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Scale criticality in estimating ecosystem carbon dynamics

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Abstract

Scaling is central to ecology and Earth system sciences. However, the importance of scale (i.e. resolution and extent) for understanding carbon dynamics across scales is poorly understood and quantified. We simulated carbon dynamics under a wide range of combinations of resolution (nine spatial resolutions of 250 m, 500 m, 1 km, 2 km, 5 km, 10 km, 20 km, 50 km, and 100 km) and extent (57 geospatial extents ranging from 108 to 1 247 034 km^2) in the southeastern United States to explore the existence of scale dependence of the simulated regional carbon balance. Results clearly show the existence of a critical threshold resolution for estimating carbon sequestration within a given extent and an error limit. Furthermore, an invariant power law scaling relationship was found between the critical resolution and the spatial extent as the critical resolution is proportional to A^n (n is a constant, and A is the extent). Scale criticality and the power law relationship might be driven by the power law probability distributions of land surface and ecological quantities including disturbances at landscape to regional scales. The current overwhelming practices without considering scale criticality might have largely contributed to difficulties in balancing carbon budgets at regional and global scales.

Keywords: carbon cycle, disturbance, geospatial extent, process, scaling, spatial resolution

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Introduction

Understanding the carbon cycle at various scales can provide critical information for policy and management actions to mitigate climate change (Fang *et al.*, 2001; Goodale *et al.*, 2002; Houghton, 2007; Parry *et al.*, 2007). Carbon budgets at regional to global scales still have many discrepancies shown by diverse modeling and synthesis efforts (Le Quéré *et al.*, 2009; Pan *et al.*, 2011; Huntzinger *et al.*, 2012). Although the importance of scale dependence in estimating CO_2 exchange between the land and the atmosphere has been recognized in a few studies (Turner *et al.*, 2000; Rastetter *et al.*, 2003; Zhao *et al.*, 2010), it is still poorly understood and seldom explicitly considered in the design of investigations. This may have contributed to the observed carbon budget discrepancies.

Scaling is central to Earth system sciences in general and models are the principal vehicle for scaling (Enquist *et al.*, 1999; Rastetter *et al.*, 2003; Peters *et al.*, 2004; Urban, 2005). Many models provide different results when applied at different scales (Costanza & Maxwell, 1994; Turner *et al.*, 2000; Zhang *et al.*, 2002; Zhao *et al.*, 2010). Given the inherent heterogeneity of landscapes at various spatial scales, estimates of carbon sources and sinks are scale-dependent; that is, they may vary with the spatial scope of the analysis (geospatial extent) and with the spatial resolution (grain size) of land cover change, disturbances, and other information. However, the importance of scale (i.e. resolution and extent) for understanding carbon dynamics across scales is poorly understood and quantified.

Most carbon simulations to date have been performed at a given spatial resolution without documenting a scientific justification for the choice of scale. It is unknown if a specific resolution is sufficient or fine enough to reach a particular uncertainty limit. Indeed, many of the model simulations performed so far, still fit the observation made more than 30 years ago by Watson that the choice of a given scale is 'a private act of faith' (Watson, 1978). We do see a limited cautious effort to identify the consequences of not considering the impacts of scale (Turner *et al.*, 2000; Zhao *et al.*, 2010). Nevertheless, fundamental questions have to be answered to justify or unjustify the overwhelming practices of 'leap of faith' in ecological scaling in general, and in carbon cycle scaling in particular.

In this study, we examined the scale dependence of estimated carbon sequestration in the southeastern United States from 1992 to 2050 using the General Ensemble biogeochemical Modeling System (GEMS). The objectives of the study are to address the following two fundamental science questions: (i) is there a critical spatial resolution threshold for estimating terrestrial carbon sequestration?; and (ii) if this critical threshold exists, does it vary with the size of geospatial extent? In

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addition, we intend to investigate the effectiveness of two scaling approaches (i.e. nearest neighbor and majority) for resampling land cover and land use change information across scales, and then evaluate the impacts of scaling approach on estimating carbon dynamics.

Materials and methods

Study area

The study area covers 1 247 034 km^2 of the southeastern United States, including all or portions of 13 US states (Fig. 1). Forest covers about 60% of the region. Other common land uses and land covers include agricultural land (25%) and urban areas (5%). Ecosystems are constantly affected by human activities and natural processes. More than half of the forests are industrial forests (loblolly pine and other Southern pine species) in rapid cycling between clear-cutting and regenerating forest. Land cover and disturbances are projected to change dramatically in the region in the future due to population growth, urban expansion, and demand for wood products (Sohl & Sayler, 2008).

Introduction of GEMS

The General Ensemble biogeochemical Modeling System (GEMS) (Liu *et al.*, 2004), developed to upscale carbon stocks and fluxes from sites to regions, was used to simulate the impacts of spatial resolution of input data on regional carbon balance. GEMS relies on a site-scale biogeochemical model, the Erosion-Deposition-Carbon Model (EDCM) (Liu *et al.*, 2003), to simulate carbon dynamics at the site scale. The spatial deployment of the site-scale model in GEMS is based on the spatial and temporal joint frequency distribution (JFD) of major driving variables (e.g., land use and land cover change, climate, soils, disturbances, and management). GEMS maximally uses the finest information contained in some data layers (land cover and land use change database in this study, for example) and other coarser-scale information scaled down to the finest resolution through representation of uncertainty. A more detailed description of the model can be found in Liu *et al.* (2004) and Liu (2009).

Land cover and land use change (LCLUC) databases

Consistent, high-quality, and spatially explicit LCLUC databases at 250 m × 250 m resolution from 1992 to 2050 were developed using the FOREcasting SCEnarios of future

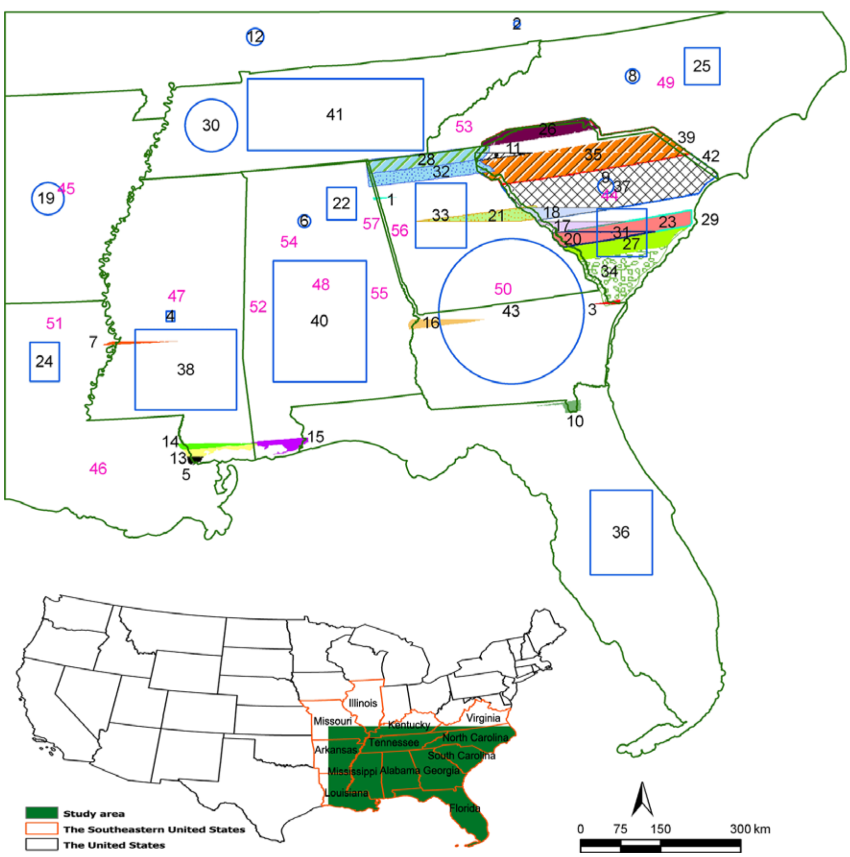

Fig. 1 Locations, shapes, and sizes of the 57 subregions or spatial extents used in this study. Each of these extents covered an area ranging from 108 to 1 247 034 km^2. The use of a large range of locations, shapes, and sizes of extents was to increase the generality of results. Colors and patterns were used to differentiate partially overlapped extents, if necessary.

land cover (FORE-SCE) model (Sohl & Sayler, 2008), which relies heavily on USGS Land Cover Trends data (Loveland *et al*., 2002) for model parameterization. The spatial resolution of the original LCLUC dataset was 250 m, and the land cover maps were resampled to grain sizes of 500 m, 1 km, 2 km, 5 km, 10 km, 20 km, 50 km, and 100 km.

The land cover maps generated from FORE-SCE provided one single general class for all croplands. To downscale the general cropland into crop species to support biogeochemical modeling, statistical information about crop composition and cropping practices (e.g., rotation probabilities) at the state level was derived from the National Resources Inventory (NRI) database, developed by the Natural Resources Conservation Service, US Department of Agriculture (http://www.nrcs.usda.gov/technical/NRI/). Once a pixel was prescribed as a cropland in 1992, its crop species was assigned using a Monte Carlo procedure with the state-level relative frequency of a crop as its probability of being assigned to the pixel. The crop species in subsequent years were derived using a crop-rotation-probability-based Monte Carlo procedure.

Other data layers

Climate data were from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) group (1992–2007) and the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) A1B scenario (2008–2050). These data were first downscaled using the ordinary Kriging procedure with the spherical model embedded in ArcGIS to 250 m resolution.

Initial soil properties were based on the State Soil Geographic (STATSGO) Database. Soil properties used included soil texture (sand, silt, and clay fractions), bulk density, organic matter content, wilting point, and field capacity. A soil map unit (MUID) in STATSGO, represented by one or more polygons, contains one or multiple soil components each with a coverage fraction. The locations of the soil components within the polygons are unknown. The area-weighted average of all soil components within each STATSGO polygon were used as the representative value of a given soil property (e.g., bulk density, etc.) of the polygon. After calculating area-weighted averages of the above-mentioned soil variables for all the STATSGO polygons, GIS grids were generated from the polygon coverages to raster grids at 250 m resolution. A 250 m resolution raster map with continuous values showing soil drainage conditions from excessively well-drained to very poorly drained were indicated by the Compound Topographic Wetness Index (http://edna.usgs.gov/Edna/datalayers/cti.asp). Point observations of total atmospheric nitrogen deposition from wet and dry sources were obtained from the National Atmospheric Deposition Program (http://nadp.sws.uiuc.edu/) and used to generate GIS grids at 250 m using the ArcGIS ordinary Kriging procedure.

In contrast to the upscaling (from finer to coarser resolution) described above, a downscaling approach was used to scale information from coarser to finer resolutions. Lacking spatially explicit information on initial forest age and biomass carbon stock, statewide forest age structure (i.e. age frequency distribution) and average age-biomass relationship by forest type (i.e. deciduous forest, evergreen forest, mixed forest, and woody wetland) were derived from the U.S. Forest Service's Forest Inventory and Analysis (FIA) National Program (http://fia.fs.fed.us/tools-data/default.asp). If a pixel was a forest in 1992 (the start year of model simulation) according to the land cover map, its age was determined using a Monte Carlo procedure with the statewide age frequency distribution as the probability for picking an age. Once age of the forest was determined, its corresponding initial biomass was obtained from the age-biomass relationship.

Scaling or resampling of input data

We understood that different resampling approaches may give different results, depending on their effectiveness on retaining finer-scale information as the spatial scale becomes coarser. In this study, we used the nearest neighbor and majority resampling approaches to scale LCLUC information from 250 m to coarser resolutions; both approaches have been used extensively in land cover research and mapping (Cain *et al*., 1997). The nearest neighbor algorithm assigns the land cover class of the center cell to the whole lower resolution cell in the target window, and majority resampling assigns the majority of the cells to that lower resolution cell.

All other data layers other than LCLUC data were resampled from 250 m to coarser resolution grids using a simple arithmetic averaging procedure in ArcGIS (ESRI, 2009). The averaging procedure for scaling continuous variables is a very common practice (Potter *et al*., 1993; Miller & White, 1998; Schwalm *et al*., 2010; Hayes *et al*., 2012).

Methods for investigating the existence of scale criticality

Is there a critical spatial resolution for estimating terrestrial carbon sequestration? To answer this question, we ran the GEMS model at nine spatial resolutions (250 m, 500 m, 1 km, 2 km, 5 km, 10 km, 20 km, 50 km, and 100 km), and then examined the differences in carbon sequestration among these resolutions. Carbon sequestration for year x was calculated as the difference of ecosystem carbon stock (including carbon accumulated in live biomass, forest floor, and soil) between x and x-*1*, which was equal to net ecosystem carbon balance (NECB) using the carbon cycle concepts and terminology of Chapin *et al.* (2006). The fate of harvested material (wood) was not included in NECB. Positive values represent uptake, and negative values indicate carbon loss from the biome.

To quantify the impact of scale of modeling on estimating carbon sequestration, we used the carbon sequestration estimates at the finest resolution (i.e. 250 m) as the base for comparison. We calculated the absolute value of the relative change in carbon sequestration as a percentage (δ_i) at any given resolution i as follows:

$$\delta_i = \frac{|C_i - C_{250m}|}{|C_{250m}|} \times 100$$

where, C_i is the mean, standard deviation (STD), or coefficient of variation (CV) of the annual mean NECB rates at spatial

resolution i (i = 250 m, 500 m, 1 km, 2 km, 5 km, 10 km, 20 km, 50 km, and 100 km). The spatial resolution at which carbon sequestration characteristics (e.g., mean and variability measures) demonstrated significant changes from the base would be considered as the critical (i.e. threshold) spatial resolution. In this study, we investigated the critical resolutions for a given error limit (i.e. δ_i = 5%, 10%, and 20%) of the mean, STD, and CV of the regional NECB values at various spatial extents. Figure 2 illustrates the detection of the critical resolution required to constrain errors of the mean NECB, STD, or CV within 10% for the state of Alabama as an example. Any bar falls in the green crossed area (the width of the crossed bar indicates ±10% of the mean NECB, its STD, and CV at 250 m resolution) would indicate that the mean, STD, or CV is not significantly different from their corresponding value at 250 m.

Methods for investigating relationship between critical resolution and extent

To further investigate whether the influence of spatial resolution of input data on carbon sequestration varies with the spatial scope of the analysis (geospatial extent), we repeated the analysis over 57 geospatial extents ranging from 108 to 1 247 034 km^2 (Fig. 1). The effect of extent was investigated by comparing among many model simulations at different extents.

To investigate if threshold resolution is related to LCLUC and landscape features, the Pearson correlation coefficients between the threshold resolution and land cover composition (e.g., fractions of forest, cropland, etc.), and landscape disturbances (e.g., forest harvesting, mining, and urbanization) and other landscape metrics (e.g., diversity, evenness, and abundance of land cover classes) (Shannon *et al.*, 1949) across all 57 extents were calculated. In addition, stepwise regression (criteria: probability-of-F-to-enter ≤0.05, and probability-of-F-to-remove ≥0.10) was also performed using SPSS (SPSS, 2004).

Results

Scale criticality

Spatial resolution has a significant impact on the spatial pattern of net ecosystem carbon balance (NECB) in the region (Fig. 3). Some of the details of regional mean NECB were gradually lost as the spatial resolution decreased with increasing pixel size, and some of the spatial features became unrecognizable at coarse resolutions. In parallel with these cross-scale changes in spatial patterns, the corresponding overall NECB characteristics have changed as well (Fig. 4). The modeled regional total annual NECB abruptly increased from 74 Tg C yr^{-1} (1 Tg = 10^{12} g) at 2 km resolution to 79 Tg C yr^{-1} at 5 km resolution, and the NECB became irregularly different from those at finer resolutions when the resolution became coarser than 2 km. The overall trends of the regional mean NECB at various spatial resolutions are similar, with an average NECB fluctuating around 60 g C m^{-2} yr^{-1} from 1992 to 2050 and a decreasing capacity of carbon sequestration over time (Fig. 5a). The magnitude and the general trend agreed well with previous studies in the region (Liu *et al.*, 2004; Binford *et al.*, 2006; Zhao *et al.*, 2010). However, the temporal variation in NECB was strongly affected by the spatial resolution. For example, some of the annual swings observed at 50 km and 100 km resolutions (e.g., NECB in 2024 and 2034 at 100 km) were much larger than those estimated at finer

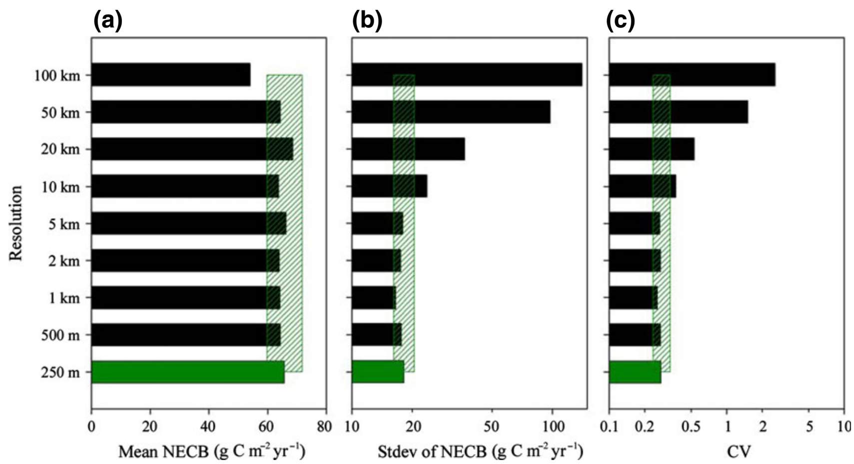

Fig. 2 Identification of the critical spatial resolution required to constrain errors of the mean (a), standard deviation (b), and coefficient of variation (c) of the net ecosystem carbon balance (NECB) within 10% of those at the 250 m for a given spatial extent (the State of Alabama). The width of the crossed bar indicates ±10% of the mean NECB, its STD, and CV at 250 m resolution, respectively. Any black bar that does not fall into the crossed green area indicates a value more than 10% different from the result for 250 m resolution. It shows that the critical resolution for the mean, standard deviation, and coefficient of variation was 50 km, 5 km, and 5 km, respectively.

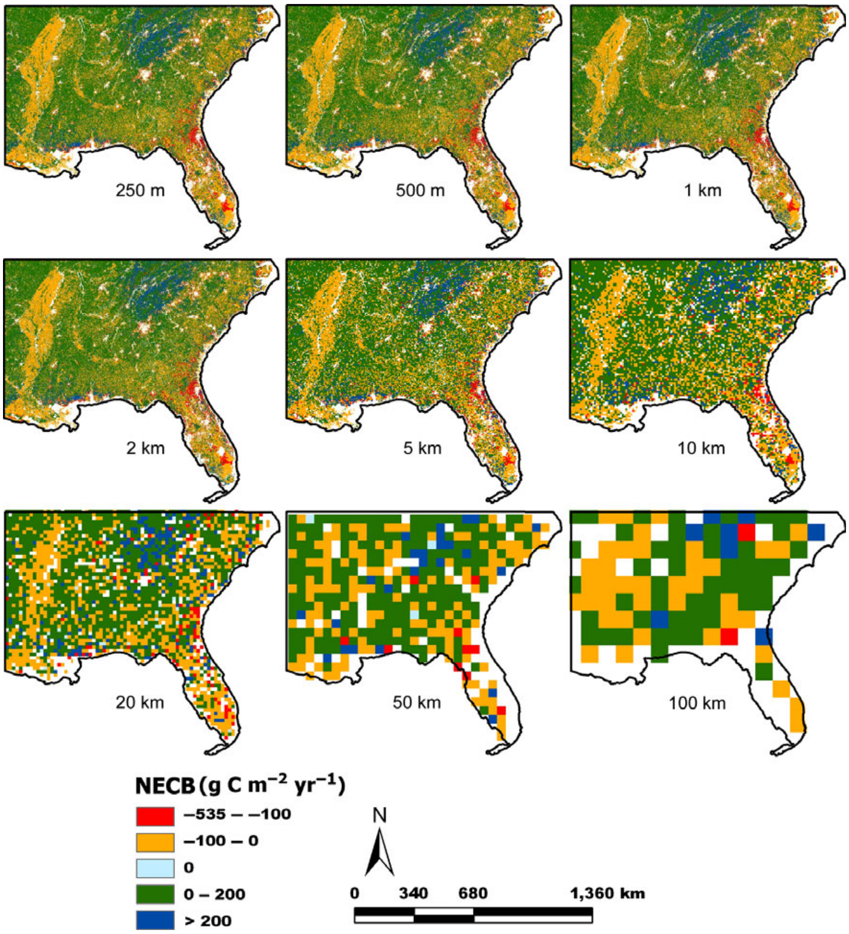

Fig. 3 Spatial distributions of net ecosystem carbon balance (NECB) from 1992 to 2050 in the southeastern United States estimated at various spatial resolutions using the nearest neighbor resampling approach for land cover scaling. The white areas on the maps indicate resampled land cover classes for pixels with impervious surfaces (e.g., in urban areas) or water bodies which were not simulated.

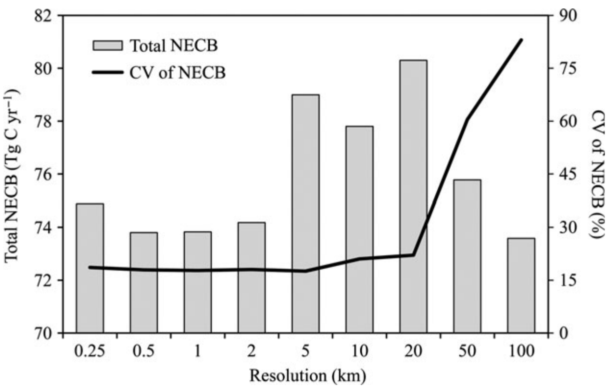

Fig. 4 Regional total net ecosystem carbon balance (NECB) and its coefficient of variation (CV) from 1992 to 2050 in the southeastern United States estimated at various spatial resolutions using the nearest neighbor resampling approach for land cover scaling.

resolutions (Fig. 5a), and the coefficient of variation of regional total NECB increased from about 18% at resolutions finer than 10 km to 83% at 100 km resolution (Fig. 4). While Fig. 5a effectively shows the general temporal trends and the interannual variability in NECB at various resolutions, it was difficult to see the differences among resolutions. To show the differences more clearly, the time-integrated or cumulative NECB deviations relative to 250 m resolution from 1992 to 2050 are shown in Fig. 5b. The cumulative difference trajectories for resolutions finer than 5 km were relatively steady and the total deviation was smaller than 40 g C m^{-2} during the 58 years period. The total deviation increased to more than 100 g C m^{-2} when the resolution was between 5 km and 20 km inclusive. The cumulative difference trajectories became irregular when the resolution was coarser than 20 km. Results from the majority resampling approach also clearly show the criticality of scale on the estimated NECB at various spatial resolutions in the region (Fig. 5c and d). Figure 5 shows that (i) time-integrated NECB difference or deviation, relative to those at 250 m, increased with coarsening spatial resolution;

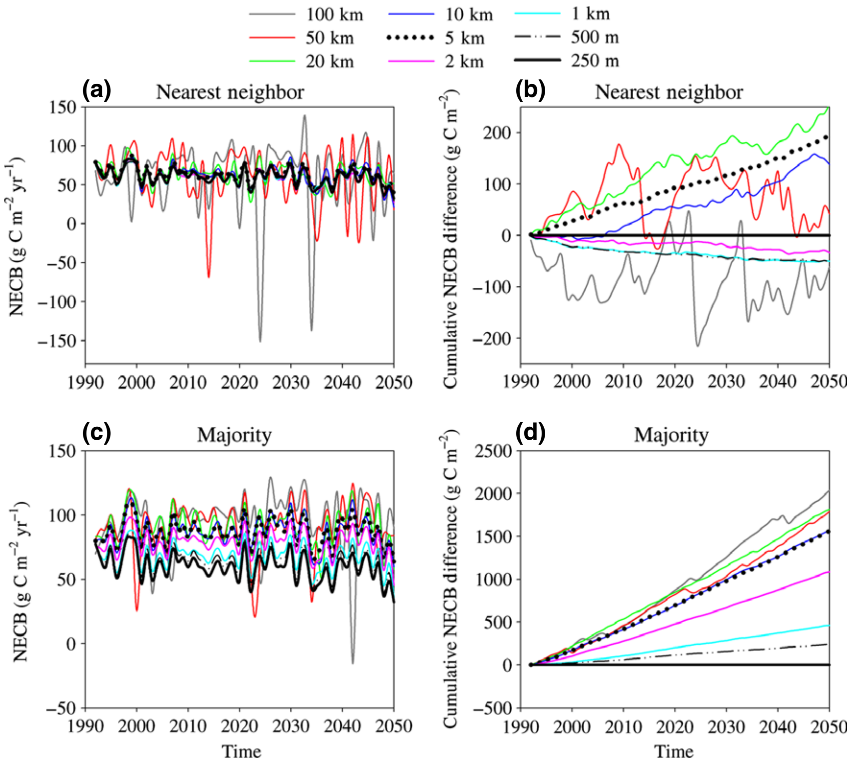

Fig. 5 Comparison of the temporal changes of simulated annual net ecosystem carbon balance (NECB) using input data with spatial resolution varying from 250 m to 100 km in the southeastern United States. To more clearly show the differences in NECB across scales, the time-integrated or cumulative deviation (or difference) of NECB at one scale relative to 250 m was plotted as well. Panel a: temporal changes of NECB with the nearest neighbor resampling approach for land cover scaling. Panel b: cumulative deviation of annual NECB relative to 250 m with the nearest neighbor resampling approach for land cover scaling. Panel c: temporal changes of NECB with the majority resampling approach for land cover scaling. Panel d: cumulative deviation of annual NECB relative to 250 m with the majority resampling approach for land cover scaling.

and (ii) the deviations suggested the coexistence of over- and under-estimation of NECB using the nearest neighbor resampling, and systematic overestimation of NECB using the majority resampling.

To further demonstrate the differences, the regional mean annual NECB values simulated at various resolutions were compared with those simulated at 250 m year by year (Fig. 6a–h). The regional average NECB values simulated at coarser resolutions and those at 250 m agreed well at resolutions finer than 10 km and did not agree well at resolutions equal or coarser than 10 km. A systematic bias toward overestimation is apparent at 5 km (Fig. 6d), and the 10 km plot had the first different slope than the 1 : 1 line (Fig. 6e). All these observations clearly suggest the importance of spatial resolution for simulating carbon dynamics.

Further observations can be made on the relative differences in NECB produced by the two resampling approaches (see Fig. 7). First, the 5th and 95th percentiles of the relative NECB differences were −56.8% and 80.9%, and −64.7% and 126.2% for the nearest neighbor and majority approach, respectively, which strongly signifies the importance of scale. Second, the median relative difference produced by the majority was 24.2%, indicating strong overall positive biases of NECB as the resolution coarsened. In contrast, the median difference was only −0.1% by the nearest neighbor approach. Third, most of the relative differences with the nearest neighbor approach were in a narrow range with −5.8% and 5.5% as the 25th and 75th percentiles, respectively. On the other hand, most of the differences with the majority approach were more widely distributed and positively biased as the 25th and 75th percentiles were 1.2% and 62.8%, respectively.

Resolution–extent scaling relationship

Examining the relationship between the critical resolution (y) and the extent (x) from the nearest neighbor approach (Fig. 8a–c), an invariant power law scaling relationship can be found for each error limit:

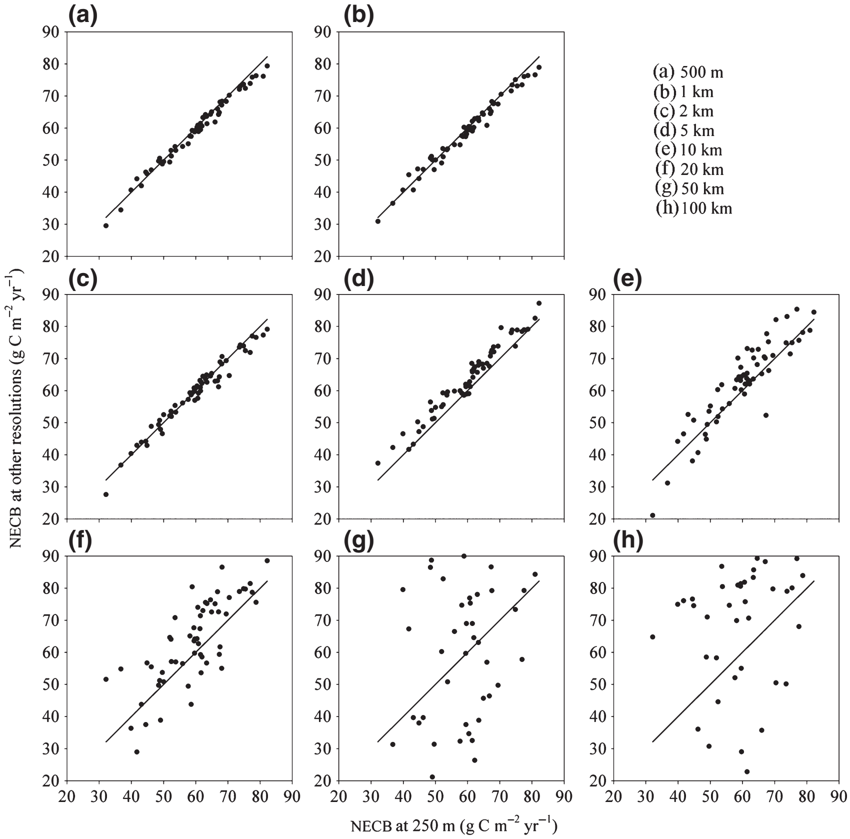

Fig. 6 Comparison of net ecosystem carbon balance (NECB) values in the southeastern United States estimated at various spatial resolutions with those at 250 m from 1992 to 2050 using the nearest neighbor resampling approach for land cover scaling. Each point represents a pair of NECB estimates at two resolutions for a given year. The straight line in each plot is the reference 1 : 1 line.

$$y_\tau(x) = k_\tau x^{\alpha_\tau} + \varepsilon$$

where, τ is a given error limit, α is the scaling exponent of the power law scaling relationship, k is a proportionality constant, and ε is an error term representing uncertainty in the estimated values of the critical resolution. Fig. 8a–c gives quantitative guidance on how to use the extent of a study area to select an appropriate resolution for running model simulations and delivering results within a certain error limit. The power laws signify the existence of scaling invariance between the threshold resolution and the extent because scaling the extent x by a constant factor c simply causes the original power law relation to be multiplied by the constant c^{α_τ}:

$$y_\tau(cx) = k_\tau(cx)^{\alpha_\tau} = k_\tau c^{\alpha_\tau} x^{\alpha_\tau}$$

In contrast to the results from the nearest neighbor approach, no distinct scaling relationship between critical resolution and extent for the regional mean NECB was emerged from the majority approach (Fig. 8d–f). The critical resolution was independent of the spatial extent as critical resolutions formed no significant trend along the gradient of >4 orders of magnitude (Fig. 8d).

Discussion

Carbon sequestration varies with extent, and many efforts have been made to estimate its variability (Liu *et al.*, 2011). For a given extent, carbon sequestration (not its estimate) is independent of resolution used for estimation as one extent can only have one single carbon cycle budget. This study was not intended to study how carbon sequestration (not its estimate) varies with scales. Instead, it investigated the impacts of varying resolution and extent on estimated regional carbon dynamics. All input variables were organized by scale first before feeding the GEMS. The observed results are therefore a function of the scaling methods or resampling of input variables, and the noted differences among scales are a result of the combination of inputs. The results clearly show the possible consequences of using various resolutions without any justification ('leap of faith') when estimating regional carbon dynamics.

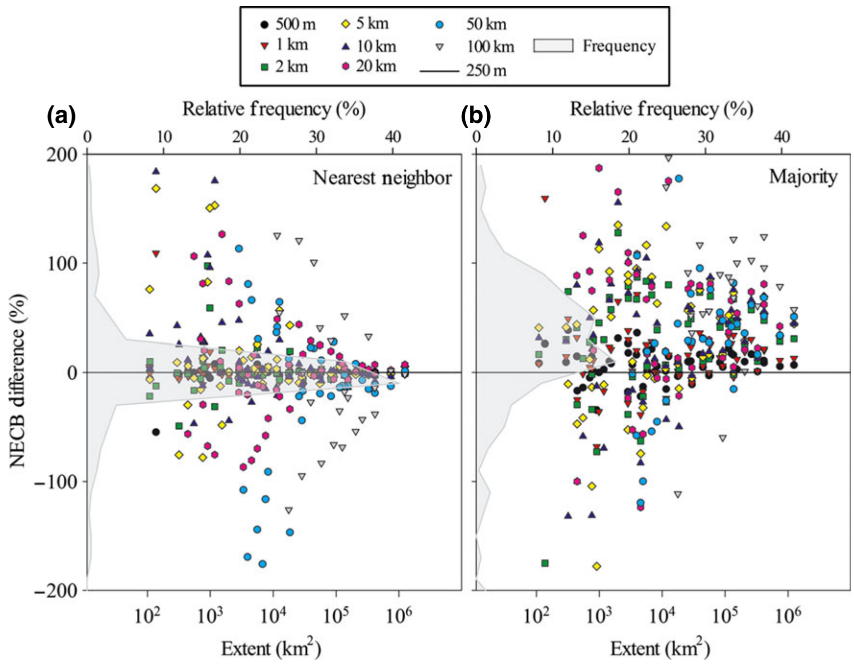

Fig. 7 Impacts of resolution on the simulated NECB, expressed as the difference relative to 250 m resolution, at various extents using two upscaling approaches. The shaded area shows the relative frequency distribution of the NECB differences.

Results, regardless of resampling approach, unequivocally showed the criticality of scale on the estimated NECB at various spatial resolutions in the region. In addition, the majority approach is not effective in scaling up localized, fine-scale events (e.g., forest harvesting seldom exceeds 4 km^2) that have significant impacts on carbon dynamics (Liu *et al.*, 2011). Forest harvesting showed the highest Pearson correlation coefficient with threshold resolution under the majority sampling (Fig. 9b, $R = -0.32$, $P = 0.008$), and it was the only significant variable in the stepwise regression analysis. Both results suggested the importance of forest harvesting activities but the negative correlation coefficient indicated the ineffectiveness and devastating deficiency of the majority approach as more extensive harvests were associated with finer resolutions. For an effective scaling approach, the critical resolution should vary with extent but not with disturbances as we see from the nearest neighbor approach (Fig. 9a). The systematic overestimation of NECB using the majority approach might also indicate that this approach was not adequate for resampling because it filtered the nonmajority disturbance events that have significant impacts on NECB.

The nonresponsiveness of the critical resolution to the change in extent using the majority approach has two important implications. First, it does not fit with our conventional wisdom that a larger pixel size could be used for a larger extent for model simulations. Second, it presents a huge challenge for quantifying carbon dynamics over large areas because it demands a very fine pixel size (usually finer than 1 km) and the 'brute force' approach has to be adopted in model simulations.

The power law relationship has been found in various studies related with phenomenological pattern scaling (Delcourt & Delcourt, 1988; Turner *et al.*, 1989; Falk *et al.*, 2007; White *et al.*, 2008). Most effort has been on investigating the effect of changing resolution, less on the effect of changing extent, and rarely with a focus on both. Process scaling, which transfers information across scales and generates new understandings that are often not obvious, is less understood than pattern scaling (Tischendorf, 2001; Fortin *et al.*, 2003). To our knowledge, no power law relationship has been reported on scaling latent processes across various resolutions and extents. It remains a great challenge to identify guiding principles for process scaling (Rastetter *et al.*, 2003; Urban, 2005; Liu *et al.*, 2011).

Three important observations can be made from the invariant power law scaling relationship in Fig. 8a–c. First, all the scaling exponents (α) in Fig. 8a–c are positive, suggesting that the critical resolutions for the mean NECB, its standard deviation, and coefficient of variation (CV) can be relaxed (i.e. with increasing grain or pixel size) as the spatial extent expands. This agrees well with perception and general practices as most global model simulations were carried out at 0.5 degree resolution (or about 55 km in latitudinal distance) and

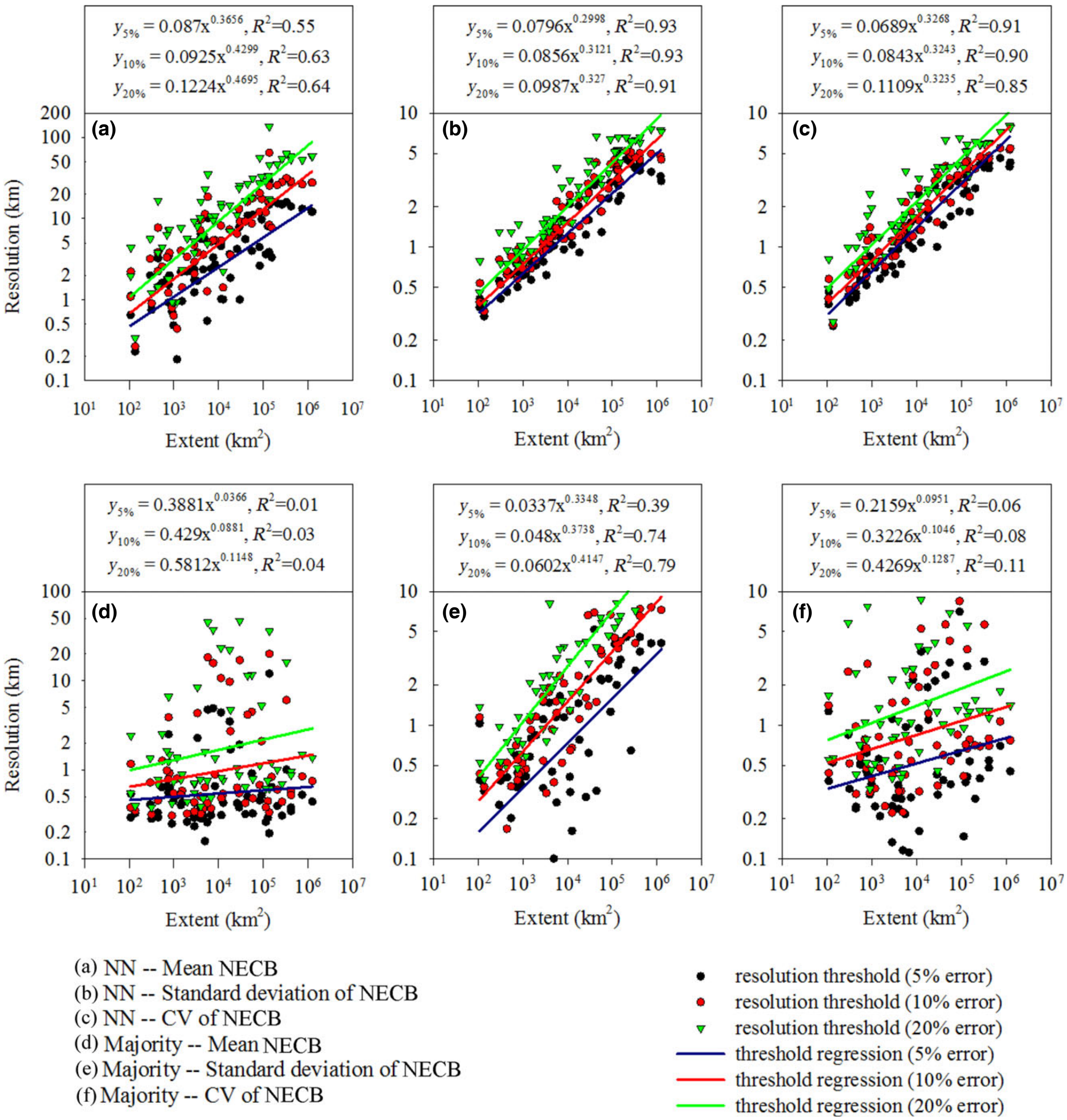

Fig. 8 Threshold resolution or maximum pixel length-size required to constrain errors of the mean NECB (a and d), its standard deviation (b and e), and coefficient of variation (c and f) within 5%, 10%, and 20% of those at 250 m for various spatial extents using the nearest neighbor (NN) and majority resampling approaches.

landscape applications at meter-scale. Nevertheless, for the first time, the invariant scaling law found in this study provides a concrete quantitative relationship that could be used to guide the selection of resolution for a given extent and error limit.

Second, the α values for the mean NECB ranged from 0.37 to 0.47, higher than that for the CV (varying from 0.32 to 0.33), while the proportionality constant k of the mean was larger than its counterpart of CV at the same resolution. This suggests that it is easier to contain the error of the mean NECB than its counterpart CV. For example, to contain the relative error within 10% for a region of 10 000 km^2, the minimum spatial resolution would be about 5 km for the mean NECB, but the

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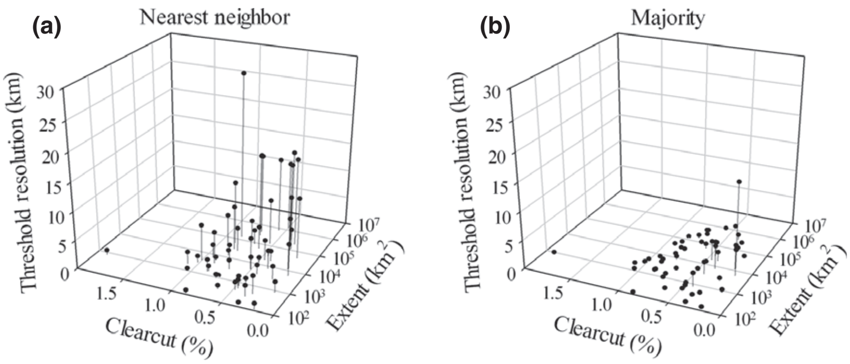

Fig. 9 Relationship among threshold resolution, spatial extent, and harvested forest area percentage for the nearest neighbor (a) and majority (b) upscaling approaches. The increase in threshold resolution with extent indicates the effectiveness of the nearest neighbor approach in upscaling fine-scale land cover and land use change (LCLUC) information. In contrast, the narrow range of threshold resolutions over a wide range of extents suggests the fine-scale LCLUC could not be scaled up using the majority approach.

minimum spatial resolution for the CV would have to be less than 2 km.

Third, the scaling exponents for various error limits were very similar (Fig. 8a–c). This equivalence of power laws with the scaling exponent might suggest a profound origin in the dynamic processes that generate the power law relationship as often seen in physics and biology (Enquist *et al.*, 1999; Brown & West, 2000; Milne *et al.*, 2002; White *et al.*, 2008). The underlying mechanisms that lead to the emergence of the power laws found in this study are not clear. Our current hypothesis is that the demonstration of a power law relation in the extent-resolution relationship might be related to the power law distribution of various disturbances and climate variability that exert strong impacts on carbon dynamics. Landscape composition and patterns change when resolution or grain size and extent are changed (Wiens, 1989). Ecological systems can be seen as nested, discontinuous hierarchies of patches that differ in size, shape, and successional stage at particular scales (Kotliar & Wiens, 1990; Holling, 1992; Wheatley & Johnson, 2009), and disturbances are believed to be the common structuring forces for the nested hierarchies (Pickett & White, 1985). A number of studies have shown that the probability distributions of a wide variety of land surface and ecological quantities including disturbances at landscape to regional scales follow a power law relationship (Pascual & Guichard, 2005; Fisher *et al.*, 2008). As the extent increases with a fixed grain size, so does the probability of finding rare ecosystem types, increased fragmentation, and previously unencountered disturbances (Wiens, 1989; Fisher *et al.*, 2008; Fraterrigo & Rusak, 2008). Similar observations can also be made with an increasing resolution within a given extent. The invariant scaling relationship between resolution and extent found in this study might suggest that the loss of some functional groups at the landscape or local scales caused by the loss of spatial resolution or grain size may be compensated by the expansion of the extent, which provides chances for the functional types that were lost during the coarsening process to reappear. Our finding supports the hypothesis that self-organization and bottom-up emergence of structure is a key cause for the existence of scaling invariance in a complex system (Manson, 2008).

Most regional and global model simulations have probably committed one of two errors. First, the resolution for model simulations might not have been fine enough (i.e. below the critical resolution), which can generate unexpected and biased results. Respecting the scope of a model and the scale of the underlying driving processes is especially important in landscape-scale or large-area extrapolations. Second, the resolution might be too fine, which causes the problem of 'overkill'. It seems that 'overkill' might not be a problem as it can generate results at higher resolution than needed and therefore can be applied to address issues related with smaller extents. This might be true when the processes are not scale-dependent. Otherwise, too fine a resolution might have similar effects in generating erroneous or misleading results (Costanza & Maxwell, 1994).

Our results clearly showed the criticality of scale in biogeochemical modeling. At the same time, we believe additional research should be conducted in the future to address the generality of the scaling relationships found in this study and the underlying processes that define the scaling relationships. Detailed studies should also be carried out to investigate the effectiveness of various scaling methods. For example, why a power law relationship is seen with one resampling method but not with the other? In this study, we believe this was due to the majority resampling method not being effective in capturing the fine-scale disturbances as

resolution coarsened. We recognize though this might be a partial or proximate reason and additional research is needed, as scaling involves uncertainty and other ecosystem features and processes we did not include here. For example, the scaling of crop information using agricultural census data and Monte Carlo procedures might contain large uncertainty especially at the pixel level. The effects of area-averaging the soil variables (e.g., wilting point and field capacity in polygons) in the lower coastal plain areas of the study could be a significant contributor to the variance observed. A step-wise evaluation of the impacts of accuracy and scale of climate data could be performed to compare the scaled climate data with observations first before examining the effects on output (Heinsch *et al.*, 2006).

Scale effects have long been studied in landscape to regional ecology and Earth system sciences. Many previous studies have focused on the effects of changing grain size rather than on the effects of changing extent. Quantitative understanding of the scaling effects for both resolution and extent has largely been lacking. Although carbon cycle scientists are well aware of the fundamental impacts of differing scales, scaling relations are yet to be explored, understood, quantified, and implemented in practice. This might be a critical missing piece in reconciling disparate estimates of the global carbon budget.

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