BAMBOO FOREST CHANGE AND ITS EFFECT ON BIOMASS CARBON STOCKS: A CASE STUDY OF ANJI COUNTY, ZHEJIANG PROVINCE, CHINA

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XU X, ZHOU G, DU H & PARTIDA A. 2012. Bamboo forest change and its effect on biomass carbon stocks: a case study of Anji county, Zhejiang province, China. The distribution of bamboo forest in south and south-eastern Asia is increasing. Based on Landsat satellite imagery data, rates and causes of change in bamboo forests and changes associated with biomass carbon stocks were analysed in Anji county, Zhejiang province, China. Results indicated notable increase in bamboo forest area and simultaneous loss in needleleaf and broadleaf forests as well as farm land between 1986 and 2008. Annual net flux of atmospheric carbon release from the increase in bamboo forest area was -66.5×10^2 to -117.6×10^2 Mg C year^{-1}. One of the most significant causative factors of biomass carbon stock losses was the conversions of needleleaf and broadleaf forests into bamboo forest. In this area of study, bamboo harvested for production accumulated carbon at a rate of 0.86 to 1.83 Mg C ha^{-1} year^{-1}. When carbon sequestration estimate in harvested bamboo was taken into consideration, the contribution of bamboo forest to the local carbon balance became significant.

Keywords: Bamboo products, Landsat thematic mapper imagery

XU X, ZHOU G, DU H & PARTIDA A. 2012. Perubahan dalam hutan buluh dan kesannya terhadap biojisim stok karbon: kajian kes di wilayah Anji, daerah Zhejiang, negara China. Taburan hutan buluh di selatan Asia dan tenggara Asia semakin meluas. Kadar dan sebab berlakunya perubahan dalam hutan buluh serta perubahan yang berkaitan dengan biojisim stok karbon dianalisis di wilayah Anji, daerah Zhejiang, negara China berdasarkan data imejan satelit Landsat. Keputusan menunjukkan pertambahan kawasan hutan buluh yang ketara dan kehilangan serentak hutan daun jejarum dan daun lebar serta tanah ladang antara tahun 1986 dengan tahun 2008. Pelepasan bersih karbon atmosfera tahunan daripada pertambahan kawasan hutan buluh adalah antara -66.5×10^2 Mg C tahun^{-1} hingga -117.6×10^2 Mg C tahun^{-1}. Salah satu faktor penyebab kehilangan biojisim stok karbon ialah penukaran hutan daun jejarum dan daun lebar menjadi hutan buluh. Di kawasan kajian, buluh yang dituai untuk penghasilan produk mengumpul karbon pada kadar 0.86 Mg C ha^{-1} tahun^{-1} hingga 1.83 Mg C ha^{-1} tahun^{-1}. Apabila anggaran pensekuesteran karbon dalam buluh yang dituai diambil kira, sumbangan hutan buluh kepada imbangan karbon tempatan menjadi ketara.

INTRODUCTION

The current rates and intensities of landuse and the resulting land cover change are greater than ever before, making unprecedented changes in ecosystems and environmental processes at local, regional and global scales (Ellis & Pontius 2007). These changes encompass the greatest environmental concerns for humans today, including climate change, biodiversity loss, wildlife habitat destruction, and the pollution of water, soil and air (Fearnside et al. 2009, Kaul et al. 2009, O'Connor & Kuyler 2009, Wang et al. 2009, Wiens et al. 2009). Monitoring and mediating the negative consequences of landuse and land-cover change (LULCC) while enhancing carbon sequestration have become a major priority for researchers and policy-makers. Presently, carbon emitted from forest land due to deforestation is substantial. However, changes in carbon levels as a result of subtle landuse changes, such as the conversions of other forests into bamboo forest, remain unclear.

Due to its high profitability, bamboo distribution in south and south-eastern Asia is continuously increasing (Sharma 1980). India (almost 11.4×10^6 ha) and China (over 5.4×10^6 ha) are the major bamboo producing countries in Asia

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(Lobovikov et al. 2006). Due to large-scale planting of bamboo (mainly moso bamboo, *Phyllostachys heterocycla* var. *pubescens*) in China over the last 15 years, bamboo areas in Asia had increased by 10% (Lobovikov et al. 2006). In 2005, it was reported that bamboo forest had reached an area of some 5×10^6 ha (Government of China 2005). This is a 1.5-fold increase compared with that of the 1950s (Lobovikov et al. 2006). Due to carbon sequestering benefits, we are interested in the impacts of bamboo forest change on biomass carbon stocks.

Remote sensing is an essential tool of LULCC because it enables observations across larger areas of the earth's surface than by ground-based observations. The post-classification comparison algorithm is one of the most common techniques used in detecting landuse changes (Ahlqvist 2008, Wang et al. 2009). The algorithm not only provides area and rate changes but also detailed information about LULCC (Lu et al. 2004). In addition, the post-classification comparison algorithm is not restricted by atmospheric, sensor and environmental differences between multi-temporal images (Coppin et al. 2004, Lu et al. 2004, Shalaby & Tateishi 2007). The post-classification comparison algorithm becomes the preferred method for detecting landuse changes because of its advantages.

LULCC plays a major role in climate change at local, regional and global levels. Hence, it is important to study effects of increasing bamboo forests on land cover and biomass carbon stocks. The objectives of this study were to: (1) explore the temporal and spatial characteristics of bamboo forest change between 1986 and 2008 based on Landsat Thematic Mapper (TM) data, (2) discover the sources facilitating bamboo forest change and (3) analyse the effects of increasing bamboo forest on changes in biomass carbon stocks. This study can provide some suggestions for enhancing carbon sequestration during landuse decision-making.

MATERIALS AND METHODS

Study area

Anji county (Figure 1) is located in the north-western part of Zhejiang province, China. The county has been named the home of moso bamboo forest because of its large area of distribution and important role in supporting the local economy. The study area covered 1886.45 km^2, of which 71.1% was covered by forests. The needleleaf forest is mainly dominated by *Pinus massoniana* and *Cunninghamia lanceolata*, while the broadleaf forest mainly consists of *Cyclobalanopsis glauca*, *Castanopsis sclerophylla*, *Castanopsis eyrei*, *Schima superba* and *Quercus fabri*. Bamboo forests accounted for 56.47% of the forested areas (79.3% moso bamboo). From 1983 till 2007, bamboo areas increased dramatically from 5.40×10^5 ha to 6.97×10^5 ha. The annual increased rate was 1.21% during that period. The terrain is undulating with elevation ranging from 4 to 1587 m above sea level. The annual precipitation average is between 1.1 and 1.9 m. Annual temperature averages between 12.2 and 15.6 °C.

Landsat TM image processing

Landsat TM images acquired on 25 July 1986 and 5 July 2008 were used in this study. These TM images were rectified to Transverse Mercator coordinate system using control points taken from topographic maps, with the root mean square errors of 0.51 and 0.67 pixels. The nearest neighbour algorithm was used to resample the TM images into pixel size of 30 m × 30 m during the image rectification. The auxiliary data were then collected, including forest inventory data, forest resource distribution maps and topographic maps.

Image classification and change detection

Land cover was classified into eight landuse categories: (1) bamboo forest, (2) broadleaf forest (BLF), (3) needleleaf forest (NLF), (4) farm land (FL), (5) orchards/nurseries/ shrub land (ONSL), (6) urban, (7) barren land (BL), and (8) water (Table 1).

Feature selection for multispectral data is an effective method to remove redundancy among bands and improve classification accuracy (Jensen 2005, Sanchez-Hernandez et al. 2007). The Jeffries–Matusita (JM) distance method was used to select the optimal feature subsets (Jensen 2005). The training data sets of each landuse category were extracted from the six bands (except for band 6), normalised difference vegetation index [NDVI, (TM4-TM3)/(TM4+TM3)] image, and infrared index vegetation index [IIVI, (TM4-TM5)/(TM4+TM5)] image using the Area of

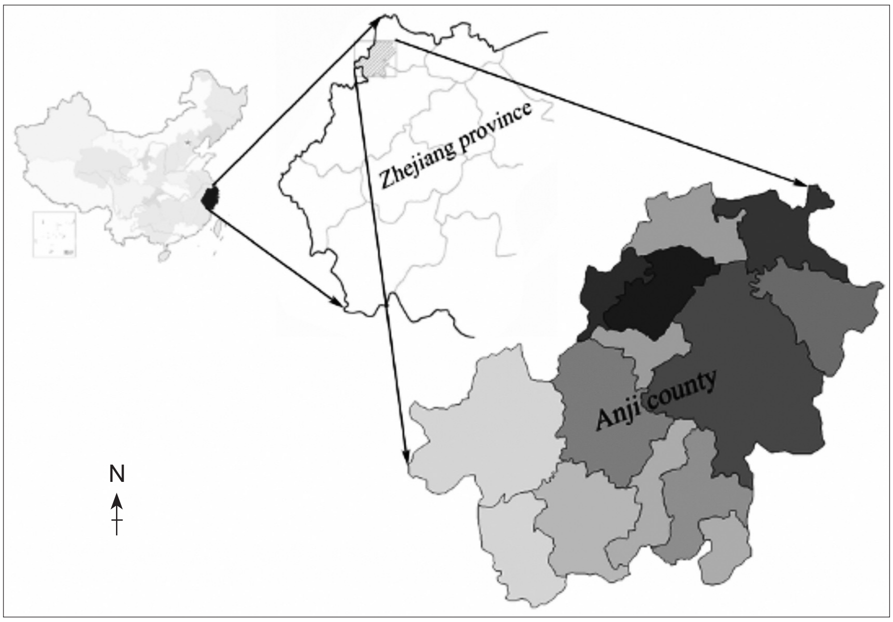

Figure 1 The study area in Anji county, Zhejiang province, China

Table 1 Descriptions of landuse categories

Landuse category	Description
Bamboo forest	Tree species mainly include moso bamboo (79.3%) and other bamboo species (20.7%)
BLF	Tree species mainly include *Cyclobalanopsis glauca*, *Castanopsis sclerophylla*, *Castanopsis eyrei*, *Schima superba*, *Quercus fabri*
NFL	Tree species mainly include *Pinus massoniana* and *Cunninghamia lanceolata*
FL	Areas used for the production of crops such as rice, wheat, corn, cotton, tea, vegetables; includes grasslands
ONSL	Areas planted or maintained for the production of fruits, nuts, berries or ornamental trees and flowers
Urban	Residential, commercial services, industrial, transportation, communications, industrial and commercial, mixed urban or built-up land, other urban or built-up land
BL	Land areas of exposed soil surface as influenced by human impacts and/or natural causes; contains sparse vegetation with very low plant cover value as a result of overgrazing, woodcutting; includes fallow and transitional
Water	Permanent open water, lakes, reservoirs, streams and rivers

BF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

Interest (AOI) tool. The NDVI stresses the difference between vegetation cover and no vegetation cover, while the IIVI is a useful index to identify relative variations of vegetation cover. The optimal feature subsets were selected according to the evaluation criterion of higher JM statistic and lesser features. Maximum likelihood classification (MLC) algorithm was applied to detect the landuse categories (Lu & Weng 2007, Dewan & Yamaguchi 2009). In this study, the post-classification comparison algorithm was used to detect landuse changes. The cross-tabulation table and spatial distribution map of changed categories were produced using the GIS analysis imbedded in ERDAS IMAGINE 9.1 software.

Classification and accuracy assessment

Accuracy assessment is an important part of classification and the change detection process (Lu et al. 2004, Lu et al. 2005). The error matrix-based accuracy assessment method was applied to determine classification map accuracies (Lu et al. 2005, Thapa & Murayama 2009). The stratified random sampling method was used to locate random sample points. In this study, 400 reference pixels were collected through forest inventory data and forest resource distribution maps. The minimum threshold of sample points for each landuse category was set at 20. The accuracies of the two classification maps were multiplied to estimate the expected accuracy for the change map (Yuan et al. 2005, Wang et al. 2009).

Biomass carbon stock change analysis

The effects of increasing bamboo forests on soil carbon stocks were not considered in this study. Annual change in biomass carbon stocks from the conversion of one landuse category to another has been estimated using equations 1 and 2. It refers to the stock-difference method described in IPCC (2006). The biomass carbon density of each landuse category was collected from published literature and forest inventory (Xu et al. 2011) (Table 2).

$$\Delta C = \sum_{i=1}^{n}\sum_{j=1}^{n} \Delta C_{i\_j,\,t_1-t_2} \qquad (1)$$

$$\Delta C_{i\_j,\,t_1-t_2} = \frac{(D_j - D_i) \times \Delta A_{i\_j,\,t_1-t_2}}{t_2 - t_1} \qquad (2)$$

where ΔC is the annual biomass carbon stocks change in the pool between time t_1 and t_2, Mg C year^{-1}; $\Delta C_{i\_j,\,t_1-t_2}$ is the annual biomass carbon stocks change in the pool from landuse category i (i =1 to n, n is total number of categories) to landuse category j (j = 1 to n) between time t_1 and t_2, Mg C year^{-1}; D_i is the biomass carbon density of landuse category i, Mg C ha^{-1}; $A_{i\_j,\,t_1-t_2}$ is change in area from landuse category i to landuse category j between time t_1 and t_2, ha.

The remaining carbon stored in biomass, in the form of different bamboo products, serves as carbon sink before decay (Upadhyay et al. 2005). Bamboo, especially moso bamboo, grows rapidly and is used to make a variety of products. These products can be preserved over decades. In this study, carbon sequestration in harvested bamboo products was taken into account. Carbon sequestration in harvested bamboo products was calculated using the following equations.

$$\Delta C_{products} = \frac{\varepsilon \times D_{above} \times \sum_{i=1}^{floor\left(\frac{t_2-t_1}{\omega}\right)} \left(A_{t_1} + \frac{A_{t_2} - A_{t_1}}{t_2 - t_1} \times (i-1) \times \omega \right)}{t_2 - t_1} \qquad (3)$$

$$\Delta RC_{products} = \frac{\Delta C_{products}}{A_{t_2}} \qquad (4)$$

Table 2 Biomass carbon densities of different categories

Landuse category		Biomass carbon density (Mg C ha^{-1})		Source
		Lower limit	Upper limit	
Bamboo forest	Aboveground	14.23	30.43	Xu et al. (2011)
	Underground	11.50	11.50	Zhou & Jiang (2004)
	Total	25.73	41.93	
BLF	Total	68.60	127.30	Fang et al. (1996)
NLF	Total	58.20	85.00	Fang et al. (1996)
FL	Total	6.80	9.30	Fang et al. (1996)
ONSL	Total	9.88	11.85	Zhang & Wang (2008)
Urban		0		
BL		0		
Water		0		

BLF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land where $\Delta C_{products}$ is the annual carbon sequestration in bamboo products, Mg C year^{-1}; $\Delta RC_{products}$ is the rate of carbon sequestration in bamboo products, Mg C ha^{-1} year^{-1}; ε is the average utilisation ratio of bamboo; D_{above} is the aboveground biomass carbon density, Mg C ha^{-1}; floor means to get the integer part; ω is the cutting cycle; A_{t_1} and A_{t_2} are the areas of bamboo in time t_1 and t_2 respectively, ha. The average utilisation ratio of bamboo (ε) was 0.4 (Zhang et al. 2006). Areas of bamboo forests in 1986 (A_{t1}) and 2008 (A_{t2}) estimated based on remote sensing classification were 529.4 × 10^2 ha and 718.4 × 10^2 ha respectively. The aboveground biomass carbon density (D_{above}) ranged from 14.23 to 30.43 Mg C ha^{-1} (Xu et al. 2011) and the cutting cycle (ω) of moso bamboo forest was five years.

RESULTS

Classification and accuracy assessment

According to JM distance method, the optimal feature subsets (including band 1, band 3, band 4, band 5, NDVI and IIVI) were used to classify the images. The classification maps based on MLC algorithm are shown in Figure 2. Figure 2 shows that most of study area is covered by bamboo forest. The land cover area changed dramatically during the 1986–2008 period.

An error matrix was generated to examine and display the overall accuracy and Kappa statistics. The overall accuracy values of the classification maps for 1986 and 2008 were 89.00 and 91.02% respectively (Table 3). The Kappa statistics were 0.869 for 1986 and 0.891 for 2008 (Table 3).

The expected accuracy of change map from 1986 till 2008 was calculated by multiplying the accuracy of the two classification maps. The overall accuracy for change map was 81.01%, with Kappa statistics of 0.775. The producer's accuracies for change map (Table 3) ranged from 67.55% (urban converted into ONSL) to 96.00% (water converted into BL) while those of the user's ranged from 63.47% (ONSL converted into BLF) to 91.43% (FL converted into bamboo forest). The level of accuracy was sufficient for detecting bamboo forest change.

Change map and statistics

The change in the spatial distribution of bamboo forest is shown in Figure 3. The most significant change of land cover was the conversions of BLF and NLF into bamboo forest. Bamboo forests have strong ability to invade adjacent landuse categories. Land cover, near existing built-up areas, is more likely to be converted into other categories, such as the conversion of farm land into urban land (Figures 2 and 3).

To further understand the status of bamboo forest conversions, changes in bamboo forest areas during the 1986–2008 period are shown in Figure 4. The bamboo forest area increased from 529.4 × 10^2 to 718.4 × 10^2 ha from 1986 till 2008

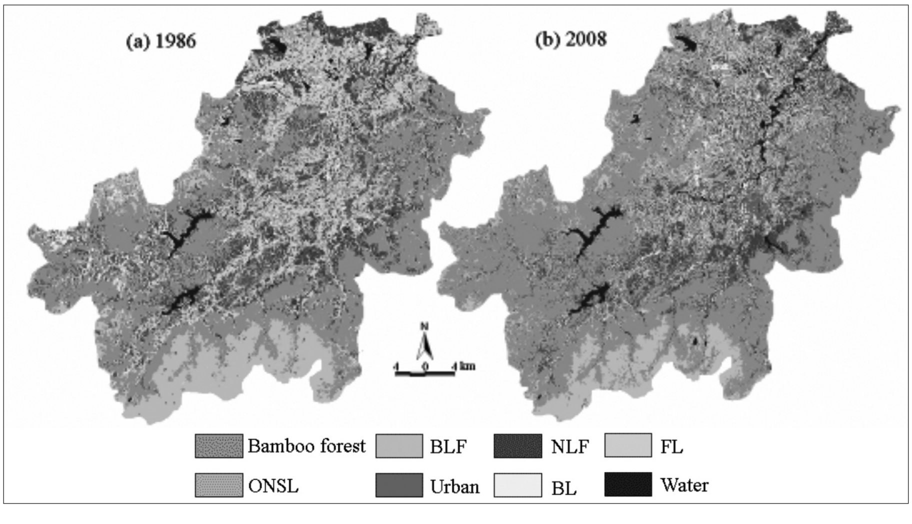

Figure 2 The classification maps of Anji Country in (a) 1986 and (b) 2008; BLF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

Table 3 Accuracy statistics for the classification results

Landuse category	Producer's accuracy (%)		User's accuracy (%)	
	1986	2008	1986	2008
Bamboo forest	87.50	91.27	87.50	95.04
BLF	84.62	89.13	80.00	77.36
NLF	92.16	88.24	88.68	90.91
FL	92.68	94.44	96.20	91.89
ONSL	82.05	84.44	82.05	92.68
Urban	80.00	90.91	94.12	90.91
BL	92.50	96.00	92.50	92.31
Water	100.00	95.00	95.24	95.00
Overall accuracy	89.00	91.02		
Kappa statistics	0.869	0.891		

BLF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

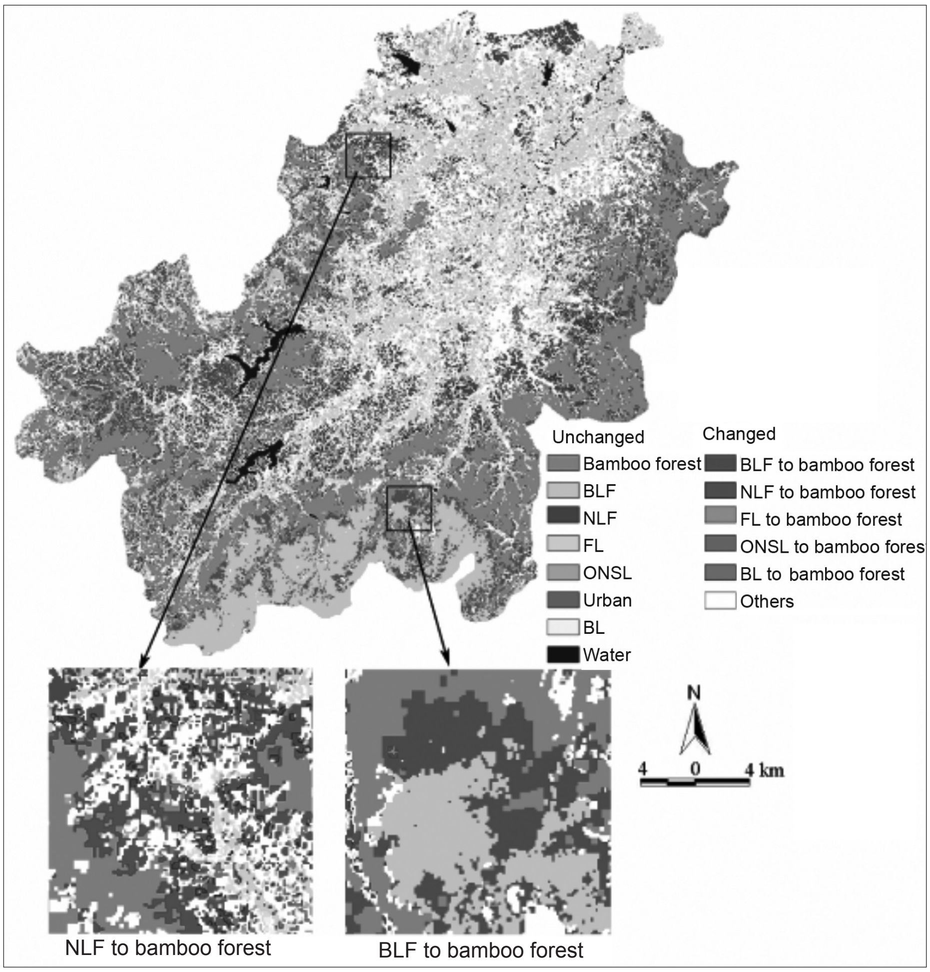

Figure 3 The change map of bamboo forest during the 1986–2008 period; BLF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

(Figure 2). The annual increase in area of bamboo forest was approximately 859 ha year^{-1}. The annual rate of increase in bamboo forest area was about 1.62% from 1986 till 2008, which was slightly larger than the result of forest inventory (1.21% from 1983 till 2007). Of the 18,900 ha of total increased bamboo forest area, 27.09% was converted from BLF, 20.20% from NLF, 19.96% from ONSL, 16.95% from FL and 16.26% from BL (Figure 4).

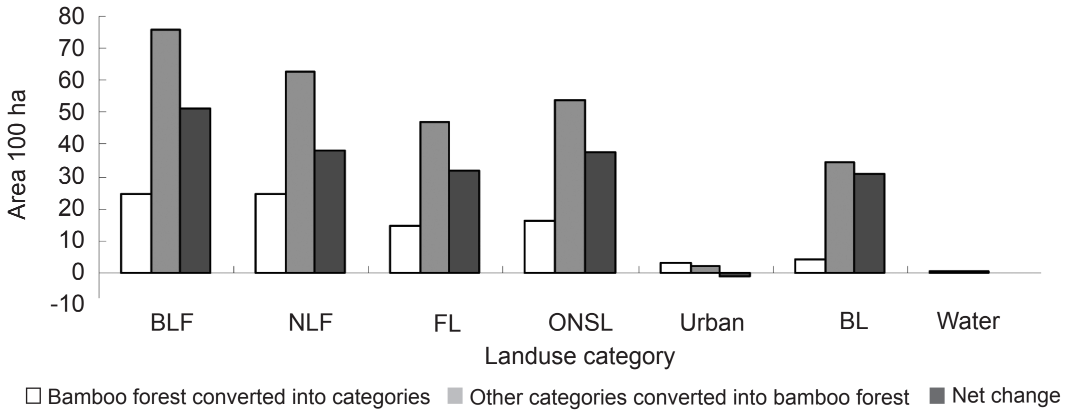

Figure 4 Changes in bamboo forest area during the 1986–2008 period; BLF = broadleaf forest, NLF = needle-leaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

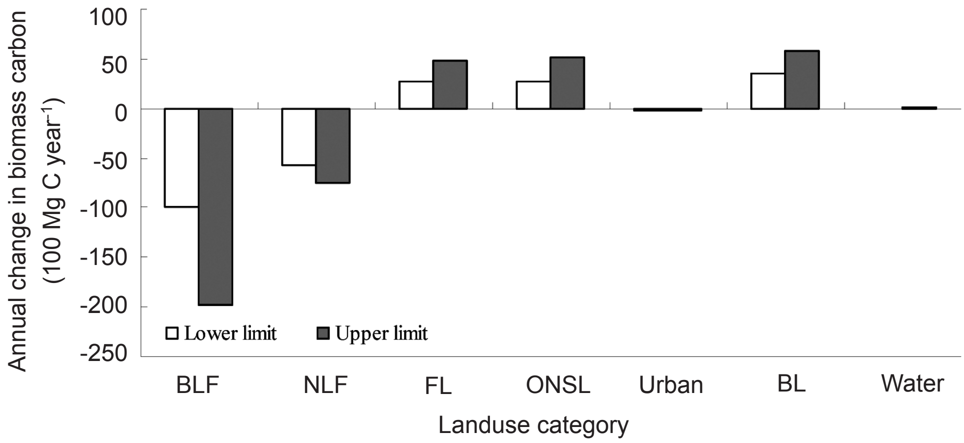

Figure 5 The annual changes in biomass carbon due to bamboo forest changes; BLF = broadleaf forest, NLF = needleleaf forest, FL = farm land, ONSL = orchards/nurseries/shrub land, BL = barren land

Biomass carbon stock change statistics

The changes in biomass carbon stocks were calculated using equations 1 and 2 (Figure 5). The annual net flux of atmospheric carbon from increase in bamboo forest area was -66.5 × 10^2 to -117.6 × 10^2 Mg C year^{-1}. Atmospheric carbon release, due to the conversions of BLF and NLF into bamboo forests, was notable during the 1986–2008 period. The annual release of atmospheric carbon from the conversion of BLF into bamboo forest was the largest (-99.8 × 10^2 to -198.7 × 10^2 Mg C year^{-1}), followed by the NLF. Meanwhile, atmospheric carbon removal was 91.0 × 10^2 to 158.1 × 10^2 Mg C year^{-1} due to the conversions of FL, ONSL and BL into bamboo forest.

Between 1986 and 2008, the carbon sequestration in bamboo products ($\Delta C_{products}$) was 614.6 × 10^2 to 1314.2 × 10^2 Mg C year^{-1} using equations 3 and 4. Bamboo products ($\Delta RC_{products}$) served as a large carbon sink and accumulated carbon at a rate of 0.86 to 1.83 Mg C ha^{-1} year^{-1}. During the study period, the annual atmospheric carbon removal by bamboo products was approximately 10 times greater than annual carbon emissions due to the increase in bamboo forest area. The annual net carbon removal rate from the atmosphere due to bamboo forest changes was 548.1 × 10^2 to 1196.6 × 10^2 Mg C year^{-1}.

DISCUSSION

Reasons for bamboo forest change

The results showed notable increase in bamboo forest area and simultaneous loss in BLF and NLF. The active process of replacing bamboo and its ability to expand are the two main reasons for the rapid increase in bamboo forest area. There is an active process of replacing other landuse categories by bamboo because of the high profitability of bamboo (Figure 3). Bamboo, characterised by shorter rotation, plays an important role in raising farmers' income (Ruiz-Pérez et al. 1999). Bamboo products also have more ability to respond to national and international market demands (Mertens et al. 2008). Afforestation activities financed by the World Bank played an important role in the conversion of barren land into bamboo forest during the study period (Anji County Forestry Bureau 1999).

Another reason for the rapid increase in bamboo forest area is its strong ability to expand. As the growth of bamboo shoot is dependent on photosynthetic products transported from other culms through the rhizome system, a bamboo shoot can reach crown height within a few months (Isagi et al. 1997). Monopodial bamboo, including the genera *Phyllostachys* and *Pleioblastus*, generates culm clumps and can be invasive (Lobovikov et al. 2006). This makes it difficult for understorey plants to absorb enough sunlight and nutrition and they gradually disappear. Figure 3 shows bamboo invading adjacent BLF and this is consistent with the results of Coggins (2000) as well as Hayashi and Yamada (2008).

Effects of bamboo forest on biomass carbon

Figures 4 and 5 show similarities in the areas converted from BLF, NLF, FL, ONLS and BL into bamboo forests. Their associated changes in biomass carbon were significantly different. Atmospheric carbon removal from FL and ONLS conversions into bamboo forest was far less than the atmospheric carbon release from BLF and NLF conversions. Subtle changes in landuse resulted in significant difference between the terrestrial ecosystem and atmosphere carbon exchanges. Based on these findings, carbon sequestration can be enhanced by converting a lower biomass carbon density landuse category into a higher one. Implementing such policies would be greatly beneficial in landuse decision-making and environmental management.

Although increase in bamboo forest areas results in carbon emitted into the atmosphere, harvested bamboo products play a very important role in carbon sequestration. When the quantity of carbon stored in bamboo products is incorporated into carbon estimations, the bamboo forest becomes a large carbon sink and makes a great contribution to decreasing carbon dioxide from the atmosphere. The rate of carbon sequestration in bamboo products (0.86 to 1.83 Mg C ha^{-1} $year^{-1}$) was 1.2 to 2.8 times greater than those from standing tree biomass in China (0.31 to 0.83 Mg C ha^{-1} $year^{-1}$), the United States (0.52 to 0.71 Mg C ha^{-1} $year^{-1}$) and Europe (0.60 to 1.50 Mg C ha^{-1} $year^{-1}$) (Pacala et al. 2001, Janssens et al. 2003, Piao et al. 2009). In order to optimise and prolong carbon stock in bamboo products, it is important to produce more durable bamboo products with longer life cycles such as construction materials, panel products and furniture.

Many factors may affect estimation results in remote-sensing-based methods. In this study, the image classification accuracy was an important factor because the area of each category was estimated by image classification. It is important to maintain image classification accuracy. Due to the lack of reliable data, this study did not include the following factors: (1) changes in soil carbon due to land cover conversion, (2) annual increase in biomass carbon stocks due to biomass increment in land remaining in the same land cover category and (3) annual decrease in carbon stocks due to biomass losses in land remaining in the same land cover category such as wood and fuelwood removal.

CONCLUSIONS

LULCC occurred dramatically in this study area. Bamboo forest had notably increased in area, while BLF and NLF had simultaneously decreased. The annual net carbon emission to the atmosphere due to increase in bamboo areas was -66.5×10^2 to -117.6×10^2 Mg C $year^{-1}$. One of the main causes for biomass carbon loss was the conversions of BLF and NLF into bamboo forest. Based on these findings, careful attention should be paid to subtle landuse changes during landuse decision-making, environmental management and policy implementation. When carbon stored in bamboo products were taken into carbon estimations, the bamboo forest became a large carbon sink. During the 1986–2008 study period, the annual net carbon removal from the atmosphere by bamboo forests was 548.1×10^2 to 1196.7×10^2 Mg C $year^{-1}$. The great carbon accumulation of bamboo forest is based on the assumption that the durability of bamboo products is long enough. Therefore, the great bamboo biomass carbon accumulation is a potential in this study. As bamboo culms are processed into products with long life cycles, the prolonged storage of carbon is possible.

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REFERENCES

Ahlqvist O. 2008. Extending post-classification change detection using semantic similarity metrics to overcome class heterogeneity: a study of 1992 and 2001 US national land cover database changes. *Remote Sensing of Environment* 112: 1226–1241.

Anji County Forestry Bureau. 1999. *Report on Forest Resource Inventory and Planning in Anji County*. Anji County Forestry Bureau, Anji. (In Chinese)

Coggins CR. 2000. Wildlife conservation and bamboo management in China's southeast uplands. *Geographical Review* 90: 83–111.

Coppin P, Jonckheere I, Nackaerts K, Muys B & Lambin E. 2004. Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing* 25: 1565–1596.

Dewan AM & Yamaguchi Y. 2009. Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. *Applied Geography* 29: 390–401.

Ellis E & Pontius R. 2007. Land-use and land-cover change. In Cleveland CJ (ed) *Encyclopedia of Earth*. National Council for Science and the Environment, Washington DC.

Fang JY, Liu GH & Xu SL. 1996. Carbon reservoir of terrestrial ecosystem in China. Pp 109–128 in Wang GC & Wen YP (eds) *Monitoring and Relevant Process of Greenhouse Gas Concentration and Emission*. Chinese Environment Sciences Press, Beijing. (In Chinese)

Fearnside PM, Righi CA, de Alencastro Craca PML, Keizer EWH, Cerri CC, Nogueira EM & Barbosa RI. 2009. Biomass and greenhouse-gas emissions from land-use change in Brazil's Amazonian "arc of deforestation": the states of Mato Grosso and Rondônia. *Forest Ecology and Management* 258: 1968–1978.

Government of China. 2005. *Sixth National Forest Resource Inventory*. State Forestry Administration, Beijing.

Hayashi K & Yamada T. 2008. Is bamboo stand expansion independent of topographic conditions? *Japanese Journal of Conservation Ecology* 13: 55–64.

IPCC. 2006. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Institute for Global Environmental Strategles, Hayama.

Isagi Y, Kawahara T, Kamo K & Ito H. 1997. Net production and carbon cycling in a bamboo *Phyllostachys pubescens* stand. *Plant Ecology* 130: 41–52.

Janssens IA, Freibauer A, Ciais P, Smith P, Nabuurs GJ, Folberth G, Schlamadinger B, Hutjes RWA, Ceulemans R, Schulze ED, Valentini R & Dolman AJ. 2003. Europe's terrestrial biosphere absorbs 7 to 12% of European anthropogenic CO_2 emissions. *Science* 300: 1538–1542.

Jensen JR. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Third edition. Pearson/Prentice Hall, New Jersey.

Kaul M, Dadhwal VK & Mohren GMJ. 2009. Land use change and net C flux in Indian forests. *Forest Ecology and Management* 258: 100–108.

Lobovikov M, Paudel S, Piazza M, Ren H & Wu J. 2006. *World Bamboo Resources*. A thematic study prepared in the framework of the Global Forest Resources Assessment 2005. <http://www.fao.org/docrep/010/ a1243e/ a1243e00.HTM>.

Lu D, Mausel P, Batistella M & Moran E. 2005. Land-cover binary change detection methods for use in the moist tropical region of the Amazon: a comparative study. *International Journal of Remote Sensing* 26: 101–114.

Lu D, Mausel P, Brondízio E & Moran E. 2004. Change detection techniques. *International Journal of Remote Sensing* 25: 2365–2407.

Lu D & Weng Q. 2007. A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing* 28: 823–870.

Mertens B, Liu H, Belcherc B, Ruiz-Pérez M, Fu MY & Yang XS. 2008. Spatial patterns and processes of bamboo expansion in southern China. *Applied Geography* 28: 16–31.

O'Connor TG & Kuyler P. 2009. Impact of land use on the biodiversity integrity of the moist sub-biome of the grassland biome, South Africa. *Journal of Environmental Management* 90: 384–395.

Pacala SW, Hurtt GC, Baker D, Peylin P, Houghton RA, Birdsey RA, Heath L, Sundquist ET, Stallard RF, Ciais P, Moorcroft P, Caspersen JP, Shevliakova E, Moore B, Kohlmaier G, Holland E, Gloor M, Harmon ME, Fan SM, Sarmiento JL, Goodale CL, Schimel D & Field CB. 2001. Consistent land- and atmosphere-based US carbon sink estimates. *Science* 292: 2316–2320.

Piao SL, Fang JY, Ciais P, Peylin P, Huang Y, Sitch S & Wang T. 2009. The carbon balance of terrestrial ecosystems in China. *Nature* 458: 1009–1013.

Ruiz-Pérez M, Zhong MG, Belcher B, Xie C, Fu MY & Xie JZ. 1999. The role of bamboo plantations in rural development: the case of Anji county, Zhejiang, China. *World Development* 27: 101–114.

Sanchez-Hernandez C, Boyd DS & Foody GM. 2007. One-class classification for mapping a specific land cover class: SVDD classification of fenland. *IEEE Transactions on Geoscience and Remote Sensing* 45: 1061–1073.

Shalaby A & Tateishi R. 2007. Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the northwestern coastal zone of Egypt. *Applied Geography* 27: 28–41.

Sharma YML. 1980. Bamboos in the Asia-Pacific region. In Lessard G & Chauinard A (eds) *Bamboo Research in*

Asia. Proceedings of the Workshop held in Singapore, 28–30 May 1980. International Development Research Centre, Ottawa.

Thapa RB & Murayama Y. 2009. Urban mapping, accuracy, and image classification: a comparison of multiple approaches in Tsukuba City, Japan. *Applied Geography* 29: 135–144.

Upadhyay TP, Sankhayan PL & Solberg B. 2005. A review of carbon sequestration dynamics in the Himalayan region as a function of land-use change and forest/soil degradation with special reference to Nepal. *Agriculture, Ecosystems and Environment* 105: 449–465.

Wang Y, Mitchell BR, Nugranad-Marzilli J, Bonynge G, Zhou Y & Shriver G. 2009. Remote sensing of land-cover change and landscape context of the National Parks: a case study of the Northeast Temperate Network. *Remote Sensing of Environment* 113: 1453–1461.

Wiens J, Sutter R, Anderson M, Blanchard J, Barnett A, Aguilar-Amuchastegui N, Avery C & Laine S. 2009. Selecting and conserving lands for biodiversity: the role of remote sensing. *Remote Sensing of Environment* 113: 1370–1381.

Xu X, Du H, Zhou G, Ge H, Shi Y, Zhou Y, Fan W & Fan W. 2011. Estimation of aboveground carbon stock of moso bamboo (*Phyllostachys heterocycla* var. *pubescens*) forest with a Landsat thematic mapper image. *International Journal of Remote Sensing* 32: 1431–1448.

Yuan F, Sawaya KE, Loeffelholz BC & Bauer ME. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment* 98: 317–328.

Zhang J, Wang K, Li Q & Hua X. 2006. Status analysis and suggestions for bamboo utilization ratio in China. *Forestry Machinery and Wood Working Equipment* 34: 7–9. (In Chinese)

Zhang M & Wang G. 2008. The forest biomass dynamics of Zhejiang Province. *Acta Ecologica Sinica* 28: 5665–5674.

Zhou G & Jiang P. 2004. Density, storage and spatial distribution of carbon in *Phyllostachy pubescens* forest. *Scientia Silvae Sinicae* 40: 20–24. (In Chinese)