage in coldspots (27.88 Mg C/ha; $p < 0.0001$). Carbon storage between the belowground and dead pools was also significantly greater in hotspots when compared to the coldspots (Table 4). Only soil carbon was significantly greater in coldspots than in hotspots. Soil carbon pools include components that may be chemically and physically protected from decomposition (Sarkhot et al., 2007). Soil carbon components with long turnover times may reflect past land use history, disturbance, hydrology, or plant community more than solely just current forest condition.

3.3. Biophysical drivers of hotspots

We analyzed C hotspots and coldspots and biophysical variables in a generalized linear mixed model to identify influential drivers (Table 5). Among the different forest types analyzed, mixed upland hardwood forest type had the highest probability of being a hotspot followed by the oak hickory and slash pine forest type (Table 6). Although the slash pine forest type had a lower probability of being a hotspot when compared to the mixed upland hardwood and oak hickory forest types; these differences were not statistically significant (Table 7). Among all the forest types analyzed, longleaf pine had the lowest probability of being an aboveground carbon storage hotspot (Table 6) and comparisons of probability with other forest types such as Mixed-upland hardwood, Oak hickory, and Slash pine were significant (Table 7). Comparison of aboveground carbon storage between different forest types did not show a significant difference except for Oak gum cypress forest type (Fig. 4).

Findings indicate that a higher site quality increased the probability of a plot being located in a carbon hotspot (Tables 6 and 7). Forests with a site quality category of 1 increased the probability of being a hotspot when compared to categories 2, 3, and 4 by 16%, 22%, and 29% respectively (Tables 6 and 7); however, other differences were not statistically significant (Table 7). This result was also supported by a significant negative correlation ($r = -0.27$) between site quality (i.e. higher category indicates lower site quality) and aboveground carbon. Similarly, productive sites had higher aboveground carbon storage than less productive sites (Fig. 5). Ownership, was not a significant predictor although being a public forests increased the probability of a forest being a hotspot; however, the difference was not statistically significant. Similarly,

Table 4
Mean forest carbon pools (Mg C/ha) for C storage hotspots and coldspots in Florida, USA (±SE; standard error).

Carbon pools	Hotspots	Coldspots	$P > \|t\|$
Aboveground	45.58 (1.76)	27.88 (1.71)	<0.0001
Belowground	9.33 (0.37)	5.64 (0.36)	<0.0001
Dead[a]	15.87 (0.32)	13.85 (0.31)	<0.0001
Soil	106 (2.38)	117 (2.38)	0.001

[a] Carbon dead includes carbon in down and dead trees, carbon in litter, and carbon in standing dead trees.

treatment was not a significant predictor ($p = 0.12$), but managed forests had a higher probability of being a hotspot when compared to unmanaged forests. Greater stand age increased the probability of a forest being a hotspot (Table 7) as demonstrated by older forests (>60 years) having greater aboveground carbon storage (Fig. 3), although the difference in carbon storage between age classes 61–80 years and 81–100 years and 81–100 years and >100 years were not statistically significant. This result was also supported by a significantly higher correlation between aboveground carbon storage and stand age ($r = 0.50$). These results are also shown by map of hotspots along with forest types, stand age, and site quality (Fig. S1, Supplementary material).

3.4. Disturbance drivers of carbon hotspots

Disturbance type and years since disturbance were also analyzed as drivers of aboveground carbon storage hotspots. However, we found that these two variables were not related to C hotspots when controlling for forest age and type. Although, we did not find significant relationships between disturbance and carbon storage hotspots, visual inspection of post-1990 hurricane landfall tracks might indicate that carbon storage coldspots are generally found in areas with a higher hurricane landfall frequency (Fig. 2). Further analysis comparing aboveground carbon storage values between different disturbance types – without considering the hotspots – while controlling for stand age and forest types; resulted in no significant statistical differences.

4. Discussion

This framework used publicly available inventory data to identify carbon hotspots in Florida at a scale of approximately 6358 km^2 by integrating plot-level inventory data and a cluster mapping technique to identify forested landscapes with high and low carbon values. It then related the mapped cluster with plot-level forest management data (i.e. biophysical, ownership, disturbance and forest management characteristics) to better glean relevant forest management drivers influencing the carbon hotspots. Although there are several studies that map forest carbon stocks at regional and global scales, our framework is unique in that we used G_i^* statistics and generalized linear mixed models to identify and analyze meso-scale carbon hotspots and related forest management drivers.

Table 5
Results of the generalized linear mixed model showing the significance of the tested predictors of the aboveground carbon hotspots in Central and Northern Florida using USDA Forest Service Forest Inventory and Analysis Data.

Predictors	F value	Pr > F
Ownership	1.48	0.22
Forest types	3.24	0.006
Site quality	4.44	0.004
Stand age	7.91	0.005
Treatment	2.40	0.12

Table 6
Probability by order for different forest types and site qualities identified as carbon storage hotspot (±SE; standard error).

	Probability	SE
Forest types		
Mixed upland hardwood forest	0.75	0.05
Oak hickory	0.71	0.06
Slash pine	0.69	0.03
Oak gum cypress forest	0.63	0.05
Other pine hardwood	0.61	0.05
Longleaf pine	0.43	0.07
Site quality		
1	0.80	0.05
2	0.64	0.04
3	0.58	0.04
4	0.51	0.04

As hypothesized, our framework identified C storage hotspots in north Florida, a region that is less urbanized and more forested, relative to south Florida (Carter and Jokela, 2003). The mean total carbon storage in all the carbon pools identified as C hotspots (177 Mg C/ha) and coldspots (165 Mg C/ha) were close to the reported average (162 Mg C/ha) and range (74–280 Mg C/ha) for forest carbon storage densities found in the southeastern U.S. according to Heath et al. (2011). The value is also within the range reported by Lal (2005) for temperate (60–130 Mg C/ha) and tropical forests (120–194 Mg C/ha). Our findings also indicate that forest type, site quality, and stand age were the most significant drivers of forest C storage hotspots (Table 5).

The hotspots identified in this framework had higher aboveground, belowground, and dead carbon storage values, but lower soil carbon storage than coldspots. Thus, the carbon hotspots identified represent the aboveground forest carbon storage and not soil C storage hotspots since coldspots had higher soil carbon values on average than hotspots. Other forest biomass components such as dead trees, litter, and belowground biomass are related to the

Table 7
Comparison of parameter estimates of a model predicting the probability of a plot being an aboveground carbon storage hotspots based on forest type, site quality, stand age, ownership (tenure) and treatment in Central and Northern Florida, USA.

		Estimate	P value
Forest types			
Longleaf pine	Mixed-upland hardwood	−1.3743	0.005
Longleaf pine	Oak gum cypress	−0.7999	0.20*
Longleaf pine	Oak hickory	−1.2029	0.04
Longleaf pine	Other pine hardwood	−0.7140	0.38*
Longleaf pine	Slash pine	−1.0647	0.02
Mixed upland hardwood	Oak gum cypress	0.5744	0.45*
Mixed upland hardwood	Oak hickory	0.1714	0.99*
Mixed upland hardwood	Other pine hardwood	0.6603	0.31*
Mixed upland hardwood	Slash pine	0.3095	0.90*
Oak gum cypress	Oak hickory	−0.4030	0.87*
Oak gum cypress	Other pine hardwood	0.0859	0.99*
Oak gum cypress	Slash pine	−0.2648	0.93*
Oak hickory	Other pine hardwood	0.4890	0.77*
Oak hickory	Slash pine	0.1382	0.99*
Other pine hardwood	Slash pine	−0.3508	0.73*
Site quality			
1	2	0.7792	0.17
1	3	1.0665	0.01
1	4	1.3155	0.003
2	3	0.2874	0.58*
2	4	0.5364	0.15*
3	4	0.2490	0.64*
Stand age		0.011	0.005
Ownership			
Private	Public	−0.2408	0.22*
Treatment			
Unmanaged	Managed	−0.3545	0.12*

*Indicates that these are not significant at $p = 0.05$.

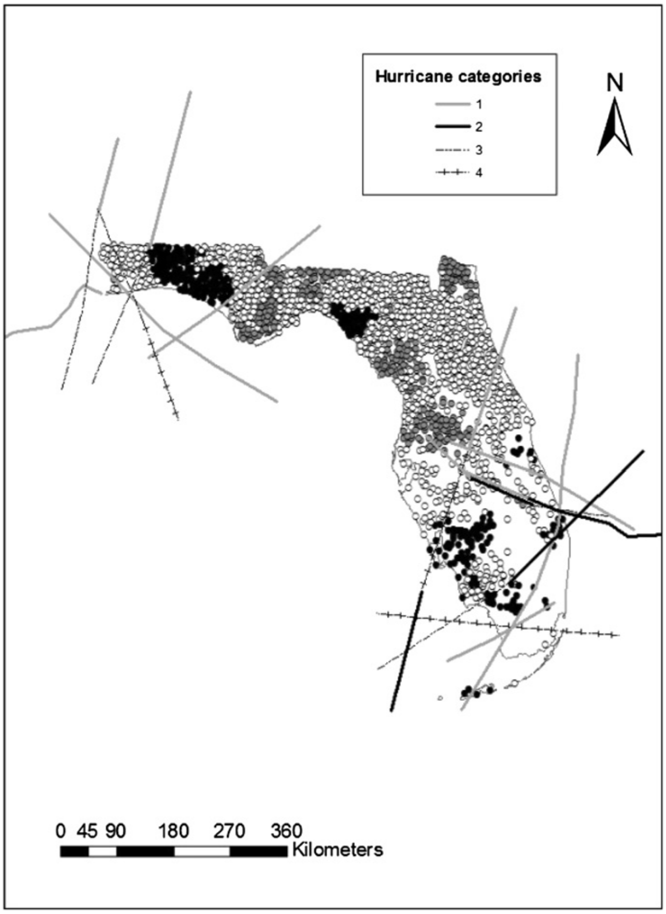

Fig. 2. Forest carbon storage hotspots and coldspots in Florida, USA with respect to recent hurricane tracks during 1998–2008.

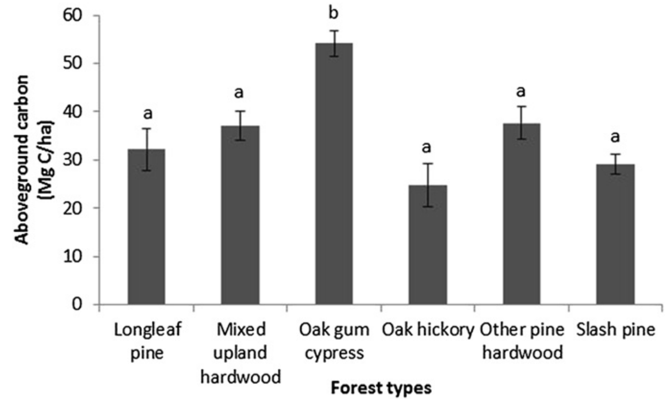

Fig. 4. Average aboveground carbon storage with standard error bars for different forest types in Florida, USA. Bars with different letters are significantly different at $p = 0.05$.

existing aboveground components. However, soil organic carbon storage might not necessarily be the result of the current aboveground component (Lal, 2005). Soil organic carbon formation and dynamics are complex and might not necessarily be increased by increasing the total forest biomass stock, because it is dependent on multiple interactions between climate, soil biological and physical properties, forest structure and management, and the chemical composition of downed tree and litter (Lal, 2005). Further, other factors such as disturbance regime and historical land use (Lal, 2005) also affect soil carbon dynamics. Our findings also indicate that land tenure was not a significant predictor of carbon storage hotspots. Although the result was not statistically significant, public lands increased the probability of a forest being a C hotspot (higher value) than private lands (Table 7). This result is consistent with that reported by Heath et al. (2011), which found that lands managed by the USDA Forest Service (including National forests in the southeastern US) had higher carbon storage densities on average than private lands.

Results from our framework indicate that mixed upland hardwood and oak hickory forests had a greater probability of being identified as a carbon hotspot relative to a single species pine forests (Table 6). The difference in forest types takes into account controlling for the stand age and site quality. When stand age and site quality are held constant, then on average mixed upland hardwood and oak hickory forests had a higher probability of being a hotspot than longleaf pine forests. This finding was consistent with those of Brown and Schroeder (1999) and Brown et al. (1999) who found that hardwood forests have higher carbon stocks and wood production than softwood forests. Stand age and site quality, as defined in this study, were also important drivers of carbon storage hotspots. Better quality sites have usually higher moisture and soil nutrient availability and overall better growing condition (Linder, 1995). In general, on more productive forests, more carbon is allocated to stem wood and leaves than to fine root production

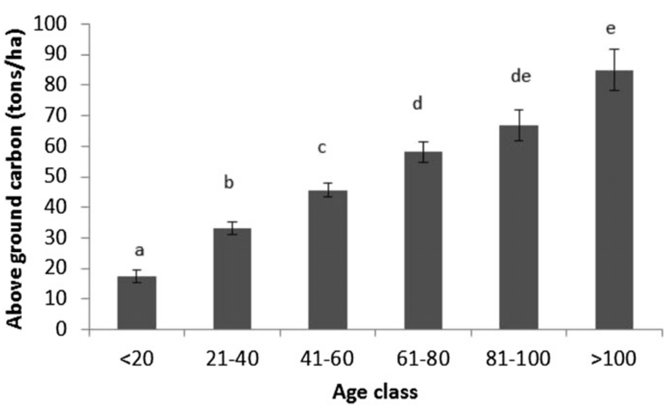

Fig. 3. Average aboveground carbon storage with standard error bars for different forest age classes in Florida, USA. Bars with different letters are significantly different at $p = 0.05$.

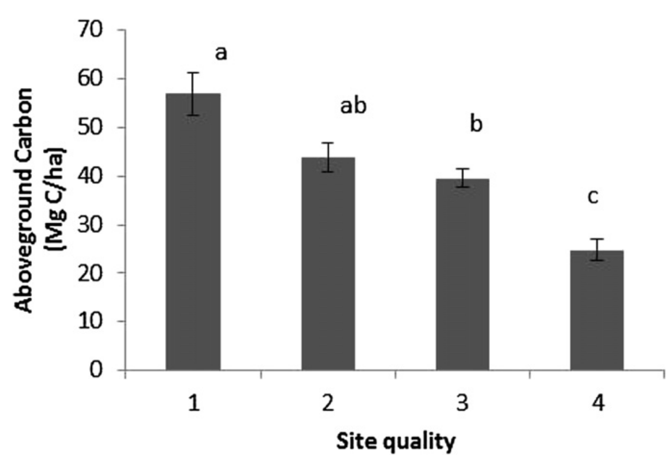

Fig. 5. Average aboveground carbon storage with standard error bars for different site quality classes in Florida, USA. Bars with different letters are significantly different at $p = 0.05$.

thus increasing aboveground biomass and subsequent carbon storage (Nadelhoffer and Raich, 1992). In an experimental study of pine plantations in North Carolina, sites with moderate to high nutrient contents were able to increase carbon sequestration under elevated atmospheric CO_2 concentration when compared to nutrient-poor forests (Oren et al., 2001). As a result, nutrient limitations will often influence carbon sequestration even under conditions of increased atmospheric CO_2.

Stand age has been found to be an important variable for determining biomass and carbon stocks in forests (Thornton et al., 2002; Gough et al., 2008; Wang et al., 2011). Our results show that carbon storage was greater with increasing age, but there were no statistically significant differences between the older stand categories (e.g. 60–80, 80–100, and >100 years old; Fig. 3). Studies have shown that younger forests are carbon sinks (i.e. higher NEE) relative to older forests (Thornton et al., 2002), but older forests have usually higher biomass and subsequent carbon storage than younger sites (Wang et al., 2011). These younger stands store less carbon due to low photosynthesis to respiration ratios, since carbon storage peaks as the stand reaches maximum canopy photosynthesis; which subsequently declines with increasing age (Odum, 1969). Younger forests in Michigan were considered moderate carbon sinks until six years after experimental cutting and burning due to higher heterotrophic respiration and lower photosynthetic carbon gains, however this trend disappeared for stands at 50 years old (Gough et al., 2008). Our results also indicate greater carbon storage for stands until an age of 60 years. But, no significant differences in carbon storage were found for older stands. So, overall our results indicate that carbon storage will be optimal in a stand of at least 60 years old.

We hypothesized that stands affected by recent fires and hurricanes would have low carbon storage values and would be identified as coldspots – as defined in this study – when compared to undisturbed areas with minimal natural and anthropogenic disturbances (McNulty, 2002; Hubbard et al., 2004). However, we did not find any relationship between disturbance types or time since disturbance with C hotspots. According to Hubbard et al. (2004) high severity fires reduce carbon stocks due to biomass combustion. Our analysis did not find any indication that fire was a significant driver of carbon storage coldspots. Although our classification of hotspots was based on aboveground tree carbon values, these data did not include foliage biomass and this could be one of the reason we did not identify any fire effects on carbon storage. According to our FIA data, most fires affecting our sample plots were surface fires, and only one plot was identified as being affected by a crown fire, and furthermore the most recent fires occurred only 1 year before sampling. Since surface fires in Florida generally do not cause tree damage and mortality, and since the understory might have recovered during the sampling period; no effect of fire was detected. Low severity fires – using "back fires" that obtain a mean maximum temperature of 135 °C – have been reported to have no effect on total live aboveground biomass of oak-pine forests of Tennessee and Georgia, but they do reduce the understory biomass by 50% (Hubbard et al., 2004).

Although we did not find any significant effect of windstorm damage on carbon storage hotspots; areas of high hurricane landfall frequency in Florida were common in forests identified as coldspots as seen in Fig. 2. McNulty (2002) found no extensive damage to forests related to hurricanes below a Saffir-Simpson Category 3. Although our dataset did not have information on the type of wind damage, Thompson et al. (2011) found that subtropical peri-urban forests generated more debris (i.e. downed biomass) than did urban forests. In addition these authors and Oswalt and Oswalt (2008) found that tree damage was a result of forest structure characteristics and not necessarily hurricane meteorology.

Our main objective was to provide a framework for spatially analyzing accessible inventory data to map and analyze carbon storage hotspots in forested landscapes. As such, this study does not provide an exhaustive analysis of all environmental and biophysical factors affecting forest ecosystem carbon dynamics. Also, the carbon estimates used in our analysis were solely based on plot coordinates and tree carbon-biomass relationships provided by FIA and Jenkins et al. (2003) methods; some of which are generalized by species, genus or wood type (hardwood vs. softwood). Similarly, there are other generalizations used with the calculation of other carbon pools analyzed in this study that are described in Smith and Heath (2002, 2008).

An additional limitation of our study was that the FIA plot locations provided in the vector digital file were within a 1.6 km from their actual location. However, this did not significantly affect our state and mesoscale results and plot-level inferences since significantly distinct C storage hotspots were individual plots clustered around other plots with similarly high- or low-values. Although we might have missed individual plots with high C storage values, these were not identified as significant hotspots since these were not located in high C storage clusters. Furthermore, since FIA sampling intensity is one plot per 24 km^2, the 45 km distance band used in this framework increases the number of FIA plots used to make mesoscale inferences and for mapping regional forest management characteristics.

5. Conclusion

This framework used geostatistical analyses and available forest inventory data to identify and map carbon hot/coldspots in Florida and influential forest management drivers. Overall, our findings indicate the importance of forest type, stand age, and site quality as better predictors of carbon hotspots, but ecological disturbances (e.g. fire, hurricanes) and land tenure were not significant drivers of C storage by forests.

In Florida, management is usually focused on restoration of longleaf pine forests and management of pine plantations, but our study identified other mixed species forests, conservation areas, national forests, and peri-urban forests that are equally interesting for management and conservation objectives involving carbon sequestration and provision of other ecosystem services (e.g. biodiversity, water yield). Additionally, although most studies on carbon dynamics are from pine flatwoods and cypress wetlands (e.g. Clark et al., 2004; Powell et al., 2008), our study has identified other forest types that could also be the basis for future studies on carbon dynamics. For example, carbon storage hotpots located adjacent to metropolitan areas in north Florida could be used to identify areas of interest for the conservation of these peri-urban forests because of the ecosystem services they provide and potential risk of forest loss due to urbanization. Also because of the relationship between site quality and increased carbon sequestration, efforts to manage forests for carbon storage could be directed towards better quality sites as defined by USDA FS FIA criteria. That said, other tradeoffs associated with managing for forest carbon storage such as biodiversity, recreation, and water yield should be considered. For example, longleaf pine savannas were characterized by relatively low carbon storage values, yet this forest type is associated with high species diversity (Bond et al., 2005).

Results from our frameworks can be used to promote forest types and species that are economically viable and at the same time store more carbon for meeting multiple objectives. For example, pines species store higher proportions of carbon in the commercial wood (stem) compared to noncommercial biomass (bark, limbs, roots and leaves); however, for CO_2 emission reduction and offset strategies, C storage in other noncommercial biomass (e.g. below-ground and soil) are equally important. Future research is warranted in the incorporation of regional spatial datasets such as fires regime condition classes or soil inventories (e.g. USDA State Soil Geographic Database) with our framework to better identify ecosystem-level drivers of C storage. Or, the framework could easily integrate census (e.g. US Census Block Group data), property appraisal, and land tenure spatial data to also analyze the socio-economic drivers of carbon storage hotspots. Although this study only analyzed carbon stocks, similar analyses could be done at the micro- and macro-scale with carbon sequestration or other ecosystem services. Additionally by analyzing specific tree species groups and size classes, this framework could be used to identify appropriate supplies and available materials for bioenergy utilization and the information used for decisions regarding the mapping and placement of future bioenergy plants and wood fuel pellet mills in Florida and elsewhere. Our methods can also be used to identify other drivers behind the provision of carbon sequestration and these other ecosystem services and goods. It is our hope that this framework facilitates other similar analyses elsewhere around the world by incorporating existing and available geo-referenced forest inventory data.

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Appendix A. Supplementary material

Supplementary material related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2012.10.020.

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