Background Paper

ESTIMATING CARBON DYNAMICS IN THE TROPICAL SEMI-DECIDUOUS FOREST OF THE YUCATAN PENINSULA

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Acronyms and Abbreviations

AGB	simulated mean aboveground biomass
Amax	maximum leaf-level photosynthetic rate (µmol CO_2 g^{-1} leaf s^{-1}); parameters AmaxA, AmaxB:
AmaxA	intercept of relationship between foliar N and maximum photosynthesis
AmaxB	slope of linear relationship between foliar N and maximum photosynthesis
AmaxFrac	daily averaged Amax
Biome-BCF	BioGeochemical Cycles model simulates NPP for multiple biomes-
C	carbon
C reserve fraction	C fraction reserved by the plant after bud allocation
CO_2	carbon dioxide
DBH	diameter at breast height
ΔLitter	change in organic carbon on forest floor
ΔOCMS	change in organic carbon in mineral soil
ΔSOC	change in soil organic carbon
DVPD1, DVPD2	Coefficients for power function that convert vapor pressure deficit (VPD, in kpa) to fractional loss in photosynthesis
E	forest performance efficiency in stockpiling carbon
Forest-DNDC	Forest DeNitrification-DeComposition model
Gg	gigagrams (10^3 megagrams)
ha	hectares
InTEC	an Integrated Terrestrial Ecosystem C-budget model
LAI	leaf area index
Leaf End TDD	Accumulative thermal degree-days for ending leaf growth
Leaf Start TDD	Accumulative thermal degree-days for starting leaf growth
Mg	megagrams (10^6 grams)
MRV	monitoring, reporting, and verification
N	nitrogen
NBP	net biome productivity (= NEP at regional or global scales)
NEE	net ecosystem exchange
NEP	net ecosystem production (the net carbon accumulation by ecosystems)
NPP	net primary production
OCMS	organic carbon in mineral soil

REDD	Reducing Deforestation and Forest Degradation
RespQ10	Q_{10} value for foliar respiration
RootMRespFrac	Ratio of fine root maintenance respiration to fine root biomass production
VPD	vapor pressure deficit
Wood End TDD	Accumulative thermal degree-days for ending wood growth
WoodMRespFrac	Wood maintenance respiration as a fraction of wood biomass production
Wood Start TDD	Accumulative thermal degree-days for starting wood growth

Abstract

Modeling carbon (C) in Mexican forest ecosystems using process-based models is an important contribution to a methodology and protocol for assessing North American forest carbon dynamics, sponsored by the Commission for Environmental Cooperation and carried out by the Forest Services of Canada, USA, and Mexico, and their partner organizations. Phase one of this project emphasized improving monitoring, reporting, and verification (MRV) for Reducing Deforestation and Forest Degradation (REDD) in Mexico. Three models (four versions), Biome-BGC or WxBGC, InTEC and Forest-DNDC, were reviewed for further testing to identify one or two models for this phase of the project. Based on the availability of data to run the models, we selected Forest-DNDC and Biome-BGC and then tested their performance using observations from forest sample plots at Kaxil Kiuic in Yucatan Peninsula, Merida, Mexico. Model testing showed that both Biome-BGC and Forest-DNDC can be used to assess C stocks in the tropical semi-deciduous forest based on the results from four model-evaluation variables. The performance efficiency of Forest-DNDC ($0.79 \leq E \leq 0.88$) was higher than that of Biome-BGC ($0.40 \leq E \leq 0.54$), and Forest-DNDC had smaller errors in C stocks in stands and soils than Biome-BGC based on the comparison of observation and simulation. There is substantial spatial variability in C stocks in the forest, ranging from 5.0 to 115.0 Mg C ha^{-1} in 2012, with a mean of 56.6 Mg C ha^{-1} based on the field observations and the simulations using polygons converted from 30 m resolution maps. The aboveground biomass, net primary production (NPP), net ecosystem exchange (NEE) and net ecosystem production (NEP) increased or decreased non-linearly with an increase in the stand age. There are differences in the spatial distributions of NPP, NEE and NEP, associated with vegetation distribution, including stand age and species, and NEP is also related to soils. Soil CO_2 and N_2O fluxes are also highly variable spatially due to soil and vegetation characteristics. The C stocks in this forest were highly sensitive to disturbances. The aboveground biomass decreased by about 73 Gg C (59.9 Mg C ha^{-1}) due to a small loss of the forestland in this area from clearing for agriculture and urbanization from 1985 to 2010.

Keywords: modeling carbon dynamics, Northern America, Mexico, process-based model

Executive Summary

Modeling carbon (C) in Mexican forest ecosystems using process-based models is an important contribution to a methodology and protocol for assessing North American forest carbon dynamics. Phase one of the project, *Ecosystem Carbon Sources and Storage: Information to Quantify and Manage for Greenhouse Gas Emissions Reductions,* supported by the Commission for Environmental Cooperation and carried out by the Forest Services of Canada, Mexico, and the United States and their partner organizations, emphasized improving monitoring, reporting, and verification (MRV) for Reducing Deforestation and Forest Degradation (REDD) in Mexico. As part of the project, three models, Biome-BGC or WxBGC, InTEC and Forest-DNDC, were reviewed to identify one or two models to test during this phase of the project. Based on the availability of data to run the models, the Forest-DNDC and Biome-BGC models were selected and tested using observations from forest sample plots at Kaxil Kiuic in Yucatan Peninsula, Merida, Mexico.

Model testing showed that both Biome-BGC and Forest-DNDC can be used to assess C stocks in the tropical semi-deciduous forest based on the results from four model-evaluation variables. The performance efficiency of Forest-DNDC ($0.79 \leq E \leq 0.88$) was higher than that of Biome-BGC ($0.40 \leq E \leq 0.54$), and Forest-DNDC had smaller errors in C stocks in stands and soils than Biome-BGC based on the comparison of observation and simulation. There is substantial spatial variability in C stocks in the forest, ranging from 5.0 to 115.0 Mg C ha^{-1} in 2012, with a mean of 56.6 Mg C ha^{-1}, based on the field observations and the simulations using polygons converted from 30 m resolution maps. The aboveground biomass, net primary production (NPP), net ecosystem exchange (NEE) and net ecosystem production (NEP) increased or decreased non-linearly with an increase in the stand age. There are differences in the spatial distributions of NPP, NEE and NEP, associated with vegetation distribution, including stand age and species, and NEP is also related to soils. Soil CO_2 and N_2O fluxes are also highly variable spatially due to soil and vegetation characteristics.

The C stocks in this forest were highly sensitive to disturbances. The aboveground biomass decreased by about 73 Gg C (59.9 Mg C ha^{-1}) due to a small loss of the forestland from clearing for agriculture and urbanization from 1985 to 2010 within this area.

The study showed that process-based models can perform better than non-process-based models for estimating C dynamics in the tropical semi-deciduous forest at Kaxil Kiuic in Yucatan Peninsula, Mexico. However, the process-based models need large and reliable datasets, including climate, soil and vegetation (species/cover type and stand age), for model setup and parameterization. Most non-process-based models need a large number of onsite observations to produce empirical relationships to build the prediction function. Generally, spatial measurements for large regions, such as nationwide or continent-wide, are time and finance consuming, or impossible. Accordingly, process-based models are more effective tools for estimating spatial C stocks. However, there are inadequate data to support the accurate C estimations elsewhere using those tools at present, in which the spatial stand age is the most important because all categories of models need stand age as their inputs. Although data have been obtained from inventories and other technologies and methods which may be used to develop a credible stand-age map, an effective method is needed to develop the spatial stand age using various existing spatial data.

Introduction

Modeling carbon dynamics in Mexican forest ecosystems is important for the assessment of long-term carbon dynamics and climate change mitigation in Mexico and North America. Geographically, Mexico is mainly located in Northern Tropical Zone. However, the forest types range from subtropical to tropical due to the changes in latitude and elevation. Plant species diversity is very high, and ranges from deciduous to evergreen, dry to wet, and subtropical to tropical plants. The impact of human activities on forests is large because of a long history of human residence in Mexico. Accordingly, estimating carbon dynamics in Mexican forest ecosystems is not only highly valuable to assess the role of those forests in mitigation of global warming, but also useful to understand the impacts of human activities on forest ecosystems.

The carbon production and consumption in forest ecosystems can be represented by using CO_2 flux measurements. Recent development and applications of eddy flux measurement technology reflect these metrics (Baldocchi 2003; Hutley et al. 2005; Barr et al. 2006; Oren et al. 2006; Kurbatova, et al. 2008). However, CO_2 fluxes are highly impacted by changing environmental factors, including topography, climate, hydrology, soil, vegetation and various disturbances (Pietch et al. 2003; He et al. 2005; Pacific et al. 2009). Therefore, there are large uncertainties in the flux estimation using this technology due to large differences in environmental conditions and inadequate equipment to cover large enough regions to do the assessments.

Although C sequestration in forests is very important for human beings, it is impossible to conduct intensive inventories everywhere to know carbon stocks and long-term carbon dynamics in forests at high spatial resolution in large regions, such as nation- or continent-wide forests, because of limitations in personnel, equipment, funds and complex environmental conditions. National forest inventories may cover large geographic areas by sampling only a very small percentage of the land. However, we can simulate carbon dynamics everywhere by means of computer models developed from expert knowledge, long-term experiences, and observations. Recent applications of biogeochemical process models for assessing forest responses to land use change and disturbances reflect their merits (Chen et al. 2003; Hanson et al. 2004; Miehle et al. 2006; Mo et al. 2008; Hlasny et al. 2011; Miao et al. 2011; He et al. 2012; Dai et al. 2013). Accordingly, application of these tools is fundamental to effective assessment of carbon stocks and long-term dynamics for forest management, restoration, and evaluating responses to various disturbances, such as hurricanes, wild and prescribed fires, insects, and deforestations.

Many C models (e.g., MAESTRO, Wang and Jarvis 1990; BIOME-BGC, Thornton et al. 2002) have been assessed to simulate C dynamics in forest ecosystems. Miehle et al. (2006) compared the performance of five forest C models (i.e., 3-PG, Landsberg and Waring 1997; BIOMASS, Hingston et al. 1998; CABALA, Battaglia et al. 2004; Forest-DNDC, Li et al. 2000; PROMOD, Battaglia and Sands 1997) using observations from 93 plantations across southeastern Australia. Their results showed that these models performed reasonably well for predicting forest C accumulation in forests. However, some models, such as CABALA and Forest-DNDC, can perform better than others based on model performance efficiency. Hanson et al. (2004) compared the performance of thirteen C models, showing that there were substantial differences in model performance efficiency ($-\infty<E\leq1$), ranged from -0.17 to 0.73, for daily net ecosystem exchange (NEE) in the period from 1995 to 1998 in Oak Ridge forest in Tennessee, USA. These differences in model performance are related to their modeling scales and their structural features. Most of existing C models are applied at field (point) scales utilizing the physical and biogeochemical average conditions of the target study sites. Therefore, large errors can be produced by using field-scale models for large catchments or regions with heterogeneous physical and biogeochemical

characteristics in space and time, especially for those landscapes consisting of mosaics of different species, hills and flats, uplands and wetlands. Therefore, simple models, such as empirical (lumped) models, are not satisfactory for estimating C sequestration for large forest landscapes with spatiotemporally heterogeneous physiochemical characteristics.

This study aimed to select one or two process-based models and test the selected models to determine whether they could be used to estimate carbon dynamics in Mexican forests. In order to select some models with potentially good performance, we evaluated some currently popular C models, based on their published descriptions and results at first, and then tested a few selected models using observations of biomass, climate and soils at Kaxil Kiuic in Yucatan Peninsula, Mexico, in order to choose one or two models that would be satisfactory for simulating C dynamics in Mexico.

1 Assessment of Available Models

Ecosystem models can be classified into three categories: empirical (lumped), process-based and mixed with both empirical and process-based (Dai et al. 2010). There is a substantial difference in treatment of processes among the categories. The process-based models do not use any empirical functions or curves produced by using observations from the target study sites, and theoretically, can be applied elsewhere without calibrations and validations using field observations, although observations are usually needed to test the models to determine whether they are performing well. This testing method is generally called model validation. In contrast, empirical models do not work well without observations from the target study sites because they need the onsite measurements to obtain empirical coefficients or relationships that are suitable for the specific study sites where the measurements were conducted, and/or for those forest environments that are similar to the measured forests.

Models are also different in spatial representation of forest landscapes. Spatially explicit representation of a landscape is an important feature of biogeochemical models used to simulate the effects of natural and/or anthropogenic disturbances on forests, especially for those models used to assess the effects on forests in large regions with complex physiochemical characteristics. However, most models are neither fully process-based, nor spatially explicit at present. Accordingly, some criteria are needed to determinate which models are proper and satisfactory for our needs. Some key criteria are given in **Table 1**.

To successfully simulate carbon dynamics in forest ecosystems in Mexico and obtain satisfactory results from the models, we reviewed 34 carbon models (**Table 2**) to determine our options for this project and related projects in the future. Most models presented in Table 2 are not spatially explicit, which can be problematic for assessing carbon dynamics in nationwide forests in Mexico. This is because of complicated climatic and geophysical conditions, and substantial differences in hydrogeological characteristics, even if the assessment is only conducted for a small landscape of several square kilometers with high plant species diversity and mosaics of mountains, hills, flats, uplands, and wetlands.

Table 1. Model Evaluation Criteria

Criterion	Description
Spatial explicitness	Spatially explicit models can employ eco-physiochemical characteristics of study sites in space and time such that they can be used for large regions; non-spatially explicit models can only use the average of the spatial bio-physiochemical characteristics of the study site.
Model complexity	Although the high model complexity can be better, there are high

	demands in data inputs and learning curve is difficult. A proper data demand and simple learning curve are important for users. However, the model must be qualified to do a good job for our project.
Key processes	The model can effectively represent the key processes that govern ecosystem responses to changes in environmental conditions in Mexico, at least.
Disturbance	The model can be linked to different disturbance data, such as remote sensing or other sources of mapped information.
Model performance	Good model performance is important for an accurate estimate of carbon stocks and long-term dynamics.
Outputs	Model outputs have to be satisfactory for the project demands.

Table 2. Model Candidates for Selection*

No	Model	Reference
1	3-PG	Landsberg and Waring 1997
2	BIOMASS	Hingston et al. 1998
3	Biome-BGC	Thornton et al. 2002
4	CABALA	Battaglia et al. 2004
5	CAMFor	Richards and Evans 2000
6	CANDY	Franko et al. 1995
7	CANOAK	Baldocchi et al. 2002
8	CENTURY	Parton et al. 1993
9	CN-SIM	Petersen et al. 2005
10	CO2FIX	Mohren et al. 1999
11	DAISY	Hansen et al. 1991
12	Forest-DNDC	Li et al. 2000; Stange et al. 2000
13	EALCO	Wang et al. 2002a, b
14	ECOSYS	Grant et al. 2000
15	InTEC	Chen et al. 2003; He et al. 2012
16	INTRASTAND	Harley et al. 1995
17	ITE	Thornley 1991
18	LaRS	Amthor et al. 1994
19	LINKAGES	Wullschleger et al. 2003
20	LoTEC	King et al. 1997
21	LPJ	Prentice et al. 2000
22	MAESTRA	Wang and Jarvis 1990
23	MBLGEM	Perruchoud and Fischlin 1995
24	NCSOIL	Molina et al. 1983
25	NuCM	Johnson and Lindberg 1992
26	PnET	Aber and Federer 1992
27	PROMOD	Battaglia and Sands 1997
28	QSOIL	Bosatta and Agren 1985

29	ROTHC	Jenkinson et al. 1991
30	SOMM	Chertov et al. 1997
31	SPA	Williams et al. 1996
32	STANDCARB	Harmon and Marks 2002
33	VVV	Verberne 1992
34	WMEM	Cao et al. 1996

*References: J. Landsberg 2003; Hanson et al. 2004.

We selected three models (**Table 3**) for further comparison and testing using observations at Kaxil Kiuic in Yucatan Peninsula, Merida: Biome-BGC, Forest-DNDC and InTEC. Table 3 presents the structure of the three models and their applicability in space and time, their demand for modeling inputs, output capacity, and main modeling processes for assessing carbon dynamics in forest ecosystems.

There are significant differences among the three selected models, although they can all be used to simulate carbon dynamics in forest ecosystems based on their publications. The differences principally involve how the models treat biogeochemical processes and the data that are necessary for model setup (Table 3). Biome-BGC/WxBGC and Forest-DNDC do not need any empirical coefficients or curves derived from onsite observations for simulating plant growth because they are fully process-based. However, the InTEC model needs an empirical relationship between net primary production (NPP) and stand age obtained from the target study regions. Accordingly, InTEC can empirically address the effects of environmental changes, including climate, soil and disturbances, on C dynamics. With enough measured NPP data from the target forest, the model can predict C stocks because the empirical relationship from the forest reflects plant growth. InTEC can be used for large regions but it is highly dependent on reliable NPP data.

Biome-BGC and Forest-DNDC simulate plant growth by simulating photosynthesis using phenological data, and soil and climate conditions. However, that means these two models require species-specific phenological data. Accordingly, there can be large errors in assessing C stocks if the phenological data are unreliable.

Biome-BGC uses a big-leaf model to simulate the photosynthetic process. Accordingly, the vegetation is considered as one layer, with an average canopy condition. However, Biome-BGC is usually set up to model different plant functional types and allow representation of the general difference in plant species' composition. Forest-DNDC employs three vegetation layers, over-story, understory and ground-growth, and the canopies of the over-story and understory are also divided into different layers. Forest-DNDC considers the differences not only in species, but also in changing radiation with the alteration in canopy depth. However, the model needs more running time to complete the photosynthetic simulation.

Table 3. Comparison of the Structure and Main Modeling Processes of the Selected Models

Process \ Model	InTEC	BGC	Forest-DNDC
Spatially explicit	Yes	Yes (WxBGC) No (Biome-BGC)	Yes
Biomass	Yes (one layer)	Yes (two layers)	Yes (three layers)
Time step	Monthly	Daily	Daily
Process for C in stands	Half Process-based*	Process-based	Process-based
Process for soil	Yes, single layer	Yes, single layer	Yes, usually1-30 layers, max=100

Evapotranspiration	No	Yes	Yes
Growth model	Empirical	Big-leaf	Layered
Disturbance & management	Fire and insects	Fire (average impact)	Event-based management, including prescribed burning, planting, harvesting, thinning, and drainage control for wetland forests, hurricanes
Process for hydrology	No	Yes (simplified, only for uplands)	Yes (simplified, only for uplands)
Important processes for outputs	C stocks in main forest components, soil carbon dynamics	C stocks, NPP, NBP, LAI, ET, carbon in soils, and runoff	Biomass in different vegetation layers, carbon in soil and forest floor, GHG, hydrology, and physiochemical soil properties

*: An empirical curve is needed for modeling carbon dynamics in regional forest ecosystems using on-site observations; GHG is greenhouse gas.

There are also differences in the way different models treat soil biogeochemical processes. Both Biome-BGC and InTEC use a single-layer soil model, like most forest models; thus, both simulate soil processes using mean soil properties of the study sites, including simulating water movement and organic matter decomposition in soils. Forest-DNDC divides the soil profile into multiple (1–100) layers, depending on soil depth and physiochemical properties—30 layers are usually used if the soil depth exceeds 30 cm. About half of the Forest-DNDC running time is because of the soil subroutine, which requires hourly simulations of the C and nitrogen (N) dynamics in each of the soil layers. Thus, the detailed emphasis on soil processes in Forest DNDC is also its greatest weakness, since long computing time is needed to simulate C and N in soils.

The required spatial input data (**Table 4**) differ among the models—binary (GIS format) data for InTEC and WxBGC, and ASCII for Forest-DNDC and Biome-BGC. Accordingly, the preparation of these input files for running Forest-DNDC and Biome-BGC is time consuming because GIS map data cannot be directly used by Forest-DNDC and Biome-BGC; it must be converted from polygon or grid to ASCII. There are some differences in necessary input parameters among the three models. Phenological data are not required for InTEC, but are necessary for the Biome-BGC and Forest-DNDC models. Obtaining phenological data for all species in the study areas can be difficult, especially in tropical forests with high species' diversity (except for plantations). Complex (synthetic) phenological datasets are, therefore, needed for modeling C dynamics in these tropical forests.

Table 4. Differences in Model Data Requirements for Modeling C Forest Dynamics

Parameters/char	BGC	InTEC	Forest-DNDC
Location and topography	Latitude, longitude, Elevation, slopes, daytime hours	Latitude, longitude, DEM, GHG,	Simulation cells, latitude for each cell

Climate data	Maximum, minimum and daytime mean temperature, Precipitation; Offset of climatic parameters (daily)	Evapotranspiration, mean temperature, precipitation, solar radiation (monthly)	Maximum and minimum temperature, precipitation (daily)
Atmospheric parameters	CO_2, N deposition, Albedo, solar radiation, vapor pressure deficit or actual vapor pressure	N deposition, CO_2	CO_2, N deposition, solar radiation (option)
Soil	Depth, texture, moisture, N and C content in different soil organic matter components (litter and mineral soil respectively)	Texture, carbon in different soil organic matter components, available water capacity	Depth, texture, layers, hydraulic conductivity; soil porosity, field capacity and wilting point, N, and C content in different soil organic matter components (litter and mineral soil)
Vegetation	Species/cover-type-based initial biomass, phenology (difference in species, and between C3 or C4 plants)	Cover type-based NPP, Age, LAI, vegetation continuous field, cover proportion, carbon stock table, plant traits info, cover type	Species/cover-type-based, initial age and biomass in different stories (over-story, understory and ground), and phenology
Hydrology	N/A	N/A	Water table needed only for wetlands
Scale	Field/ point scale (Biome-BGC), Spatial (WxBGC)	Spatial	Spatial
Disturbance	Fire (average)	Fire, insect, hurricane? management? (depending on NPP and LAI data)	Wild and prescribed fires, thinning, planting, harvest, hurricane (driven by events)
Time-step	Daily	Monthly	Daily
Learning curve	Easy (Biome-BGC), moderate (WxBGC)	Moderate	Easy to moderate

Other necessary parameters, such as leaf area index (LAI), solar radiation (SR) and vapor pressure (VP), are necessary for InTEC and Biome-BGC, not for Forest-DNDC. Although a good dataset of LAI can be obtained from existing spatial databases such as MODIS, it is difficult to obtain good datasets of SR and VP because there are often not enough meteorological observation data to calculate these values, and SR and VP are highly variable in space and time.

2 Testing Selected Models

Based on our evaluation of models, we selected two for further testing: the biogeochemical Forest-DNDC model (Li et al. 2000; Stange et al. 2000) with a spatially explicit modeling approach (Dai et al. 2012), and the point model Biome-BGC (White et al. 2000; Thornton et al. 2002). We decided not to test the InTEC model at present because much of the required empirical data are unavailable for creating the spatial relationship between NPP and stand age. Likewise, WxBGC was not tested because spatial map data are unavailable. In future work we will consider these models as the required data become more available.

2.1 Site Description

The site used to evaluate the models is a tropical semi-deciduous forested landscape located at Kaxil Kiuic in the Yucatan Peninsula, near Merida, Mexico, between 20.02°–20.16°N and 89.60°–89.39°W (**Figure 1**), comprised of forestlands, scattered croplands (about 5.35%) and urban areas (about 0.75%) at present (**Figure 2**). Historically, this area has seen slash-and-burn agricultural use for at least one thousand years (Hernandez-Stefanoni et al. 2011; Dupuy et al. 2012). The current forest is secondary regrowth after the abandonment of croplands and the prior deforestation.

Figure 1. Kaxil Kiuic forest in Yucatan Peninsula, Merida, Mexico

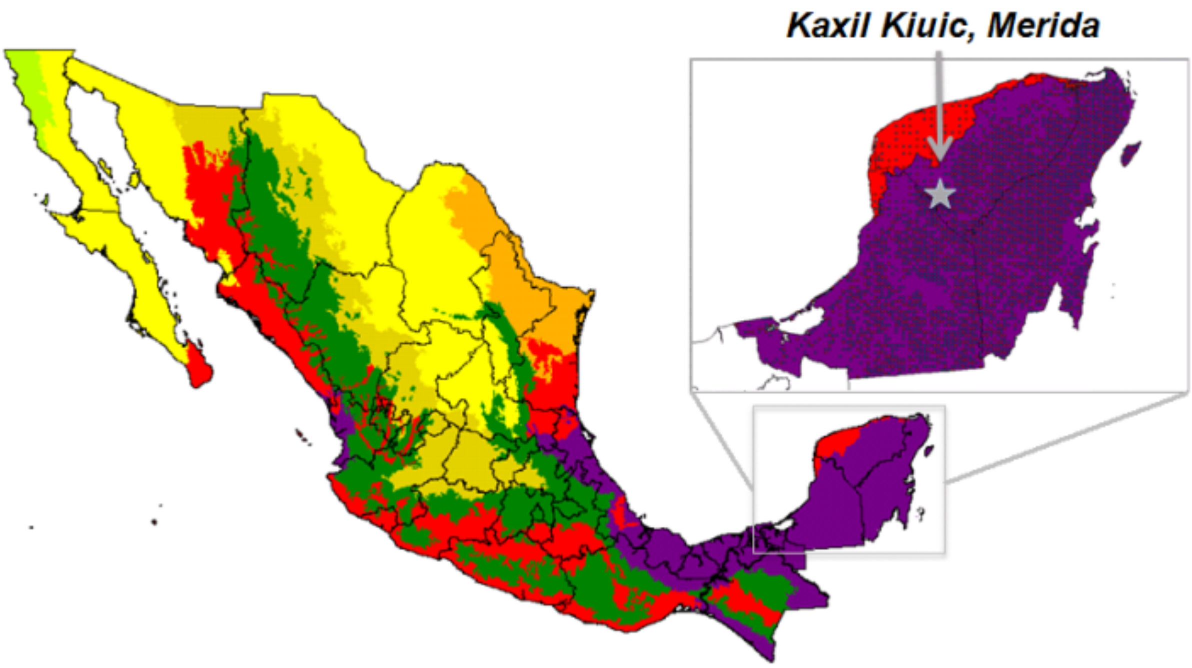
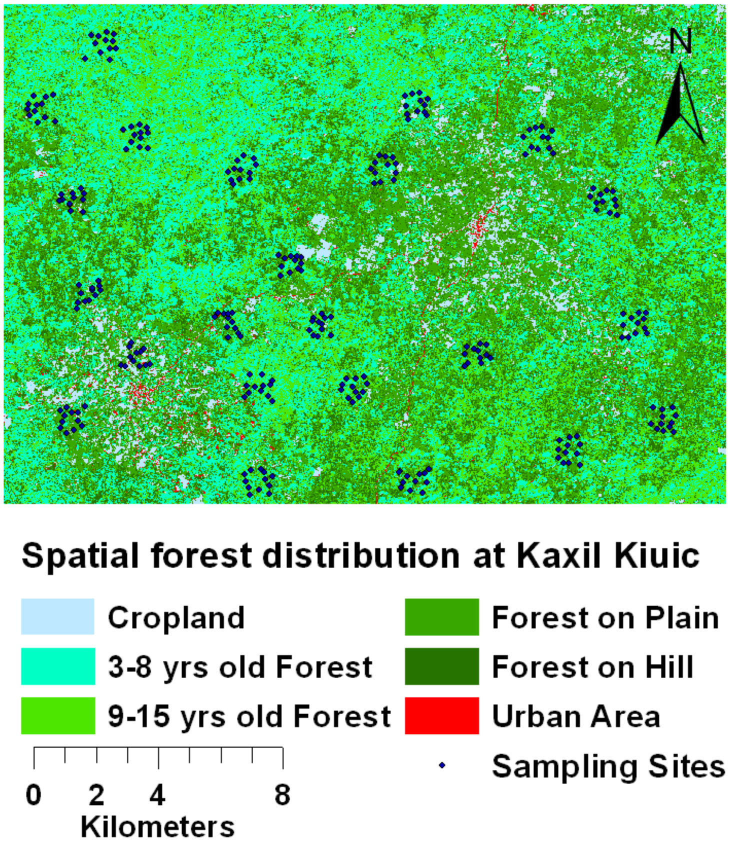


Figure 2. Biomass and Soil Observation Sites and Vegetation Distribution in 2004



Note: Derived from a SPOT-5 satellite image of January 2005 (Hernandez-Stefanoni et al. 2011) [yrs=years]

The landscape mainly consists of mosaics of low and moderate hills with small flat areas. The slope alters between 0 and 90%, with an average slope of 7%. The elevation varies from 0 to 176 m above mean sea level; the mean is 116 m. The climate is tropical, with a summer rain period from June-October and a prominent dry season between November and April. The mean annual precipitation is about 1190 mm during the 38-year period from 1970 to 2007, based on climate data observed at five weather stations around the forest, downloaded from Mexico meteorological network database. The mean temperature is 26.5° in this 38-year period.

The soil developed on limestone and is approximately neutral; pH is between 5.48 and 7.84 with mean pH 7.22. Clay content varies considerably, ranging from 20.68 to 84.0% in rock-free soil, with a mean of 49.0%. The main soil types range from sandy clay to clay but a few soils are loam. The stone content in most soils is high and rock-free soil is rare in this region with rock content between 0 and 90% and an average of 29%. Soil organic matter (SOM) alters from 2.5 to 72.0% in rock-free soil, with a mean of 23%. Because of the specific hydrogeological environment of limestone bedrock as the soil parent material and a tropical climate, the soil layer is thin and stony so that drainage systems have not developed in this area and soil water movement is mainly vertical.

Vegetation in the forest is naturally regenerated either after deforestation or cropland abandonment. Most trees were 7–74 years old in 2012, based on the inventory conducted in 2008–2009 (Hernandez-Stefanoni et al. 2011). The mean age was 27. The canopy is relatively low, with a main canopy 8–13 m in height and occasional emergent trees exceeding 13 m only in some relatively rare old forest plots (>50 years) (Hernandez-Stefanoni et al. 2011). However, the stem density is largely different from place to place;

stems of woody plants ≥1 cm in DBH (diameter at breast height) numbered about 2,550–24,550 individuals per hectare, with a mean of 11,165 trees ha^{-1} in 2008–2009, in which the trees >5 cm in DBH were 0–4,950 per hectare, with an average of 1,654 stems ha^{-1}, and trees 1–5 cm (1≤DBH≤5 cm) were 1,400–24,000 per hectare, with a mean of 9,511. Plant species' diversity in this area is relatively rich, although the richness may be lower than in humid tropical forests in Mexico. There were 123 species of trees >5 cm DBH, compared to 41 species of trees 1–5 cm DBH in 2008–2009.

2.2 Field Measurements and Data Collection

Wood biomass was measured using 276 circular plots in this study, whose catchment superficie (**Figure 2**) measured about 330 km^2. Twenty-three landscape units were delineated to measure the biomass and collect soil samples for the entire site. The size of each landscape unit measured about 1 km^2 and, in each, twelve plots of 200 m^2 were designated for collecting soil samples, measuring tree height (TH, m) and estimating the biomass for trees with diameter at breast height (DBH, cm) greater than 5 cm. Within the 200 m^2 plots, a 50 m^2 subplot was marked off for measuring tree height and diameter for the trees 1–5 cm DBH (1≤DBH≤5 cm) (Hernandez-Stefanoni et al. 2011). Biomass for those trees ≥10 cm DBH was estimated using the equation developed by Cairns et al. (2003); the equation developed by Hughes et al. (1999) was used to calculate the biomass for the trees <10 cm DBH. The total biomass for each plot was converted to Mg/ha. The stand age for each of the inventoried forest plots was estimated by interviewing the landowners or users (Hernandez-Stefanoni et al. 2011). However, stand age data for non-sampled forest areas are not available.

Soil samples were collected at each inventory plot. Three 10-cm-deep soil samples were collected from each plot at the center, northern and southern edges. The soil organic matter (SOM), pH, and texture were analyzed. The detailed method used and the results obtained were reported by Dupuy et al. (2012).

Climate data, including daily minimum and maximum temperature and daily precipitation, were obtained from six weather stations, five of which are scattered around this study terrain, for a recording period lasting from 1969 to 2007. One station is located within this forest, but its climate recording period is shorter, from 2006 to 2012. Because of data gaps at different times from different stations, the overall data were integrated for this study into one dataset for a 43-year period, from 1970 to 2012.

2.3 Models and Setup

2.3.1 Forest-DNDC

Forest-DNDC is process-based, employed to simulate forest growth and C and N dynamics in forest ecosystems, including trace gas emissions from the soils, based on the balance of water, light, and nutrition in the ecosystems (Li et al. 2000; Stange et al. 2000; Miehle et al. 2006). The model integrates photosynthesis, decomposition, nitrification-denitrification, carbon storage and consumption, and hydro-thermal balance in forest ecosystems. Vegetation is divided into three layers, i.e., over-story, understory and ground-growth. Vegetation dynamics on each layer are simulated, based on competition for energy and nutrients. The model simulates the hourly soil moisture regime based on physiochemical soil properties, daily precipitation and evapotranspiration, and hydrogeological conditions. The time-step to model trace-gas movement in soil systems is hourly. This model has been widely tested and used for estimating GHG (greenhouse gas) emission from forested wetland and upland ecosystems, and for assessing C sequestration in forests in a wide range of climatic regions, from boreal to tropical (Stange et al. 2000, Zhang et al. 2002, Li et al. 2004, Kiese et al. 2005, Kesik et al. 2006, Kurbatova et al. 2008; Dai et al. 2012). The model's structure and algorithms can be found in various publications (Li et al. 2000; Stange et al. 2000; Zhang et al. 2002; Li et al. 2004).

2.3.2 Biome-BGC

Biome-BGC is a process-based model used to estimate C in forest ecosystems using mean spatial conditions of the forest under study, including climate, soil, and vegetation. The model simulates biomass and gaseous fluxes and states of C, N and water in defined spaces. Similar to their treatment in Forest-DNDC, plant physiological processes modeled in Biome-BGC respond to diurnal variations in environmental conditions, mainly including daytime means of short wave radiation and temperature, and vapor pressure deficit and precipitation. However, this model only uses a constant ratio of shaded leaf to sunlight to simulate the effect of canopy development on luminous flux. Biome-BGC simulates daily soil moisture variations based on precipitation and evapotranspiration. However, it does not simulate the variations among soil layers due to its single soil layer model. This model has been used by many investigators to quantify C dynamics in forest ecosystems (Tatarinov and Cienciala 2006; Chiesi et al. 2007; Wang et al. 2009). The model parameterization and algorithms can be found at: <http://www.ntsg.umt.edu/project/>.

2.3.3 Model Setup

Forest-DNDC was set up to: (1) simulate C in the Kaxil Kiuic forest using observations for the model validation, and (2) estimate C stocks, the effect of disturbances on C stocks, and long-term C dynamics in the forest using the data interpolated from the observations by using ordinary Kriging method (Li and Heap 2008; Jassim and Altaany 2013) (see Spatial Data for Vegetation and Soil, below). Biome-BGC was set up for each observed plot to validate this model and individually run for each plot to estimate C stocks in this forest for 2012, so that there were 2×276 runs to simulate C for the forest at Kaxil Kiuic. The main parameters for modeling C dynamics in this forested terrain using Forest-DNDC and Biome-BGC are presented in Tables 5 and 6.

2.4 Model Evaluation

The models were validated using biomass observations from 276 plots within the tropical semi-deciduous forest at Kaxil Kiuic, Merida, Mexico. The model performance was evaluated employing four widely used quantitative methods (Dai et al. 2011), i.e., the coefficient of determination (R^2, squared correlation coefficient), model performance efficiency (E) (Nash and Sutcliffe 1970), percent bias (PBIAS), and the the ratio (RSR) of the root mean square error (RMSE) to the standard deviation (SD) (Moriasi et al. 2007).

The E $(-\infty, 1)$ is the key variable used to evaluate the model performance, calculated as:

$$E = 1 - \frac{\sum(O_i - P_i)^2}{\sum(O_i - \bar{O})^2} \tag{1}$$

where O_i, $\bar{O}$ and P_i are observed values, observation mean and simulated results, respectively.

The other evaluation variables, PBIAS and RSR, are computed, respectively, as:

$$\text{PBIAS} = \frac{\sum(O_i - P_i)}{\sum O_i} \times 100 \tag{2}$$

$$\text{RSR} = \frac{\text{RMSE}}{\text{SD}} \tag{3}$$

where SD is the observation standard deviation; RMSE is the root mean square error, the equation is:

$$\text{RMSE} = \sqrt{\frac{\sum(O_i - P_i)^2}{n}} \tag{4}$$

where n is the number of samples, or the pairs of the observed and simulated values.

Table 5. Key Vegetation and Soil Parameters for Forest-DNDC

Parameter	Parameter
Initial leaf N (%)	Leaf start TDD
AmaxA (μmol CO_2 $g^{-1}s^{-1}$)	Wood start TDD
AmaxB	Leaf end TDD
Optimum photosynthetic temperature (°C)	Wood end TDD
Minimum photosynthetic temperature (°C)	Leaf N, re: translocation
AmaxFrac	Senescence start day
Growth respiration fraction	Leaf C/N
Dark respiration fraction	Wood C/N
Wood maintenance respiration fraction	Leaf retention years
Root maintenance respiration fraction	C reserve fraction
Light half saturation constant	C fraction of dry matter
Respiration Q10	Specific leaf weight (g m^{-2})
Canopy light attenuation	Minimum wood/leaf
Water use efficiency	Leaf geometry
DVPD1	Maximum N storage (kg N ha^{-1})
DVPD2	Maximum wood growth rate
Maximum leaf growth rate (% yr^{-1})	Coefficient of stem density (0-1)#
Spatial soil, climate, vegetation and hydraulic parameters	
Soil organic carbon (%)	Hydraulic conductivities (cm hr^{-1})
pH	Wilting point (0-1)
Clay (%)	Capacity (0-1)
Soil depth (cm, ≤150cm)	Porosity (0-1)
Over-story species	Over-story age
Understory species	Understory age
Ground growth (sedge and moss)	Daily minimum temperature (°C)
Daily maximum temperature (°C)	Daily precipitation (mm)

= Usually, the coefficient of stem density is the ratio of the forested to bare (non-forest) areas in each simulating unit, and from 0 to 1.

Table 6. Key Parameters for Biome-BGC*

Parameter	Parameter
Offset for maximum temperature	Offset for minimum temperature
Multiplier for precipitation	Multiplier for VPD
Multiplier for short wave radiation	Atmospheric CO_2 concentration
Soil depth	Sand in soil (%)
Silt in soil (%)	Clay in soil (%)
Site elevation (m)	Latitude
Albedo at the site	Atmospheric N deposition
N fixation	Variable N deposition
Soil water content	First-year maximum leaf C
First-year maximum stem C	Coarse woody debris C
Litter C in labile pool	Litter C in unshielded pool
Litter C in shielded pool	Litter C in lignin pool
Soil C in fast microbial recycling pool	Soil C in medium microbial recycling pool
Soil C in slow microbial recycling pool	Soil C in recalcitrant pool
Litter N in labile pool	Soil N in mineral pool
Transfer growth as fraction of growing season	Litterfall as fraction of growing season
Annual leaf and fine root turnover fraction	Annual live wood turnover fraction
Annual fire mortality fraction	Ratio of new fine root C to new leaf C
Ratio of new stem C to new leaf C	Ratio of new root to new stem
Current growth proportion	C:N of leaf
C:N of leaf litter after translocation	C:N of fine root
C:N of live wood	C:N of dead wood
Leaf litter labile proportion	Leaf litter cellulose proportion
Leaf litter lignin proportion	Fine root labile proportion
Fine root cellulose proportion	Fine root lignin proportion
Dead wood cellulose proportion	Dead wood lignin proportion
Canopy water intercept coefficient	Canopy light extinction coefficient
All-sided to projected leaf area ratio	Canopy average specific leaf area (SLA)
Ratio of shaded specific leaf area (SLA) to full sunlight SLA	Fraction of leaf N in rubisco
Maximum stomatal conductance	Cuticular conductance
Leaf water potential at start of [stomatal] conductance reduction	Leaf water potential at completion of [stomatal] conductance reduction
Vapor pressure deficit at start of [stomatal] conductance reduction	Vapor pressure deficit at completion of [stomatal] conductance reduction
Boundary layer conductance	

* Climate data are not included, such as daily precipitation, temperature, radiation and vapor pressure deficit.

3 Application of Selected Models

Based on the results of the model performance evaluation, Forest-DNDC was used to estimate spatial C stocks, long-term C dynamics and the effects of disturbances on C stocks in forests at the regional scale in Mexico because this model is spatially explicit. Biome-BGC was employed to assess C stocks at the plot scale. The models were run for a 75-year period, beginning in 1938, one year before the oldest trees regenerated in the forest. We assessed C stocks using both models, and estimated the effect of the disturbances using Forest-DNDC alone. Because there were no available climate data for the period from 1938 to 1969, we used the data from 1970 to 2002 to replace the missing earlier data for modeling C stocks and the effect of disturbances on C stocks. Forest-DNDC was also run for a 150-year period to assess long-term C dynamics. Similar to the simulation for assessing C stocks, the 75-year climate dataset was repeated for the 150-year period.

3.1 Spatial Data for Vegetation and Soil

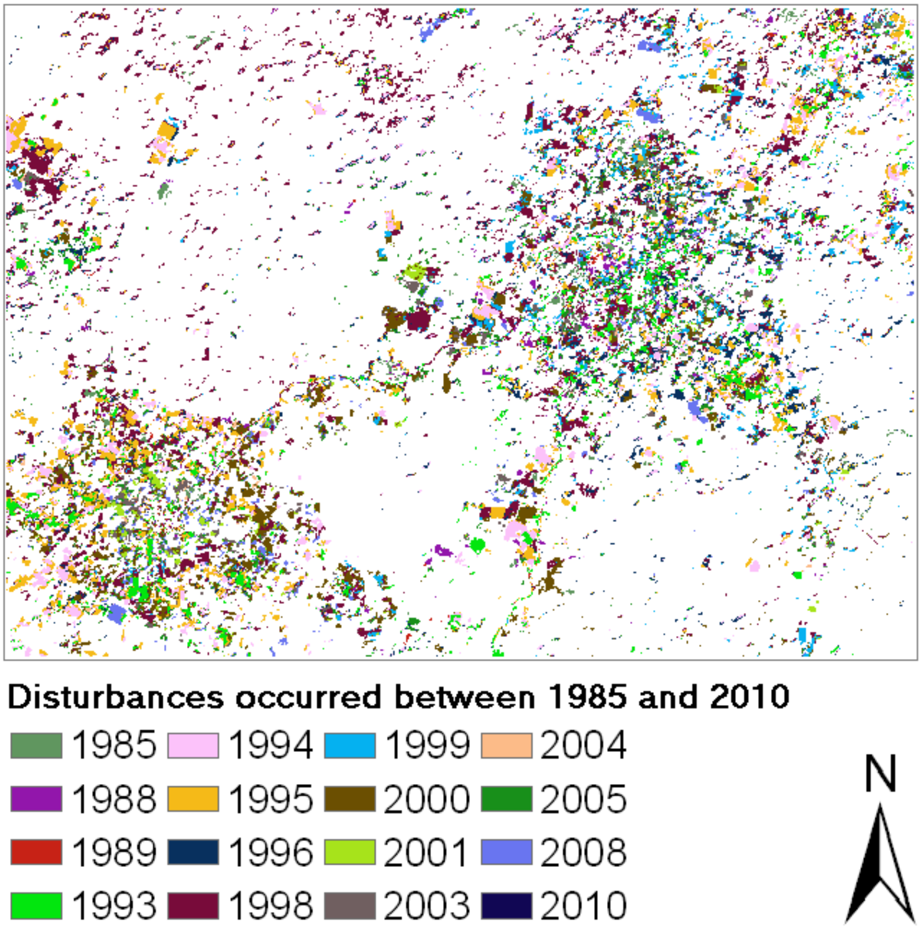
The spatial vegetation distribution was derived from the SPOT-5 satellite image of January 2005, created by Hernandez-Stefanoni et al. (2011). However, the spatial distribution of stand ages for the entire forest is not available. Because stand age is an important parameter to estimate C stocks in space using a modeling approach, a Kriging interpolation method (Li and Heap 2008; Jassim and Altaany 2013) was used to estimate the spatial distribution of stand ages to model the entire forest using Forest-DNDC. The stand ages from the 276 plots in this forest were used to create a poly-point map using ArcGIS 10, and then the poly-point map was used to create the spatial stand age using the ordinary Kriging interpolation method. The spatial stand age map was combined with vegetation map for modeling spatial C dynamics in the forest.

Similarly, spatial soil distribution and associated parameters, including soil texture and SOM, were derived from the field data reported by Dupuy et al. (2012). The spatial polygon vegetation map based on the vegetation types was used to obtain the simulation units for the spatially explicit modeling approach. Finally, the maps of soil conditions and vegetation were used as model inputs.

3.2 Disturbances

The perturbation data for the period from 1985 to 2010 were derived from the disturbance map (Figure 3). The disturbance types were determined by comparing the disturbance map with the vegetation map (Figure 2) derived from the SPOT-5 satellite image. We assumed that the disturbances that occurred between 1985 and 2010 were mainly from land use change, including urbanization and the conversion of lands from forests to crops, as well as agricultural abandonment. Three disturbance types, the development of agriculture and urbanization, agricultural abandonment and woody product harvest, were determined to model the effects of disturbances on C stocks in this forest based on the comparison of the maps. If the vegetation map showed the disturbed lands as forestlands at present and the disturbance map did not show the land areas as persistent forest, the disturbed lands were considered to be secondary forests regenerated after agricultural abandonment. However, if the disturbance map showed the lands as persistent forests with perturbations and the vegetation map showed the lands as forest at present, we assumed that the disturbances were from timber product harvests, and that the forests regenerated after the deforestation. The other disturbances were attributed to development of agriculture and urbanization.

Figure 3. Disturbances in Kaxil Kiuic Forest, 1985–2010



4 Results

4.1 Testing

4.1.1 Model Evaluation

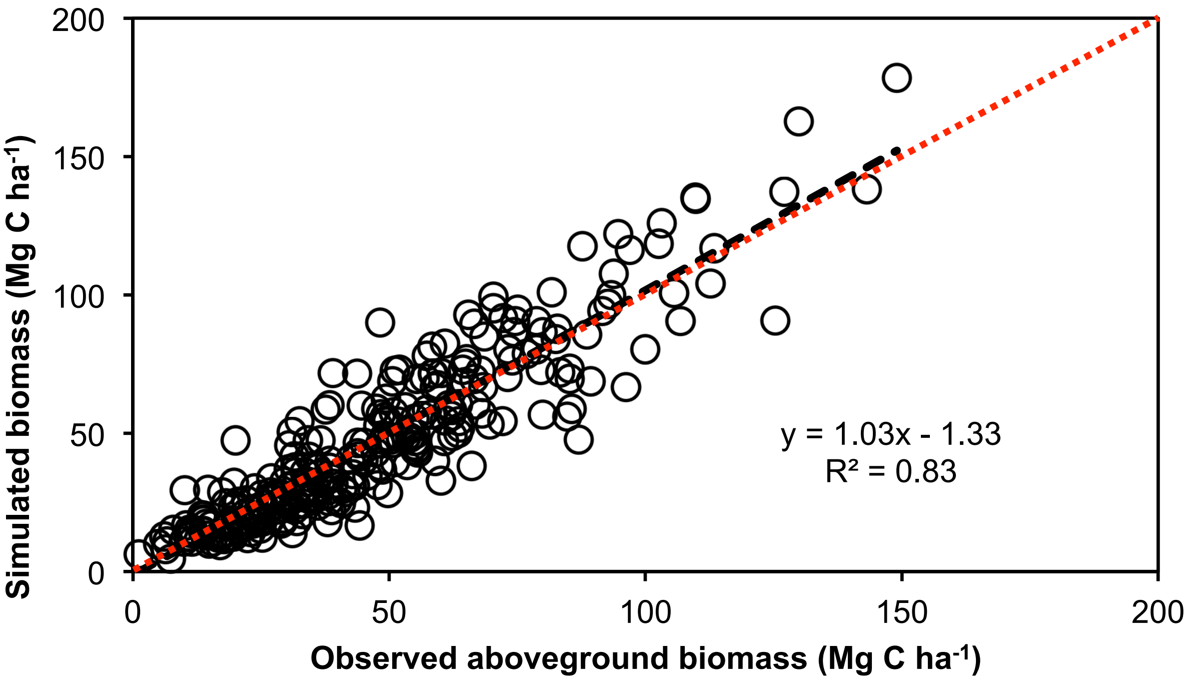
Both models Forest-DNDC and Biome-BGC were validated against biomass observations from 276 plots in Kaxil Kiuic forest conducted in 2008 (Hernandez-Stefanoni et al. 2011; Dupuy et al. 2012). Forest-DNDC was run for a 75-year period for the 276 plots in a spatially way, and Biome-BGC was run separately for each plot for the same period, using 43-year climatic observation from 1970 to 2012. The results from Forest-DNDC (Figure 4a) and Biome-BGC (Figure 4b) were compared to the observations. Figure 4a shows that the biomass simulated by Forest-DNDC significantly correlates with the observed value (R^2=0.83, P<<0.001); the slope of the regression model between the observation and simulation was close to 1.0 (b=1.03), and the intercept (a=1.33) was small, about 2.84% of the average. **Figure 4b** indicated that the biomass simulated by Biome-BGC was significantly correlated with the observed value (R^2=0.59, P<<0.001) with a reasonable slope (b=0.93) and intercept (a=3.03, about 6.5% of the average) of the regression model between the observation and the simulation. These qualitative metrics show that both Forest-DNDC and Biome-BGC can be used to assess C stocks in Kaxil Kiuic forest in Yucatan Peninsula, Mexico.

The results of the four model-evaluation variables are presented in **Table 7**. Based on the model performance rating ranges (see the note for that table) suggested by Moriasi et al. (2007), both models Biome-BGC and Forest- DNDC can be used to estimate the C stocks in the Kaxil Kiuic forest with good model performance efficiency ($E \geq 0.25$). However, there is a substantial difference in model performance between the two models. Biome-BGC performs well ($0.25 < E < 0.75$) and Forest-DNDC performs excellently ($E > 0.75$) (**Table 7**).

4.1.2 Carbon Stocks and Fluxes of Water and Gases

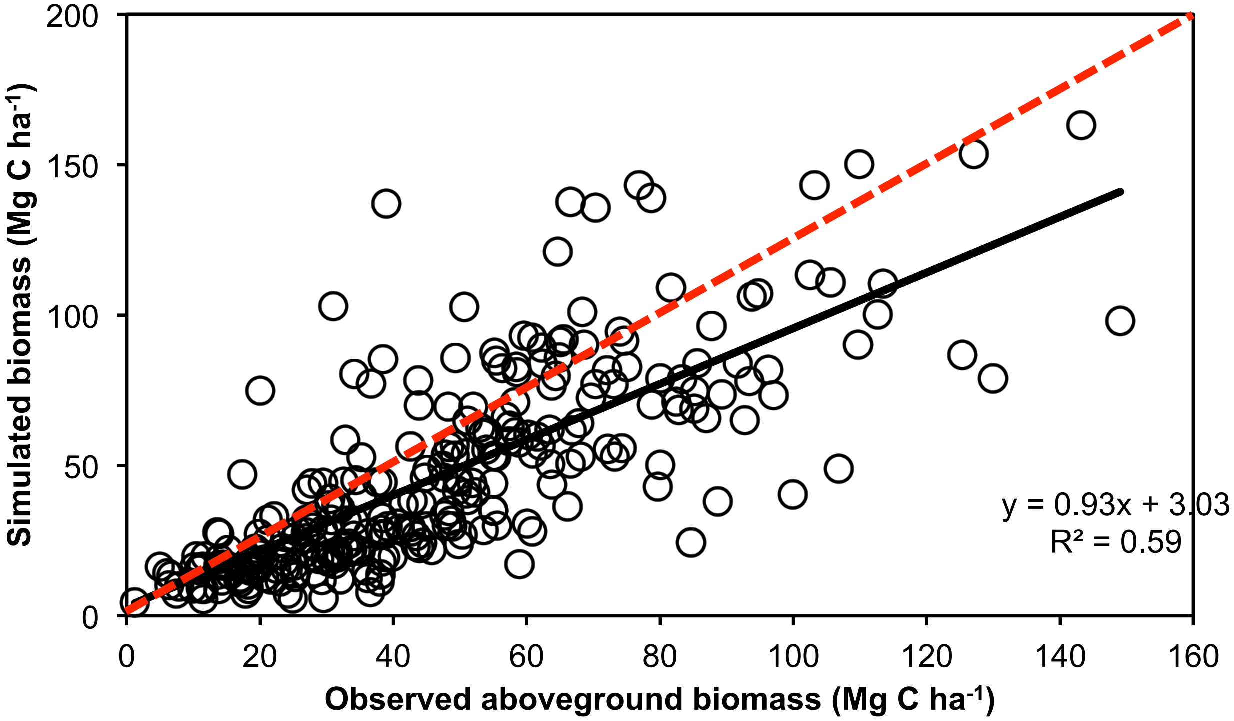
The aboveground biomass (AGB), net primary production (NPP), net biome production (NBP), leaf area index (LAI), evapotranspiration (ET), changes in soil C (the difference in forest floor, ΔLitter; and the divergence in organic C in mineral soils, ΔOCMS), as well as soil-borne trace gases simulated by using Forest-DNDC and Biome-BGC are presented in **Table 8**.

Figure 4a. Observed versus Simulated (Forest-DNDC) Aboveground Biomass in Kaxil Kiuic Tropical Semi-Deciduous Forest



Notes: Carbon biomass observed and simulated for the 276 Kaxil Kiuic forest plots.

Figure 4b. Observed versus Simulated (Biome-BGC) Aboveground Biomass in Kaxil Kiuic Tropical Semi-Deciduous Forest



Notes: Carbon biomass observed and simulated for the 276 Kaxil Kiuic forest plots.

Table 7. Evaluation of Model Performance*

Biome-BGC (>5cm)		Biome-BGC (≥1cm)		Forest-DNDC (>5cm)		Forest-DNDC (≥1cm)	
Variable	Value	Variable	Value	Variable	Value	Variable	Value
R^2	0.61	R^2	0.59	R^2	0.89	R^2	0.83
E	0.54	E	0.40	E	0.88	E	0.79
PBIAS	8.87	PBIAS	-0.99	PBIAS	0.36	PBIAS	0.14
RSR	0.67	RSR	0.78	RSR	0.34	RSR	0.46
A	0.79	*a*	0.93	*a*	0.91	*a*	1.03
B	10.59	*b*	3.03	*b*	3.24	*b*	-1.33

*= R^2 is the coefficient of determination; E is the model performance efficiency (Nash and Sutcliffe 1970); PBIAS is percent bias; RSR is the ratio of the root mean square error (RMSE) to SD (standard deviation); *a* and *b* are the slope and intercept of the regression model between observation and simulation, respectively; (≥1cm) and (>5cm) represent the size in diameter at breast height; model performance rating ranges: 0.25≤E<0.5, 0.5≤E<0.75, and E≥0.75 represent the model performance general, well and excellent, respectively, and the PBIAS is between -25 and 25 and RSR is less than 0.7 (Moriasi et al. 2007).

Table 8. Comparison of the Simulated C, N and Hydrologic Results from Forest-DNDC and Biome-BGC*

Item	Forest-DNDC	Biome-BGC	Item	Forest-DNDC
NPP (Mg C ha^{-1})	5.01	6.81	CH_4-C (kg C ha^{-1})	-6.52
NBP (Mg C ha^{-1})	2.81	2.77	Leached C (g C m^{-2})	4.39
LAI (m^2 m^{-2})	2.73	2.51	Leached N (mg N m^{-2})	19.20
ΔLitter (Mg C ha^{-1}) #	2.26	1.14	N_2O-N (mg N m^{-2})	67.50
ΔOCMS (Mg C ha^{-1}) #	2.63	-9.86	Total N loss (kg N ha^{-1})	2.68
Flow (mm)§	651.70	517.05	SoilCO_2-C (Mg C ha^{-1})	2.16
ET (mm)	794.50	816.10	ΔSOC (kg C ha^{-1})	57.40
AGB (Mg C ha^{-1})	46.92	46.39		

*= The results are simulated using the models Forest-DNDC and Biome-BGC to estimate the C stocks and gas fluxes in the forest in 2008; NPP is the net primary production; NBP is the net biome production; LAI is leaf area index; ΔLitter is the increase in organic carbon on forest floor; ΔOCMS is the increment in organic carbon in mineral soil; ET is the simulated evapotranspiration (mm); ΔSOC is the change in soil organic carbon; AGB is the simulated mean aboveground biomass, the observed mean is 46.86 Mg C ha^{-1}.

#= The initial mean litter and organic carbon in mineral soil for both the models were 3.55 and 58.93 Mg C ha^{-1}, respectively; the average stand age was between 3 and 70 years old in space in 2008.

§= The flow is only the subsurface flow simulated by Forest-DNDC, total flow by Biome-BGC; the unit is mm so that it can be compared to precipitation; the precipitation was 1500.5 mm in 2008.

Although verification of these outputs is difficult without comparable measurement data (except in the case of AGB), they are still useful because these parameters, especially NPP, NBP and LAI, are closely related to biomass production.

The results from both Biome-BGC and Forest-DNDC for NBP, LAI, ET and AGB are similar. However, the NPP estimated by Biome-BGC was more than 35% higher than Forest-DNDC. The over-predicted NPP without producing a high NBP from Biome-BGC might be because the soil moisture subroutine used by Biome-BGC was not suitable for assessing soil C dynamics in this tropical environment (see more explanations below).

The simulated changes in forest floor C pools (ΔLitter) by Biome-BGC and Forest-DNDC were 1.14 and 2.26 Mg C ha^{-1}, respectively. An increase in litter should be related to increasing biomass or higher biomass. However, the biomass increase might result in a small contribution to an increase in forest floor due to high SOM decomposition rate in tropical regions. An increase in litter (forest floor) may be mainly associated with dead woods. The average accumulated dead wood (including decomposed dead woods) estimated by Forest-DNDC was 7.5 Mg C ha^{-1} across the forest in the simulation period. However, the mean residue on the forest floor was less than 2.0 Mg C ha^{-1} for both Biome-BGC and Forest-DNDC due to the tropical climate and fast SOM decomposition. Thus, the small litter increase simulated by Biome-BGC and Forest-DNDC is feasible.

Surprisingly, the organic matter in mineral soils simulated by the both the models was very different; the mineral soil organic matter decreased by 9.86 Mg C ha^{-1} (ΔOCMS = -9.86 in **Table 8**) according to Biome-BGC during the simulation period, but Forest-DNDC suggested a small increase of 2.63 Mg C ha^{-1}. The small increase in mineral soil C simulated by Forest-DNDC is possible, and related to the decomposition of dead wood. The roots of the dead woods remained in soils, decomposing year by year. Additionally, it is highly unlikely that there is a continuous decrease in mineral soil C under forested conditions for several decades. It may be that Biome-BGC over-estimated the soil moisture regime (see some explanations next paragraph) for forest environments, which led to an over-predicted SOM decomposition in mineral soils in this semi-deciduous forest.

The flow (runoff) is mainly subsurface flow due to very low surface flow in this forest, which is related to the specific hydrogeological environment: a thin soil layer with high rock content and limestone bedrock, such that there is little drainage system development in this area. The flow simulated by using Forest-DNDC is about 652 mm in 2008 (Table 8). However, the total flow simulated by using Biome-BGC is about 517 mm, which may be under-estimated due to very thin and stony soil layers and limestone bedrock. The low flow simulated by Biome-BGC may lead to an over-predicted soil moisture regime and high SOM decomposition rate. The yearly mean loss of mineral soil carbon simulated by Biome-BGC was about 300 kg C ha^{-1} yr^{-1} over the simulation period of 3-70 years. It seems unlikely that this rate of continuous decrease in mineral soil organic carbon over a long time period could occur in any of the regenerating forested conditions represented at Kiuic.

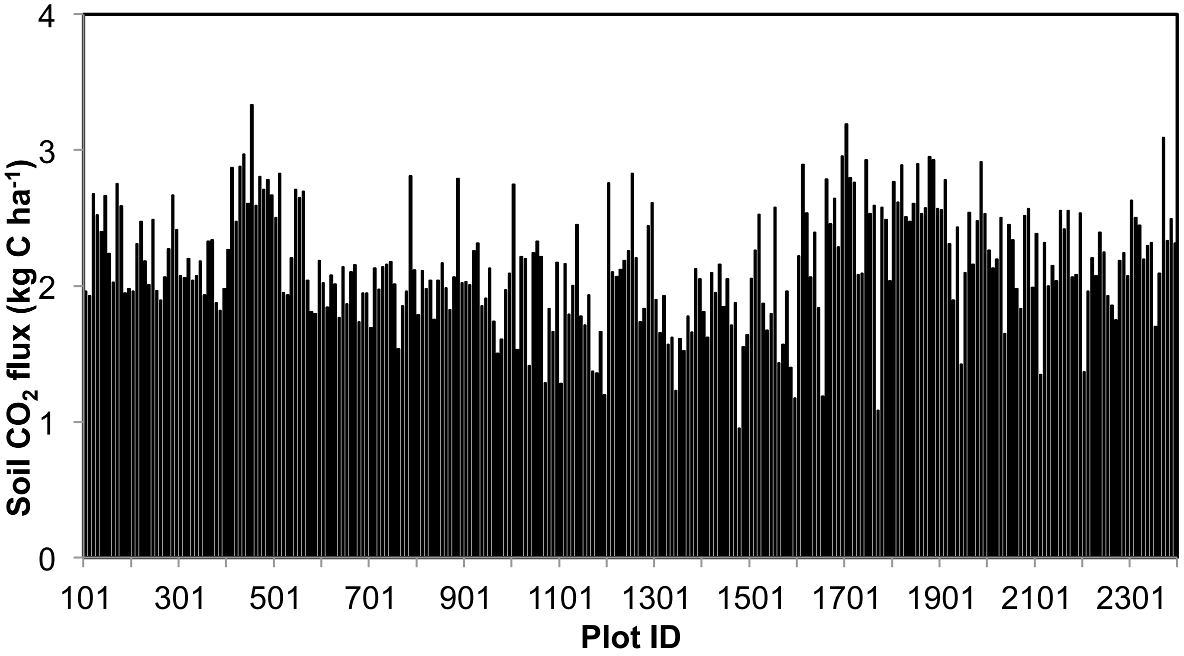
The spatial variability of soil N_2O flux from the forestland at Kaxil Kiuic was large, ranging from 24 to 189 mg N m^{-2} in 2008, with a mean of 67.5 mg N m^{-2}. However, the spatial distribution of the N_2O flux is normal because the average, median flux and geometric mean are approximate (67.5, 63.5 and 63.9 mg N m^{-2}, respectively). The spatial variability in N_2O flux is correlated with soil organic matter (SOM). The discrepancy in annual N_2O flux is also associated with annual precipitation (Li et al. 1992). The higher SOM and annual precipitation, the larger the annual N_2O flux will be, due to SOM decomposition releasing organic nitrogen and precipitation regulating the processes of nitrification and denitrification in upland ecosystems (Li et al. 1992).

The spatial variability in annual CH_4 uptake by the soils in this forestland was small, ranging from 5.83-8.72 kg CH_4-C ha^{-1} in 2008, with the mean of 6.52 kg CH_4-C ha^{-1}. The methane uptake rate in this forest was higher than the rates in the temperate forests in New Hampshire (4.3–4.6 kg C ha^{-1} yr^{-1}) measured by Crill (1991), in German forests (2.0-3.2 kg C ha^{-1} yr^{-1}) as reported by Guckland et al. (2009), and in Swedish forests (0.6-1.6 kg C ha^{-1} yr^{-1}) found by Klemedtsson and Klemedtsson (1997). However, our rate was similar to or slightly lower than the average methane uptake rate (8.18 kg C ha^{-1} yr^{-1}) in forests within the latitude range from 26 °N-44 °N in Japan (Ishizuka et al. 2009), and within the uptake rate range (0-11.57 kg C ha^{-1} yr^{-1}) in Harvard Forest in Massachusetts found by Steudler et al. (1989), and lower than the rate (6.94–26.65 kg C ha^{-1} yr^{-1}) in a subtropical forest within the Francis Marion National Forest in South Carolina observed by Renaud (2008). These differences might be associated with the physiochemical soil conditions.

The mean C loss to leachate as dissolved organic carbon (DOC) was about 0.98 g m^{-2} yr^{-1} in the simulation period, much less than the mean level of riverine C loss (3.26 g C m^{-2} yr^{-1}) from USA's temperate forest watersheds with areas less than 10,000 km^{-2} as reported by Schlesinger and Melack (1981). However, temporal variability in DOC loss is considerable. For example, the DOC loss was about 1.1, 2.6 and 4.4 g m^{-2} in 2006, 2007 and 2008, respectively. Similarly to DOC, temporal differences in dissolved nitrogen loss to leachate were large: 5.83 mg m^{-2} yr^{-1} for the mean loss, 19.2 mg m^{-2} in 2008 for the maximum loss. However, the temporal difference in total N loss, including the loss to air and water, was small, 2.21 kg N ha^{-1} yr^{-1} for the long-term average, 2.69 kg N ha^{-1} in 2008 for the maximum.

Soil CO_2 flux at the Kaxil Kiuic plots varied significantly. **Figure 5** shows the simulated flux from the 276 plots in 2008, ranging spatially from 0.95 to 3.33 Mg C ha^{-1}, with arithmetic mean of 2.16 Mg C ha^{-1} and median of 2.12 Mg C ha^{-1}. The small difference between the arithmetic mean and the median of soil CO_2 flux suggests a spatially normal distribution in this catchment. The spatial variability in soil CO_2 flux is mainly related to differences in soil and, especially, in vegetation, due to its heterogeneous distribution in space that produces the differences in heterotrophic respiration associated with the roots and litter. The litter and debris of the plants are the main sources of the soil organic matter in this forest and their decomposition is considerably faster due to a combination of tropical climate, fire activity, and logging.

Figure 5. Soil CO_2 Flux from the 276 Plots Simulated for 2008



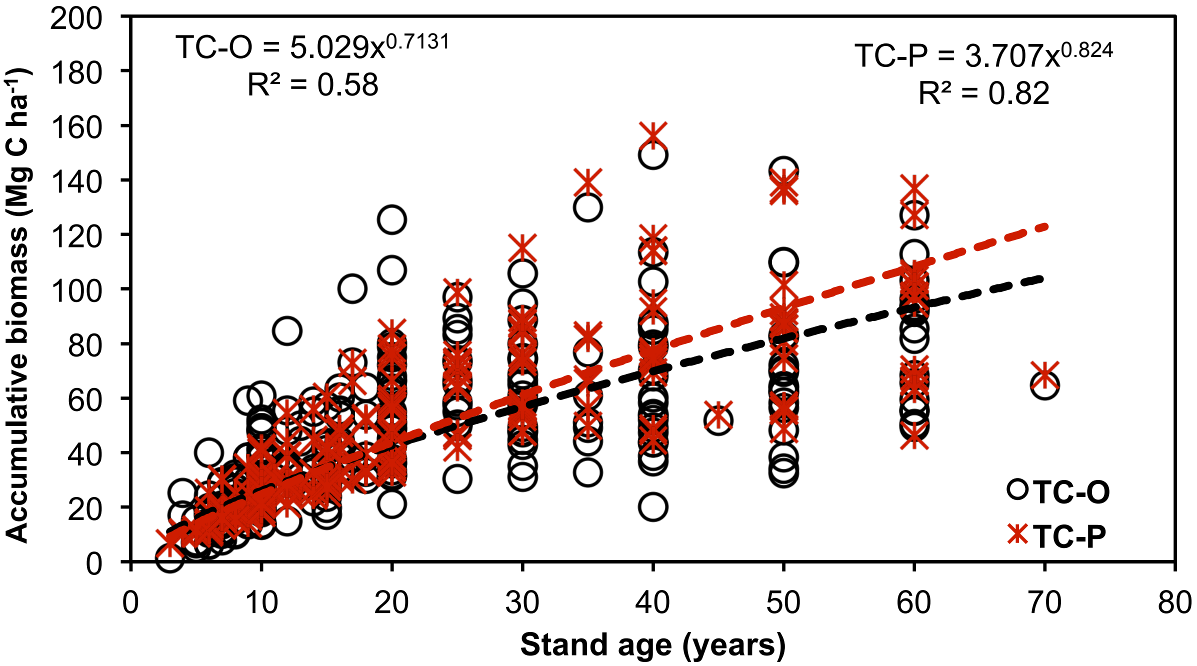
4.1.3 Rate of Carbon Sequestration in Biomass

The rate of C sequestration in woody biomass in the Kaxil Kiuic forest indicates the role of this forest in reducing atmospheric CO_2 and mitigating global warming. The correlation between the aboveground biomass C and stand age is presented in **Figure 6a** based on the simulation and the observation for the 276 plots. The results from both the simulation and observation showed that biomass (Mg C ha^{-1}) increased non-linearly with an increase in the stand age. However, when the equations of Figure 6a were applied to calculate plot biomass, there were small slopes and large intercepts of the regression models between the observation and the calculated plot biomass (**Figure 6b**). A high-order polynomial equation may better describe the relationship between the stand age and accumulative biomass in Kaxil Kiuic (P<2.0E-120), as follows:

$$AGB_{Age} = K_0 \times Age + \sum_{j=1}^{m} K_j \times [\ln(Age)]^j \qquad (5)$$

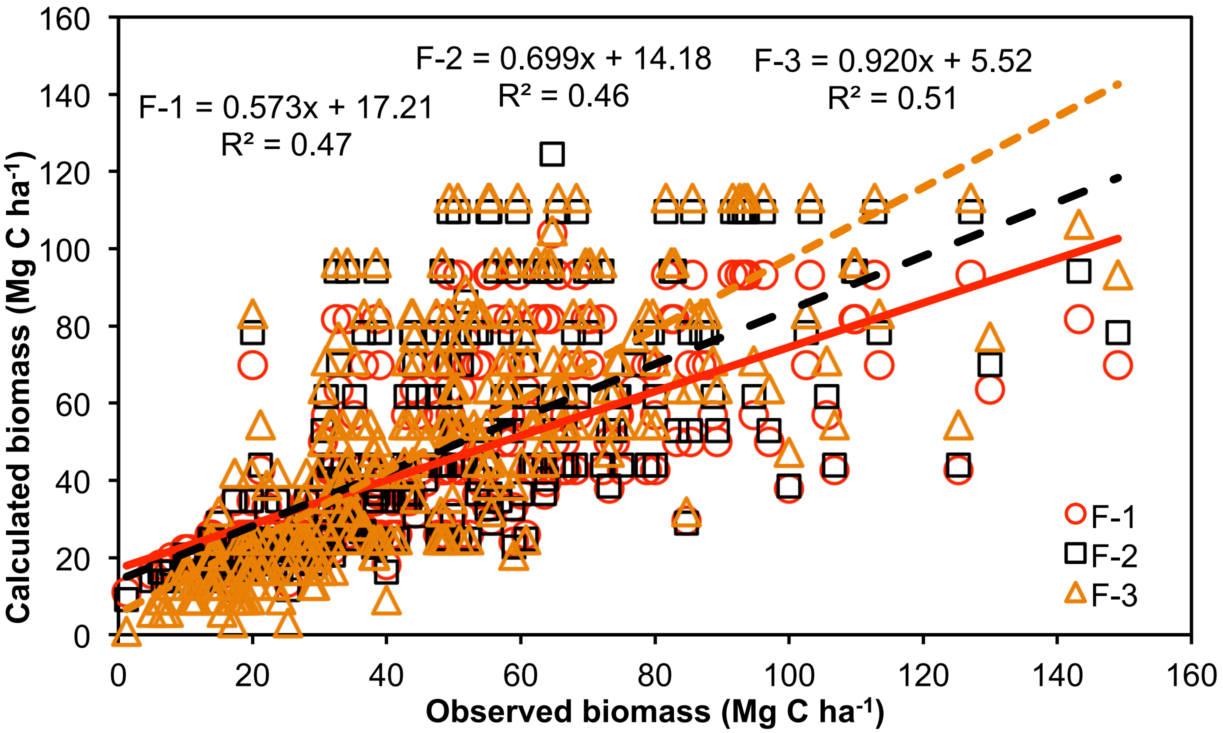
where AGB is the aboveground biomass at the specific stand age (Age); K_0 and K_j are coefficients; m = 6.

Figure 6a. Correlation between Stand Age and Aboveground Biomass



Note: tc-o: measured biomass, tc-p: simulated biomass

Figure 6b. Comparison of the Observed Biomass and the Results Calculated Using the Equations in Figure 6a (F-1 and F-2) Versus Using Equation 5 (F-3)



4.2 Application

Forest-DNDC using a spatially explicit approach was applied to assess C stocks, the effect of disturbances on the C stocks, and long-term C dynamics in the forest at Kaxil Kiuic in the Yucatan Peninsula, Mexico. The results from the simulation for assessing long-term C dynamics were also used to estimate the growth curve of plants in this forest.

4.2.1 Biomass Distribution in Space

The spatial distribution of aboveground biomass C was simulated by employing Forest-DNDC for the entire region using polygons converted from the 30 m resolution map. The simulated C stocks for 2012 are presented in **Figure 7**. There was a large spatial variability in biomass C, with the stocks ranging spatially from 5.0 to 115.0 Mg C ha^{-1} and a mean of 56.6 Mg C ha^{-1} (urban and crop areas excluded). The spatial variability in aboveground biomass C is mainly related to the distinct stand ages, between 7 and 74 years old in 2012, based on the inventory conducted in 2008–2009 (Hernandez-Stefanoni et al. 2011; Dupuy et al. 2012).

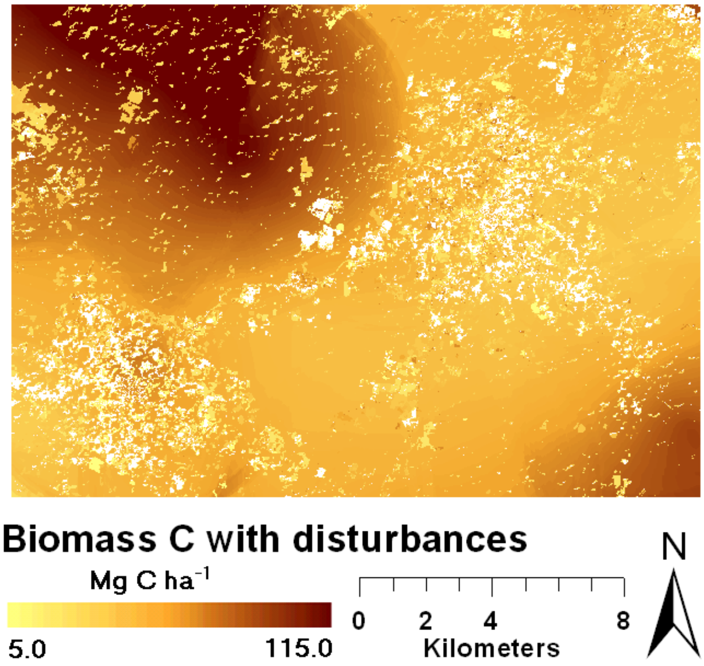
The simulated spatial average of the 276 plots (53.2 Mg C ha^{-1} for 2012) was close to the mean of the entire catchment as simulated using the polygons (56.6 Mg C ha^{-1} in 2012). When the result from the simulation for the entire forest using polygons was compared with results from the 276 plots, however, there was a substantial difference in aboveground biomass simulated for some places. For example, the largest error between the two simulations using distinct cell sizes occurred at Plot 106: the polygon-simulated aboveground biomass for this plot was 113.7 Mg C ha^{-1}, but the simulated value using the observation plot data as inputs was 156.1 Mg C ha^{-1}, which compares well to the observed biomass of 149.0 Mg C ha^{-1}. This large discrepancy in C stocks between the two simulations might be because of errors in the stand age and the size of simulation units (see the explanation below).

4.2.2 Impact of Disturbances on Carbon Stocks

The impact of disturbance on C stocks was simulated based on comparisons between the disturbance map and vegetation map (see details in Methods and Data). The total increase in disturbed area between 1985 and 2010, calculated from the disturbance map, was 5785.5 ha. However, the forest area only decreased by 1227.74 ha because of loss to agriculture and urbanization developments affecting about 21.2% of the total disturbance area. Accordingly, we might estimate that there were about 4557.7 ha of the land perturbed by timber product harvest and cropland abandonment, and then the forest regenerated afterwards.

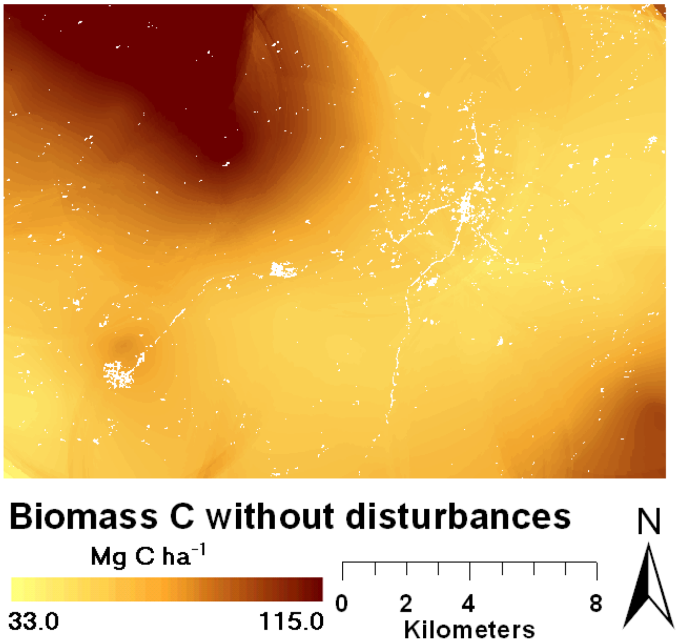
The storage of biomass C in Kaxil Kiuic is obviously influenced by disturbances that have occurred between 1985 and 2010, as indicated by the comparison of the simulation outputs with and without disturbances (**Figure 7** and **Figure 8**, respectively). The estimated total biomass C storage of the stands in this forest for 2012, with and without disturbances, was 1667.6 and 1822.3 Gg C, respectively. The estimated biomass C loss to those disturbances was about 154.7 Gg C; and the spatial mean biomass C storage in the stands reduced from 59.9 to 56.6 Mg C ha^{-1} in 2012. Accordingly, we could consider that the biomass C storage in the stands in this forest reduced by over 73 Gg C at the 2012 time point due only to the forestland loss to agriculture and urbanization in the time period from 1985-2010, and this value did not count soil C loss, in which the stock of C in roots was estimated to be over 20 Gg C at the same time point.

Figure 7. Spatial Distribution of Estimated Biomass (Mg C ha^{-1}) for 2012 in Kaxil Kiuic Forest



Note: White areas are agricultural and urban zones.

Figure 8. Simulated Spatial Biomass Carbon Distribution for 2012 without Disturbances that occurred between 1985 and 2010 in Kaxil Kiuic Forest



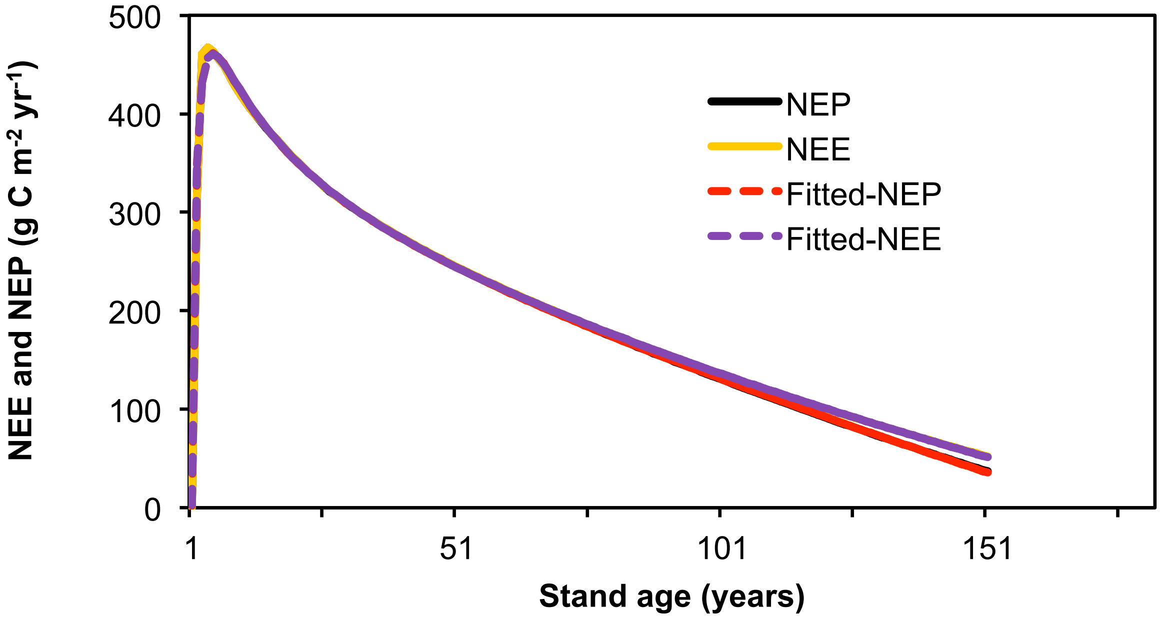
Note: White areas are pre-1985 agricultural and urban zones.

4.2.3 Temporal Changes in Carbon Sequestration Rate

The validated model was used to assess long-term C dynamics in Kaxil Kiuic forest for a 150-year period, using the 43-year (1970–2012) climate data for the entire modeling period. We assumed that: (1) the soil and vegetation types were as same as current, and (2) all woody plants were regenerated in the first year of this 150-year period. Three variables, NPP, NEP and NEE, were estimated based on the simulation.

The result from the simulation for the net ecosystem exchange (NEE) in Kaxil Kiuic forest (**Figure 9a**) showed that the NEE reached a peak value several years after the tree regeneration, and then followed a decline. This trend in the NEE is similar to the trend in NPP (see discussion below), but the decline of NEE is steeper. The factor that is responsible for the steep NEE decline may be an increase in respiration, including root respiration and SOM decomposition, because there is no a decrease in the GPP in the simulation period (**Figure 9b**).

Figure 9a. Temporal changes in annual net ecosystem exchange (NEE) and annual net ecosystem production (NEP) (g C m^{-2} yr^{-1}) in Kaxil Kiuic forest



The temporal change in NEE is obviously nonlinear. Based on the relationship between the NEE and stand age from this study, the fitted equation can be expressed as:

$$NEE_{Age} = K_0 \times Age + \sum_{j=1}^{m} K_j \times [\ln(Age)]^j \qquad (6)$$

where K_0 and K_j are coefficients; *Age* is stand age; $m = 4$. The NEE is significantly correlated to the stand age ($F = 117523.0$, $P << 0.0001$, and sample number $n = 150$).

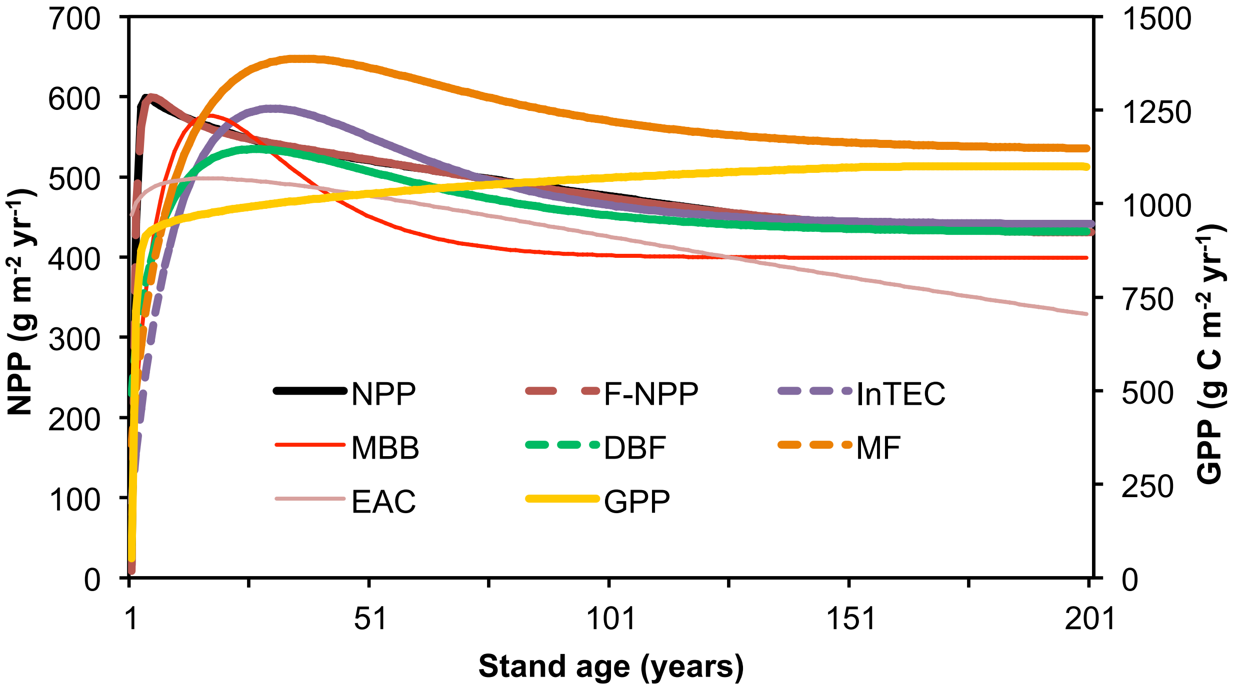
The correlation between the NEP and stand age (**Figure 9a**) clearly showed that the trend in annual NEP was as almost same as the NEE over a long period. However, the annual NEP is slightly smaller than annual NEE with an increase in the stand age. The mean difference in the 150-year period was about 4.22 g m^{-2} yr^{-1}. The relationship between stand age and NEP is the same as the correlation between NEE and stand age (Eq. 6), only with different coefficients. This small discrepancy between the NEP and NEE is due primarily to the rare surface flow in this area which is necessary to remove C from forest floor and topsoil, except for leaching, without other external forces simulated to remove C from the ecosystems.

The relationship between the NPP and stand age is presented in **Figure 9b**. It was obvious that the NPP did not change significantly after reaching the peak, but did slowly decrease with an increase in the stand age, indicating that plant respiration in the simulation period increased slowly with an increase in the stand age after reaching the peak NPP. The relationship between the NPP and stand age, based on the simulated results, is suggested to be:

$$NPP_{Age} = K_0 \times Age + \sum_{j=1}^{m} K_j \times [\ln(Age)]^j \qquad (7)$$

where K_0 and K_j are coefficients; *Age* is stand age; $m = 5$. The NPP is significantly correlated to the stand age ($F = 734985.2$, $P << 0.0001$, and $n = 150$).

Figure 9b. Temporal Changes in Annual Net Primary Production (NPP) and Gross Primary Production (GPP) (g C m^{-2} yr^{-1}) in Kaxil Kiuic Forest



Note: GPP and NPP are simulated; F-NPP is calculated NPP using Eq. 7 from this study; InTEC is calculated NPP using Chen et al. (2003) equation with specific coefficients for this forest; MBB (Maple/Beech/Birch), DBF (Deciduous Broad-Leaved Forest), MF (Mixed Forest) and EAC (Elm/Ash/Cottonwood) are calculated NPP using Chen et al. (2003) equation with He et al. (2012) coefficients for the four forest types, respectively.

The equation used to express the relationship between the NPP and stand age in this study is similar to those reported for the deciduous broad-leaved community and mixed forest in the United States by He et al. (2012) (**Figure 9b**). The NPP from the simulation for the forest at Kaxil Kiuic during a short period before the forest matures is higher than the calculated result using the Chen et al. (2003) equation with specific coefficients for this forest (**Figure 9b**). One reason for the higher NPP simulated by Forest-DNDC compared to the NPP calculated using the equation suggested for the InTEC model by Chen et al. (2003) may be because the modeled NPP included the contributions from all plants, sedges, understory and over-story vegetation. We included these contributions because the non-dominant plant is a part of the entire ecosystem. Moreover, this error becomes small after the forests mature because sedges are small or almost absent, and understory can be substantially reduced with the canopy closure.

4.2.4 Spatial Differences in Net Primary Production and Net Ecosystem Production

The simulated net primary production (NPP*, where the NPP is from all forest layers, or over-story, understory and ground-growth*) for the forest at Kaxil Kiuic using polygons (**Figure 10a**) showed low spatial variability (130 g m^{-2}), ranging from 460-590 g m^{-2} in 2012. The polygons used varied in their size from 0.0576 to 746.7 ha, with average of 1.17 ha. The NPP from the 276 plots simulated for the same year differentiates from 250 to 800 g m^{-2} although the spatial means from the both simulations using different sizes of simulation units are approximate, about 510 g m^{-2} yr^{-1}. The spatial difference in the NPP between the two distinct simulation cell sizes is primarily from the variation in vegetation characteristics, including cover-type/species and stand age.

Net ecosystem production (NEP) is an important parameter to assess C sequestration in forest ecosystems. The NEP is, here, the difference between the net ecosystem exchange (NEE) and the loss of dissolved organic carbon (DOC) to leachate without considering other factors to simulate for biomass removal. The estimated NEP from the simulation using polygons is presented in **Figure 10b**. The result showed that the spatial variation (the difference equals 219 g m^{-2}) in NEP was considerably. The spatial differentiation in NEP is mainly from the divergences in the soil and vegetation among simulation cells, which lead to differences in autotrophic and heterotrophic respiration and DOC loss to leachate (<3.1 g C m^{-2}, on average) among the simulating units.

Figure 10a. Spatial Net Primary Production in 2012

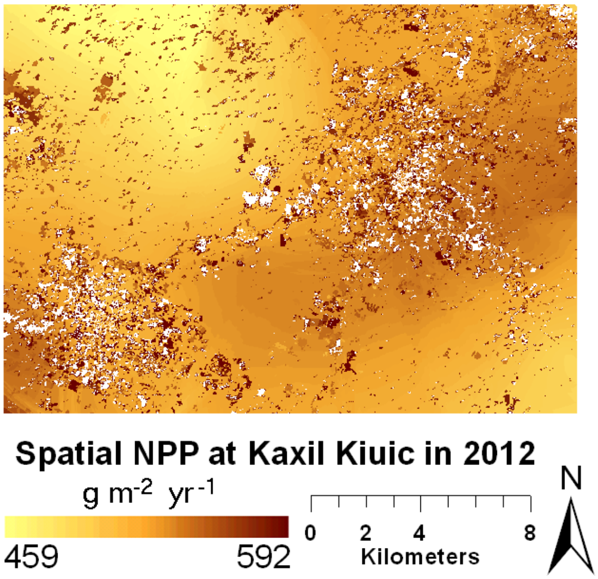
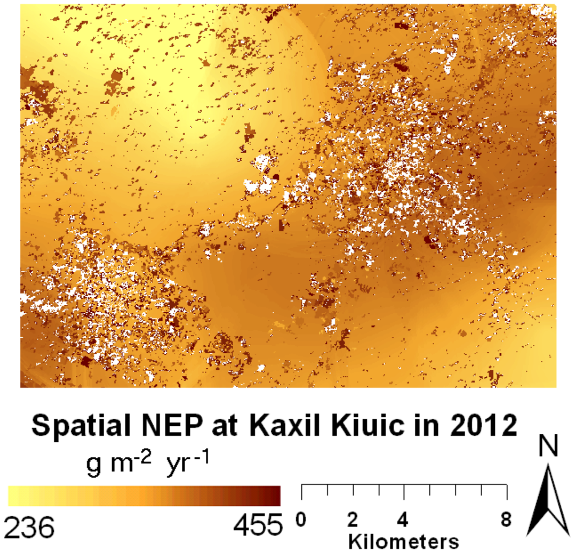


Figure 10b. Spatial Net Ecosystem Production (NEP) in 2012 in Kaxil Kiuic Forest

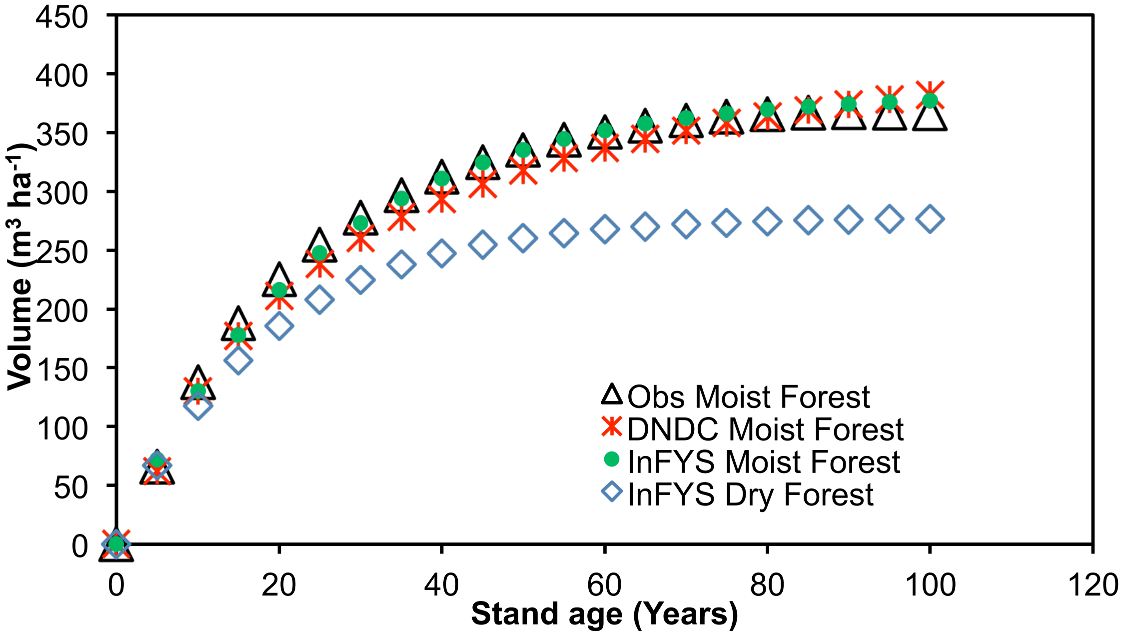


Note: In each case, the white areas are agricultural and urban zones.

4.2.5 Comparison of Growth Curves from Different Methods

Here we show a preliminary comparison between the estimated growth curves from InFYS, intensive sites, and the Forest-DNDC model for the tropical moist/wet forest type in the Kaxil Kiuic area of the Yucatan Peninsula (**Figure 11**). The estimated volumes for each age class show excellent consistency among the different methods for this forest type, indicating that the model may be used in the future with some confidence for simulating other forest types and disturbances in the region. The InFYS results for tropical dry forests are shown for comparison—field observations are not available for this forest type and nor have we run the Forest-DNDC model for it. This preliminary comparison illustrates the work that will be done on a much more extensive basis in Phase 2 of this project.

Figure 11. Comparison of Observed Volume with Estimated Growth Curves from Different Methods



Note: The observed volume (Obs) is from the field measurements of intensive-site sample plots in the Kaxil Kiuic area; the DNDC estimates are from the model (Forest-DNDC) results for the same sample plots; the InFYS estimates are calculated from the national forest inventory for the moist forest type and for the dry forest type (for comparison).

5 Discussion

5.1 Model Validation

The results from the model validation for Biome-BGC and Forest-DNDC using biomass measurement from 276 plots in the Kaxial Kiuic forest indicate that both models can be used to assess C storage in stands in this forest based on model performance. However, Forest-DNDC appears to function better than Biome-BGC because the model performance efficiency (E≥0.79) from Forest-DNDC is larger than from Biome-BGC (E≥0.40) and the error between the measurement and simulation from Biome-BGC is larger than the error from Forest-DNDC. Furthermore, all model performance evaluation variables, including RSR, PBIAS and R^2, indicate that Forest-DNDC may be more suitable to estimate C stocks and long-term dynamics for the Kaxil Kiuic forest and similar forests in this area. Differences in the performance between the two models may be related to different methods of modeling vegetation and soil processes.

Biome-BGC uses a big-leaf model to simulate photosynthesis, but Forest-DNDC uses a multilayer model, and as such it can better simulate the photosynthetic process and canopy evapotranspiration. Similarly, Forest-DNDC divides soil into multiple layers, each of about 1–3 cm thick. Soil water movement and the dynamics of C and N in each soil layer are simulated on an hourly basis. Accordingly, the Forest-DNDC can better deal with the SOM decomposition and water movement in soils. These differences in modeling processes for vegetation and soils as applied by the two models that lead to different performance efficiencies.

5.2 Impact of Spatial Resolutions

There are some substantial differences in biomass simulated using differential sizes of simulation units, polygons and 200-m^2 plots. This is mainly because there are some discrepancies between the stand age estimated by interviewing local people and the age interpolated using the Kriging interpolation method based on the stand age data of the 276 plots. For instance, the stand age for the Plot 106 was 40 years, based on the estimation for the 200 m^2 plot, but the age for the polygon (about 1800 m^2), in which the Plot 106 was located, was only 30 years: a result obtained by interpolation, using a 30 m resolution map, on the basis of the field data. This was because one of the neighbors of this plot was only 7 years old. The substantial error in stand age can produce a large difference in C stock estimation when using a modeling approach. Accordingly, the simulated biomass for the polygon in which the Plot 106 was located was lower than that simulated for the plot due to a 10-year difference in the stand age between these two simulations.

Except for the difference in the stand age caused by using different simulation cell sizes, the divergence in soil and vegetation conditions caused by using the distinct cell sizes should not be ignored because the polygon size (ranging from 0.0576 to 746.7 ha, with the mean of 1.17 ha) was much larger than the plot size (0.02 ha). The new combination of vegetation and soil conditions for polygon simulation can produce significantly different simulation conditions, causing an under-estimation biomass for some spots.

Using polygon simulation also resulted in the over-estimation of biomass C for some places. This results from over-estimated stand age and distinct cell sizes for different simulations. These consequences indicated that modeling C using lower resolution might produce under- or over-estimation of C stocks for some places if the forest parameters obtained from points were extrapolated to the entire site by using an interpolation method based on the inventoried data, but this difference might influence only slightly the estimation of C stocks for the regional average. Yet, the errors related to the resolution issues that resulted in under- or over-estimation of C stocks at some locations should be considered if the estimations are used to inform landscape-scale management plans.

5.3 Spatiotemporal Variation and Distribution of Carbon

Overall C storage has high spatial variation, ranging from 5.0 to 115.0 Mg C ha^{-1}, with a mean of 56.6 Mg C ha^{-1}, and mainly associated with the stand age, ranging from 7 to 74 years old in 2012 based on the field data. The spatial difference in C stocks in this forest is first related to the stand age, secondly to plant species and finally to soil conditions. The spatial difference in stand age was caused by disturbances, including forest product harvest and farmland abandonment.

The C storage in stands increases in a nonlinear fashion and does so significantly as the stand ages, as determined both by the results of observation and simulation. However, the annual incremental rate decreases as the stand approaches maturity. The simulated NPP and NEP (refer to **Figures 9a** and **9b**) show a substantial decrement in annual C sequestration rate with an increase in stand age in this forest ecosystem, although there is no a decrease in GPP after the forest mature (**Figure 9b**), due to an increase in the respiration.

Soil CO_2 flux is highly variable (Figure 5). The spatial variation is related both to soil and also to vegetation in this forest. **Figure 12a** shows the relationship between soil CO_2 flux and stand age, indicating that the root respiration can substantially influence soil CO_2 flux because of an increased in root mass with stand age. The annual soil CO_2 flux is substantially variable year-to-year (**Figure 12b**), mainly related to precipitation. The annual soil CO_2 flux increased with increasing annual precipitation from 1970 to 2012 (R^2=0.43, n=43, P<0.01), indicating that soil CO_2 flux is significantly influenced by precipitation. This is because precipitation in this forest is much less than potential evapotranspiration (PET)—about 60% of PET—leading to SOM decomposition that is impacted substantially by soil moisture as regulated by precipitation, indicating that the soil moisture regime is among the important factors influencing soil CO_2 flux in this forest. Accordingly, an accurate soil moisture simulation for tropical semi-deciduous forests is important to correctly assess the C and N dynamics in the soils. The relationship to annual precipitation and soil moisture is consistent with other findings (Raich and Schlesinger 1992; Amacher and Mackowiak 2011). However, the relationship in this semi-deciduous forest is the reverse of that observed in wet areas, especially the locations near riparian zones, where the annual soil CO_2 flux may decrease with an increase in annual precipitation due to a long soil saturation period and a low rate of microbial decomposition (Dai et al. 2013).

Figure 12a. Stand Age versus Soil CO_2 Flux in 2008

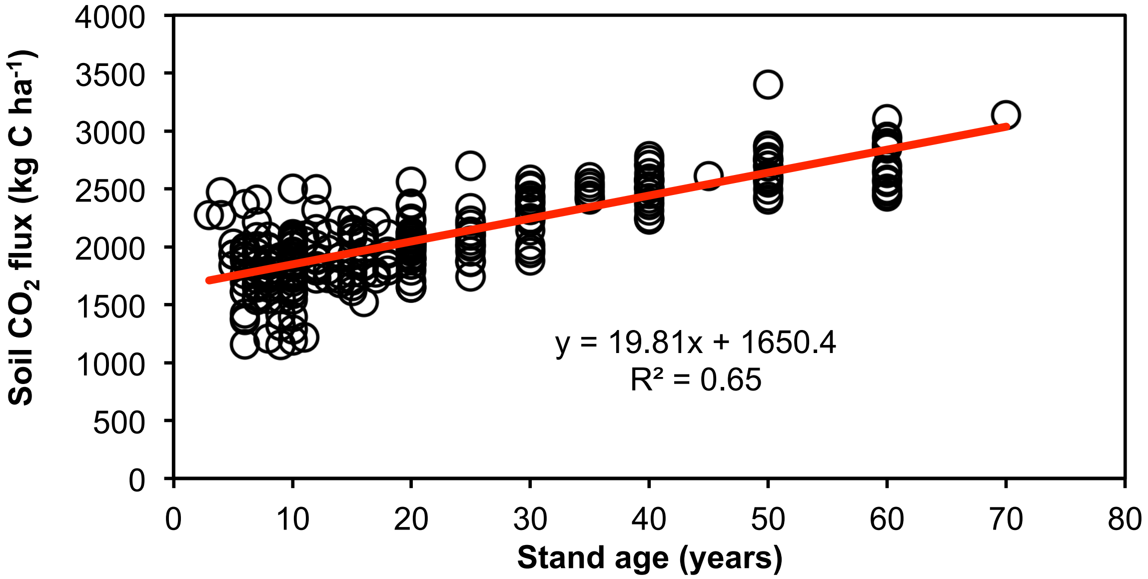
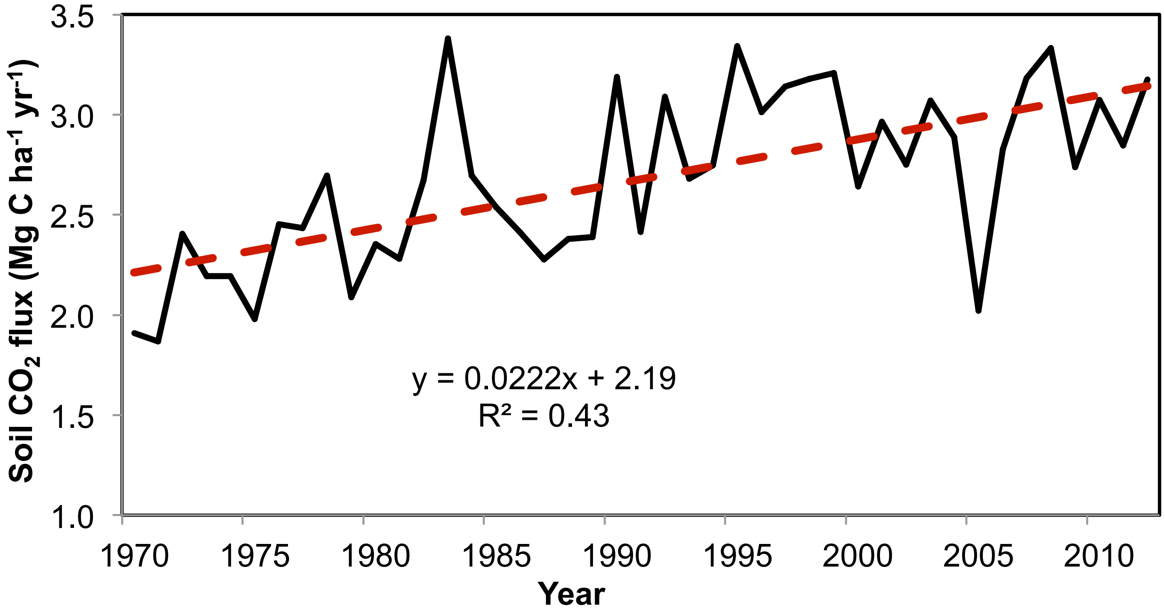


Figure 12b. Simulated Annual Soil CO_2 Flux for the Plot 407 from 1970 to 2012



5.4 Impact of Disturbances on Carbon Stocks

Disturbances have had an obvious impact on C stocks in this forest. The aboveground biomass C decreased by about 155 Gg due to disturbance of the forest between 1985 and 2000.Approximately half of the biomass C lost (73 Gg) was due to the conversion of about 12 km^2 of the original forestland to agriculture and urbanizations, even though that area was only about 21.2% of the total disturbance area. This loss does not include the loss of roots. Accordingly, the total C loss due to conversion to agriculture and urbanization would be about 100 Gg, indicating that land-use changes from forest to non-forest can substantially influence C stocks.

6 Conclusions and Perspective

The results from model evaluation, using four variables, indicated that both Biome-BGC and Forest-DNDC can be used to assess the C storage in stands in the tropical semi-deciduous forest at Kaxil Kiuic in the Yucatan Peninsula of Mexico. However, the performance efficiency of the models differs: $0.40 \leq E \leq 0.54$ with Biome-BGC and $0.79 \leq E \leq 0.88$ with Forest-DNDC. Therefore, we conclude that Biome-BGC might not be as effective in estimating C dynamics in soils in this tropical, semi-deciduous forest.

The spatial variability in biomass is large: aboveground, biomass ranged from about 5 to 115 Mg C ha^{-1} in 2012. The difference is mainly associated with stand age and with species/cover type. In this tropical forest, biomass increases in a non-linear fashion per increment of stand age. Similarly to the relationship between biomass and stand age, NEE, NEP and NBP also show a significantly non-linear correlation to the stand age.

There is a large spatial variation in soil CO_2, with more than a three-fold difference between minimum and maximum fluxes. The difference in levels mainly relates to the differences in soil properties and vegetation characteristics. Soil CO_2 flux can be influenced by soil moisture, as regulated by precipitation. Similarly, there is substantial spatial differentiation in N_2O flux, which varies by more than seven-fold, but the total N loss from this ecosystem shows low spatial variability. The C loss to leachate varies mainly with precipitation, producing the subsurface flow in the forest.

Process-based models can perform better than non-process-based models for estimating C dynamics in the tropical semi-deciduous forest at Kaxil Kiuic. However, process-based models need large, reliable datasets that include climate, soil and vegetation (species/cover type and stand age) data for model setup and parameterization. On the other hand, most non-process-based models need a large number of on-site observations for the empirical relationships that build the predictive function. Generally, spatial measurements for large regions, such as encompassing entire nations or continents, are either impossible or would consume vast amounts of time and finances. Process-based models would thus be more effective tools for estimating spatial C stocks, except that the data necessary to support accurate C estimations elsewhere are largely inadequate at present. Of these data, spatial stand age is the most important because all categories of models need that parameter among their inputs. An effective method to develop spatial stand age using various existing spatial data is needed.

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