

Simulation and sensitivity analysis of carbon storage and fluxes in the New Jersey Pinelands

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ABSTRACT

A major challenge in modeling the carbon dynamics of vegetation communities is the proper parameterization and calibration of eco-physiological variables that are critical determinants of the ecosystem process-based model behavior. In this study, we improved and calibrated a biochemical process-based WxBGC model by using in situ AmeriFlux eddy covariance tower observations. We simulated carbon dynamics of fire-dominated forests at tower sites and upscaled the tower site-based simulations to regional scale for the New Jersey Pinelands using LANDSAT-ETM land cover and DAYMET climate data. The Extended Fourier Amplitude Sensitivity Test approach was used to assess the higher-order sensitivity of model to critical eco-physiological parameters. The model predictions of CO₂ net ecosystem exchange (NEE) and gross ecosystem production (GEP) were in agreement with the eddy covariance measurements at the three tower sites in 2005. However, the model showed poor fit in 2006, grossly overestimating NEE and the ratio of ecosystem respiration to GEP because the model did not reflect the carbon loss caused by severe defoliation related to an outbreak of gypsy moths in that year. The model simulations indicated that wildfire reduced annual NEE in pine/scrub oak forest, while prescribed burning in oak/pine and pine/oak stands led to temporary increase in NEE for a period 1–2 years post burning. The uncertainty and sensitivity of the model carbon simulations were mainly attributable to the 2nd- and higher-order interactions between carbon allocation parameters, specific leaf area and fire mortality intensity.

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1. Introduction

Terrestrial ecosystems can serve as either a net carbon sink or a net source, and play an important role in determining carbon storage and fluxes at regional and global levels (Aber and Driscoll, 1997; Law et al., 2001; Walther et al., 2002; Sitch et al., 2003; Wang et al., 2010). In the past decade, the rate of sequestration by North American forests has been estimated at 0.23 petagrams of carbon per year (Goward et al., 2008). This offsets about 13% of the fossil fuel emissions from the continent. However, the uncertainty about the estimate of forest carbon flux is as high as nearly 50% (Goward et al., 2008). Part of this uncertainty in quantifying carbon flux is due to carbon dynamics of landscape or regional forest ecosystems in response to natural and anthropogenic disturbances (Lane et al., 2010; Wang et al., 2010).

In recent years, great strides have been made through the integration of spatially-explicit ecosystem models, remote sensing derived land cover, eddy covariance measurements and environmental variables to quantify carbon cycling dynamics across multiple spatial and temporal scales (Keane et al., 2002; Rollins et al., 2006; Updegraff et al., 2010). As conventional forest inventory techniques and eddy covariance measurements are useful benchmarks to determine carbon sequestration for a specific vegetation types in certain landscape settings, ecosystem process models provide an important means of estimating the spatial and temporal details of changes in carbon storage and fluxes (White et al., 2000; Law et al., 2001; Thornton et al., 2002; Pan et al., 2006; Updegraff et al., 2010). Previous literature suggested that spatially explicit ecosystem models should not only capture the most critical interactions between environmental drivers and ecosystem processes, but also accurately convey the impact of natural and human disturbances on the processes of CO₂ uptake, storage and emission (White et al., 2000; Thornton et al., 2002; Lane et al., 2010; Updegraff et al., 2010). A critical evaluation of

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a model's ability to explain the within-site and between-site variability in forest inventory data or flux measurements is essential before broader scale applications of the model can be pursued (Law et al., 2001; Thornton et al., 2002; Pan et al., 2006). Thus, there is a growing need for coupled observational and modeling strategies to simulate and map response of carbon storage and cycling to natural and human disturbances for particular regions of concern.

A key determinant of a model's utility for specific landscapes or regions is the proper calibration of the model's driving variables with locally-applicable parameterization and sensitivity of the model's input parameters (Aber et al., 1997; White et al., 2000; Gertner, 2003; Matsushita et al., 2004; Miao et al., 2004, 2009; Makler-Pick et al., 2011). To examine the applicability of the Biome-BGC model across a range of conditions, for example, White et al. (2000) collected highly site- and species-specific eco-physiological parameters for major temperate biomes and assessed the factorial sensitivity of NPP (net primary productivity) for five critical parameters. For a given species or biomes, variances of many eco-physiological parameters are high enough to significantly influence prediction quality. For instance, the allocation ratio of new stem carbon to new leaf carbon of pitch pine (*Pinus rigida* Mill.) and white oak (*Quercus alba* L.) ranged from 1.28 to 1.99 and from 0.80 to 1.36, respectively (Olsvig, 1980; White et al., 2000). Specific leaf area of the evergreen needle leaf (ENF) biome varied from $2.8 \text{ m}^2 \text{ kgC}^{-1}$ for *Pinus resinosa* to $11.5 \text{ m}^2 \text{ kgC}^{-1}$ for *Pinus taeda* of the eastern US forests (Scherzer and Hom, 2008). Thus in approaching a finer scale application of a broadly parameterized ecosystem process model, careful attention must be paid to examining this uncertainty. Further, the specific form and coefficients of the biogeochemical model equations are generally based on empirical laboratory and/or field observations, and thus are not always applicable under all conditions. Accordingly, sensitivity analyses are prerequisites for model building and application in any setting, be they diagnostic or prognostic (White et al., 2000; Saltelli, 2002; Saltelli et al., 2000; Miao et al., 2004; Miao and Li, 2007, 2010; Saltelli and Annoni, 2010).

The objective of this study is (i) to improve and calibrate the WxBGC model tool, a coupled Biome-BGC and WxFIRE model, by using locally-derived eco-physiological parameters and historical fire records; (ii) to make higher-order sensitivity and uncertainty analysis of the model carbon simulations to eco-physiological parameters; and (iii) to simulate and map carbon storage and fluxes of the US New Jersey Pinelands region. In this study, the WxBGC model was modified and validated against AmeriFlux (Long-term flux measurement network of the Americas) eddy covariance measurements in representative uplands forests that spanned the gradient from oak/pine to pine/oak to even more heavily fire disturbed pine/scrub oak during the years of 2005 and 2006 (Clark et al., 2004, 2009). Sensitivity analysis was carried out through the Extended Fourier Amplitude Sensitivity Test (EFAST) approach to examine the main effects and higher-order interactions between the eco-physiological input parameters and their contribution to the uncertainty of carbon dynamic predictions. The validated WxBGC model was then applied across a longer time span to examine model behavior in relation to fire disturbance and across the broader New Jersey Pinelands region to predict and map carbon dynamics and distribution at the regional scale.

2. Materials and methods

2.1. Model description

The WxBGC model was developed by the USDA Forest Service National LANDFIRE project (Steinwand and Nelson, 2005; personal communication) to generate consistent and comprehensive spatially explicit biophysical layers

containing vegetation, litter, soil carbon, water vapor, fire disturbances, etc. of Multi-Resolution Land Characterization (MRLC) zones, in support of the US national LANDFIRE prototype and vegetation mapping. The WxBGC model integrate the WxFIRE and Biome-BGC models and is able to implement parallel simulations for large-scale landscape ecosystems at a finer resolution on a Linux (Red Hat 8.0)-based multiple-node cluster. As a widely calibrated model, the Biome-BGC model seeks to mechanistically represent ecosystem cycles of carbon, water, and nutrients through an integrated consideration of biology and geochemistry (Running and Gower, 1991; White et al., 2000; Thornton et al., 2002). The WxFIRE model is used to map vegetation, fuels, fire regimes and fire condition classes in the LANDFIRE project, and computes climate-based biophysical variables at any landscape scale or resolution using daily weather data, topography and soil parameters, and a diverse set of integrated environmental functions (Keane et al., 2002). Detailed descriptions of the Biome-BGC and WxFIRE models can be found in Running and Gower (1991), Thornton et al. (2002) and Keane and Holsinger (2005), respectively.

In the current study, we modified the WxBGC model to simulate carbon storage and dynamics of the New Jersey Pinelands. The model improvements are summarized as follows:

- (i) *Combination of random and spatially heterogeneous fire disturbances into the model.* Inherited from the Biome-BGC model, the original WxBGC model set disturbance intensity (i.e., the whole-plant mortality rate parameters) through plant eco-physiological parameter input files and considered disturbance as a continuous and spatially homogenous disturbance. In other words, disturbance occurs at every pixel every time step with a constant intensity. The assumption may be true for chronic harvest cutting, herbivory and insect defoliation within large areas, but may not be applicable to episodic and spatially heterogeneous disturbances such as wildfire and windfall. Based on our review of historical fire occurrence records of the New Jersey Pinelands for the years between 1924 and 2007, we improved the model to randomly generate fire events between March and April for spring prescribed burning by using uniform random distribution and stochastically initiate wildfire event dates using a Gaussian distribution. In this study, we set April 20 as the mean and 40 days as the standard deviation of Gaussian distribution for New Jersey pinelands wildfire disturbance events, respectively. Therefore, our modified WxBGC version includes stochastic rather than deterministic fire disturbance. We empirically classified fire intensity (i.e., fire mortality rate) into five levels: no fire, prescribed burning (we assumed prescribed fire burned 30% of dead stem, litter and coarse woody debris, and 5% of live carbon which represents burned shrub and grass), moderate non-replacement wildfire (35% of all carbon to be burned), heavy non-replacement wildfire (50% of all carbon to be burned) and replacement wildfire (>60% of all carbon to be burned) (Little, 1979; Boerner, 1981; Boerner et al., 1988). We set fire disturbance to directly reduce a proportion of the initial values of all plant and fine litter state variables immediately before the disturbance as did Thornton et al. (2002). The affected proportions of the leaf, fine root, live wood, and fine litter C and N pools are assumed to be lost to the atmosphere.
- (ii) *Combination of remote sensing land cover data into the model.* In order to generate consistent and comprehensive biophysical layers of carbon and water dynamics of MRLC zones, the original WxBGC model hypothetically assumes a spatially homogeneous land cover (i.e., evergreen needle leaf or grass) for given landscape or region. We coupled remote sensing-derived land cover mosaics into the model to spatially explicitly simulate comprehensive biophysical layers of real heterogeneous ecosystem mosaics. Except for meteorological data, the improved version includes 11-layers of geo-reference spatial inputs such as elevation (m), aspect ($^{\circ}$), slope (%), hillshade (dimensionless), soil depth (m), sand percent, silt percent, clay percent, land cover type, fire time and intensity (percent of tree fire mortality). We set other geographic or environmental variables (e.g., albedo, N-deposition, etc.) to Biome-BGC default values (White et al., 2000; Thornton et al., 2002).
- (iii) *Improvements of output functions.* The original WxBGC model does not output monthly and annual predictions but the 18-yr average predictions of 42 variables. We restructured the output functions of the WxBGC model into timely and spatially explicit variable-oriented output functions, i.e., 42 monthly and annual biophysical variables including transpiration, actual evapotranspiration, leaf area index, net ecosystem exchange of CO_2 , gross primary productivity (GPP), soil carbon, etc. The internal time step of the model is still daily. Theoretically, the model could output daily predictions, but output file sizes would be as high as over hundreds gigabytes for the New Jersey Pineland at finer resolution (say less than 100-m resolution), therefore the daily output function was inactivated.

It is worth noting that the original model classified DEM and DEM derivatives into several group levels and aggregated some similar neighbor pixels into one map unit to reduce total pixel numbers and computations due to the large spatial scale of MRLC zone 60. The improved version is straight up the original pixels of land cover and geo-referenced environmental variables.

2.2. Study area

The study was conducted in the New Jersey Pinelands, which consists of approximately 1.1 million acres in southern New Jersey. The New Jersey Pinelands was the first US National Reserve designated as such and a U.S. Biosphere Reserve of the Man and the Biosphere Program. Two relatively distinct floristic complexes are present in the Pinelands, a lowland complex (wetland) and an upland complex. The wetlands are composed principally of white cedar (*Chamaecyparis thyoides* (L.) B.S.P.), trident red maple (*Acer rubrum* L.), and black gum (*Nyssa sylvatica* Marsh.). The uplands comprise approximately 62% of the Pine Barrens, and are dominated by three major forest communities: black oak/pine forest types, pine/black oak, and pine/scrub oak in the understory (McCormick and Jones, 1973; McCormick, 1979; Forman, 1979; Lathrop and Kaplan, 2004; Skowronski et al., 2007). All stands have ericaceous shrubs in the understory, primarily huckleberry (*Gaylussacia baccata* (Wangenh.) K. Koch, *G. frondosa*) and blueberry species (*Vaccinium* spp.) (Skowronski et al., 2007). In the New Jersey Pinelands, fire and human disturbances are considered as secondary environmental factors in determining vegetation community composition following soil texture and nutrients. Fire frequency is fairly high (e.g., 5–15 yrs for dwarf pine plains and 15–25 years for pitch pine-scrub oak barrens) and fire disturbances can apparently affect the current process and future direction of carbon flux for some forest community types (Boerner, 1981; Forman and Boerner, 1981; Buchholz and Zampella, 1987; Boerner et al., 1988).

In the Pinelands, in winter, a strong northwesterly flow of cold, dry air masses from Canada predominates, and temperatures average 0–2 °C (32–36 °F). In summer, a southwesterly flow of warm, humid air, around the Bermuda high-pressure area dominates the Pinelands, with temperatures averaging 22–24 °C (72–75 °F). Average annual precipitation throughout the Pinelands is 1067–1168 mm. Both precipitation and temperatures are highly variable from year to year (Havens, 1979).

Three upland AmeriFlux eddy tower sites operated by the U.S. Forest Service out of the Silas Little Experimental Forest were used as calibration/validation sites. These sites consisted of a mixed oak and pitch pine stand (oak dominated) (Silas Little, 39.9161 °N, 74.5986 °W), a mixed pine/oak stand (pine dominated) (Fort Dix, 39.9731 °N, 74.4341 °W), and a pitch pine overstory/scrub Oak dominated understory stand (Cedar Bridge, 39.8302 °N, 74.3403 °W) (Skowronski et al., 2007) (Fig. 1). The climate of three sites is cool temperate, with mean monthly temperatures of 0.3 and 23.8 °C in January and June (1930–2004), respectively. Mean annual precipitation is 1123 ± 182 mm. Soils are derived from the Cohansey and Kirkwood Formations (Lakewood and Sassafras soils), and are coarse-textured, sandy, acidic, and have extremely low cation exchange capacity and nutrient status (Tedrow, 1986). A wildfire event occurred in 1995 at the Cedar Bridge tower site. Two prescribed burning events occurred in 2002 and 2003 at the Fort Dix tower site. Four prescribed fire events occurred in 1980, 1981, 1982 and 1997 at the Silas Little tower site.

2.3. Remote sensing derived land covers and eco-physiological parameterizations

We used New Jersey 2001 Landsat-7.0 + ETM (Enhanced Thematic Mapper) level-3 land cover data set (Lathrop and Kaplan, 2004) as the basis for land cover for the New Jersey Pinelands study area (Fig. 2). The Level 3 data was aggregated to ten categories: grassland, scrub/shrub (including upland/wetland shrub), upland oak

forest (oak > 75%), upland oak-pine (oak: 50–75%), upland pine-oak, upland pine, hardwood swamp, pine wetland, mixed hardwood/white cedar-pine-holly wetland, and white cedar swamp. To reduce model computation time, we masked out developed land (>25% impervious surface), cultivated land, barren soil/rock, water and marine coast/estuarine area (21.99% of total area). In this study, regional simulations were implemented at a 100-m resolution by using parallel simulation technology on a LINUX-based cluster with 12 nodes.

We parameterized eco-physiological input parameters for the ten categories of 2001 Landsat-7 level 3 land cover of the New Jersey Pinelands based on information available in the literature and the USDA Forest Service physiological database (Scherzer and Hom, 2008). If regionally relevant information on trees and shrubs derived for either the New Jersey Pinelands (Little, 1979; Ehrenfeld and Gulick, 1981; Wang, 1984; Ehrenfeld and Schneider, 1991) or the New York Long Island Pine Barrens (Whittaker and Woodwell, 1968) were not available, we relied on White et al. (2000) (Table 1). The upland forests generally represent a gradient from pitch pine dominated to mixed oak (*Quercus* spp.) dominated, so eco-physiological parameters of oak-pine and pine-oak were used in a weighted average of individual oak and pine parameters based on the component percentage in the land cover mapping. For example, for the upland oak-pine, the eco-physiological parameters were the weighted mean of oak and pine parameters based on the component percentage of 50 ~ 75% of oak and 25% ~ 50% of pine. The parameters of wetland pine were nearly identical to upland pine, but the C:N ratio of leaves, fine roots, and environmental variables were specific for the wetlands. We used the mean of V_{cmax} gas-exchange measurements of four shrub species to calculate fraction of shrub leaf N in Rubisco (Miao et al., 2009). Most of grass parameters were directly cited from White et al. (2000).

2.4. Meteorological data

For three tower sites, eddy covariance meteorological data (2004–2006) were provided by Silas Little Experimental Forest, USDA Forest Services. Continuous meteorological measurements were conducted at each flux tower from 2004 to 2006 (Clark et al., 2004, 2009, 2010). Incoming shortwave radiation (LI-200, Li-Cor, Inc.), photosynthetically active radiation (PPFD; LI-190, Li-Cor, Inc.), net radiation (NRLite, Kipp and Zonen, Inc.), air temperature and relative humidity (#HMP45, Vaisala, Inc.), windspeed and direction (05013-5, R. M. Young Co.), and precipitation (TE525, Texas Electronics, Inc.) were measured above the canopy at 15–20 meter height. Barometric pressure (PTB 100A, Vaisala, Inc.) was measured from the tower at the Silas Little Experimental Forest. Meteorological data were recorded with automated data loggers (CR23x, Campbell Scientific) every 30 min. We determined maximum, minimum and daily mean temperature, daily precipitation and solar radiation based on sunrise and sunset time of three tower sites. Vapor pressure was calculated with the MTCLIM43 model based on daily tower temperature and precipitation (Thornton et al., 1997). To lengthen the period of record for the tower site scale simulations, 24 years of DAYMET (1980–2003) were employed as well.

For the New Jersey Pinelands-wide simulations, we employed DAYMET data for an 18 year time period (1980–1997). DAYMET is a collection of algorithms and computer software designed to interpolate and extrapolate from daily meteorological observations to produce gridded estimates of daily weather parameters over large regions (www.daymet.org). The DAYMET data includes daily weather

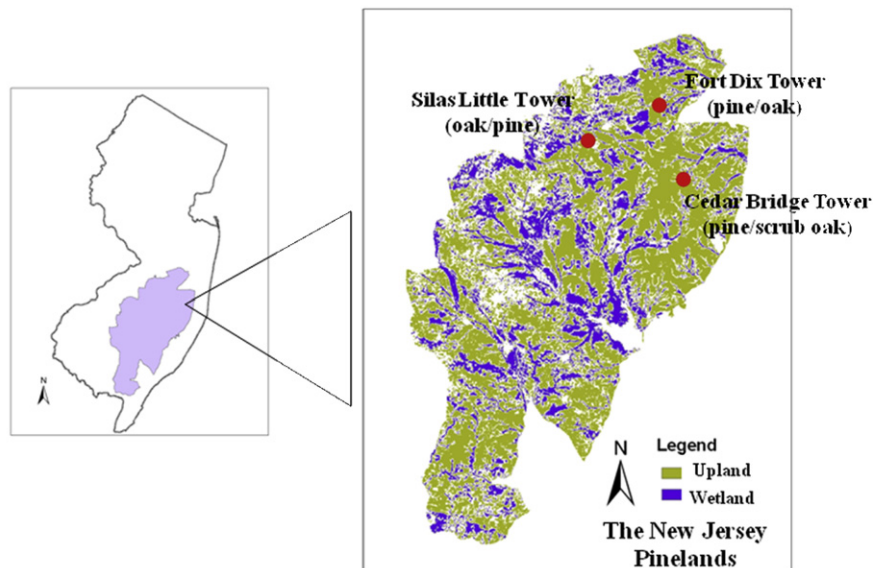


Fig. 1. The US New Jersey Pinelands and eddy covariance tower sites.

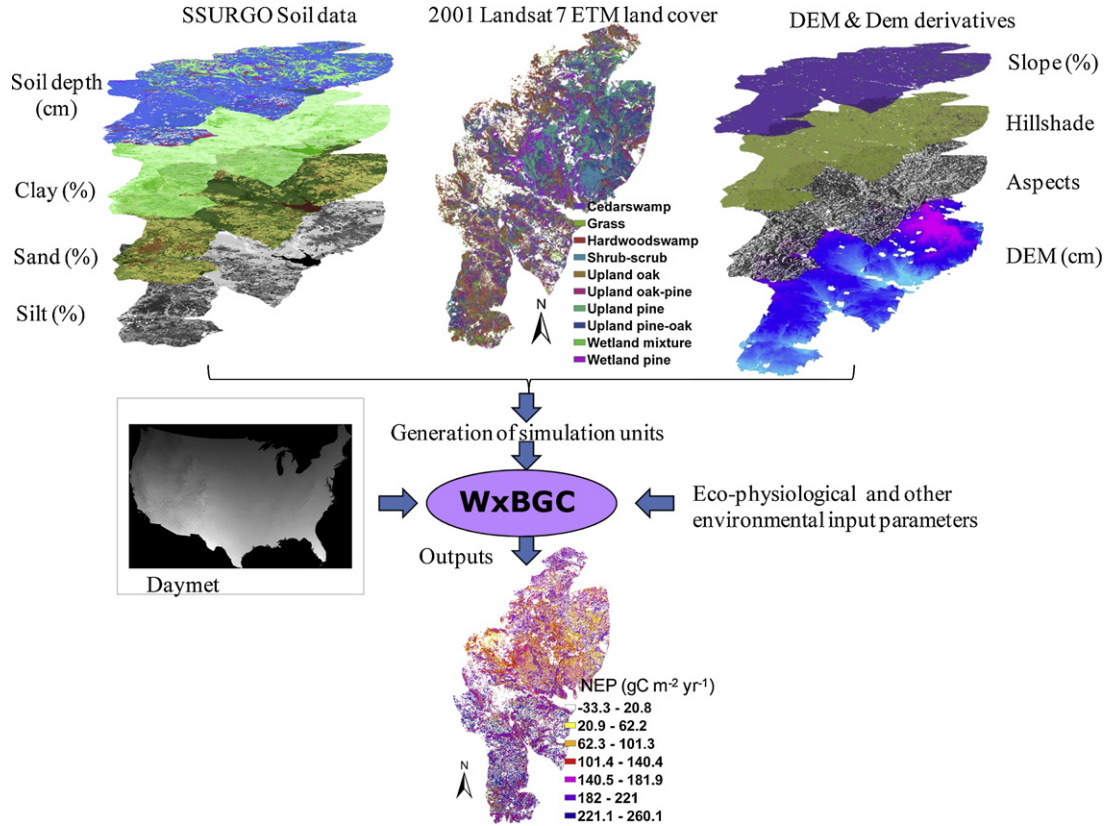


Fig. 2. Input variables and structure of the WxBGC model.

parameters such as temperature, precipitation, solar radiation, vapor pressure deficit and day length, and it was produced on a 1 kilometer grid over the entire conterminous United States for the period of record 1980–1997. The daily observations used to produce the gridded surfaces came from approximately 6000 stations in the U.S. National Weather Service Co-op network and the Natural Resources Conservation Service SNOTEL network (automated stations in mountainous terrain) (Thornton et al., 1997, 2000; Thornton and Running, 1999).

2.5. Geo-referenced environmental gradients

We used the USDA Natural Resources Conservation Service SSURGO (Soil Survey Geographic) database (<http://soildatamart.nrcs.usda.gov/>) to derive soil texture (sand, clay and silt percent) and soil profile depth (soil depth in m) maps for the NJ Pinelands study area. Elevation (m) and slope (%), aspect (degree) and topographic shade (hillshade) maps were developed from a seamless DEM mosaic of the USGS National Elevation Database (NED) (<http://edc2.usgs.gov/geodata/index.php>).

2.6. Eddy covariance towers and NEE measurements

We used closed-path eddy covariance (EC) measurements from the U.S. Forest Service's three eddy tower sites to evaluate the model predictions of net ecosystem exchange (NEE). EC systems were composed of a 3-dimensional sonic anemometer (Windmaster Pro or R3A, Gill Instruments Ltd., Lymington, UK, or RM 80001V, R.M. Young, Inc.) mounted approximately 4 m above the canopy on an antenna tower at each site, a closed-path infrared gas analyzer (LI-7000, Li-Cor Inc., Lincoln, Nebraska) in an enclosure on the tower, a 5 m long, 0.4 cm ID teflon coated tube and an air pump sampling 8 l min⁻¹, and a lap-top PC to collect data (Moncrieff et al., 1997; Clark et al., 2004). The LI-7000s were calibrated every 2–7 days using CO₂ tanks that were traceable to primary standards. Net CO₂ exchange was then calculated at half-hour intervals using EdiRe software. The flux associated with the change in storage of CO₂ in the air column beneath the inlet was estimated using top of tower and 2-m height measurements or a profile system with inlets at 0.2, 2, 5, 10, 15 and 20 m height.

Annual NEE estimates require continuous values of half-hourly CO₂ exchange. To estimate daytime net CO₂ exchange (NEE_{day}) for periods when we did not have measurements (due to precipitation, low windspeed conditions, instrument failure, etc.), a rectangular hyperbola to the relationship between PPFD and NEE_{day} were fitted (Ruimy et al., 1995; Clark et al., 2004). To estimate nighttime net CO₂ exchange (NEE_{night}), half-hourly net exchange rates were regressed on air or soil temperature using an exponential function. We then used modeled data calculated from the

continuous meteorological data for periods when we did not have measured fluxes to estimate daily to annual NEE for each site. Annual ecosystem respiration (R_{eco}) was calculated for each site using continuous half-hourly air or soil temperature. Annual NEE and R_{eco} were summed to estimate gross ecosystem productivity (GEP) (Reichstein et al., 2005; Clark et al., 2009) (Table 2). GPP and GEP are often interchangeable in the field of ecological modeling, but GEP contains a photorespiratory component that GPP does not (Law et al., 2001; Clark et al., 2004, 2009; Reichstein et al., 2005).

2.7. Sensitivity and uncertainty analysis

We employed the EFAST approach to analyze the sensitivity of the carbon storage and flux predictions to 11 crucial eco-physiological input parameters. As a procedure widely used for uncertainty and sensitivity analysis, the Fourier Amplitude Sensitivity Test (FAST) method is more efficient than the Monte Carlo approach and used to estimate the expected value and variance of the output and the contribution of individual inputs to uncertainty and sensitivity of the outputs (Saltelli, 2002; Frey and Patil, 2002; Saltelli and Annoni, 2010; Yang, 2011). The EFAST method developed by Saltelli et al. (2000) was used to address higher order interactions between the inputs. The EFAST method used a decomposition of the Fourier series representation to obtain the fractional contribution of the individual input variables to the variance of the model predictions (Saltelli and Bolado, 1998; Saltelli et al., 2000; Saltelli, 2002; Frey and Patil, 2002). The total variances of the model output can be described as:

$$V(Y) = \sum_{i=1}^k V_i + \sum_{i=1}^k \sum_{j>i}^k V_{ij} + \sum_{i=1}^k \sum_{j>i}^k \sum_{m>j}^k V_{ijm} + \dots + V_{12\dots k}$$

where $V(Y)$ is total unconditional variance of the model output (Y) with k input variables, V_i is the first-order conditional variance of the model output (Y) when input variable $X_i = x_i^*$, i.e., $V_i = V(E(Y|X_i = x_i^*))$, x_i^* is untrue or random value of X_i , V_{ij} is the second-order variance when $X_i = x_i^*$ and $X_j = x_j^*$, i.e., the variance of the interaction between variables i and j , $V_{ij} = V(E(Y|X_i = x_i^*, X_j = x_j^*)) - V_i - V_j$, V_{ijm} and $V_{12\dots k}$ are the higher order variance of interaction among multiple (≥ 3) variables $i, j, m, \dots, k$.

The first-order sensitivity index (S) is: $S_i = V_i/V(Y)$, i.e., the contribution of individual parameter to the model performance. Similarly, the second- and higher-order sensitivity index are: $S_{ij} = V_{ij}/V(Y)$, $S_{ijm} = V_{ijm}/V(Y)$. The total order

Table 1

The crucial eco-physiological parameters used in the current study.

Name	Unit	Description	Silas Little	Fort Dix	Cedar Bridge	Sources
leafturnover	1/yr	Annual leaf and fine root turnover fraction	0.8933	0.5735	0.4609	Whittaker, 1962; Olsvig, 1980; White et al., 2000
NFRC:NLC	DIM ^a	(ALLOCATION) new fine root C: new leaf C	1.4173	1.3810	1.3695	Whittaker and Woodwell, 1968; White et al., 2000
NSC:NLC	DIM	(ALLOCATION) new stem C: new leaf C	1.3501	2.1594	2.1482	Whittaker and Woodwell, 1968
NLWC:NWC	DIM	(ALLOCATION) new live wood C: new total wood C	0.1463	0.1072	0.1674	White et al., 2000
NCRC:NSC	DIM	(ALLOCATION) new croot C: new stem C	0.3014	0.2187	0.1947	Whittaker and Woodwell, 1968
C:Nleaf	kgC/kgN	C:N of leaves	29.9708	40.0872	42.9395	Ehrenfeld, 1981; Wang, 1984
C:Nlitter	kgC/kgN	C:N of leaf litter, after retranslocation	76.4527	100.0945	103.8611	Melin, 1930; White et al., 2000
C:Nfroot	kgC/kgN	C:N of fine roots	61.9475	57.5269	55.7099	White et al., 2000
C:Nlwood	kgC/kgN	C:N of live wood	88.6978	87.0239	81.7630	Ehrenfeld, 1981; Wang, 1984
C:Ndwood	kgC/kgN	C:N of dead wood	557.6741	608.9501	637.5739	Wang, 1984; Woodwell et al., 1975
leaflabile	DIM	Leaf litter labile proportion	0.3522	0.3871	0.4141	Aber et al., 1990; Melin, 1930
leafcellulose	DIM	Leaf litter cellulose proportion	0.4502	0.3826	0.3505	Aber et al., 1990; Melin, 1930; White et al., 2000
leafignin	DIM	Leaf litter lignin proportion	0.1975	0.2303	0.2355	Melin, 1930
dwoodcellulose	DIM	Dead wood cellulose proportion	0.7438	0.7263	0.7185	White et al., 2000
dwoodlignin	DIM	Dead wood lignin proportion	0.2562	0.2738	0.2815	White et al., 2000
CLEC	DIM	Canopy light extinction coefficient	0.5354	0.4024	0.4024	Wood, 1937; Whittaker and Woodwell, 1969; Collins and Good, 1987
LAratio	DIM	All-sided to projected leaf area ratio	2.0926	2.3563	2.4469	White et al., 2000
SLA	m ² /kgC	Canopy average specific leaf area (projected area basis)	20.5545	16.0334	15.3131	Scherzer and Hom, 2008; White et al., 2000
PLNR	DIM	Fraction of leaf N in Rubisco	0.0520	0.0383	0.0333	Wullschlegel, 1993; Reich et al., 1995; White et al., 2000; Scherzer and Hom, 2008; Miao and Li, 2010
Boundcond	m/s	Boundary layer conductance (projected area basis)	0.0223	0.0575	0.0671	White et al., 2000
LWP:scond	MPa	Leaf water potential: start of conductance reduction	−0.2694	−0.4672	−0.5014	Xu et al., 2007; White et al., 2000
LWP:fcond	MPa	Leaf water potential: complete conductance reduction	−1.8657	−2.1953	−2.4898	Xu et al., 2007; White et al., 2000
VPF:scond	Pa	Vapor pressure deficit: start of conductance reduction	1024.3827	809.0625	744.6355	White et al., 2000
VPF:ccond	Pa	Vapor pressure deficit: complete conductance reduction	3522.8395	3303.1250	3290.1040	White et al., 2000

^a Dimensionless.

sensitivity index for variable i (S_i^T) is defined as the sum of all above index, that is: $S_i^T = (V(Y) - V(E(Y|X_{-i}))) / V(Y) = (E(V(Y|X_{-i}))) / V(Y) = S_i + S_{ij} + S_{ijm} + S_{ijm...k}$. In other words, the total order sensitivity includes not only the contribution of individual parameter but also the contributions of two- and multi-dimensional interactions between a specific parameter and all other parameters. If there are no interactions among the variables in the model, the terms of S_{ij} , S_{ijm} and $S_{ijm...k}$ equal zero, and the total variances of the model output can be described as: $V(Y) = \sum_{i=1}^k V_i$, which can be addressed by OAT (test one parameter at a time) or multivariate regression methods (Saltelli et al., 2000; Saltelli, 2002; Matsushita et al., 2004; Miao et al., 2004; Yang, 2011).

In the current study, using the EFAST approach (SimLab version 2.2, 2003), we generated 7000 pseudo values for each input parameter sets (Table 3). In actual, we simulated 6943 iterations for oak/pine at Silas Little site and 6923 iterations for pine/oak at Fort Dix site and pine/scrub oak at Cedar Bridge site, respectively, because some pseudo values do not meet the WxBGC model requirements that the C:N ratio

of leaves > C:N of live wood > C:N of deadwood. We undertook a total of 20,789 runs for the sensitivity analysis of the three vegetation types for the three validation sites. We used the contributions of 11 eco-physiological parameters to the 27-yr averages and coefficient of variations of NEE, GPP and total carbon to measure sensitivity of model to critical parameters.

2.8. Model spin-up and simulation

A steady state of soil organic matter (SOM) pools and nitrogen variables was attained under the specified vegetation ecophysiology for three tower sites and each pixel for New Jersey Pinelands by performing precursor (spin-up) simulations. The precursor simulations were run with the respect to 27-yr climate data (observed 2004–2006 tower weather data plus 1980–2003 DAYMET) for three tower sites and 18-yr DAYMET (1980–1997) data for the regional New Jersey Pinelands, respectively. The spin-up simulations begin with no SOM and are driven by repeated use of the

Table 2The model predictions and eddy covariance measurements of NEE (net ecosystem exchange of CO₂) and GEP (gross ecosystem production) of naturally-regenerated stands at three tower sites (gC m^{−2} yr^{−1}).

Site	Years	Stand age (yrs)	NEE		GEP (or GPP) ^a		Reco/GEP(%)	
			Observed	Predicted	Observed	Predicted	Observed	Predicted
Oak/Pine (Silas Little)	2005	ca. 90	187	208	1133	866	79.1	76.0
	2006	ca. 91	122	218 ^b	1167	913	89.5	76.1
Pine/Mixed Oak (Fort Dix)	2005	ca. 74	137	170	876	1012	84.4	83.2
	2006	ca. 75	−103	249 ^b	784	1090 ^b	113.1	77.2
Pine/Scrub Oak (Cedar Bridge)	2005	ca. 81	222	234	1388	1098	84.0	78.8
	2006	ca. 82	161	250 ^b	1403	1160	88.5	78.4

^a The model prediction was GPP, which approximated to GEP here.^b Significant at the confidence level of 95% by *t*-test.

Table 3
Distribution and initial values of key parameters for EFAST analysis.

Code	Description	Unit	Distribution/parameters ^a		
			Oak/pine at Silas Little site	Pine/oak at Fort Dix site	Pine/scrub oak at Cedar Bridge
Plantmortality	Annual whole-plant mortality fraction	1/yr	U (0, 0.020)	U (0, 0.020)	U (0, 0.020)
Firemortality	Annual fire mortality fraction	1/yr	U (0, 0.050)	U (0, 0.050)	U (0, 0.050)
NFRC:NLC	(ALLOCATION) new fine root C: new leaf C	Dimensionless	U (0.545, 1.590)	U (0.347, 12.700)	U (0.347, 12.700)
NSC:NLC	(ALLOCATION) new stem C: new leaf C	Dimensionless	U (0.533, 5.280)	U (0.596, 5.320)	U (0.596, 5.320)
NLWC:NWC	(ALLOCATION) new live wood C: new total wood C	Dimensionless	U (0.006, 0.279)	U (0.056, 0.100)	U (0.056, 0.100)
NCRC:NSC	(ALLOCATION) new croot C: new stem C	Dimensionless	U (0.077, 0.563)	U (0.151, 0.841)	U (0.151, 0.841)
RatioCNleaf	C:N of leaves	kgC/kgN	N (25.000, 5.400)	N (42.000, 8.000)	N (42.000, 8.000)
RatioCNlitter	C:N of leaf litter, after retranslocation	kgC/kgN	N (55.00, 16.00)	N (93.00, 19.00)	N (93.00, 19.00)
RatioCNfroot	C:N of fine roots	kgC/kgN	N (48.00, 15.00)	N (58.00, 16.00)	N (58.00, 16.00)
SLA	Canopy average specific leaf area (projected area basis)	m ² /kgC	U (16.300, 66.700)	U (2.010, 28.200)	U (2.010, 28.200)
PLNR	Fraction of leaf N in Rubisco	Dimensionless	U (0.0001, 0.300)	U (0.0001, 0.300)	U (0.0001, 0.300)

^a U (Min., Max.) = uniform distribution, N (Mean, S.D.) = normal distribution. The mean for Gaussian distribution, minimum and maximum for uniform distribution were all cited from White et al. (2000)'s Biome-BGC ENF and DBF parameters, respectively. Standard deviations for Gaussian distribution were arbitrarily reduced according to White et al. (2000).

above surface weather records, and in most cases, more than thousand model years elapse before reaching this steady state, the length of time controlled largely by rates of nutrient input and loss, which together with climate and vegetation physiology control the accumulation and loss of slowly responding soil organic matter pools (Law et al., 2001). The endpoint of the spin-up run was used as initial condition for normal simulation of carbon dynamics with specific fire disturbance for a given pixel (e.g., tower sites). To investigate the relationships between land cover vegetation and climate variables, we simulated annual NEE and GEP with pure pine and oak land cover scenarios, based on Cedar Bridge site climate and environmental variables.

3. Results

3.1. Estimating NEE, GEP and the ratios of ecosystem respiration to GEP of the New Jersey Pinelands

Comparison of the locally parameterized WxBGC model simulations with the flux tower eddy covariance measurements revealed that the model annual NEE estimates were within a confidence level of 95% in 2005 by Student's t-test but significantly overestimated in 2006. This overestimate was especially apparent for the pine/oak forest at Fort Dix site where the observed annual NEE was negative (a carbon source). Differences in the 2-yr GEPs (or GPPs) between the predictions and measurements were not significant at the confidence level of 95% by t-test for the three sites in 2005 and 2006, though the GEP predictions were higher than the measurements for pine/oak at the Fort Dix site in 2005 and 2006. The predicted ratios of ecosystem respiration to GEP were significantly lower than the eddy measurements for all three tower sites at the confidence level of 95% in 2006 but not in 2005, particularly for pine/oak at the Fort Dix site (Table 2). It should be noted that both the pine and oak overstory as well as the oak understory in the Pinelands study area, and in particular the Ft. Dix tower site, underwent severe defoliation by a major infestation of gypsy moth (*Lymantria dispar* L.) in 2006.

Both prescribed burning and wildfire disturbance had a large impact on the model estimates of NEE. While cool season prescribed burning increased NEE estimates for 1–2 years after the event, wildfire disturbance greatly reduced the estimated NEE. For example, after spring prescribed burning at the Ft. Dix pine/oak site in 2002 and 2003, annual NEE estimates in 2002, 2003 and 2004 were approximately 25–50% higher than the corresponding NEE estimates for no-fire scenarios (prescribed burning: 174, 323 and 416 gC m⁻² yr⁻¹, vs. no fire: 131, 211 and 335 gC m⁻² yr⁻¹) (Fig. 3). Likewise, similar patterns were observed at the Silas Little oak/pine site after prescribed burning in 1980, 1981, 1982 and 1997. The impact of wildfire disturbance was simulated at the Cedar Bridge

pine/scrub oak site under several different scenarios subsequent to a wildfire in 1995. Estimates of annual NEE decreased from a high of 230 gC m⁻² yr⁻¹ for the no-fire scenario to –26 gC m⁻² yr⁻¹ where the wildfire mortality rate of 50% was assumed (Fig. 3).

3.2. Estimating the NPP of the New Jersey Pinelands

Using the locally-derived parameters, the WxBGC model NPP predictions were closely aligned with the Pinelands region-wide estimate made by Pan et al. (2006) based on USDA Forest Service FIA (forest inventory and analysis) data (Fig. 4). The NPP predictions based on White et al. (2000)'s Biome-BGC eco-physiological parameterization were from 25 to 35% higher than the WxBGC simulations with the locally-derived parameters as well as Pan et al. (2006) (Fig. 4).

Wildfire disturbance considerably reduced the NPP estimates while the prescribed burning increased the NPP estimates. For instance, the NPP predictions with and without prescribed fires were 567 and 496 gC m⁻² yr⁻¹ for oak/pine at Silas Little site in 1981, 351 and 314 gC m⁻² yr⁻¹ for pine/oak at Fort Dix site in 2003, respectively. For pine/scrub oak at Cedar Bridge site, NPP estimates reduced from 543 gC m⁻² yr⁻¹ of no wildfire to 249 gC m⁻² yr⁻¹ with wildfire disturbance (50% of mortality rate) in 1996 (unshown).

3.3. Correlation between the carbon flux simulations and meteorological driving variables

Annual NEE estimates of the model for pine-dominated community were more related to precipitation than that of oak-dominated community (Fig. 5a). Without considering fire disturbance, for example, the correlations between annual NEE predictions and annual precipitation were 0.2850 for pine/scrub oak at Cedar Bridge site and 0.0351 for pine/oak at Fort Dix site, respectively, because vegetation cover at Cedar Bridge site has more pine components than that at Fort Dix site. We simulated annual NEE with hypothetical vegetation scenarios, pure pine or pure oak scenarios, based on Cedar Bridge site (not shown). The correlation coefficient between annual NEE predictions and precipitation increased to 0.5727, while the correlation coefficient between annual precipitation and annual NEE predictions for hypothetical pure oak scenario was –0.22.

For three vegetations types, monthly mean NEE predictions were all significantly associated with temperature. In 2005, correlation coefficients between monthly NEE predictions and

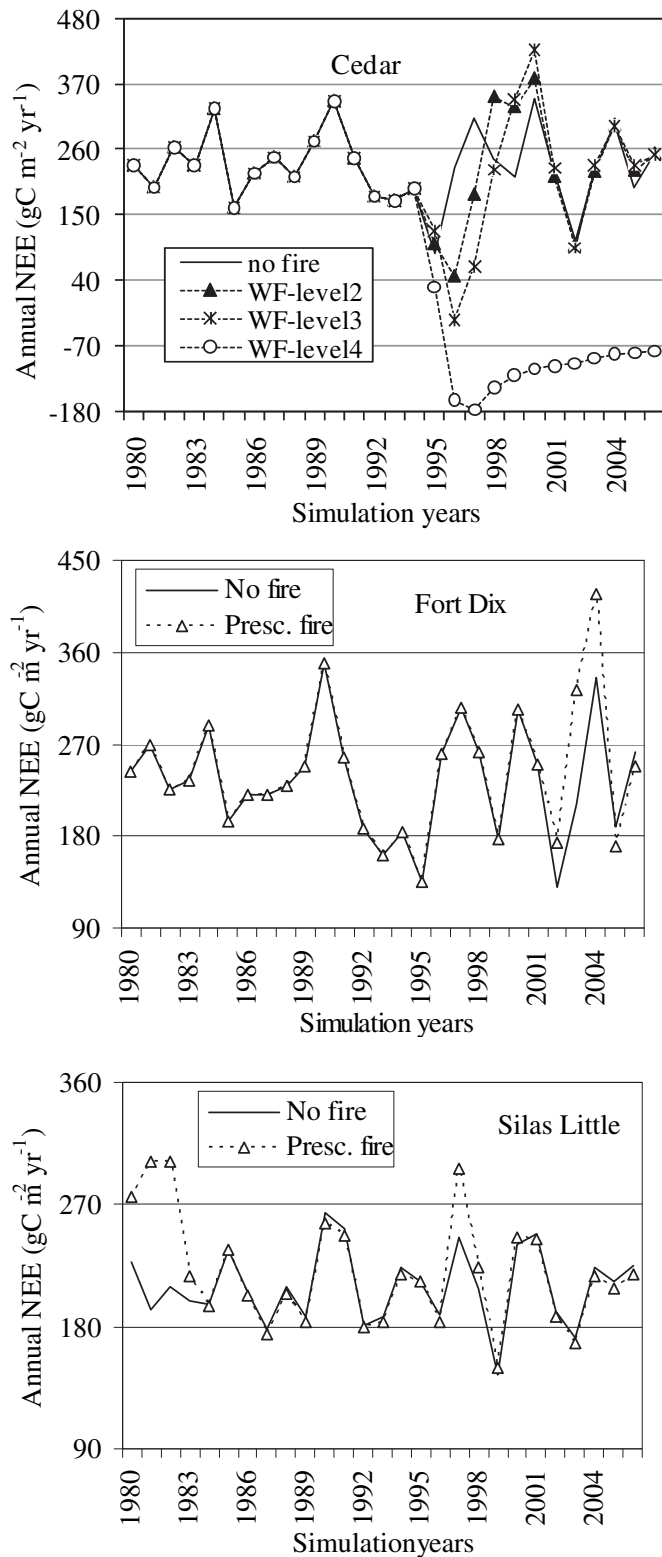


Fig. 3. Fire effects on annual NEE predictions at three tower sites. Note: According to historical record, prescribed burnings occurred in 2002 and 2003 at Fort Dix site, and in 1980, 1981, 1982 and 1997 at Silas Little site, respectively. A wildfire event occurred at Cedar Bridge in 1995. No fire is annual NEE predictions with no-fire scenario, WF-Level2 is annual NEE predictions disturbed by one wildfire event with hypothetical 35% of fire mortality rate, WF-level3 is annual NEE predictions disturbed by one wildfire event with hypothetical 50% of mortality rate, and WF-level4 is annual NEE predictions disturbed by one wildfire event with hypothetical >60% of fire mortality rate.

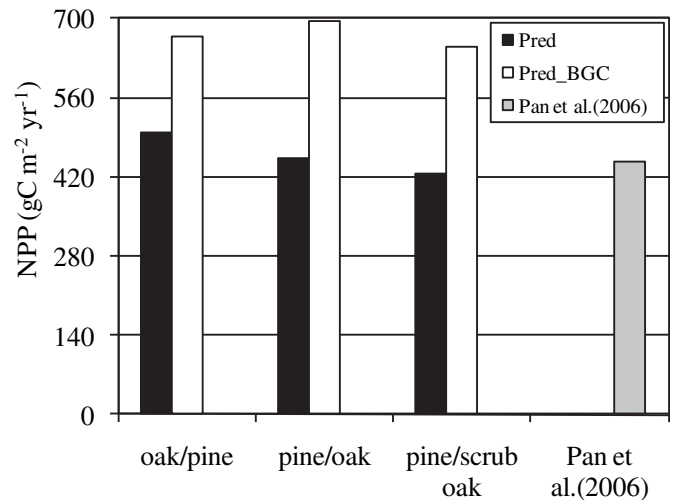


Fig. 4. The WxBGC-predicted vs. FIA-estimated NPP (net primary productivity) for the US New Jersey Pinelands. Pred is annual NPP predictions with our local-derived parameters, Pred_BGC is annual NPP predictions with White et al. (2000)'s Biome-BGC eco-physiological parameters, Pan et al. (2006) is NPP estimates from FIA (Forest inventory data) by Pan et al. (2006).

temperature were 0.8969 for oak/pine at the Silas Little site, 0.4606 for pine/oak at the Fort Dix site, and 0.7449 for pine/scrub oak at the Cedar Bridge site, respectively, which were close to that between eddy covariance measured NEE and temperature, 0.8386 for oak/pine at Silas Little site, 0.7472 for pine/oak at Fort Dix site and 0.8725 for pine/scrub oak at Cedar Bridge site, respectively (Fig. 5b).

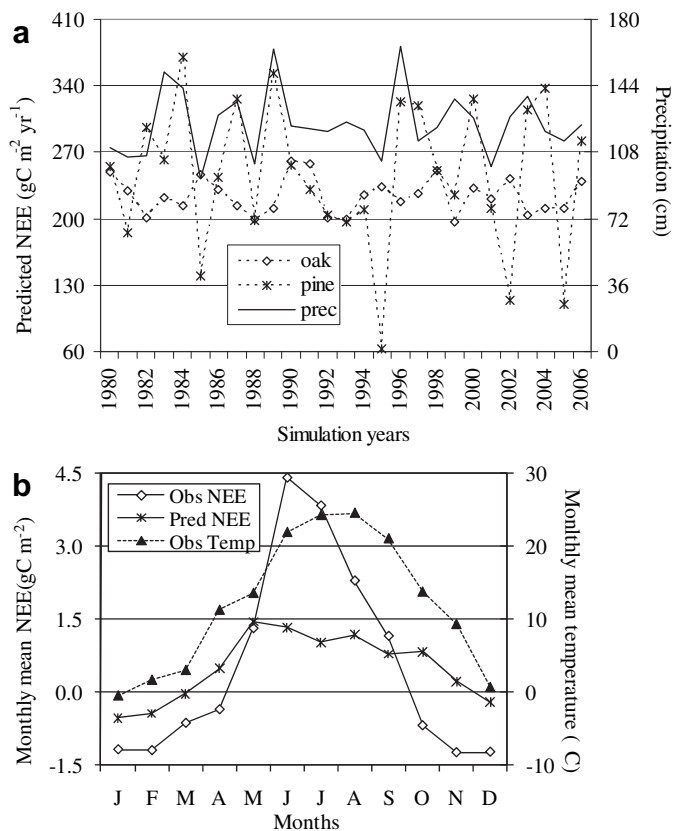


Fig. 5. The relationships between annual precipitation (cm) and predicted NEE for hypothetical pine and oak at Cedar Bridge site (a) and between monthly temperature and 3-site mean predicted and observed NEE with real vegetation type (b).

3.4. Contribution of eco-physiological parameters to prediction of carbon storage and flux

Examination of the results from the EFAST sensitivity analysis revealed that total order sensitivity indexes were higher than the 1st order indices across all the parameters including fire mortality (Fig. 6). In other words, the contributions of interactions among the 11 eco-physiological input parameters were much more significant to the model predictions of carbon storage and flux than that of each individual input parameter (Fig. 6). For example, the 3-site average of total order sensitivity index for the 27-yr mean NEE predictions ranged from 0.0476 for the carbon allocation ratio of new coarse root to new stem (NCRC:NSC) to 0.5884 for the allocation ratio of fine root carbon to leaf carbon (NFRC:NLC), while the 1st order index varied from 0.0004 for PLNR (fraction of leaf N in Rubisco) to 0.0741 for NFRC:NLC (new fine root carbon:new leaf carbon).

As fire mortality rate strongly affected the GPP and total carbon predictions, the allocation ratio of NFRC:NLC and specific leaf area (SLA) were the most important eco-physiological contributors to the NEE and GPP predictions. For example, for the 3-site mean total carbon prediction, the contributions of NFRC:NLC, annual fire mortality rate and specific leaf area were 0.5386, 0.4210 and 0.3058, which were significantly higher than that of other parameters (Fig. 6).

Except for meteorological variables, the eco-physiological inputs played an important role in the inter-annual variations of the carbon storage and flux predictions (i.e., the model inter-annual uncertainty). For example, for the inter-annual coefficient of variations of the 3-site GPP predictions, the contributions of eco-physiological parameters varied from 0.0612 for PLNR to 0.5903 for NFRC:NLC.

3.5. NEE predictions and mapping on the scale of the US New Jersey Pinelands

Fig. 7 displays the NEE distribution in 1997 (DAYMET climate year) across the New Jersey Pinelands. For upland forests of the Pinelands, the 18-yr mean NEE estimate for the pine community was $215 \text{ gC m}^{-2} \text{ yr}^{-1}$. This was higher than the measurements of $201 \text{ gC m}^{-2} \text{ yr}^{-1}$ for upland oak, $194 \text{ gC m}^{-2} \text{ yr}^{-1}$ for upland oak/pine and $207 \text{ gC m}^{-2} \text{ yr}^{-1}$ for upland pine/oak community, respectively. For the wetlands, the mean NEE estimate of cedar swamp was $256 \text{ gC m}^{-2} \text{ yr}^{-1}$, which was higher than that of hardwood swamp, mixed and pine vegetation types, respectively. In the New Jersey Pinelands, annual total NEE predictions were mainly dependent upon the land use area, i.e., the bigger area for a specific vegetation type, the higher total NEE for the vegetation type.

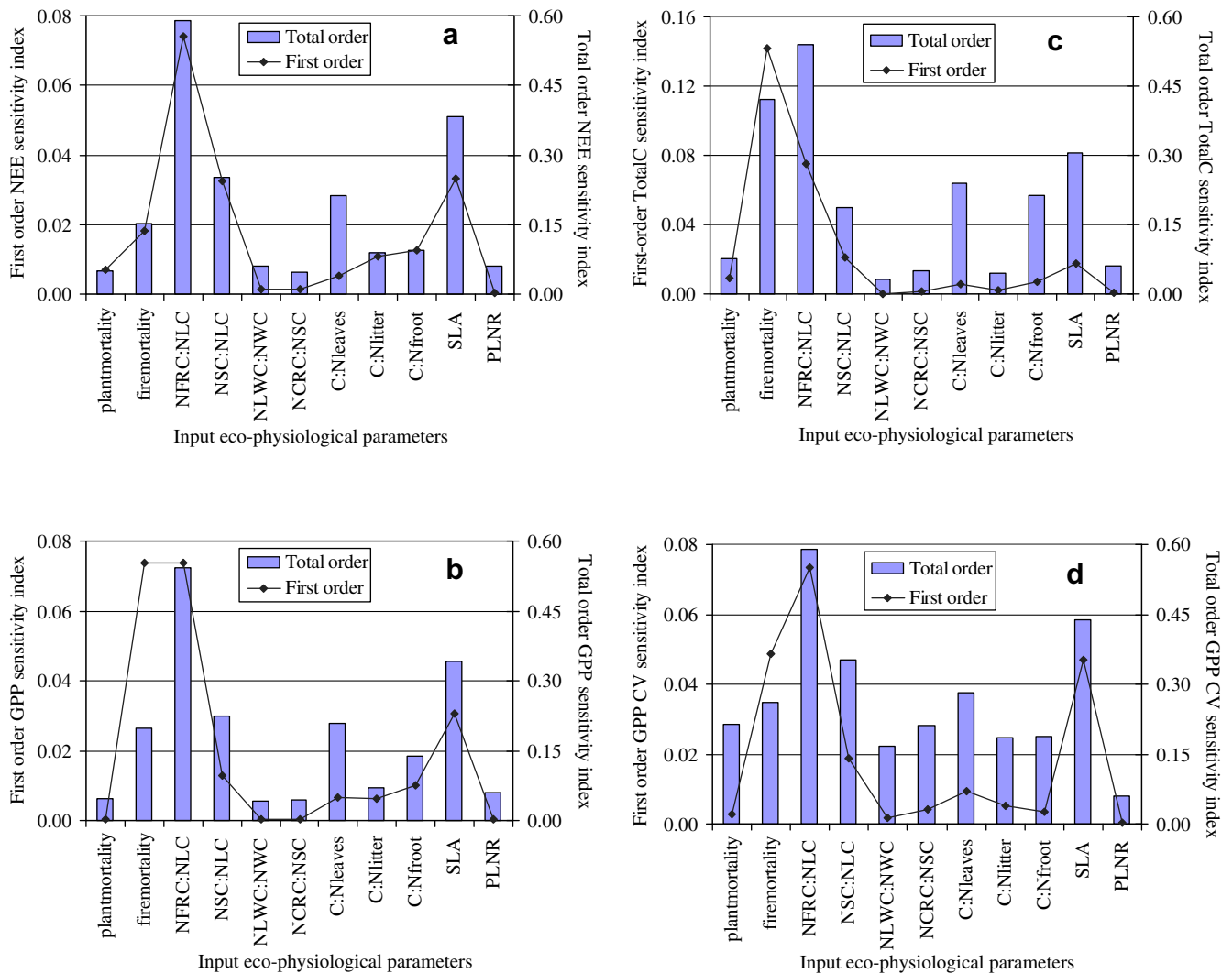


Fig. 6. The 1st and total order contributions of eco-physiological input parameters to annual NEE, NPP, total carbon predictions and GPP coefficient of variations. Parameters abbreviation can be found in Tables 1 and 3.

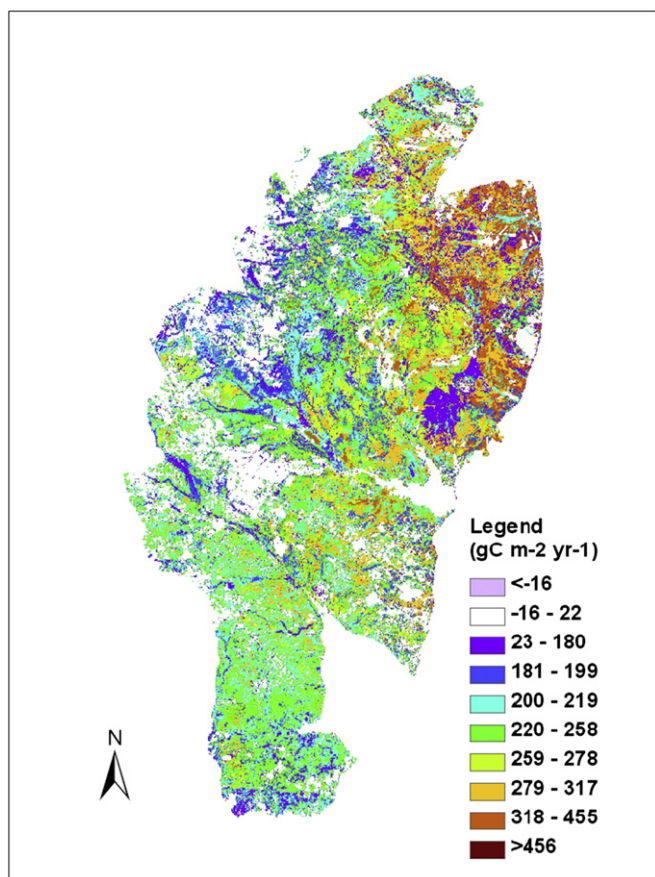


Fig. 7. NEE simulation and mapping on the scale of the New Jersey Pinelands ($\text{gC m}^{-2} \text{yr}^{-1}$).

4. Discussion and conclusions

4.1. Sensitivity of the model carbon dynamics predictions to eco-physiological parameters

As White et al. (2000) pointed out, research on the multi-dimensional interactions among input parameters on the biogeochemical model performance and prediction quality is critically needed. Our results suggest that interactions among the crucial eco-physiological parameters are the major contributors to uncertainty of the WxBGC model carbon simulations. In other words, apart from influences of individual parameters on the carbon dynamic simulations, one parameter may enlarge the contributions of other parameters. Using the EFAST approach to sensitivity analysis, results suggested that the 2nd- and higher-order interactions among the 11 key eco-physiological parameters had much higher contributions to the NEP, GPP and total carbon predictions than the 1st-order (i.e., effects of individual parameter) for the three tower sites (Fig. 6). For example, for the allocation ratio of new fine root carbon to new leaf carbon, the 2nd- and higher-order sensitivity index (i.e., S_i^T (total order sensitivity index) – S_i (the 1st order sensitivity index)) was 0.5143 for the 27-yr mean of NEP, while the 1st order sensitivity index was just 0.0741. These results do not conform to White et al. (2000) study of Biome-BGC which found that main effects (1st order) of individual parameters were statistically more significant than two-way interaction effects (2nd order). Our higher-order sensitivity index were the sum of all sensitivity effects including two- and multiple-way interactions between a specific variable and other variables rather than the

mere two-way interactions effects between every pair of five parameters as in White et al. (2000). Therefore, the total interplay between interactions of 11 parameters, which includes the 2nd and higher order contributions, should be higher than contributions of two-way interactions (merely 2nd order contribution) of five parameters in White et al. (2000). In the New Jersey Pine Barrens area, for instance, the one- or two-growing season's recovery of forest structure dynamics following wildfire showed that the interactions of multiple variables (e.g., forest succession, carbon allocation ratio and soil variables) may have higher impacts on forest ecosystems than the only fire mortality rate (Boerner, 1981; Boerner et al., 1988). In our sensitivity analysis, we did not include maximum stomatal conductance (g_{smax}) as White et al. (2000) did, since stomatal conductance does not play a very significant role in the model simulations as determined by our OAT test of the individual parameters.

As illustrated by our results, there is a great need for locally-relevant parameterizations of the eco-physiological inputs to ecosystem models to reduce the uncertainty in simulating landscape scale carbon dynamics. Several of the crucial eco-physiological parameters are especially problematic as they are difficult and laborious to measure in field or laboratory and are rarely reported in forest literature. In parameterizing carbon allocation, the literature can be mined for information on the distribution of carbon (or biomass) between root, stem, branch and leaf partitions. However, much more difficult to obtain but more relevant is the information on new fine root, new coarse root, new stem, new live wood and new leaf carbon. For example, the NEE and NPP simulations using White et al. (2000)'s Biome-BGC parameters for evergreen needleleaf and deciduous broadleaf forests (ENF and DBF) were significantly higher than the simulations with our locally-derived parameters and eddy covariance measurements (Fig. 4). We attribute this difference in model estimates to the difference in the allocation ratio of new fine root carbon to new leaf carbon and configuration of fire disturbances. We parameterized the allocation ratio of new fine root carbon to new leaf carbon to 1.43 for oak type, while White et al. (2000)'s value is 1.20 for the DBF biome.

Our results from the sensitivity analysis, as well as the model simulations, suggest that the WxBGC forest ecosystem model is very sensitive to specific leaf area. The model simulations showed a big gap between the predicted and measured NEE and the ratios of ecosystem respirations to gross ecosystem productions in 2006, which we attribute to defoliation of both the pine and oak overstory as well as the oak understory, by a major infestation of gypsy moth. Those differences were especially evident at the Fort Dix site which underwent a nearly complete defoliation in 2006 (Table 2) (Clark et al., 2010). As might be expected because the present model simulation did not incorporate temporal dynamic data on leaf area, instead relying on periodic land cover maps, it completely missed the 2006 defoliation event.

4.2. Impacts of fire disturbance on carbon storage and fluxes in the New Jersey Pinelands

The New Jersey Pinelands has long been noted as a fire-dominated landscape with fire frequencies ranging from 5–25 yrs in some of its most fire-prone forest community types (e.g., the dwarf pine plains and pitch pine-scrub oak barrens) (Little, 1979). In such a fire dominated system, fire disturbance could have a major impact on the current and future direction of the forest carbon dynamics through the: (i) combustion of vegetation and soil biomass and release of carbon to atmosphere, (ii) modifying forest stand age distribution and ecosystem succession direction and speed, and (iii) modifying the rate of CO_2 release from soil

microbial decomposition. In this present study, we concentrated on fire direct impacts on forest carbon storage and flux (Law et al., 2001; Thornton et al., 2002) and ignored fire effects on ecosystem succession and soil microbial activity.

The WxBGC simulations demonstrate that wildfire disturbance temporarily reduces both NEE and NPP, while spring prescribed burnings increased NPP and NEE. For example, for oak/pine at Silas Little site where prescribed fire occurred in 1980, 1981, 1982 and 1997, annual NEE predictions are increased by 21%, 56%, 45% and 20% than that of no prescribed fires, respectively. After prescribed burning, it usually takes 1–2 years for the model estimates of annual NEE to gradually decline to those where no prescribed burning has occurred. Hood et al. (2007) and Battaglia et al. (2008) also reported that the success of using prescribed fire to control regeneration density in fuel treatments is strongly dependent upon the frequency and initial time of burning in ponderosa pine (*Pinus ponderosa* (Dougl.) Laws.). An increase of NEE for post prescribed fire has not been observed in the eddy covariance measurements of carbon dynamics pre- vs. post-prescribed fire (Clark et al., 2009). Our modeled increase is mainly due to the assumption that prescribed fires merely burn litter and coarse woody debris (CWD) while only slightly impacting the shrub layer, thus autotrophic and heterotrophic respiration contributed by litter and CWD is greatly reduced while the GPP (from the shrub layer) is only slightly reduced. With a wildfire carbon burning ratio of 35%, annual NEE predictions for the pine/scrub oak community were decreased by 80% and 41% at the first two years after wildfire burning (Fig. 4). Provided that a replacement wildfire disturbance occurred for pine/scrub oak at Cedar Bridge in 1995 with carbon burning proportion of above 60% (i.e., fire carbon burning rate), annual NEE predictions were negative from 1995 to 2006. In other words, if vegetation canopy is completely burned by replacement wildfire, there will be no carbon assimilation rather respiration from coarse woody debris, litter and soil will continue and annual NEE will be less than or equal to zero in the terrestrial ecosystems until new plants sprout and re-grow. In this study, we fixed a wildfire carbon combustion loss rate for all forest carbon components and did not take into account different combustion rates for different forest components (i.e., foliage, stem, litter, CWD, root, etc.). The model did not consider the change in plant carbon allocation ratio after fire either. In reality, wildfires are known to burn different forest components unevenly as well as change plant carbon allocation ratio post-burning (Little, 1979; Clark et al., 2009). For example, Clark et al. (2009, 2010) noted that during the Warren Grove wildfire in our New Jersey Pinelands study area, the combustion loss rate of understory carbon was significantly higher than that of the overstory carbon. To improve the accuracy and reliability of post-fire simulation of Pinelands carbon dynamics, improved parameterization based on a wider range of field measured fire disturbance intensity impacts, e.g., carbon combustion loss rate of different forest components and fire effects on forest carbon allocation ratio, are needed. Further model improvement and simulations of the long-term effects of fire disturbance on soil microbial activity and ecosystem successions should be addressed in the future.

Comparing the improved WxBGC model tool to Biome-BGC version 4.1.2 for ENF and DBF (White et al., 2000), we found that the way the Biome-BGC model included continuous and homogenous prescribed or wildfire disturbance led to significantly reduced annual NEE estimates. These lower NEE estimates are due to the way the model burns carbon at every time step at every pixel with a specific disturbance intensity, even when the fire intensity parameter is set to a small value. In lieu of this approach, we coupled stochastic and spatially heterogeneous fire disturbances into the model for improved treatment at the landscape level. Our WxBGC model result corroborates previous studies which have

suggested that disturbance type, intensity, frequency and time since disturbance all exert significant impacts on the net ecosystem exchange of forest carbon and that a forest stand will commonly act as a source of carbon to the atmosphere until respiration from decomposers become less than photosynthetic uptake from regrowing vegetation (Law et al., 2001; Thornton et al., 2002; Goward et al., 2008; Zinck et al., 2010).

4.3. NEE prediction gradients of the US New Jersey Pinelands

The WxBGC model was used to predict and map NEE across the entire Pinelands study area (Fig. 7). Visual examination reveals a high degree of spatial heterogeneity in NEE which are driven by land cover, soil properties and climate of the Pinelands. NEE was estimated to be generally higher for wetland as compared to upland forest community types. In addition to the fine scale upland vs. wetland variation, there was subtler between-community differences. Uplands NEE predictions were ranked with pine > pine/oak > oak/pine > oak > shrub > grass. Wetlands NEE predictions were generally ranked with cedar swamp > lowland pine > mixed hardwood community (white cedar/pine/American holly) > hardwood swamp. Further field eddy covariance measurements of wetlands forests are required to better calibrate the model prediction of wetlands carbon dynamics. Coarser scale geographic gradients are also evident as a result of regional scale trends in soil characteristics and climate that also interact with vegetation community composition differences. For example, the northeastern quadrant of the study area is largely dominated by pine and the model suggests that the pine-dominated community is sensitive to annual precipitation. Higher soil moisture and precipitation in this portion of the study area result in a higher estimate of NEE. Further field measurements are needed to validate these results.

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