LINKING STATSGO AND FIA DATA FOR SPATIAL ANALYSES OF LAND CARBON DNESITIES

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ABSTRACT

Carbon storage in soils and forest biomass is geographically variable. The spatial distribution can be a result of: i) local site conditions such as climate, geomorphology, and soil that determine long-term carbon sequestration potential; ii) disturbance such as previous land use, current forest management practices, and natural disasters, e.g., forest fire and disease that manipulate carbon pools; iii) forest types, a consequence of i and ii; and iv) forest growth phases, which determine temporal biomass accumulation rates. During the past decade, many studies on carbon accounting of forests and soils have been conducted. Until recently, however, most estimates of regional and global carbon stocks are based on extrapolating means for broad categories of soils and vegetation types. Uncertainties exist in both the estimates of mean carbon contents and the estimates of land area covered for each category. The challenge remains of how to constrain these uncertainties and especially, how to incorporate various environmental and management factors to estimate and predict carbon storage and dynamics. The US government has invested in the establishment of the State Soil Geographic Database (STATSGO) and the nationwide data for the Forest Inventory and Analysis (FIA) program. However, no attempt to link the two geographic information databases for carbon analysis has been published. This study examines a methodology to link STATSGO and FIA data for carbon accounting of soils and forests. In this process, using the data for South Carolina as an example, total soil carbon stock and forest biomass were quantified, carbon densities of soils and forests were estimated, and the distributions of the soil and biomass carbon densities across the state were analyzed. The study shows that both the STATSGO database and the FIA database offer promise of scaling up map unit soil data and forest inventory plot data to county and regional scales, and suggests that linking these two databases is a credible approach to integrate soil and forest attributes, combined in a form conducive to spatial analysis, to predict changes in land carbon storage.

INTRODUCTION

Spatial distribution of terrestrial carbon pools and fluxes plays an important role in global carbon cycle studies. In his review article, Schlesinger (1993) pointed out that despite 20 years of intensive effort to understand the global carbon cycle, the budget for carbon dioxide (CO_2) in the atmosphere is unbalanced. Recent estimates for annual emissions of CO_2 from fossil fuel combustion and land use change for 1980-1989 are 5.4 Gt C yr^{-1} and 1.6 Gt C yr^{-1}, respectively (Houghton et al., 1992). Global oceans are estimated to absorb 2.0 Gt C yr^{-1}, and about 3.2 Gt C yr^{-1} remains in the atmosphere (Dixon et al, 1994), which leaves about 1.8 Gt C yr^{-1} at the global scale unaccounted for. This imbalance, a so-called missing sink, reveals that our present understanding of the global carbon cycle is limited by uncertainty over terrestrial ecosystem carbon cycles. Among terrestrial ecosystems, forests (including soils) are the largest, most influential, and most variable components of the carbon cycle. Carbon storage and sequestration in forests are highly variable, both temporally and geographically. The spatial and temporal dynamics can be a result of: i) local site conditions such as climate, geomorphology, and soil that determine long-term carbon sequestration potential; ii) disturbance such as previous land use, current forest management practices, and natural disasters, e.g., forest fire and disease that manipulate carbon pools; iii) forest types, a consequence of i and ii; and iv) forest growth phases, which determine temporal biomass accumulation rates.

Until recently, most estimates of regional and global carbon stocks are based on extrapolating means for broad categories of soils and vegetation types. Significant uncertainties exist in both the estimate of mean carbon contents and the estimates of land area covered for each category. The challenge remains of how to constrain some of these uncertainties. The US government has invested in the establishment of the State Soil Geographic Database STATSGO) and the nationwide data for the Forest Inventory and Analysis (FIA) program. The STATSGO database contains a variety of soil attributes including those relevant to soil carbon estimation, such as soil layer depth, bulk density, and organic matter content. The FIA database provides forest inventory data across the nation and all land ownerships. FIA also collects data from loggers, wood processing mills and private landowners on utilization efficiency, types of wood product, and demographics. As many regions and countries develop and build GIS-based natural resources databases, there is a tremendous opportunity for using these geographically referenced data sources for regional, national and global carbon accounting of land areas under various use types. In the US, few studies have used STATSGO for quantifying soil carbon (e.g., Davidson and Lefebvre, 1993; Homann et al., 1998) and FIA for forest biomass carbon (Birdsey et al., 1993). However, no attempt to link these two potentially valuable sources for spatial and temporal carbon analyses has been published.

The objectives of this study are: i) to examine a methodology to link STATSGO and FIA databases; ii) to create a credible tool that easily integrates attributes of forest, soil, land use, management practices, and climate; iii) to analyze carbon pools and flux of the US forest ecosystems. The final goal of this research is to develop a carbon modeling system that is more responsive and sensitive to the variability inherent in terrestrial ecosystems by taking full advantage of GIS databases. Using South Carolina soil and forest datasets as an example, this paper presents our preliminary results and discusses opportunities of dynamic modeling of carbon storage by linking STATSGO and FIA.

METHODS

Estimation of Soil Carbon Densities

Soil data for South Carolina were obtained from the National STATSGO Database website (*http://www.ftw.nrcs.usda.gov/stat_data.html*) maintained by the USDA Natural Resources Conservation Service. The STATSGO database includes a digitized map (USGS 1:250,000 topographic quadrangle) of polygons classified as map units and contains a hierarchic data structure with three levels. The order from the top to the bottom is soil map unit, component, and layer. For South Carolina, there are in total 858 polygons and 159 map units with an identifier *Muid*. This map unit identifier is keyed to the map component table that contains information on soil series and their percentage presence in each map unit. The component data table contains a sequence number, called *Seqnum* in STATSGO, which is related to the layer data table that provides more than 20 different soil attributes for soil layers from the surface down to the maximum depth. Detailed information on the STATSGO data and the data structure can be found in State Soil Geographic (STATSGO) Data Base Data Use Information by USDA NRCS (1994).

In this study, we used attributes of the soil layer depth, bulk density, and percentage of soil organic matter in the layer data table for calculating soil carbon density (metric C tons per hectare from soil surface down to maximum soil depth). Soil carbon densities (C_s) for each map unit were quantified as follows:

$$C_s \; ? \; [? \quad ? \; (BD_{ij} \; ? \; D_{ij} \; ? \; SOM_{ij}) \; ? \; Comp_i] \; ? \; 1.724$$

where *BD* is the soil bulk density in kg m^{-3}, *D* is the depth of soil layers in meters, *SOM* is the soil organic matter content in percent, *Comp* is the percent of the area that the soil represents within each map unit, and the subscript *i* and *j* are the identifiers for soil layers and components, respectively. The factor, 1.724, is used as the assumed fraction of carbon content of soil organic matter (Nelson and Sommers, 1982).

The results of this calculation represent an average soil carbon density, from the soil surface down to the maximum soil depth as given in the STATSGO layer data, in tons per square meter for each map unit. These were area-weighted for each county of South Carolina and converted into tons per ha for presenting a county average of soil carbon density.

Estimation of Forest Biomass Carbon Densities

Tree biomass data for South Carolina were downloaded from the USDA FIA Database Retrieval System at the website *http://www.srsfia.usfs.msstate.edu/wo/dbrs_setup.htm*. The most recent forest inventory in the state was completed in 1993, administrated by the Forest Inventory and Analysis Research Unit at the Southeastern Forest Experiment Station, Asheville NC. There were six previous surveys completed in 1936, 1947, 1958, 1968, and 1986.

The FIA database contains three data tables: county, plot, and tree. Similarly like the structure of the STATSGO database, the FIA data tables are related to each other in the order from the top to the bottom: county data table, plot data table, and tree data table. Among others, the county data table contains the county names and the regional units that are related to the plot data table. The plot data table has information on the plot location, the number of acres that a plot represents (an expansion factor, *expvol*), the land ownership, and others, with a plot number that is related to the tree data table. Among other tree growth data, the tree table contains green weight of biomass (*totbio*, including the top and all limbs) and a volume expansion factor (*volfac*) for converting a single tree biomass into an acre unit. All sampled trees with a DBH larger than 2.54 cm obtain a biomass weight. More details about the attributes and structure of FIA data is found in Hansen et al. (1992), and specific information on the 1993 inventory for South Carolina is available in *Forest Statistics for South Carolina* by Conner (1993).

Using these FIA data, forest biomass (above and belowground) carbon densities were estimated for both the plot level and the county level. Forest aboveground biomass (B_{above}) was calculated for each plot simply by multiplying biomass of the sampled trees (*totbio*) by the volume expansion factor (*volfac*). Belowground biomass (B_{below}) was estimated using the following equation developed by Cairns and others (1997):

$$B_{below} \ ? \ \exp[?1.059 \ ? \ 0.884 \ ? \ \ln(B_{above}) \ ? \ 0.284]$$

The sum of B_{above} and B_{below} presents a total biomass in each plot and, for FIA, this is in the unit of pounds of fresh biomass per acre. These estimates were converted into t ha^{-1} and multiplied by a factor of 0.4, the assumed fraction of carbon content of green biomass, for presenting biomass carbon density (C_b). At the county level, the estimates of total fresh biomass from all plots were first multiplied by the expansion factor, *expvol* (refer to the FIA plot data table), and then summed up by each county. The estimates of total biomass of each county were multiplied by 0.4 and divided by the county land areas for an average biomass carbon density.

Land Carbon Densities and Mapping

Estimates of the soil carbon densities (C_s) and forest biomass carbon densities (C_b) at the county level were summed up for presenting an average of land carbon densities. Because the land carbon density does not include agricultural crop and rangeland grass biomass, the estimates may be lower than they should be, especially for the counties with a large potion of farmer lands. However, compared to the amount of carbon stored in soils and forests, this has little effect on the land carbon density.

FIA forest plots are coordinated in geographic decimal degrees, while the STATSGO soil map is projected in Albers Equal Area Conic. To incorporate the different coordinates, we converted the STATSGO map for South Carolina to geographic decimal degrees. The converted soil map was overlaid with the US county map for South Carolina (the U.S. Census Bureau 1990) and a geoprocessing procedure was done to create an overlay coverage (Figure 1).

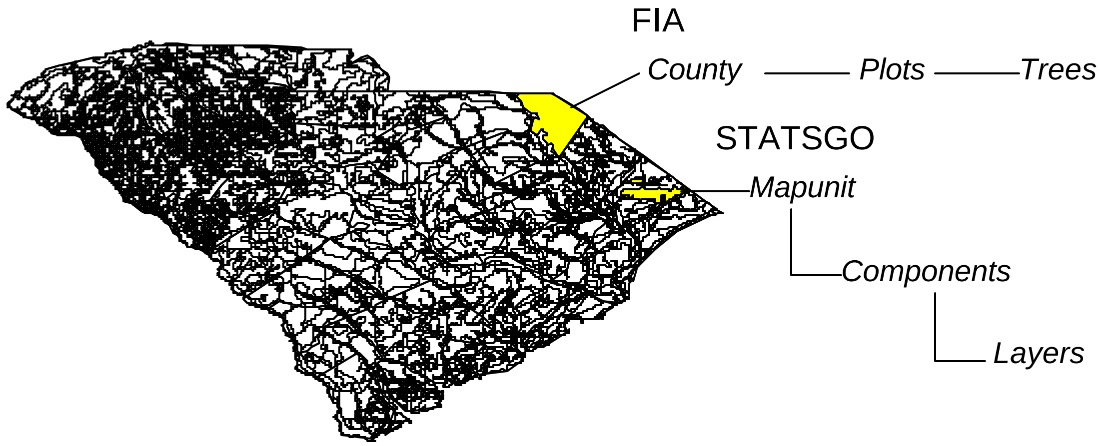

Figure 1. Overlay coverage linking STATSGO and FIA and the data structure.

Maps were made for soil carbon densities and forest biomass carbon densities at the map unit, the plot level, and the county level. All maps and mapping procedures were done using ArcView GIS 3.2 software (ESRI, 380 New York St., Redlands, Ca 92373).

RESULTS AND DISCUSSION

Distribution of Soil Carbon Densities

Soil carbon densities in South Carolina are highly variable, ranging from about 45 to nearly 3500 tons per hectare at the STATSGO map unit level (Figure 2). The highest density was found in a wetland with a very deep soil in Colleton county and the lowest density occurred in a unit with shallow soils in Cherokee county. At the county level, soil carbon densities are highest on the southeastern corner and lowest in the central Piedmont region of the state (Figure 2). All 18 counties located in Piedmont (except for Saluda) showed low soil carbon densities (< 100 t ha^{-1}, Table 2), while the counties on the lower Coastal Plain exhibited high soil carbon density (>300 t ha^{-1}). Among the 46 counties of South Carolina, Beaufort and Charleston showed extremely high soil carbon densities (1281 and 848 t ha^{-1}, respectively). Across the state, there exists a clear

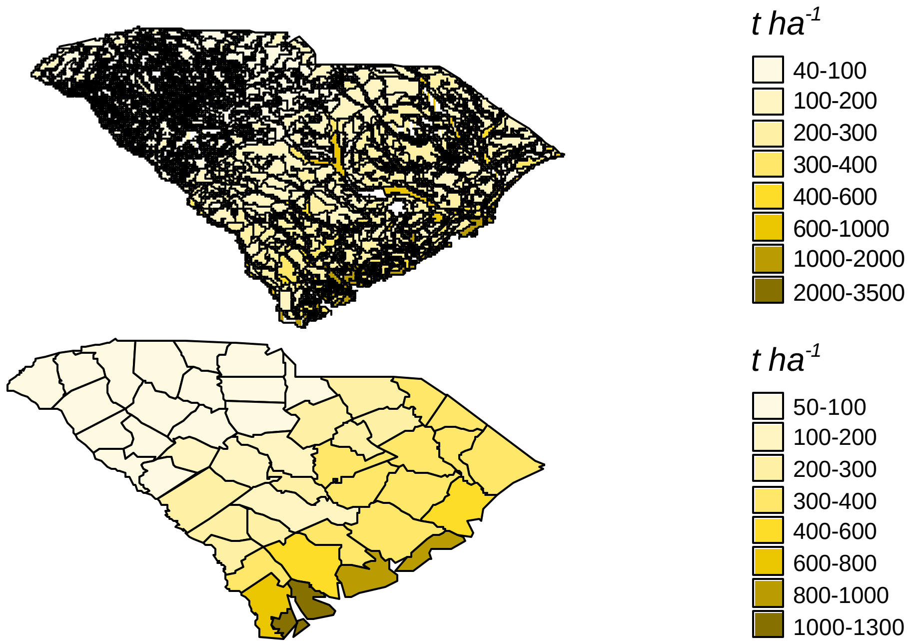

Figure 2. a) Distribution of soil carbon densities at the STATSGO map unit (above) and b) the county scale of resolution (below) in South Carolina.

Table 1. Soil carbon density (C_s) in South Carolina

County	C_s (t ha^{-1})	Rank	County	C_s (t ha^{-1})	Rank
Abbeville	58.5688	46	Greenwood	75.4160	36
Aiken	213.3476	24	Hampton	302.3517	16
Allendale	251.1884	20	Horry	320.3875	10
Anderson	60.7164	45	Jasper	624.4800	3
Bamberg	247.4271	21	Kershaw	203.0971	25
Barnwell	243.3059	22	Lancaster	90.4831	31
Beaufort	1280.6280	1	Laurens	63.6473	43
Berkeley	315.6564	13	Lee	298.7171	17
Calhoun	238.4552	23	Lexington	150.9137	28
Charleston	847.6755	2	Marion	352.7700	7
Cherokee	68.9281	39	Marlboro	329.8932	8
Chester	68.0243	41	McCormick	74.1359	37
Chesterfield	263.0726	19	Newberry	62.9743	44
Clarendon	326.9997	9	Oconee	85.2266	32
Colleton	565.5419	4	Orangeburg	184.2433	26
Darlington	297.6758	18	Pickens	75.8658	35
Dillon	319.7741	11	Richland	183.5276	27
Dorchester	367.6565	6	Saluda	113.8318	29
Edgefield	98.5722	30	Spartanburg	68.8503	40
Fairfield	79.5249	33	Sumter	307.5703	14
Florence	318.4132	12	Union	65.7801	42
Georgetown	526.2665	5	Williamsburg	304.7712	15
Greenville	76.3859	34	York	70.6314	38

trend that the soil carbon densities decrease from the lower Coastal Plain, via the upper Coastal Plain, to the Piedmont uplands.

Soils on the Coastal Plain are derived from marine and fluvial deposits. They are often several meters deeper and carbon richer than those of the Piedmont, resulting much high carbon densities in the Coastal Plain region. In addition to the difference in geologic origins, the flat topography of the Coastal Plain provides a transitional zone between the upland and the aquatic system, causing long-periodic high water tables and floods. This unique hydrologic condition and the underlying pedologic process are beneficial to the accumulation of soil organic matter in the coastal region. Furthermore, human activities such as intensive land use in agriculture, forestry and mining, can be another important factor contributing to this large gradient of soil carbon density in South Carolina.

Distribution of Forest Biomass Carbon Densities

For South Carolina, there are in total 7031 inventory plots across its 46 counties. But 2914 plots of them have no biomass records. Figure 1a shows estimates of the forest biomass carbon densities at the plot scale, ranging from 0 to 202 t ha^{-1}. The highest biomass density at the plot level was recorded in a forest industry owned land in Mario county. However, among 10 recorded ownerships, the highest average of biomass carbon density at the plot level appeared in a land owned by "other federal" (not USDA Forest Service; owner code 14, refer to Hansen et al, 1992) and the lowest average in the land owned by private individuals but leased to forest industry (owner code 90). At the county level, average biomass carbon densities ranged from 27 to 76 t ha^{-1} (Table 3). Three counties (Charleston, Clarendon, and Lee) show an average density below 30 t ha^{-1} and two counties (Hampton and Union) have an average density above 70 t ha^{-1}.

Unlike the distribution of soil carbon density, which essentially resulted from geologic and geomorphologic conditions, the distribution of forest biomass density in South Carolina reflects human activities and land management practices. The three counties with the smallest forest resources are subject either to intensive agriculture (Clarendon county and Lee county) or to urbanization (Charleston county). The counties with the high forest biomass densities show a strong presence of industrial forestry.

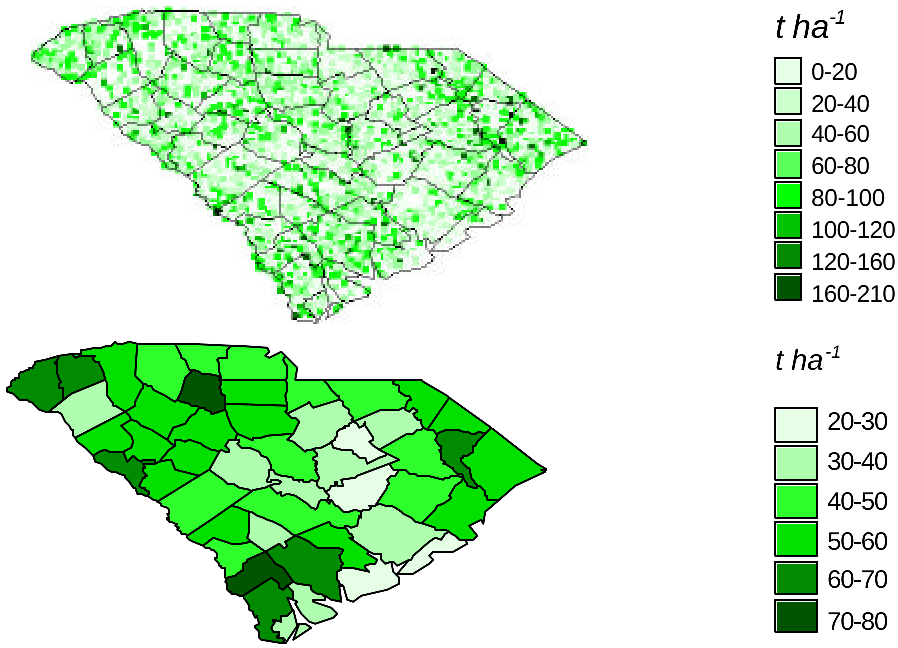

Figure 3. a) Distribution of forest biomass carbon densities at the plot level (above) and b) the county scale of resolution (below) in South Carolina.

Table 2. Forest biomass carbon density (C_s) in South Carolina

County	C_b (t ha^{-1})	Rank	County	C_b (t ha^{-1})	Rank
Abbeville	50.2426	23	Greenwood	50.6192	21
Aiken	44.4304	29	Hampton	72.1243	2
Allendale	44.9716	27	Horry	58.0197	12
Anderson	33.3726	43	Jasper	66.8836	3
Bamberg	38.0595	37	Kershaw	38.8645	35
Barnwell	53.8022	15	Lancaster	41.4170	32
Beaufort	34.7040	42	Laurens	50.4597	22
Berkeley	38.7132	36	Lee	27.9008	45
Calhoun	36.7588	39	Lexington	35.5420	41
Charleston	29.0634	44	Marion	64.4162	5
Cherokee	45.6862	25	Marlboro	53.5892	17
Chester	59.3454	10	McCormick	65.3471	4
Chesterfield	45.6112	26	Newberry	54.3254	14
Clarendon	26.7846	46	Oconee	61.6199	8
Colleton	61.9510	7	Orangeburg	42.6774	30
Darlington	36.1903	40	Pickens	63.2868	6
Dillon	52.5406	18	Richland	45.9580	24
Dorchester	59.1780	11	Saluda	53.6904	16
Edgefield	57.3162	13	Spartanburg	41.9808	31
Fairfield	59.6857	9	Sumter	37.3032	38
Florence	40.6360	33	Union	76.3541	1
Georgetown	51.8574	19	Williamsburg	40.3415	34
Greenville	51.7103	20	York	44.4916	28

Land Carbon Densities and Potential Future Changes

Figure 4a is a map of the distribution of the land carbon densities, combined from soil and forest biomass carbon storage values, at the county level. Figure 4b displays the distribution of the ratios of forest biomass carbon densities to soil carbon densities ($C_b : C_s$). These estimates are summarized in Table 3 for all 46 counties in South Carolina.

The land carbon densities have a similar distribution to that of the soil carbon density: a decreasing trend from the Coastal Plain to the Piedmont region (Figure 4a). This is due to the high proportion of soil carbon storage to forest biomass carbon storage. In all South Carolina counties, except for one (Union), the soil carbon storages account for more than half of the total land carbon (Table 3). The counties in the coastal region occupy extremely carbon-rich soils that store more than 80% (up to nearly 100%) of the land carbon stocks. The proportion of soil carbon storage decreases largely in the Piedmont uplands, and the exception, Union county, can be explained by a higher proportion of biomass carbon to soil carbon (Figure 4b).

The soils of the world are considered to store two to three times as much carbon as the atmosphere (Eswaran et al., 1993; Kimble et al., 1991), which is a substantial gap. There are two fundamental questions as to how much carbon is actually present in soils and how these carbon stocks across various landscapes will change over time. For the South Carolina coastal region, the most critical issues for the future are land use change as urbanization continues, and sea-level rise as climate change models have projected (e.g., Nicholls and Leatherman, 1996; West and Dowlatabadi, 1999). In previous decades, wetlands on the lower Coastal Plain in the southeastern United States were generally undervalued. In conjunction, large-scale pine plantations have been established and intensive forest management have been introduced to most of the region. Forest practices in this region such as ditching, harvesting and site preparation can greatly manipulate site hydrology and change carbon pools, as evidenced by a 40 cm rise of water table during the growing season (Xu et al., 1999a) and an increase of 30-ton-carbon per ha in the soils after harvesting wetland pine forest in Colleton county (Xu et al., 1999b). In the Piedmont uplands, which have traditionally been under surface erosion due to intensive farming and mining, future land management practices will be important to the soil carbon loss/gain questions.

Forest biomass stocks have been, and will continue to be, subject to human activities and land management practices. It is likely that future biomass density will increase due to the use of genetically improved trees and intensive fertilization increase forest industry biomass production per unit area.

There are a variety of factors that add to the uncertainty of future land carbon stocks in South Carolina. A credible tool that is capable of bringing together all relevant land and forest attributes, both spatially and temporally, would provide an avenue to better predict future land carbon changes. The GIS approach presented in this study demonstrates that linking spatially associated databases can provide a better picture of land carbon storage and at higher resolution than before. It offers the potential of incorporating different soil or ecosystem carbon models to study carbon changes and dynamics over time.

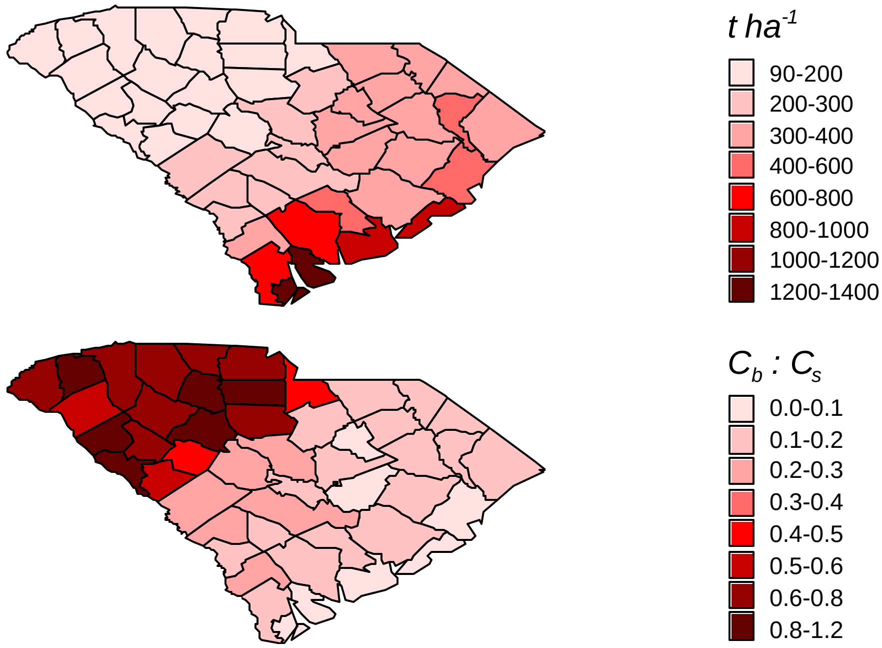

Figure 4. a) Distribution of land carbon density ($C_s + C_b$, above) and b) ratio of biomass Carbon density to soil carbon density (below)

Table 3. Land carbon density carbon density (C_{s+b}) in South Carolina

County	C_{s+b} t ha^{-1}	C_b/C_s	County	C_{s+b} t ha^{-1}	C_b/C_s
Abbeville	108.8114	0.8578	Greenwood	126.0352	0.6712
Aiken	257.7780	0.2083	Hampton	374.4760	0.2385
Allendale	296.1600	0.179	Horry	378.4072	0.1811
Anderson	94.0890	0.5496	Jasper	691.3636	0.1071
Bamberg	285.4866	0.1538	Kershaw	241.9616	0.1914
Barnwell	297.1081	0.2211	Lancaster	131.9001	0.4577
Beaufort	1315.3320	0.0271	Laurens	114.1070	0.7928
Berkeley	354.3696	0.1226	Lee	326.6179	0.0934
Calhoun	275.2140	0.1542	Lexington	186.4557	0.2355
Charleston	876.7389	0.0343	Marion	417.1862	0.1826
Cherokee	114.6143	0.6628	Marlboro	383.4824	0.1624
Chester	127.3697	0.8724	McCormick	139.4830	0.8815
Chesterfield	308.6838	0.1734	Newberry	117.2997	0.8627
Clarendon	353.7843	0.0819	Oconee	146.8465	0.723
Colleton	627.4929	0.1095	Orangeburg	226.9207	0.2316
Darlington	333.8661	0.1216	Pickens	139.1526	0.8342
Dillon	372.3147	0.1643	Richland	229.4856	0.2504
Dorchester	426.8345	0.161	Saluda	167.5222	0.4717
Edgefield	155.8884	0.5815	Spartanburg	110.8311	0.6097
Fairfield	139.2106	0.7505	Sumter	344.8735	0.1213
Florence	359.0492	0.1276	Union	142.1342	1.1607
Georgetown	578.1239	0.0985	Williamsburg	345.1127	0.1324
Greenville	128.0962	0.677	York	115.1230	0.6299

CONCLUSIONS

An approach of linking two geographically referenced databases, STATSGO and FIA, was taken to quantify soil and forest and the combined land carbon densities. As an example using South Carolina soil and forest datasets, this study demonstrated the credibility of geographic information systems in permitting the estimations and spatial analyses of soil, forest and land carbon storages at finer scales of resolution. Beyond assessment of the methodology, this study yielded insight into carbon dynamics in a state where agriculture and forestry play a large part in the economy. The soil carbon densities of South Carolina are closely associated with the state's geomorphologic features - a decreasing gradient coincided with the landscape forms from the lower Coastal Plain, via the upper Coastal Plain, to the Piedmont region. The forest biomass densities, on the other side, are highly reflected by the land use types and management practices in the state, resulting a decreasing trend of the ratios of biomass carbon densities to soil carbon densities from the Piedmont eastward to the lower Coastal plain. In addition to providing information for land managers, the current study may help provide a framework for continued investigation of state, regional, and even global land carbon balance.

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