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A spatial resolution threshold of land cover in estimating regional terrestrial carbon sequestration

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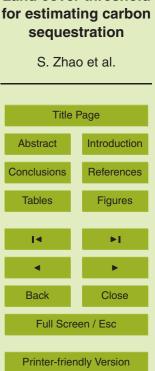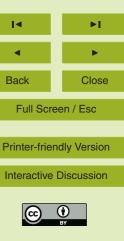[3]USGS EROS Center, Sioux Falls, SD 57198, USA
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BGD

6, 7983–8006, 2009

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Abstract

Changes in carbon density (i.e., carbon stock per unit area) and land cover greatly affect carbon sequestration. Previous studies have shown that land cover change detection strongly depends on spatial scale. However, the influence of the spatial resolution of land cover change information on the estimated terrestrial carbon sequestration is not known. Here, we quantified and evaluated the impact of land cover change databases at various spatial resolutions (250 m, 500 m, 1 km, 2 km, and 4 km) on the magnitude and spatial patterns of regional carbon sequestration in the southeastern United States using the General Ensemble biogeochemical Modeling System (GEMS). Results indicated a threshold of 1 km in the land cover change databases and in the estimated regional terrestrial carbon sequestration. Beyond this threshold, significant biases occurred in the estimation of terrestrial carbon sequestration, its interannual variability, and spatial patterns. In addition, the overriding impact of interannual climate variability on the temporal change of regional carbon sequestration was unrealistically overshadowed by the impact of land cover change beyond the threshold. The implications of these findings directly challenge current continental- to global-scale carbon modeling efforts relying on information at coarse spatial resolution without incorporating fine-scale land cover dynamics.

1 Introduction

Various approaches have been proposed to study the role of terrestrial biosphere on regulating CO_2 concentration in the atmosphere, ranging from measuring forest biomass change using national monitoring networks (Fang et al., 2001; Goodale et al., 2002; Smith et al., 2004, 2006; Kauppi et al., 2006) to remote sensing and biogeochemical modeling (McGuire et al., 2001; Myneni et al., 2001; Sitch et al., 2005; Quaife et al., 2008). Measurements from the field have to be the ultimate reference for these approaches. However, establishing and maintaining ground-based monitor-

ing networks are expensive and usually can only cover a fraction of the landscape (i.e., sampling plots). Biogeochemical modeling with input from remote sensing (e.g., land cover change) and constrained by field measurements is an effective alternative approach in estimating regional carbon sequestration.

5　　Land use and land cover change is one of the key driving forces for biogeochemical modeling, and sometimes an essential component for scaling up plot measurements to regional and national scales. Land use and land cover change directly affect the biogeochemical interactions between the terrestrial biosphere and the atmosphere (Schimel et al., 2001; Houghton and Goodale, 2004) and are responsible for large

10　carbon fluxes in and out of the terrestrial ecosystems (Fang et al., 2001; Canadell, 2002; Houghton, 2003; Kauppi et al., 2006). However, it has been a primary challenge to quantify the carbon exchange between the terrestrial biosphere and the atmosphere induced by land cover change, mainly due to the lack of detailed land cover change databases and appropriate models capable of dynamically assimilating land

15　cover change information into simulations over large areas (Houghton et al., 1999; Prentice et al., 2001; Achard et al., 2004; Ramankutty et al., 2007). In a previous study, we investigated the possible biases in quantifying carbon exchange between the land and atmosphere caused by ignoring detailed fast-changing dynamics of land cover, using the General Ensemble biogeochemical Modeling System (GEMS). GEMS

20　is capable of dynamically assimilating land cover change information into the simulation process over large areas. We found that ignoring the detailed fast-changing dynamics of land cover can lead to a significant overestimation of carbon uptake by the terrestrial ecosystem (Zhao et al., 2009). Given the inherent heterogeneity of landscapes at various spatial scales, modeled carbon exchange between the land and atmosphere may

25　vary with the spatial resolution or grain size of land cover information. Therefore, the present study was conducted to examine the possible influence of spatial resolution of land cover change information on the estimation of terrestrial carbon sequestration in four counties of the southeastern United States over the period 1992–2007, using the GEMS model, coupled with land cover information at spatial resolutions of 250 m,

500 m, 1 km, 2 km, and 4 km.

2 Methods

2.1 Study area

The study area, with a total area of 3852 km^2, is located along the border of Georgia
and Alabama, United States, consisting of four counties with Chattahoochee, Marion,
and Muscogee counties in Georgia and Russell county in Alabama (Fig. 1). The cli-
mate is subtropical with an annual mean precipitation of 1245 mm and annual mean air
temperature of 17.8°C between 1972 and 2007. Forest is the dominant land cover in
the region (~75%). Most of the forests are intensively managed for timber production
resulting in rapid turnover between clear-cutting and regenerating forest. The city of
Columbus, Georgia, and the Fort Benning military complexes account for much of the
developed land, while agricultural land and wetland accounted for much of the rest.
Because of the heterogeneity of land cover and short rotational forestry, this area is
ideal for investigating the impacts of spatial grain size of land cover change map on
carbon dynamics at the regional scale.

2.2 Model description

To simulate the impacts of land use change and spatial resolution of land use change
maps on regional carbon sources and sinks, it is apparent that the underlying model
should have the capability of simulating carbon dynamics over large areas with explicit
incorporation of dynamic land use change information. GEMS, developed to upscale
carbon stocks and fluxes from sites to regions, is one of such models (Liu et al., 2004a).
GEMS has the potential of take control of various site scale models such as CENTURY
(Parton et al., 1987; Reiners et al., 2002) and EDCM (Liu et al., 2003, 2004a; Zhao
et al., 2009). In this study, we use EDCM as the underlying biogeochemical model
within GEMS to simulate carbon dynamics at the site scale. The spatial deployment

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of the site-scale model in GEMS is based on the unique spatial and temporal combinations (i.e., joint frequency distribution or JFD) of major driving variables (e.g., land cover and land use change, climate, soils, disturbances, and management). The JFD was generated by overlaying these geospatial data layers with a common grid size of 250 m by 250 m spatial resolution. Model simulation units were the unique combinations of these data layers with the finest simulation unit being one grid cell (i.e., 250 m by 250 m). The uncertainties of data layers at coarser resolutions were incorporated into GEMS simulations via a probability-based Monte Carlo approach to generate parameter values from probability density functions of properties. The combination of JFD and probability-based model parameterization enables GEMS maximally use the finest information contained in some data layers (land cover change database in this study, for example), and at the same time other coarser resolution data layers are scaled down to the finest resolution through ensemble probabilistic representations of uncertainty. Ensemble simulations (size=20), each with input values sampled from the value ranges and corresponding probability density functions of the biophysical parameters, were performed to transfer input data uncertainty into GEMS output. A more detailed description of the model can be found in Liu et al. (2004a, b) and Liu (2009).

2.3 Land cover change database

Consistent, high-quality, and spatially explicit land cover change databases at 250 m×250 m resolution were developed using the FORE-SCE (FOREcasting SCEnarios of future land cover) model (Sohl et al., 2007). FORE-SCE can project future land use changes from spatial and temporal characteristics of historical land cover change, and probability-of-occurrence surfaces for each unique land cover type. In this study, FORE-SCE relied heavily on the data generated by the US Geological Survey's Land Cover Trends project (Loveland et al., 2002) for model parameterization. Specifically, FORE-SCE projections were based on extrapolation of annual "prescriptions" of key land use change variables derived from Land Cover Trends project (e.g., the rates of change for individual land cover types, likelihood of specific land cover transitions, and
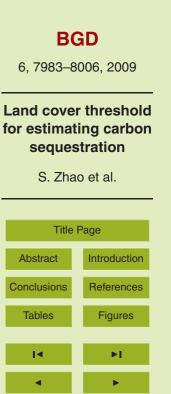
basic characteristics of patch size) from the 1992–2000 time period to 2001–2007. Logistic regression was used to develop probability-of-occurrence surfaces for each land cover type based on biophysical and socioeconomic drivers related to land use type at a given location. Individual patches of new land cover were placed on the landscape in an iterative process until the annual scenario prescriptions had been met. Patch sizes of land use change were uniquely assigned by approximating the historical distribution of patch sizes for each land cover type in the region. The process continues with yearly iterations, with a history variable tracking age classes for forest and other classes. A more detailed description of the model can be found in Sohl and Sayler (2008).

To investigate the potential influence of spatial resolution of land use change data on carbon sequestration, we used land cover information at five spatial resolutions (i.e., 250 m, 500 m, 1 km, 2 km, and 4 km). The spatial resolution of the original land cover dataset was 250 m, and the land cover maps were resampled to grain sizes of 500 m, 1 km, 2 km, and 4 km using the nearest-neighbor resampling algorithm. Resampling land cover data can also be done using other approaches such as majority resampling, and each has its strength and weakness. For example, majority resampling can be very useful to generate a general view of land cover distribution but can be problematic because it drops minor (in area) but wide-spread land use activities during the resampling process. Although the nearest-neighbor resampling algorithm may not be as effective in reproducing the detailed picture of land cover distribution as the majority resampling approach, it is more effective in keeping the disturbance information probabilistically at the regional scale. We selected the nearest-neighbor resampling algorithm for this study because our main focus was to investigate the impact of land use change and disturbances at various spatial scales. In essence, the nearest-neighbor algorithm is similar to a cover-area-based or cover-fractional probability resampling approach.

2.4 Carbon stocks, NPP, and geospatial data layers

Key forest parameters were derived from the Forest Service's Forest Inventory and Analysis (FIA) database (http://fia.fs.fed.us/tools-data/default.asp). The estimates of net primary productivity (NPP) and carbon stock were used for model validation, and
forest age distribution, mortality, and selective cutting were used for model parameterization (see Liu et al., 2004a). The stock and annual increment of aboveground live biomass carbon density, natural mortality, selective and clear-cut harvesting were derived from all the FIA field plots of 21 inventories (spanning from 1970 to 2005) in the southeastern United States.

NPP of any forest inventory plot was estimated using the common assumption that annual root production equals annual fine litterfall (Raich and Nadelhoffer, 1989; Jenkins et al., 2001):

$$NPP_i = 2L_i + G_i \,,$$

where L_i is annual fine litterfall, and G_i is the annual increment of aboveground woody components, including stems and branches. According to the above equation, the average NPP of forests at the county level can be estimated by:

$$NPP = 2L + G \,,$$

where NPP, L, and G are county-wide mean NPP, L_i, and G_i, respectively. The values of G for the counties were estimated from the FIA database. The average annual fine litter was estimated to be $2 \, \mathrm{Mg \, C \, ha^{-1} \, yr^{-1}}$ in this region on the basis of Meldahl et al. (1998) and Jenkins et al. (2001). Belowground biomass C stock in live roots was estimated using the regression equation for temperate forests (Cairns et al., 1997). Estimated belowground biomass C stock was then added to the aboveground estimate to produce an estimate of total biomass C stock.

Two inventory datasets were used to characterize forest status and changes at Fort Benning military installation. Current inventory data (including inventories from 2006 to June 2007), containing detailed records of diameter at breast height (DBH), height, and

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total basal area (BA) for each tallied tree within each inventory plots. Historical inventory data were collected from 1981 to 2000, and contained only stand basal area with no information on tree DBH and height. Total aboveground and belowground biomass carbon of each tallied tree (abgc and bgc, $kg\,C\,tree^{-1}$) in the current inventory were estimated using the equations from Brown et al. (1997) and Cairns et al. (1997). The biomass of midstory (DBH<5 inches) and understory was not estimated. To estimate biomass from stand BA in the historical database, a relationship between stand BA and stand biomass was developed from the current inventory dataset. Forest change was assessed using forest stands that were inventoried in both the current and historical databases. Other data used in this study are listed in Table 1.

2.5 Model simulations

Adequately representing the spatial variability of net primary production (NPP) is a key challenge in simulating the impacts of land use change on carbon sequestration from landscape to regional scales. NPP in EDCM is estimated by multiplying site-specific potential NPP with scalars representing the impacts of environmental factors such as temperature, moisture, and nutrient status. It is impossible to manually parameterize EDCM with realistic site-specific potential NPP values over large area. We developed a data assimilation approach to inversely calculate spatially explicit potential NPP from Moderate Resolution Imaging Spectroradiometer (MODIS) NPP from 2000 to 2004. These spatially explicit pontential NPP values, along with the changes of temperature, soil moisture, and nutrient (N) conditions, were then used to predict monthly NPP during the study period (1992–2007). We used 2005 MODIS NPP for model validation. It can be seen that model simulations were in good agreement with MODIS NPP (Fig. 2). In addition, the simulated total SOC in the top 20 cm layer for Fort Benning in 2000 was $2414\,g\,C\,m^{-2}$, which compared well with the field measurement of $2424\,g\,C\,m^{-2}$ (Garten and Ashwood, 2004). The simulated total forest biomass carbon for counties Russell, Chattahoochee, and Marion in 2007 was 5126, 5839, and $4236\,g\,C\,m^{-2}$, which were in good agreement with the forest inventories of 5063, 5479, and $3968\,g\,C\,m^{-2}$

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(excluding foliage), respectively (USDA Forest Service, 2007 RPA data, available at: http://www.fia.fs.fed.us/tools-data/).

2.6 Analysis

Current year carbon sequestration was calculated as the difference between current year's and previous year's ecosystem carbon stock (including carbon accumulated in live biomass, forest floor, and soil), which was equal to net biome productivity (NBP) using the carbon cycle concepts and terminology of Chapin et al. (2006). Positive values represent uptake, and negative values indicate carbon loss from the biome.

3 Results

3.1 Influence of the spatial resolution on land cover

Forest was the dominant land cover type in the region (>75%), followed by cropland and urban areas. Combined, they accounted for more than 90% of the study area. The transitional barren category, caused primarily by forest harvesting, was closely associated with the dynamics of forest. We analyzed the detailed area changes of these four land cover types with the degradation of spatial resolution over the period 1992–2007 (Fig. 3). Overall, the area of forestland and cropland decreased while urban area expanded based on the 250 m resolution data.

The overall temporal pattern of land cover change remained unchanged as the resolution coarsened from 250 m to 1 km. In addition, the magnitudes or compositions of land cover showed little change among these spatial resolutions. In contrast, as the resolution coarsened from 1 km to 4 km, these four land cover types demonstrated apparent changes in magnitude, suggesting changes in land cover composition (Fig. 3). For the year 1992, for example, as the resolution coarsened from 1 km to 4 km, urban area increased from 5.6 to 6.9%, forest area decreased from 79.1 to 77.2%, and cropland increased from 6.7 to 8.5%.

The transitional barren coverage was not significantly affected by change in the spatial resolution from 250 m to 1 km. As the spatial resolution was further coarsened to 2 km and 4 km, the interannual variation in the area percentage of transitional barren became pronounced, and even the original pattern was altered when the spatial resolution degraded to 4 km (Fig. 3d). Although the long-term average percentage of transitional barren did not change significantly, the coefficient of variability (i.e., standard deviation divided by the mean) increased from 0.29 to 0.88. Since the transitional barren was caused primarily by forest harvesting, the interannual variation in transitional barren corresponded closely with the variation in forest. At the resolution of 4 km, transitional barren coverage was anomalously high in 2004 and anomalously low in 2002 and 2003. Correspondingly, forest was anomalously low in 2004 and anomalously high in 2002 and 2003 (Fig. 3a, d).

3.2 Influence of the spatial resolution on carbon sequestration

As the spatial resolution degraded from 250 m to 500 m, 1 km, 2 km, and 4 km, the estimated mean carbon sequestration rate during the study period changed from 0.27 to 0.26, 0.27, 0.18, and 0.40 Mg C ha^{-1} yr^{-1}, respectively. The carbon sequestration rate remained relatively stable when the resolution changed from 250 m to 1 km. It changed drastically and unpredictably, however, when the resolution was further degraded to 4 km. The change was a decrease of 33% from 1 to 2 km but an increase of 48% from 1 to 4 km. The results suggested that 1 km resolution was the threshold for estimating carbon sequestration in the region, corresponding well with the land cover change threshold described above. Beyond this critical resolution, the estimated regional carbon sequestration rate became unreliable.

The finding that a 1 km resolution was the critical threshold for estimating regional carbon dynamics in this region was manifested in the change of interannual variability of carbon sequestration estimated using land cover maps of various resolutions (Fig. 4). Temporal change of carbon sequestration was not significantly affected by degradation of the spatial resolution from 250 m to 1 km. However, this general pattern

was altered when the spatial resolution was further coarsened to 2 and 4 km. For example, the ecosystem was a strong source in 2004 at 4 km, whereas it was a strong sink at 2 km and a relatively small sink at 250 m, 500 m, and 1 km (Fig. 4). Interannual variability in forest disturbances caused this result (Fig. 3d). The minimum annual carbon sequestration was -0.02, -0.03, -0.11, -0.58, and -0.64 Mg C ha^{-1} yr^{-1} under spatial resolutions of 250 m, 500 m, 1 km, 2 km, and 4 km, respectively. A sudden change was found in the minimum rate when the resolution changed from 1 km to 2 km. The change of maximum annual carbon sequestration was gradual, but it increased significantly from 0.44 to 0.47, 0.62, 0.59, and 1.07 Mg C ha^{-1} yr^{-1} as the spatial resolution coarsened. The standard deviation of annual carbon sequestration changed from 0.12 to 0.13, 0.21, 0.39, and 0.43 Mg C ha^{-1} yr^{-1} as the spatial resolution of land cover coarsened, indicating that 1 km was the critical spatial resolution for adequately characterizing the interannual variability of carbon sequestration at the regional scale. Beyond the threshold, the interannual variability would be exaggerated.

The spatial distributions of the average rate of carbon sequestration between 1992 and 2007 at the five spatial resolutions showed a high degree of spatial heterogeneity (Fig. 5). At 250 m resolution, the carbon sequestration map showed detailed spatial patterns and variability. As the spatial resolution was coarsened, many spatial details of carbon sequestration disappeared (Fig. 5). Averaging across all the years for all pixels, the minimum mean carbon sequestration rate at the pixel level in the region was -15.9, -14.1, -13.0, -10.9, and -9.0 Mg C ha^{-1} yr^{-1} as the resolution changed from 250 m to 4 km, and the maximum changed from 3.8 to 3.6, 3.0, 2.7, and 2.3 Mg C ha^{-1} yr^{-1}. This clearly shows that aggregating land cover information in space diminished the range of spatial variability of simulated carbon sequestration on the landscape. Our results highlight the necessity of characterizing land cover changes that influence carbon exchange between the terrestrial biosphere and the atmosphere using spatially explicit information at the scale where land cover change activities happen (i.e., at the field scale).

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Model simulations, using remotely sensed observations of land cover and land use change information, are one of the effective ways for estimating carbon sequestration over large areas (Fang et al., 2001; Myneni et al., 2001; Goodale et al., 2002; Smith et al., 2004, 2006; Sitch et al., 2005; Kauppi et al., 2006; Quaife et al., 2008). Land cover change is just one driver of carbon sequestration. Another driver, maybe more important than land cover change in areas where land cover change rates are low (e.g., United States, Japan, and Europe), is the change of biomass stock in forest lands. It is important that model simulations agreed well with observations of carbon stocks and fluxes. Our model simulations in the region were well constrained with field measurements from the US Forest Inventory and Analysis (FIA) (Liu et al., 2004a) and remotely sensed net primary production (see supplementary materials). The carbon sequestration strength during the study period at the 250 m resolution was consistent with other studies (e.g., Myneni et al., 2001; Liu et al., 2004a; Binford et al., 2005).

Several previous studies have documented the effects of spatial resolution on land cover classification/mapping and consequent carbon exchange between the terrestrial biosphere and the atmosphere. For example, Kimball et al. (1999) found that net primary productivity was strongly sensitive to land cover spatial scale due primarily to land cover aggregation effects on the representation of deciduous and coniferous life-forms. Jung et al. (2007), on the other hand, documented that the spatial land cover resolution has little effect on modeling gross primary productivity over Europe. However, both of these studies used a general ecosystem process model, Biome-BGC, which is incapable of dynamically assimilating land cover change information into the simulation process across large spatial extents. This represents a limitation in the ability to use such models to examine the possible impacts of the spatial resolution of land cover maps over time. In addition, Turner et al. (2000) reported detailed effects of alternative spatial resolution on land cover mapping over a managed forest landscape in western Oregon, and evaluated its influences on the estimation of net primary productivity

and net ecosystem productivity using a simple bookkeeping approach. Unfortunately, this approach was unable to capture the spatial and temporal influences of land cover change information on carbon fluxes. Our study relied on consistent and spatially explicit land cover change databases and a robust biogeochemical modeling system that is capable of dynamically assimilating land use change information into the simulation process across large spatial extents (Liu et al., 2003, 2004a, b; Liu, 2009; Tan et al., 2005, 2006, 2007).

This study showed that the coarsening of spatial resolution in land cover databases altered land cover patterns and ignored the spatial details of land cover change, resulting in significant biases in estimated terrestrial ecosystem carbon sequestration. Our results also indicated that a resolution threshold of 1 km existed in the study area, and beyond this critical threshold not only the magnitude but also the general patterns of land cover and carbon sequestration would be altered. This finding has important implications for continental to global carbon studies because most modeling efforts rely heavily on land cover data at coarse spatial resolution (often coarser than 0.5° grid cells) (e.g., Schimel et al., 2000; Hurtt et al., 2002; Krinner et al., 2005). Two issues should be addressed properly at the continental and global scales. First, is the threshold of 1 km found in this study still valid as we deal with modeling efforts at the continental and global scale? The critical threshold value of 1 km might be universal because most of the land disturbances and management activities occur at or below this spatial scale. However, more studies should be performed to confirm or unconfirm the generality of this finding in other areas or other land cover resampling approaches. The issue of spatial resolution is not only related to the estimation of carbon sequestration as demonstrated in this study, but also relevant to any surveys on forests and land use activities such as estimating timber reserves, forest area, or regional biodiversity (Crawley and Harral, 2001; Hame et al., 2001; Chase and Leibold, 2002).

Second, approaches for upscaling carbon dynamics at the plot scale to global scale with adequate assimilation of land cover change dynamics at the finer spatial resolution have to be developed at continental to global scales. Without proper up-scaling

techniques, significant errors can be introduced to the estimated spatial and temporal changes of carbon sequestration. Our study showed that beyond the threshold of 1 km the magnitude and the interannual variability of carbon sequestration estimates differed significantly from those within the threshold. In addition, the overriding effect of inter-annual climate variability on the temporal change of regional carbon sequestration was unrealistically overshadowed by the impacts of land cover change once the threshold was crossed.

Land cover change is critical in determining the distribution, magnitude, and mechanisms of terrestrial carbon sources and sinks at local to global scales (Canadell, 2002; Houghton, 2003; Kauppi et al., 2006). More importantly, it is critical to examine land cover change and its subsequent influence on carbon sequestration at the scale where land cover change activities occur. Otherwise, it is impossible to accurately quantify biological carbon sequestration potential and to further formulate strategies to mitigate global climate change.

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Tan, Z., Liu, S. G., Johnston, C. A., Loveland, T. R., Tieszen, L. L., Liu, J. X., and Kurtz, R.: Soil organic carbon dynamics as related to land use history in the northwestern great plains, Global Biogeochem. Cy., 19, GB3011, doi:10.1029/2005GB002536, 2005.

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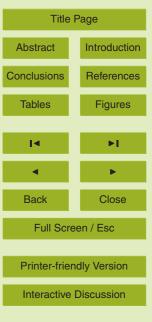http://www.biogeosciences-discuss.net/6/3215/2009/.

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Table 1. Other geospatial data layers used in this study.

Variables	Data source
Climate Monthly minimum temperature, monthly maximum temperature, and monthly precipitation	http://www.prism.oregonstate.edu/products/
Soil Soil texture, bulk density, organic matter content, wilting point, and field capacity	http://soils.usda.gov/survey/geography/ssurgo/
Drainage classes	http://edna.usgs.gov/Edna/datalayers/cti.asp
Forest Species composition, forest age, and biomass distribution data	http://fia.fs.fed.us/tools-data/default.asp
Cropping practices Shares of various crops and rotation probabilities	http://www.nrcs.usda.gov/technical/NRI/
Total atmospheric nitrogen deposition	http://nadp.sws.uiuc.edu/

Open Water
Developed, Open Space
Developed, Low-Intensity
Developed, Medium Intensity
Developed, High-Intensity
Barren Land (Rock, Sand, Clay)
Deciduous Forest

Evergreen Forest
Mixed Forest
Shrub/Scrub
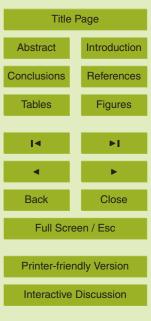Grassland/Herbaceous
Pasture/Hay
Cultivated Crops
Wetland

Fig. 1. The study area in Georgia and Alabama. Nearly 75% of the study area is forested, with cropland, wetland, and developed land covering most of the rest of the region.
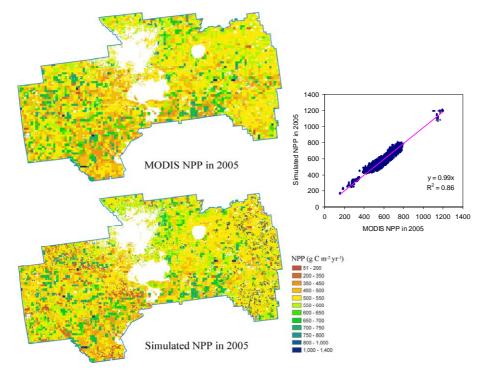
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Fig. 2. Comparison of GEMS simulated (y) and MODIS NPP (x) in 2005 ($y=0.99x$, $R^2=0.86$, $n=43\,166$).

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Fig. 3. Temporal changes in area percentage (%) of land cover types – **(a)** forest, **(b)** cropland, **(c)** urban, and **(d)** transitional barren – from 1992 to 2007 for different spatial resolutions.

Fig. 4. Temporal changes of carbon sequestration between 1992 and 2007 for five spatial resolutions.

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Fig. 5. The distributions of carbon sequestration between 1992 and 2007 for five spatial resolutions.