Analyzing the uncertainty of estimating forest carbon stocks in China

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Abstract. Earth surface systems are controlled by a combination of global and local factors, which cannot be understood without accounting for both the local and global components. The system dynamics cannot be recovered from the global or local controls alone. Ground forest inventory is able to accurately estimate forest carbon stocks at sample plots, but these sample plots are too sparse to support the spatial simulation of carbon stocks with required accuracy. Satellite observation is an important source of global information for the simulation of carbon stocks. Satellite remote-sensing can supply spatially continuous information about the surface of forest carbon stocks, which is impossible from ground-based investigations, but their description has considerable uncertainty. In this paper, we validated the Kriging method for spatial interpolation of ground sample plots and a satellite-observation-based approach as well as an approach for fusing the ground sample plots with satellite observations. The validation results indicated that the data fusion approach reduced the uncertainty of estimating carbon stocks. The data fusion had the lowest uncertainty by using an existing method for high accuracy surface modeling to fuse the ground sample plots with the satellite observations (HASM-SOA). The estimates produced with HASM-SOA were 26.1 and 28.4% more accurate than the satellite-based approach and spatial interpolation of the sample plots, respectively. Forest carbon stocks of 7.08 Pg were estimated for China during the period from 2004 to 2008, an increase of 2.24 Pg from 1984 to 2008, using the preferred HASM-SOA method.

Key words

Satellite observation; Ground observation; Carbon stocks; HASM; Spatial interpolation; Data fusion

1 Introduction

Biomass dynamics reflect the potential of vegetation to act as a carbon sink over the long-term, as they integrate photosynthesis, autotrophic respiration and litter fall fluxes (Thurner et al., 2014). Forest ecosystems cover more than 41 million km^2 of the Earth's land surface and forests are thought to contain about half of the carbon in terrestrial biomes (Prentice et al., 2001). Forests play an important role in the active mitigation of atmospheric CO_2 through increased carbon stocks. The fixation of atmospheric CO_2 into plant tissue through the process of photosynthesis is one of the most effective mechanisms for offsetting carbon emissions (Canadell and Raupach, 2008; Gonzalez-Benecke et al., 2010).

Carbon sequestration by trees is the best way to store a large amount of terrestrial carbon over long durations (Jung et al., 2013). Estimation of carbon stocks at scales ranging from local to global is crucial for accurately predicting future changes in atmospheric carbon dioxide (Yu et al., 2014). However, substantial uncertainties remain in current model estimates of terrestrial carbon and there is an increasing need to quantify and reduce these uncertainties (Barman et al., 2014; Ahlstrom et al., 2012).

Several studies have estimated the forest carbon stocks in China. Piao et al. (2005), for example, used a satellite-based approach and estimated that: (1) the total forest biomass of China averaged 5.79 Pg C during the period 1981-1999, with an average biomass density of 4.531 kg C m^{-2}; and (2) the total forest biomass C stock increased from 5.62 Pg C in the early 1980s to 5.99 Pg C by the end of the 1990s, giving a total increase of 0.37 Pg C and an annual sequestration rate of 19 kg C yr^{-1}. Zhang et al. (2007), on the other hand, analyzed seven forest inventories from 1973 to 2008 and suggested that the total biomass carbon stocks of all forest types increased

616 by 65% during this period, reaching 8.12 Pg C in 2008.

617 Wang et al. (2007) used the Integrated Terrestrial Ecosystem C-budget model and
618 estimated that China's forests were a source of 21.0±7.8 Tg C yr^{-1} due to human
619 activities during the period 1901-1949 and that this flux increased to 122.3±25.3 Tg C
620 yr^{-1} due to intensified human activities during the period 1950-1987. However, these
621 forests became large sinks of 176.7±44.8 Tg C yr^{-1} during the period 1988-2001
622 owing to large-scale plantation and forest regrowth in previously disturbed areas (see
623 the description of the Grain for Green Program below) as well as climatic warming,
624 atmospheric CO_2 fertilization, and N deposition.

625 Yang and Guan (2008), on the other hand, utilized the continuous Biomass
626 Expansion Factor (BEF) method with field measurements of forests plots in different
627 age classes and forest inventory data, and showed that the carbon density of the
628 forests in the Pearl River Delta increased by 14.3% from 19.08 to 21.81 kg C m^{-2}
629 during the period 1989-2003. Similarly, Piao et al. (2009) reported that China's
630 terrestrial ecosystems were a net carbon sink of 0.19-0.26 Pg carbon per year and that
631 they absorbed 28-37% of the fossil carbon emissions during the 1980s and 1990s.
632 However, their results also showed that northeast China is a net source of CO_2 to the
633 atmosphere due to the over-harvesting and degradation of forests, while southern
634 China accounts for more than 65% of the carbon sink, which can be attributed to
635 regional climate change, large-scale plantation programs started in the 1980s, and
636 shrub recovery (Piao et al., 2009).

637 Guo et al. (2010) used three different approaches – the mean biomass density
638 (MBD) method, the mean ratio (MR) method, and the continuous BEF method (CBM)
639 – with forest inventory data to estimate China's forest biomass C stocks and their
640 changes from 1984 to 2003. The MBD, MR, and CBM estimated that forest biomass

641 C stocks increased from 5.7 to 7.7, 4.2 to 6.2, and 4.0 to 5.9 Pg C, respectively.

642 Deng et al. (2011) deployed a GIS approach and defined the vegetation carbon
643 sink as the carbon sequestration from the atmosphere (1.63 x NPP), the vegetation
644 carbon stock as the carbon content that aboveground vegetation holds, and the soil
645 carbon stock as the carbon content that soil organic matter holds. These author's
646 estimated vegetation and soil carbon stocks of 1.58 and 1.41 Pg C, respectively in the
647 forest ecosystems of China for the period 1981-2000.

648 Ni (2013) used available national-scale information to estimate that: (1) the mean
649 vegetation carbon in China was 36.98 Pg and mean soil carbon was 100.75 Pg C; and
650 (2) that the forest and grassland sectors supported mean carbon stocks of 5.49 and
651 1.41 Pg C, respectively.

652 The aforementioned studies show that the forest ecosystems of China store
653 steadily increasing stocks of carbon and that these forest stands have great potential to
654 absorb more biomass carbon in the future due to large fractions of young and
655 middle-aged forests and programs to promote the conservation of soil and biological
656 resources.

657 All these published results relied on either ground- or satellite-observation-based
658 estimation unlike our own work in which we have tried to fuse these data sources to
659 reduce the uncertainty associated with the final carbon stock estimates.

660

661 ## 2. Data and Materials

662 The forest distribution data were created by combining the Vegetation Map of the
663 People's Republic of China (Editorial Committee of Vegetation Map of China, 2007)
664 with a vegetation map produced from the forest inventory conducted during the period
665 from 2004 to 2008 (State Forestry Administration of China, 2009). The former

provides a detailed classification of plant functional types and describes the phenological and regional character of forests in China, but it is not so exact. The latter shows the forest distribution in the period of the forest inventory, but its classification provides less information about plant functional types. The combination of the two kinds of maps retains the the advantages of both.

The forest distribution data covers 161 plant biomes, including five classes of deciduous needle-leaved trees, 57 classes of evergreen needle-leaved trees, 39 classes of deciduous broad-leaved trees, 56 classes of evergreen broad-leaved trees and four classes of mixed trees (Fig01).

Fig01

The national forestry inventory database (FID) for the period 2004-2008 includes 160,000 permanent sample plots and 90,000 temporary sample plots scattered across China. The biomass density of each forest type in each province was calculated from timber volume, using a BEF (Fang et al., 2007). The biomass carbon density (BCD) of each forest type in each province was calculated next by multiplying the biomass density by a carbon factor (CF) (Li and Lei, 2010). And finally, the biomass carbon stock (BCS) of each forest type in each province was calculated by multiplying the BCD by the area of that forest type. The total BCS in China is a sum of the BCS of all of the forest types in the 31 provinces of China, excluding Taiwan, Hong Kong and Macao.

The following formulations were used to calculate the forest BCS in China:

$$TCS = \sum_{i=1}^{M}\sum_{j=1}^{N}(A_{i,j} \cdot BCD_{i,j}) \cdot 10^{-12} \quad (1)$$

$$BCD_{i,j} = W_{i,j} \cdot CF_i \quad (2)$$

691 $$W_{i,j} = BEF_i \cdot V_{i,j} \quad (3)$$

692 $$BEF_{i,j} = a_i + \frac{b_i}{V_{i,j}} \quad (4)$$

693 where TCS is the total forest BCSs of China (Pg); $BCD_{i,j}$ is the area weighted
694 biomass carbon density of the *i*th forest type in the *j*th province (kg/m^2); $A_{i,j}$ is the
695 area of the *i*th forest type in the *j*th province (m^2); *M* and *N* refer to the numbers of
696 forest types and provinces in China, respectively; $W_{i,j}$ is the area weighted mean
697 forest biomass of the *i*th forest type in the *j*th province (kg /m^2); CF_i is the CF of the
698 *i*th forest type; $V_{i,j}$ is the area weighted mean timber volume of the *i*th forest type in
699 the *j*th province (m^3 /m^2); BEF_i is the BEF of the *i*th forest type (kg /m^3); and a_i
700 (kg /m^3) and b_i (kg /m^2) are constants of the *i*th forest type to be simulated. The mean
701 CF_i of all coniferous forest types was used for coniferous mixed forest. The mean
702 CF_i of all broad-leaved forest types was used for broad-leaved mixed forest. The
703 mean CF_i of all broad-leaved and coniferous forest types was used for broad-leaved
704 and coniferous mixed forest.

705 The land mass of China was next divided into nine regions (Fig02) with similar
706 temperature, precipitation and soil regimes to make it easier to analyze changes in
707 forest carbon storage from one place to another (Zhou et al., 1981). The nine regions
708 are referred to as R_k where k = 1 to 9 and we use periods 1, 2, 3, 4 and 5 to
709 represent the periods 1984-1988, 1989-1993, 1994-1998, 1999-2003 and 2004-2008,
710 respectively.

711

712 **Fig02**

713

3. Methods

3.1 Satellite-observation-based approach (SOA)

The SOA used the normalized differential vegetation index (NDVI) at a temporal resolution of one month and at a spatial resolution of 1 km x 1 km from the Earth Observation System's moderate-resolution imaging spectroradiometer (EOS MODIS) (Piao et al., 2009). The BCD from the FID data was matched with the NDVI data through the map of forest in China reproduced in Fig01.

The BCD mirrored the latitude, longitude and maximum value of the monthly-averaged NDVI values during the Seventh National Forest Inventory conducted from 2004 to 2008:

$$BCD_j = 93.351\ln(NDVI_j) - 2.96Lat_j - 21.388Lon_j + 0.047Lat_j^{\,2} + 0.091Lon_j^{\,2} + 1339.03 \quad (5)$$

where $NDVI_j$ is the mean of the maximum values of the monthly-averaged NDVI values during the period 2004-2008 in the *j*th province and Lat_j and Lon_j refer to the latitude and longitude of the center of the *j*th province, respectively. The coefficient of correlation (R=0.91) and significance (P<0.001) show how latitude, longitude, and NDVI explained 83% of the variability in BCD.

3.2 High accuracy surface modeling (HASM)

HASM was developed for efficiently fusing satellite- with ground-observations to find solutions for error problems which have long troubled earth surface modeling (Yue, 2011). HASM has been successfully used to construct digital elevation models (Yue et al. 2007, 2010a, 2010b; Yue and Wang, 2010; Chen and Yue 2010; Chen et al. 2013a, b), model surface soil properties (Shi et al. 2011) and soil pollution (Shi et al.

2009), fill voids in the Shuttle Radar Topography Mission (SRTM) dataset (Yue et al. 2012), simulate climate change (Yue et al. 2013a, b; Zhao and Yue 2014a, b), fill voids in remotely sensed XCO2 surfaces (Yue et al. 2015a), and to analyze ecosystem responses to climatic change (Yue et al. 2015b). In all of these applications, HASM produced more accurate results than the classical methods (Yue et al., 2015c).

3.3 Estimation of carbon stocks

Forest carbon stocks and carbon densities were estimated by methods of spatial interpolation, SOA and data fusion. The spatial interpolation provided an effective approach to construct a continuous surface from the FID by means of Kriging; it took advantage of limited observation data to estimate the most plausible spatial distribution by filling in missing data. The data fusion approach integrated the forest inventory and satellite data into a consistent, accurate and useful representation using HASM (HASM-SOA) (see supplement 1 in details); the aim of the data fusion was to improve the quality of the information so that it was more accurate than would be possible if the data sources had been used individually.

3.4 Validation

The uncertainties of the carbon stock estimates reported in earlier studies relied on several different concepts and metrics. The same formula for absolute and relative error should be used to evaluate all estimates of carbon stocks so that the estimation results are comparable. We calculated the mean absolute errors (MAE) and mean relative errors (MRE), respectively, as:

$$MAE = \frac{1}{n}\sum_{i}^{n}|o_i - s_i| \quad (6)$$

$$MRE = \frac{MAE}{\frac{1}{n}\sum_{i}^{n}|o_i|} \quad (7)$$

where o_i represents the forest carbon stocks at the *i*th control point; s_i represents the simulated value at the *i*th control point; and n_i is the total number of control points used for validation.

Cross-validation is used to estimate how accurately a model performs, which is analyzed by removing certain data points in turn and summing the absolute value of the discrepancy of each removed data point from the simulated one at the same location (Hulme et al., 1995). It was comprised of four steps: (1) 5 % of the sample plots from the national forest inventory were removed for validation; (2) the spatial distribution of average forest BCSs in China during the period 2004-2008 were simulated at a spatial resolution of 5 km × 5 km using the remaining 95% of the sample plots from the national forest inventory by means of the different methods; (3) the MAEs and MREs were calculated using the 5% validation set; and (4) the 5% validation set was returned to the pool for the next iteration, and another 5% validation set was removed. This final process was repeated until all the sample plots were used for validation at least one time and the simulation error statistics could be calculated for each sample plot.

4 Results

The three maps of mean annual carbon stocks during the period 2004-2008 reproduced with each of the aforementioned methods shows how each of the methods was able to generate the same overall patterns based on the underlying forest cover on the one hand, and how the estimates varied using each of these methods over large parts of the China on the other hand (Fig03). This variability raises questions related

786 to the reliability of the estimates produced with the three aforementioned approaches.

787

788 **Fig03**

789

790 The cross-validation results indicated that Kriging and SOA had larger errors, with
791 MREs of 50.12 and 48.77%, respectively. Kriging over-estimated the carbon stocks,
792 while SOA under-estimated the carbon stocks (Table 1). Accuracy was considerably
793 improved when the forest inventory and satellite data were fused by using
794 HASM-SOA. The MRE of HASM-SOA was 22.71%.

795

796 **Table 1**

797

798 The BCSs of all forest types estimated with HASM-SOA (the best approach) was
799 7.08 Pg in China during the period 2004-2008. The BCSs of coniferous, broadleaf and
800 mixed forests were 2.74, 3.95 and 0.39 Pg, respectively (Table 1). The mean carbon
801 densities (MBCDs) of the coniferous, broadleaf and mixed forests were 4.35, 4.74 and
802 4.20 kg/m^2, respectively.

803 The HASM-SOA estimates showed that 89.9% of the MBCSs were found in the
804 regions R5, R3, R6, R9 and R7 during the period P5, accounting for 28.61, 28.41,
805 14.48, 12.52 and 5.89% of the BCSs, respectively. The three largest BCDs occurred in
806 R5 (Tibet plateau; 10.53 kg/m^2), R2 (arid area; 6.33 kg/m^2) and R3 (northeastern
807 China; 4.44 kg/m^2) (Table 2 and Fig03c). The two smallest BCDs were predicted in
808 the R8 (2.14 kg/m^2) and R9 (2.60 kg/m^2) regions.

809

810 **Table 2**

811

The HASM-SOA estimates can be parsed by forest type as well (Table 3). Hence, the BCDs of evergreen broad-leaved and evergreen coniferous forests were 6.23 and 4.47 kg/m^2, respectively, while the BCDs for deciduous broad-leaved and deciduous coniferous forests were 3.93 and 3.77 kg/m^2, respectively in P5. The BCD of evergreen forests was 50% larger than that of deciduous forests, and the BCDs for broad-leaved forests were greater than those for both coniferous and deciduous forests. Turning next to the BCSs, the evergreen coniferous forests contributed the largest proportion, accounting for 33.05%, followed by deciduous broad-leaved forests (29.8%), and evergreen broad-leaved forests (25.99%). The deciduous coniferous and the broad-leaved and coniferous mixed forests accounted for the first two smallest proportions of the total BCS, 5.65 and 5.51%, respectively.

Table 3

The HASM-SOA estimates also indicate that BCSs rose from 4.84 Pg in period 1 to 7.08 Pg in P5 due to the increase of BCD and the expansion of forest area (Table 4). The BCD rose from 4.00 kg/m^2 in P1 to 4.55 kg/m^2 in P5 and the forest area grew from 1.21 million km^2 in P1 to 1.56 million km^2 in P5. The increasing trends of the BCS, BCD and forest area (FA) are captured by the following regression equations:

$$BCS(t) = 0.531t + 4.297 \qquad R = 0.976 \tag{8}$$

$$BCD(t) = 0.125t + 3.958 \qquad R = 0.943 \tag{9}$$

$$FA(t) = 0.083t + 1.1045 \qquad R = 0.96 \tag{10}$$

where t corresponds to periods 1, 2, 3, 4 and 5; $BCS(t)$, $BCD(t)$ and $FA(t)$ are BCS, BCD and FA, respectively in the period t; and R represents the correlation coefficient for the corresponding regression equation.

838 **Table 4**

839

840 Although BCS rose in all nine regions from period 1 to period 5, the spatial
841 variability over China more or less mirrors the variability in the distribution of forests
842 (Fig04, Fig05, Table 4). For regions R1 and R8, for example, both BCS and BCD
843 have continuously increased from period 1 to period 5. R8 has the smallest BCS,
844 which only accounted for 0.83% of the BCS of the whole of China, and the smallest
845 BCD of 2.14 kg/m^2 in P5 as well as the lowest BCS accumulation rate of 1.3Tg yr^{-1}.
846 In R1, BCS accounted for 3.94% of the total BCS of China for the period of P5 and
847 the BCS accumulation rate has averaged 6.2 Tg yr^{-1} from P1 to P5.

848

849 **Fig04**

850

851 **Fig05**

852

853 The region R5 had the largest BCS accounting for 28.61% of the total BCS of
854 China in P5, the largest BCD of 10.53 kg/m^2 and the fastest BCS accumulation rate of
855 52 Tg yr^{-1}; the BCS has shown a monotonically increasing trend since P1. The second
856 largest BCS occurred in R3 (Northeastern China). The BCS in R3 accounted for 28.41%
857 of the total BCS of China. However, the BCD in R3 has declined since P3 following
858 increases from P1 to P2 and from P2 to P3. The mean BCS accumulation rate in R3
859 was 21.3 Tg/yr.

860 In the regions R4 (Loess Plateau), R6 and R9, both BCS and BCD have increased
861 since P3. The BCSs in R4, R6 and R9 accounted for 2.68, 14.48 and 12.26% of the
862 BCS in the whole of China in P5, respectively. The average BCS accumulation rates
863 were 2.8, 10.4 and 12.7 Tg yr^{-1}, respectively in R4, R6, and R9. In R2 (an arid area of

China), the BCS accounted for 2.80% of the total for China in the period P5. The BCS and BCD increased from P4 to P5, but the mean accumulation rate of BCS was only 2.3 Tg yr^{-1}. The BCS accounted for 5.89% of the total for China in R7. The BCS and BCD both increased from P4 to P5 but like in R2, the mean BCS accumulation rate was relatively low at just 2.9 Pg yr^{-1}.

In terms of forest types, evergreen broad-leaved forests had the fastest BCS accumulation rate and the largest BCD, while evergreen coniferous forests contributed the largest BCS. The BCSs of broad-leaved forests increased during all five periods. The BCS of evergreen broad-leaved forests increased from 0.63 Pg in period 1 to 1.84 Pg in period 5, and the BCSs for deciduous broad-leaved forests rose from 1.38 Pg in period 1 to 2.11 Pg in period 5. These trends can be modeled with the following regression equations:

$$BCS_1(t) = 0.312t + 0.286, \quad R = 0.998 \tag{11}$$

$$BCS_2(t) = 0.199t + 1.115, \quad R = 0.981 \tag{12}$$

where t corresponds to period t, $t = 1, 2, 3, 4$ and 5; $BCS_1(t)$ and $BCS_2(t)$ are respectively the BCSs of evergreen broad-leaved forests and deciduous broad-leaved forests in the period t and R represents the correlation coefficient of the corresponding regression equation.

The BCSs of deciduous coniferous forests fluctuated from period to period. Evergreen coniferous forests and broad-leaved and coniferous mixed forests exhibited an increasing trend of BCS in general but declined in period 3. Their trends were modeled with the following regression equations:

$$BCS_3(t) = 0.207t + 1.391, \quad R = 0.932 \tag{13}$$

$$BCS_4(t) = 0.076t - 0.068, \quad R = 0.867 \tag{14}$$

where t corresponds to periods 1, 2, 3, 4 and 5; $BCS_3(t)$ represents the BCSs of evergreen coniferous forests in the period t; $BCS_4(t)$ refers to the broad-leaved and coniferous mixed forests; and R represents the correlation coefficient of the corresponding regression equation.

The equations (8), (9) and (10) indicate that increasing rates of BCS, BCD and FA were 0.531 Pg, 0.125 kg/ m^2 and 0.083 million km^2, respectively over a five-year period on average. According to equations (11) and (12), the BCS of evergreen broad-leaved forests had a growth rate of 0.312 Pg over a five-year period, which was 0.113 Pg higher than that for deciduous broad-leaved forests because of the different increasing rates of BCD; the BCD of evergreen broad-leaved forests increased by 1.87 kg/m^2, while the BCD of deciduous broad-leaved forests increased by 0.18 kg/m^2 from period 1 to period 5. The equations (13) and (14) show that carbon stocks of evergreen coniferous forests grew much faster than those for broad-leaved and coniferous mixed forests. The former grew by 0.207 Pg but the latter by only 0.076 Pg in a five-year period on average because the area of evergreen coniferous forests was five times larger (0.50×10^6 km^2 compared to 0.09 x 10^6 km^2 for broad-leaved and coniferous mixed forests) and offset the lower BCD growth rate of the former (0.132 kg/m^2) compared to 0.56 kg/m^2 for broad-leaved and coniferous mixed forests per five-year period.

The results from Kriging and HASM-SOA exhibit a similar spatial pattern on the national level, especially in southern Tibet, the Xiao Hinggan Moutains, the Changbai Mountains, and south China. Some differences occur in Taiwan and Xinjiang as well as the Qinling Mountains. Compared to HASM-SOA, Kriging is strongly influenced by sample-plot density. The spatial heterogeneity of the results from SOA is not so obvious because NDVI, a critical variable of SOA, is not so sensitive to a change of

913 carbon stocks, especially in northeast China and the lower reaches of Yangtze River.

914 The scatter diagrams of simulated BCD against observed BCD (Fig06) indicate
915 that the BCD surface created by Kriging exhibits a higher correlation with observed
916 BCD, R^2=0.826. But the Kriging interpolation generated large errors in the
917 Xizang/Tibet and Xinjing regions, with the highest BCD. The BCD was
918 overestimated in Xizang and underestimated in Xinjiang. The BCD surface created by
919 SOA has the smallest correlation coefficient, R^2= 0.627, with the observed one. The
920 SOA results show that BCDs in higher and lower latitudes are larger than those in
921 middle latitudes, but for Xinjiang and Xizang. The BCD was overestimated in
922 Xinjiang but underestimated in Xizang. The surface of BCDs generated by
923 HASM-SOA has the best correlation with the observed one, R^2=0.943 and it
924 generated the smallest errors in the regions of Xizang and Xinjiang, compared with
925 the other methods.

926

927 Fig06

928

929

930 ## 5 Discussion and Conclusions

931 The fusion of forest inventory data with satellite observations achieved with
932 HASM-SOA provided much more accurate estimates of forest biomass carbon stocks
933 and their changes. This kind of method can increase our understanding of the role of
934 forests in the carbon cycle, for greenhouse gas inventories, and terrestrial carbon
935 accounting (Muukkonen and Heiskanen, 2007).

936 Turning to the work at hand, HASM-SOA overcame the shortcomings of both the
937 ground-based national forest inventory and the satellite remote-sensing observations

by fusing information about the details of the carbon stocks observed on the Earth's surface and the variability of the carbon surface observed from space. The cross-validation demonstrated that HASM-SOA was 26.1% more accurate than the satellite-based approach and 28.4% more accurate than spatial interpolation of the sample plots. These findings suggest that China's forest biomass carbon stocks are more likely to match our estimates than those generated by past efforts to estimate these same carbon stocks and their change over time.

Taken as a whole, the HASM-SOA results show that the forest carbon stocks of China have increased by 2.24 Pg during the period 1984-2008 to a new high of 7.08 Pg C in 2008. These numbers fall in the middle of the previously published estimates. All of the estimates show forest biomass carbon stocks in China increasing from 1973 to 2008, notwithstanding the various methods used and the varying levels of uncertainty embedded in these different methods and the data sources used.

The results from HASM-SOA are more or less different from those of other studies. For instance, the annual growth of total BCS from period 1 (circa 1986) to period 5 (circa 2006) in China was 0.112 $PgCyr^{-1}$. This estimate was higher than that of Zhang et al. (2013), which was 0.103 $PgCyr^{-1}$. However, our estimate of 0.148 $PgCyr^{-1}$ from period 3（circa 1996） to period 5（circa 2006）-was lower than the 0.174 $PgCyr^{-1}$ estimated by Zhang et al. (2013). From period 4 (circa 2001) to period 5 (circa 2006), the 0.14 $PgCyr^{-1}$ estimated by HASM-SOA was twice that estimated by Liu et al. (2015).

The Grain for Green program, which was launched in 1999 and aims to restore the country's forests and grasslands to prevent soil erosion, has emerged as one of the key drivers of carbon sequestration. This program targets land with slopes > 25^{o} (Xu et al., 2006; Yue et al., 2010c) and has been implemented in four phases: (1) a pilot

963 phase (1999-2001); (2) an initial construction phase (2002-2010); (3) a consolidation
964 phase (2011-2013); and (4) a second construction phase to be built around a new
965 round of Grain for Green program expenditures (2014-2020).

966 The pilot program launched in 1999 focused on three provinces: Gansu, Shaanxi
967 and Sichuan. Approximately 381,000 ha of farmland was converted into forestland
968 and 66,000 ha of bare land was reforested. In 2000, the program was expanded to 17
969 provinces, and the converted farmland and reforested bare land totals grew to 410,000
970 and 449,000 ha, respectively. By 2001, 20 provinces were involved in the program
971 and 420,000 and 563,000 ha of farm and bare land had been reforested, respectively
972 (Table 5). The national Grain for Green program was launched in China in 2002 and
973 by the end of 2010, 14.667 million ha of farmland had been converted to forest or
974 grassland and 17.333 million ha of bare land had been reforested. During the
975 consolidation phase from 2011 to 2013, scientific monitoring and management of the
976 converted and reforested lands was strengthened to sustain the aforementioned
977 achievements of the Grain for Green program over the long-term.

978

979 **Table 5**

980

981 To grow and consolidate these gains, the potential for farmland conversion at the
982 county level during the period 2014-2020 was estimated in 2014 by counting up
983 farmers' voluntary applications to determine how large an area could be converted to
984 forest or grassland. By 2020, 2.827 million ha of farmland could be converted, which
985 includes 1.449 million ha of farmland with slopes >25^{o}, 1.133 million ha of cultivated
986 land threatened by desertification, and 247,000 ha of farmland with slopes between 15
987 and 25^{o} around the Danjiangkou and Three Gorges reservoirs.

The results from this latest phase of the Grain for Green program are encouraging. Participating farmers can choose whether farmland is to be converted to forest or grassland, and which species will be planted, and they will receive a 22,500 RMB subsidy for every hectare of farmland converted to forest or grassland. In 2014, 322,000 ha were converted to forest and 11,000 ha were converted to grassland, and in 2015 another 667,000 ha of farmland will be converted to either forest or grassland.

The BCS growth was contributed by already existing forests and newly planted forests. The former accounted for about 55% while the latter about 40%. The BCS in existing forests had a growth rate of about 0.55 kg/m^2 per five-year period and the BCS in newly planted forests grew at 1.8 kg/m^2 per five-year period.

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Table 1. Biomass carbon stocks and biomass carbon densities as well as their errors produced by different methods.

Method	Calculated object	Coniferous forests	Mixed forests	Broadleaf forests	Total	MAE (kg m^{-2})	MRE (%)
SOA	BCS (Pg)	2.48	0.46	3.61	6.55	1.92	48.77
	BCD (kg m^{-2})	3.94	4.93	4.34			
Kriging	BCS (Pg)	2.76	0.39	4.11	7.26	1.97	50.12
	BCD (kg m^{-2})	4.38	4.24	4.94			
HASM-SOA	BCS (Pg)	2.74	0.39	3.95	7.08	0.89	22.71
	BCD (kg m^{-2})	4.35	4.2	4.74			

1183 **Table 2. BCS and BCD of the forests in the nine regions of China during the periods 2004-2008 and**
1184 **1984-1988**

Regions	P5 (from 2004 to 2008)			P1 (from 1984 to 1988)		BCS accumulation rate
	BCD	BCS	Percentage	BCD	BCS	
	kg m^{-2}	(Pg)	(%)	kg m^{-2}	(Pg)	(Tg yr^{-1})
R1	3.710	0.28	3.94	2.666	0.16	6.2
R2	6.330	0.20	2.80	6.358	0.15	2.3
R3	4.445	2.01	28.41	4.493	1.59	21.3
R4	3.274	0.19	2.68	3.035	0.13	2.8
R5	10.525	2.03	28.61	6.718	0.99	52.0
R6	3.671	1.03	14.48	3.734	0.82	10.4
R7	3.693	0.42	5.89	3.643	0.36	2.9
R8	2.138	0.06	0.83	1.515	0.03	1.3
R9	2.598	0.87	12.26	2.358	0.62	12.7
Total		7.08	100		4.84	112

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Table 3. BCSs and BCDs for all forest types during the five periods estimated using HASM-SOA

Period	Calculation object	Deciduous coniferous forests	Evergreen coniferous forests	Broad-leaved and coniferous mixed forests	Deciduous broad-leaved forests	Evergreen broad-leaved forests
P1	**BCS (Pg)**	0.41	1.50	0.06	1.38	0.63
	BCD (kg/m^2)	4.35	3.81	3.08	3.75	4.35
P2	**BCS (Pg)**	0.39	1.80	0.09	1.44	0.87
	BCD (kg/m^2)	4.28	4.13	3.75	3.77	5.65
P3	**BCS (Pg)**	0.44	2.23	0.07	1.66	1.20
	BCD (kg/m^2)	4.20	4.09	3.03	3.87	6.35
P4	**BCS (Pg)**	0.47	2.19	0.19	1.97	1.57
	BCD (kg/m^2)	4.37	4.40	5.18	3.89	7.49
P5	**BCS (Pg)**	0.40	2.34	0.39	2.11	1.84
	BCD (kg/m^2)	3.77	4.47	4.20	3.93	6.22

Table 4 Biomass carbon stocks and biomass carbon densities estimated by HASM-SOA

Regions	Calculation object	Period 1	Period 2	Period 3	Period 4	Period 5
R1	BCS (Pg)	0.16	0.17	0.17	0.2	0.28
	BCD (kg m^{-2})	2.67	2.71	2.88	2.98	3.71
R2	BCS (Pg)	0.15	0.16	0.15	0.18	0.2
	BCD (kg m^{-2})	6.36	6.27	6.25	6.23	6.33
R3	BCS (Pg)	1.59	1.64	1.64	1.77	2.01
	BCD (kg m^{-2})	4.49	4.42	4.5	4.43	4.44
R4	BCS (Pg)	0.13	0.15	0.14	0.16	0.19
	BCD (kg m^{-2})	3.04	3.23	3.13	3.15	3.27
R5	BCS (Pg)	0.99	1.57	1.64	1.94	2.03
	BCD (kg m^{-2})	6.72	10.15	10.83	11.49	10.53
R6	BCS (Pg)	0.82	0.87	0.82	0.96	1.03
	BCD (kg m^{-2})	3.73	3.78	3.66	3.88	3.67
R7	BCS (Pg)	0.36	0.39	0.37	0.4	0.42
	BCD (kg m^{-2})	3.64	3.79	3.66	3.54	3.69
R8	BCS (Pg)	0.03	0.04	0.04	0.05	0.06
	BCD (kg m^{-2})	1.52	1.64	1.89	1.89	2.14
R9	BCS (Pg)	0.62	0.56	0.62	0.73	0.87
	BCD (kg m^{-2})	2.36	2.05	2.3	2.51	2.6
The whole of China	BCS (Pg)	4.84	5.55	5.6	6.38	7.08
	BCD (kg m^{-2})	4	4.32	4.33	4.47	4.55
	Area (million km^2)	1.2101	1.2864	1.292	1.4279	1.5559

Table 5. Converted farmland and reforested bare land included in China's Grain for Green Program (millions hectares) (Office of Converting Farmland to Forestry, State Forestry Administration of China, 2014, 2016)

Year	Converted farmland	Afforestation on bare land	Total
1999	0.381	0.066	0.448
2000	0.405	0.468	0.872
2001	0.42	0.563	0.983
2002	2.647	3.082	5.729
2003	3.367	3.767	7.133
2004	0.667	3.333	4
2005	1.114	1.321	2.435
2006-2010	5.666	4.733	10.4
2014	0.333		0.333
2015	0.667		0.667
1999-2015	15.667	17.333	33
2016-2020	1.827		1.827

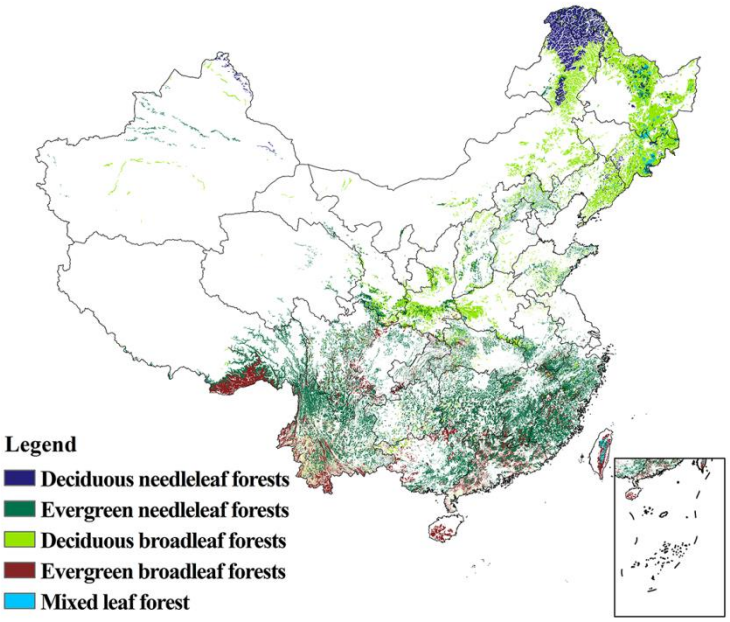

Fig01. The forest cover map of China

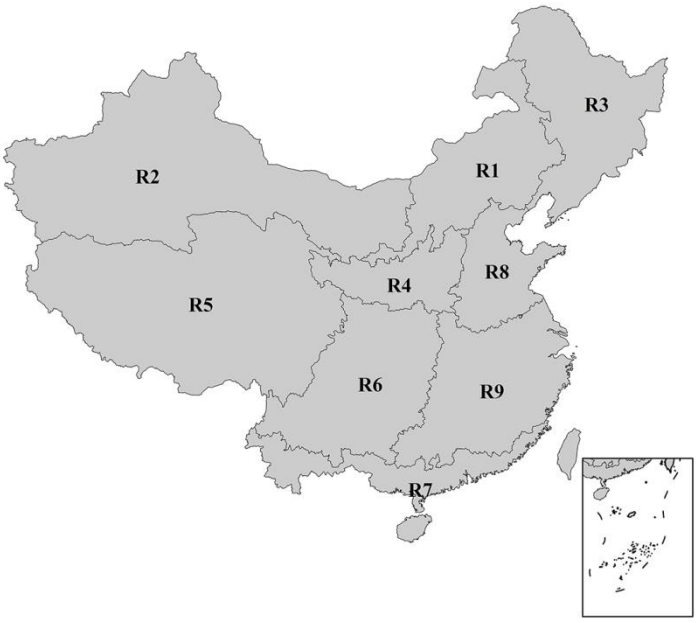

Fig02. Map showing the nine regions of China used for detailed analysis

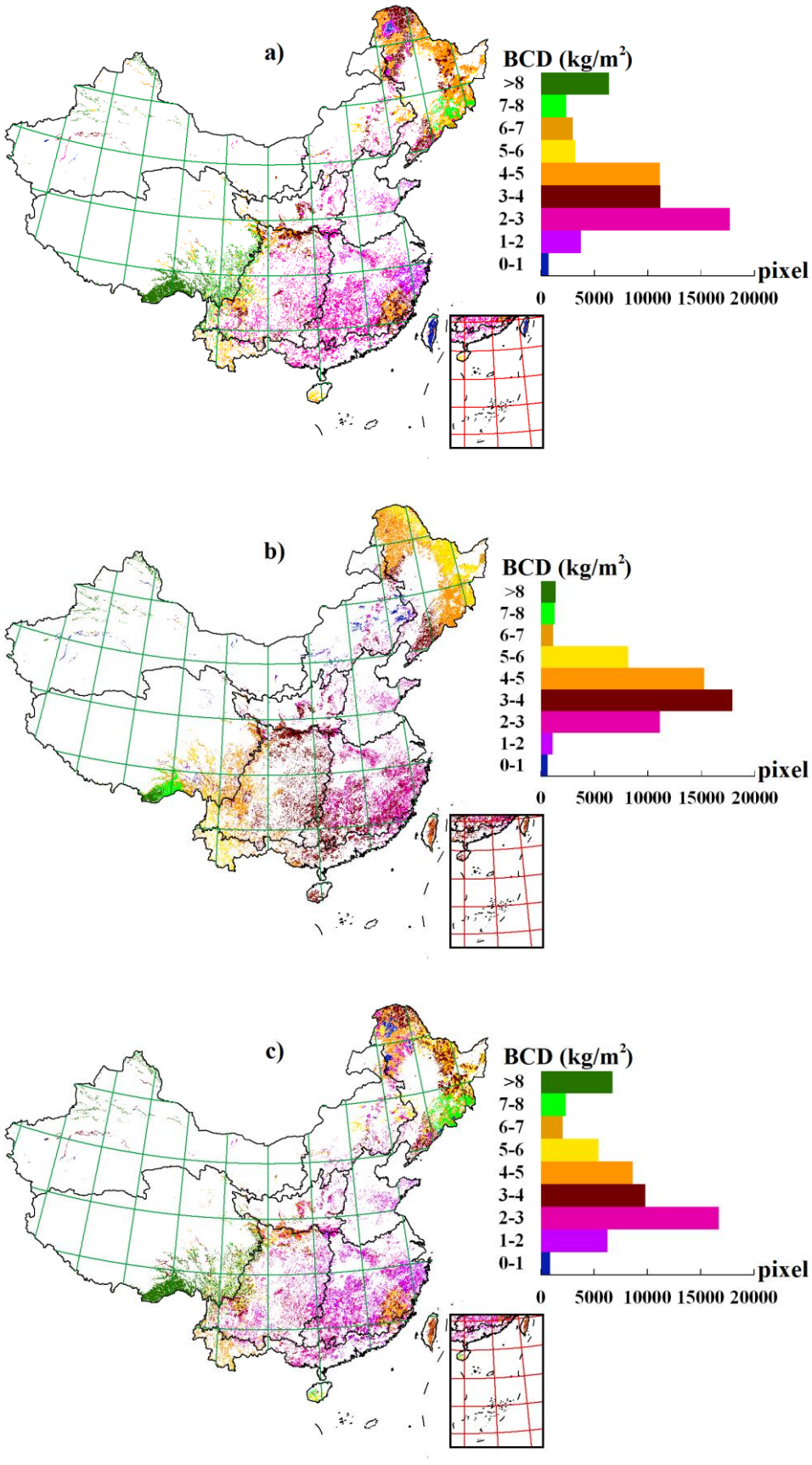

Fig03. The spatial distribution of forest biomass BCDs estimated during the period 2004-2008 in China using: (a) Kriging; (b) SOA; and (c) HASM-S

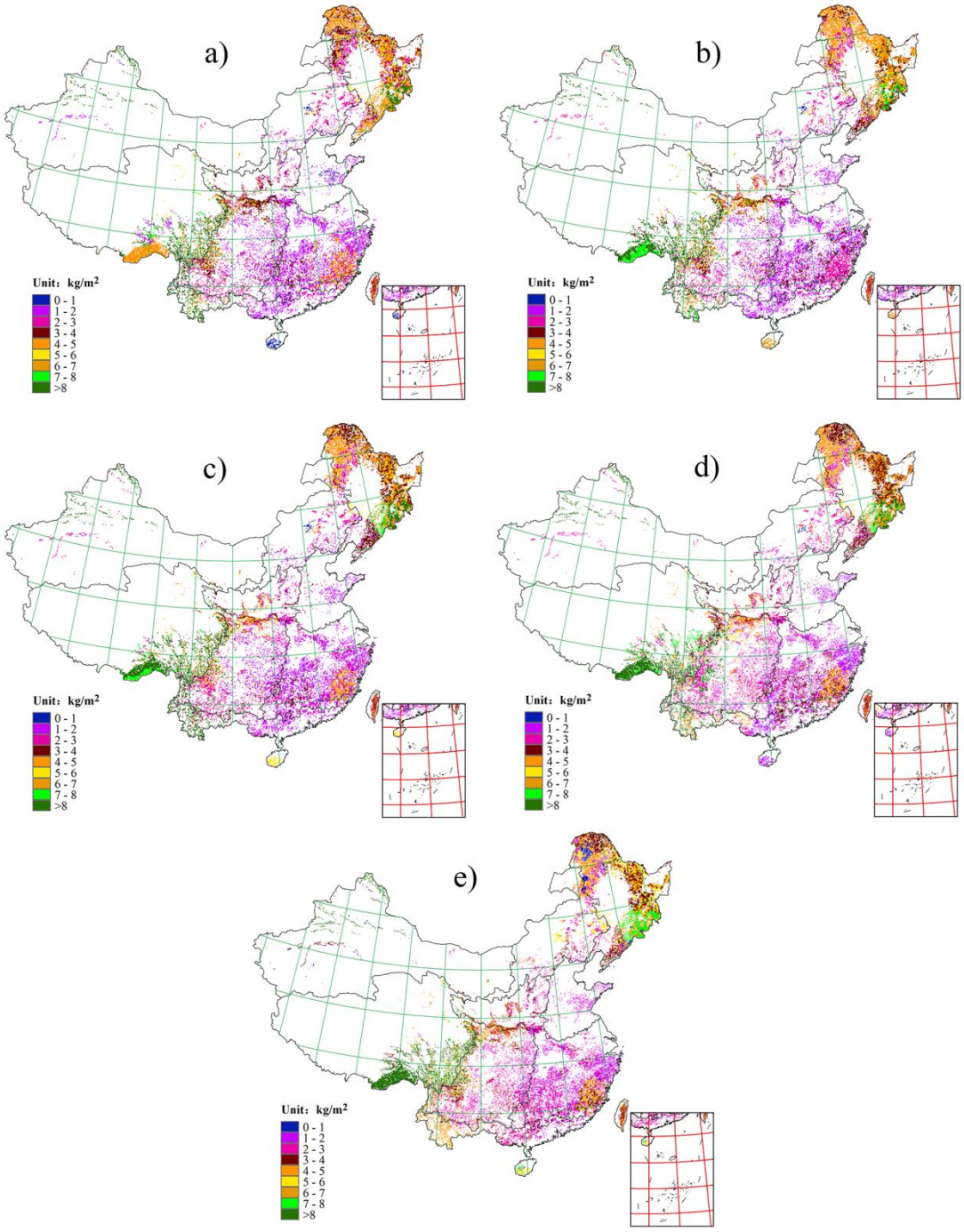

Fig04. The spatial distribution of forest BCDs in China estimated during the five periods using HASM-SOA: (a) 1984-1988 (P1); (b) 1989-1993 (P2); (c) 1994-1998 (P3); (d) 1999-2003 (P4); and (e) 2004-2008 (P5)

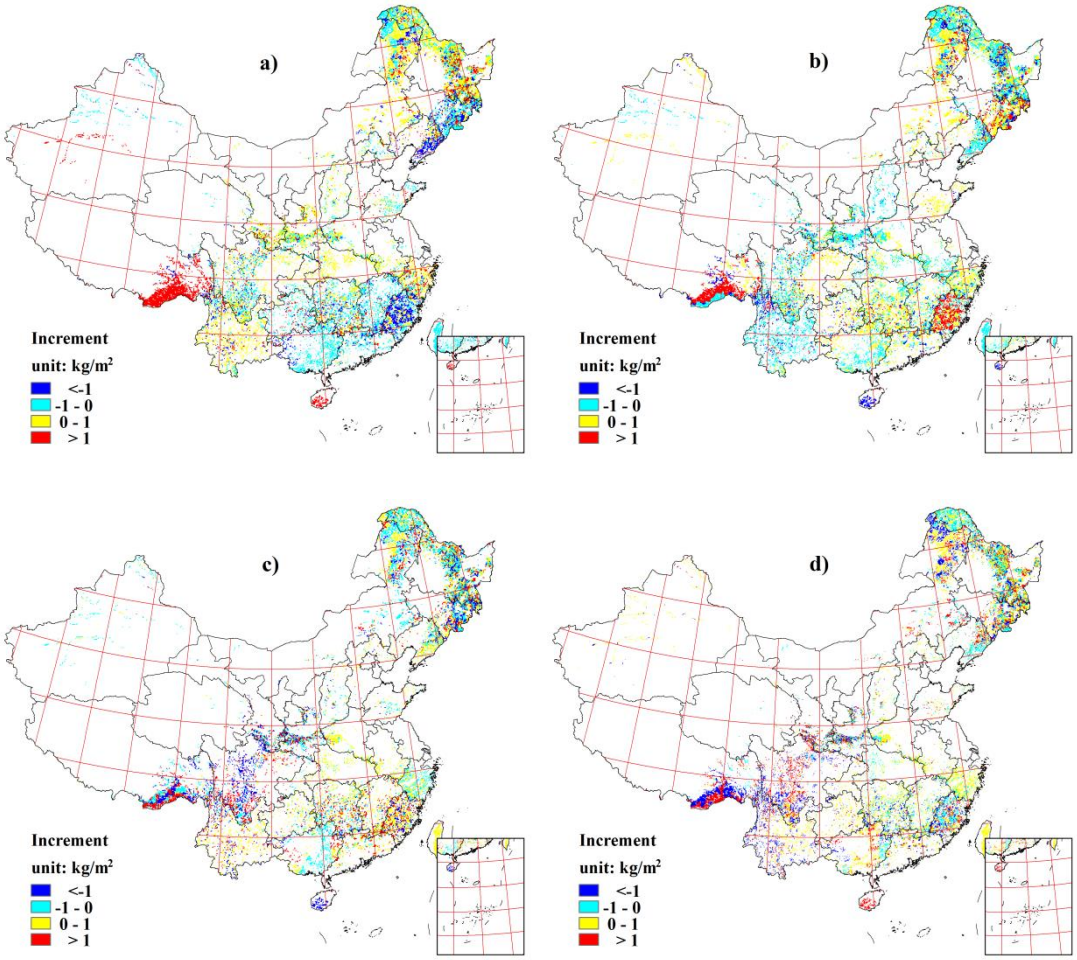

Fig05. The increment maps of biomass carbon stocks from comparing two adjacent periods : a) BCS in Period 2 minus BCS in Period 1, b) BCS in Period 3 minus BCS in Period 2, c) BCS in Period 4 minus BCS in Period 3, and d) BCS in Period 5 minus BCS in Period 4

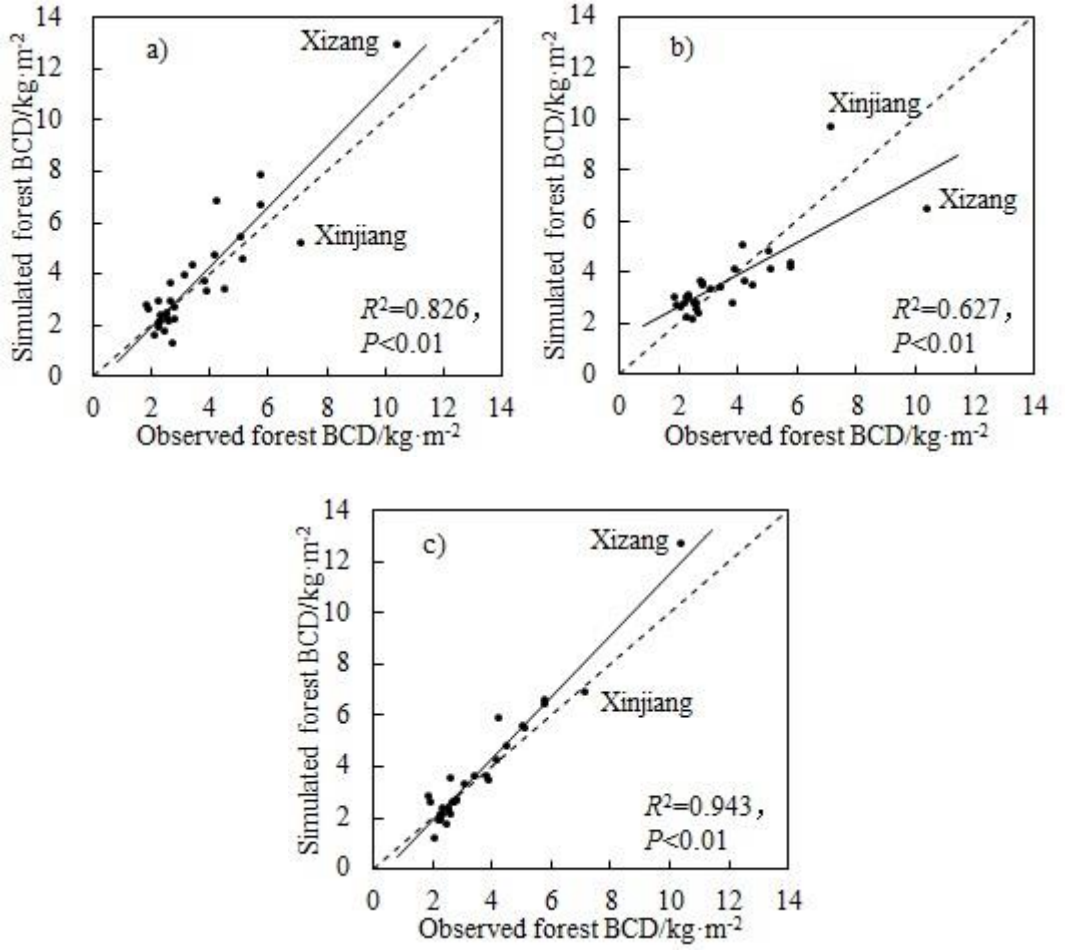

Fig06. The scatter diagrams of simulated BCD against observed BCD: a）Kriging, b）SOA, and c）HASM-SOA

List of Abbreviations

BCD	Biomass Carbon Density
BCS	Biomass Carbon Stock
BEF	Biomass Expansion Factor (method)
CBM	Continuous BEF Method
CF	Carbon Factor
EOS	Earth Observation System
FA	Forest Area
FID	Forestry Inventory Database
HASM	High Accuracy Surface Modeling (method)
MAE	Mean Absolute Error
MBCD	Mean Biomass Carbon Density
MBD	Mean Biomass Density
MRE	Mean Relative Error
MODIS	Moderate-Resolution Imaging System
MR	Mean Ratio
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
SOA	Satellite-Observation-based Approach