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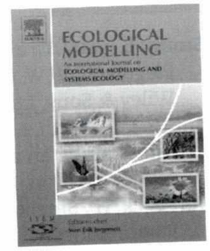

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TRIPLEX model testing and application for predicting forest growth and biomass production in the subtropical forest zone of China's Zhejiang Province

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ABSTRACT

This study has analyzed TRIPLEX1.0 by applying the model to the subtropical forest regions in Zhejiang Province, southeastern China. The main objective was to test the process-based hybrid model TRIPLEX1.0 in simulating density, tree height (H), diameter at breast height (DBH), litter pool and biomass using forest growth and yield data collected from three forest types: subtropical evergreen broad-leaved, coniferous broad-leaved mixed and warm temperate pine (*Pinus massoniana* Lamb.) forests. The results show that simulated density, H, DBH, litter pool, aboveground and total biomass are consistent with observed data collected through Zhejiang Province, suggesting that the TRIPLEX1.0 model is capable in simulating forest growth and biomass dynamics of subtropical forest ecosystems. The coefficient of determination (r^2) between simulated values and yield measurements show a 0.91 variability for density, 0.86 for DBH, 0.83 for H, 0.89 for aboveground biomass and 0.91 for total biomass (except for litter pool that showed a 0.54 variability). The independent validations obtained by utilizing TRIPLEX1.0 demonstrate that the model offers competency while providing confidence when applying its ability to extrapolate outcomes at regional scales and its ability to withstand rigorous testing for simulating carbon storage in subtropical forest ecosystems.

1. Introduction

Accurately estimating carbon storage and its dynamics on vegetation and soil is critical for predicting how terrestrial ecosystem carbon pools may change as climate and land use change in the future (Melillo et al., 1996). Accurate estimates, however, of forest ecosystem contribution to the global carbon cycle remains a major challenge (Dixon et al., 1994; Song

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and Woodcock, 2003; Houghton, 2005). There is a growing need for computer simulation models that can assist in the estimation of carbon budgets, net ecosystem exchange or trace gas emissions (Mosier, 1998; Landsberg, 2003; Van Vliet et al., 2003; Battaglia et al., 2004; Miehle et al., 2006). Traditionally, empirical statistical models (growth and yield) have been used to estimate tree height (H), diameter at breast height (DBH), and total volume. These statistical models are limited, however, by their inability to simulate either the impacts of future climate change on forest stands or the growth dynamics of some forest regions, because growth and yield predictions are completely based upon past measurements and simulate forest stands without considering climatic variables such as temperature, precipitation, and change in CO_2 concentrations (Kimmins, 1993; Bossel, 1996; Peng, 2000).

In order to improve on the shortcomings of empirical statistical models, a number of process-based models have been developed (Running and Coughlan, 1988; Parton et al., 1993; Kimmins, 1993; Korol et al., 1994; Kimmins and Scoullar, 1995; Bossel, 1996; Landsberg and Waring, 1997) for describing the complex process interactions of forest ecosystems. Bossel (1991) and Kimmins (1993) have reviewed the historical developments of process-based models while Battaglia and Sands (1998), Landsberg and Coops (1999), Mäkelä et al. (2000) and Peng (2000) have recently discussed the features and specifications of process-based models for applications aligned towards sustainable forest management. As these researchers suggested, process-based models have obvious advantages in predicting future ecosystem structure and functions under different scenarios of climate change, silviculture practices, and land use. However, most process-based models are unable to simulate forest stand variables (e.g., H, DBH, and volume) since they were not designed for forest management and do not predict forest stand attributes. TRIPLIEX 1.0 combines the advantages of both empirical and process-based models; it bridges the gap between empirical forest growth and yield and process-based carbon balance models (Peng et al., 2002). To date, TRIPLEX1.0 has been successfully calibrated and validated against age-dependent growth measurements from 12 permanent sample plots (PSPs) at jack pine stands in northern Ontario (Peng et al., 2002), boreal mixedwood stands in the Lake Abitibi Model Forest (Zhou et al., 2004, 2005, 2006a), and other boreal tree stands in BOREAS sites located in central Canada (Zhou et al., 2004). TRIPLEX1.0 can be used successfully for simulating both the short and long-term carbon and nitrogen dynamics of boreal regions in Canada, but needs further testing for larger scale areas. This study presents the first attempt at testing the TRIPLEX1.0 model in applying it to simulate forest growth and the carbon dynamics of forests in subtropical forest ecosystems in southeastern China. To expand the TRIPLEX1.0 application to regions around the world, some parameters of the model were calibrated and improved upon for this study to render it more specific to China's subtropical zone.

The carbon budget of China's subtropical forests has received little attention until recently (Zhang et al., 2007), although there have been many studies that have focused mainly on carbon sequestration within tropical, temperate and boreal forests (Sundquist, 1993; Dixon et al., 1994; Chave et al., 2003; Martin et al., 2003; Houghton, 2005). Large areas of afforestation and reforestation have been established in the subtropical zones of China that influence its carbon budget in terms of sinks or sources, however, significant uncertainties in the reliability of carbon budget measurements in these regions exist despite previous research (Fang and Chen, 2001; Wang et al., 2001; Cao et al., 2003). This study sought to test the accuracy of TRIPLEX1.0 to expand the application of the model. Sites based upon data from local measurements were investigated that incorporate the diverse forest types found in this region.

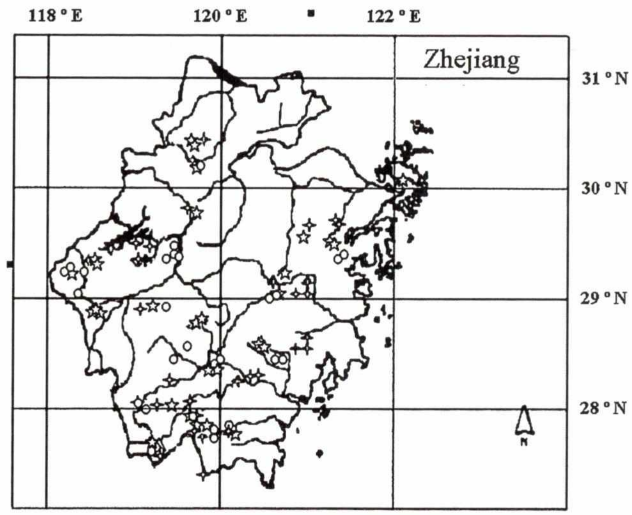

Fig. 1 – Sample plots in subtropical forests in Zhejiang Province, southeastern China (modified from Zhang et al., 2007). ○, ✧, ☆ represent data measured in 47 evergreen broad-leaved forest stands, 32 mixed forest stands and 38 *Pinus massoniana* forest stands, respectively.

The goal of this study, therefore, was to calibrate and validate the TRIPLEX1.0 hybrid model in simulating height, diameter, litter pool and biomass by applying the forest growth and yield data collected from three forest types in the subtropical forest ecosystems of Zhejiang Province, southeastern China, to the model.

2. Data and methods

2.1. Study area

Zhejiang Province (118°01′ to 123°10′E, 27°06′ to 31°31′N), is located south of the Yangtze River Delta, along the southeastern coast of China (Fig. 1). The whole study area maintains an average annual temperature between 15.3 and 18.5 °C with the average temperature of the coldest month (January) between 2.7 and 7.9 °C and the average temperature of the hottest month (July) between 27.0 and 29.5 °C. Annual precipitation is between 1000 and 2000 mm and has a tendency to increase from the northeast to the southwest. The region is characteristic of a subtropical monsoon climate featuring long severe summers and short cold to moderate winters. Major soil types include mainly red, yellow and red-yellow earth and also includes a small amount of lime soil, purple soil, etc. (Liu et al., 2002a). Initially, the vegetation type of the region was composed of evergreen broad-leaved forests, but after thousands of years of human disturbance, particularly after the last century, this primary vegetation type is now uncommon. Other types of vegetation, such as coniferous, deciduous broad-leaved, bamboo and mixed forests can also be found in this region (Yu, 1997). Afforestation and natural forest restoration processes in Zhejiang have increased rapidly in the past 20 years in which forest cover has reached 59.4% of the total land area (Liu et al., 2002a).

2.2. *Input data*

2.2.1. *Forest stands*

TRIPLEX1.0 required input data concerning stand and forest type, tree age, stocking, and tree species to simulate each distinct stand. Stand data were derived from the 1999 Inventory Investigations, which provides information for a total of 117 forest stands across 21 counties (Fig. 1). Tree age ranged from between 5 and 50 years in 1999. The vegetation of subtropical forests in Zhejiang can be categorized into three types, evergreen broad-leaved forest (EF), coniferous and broad-leaved mixed forest (MF) and *Pinus massoniana* forest (PF) (Zhang et al., 2007). Shrub and herb layer data were not included in the TRIPLEX1.0 simulation for this study since the model is forest-based and does not include the shrub component.

EF is mainly composed of three dominant broad-leaved species: *Castanopsis sclerophylla* (Lindlo) Schott, *Schima superba* Gardn. et Champ., *Cyclobalanopsis glauca* (Thunb.) Oerst; and *Liquidambar formosana* Hance. The former two are the evergreen species, and the latter is deciduous specie.

2.2.2. *Climate conditions*

The spatial patterns of mean temperatures and annual precipitation (Fig. 2), which generalized the climate condition averages for all counties, were used in the TRIPLEX1.0 simulations for forest growth, biomass, productivity and soil carbon quantity. Average precipitation, temperature and relative humidity data were obtained from the publication "Climography of Zhejiang Province" (Zhu and Chen, 1999) while vapor pressure deficiency (VPD, Campbell and Norman, 1998) was derived from the monthly average precipitation and temperature based upon Zhou et al. (2004) as follows:

$$svp = 6.1076 \times \exp\left(\frac{17.269 \times T}{T + 237.3}\right) \quad (1)$$

$$vp = RH \times \frac{svp}{100} \quad (2)$$

$$VPD = svp - vp \quad (3)$$

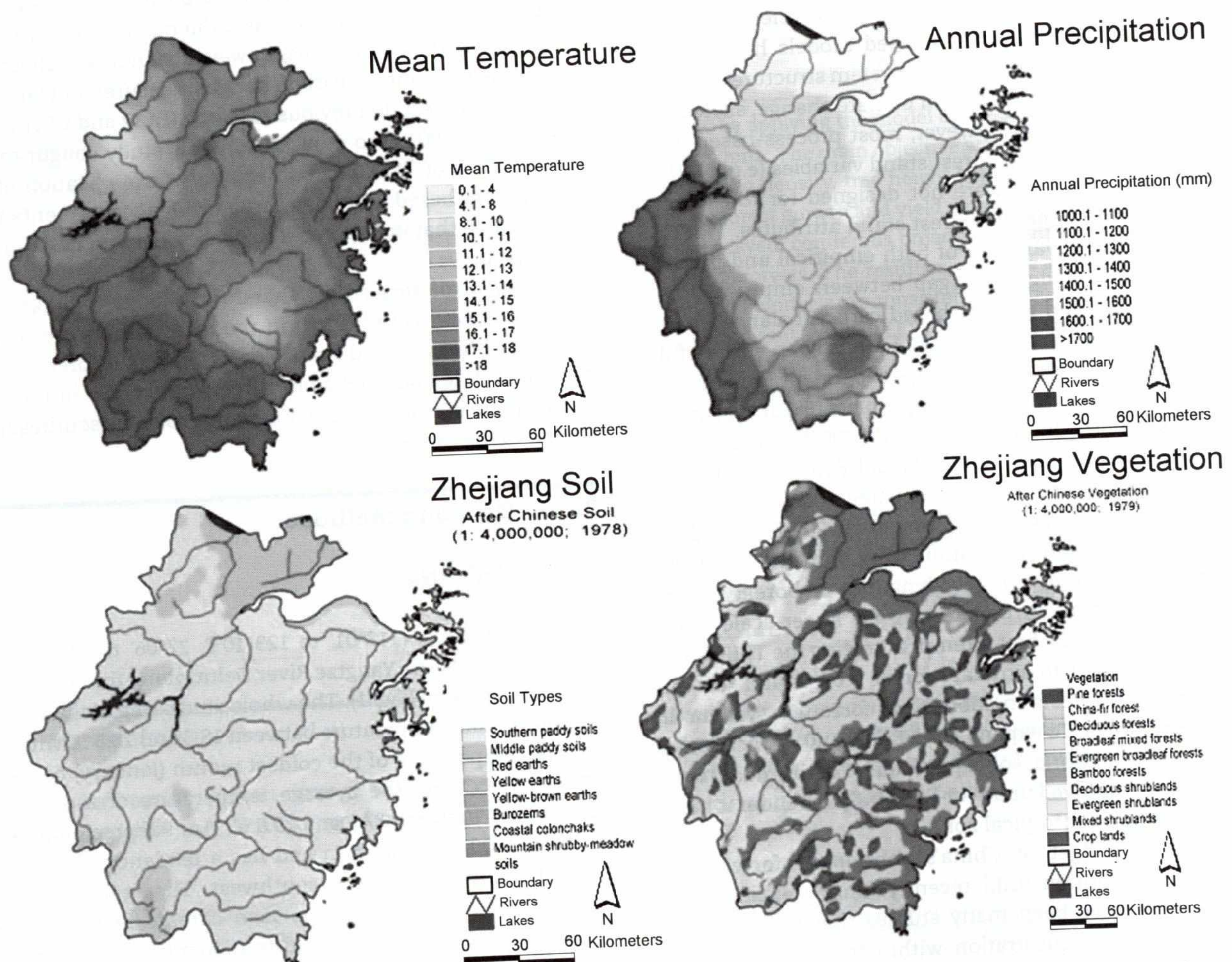

Fig. 2 – Spatial pattern of mean temperature, annual precipitation, soil and vegetation for Zhejiang Province, southeastern China. Data was obtained from the publication "Climography of Zhejiang province" (Zhu and Chen, 1999).

where svp represents saturation vapor pressure (mbar), vp vapor pressure (mbar), T the average temperature per month (°C) and RH relative humidity (%). The ratio of frost days required to calculate GPP was determined by the average monthly temperature.

2.3. TRIPLEX model description

TRIPLEX1.0 is a hybrid model incorporating forest growth as well as carbon and nitrogen dynamics that were integrated from features from three well-established models: 3-PG (Landsberg and Waring, 1997), TREEDYN3.0 (Bossel, 1996), and CENTURY4.0 (Parton et al., 1993). One special feature is its ability to simulate growth and yield of a stand based upon ecological mechanisms and subsequently provide growth and yield information. The structure of TRIPLEX1.0 (shown in Fig. 3) includes four submodels: (1) forest production; (2) forest growth and yield; (3) soil carbon and nitrogen; (4) soil water balance. The TRIPLEX1.0 simulation involves key variables including photosynthetically active radiation (PAR), GPP, forest growth, biomass, soil carbon, soil nitrogen and soil water. All simulations were conducted in a monthly time step while the simulation output was summarized yearly.

In the TRIPLEX simulation, initial PAR (I_{0PAR}) was calculated as a function of the solar constant (1360 W m^{-2}), radiation fraction (φ_{PAR}), solar height ($\sin\beta$), and atmospheric absorption (K_{atm}):

$$I_{0PAR} = 1360\varphi_{PAR}\sin(\beta)e^{-(K_{atm})/(\sin(\beta))} \tag{4}$$

Monthly canopy received PAR (I_m) is estimated from a 'mixture' of monthly PAR under both clear sky (I_{mclr}) and cloudy sky(I_{mcld}):

$$I_m = (1 - C_{cld})I_{mclr} + C_{cld}I_{mcld} \tag{5}$$

A cloud factor (C_{cld}) is used by Bossel (1996) to calculate monthly PAR.

GPP was calculated as a function of I_m modified by the conversion constant k as well as the leaf area index (LAI), mean monthly air temperature (f_t), soil drought (f_w), and the percentage of frost days within a 1-month period (f_d):

$$\mathrm{GPP} = kI_m\,\mathrm{LAI}\,f_a f_t f_w f_d \tag{6}$$

Carbon allocation features from 3-PG (Landsberg and Waring, 1997) were utilized by parameterizing based upon field data and empirical coefficients (Zhou et al., 2006b); the biomass growth rate was calculated from annual increments while soil water, carbon and nitrogen were calculated by the corresponding modules based upon the CENTURY4.0 model (Parton et al., 1993). A detailed description of the features, structure, mathematical algorithm sensitivity analysis and building strategy of the TRIPLEX1.0 model have been previously provided by Peng et al. (2002) and Liu et al. (2002b).

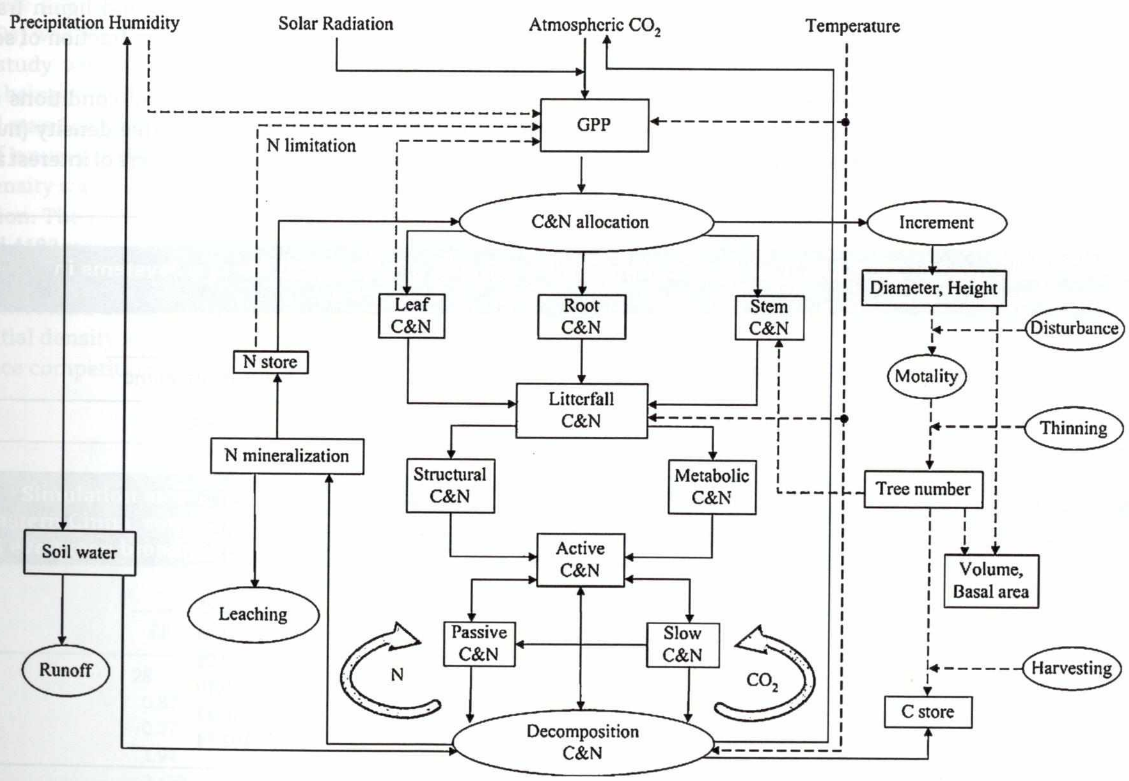

Fig. 3 – The structural model of forest growth and carbon simulation from TRIPLEX1.0 (modified from Peng et al., 2002). Rectangles represent key pools or state variables, ovals represent core simulation processes, dotted lines represent controls, and solid lines represent the flow of carbon (C), nitrogen (N), water, and the fluxes between the forest ecosystem and external environment. Two arrow cycles refer to two feedbacks.

Table 1 – Parameters used in TRIPLEX1.0 for simulating subtropical forest ecosystems in southeastern China

Parameter	Description	Note
PAR		
Absorp = 0.15	Atmospheric absorption factor	a
PARfactor = 0.47	Solar radiation fraction	c
GPP		
MaxCond = 0.02	Max canopy conductance (ml m^{-2} s^{-1})	e
StomCond = 0.005	Stomata conductance (ml m^{-2} s^{-1})	e
BlCond = 0.2	Canopy boundary layer conductance (ml m^{-2} s^{-1})	e
CoeffCond = −0.5	Coefficient for Conductance to VPD	e
ExtCoef = 0.5	Radiation extinction coefficient	e
TaMin = 5	Min temperature for growth	a
TaMax = 40	Max temperature for growth	a
Topt = 15	Optimum temperature for growth	b
NitrogenFactor = 0.2	Nitrogen factor for tree growth	d
Soil C and N		
Lnr = 0.26	Lignin–nitrogen ratio	d
Ls = 0.215, 0.215, 0.255, 0.235, 0.255	Lignin for leaf, fine root, coarse root, branch, and wood	d
Soil water		
A1, A2, A3 = 15	Depth of layer 1, 2, and 3	d
AWL1, 2, and 3 = 0.5, 0.3, and 0.2	Relative root density for layer 1, 2, and 3	d
KF = 0.5	Fraction of water flow (except field capacity) to stream	Assumption
KD = 0.5	Fraction of water flow (except field capacity) to deep storage	Assumption
KX = 0.3	Fraction of deep storage water to stream	Assumption
AWater = 250.0	Max soil water (mm)	Assumption

[a]Bossel (1996); [b]Kimball et al. (1997); [c]Ryan et al. (1997); [d]the values are given by CENTURY (Parton et al., 1993; Metherell et al., 1993); [e]Coops et al. (2001).

2.4. *Parameterization and initialization*

To provide a robust test condition of the TRIPLEX1.0 model, most of the general and nonspecific site parameters from previous studies (Peng et al., 2002; Zhou et al., 2004, 2005, 2006a) were left unchanged (Table 1). These include PAR parameters; the minimum, maximum, and optimum temperature for tree growth; stomata and canopy conductance; initial nitrogen for tree growth; the lignin–nitrogen ratio and lignin fraction of leaf, fine and coarse roots as well as the fraction of soil water flow.

Three key variables related to initial conditions exist for forest growth and yield simulations: tree density (number of trees), H and DBH. Several new parameters of interest are listed

Table 2 – Parameters used in TRIPLEX1.0 to simulate different forest types of subtropical forest ecosystems in southeastern China

Parameter	Forest type: Evergreen broad-leaved	Forest type: Mixed	Forest type: *Pinus massoniana*	Note
Conversion of GPP to NPP	0.495	0.490	0.450	a
Wood carbon density (tC m^{-3})	0.54	0.51	0.26	b
Specific leaf area (m^2 kg^{-1})	20	15	6	c
Normal mortality (yearly)	0.004	0.004	0.006	d
Crowding mortality (yearly)	0.02	0.02	0.01	
Crown/DBH	20	20	20	e
Leaf fraction	0.18	0.39	0.23	
Branch fraction	0.22	0.19	0.25	
Wood fraction	0.38	0.13	0.38	
Coarse root fraction	0.06	0.08	0.04	
Fine root fraction	0.16	0.21	0.10	
Min growth factors	47.16	50.46	56.23	
Max growth factors	114.95	125.96	102.14	

[a] Estimation based upon Ryan et al. (1997).
[b] Estimation based upon Fang et al. (1996).
[c] Estimation based upon Kimball et al. (1997).
[d] Suggested by Bossel (1996), stand mortality was assumed as normal mortality (no canopy competition for light) plus crowding mortality.
[e] Based upon forest estimated in the present study.

Table 3 – Simulation errors of TRIPLEX1.0 applied to subtropical forest ecosystems in southeastern China, comparing density (stems ha^{-1}), DBH (cm), height (m), litter pool (t ha^{-1}), aboveground and total biomass (t ha^{-1}) between modeled values and forest inventory data collected from 89 forest stands

Forest	Density (stems ha^{-1})	DBH (cm)	Height (m)	Litter pool (t ha^{-1})	Aboveground Biomass (t ha^{-1})	Total biomass (t ha^{-1})
n	79	89	86	81	85	88
r^2	0.91	0.86	0.83	0.54	0.89	0.91
e	121.59	−0.29	−0.65	1.16	−0.51	−2.64
Se	400.17	1.44	1.08	2.24	13.53	16.46
Bias	6.7%	−3.0%	−9.3%	15.7%	−0.9%	−3.9%
p-Value	<0.001	<0.001	<0.001	<0.001	< 0.001	<0.001

Note: *n*, numbers of stands; r^2, coefficient of determination; *e*, average prediction error; Se, standard error of the predicted value for each observed value in their regression, which is a measure of the amount of error in the prediction for an individual observation.

in Table 2, like wood carbon density, specific leaf area (SLA), mortality, the fraction of leaf, branch, wood and coarse and fine roots were adopted and adjusted from default model values to better represent the forest ecosystems of subtropical China for this study.

2.5. *Simulation runs*

TRIPLEX1.0 was calibrated and validated by randomly selecting each forest type, respectively, before simulation runs. The simulation was executed for H, DBH, litter pool, aboveground and total biomass. We simulated each stand from its respective year of regeneration to the year 1999 at which point all simulations across all stands within the subtropical forest region were summed up. The same procedure used by Zhou et al. (2004) was followed for all model runs.

This study performed regional simulation runs that first required being initialized within a spatial dimension (Fig. 2). All initial stand biomass measurements were launched on the month of January of the regeneration year. The spatial pattern of tree density was initialized depending on the species and its distribution. The initial tree density was assumed to be 4950, 2500, and 4183 stems ha^{-1} for evergreen broad-leaved, mixed, and pine forest stands for the regeneration year, respectively. Subsequent stand density was then simulated from the point of the initial density and incorporates the crowding mortality factor once competition starts.

3. Results

3.1. *Model validation*

The simulated H and DBH were compared to the yield measurements from the subtropical forest region to test the accuracy of the model. A summary of the results from the TRIPLEX1.0 validation tests for the subtropical forest region is shown in Table 3. We also validated the model against all EF indices as well as 29 MF and 32 PF indices (Tables 4 and 5). The comparison revealed high coefficient of determination (r^2) results (0.91 for density, 0.86 for DBH, 0.83 for H, 0.89 for aboveground biomass and 0.91 for total biomass) except for litter pool that showed a variability of 0.54. Small average prediction errors (*e*) were detected (−0.29 for DBH, −0.65 for H, 1.16 for litter pool, −0.51 for aboveground biomass and −2.64 for total biomass) except for density that showed a variability of 121.6. And low biases (the averaged prediction error divided by the averaged observation) were also detected (6.7% for density, −3.0% for DBH, −9.3% for H, −0.9% for aboveground biomass and −3.9% for total biomass) except for litter pool that showed a variability of 15.7% (Fig. 4 and Table 3).

To conduct a model validation using large samples of growth and yield data in the subtropical forest ecosystems at a regional scale, we also compared simulations with

Table 4 – Simulation errors of TRIPLEX1.0 applied to three forest types in the subtropical forest ecosystems of southeastern China, comparing height (m) and DBH (cm) between modeled values and forest inventory data collected from 28 evergreen broad-leaved forest (EF) stands, 29 mixed forest (MF) stands and 32 *Pinus massoniana* forest (PF) stands

	Height (m)			DBH (cm)		
	EF	MF	PF	EF	MF	PF
n	28	29	32	28	29	32
r^2	0.83	0.57	0.92	0.84	0.85	0.94
e	−0.27	−1.06	−0.73	−0.41	−0.48	−0.14
Se	1.94	1.48	0.68	1.32	1.30	1.00
Bias	−2.46%	−14.89%	−11.11%	−5.59%	−5.19%	−1.55%
p-Value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Note: *n*, numbers of stands; r^2, coefficient of determination; *e*, average prediction error; Se, standard error of the predicted value for each observed value in their regression, which is a measure of the amount of error in the prediction for an individual observation.

Table 5 – Simulation errors of TRIPLEX1.0 applied to three forest types in the subtropical forest ecosystems of southeastern China, comparing litter pool (t ha^{-1}), aboveground and total biomass (t ha^{-1}) between simulations and estimates collected from 33 evergreen broad-leaved forest (EF) stands, 29 mixed forest (MF) stands and 32 *Pinus massoniana* forest (PF) stands

	Litter pool (t ha^{-1})			Aboveground biomass (t ha^{-1})			Total biomass (t ha^{-1})		
	EF	MF	PF	EF	MF	PF	EF	MF	PF
N	27	25	32	27	29	32	33	29	32
r^2	0.79	0.59	0.50	0.79	0.83	0.95	0.81	0.88	0.94
e	−0.76	0.55	−1.06	−0.76	−3.84	−0.54	−6.72	−10.67	−0.57
Se	1.92	1.99	0.86	1.92	16.21	5.93	29.25	19.18	6.92
Bias	−7.92%	7.18%	13.34%	−2.81%	−7.72%	−1.33%	0.81%	−16.57%	−1.21%
p-Value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Note: *n*, numbers of stands; r^2, coefficient of determination; *e*, average prediction error; Se, standard error of the predicted value for each observed value in the regression, which is a measure of the amount of error in the prediction for an individual observation.

observations for the averaged density, H, DBH, litter pool, aboveground biomass and the total biomass within subtropical forest stands reported by Zhang et al. (2007). The predictions were found to be highly correlated to field measurements (Fig. 4).

3.2. *Modeling H and DBH for three main forest types*

Comparisons between H and DBH predicted by TRIPLEX1.0 with those observed from the field sites showed a significant correlation (Table 4). The highest coefficient of determination (r^2) throughout the three forest types was approximately 0.92 for H and 0.94 for DBH of PF. Mean prediction errors and biases were calculated for both H and DBH for each forest type separately (EF, MF and PF). The biases were within −2 to −15% for both H and DBH. All *p* values were less than the critical value of $\alpha = 0.001$ (Table 4).

3.3. *Modeling litter pool and biomass for three main forest types*

Table 5 shows the comparison results and the statistical analysis for litter pool and aboveground and total biomass for all three forest types. The r^2 correlation between the model simulations and the field observations were relatively high: $r^2 = 0.79$ for litter pool of EF, $r^2 = 0.95$ for aboveground biomass of PF and $r^2 = 0.94$ for total biomass of PF. The comparison between litter pool (t ha^{-1}) simulated by TRIPLEX1.0 with litter pool field data measured from 79 forest plots located within all three forest types showed a significant correlation (Table 5). The mean coefficient of determination (r^2) for litter pool was 0.59 for MF and 0.50 for PF while simulated errors were relatively small, between −1.06 and 0.55 t ha^{-1} exhibiting a high bias (−7.92% to 13.34%). Litter pool simulated by TRIPLEX1.0, however,

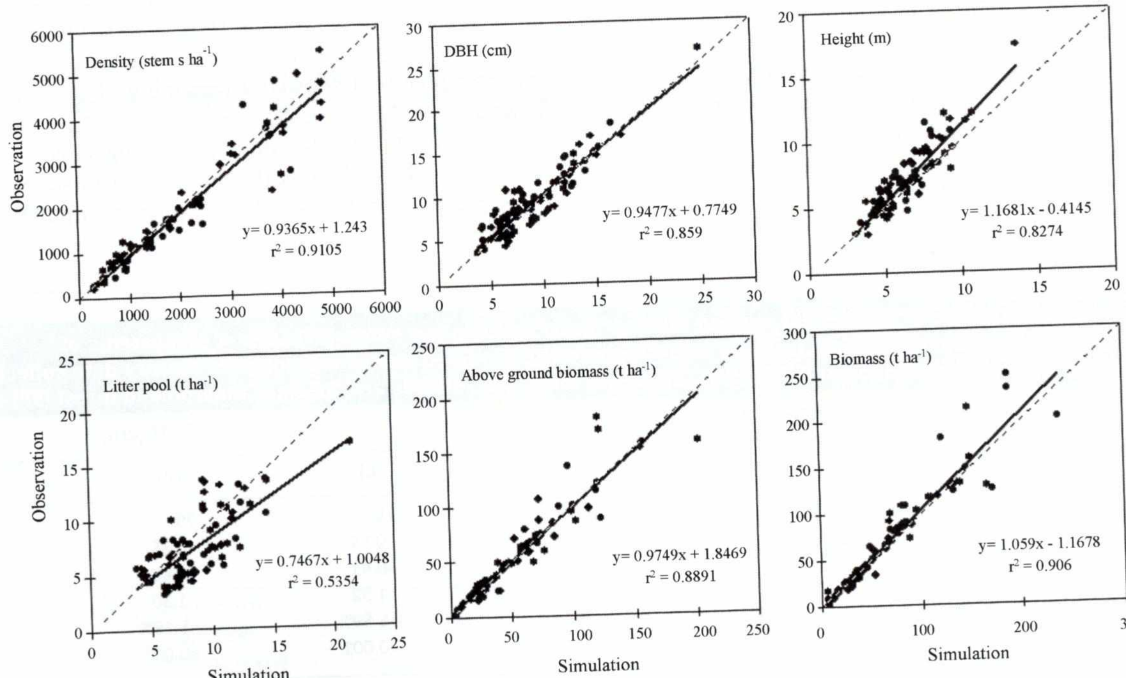

Fig. 4 – The comparisons of tree density, height, DBH, litter pool, aboveground and total biomass between simulations and observations from yield measurements in the subtropical forest zone of Zhejiang Province ($n = 79$–89, $p < 0.001$).

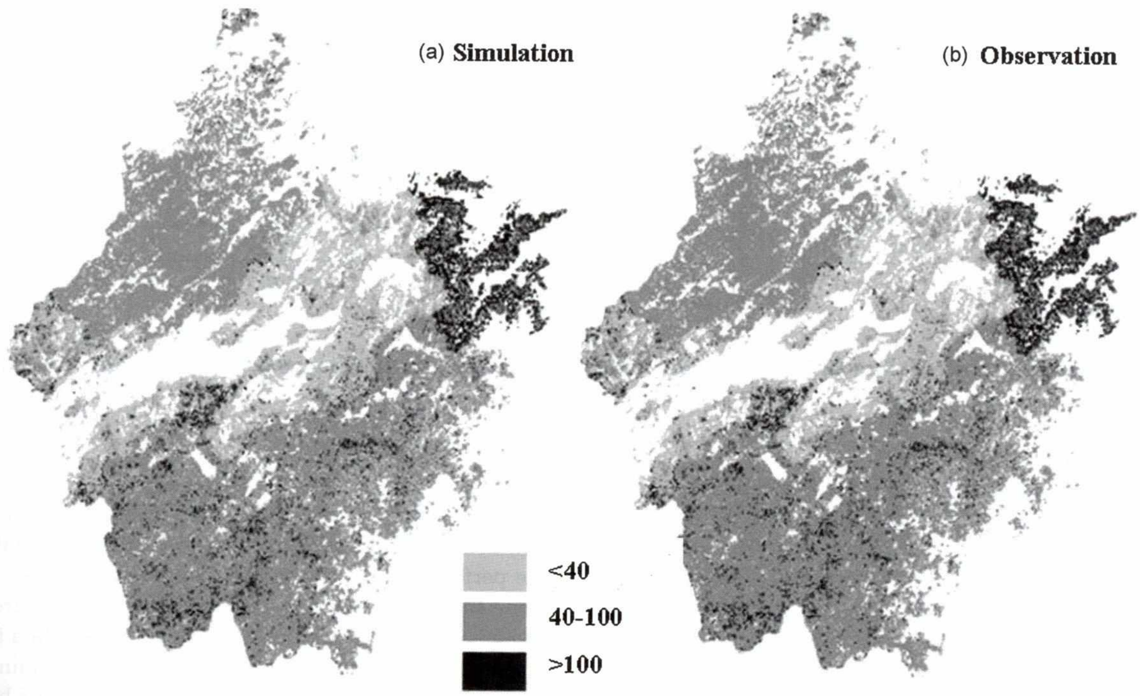

Fig. 5 – Comparison between total biomass ($t\,ha^{-1}$) simulations (a) and estimates based upon field measurements (b) for Zhejiang Province, southeastern China. The grid size is 30 m × 30 m.

appears to be inaccurate compared to aboveground and total biomass. The simulated mean errors for the total biomass are approximately −0.57 to −10.67 $t\,ha^{-1}$, which translates into biases −16.6 to 0.8%, respectively (Table 5). All p values were less than the critical value of $\alpha = 0.001$. In addition, the simulated spatial pattern of total biomass (Fig. 5a) is consistent with the observed total biomass distribution (Fig. 5b).

3.4. *Spatial pattern of NPP*

NPP is a key ecosystem variable and an important component of forest carbon budgets due to its important role in terrestrial carbon cycles and ecosystem processes. The simulated NPP distribution was also compared to the NPP estimated from field measurements at the landscape level (Fig. 6). The simulation results showed that the averaged NPP was predicted by

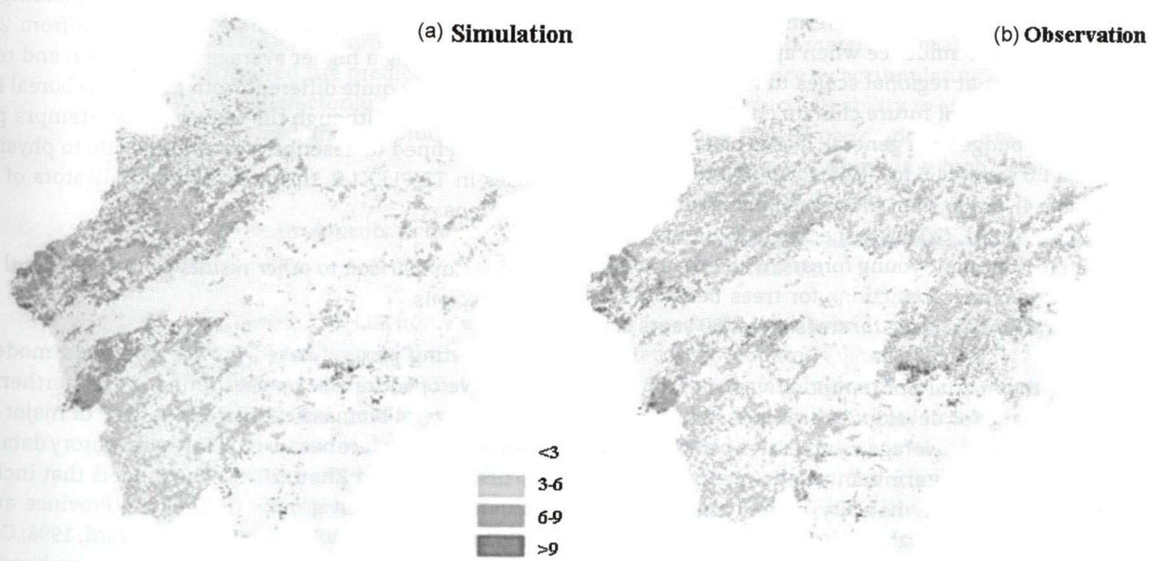

Fig. 6 – Comparison at landscape levels between (a) net primary productivity (NPP) ($t\,ha^{-1}\,year^{-1}$) simulations and (b) estimates based upon field measurements for Zhejiang Province, southeastern China (Zhang et al., 2007). The grid size is 30 m × 30 m.

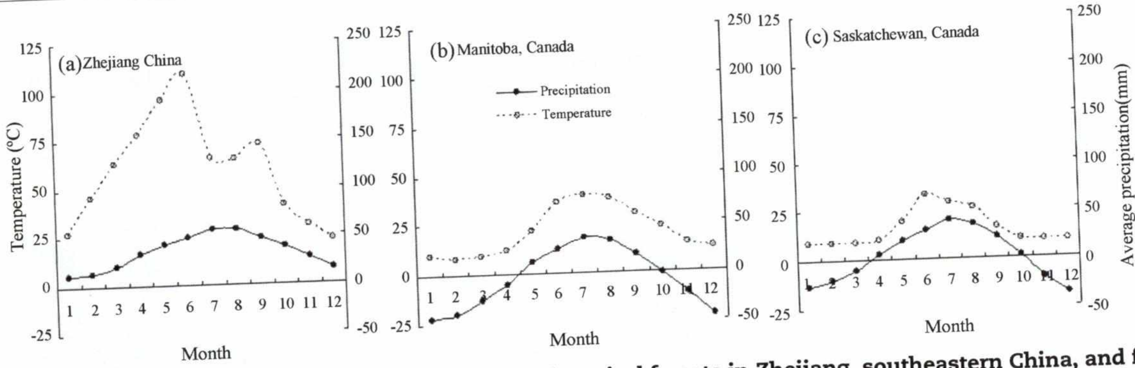

Fig. 7 – Mean monthly precipitation and temperature for subtropical forests in Zhejiang, southeastern China, and for boreal forests in Canada.

TRIPLEX1.0 to be 4.19 t ha^{-1} $year^{-1}$ for 1999 within the subtropical forest ecosystems, which is consistent with the estimated average NPP (5.59 t ha^{-1} $year^{-1}$). The simulated NPP spatial distribution pattern (Fig. 6a) was similar to the estimation from field measurements of Zhang et al. (2007) (Fig. 6b). Both of them have higher NPP in southwest mountainous region and lower NPP in northeast coastland.

4. Discussion

4.1. *Model performance and parameter effects on model accuracy*

Process-based carbon dynamic models are rarely validated against empirical statistical forest growth and yield data and are difficult to use as a practical tool for management (Landsberg and Waring, 1997; Landsberg and Coops, 1999; Peng et al., 2002; Zhou et al., 2005). The process-based hybrid model of TRIPLEX1.0 has been calibrated and validated firstly for growth and carbon budget in the subtropical forest regions of China. This validation of the TRIPLEX1.0 model demonstrates that it is capable in simulating density, H, DBH, litter pool, aboveground and total biomass offering, therefore, competency while providing confidence when applying its ability to extrapolate outcomes at regional scales to further investigate the potential impacts of future climate change on forest biomass and carbon budgets. In general, biases of values predicted by TRIPLEX1.0 were −1.6 to −5.6% for DBH and −14.9 to −11.1% for H (Table 4), larger than those seen in boreal forests as reported by Zhou et al. (2005), respectively. This discrepancy may be due to dominant young forests, while the model provided the best dynamic predictions for trees between 50 and 90 years old and less accurate for trees under 50 years old (Peng et al., 2002).

Understanding the spatial and temporal variation of site conditions is important for developing accurate carbon estimates. Site factors, such as average rainfall, temperature and soil fertility are significant determinants to the potential total biomass carrying capacity at maturity and to the average rate of forest growth (Waterworth et al., 2007). Actual growth and yield over short periods is sensitive to climate variability and forest age. Model calibration and validation were implemented for climate data variables, which have implications to biodiversity, carbon sequestration and the exchange of greenhouse gases (Coops et al., 2005), but local site conditions, such as exposure to wind or aspect differences, were not captured. Climate data may have introduced further uncertainties to the performance of the model (Miehle et al., 2006). To overcome these uncertainties and distinguish model errors from climate data errors, we need to collect climate data from the forest stand scale in future work. Another uncertainty could be that Zhejiang Province has over thousands years history of anthropogenic disturbances in the form of intensive human activity over large-scale areas that have left almost no mature forests intact. Since China's Resistance War against Japanese Aggression and national scale steel production from 1958, have caused truculence deforestation, and during the past 28 years the regional landscape was modified significantly by the rapid economic developing process.

TRIPLEX1.0 calibrations were conducted to determine a set of suitable parameters and to generalize those parameters for making the model practicable to wider subtropical forest regions. To apply the model for subtropical forest ecosystems in southeastern China, we need to adjust some parameters (Table 2). This was especially true for parameters like Stemprn and Stempra that affect the growth rate (Landsberg and Waring, 1997) of tree stems in some plots depending on certain site conditions since forest climate data from Zhejiang Province, having a higher average precipitation and temperature, which are quite different from that of the boreal forest in Canada (Fig. 7). Although the Stemprn and Stempra parameters are defined to describe growth rates due to physiological causes in TRIPLEX1.0, they can also be indicators of climate conditions.

4.2. *Comparison to other results from subtropical forest regions*

Most existing process-based growth and yield models have been developed for tree species found in the northern hemisphere. Several biomass estimates and NPP of major planted forests in China were based upon forest inventory data (Fang et al., 1996; Zhao and Zhou, 2005). The models that include the simulations of forest growth in Zhejiang Province are CASA (Fang et al., 2003), CEVSA (Cao and Woodward, 1998; Cao et al., 2003) and GLO-PEM (Cao et al., 2003), which have been applied mainly in China. A comparison between the predictive capacity of these models and inventory measurements is presented in Table 6.

Table 6 – Estimates of biomass and NPP in the present study and from similar regions reported in different studies

Forest type	Source	Biomass ($t\,ha^{-1}$)	NPP ($t\,ha^{-1}\,year^{-1}$)	Age range	Site	Reference
Evergreen broad-leaved forest	TRIPLEX	92.86	3.323	8–50	Zhejiang	This study
	Field	89.19	8.35	5–50	Zhejiang	Zhang et al. (2007)
	Inventory	133	10.43	5–50	China	Fang et al. (1996)
	CASA	–	4.183	–	China	Fang et al. (2003)
	CEVSA	–	0.4–12	–	China	Cao et al. (2003)
	GLO-PEM	–	0.4–0.6	–	China	Cao et al. (2003)
Coniferous and broad-leaved mixed forest	TRIPLEX	53.68	7.845	5–33	Zhejiang	This study
	Field	70.06	6.59	5–33	Zhejiang	Zhang et al. (2007)
	Inventory	97.6	11.26	–	China	Fang et al. (1996)
	CASA	–	2.960	–	China	Fang et al. (2003)
	CEVSA	–	0.4–12	–	China	Cao et al. (2003)
	GLO-PEM	–	0.4–0.6	–	China	Cao et al. (2003)
Pinus massoniana forest	TRIPLEX	46.10	2.628	9–41	Zhejiang	This study
	Field	51.25	4.85	9–41	Zhejiang	Zhang et al. (2007)
	Inventory	40	4.30	3–37	Eastern China	Zhao and Zhou (2005)
	Inventory	36.52	8.412	–	China	Fang et al. (1996)
	CASA	–	2.455	–	China	Fang et al. (2003)
	CEVSA	–	0.4–12	–	China	Cao et al. (2003)
	GLO-PEM	–	0.4–0.6	–	China	Cao et al. (2003)

Comparing with similar regions reported in different studies, TRIPLEX1.0 can predict biomass with a high level of accuracy for all three forest types (Table 6). The results from this study indicated that TRIPLEX1.0 biomass simulated for EF ($92.86\,t\,ha^{-1}$) and PF ($46.10\,t\,ha^{-1}$) was between the field inventory results, whereas modeled result for MF ($53.68\,t\,ha^{-1}$) was lower than other estimates. As shown in Table 6, the NPP for both MF and PF simulated by TRIPLEX1.0 was similar to estimated by Zhang et al. (2007) and Fang et al. (1996), but was significantly different from other model results for whole China (Cao et al., 2003; Fang et al., 2003). For three forest types, the TRIPLEX1.0 model performed higher accuracy than other three models CASA, CEVSA and GLO-PEM in predicting NPP by contrast with field estimations.

TRIPLEX1.0 has kept a minimal amount of input parameters so that it can operate from readily available datasets to produce regional growth and yield as well as biomass and NPP results (Fig. 6). These low parameter requirements, however, do not appear to have compromised the predictive precision of TRIPLEX1.0; it was able to satisfactorily predict biomass growth across a variety of climatic and edaphic situations within the subtropical zone.

4.3. *Future application and improvements to the model for subtropical forests*

Prior studies have extensively tested TRIPLEX1.0 by applying various field measurements collected within the Canadian boreal forest (Peng et al., 2002; Zhou et al., 2004, 2005, 2006a,b). This study has shown through model validation applying independent observations from subtropical forests in Zhejiang, China, that TRIPLEX1.0 is able to estimate forest H, DBH, litter pool, aboveground and total biomass under subtropical forest ecosystem conditions. Carbon accumulation is affected by forest management, age, structure and specie or ecosystem type (Waterworth et al., 2007). Human induced changes such as agriculture, forest resource harvesting and urbanization, which can add further complications by enhancing changes to terrestrial ecosystems (Chapin et al., 2004), are extremely serious in Zhejiang Province. Unfortunately, TRIPLEX1.0 simulates forested land without consideration of this component. Moreover, the absence of a shrub module and herb layer within the forest is an additional weakness of the model.

Another aspect is the difficulties in obtaining sufficient field sample measurements that, statistically speaking, has limited the application of process-based ecological models, although they have, in theory, a strong long-term forecasting ability under changing climatic and other environmental conditions. The best way to validate process-based models is to compare model simulations to field data from growth and yield measurements (Fig. 4). Our results suggest that TRIPLEX1.0 produced less bias (about ±4%) when comparing simulated aboveground and total biomass and could produce a higher bias (about ±16%) when predicting H, DBH, and litter pool based upon forest field measurements (Table 3). In general, model parameterization always affects process-based model performance by accumulating errors at each time step. Increasing the model's ability to simulate soil carbon storage, carbon dynamics, N cycle and water balance for subtropical forest ecosystems in China is a high priority in the ongoing development of the model.

5. Conclusion

The process-based hybrid model TRIPLEX1.0 has been calibrated and validated successfully for 117 forest stands aged from 5 to 50 years in southeastern China for the first time. The results suggest that simulated forest growth, litter pool, aboveground biomass and total biomass are consistent with the observed data across Zhejiang Province. It was also demonstrated that TRIPLEX1.0 worked well for subtropical ecosystems at regional scales, even though it was originally developed for boreal ecosystems. The model, however, does not consider factors such as land use alteration, changes to forest structure and succession as well as fire disturbances, which inevitably introduce some uncertainty into model simulations. Future study regarding these issues and further model improvements will certainly advance our understanding of forest growth and carbon cycles of subtropical forest ecosystems in southeastern China. More tests in the model's ability to simulate soil carbon, carbon dynamics, N cycle and water balance for subtropical forest ecosystems in China are ongoing in advancing the model application. So it can assist in global change modeling and monitoring the sustainability of forest ecosystems.

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