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Ecosystem carbon stock changes under different land-use and land-use changes at tropical forest margins: developing simple models

REDD ALERT
Reducing Emissions from Deforestation and Degradation through Alternative Landuses in Rainforests of the Tropics

Deliverable D.5.1

Shibu Muhammed[1], Robin Matthews[1]

[1]Macaulay Land Use Research Institute, Aberdeen, UK.

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Contact Information: Dr. Shibu Muhammed
Ecosystem Modeller
The James Hutton Institute
Cragiebuckler, Aberdeen,
AB15 8QH, UK

Dr. Robin Matthews
Climate Change Theme Coordinator
The James Hutton Institute
Craigiebuckler, Aberdeen
AB15 8QH, UK

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1 Introduction

Tropical forests are a huge reservoir of carbon, storing 59% of the total global carbon even though they cover only 22% of the total vegetation by area (Melillo et al., 1993; Dixon et al., 1994). Deforestation and degradation of tropical forests are major sources of green house gas (GHG) emissions, accounting for approximately 12-20% of the total anthropogenic GHG emissions (Baumert et al., 2005; Stern, 2007; van der Werf et al., 2009). Conversion of forests to agricultural land is the major driver for deforestation in many of these deforesting countries in South America, Africa and Asia. Agriculture (small scale agriculture or shifting cultivation and commercial farming) alone contributes to 62% of the tropical deforestation (UNFCCC, 2007). Currently, a gross figure of 13 million ha of forests are lost annually (FAO, 2006) releasing an estimated 5.8 Gt CO_2 y^{-1} into the atmosphere (Nabuurs et al., 2007). Other GHGs, such as CH_4 and N_2O, may also be emitted during slash-and-burn and subsequent land use. Reducing deforestation is a highly cost-effective way to reduce GHG emissions relatively quickly with providing co-benefits in terms of ecosystems services (Stern, 2007). Recently, the international community has paid much attention to the approaches of Reducing Emissions from Deforestation and Degradation (REDD) in climate policy negotiations with a Road Map being defined at the UNFCCC Thirteenth Conference of Parties (COP-13) in 2007 in Bali, Indonesia. In 2010, a Green Climate Fund was established to pay for REDD carbon credits with contributions from major developed countries to halt deforestation in the tropical countries (Engel et al., 2010). To quantify the gains from REDD mechanisms, the national GHG reporting systems in tropical forest countries need to be improved with simple and robust approaches. The emission of CO_2 alone from land-use change activities contributes to more than 12% (van der Werf et al., 2009) of the total GHG emissions globally (IPCC, 2007). Therefore, ecosystem carbon stock (above, below and soil organic carbon) changes resulting from land-use change need to be more accurately quantified to understand how they vary with land-use, management, soils, and climate. There are a number of common tools that can be used to estimate the carbon stocks such as inventories of above- and below-ground biomass, plot scale soil analysis including C isotope studies, eddy covariance methods, process modelling, remote sensing etc (Smith et al., 2008). The most commonly used methodology for estimating carbon stocks in the forest systems is the inventory method from repeated plot-level surveys or from one larger scale survey in combination with empirical age-class yield models. However, estimates of forest C uptake from this approach do not include any changes in tree growth rate that might occur after model construction and make a difference when environmental conditions are altered (Smith et al., 2008). Although experimental approaches such as C-isotope studies and eddy covariance measurements are more accurate, their direct use on a larger scale such as in the tropical forest margins would be difficult due to lack of resources in these countries. Similarly, in the last few decades, remote sensing has become a useful tool in monitoring land use and land cover changes in tropical forest regions by giving a better estimate of area changes and aboveground biomass (AGBM) stocks (Asner, 2009). However, remote sensing is currently not a reliable option for measuring of C stocks in soil. Modelling approaches seem promising, especially using process-based models, as they are built based on the dynamic processes and calibrated for few individual sites and tested more widely with independent data sets. However, the main hurdle to apply such models at a wider scale in the data scarce tropical countries is their large data requirement. Developing simple models or relationships between key variables determining the process of growth and formation of aboveground biomass and SOC changes will be an alternative approach to overcome such constraints.

Estimating ecosystem carbon stocks under forests is more challenging compared to other land uses such as crops or pastures. At a plot scale, empirically derived allometric relationships were more commonly used to estimate the aboveground-biomass stocks in the forests and further root-shoot ratio was used to calculate the below-ground biomass. At a regional and the global scale, net primary productivity (NPP[1]) was used to estimate the carbon stocks based on few major growth determining factors such as temperature and precipitation (Lieth, 1975; Friedlingstein et al., 1992; Zhang et al., 2002; Schuur, 2003; Del Grosso et al., 2008) (Table 1). Similarly, some other studies (Clark et al., 2001; Malhi et al., 2004; Malhi et al., 2006; Raich et al., 2006; Keeling and Phillips, 2007) attempted to analyse the relationship of NPP of the forests with a wider range of environmental factors including temperature, precipitation, radiation, soil type and soil fertility. The above-mentioned studies review and analyse the aboveground biomass, coarse wood productivity and NPP data from tropical forests mainly in South America and tropical Asia with only very limited data from Africa. However, the outcomes of these reviews show different results. The original relationships between climate and NPP (Lieth, 1972; Lieth, 1975; Friedlingstein et al., 1992) show that NPP increases linearly with increases in mean annual temperature (MAT) and mean annual precipitation (MAP) for temperate forests, but no change in NPP for tropical forest systems. Clark et al. (2001) also found no clear relationship of NPP with MAT and MAP in their analysis reviewing 39 diverse tropical forest sites, however, they found a predictive relationship between annual litterfall and aboveground biomass increment. Schuur (2003) reanalysed the data by combining the above two datasets (Lieth, 1972; Lieth, 1975; Clark et al., 2001) and found that NPP continues to increase in warm and wet tropical ecosystems with increase in temperature but declines at higher precipitation (MAP >2455 mm). Increased precipitation may reduce NPP by decreasing solar radiation inputs, decreased nutrient cycling and reduced plant uptake with increased nutrient leaching, and/or reduced soil oxygen availability in humid tropical forests. Malhi et al. (2004) analysed aboveground coarse wood carbon productivity as a proxy for NPP for 104 sites across the neo-tropics has found a strong relationship between wood productivity and soil fertility and some increase with a decrease in temperature without any obvious relation to rainfall, dry season length or sunshine. In a meta-analysis of the published data to evaluate the effects of temperature on carbon fluxes and storages in mature tropical forests, Raich et al. (2006) have found that NPP, litter production, tree growth and belowground carbon allocation increased significantly with increase in MAT. Forest biomass increased with MAT at a rate of 5-13 Mg C ha^{-1} $°C^{-1}$. Despite higher productivity in warmer forests, SOC decreased with MAT suggesting that rate of decomposition of SOC increased with increasing temperatures faster than the rate of NPP. They did not find any change in total carbon storage, but a shift in the carbon distribution with a large accumulation of detritus and a lower standing biomass in the cooler sites to relatively lower detritus and a higher standing biomass in warmer locations. Malhi et al. (2006) analysed data from 227 forest plots to understand the spatial variation in aboveground biomass with regional-scale environmental factors across the Amazonia. For most of these plots, the AGBM was estimated by using basal area and wood density. They found that basal area generally declines with increasing dry season length and the wood density is higher in a slow-growing forest of low fertility soils compared to a more dynamic forest in highly fertile soils. Keeling and Phillips (2007) report that unlike temperate forests, a strong relationship between the aboveground net primary productivity (ANPP) and the aboveground biomass is

[1] NPP: the difference between CO_2 fixed by photosynthesis and CO_2 lost to autotrophic respiration (Del Grosso et al., 2008)

Table 1. A review of simple models of net primary production and biomass estimation for tropical forest regions

Country /region	Model	Reference
Tropical forests	$NPP = 1125(1-e^{(-0.000664\,P)})$	Friedlingstein et al.(1992)
Central Africa	for Secondary forest <40 yr $NPP = 142.578(1 - \exp(-t/14.695))$ for Secondary forest >40 and <150 yr $NPP = 133.20 + 0.698(t - 40)$ for Mature forest >150 yr $NPP = 210$	Zhang et al. (2002)
Global	$NPP = MIN(NPP_{MAP}, NPP_{MAT})$ $NPP_{MAP} = 0.005212\ (MAP^{1.12363}) / e^{0.000459532\ (MAP)}$ $NPP_{MAT} = 17.6243 / (1+e^{(1.3496-0.071514[MAT])})$	Schuur (2003)
Global	$TNPP = MIN(TNPP_{MAP}, TNPP_{MAT})$ $TNPP_{MAP} = 0.551\ MAP^{1.055} / e^{(0.000306\ MAP)}$ $TNPP_{MAT} = 2540/[1+e^{(1.584-0.0622MAT)}]$ $ANPP = MIN(ANPP_{MAP}, ANPP_{MAT})$ $ANPP_{MAP} = 0.1665\ MAP^{1.185} / e^{(0.000414\ MAP)}$ $ANPP_{MAT} = 3139/[1+e^{(2.2-0.0307MAT)}]$	Del Grosso et al. (2008)
Global	$AGB = 11+25.33\ ANPP - 0.555\ ANPP^2$	Keeling and Phillips (2007)

NPP: net primary productivity (Mg C ha^{-1} y^{-1}); TNPP: total net primary productivity (Mg C ha^{-1} y^{-1}); ANPP: aboveground net primary productivity (Mg C ha^{-1} y^{-1}); $TNPP_{MAP}$ P: precipitation limited total net primary productivity (g C m^{-2} y^{-1}); $TNPP_{MAT}$: ; temperature limited total net primary productivity (g C m^{-2} y^{-1}); $ANPP_{MAP}$: precipitation limited aboveground net primary productivity (g C m^{-2} y^{-1}); $ANPP_{MAT}$: ; temperature limited aboveground net primary productivity (g C m^{-2} y^{-1}); precipitation (mm); MAT: mean annual temperature (°C); MAP: mean annual precipitation (mm).

lacking in the tropical forests. Therefore, the greatest ANPP is found in the tropics but the highest aboveground biomass forests are found in the temperate regions. The AGBM peaks at about 15-20 Mg ha^{-1} y^{-1} of ANPP plateaus at >20-25 Mg ha^{-1} y^{-1}. This suggests that forest productivity and stem turn-over rates are positively correlated. The NCEAS model developed by Del Grosso et al. (2008) by compiling 5600 global data points with observed mean annual NPP, land cover class, precipitation and temperature predicts NPP for tree based systems on the basis of temperature and precipitation and non-tree (grass or shrub) dominated systems on the basis of precipitation alone. IPCC also recommends a set of equations (Tier-1) for estimating biomass under varying land-uses including forests, pasture and crop (IPCC-LULUCF-GL-2006). A global carbon map with aboveground and belowground carbon density was developed by Ruesch and Gibbs (2008) using the IPCC Tier-1 methodology applying to 124 carbon zones created globally by overlaying Global Land Cover map (2000), continental and eco-floristic maps.

For land use systems other than forests, ecosystem structure and C pools vary greatly across landscapes and estimating NPP and biomass would depend on the land-use (pasture or crops), species (annual or perennial). The mean annual temperature and precipitation will influence the perennial crop productivity. However, for seasonal crops such as crops, the growth determining factors will be growing season temperature (GST), precipitation (GSP) and soil fertility.

Land-use change results in the quality of carbon substrate inputs, which in turn results in a change in the composition and structure of the soil carbon pool. Impact of land-use change on soil carbon stock is uncertain (Trumbore et al., 1995; McGrath et al., 2001) and depends on the land-use history, land-use that follows and soil properties. Using average values for carbon stock changes from a specific land-use change study in one site to another without considering the related biophysical drivers may result in large errors in the SOC stock values in the tropics (Powers et al., 2011). A meta-analysis of the land-use change data from 80 studies examining the relationship of biophysical drivers on soil C dynamics show that the effects of land-use change on soil C stocks depend upon both precipitation regime and soil clay mineralogy, and that the interactions between these two drivers are significant (Powers et al., 2011).

Most of the literature review and meta-analysis related to carbon stock changes associated with land-use changes in the tropical forest margins were partial with the analysis of either only NPP productivity or aboveground biomass or soil changes. To understand the effect of land-use change on the overall carbon stock changes, we need a whole system approach in which carbon in soils, roots, detritus, and other aboveground components are estimated following the pattern of land-use change. No review studies to our knowledge have been done to establish such relationships between the ecosystem carbon (sum of all organically derived carbon in various pools: both aboveground and belowground including soil) and various climatic or soil factors. Therefore, the objective of this paper is to derive simple relationships between environmental variables such as temperature, water and soil variables such as clay and SOC content with the ecosystem carbon stock under a land-use or land-use change following deforestation in tropical forest regions. Our attempt is to develop some simple and robust models or relations from the land-use change data in these tropical countries and compare these relations with those derived from the results of a process-based model applied to a number of case study countries such as Cameroon, Peru and Vietnam.

2 Methodology

2.1 Deriving simple relationships of above and below-ground biomass and soil organic carbon changes- Literature review

A literature review was done to develop a database of above and below-ground carbon stocks across the tropical forests. We collated 6 studies in six different countries giving information on carbon stock changes under both above and-belowground biomass and soil carbon (Table 2). The different carbon pools (AGBM, BGBM, necromass, soil and total ecosystem carbon) in different land use systems are given in Table 3. In the review, we considered only those studies where the organic soil carbon pool is estimated up to a depth deeper than 1m.

Table 2. Details of soil and climatic characteristics of the various sites reviewed for deriving the relations between SOC changes under different land-use changes.

Country	Location	Soil type	Latitude	longitude	MAT (°C)	MAP (mm)	Altitude (m)	Clay (%)	References
Colombia	Porce	Ustoxic Dystropept, Typic Tropaquent, Typic Tropopsamment	6°45'37" N	75°06'28" W	22.70	2078	900-1500		Sierra et al.(2007); Sierra et al. (2009)
			6°45'37" N	75°06'28" W	22.70	2078			
Brazil	Rondônia/Santa Barbara	sandy clay loam	9°12' S	60°3' W	25.2	2354		27.0	Hughes (2002); Guild (1998)
		clay	9°12' S	60°3' W	25.2	2354		51.0	
		sandy loam	9°12' S	60°3' W	25.2	2354		16.3	
		sandy clay	9°12' S	60°3' W	25.2	2354		43.7	
		sandy clay loam	9°12' S	60°3' W	25.2	2354		23.3	
Peru	Manu National park		13°00' S	71°40' W	11.00	2200	3345		Gibbon et al. (2010); Zimmermann et al. (2010)
			13°00' S	71°40' W	11.00	2200	3540		
China	Xishuangbanna/ Menglun	Haplic Acrisol	21°57’	101°12’	21.70	1539	730		Lü et al. (2010)
	Xishuangbanna/Mengla		21°32’	101°33’	21.70	1539	581		
	Xishuangbanna/Manyang		21°27’	101°36’	21.70	1539	643		
Mexico	Veracruz/ Los Tuxtlas biological station (LTBS)		18°35' N	95°05' W	27.0	4700			Hughes et al. (2000)
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
			18°35' N	95°05' W	27.0	4700			
Venezuela	Cero El Coco	clay loam	10 °N	66 °W	27.00	800	130		Delaney et al. (1997)
	Caimital& Ticoporo	clay,clay Ioam,sandy clay loam,silty clay loam	9 °30' N	70 °W	26.00	1500	150		
	Rio Grande& KM92	sandy loam, sandy clay laom	9 ° N	64 °W	25.50	2850	210-270		
	Carbonera	clay,clay loam,loamy,clay	9 °30' N	71 °W	15.00	1480	2310-2450		
	Mucuy	sandy loam, silty loam	10 °30' N	72 °W	10.50	1970	2640-3000		

Table 3 Carbon pools in various sites under different land uses from literature review.

	Location	Land-use	Age (y)	Carbon pools (Mg C ha^{-1})				
				AGBM	TN	TGBM	SOC†	ESC
Colombia	Country Porce	PF		112	7	38	228‡	384
		SF	8	21	3	12	193‡	228
Brazil	Rondônia/Santa Barbara	PF		195		47	87	329
		SC	1	103		25	97	225
		SF	6	51		12	72	135
		SF	12	34		8	73	115
		P	14	31		7	75	113
Peru	Manu National park	PF		63		14	118	195
		G		8		0.1	119	127
China	Xishuangbanna/ Menglun	PF		150		35	87	272
	Xishuangbanna/ Mengla	PF		224		52	102	377
	Xishuangbanna/ Manyang	PF		144		32	84	261
Mexico	Veracruz/ Los Tuxtlas biological station (LTBS)	PF		201		52	210	464
		P	8	15		4	163	181
		P	9	24		6	154	184
		P	33	4		1	193	198
		P	33	3		1	157	161
		C	5	21		5	130	156
		C	32	5		1	291	298
		C	45	2		1	180	183
Venezuela	Cero El Coco	PM-vd		70	8	33	233	344
	Caimital& Ticoporo	PM-m/d		148	6	24	125	303
	Rio Grande& KM92	PF-m		179	19	29	160	387
	Carbonera	PF-LM-m		173	24	38	253	488
	Mucuy	PF-M-w		157	20	35	257	468

PF:Primary forest; SF:Secondary forest; SC:Shifting cultivation; P:Pasture; G:Grass; C:Crop; PM-vd: Primary forest-very dry; PM-m/d: Primary forest-moist to dry transition; PF-m: primary forest-moist; PF-LM-m: Primary forest-lower montane-moist; Primary forest-montane-wet; AGBM: Aboveground biomass; TN: Total necromass; BGBM: Belowground biomass; SOC: Soil organic carbon; ESC: Ecosystem carbon.
†Soil depth 1 m.
‡Soil depth 4 m.

2.2 Deriving simple relationships of above and below-ground biomass and soil organic carbon changes- using PALM

The People and Landscape Model (PALM) (Matthews and Pilbeam, 2005; Matthews, 2006) is an agent-based model operating at the level of a catchment, which contains a number of decision-making entities (e.g. farm households) located on a landscape made up of a number of heterogeneous land units, each of which contains routines to simulate its water balance and carbon and nitrogen dynamics over time. A detailed description of the PALM, its structure and agents are given by Matthews (2006). Soil is represented in the model as a profile consisting of a number of layers depending on the site. The soil water dynamics in the model is based on that used in the DSSAT family of models (Ritchie and Otter, 1985). Processes of SOC and nitrogen dynamics are described by CENTURY (Parton et al., 1988; Gijsman et al., 2002) and DAYCENT (Parton et al., 2001; Del Grosso et al., 2002). The soil processes are simulated continuously, and vegetations (crops, weeds, trees) can come and go as similar to the land-use and land-use change occurring in reality at the landscape level. Decisions made by the household agents result in land management actions, which may influence the fluxes of water, carbon and nitrogen within the landscape. In the current work, we used the tree module within PALM to simulate the tropical forest growth after re-parameterising the model for tropical conditions.

PALM was run for LU transition(s) following deforestation representing primary forest (PF)-to-agriculture and agriculture-to-secondary forest (SF) in the REDD-ALERT project sites in three case study countries (Cameroon, Vietnam and Peru) (Table 4) for about 100 years. The model was run for a number of years (80 years) under mature primary forest to bring biomass and SOC content into equilibrium. Following deforestation, the land was subjected to cropping for about four-years before being abandoned and becoming a secondary forest for the remaining 15 years. The crop represents maize (MZ) in all the three countries. The weather data for the selected sites was derived from the MARKSIM (Jones and Thornton, 2000) weather generator and the soil data from Harmonised World Soil Database (HWSD).

The effect of temperature and rainfall on the above-and-belowground biomass production under each land use was studied by running the model for a range of temperature, rainfall and solar radiation and in their combinations. The temperature has been changed by ±4 °C from the average temperature in combination with the rainfall and solar radiation which are changed by ±20% from the mean annual values for these sites in these countries (Table 5).

The effect of temperature, rainfall and clay content on the change in SOC content under different land-use and land-use changes following deforestation was also estimated by varying the temperature (±4 °C), rainfall (±20 %), clay content (±20 % from the given value) and initial SOM content (±20 % from the given value) and in their combinations (Table 5). From the large set of model output, relationships were derived by a stepwise multi-regressional analysis for above-and-belowground biomass and equilibrium SOC changes with changes in temperature and rainfall. These simple models were tested with the data compiled under literature review.

2.2.1 Case study countries

Cameroon

Cameroon occupies about 17 Mha (10%) of the tropical humid forest in the Congo Basin that covers almost 40% of the national territory (Robiglio et al., 2010). Deforestation rate in Cameroon is 0.14% and agriculture is the major driver for deforestation particularly, the

Table 4. Different sites/villages selected in various REDD-countries for the simulation study.

*Site	Depth (cm)	Soil type†	Clay (%)	pH	BD (kg m^{-3})	SOC (g kg^{-1})	MAT‡ (°C)	MAP (mm)	MAR (MJ $m^{-2}d^{-1}$)
Cameroon									
Aloum	30	Orthic Ferralsol	22 (28)	5.0 (5.0)	1380 (1350)	37.1 (6.1)	23.2	2011	14.0
Alangana	30	Orthic Ferralsol	26 (35)	5.0 (5.0)	1410 (1350)	10.6 (3.5)	23.4	1561	17.2
BibaYezoum	30	Orthic Ferralsols	26 (35)	5.0 (5.0)	1410 (1350)	10.6 (3.5)	23.8	1630	17.5
Keeke	30	Orthic Ferralsols	26 (35)	5.0 (5.0)	1410 (1350)	10.6 (3.5)	24.4	1742	15.6
Nyabessan	30	Orthic Ferralsols	26 (35)	5.0 (5.0)	1410 (1350)	10.6 (3.5)	23.2	2159	13.7
Ongolzok	30	Orthic Ferralsols	26 (35)	5.0 (5.0)	1410 (1350)	10.6 (3.5)	24.0	1517	17.6
Peru									
Ucayali	30	Eutric Gleysols	51 (51)	4.6 (4.7)	1210 (1210)	14.2 (4.3)	26.2	1606	19.4
Loreto	30	Eutric Gleysols	51 (51)	4.6 (4.7)	1210 (1210)	14.2 (4.3)	26.5	2913	19.0
SanMartin	30	Dystric Cambisols	37 (59)	5.3 (5.5)	1270 (1200)	19.1 (8.6)	21.6	1521	18.9
Madrede	30	Plinthic Acrisols	25 (38)	4.1 (4.5)	1390 (1310)	16.2 (6.5)	25.3	2236	18.4
Vietnam									
Bac Kan	30	Orthic Acrisols	24 (36)	4.6 (4.8)	1220 (1230)	12.5 (4.5)	17.7	1615	12.1
Dak Lak	30	Ferric Acrisols	10 (23)	6.2 (5.7)	1580 (1430)	6.1 (3.0)	24.4	1753	18.1
Lam Dong	30	Orthic Ferralsols	52 (58)	4.9 (5.1)	1240 (1220)	16.5 (6.8)	21.1	2565	14.9
Son La	30	Luvisols	24 (34)	6.4 (6.3)	1400 (1320)	10 (4.2)	19.7	1453	15.2

* Values in paranthesis correspond to that in 30-70 cm depth
†Soil data source: HWSD (Harmonised World Soil Database)
‡ Weather data generated from MARKSIM (Jones and Thornton, 1993)

Table 5. Scenarios of changes in weather and soil factors used as input in the model for simulating their effect on biomass and soil carbon changes under tropical landuse change

Scenarios	MAT change (° C)	MAP change (%)	MAR change (%)	Clay change (%)	SOC change (%)
T1	-4	0	0	0	0
T2	4	0	0	0	0
P1	0	-20	0	0	0
P2	0	20	0	0	0
Cl1	0	0	0	-20	0
Cl2	0	0	0	20	0
OM1	0	0	0	0	-20
OM2	0	0	0	0	20
DSo1	0	0	-20	0	0
DSo2	0	0	20	0	0
T1P1	-4	-20	0	0	0
T1P2	-4	20	0	0	0
T2P1	4	-20	0	0	0
T2P2	4	20	0	0	0
T1Cl1	-4	0	0	-20	0
T1Cl2	-4	0	0	20	0
T2Cl1	4	0	0	-20	0
T2Cl2	4	0	0	20	0
T1OM1	-4	0	0	0	-20
T1OM2	-4	0	0	0	20
T2OM1	4	0	0	0	-20
T2OM2	4	0	0	0	20
T1DSo1	-4	0	-20	0	0
T1DSo2	-4	0	20	0	0
T2DSo1	4	0	-20	0	0
T2DSo2	4	0	20	0	0
P1Cl1	0	-20	0	-20	0
P1Cl2	0	-20	0	20	0
P2Cl1	0	20	0	-20	0
P2Cl2	0	20	0	20	0
P1OM1	0	-20	0	0	-20
P1OM2	0	-20	0	0	20
P2OM1	0	20	0	0	-20
P2OM2	0	20	0	0	20
P1DSo1	0	-20	-20	0	0
P1DSo2	0	-20	20	0	0
P2DSo1	0	20	-20	0	0
P2DSo2	0	20	20	0	0
Cl1OM1	0	0	0	-20	-20
Cl1OM2	0	0	0	-20	20
Cl2OM1	0	0	0	20	-20
Cl2OM2	0	0	0	20	20
Cl1DSo1	0	0	-20	-20	0
Cl1DSo2	0	0	20	-20	0

MAT: Mean annual temperature; MAP: Mean annual precipitation; MAR: Mean annual solar radiation; SOC: Soil organic carbon shifting cultivation (Achard 2002; FAO 2001). Six sites (Table 4) representing six regions in the Cameroon selected as part of the REDD-ALERT project are used for this study.

Peru

Peru contains 70 Mha million (13%) of the tropical Amazon forests with a relatively low rate of deforestation (~0.14%) (Velarde et al., 2010). Four sites/regions were selected in Peru one of which, Ucayali, is a part of the REDD-ALERT project. The climate and soil characteristics of these regions are given in Table 4.

Vietnam

The forest sites/regions selected in Vietnam represents the topography of the country from the mountains to central highlands. Four sites/villages were selected from the four provinces of which three are part of the REDD-ALERT project. The climate and soil characteristics of these regions are given in Table 4.

3 Results

3.1 Deriving simple relationships of above-and-below-ground biomass and soil organic carbon changes-by literature review

The results show a poor correlation between the aboveground biomass carbon (AGBM-C) of forest and pasture with the environmental variables such as MAT and MAP (Figure 1). For secondary forest, AGBM-C has a good correlation with MAT and MAP, however, it contains only three data points. Similar to AGBM-C, soil organic carbon also shows a poor relation between MAT and MAP (Figure 2). For pasture, SOC shows a good correlation with MAP. For SF, a best correlation may be the artefact of the three data points in the analysis. As similar to the AGBM-C, ecosystem carbon under forest also shows a poor correlation with the MAT and MAP, and a good and strong relationship between MAT and MAP under pasture and SF (Figure 3). Similarly, change in ecosystem carbon associated with land-use change from PF-to-Pasture and PF-to-SF also shows a good correlation to MAT and MAP (Figure 4). Since there were only three data points for crop and two of them were from the same site, we did not include these in the analysis.

The multi-linear regression analysis of the data with MAT and MAP for different variables under different land-use systems show a higher correlation (with R^2= 0.54) for ecosystem carbon under forest and pasture (Table 6). Soil organic carbon stock under pasture also shows a strong correlation to MAT and MAP.

3.2 Deriving simple relationships of above-and-below-ground biomass and soil organic carbon changes-from PALM results

The model simulated results of total, above- and- belowground biomass and SOC content under different land-uses for the various sites are given in figures 5, 6 and 7. The results show a varying degree of equilibrium forest biomass carbon among different sites depending on the climate and soil conditions. In Cameroon, the highest forest biomass carbon (above + below-

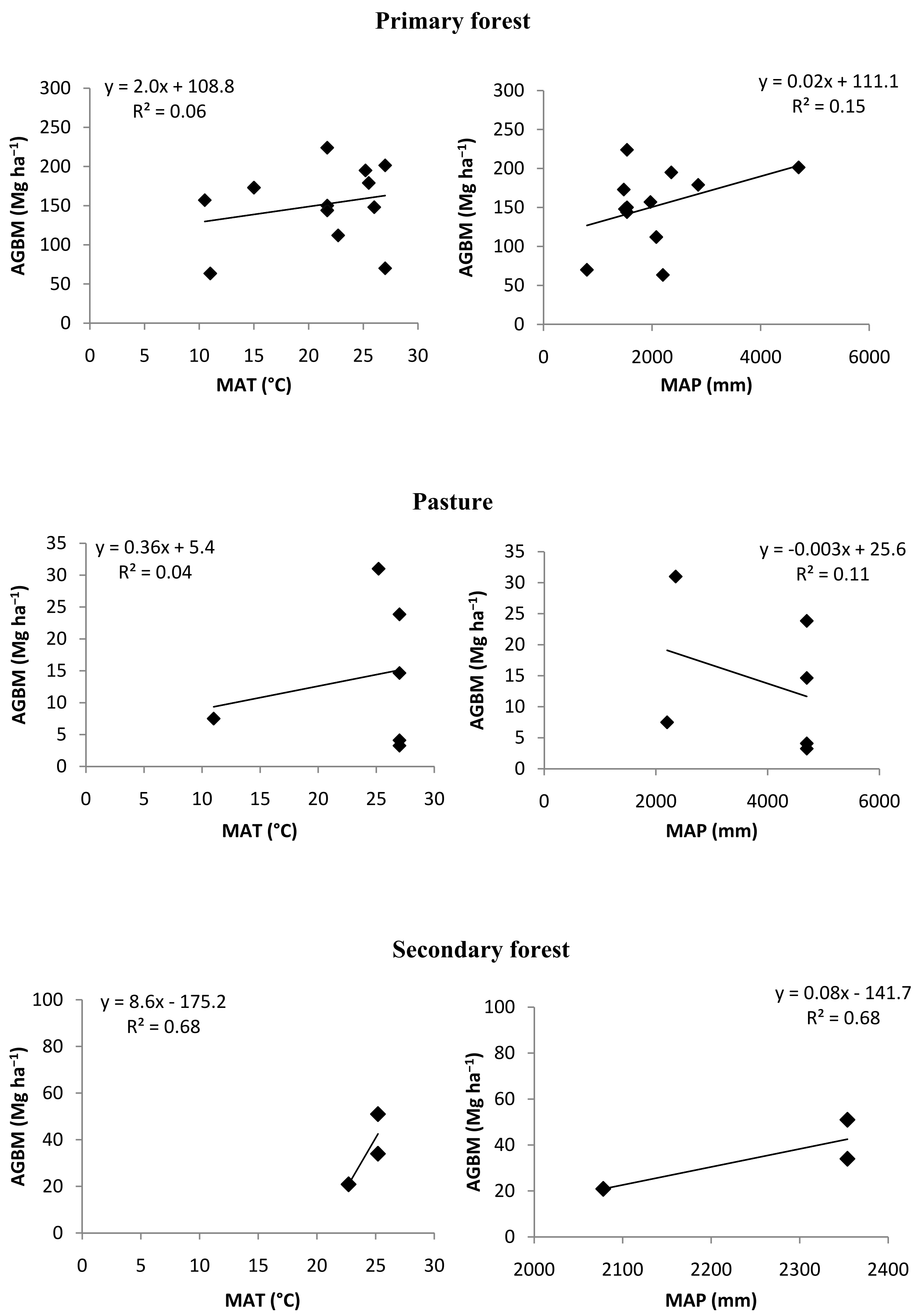


Figure 1. The relation of aboveground biomass (AGBM, Mg ha^{-1}) with the environmental variables of temperature (MAT) and moisture (MAP) under various land uses.

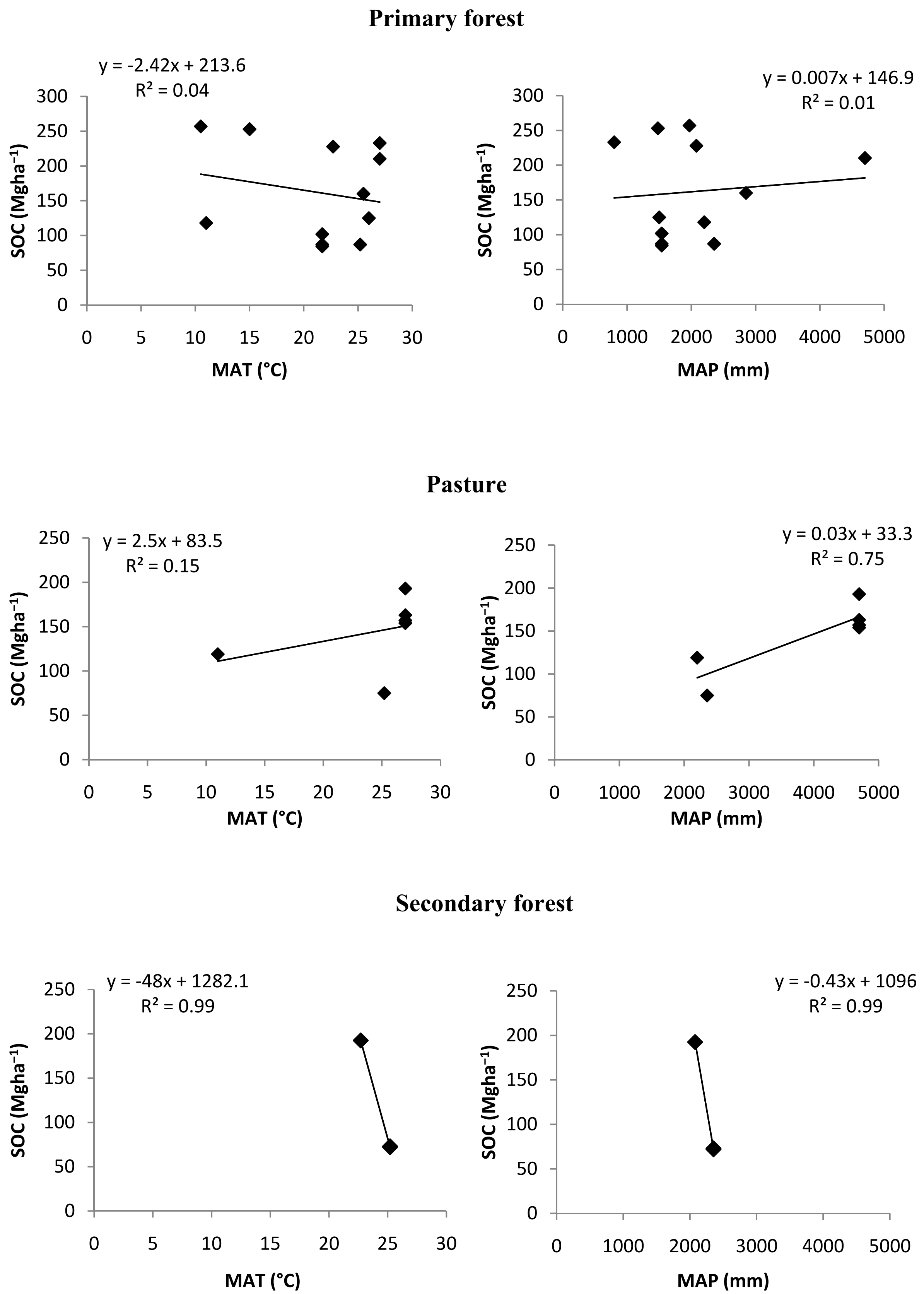
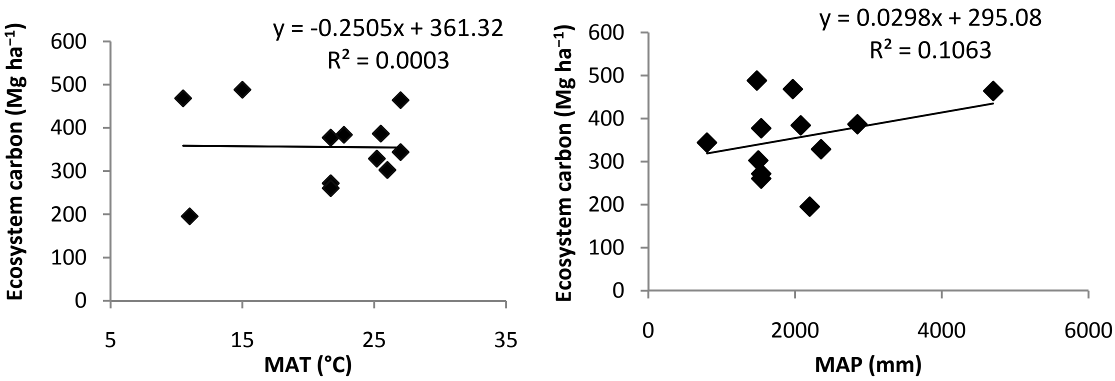
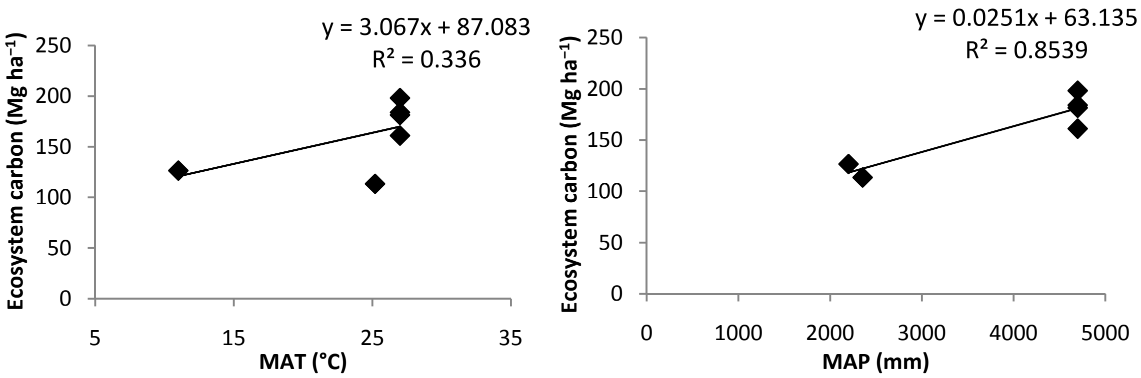


Figure 2. The relation of soil organic carbon (SOC, Mg ha^{-1}) with the environmental variables of temperature (MAT) and moisture (MAP) under various land uses.

Primary forest



Pasture



Secondary forest

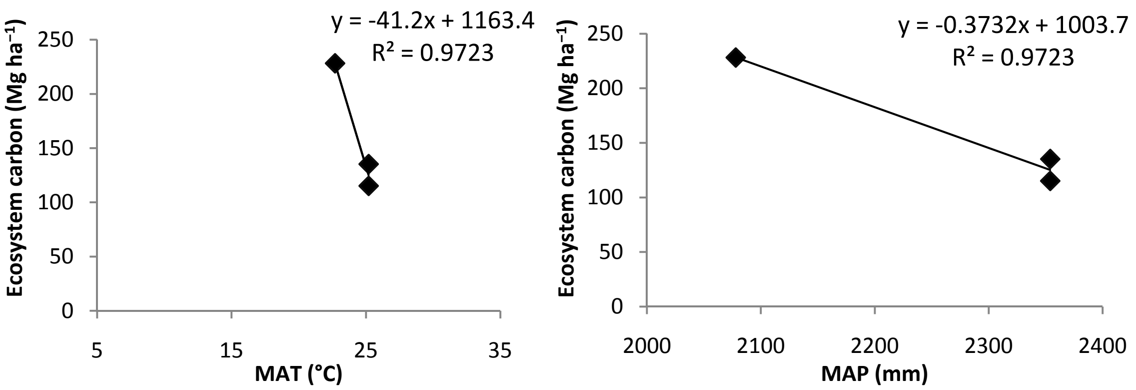


Figure 3. The relation of ecosystem carbon stock (Mg ha^{-1}) with the environmental variables of temperature (MAT) and moisture (MAP) under various land uses.

ground) is formed in the Ongolzok and BibaYezoum (240-250 Mg C ha^{-1}) whereas the lowest biomass was formed in Nyabessan and Aloum (180-190 Mg C ha^{-1}) (Figure 5). Soil organic carbon (humus) is almost maintained or increased especially under forest except for Aloum with a higher initial SOC level of 220 Mg ha^{-1}, which stabilises at 170 Mg ha^{-1}. In general, forest biomass carbon in Peru sites (250-300 Mg ha^{-1}) is higher than that in Cameroon sites (Figure 6) and SOC found to increase in most of these sites except for San Martin where initial SOC stock is relatively high (400 Mg ha^{-1}). As similar to Aloum in Cameroon, aboveground and total biomass-C is lower in San Martin with a higher SOC stock. In comparison to Cameroon and Peru sites, the aboveground and total biomass carbon in Vietnam is lower and is in the range of 70-150 Mg ha^{-1}. Within Vietnam, Lam Dong and Dak Lak, in the Central Highlands have a higher biomass-C compared to the Northern mountain forests. Soil organic carbon in most of the sites in Vietnam is found to stabilise at a lower value compared to the initial except for Dak Lak Province.

In almost all the sites, simulated maize yields were higher in the first year following deforestation (Figure 8) and then quickly declined over the years as no external fertilizers were applied. Average maize yield varies within a country and is highest in Peru followed by Cameroon.

With land-use change from primary forest to crop, SOC (humus) slightly increases in the initial years due to the addition of litter and necromass to the soil from the forest (Figure 9). However, in the long run, SOC declines even under the secondary forest.

To analyse the effect of environmental (MAT, MAP, MAR) and soil factors (clay and initial SOC stock) on the biomass and soil C stock under different land-use and land-use changes, the model has been run for a range of these values individually and in combinations (Table 5). Simulated results show that AGBM and ecosystem-C under forest have some positive correlation with MAT (R^2=0.59 and R^2=0.47), MAR (R^2=0.41 and R^2=0.30) and a poor correlation with MAP, clay and initial SOC stock (Figure 10). Soil organic carbon shows a poor fit with all the above factors except that for initial SOC (R^2 = 0.70).

Crop biomass shows a poor fit with all the above factors except that for MAR (R^2= 0.34) (Figure 11). Similar to forest, SOC is strongly correlated to the initial SOC. Since the major share of ecosystem carbon under crops belong to the soil, ecosystem-C also shows a good correlation with the initial SOC stock. Similar to the PF, secondary forest also shows some correlation to MAT and poor correlation to all the other factors (Figure 12). However, as similar to crop, SOC and ecosystem carbon shows a good correlation to the initial SOC and a poor correlation to all the other factors. A stepwise-multi-linear regression analysis was performed to derive the coefficients for different environmental factors that best describe their relations with the variables in combinations. The combination of these four or five factors was able to explain most of the variation in the results (Table 7). About 70-90% of the variability (R^2 = 0.72-0.88) in the model results for different variables could be explained with these factors except that for crop total biomass (R^2 = 0.49). The regressional model was applied to the data collected as part of the review (Table 3) to estimate the ecosystem-C with limited parameters available (MAT MAP and SOC). The results show poor fit with the observed (Figure 13) under forest. However, when those sites with MAT< 15 °C were removed from the analysis, and the model was built on the data from such sites with MAT> 15 °C, a better fit was found (Figure 13).

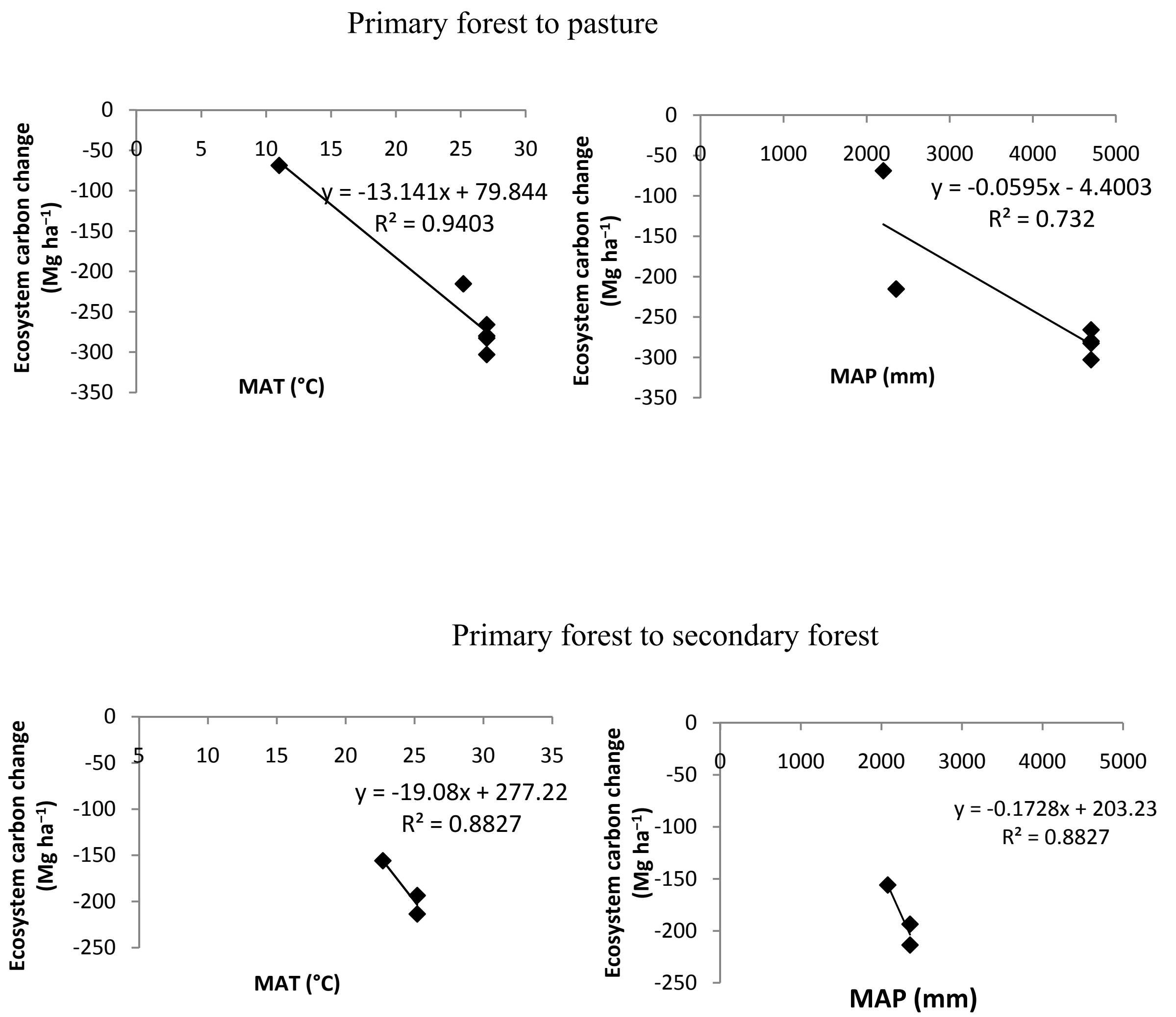


Figure 4. The relation of ecosystem carbon stock change (Mg ha^{-1}) with the environmental variables of temperature (MAT) and moisture (MAP) under various land uses.

Table 6. Results of the regression analysis for the different variables in relation to the mean annual temperature (MAT) and mean annual precipitation (MAP) under various land-uses for the data compiled by literature review.

		Coefficient	**SE**	**n**	**R**	**R^2**	**ΔR^2**
			Primary forest				
AGBM-C	Constant	82.453	59.985	12	0.43	0.18	0.00252
	MAT	1.508	2.587				
	MAP	0.0179	0.0154				
SOC							
	MAT	-2.76	3.90	12	0.3	0.06	0.000
	MAP	0.01	0.02				
	MAP	0.01	0.02				
ESC							
	Constant	316.418	114.055	12	0.7	0.54	0.235
	MAT	-1.114	4.919				
	MAP	0.031	0.029				
			Pasture				
AGBM-C	Constant	10.312	17.247	6	0.3	0.11	0.000
	MAT	1.751	1.049				
	MAP	-0.010	0.005				
SOC	Constant	65.871	31.021	6	0.9	0.88	0.810
	MAT	-3.607	1.886				
	MAP	0.04	0.01				
ESC	Constant	75.38	26.441	6	0.9	0.88	0.810
	MAT	-1.331	1.608				
	MAP	0.0301	0.00824				

AGBM-C: Aboveground biomass carbon; SOC: Soil organic carbon; ESC; Ecosystem carbon; SE: standard error; n is the number of data points; R: correlation coefficient; R^2: coefficient of determination; ΔR^2= delta R^2.

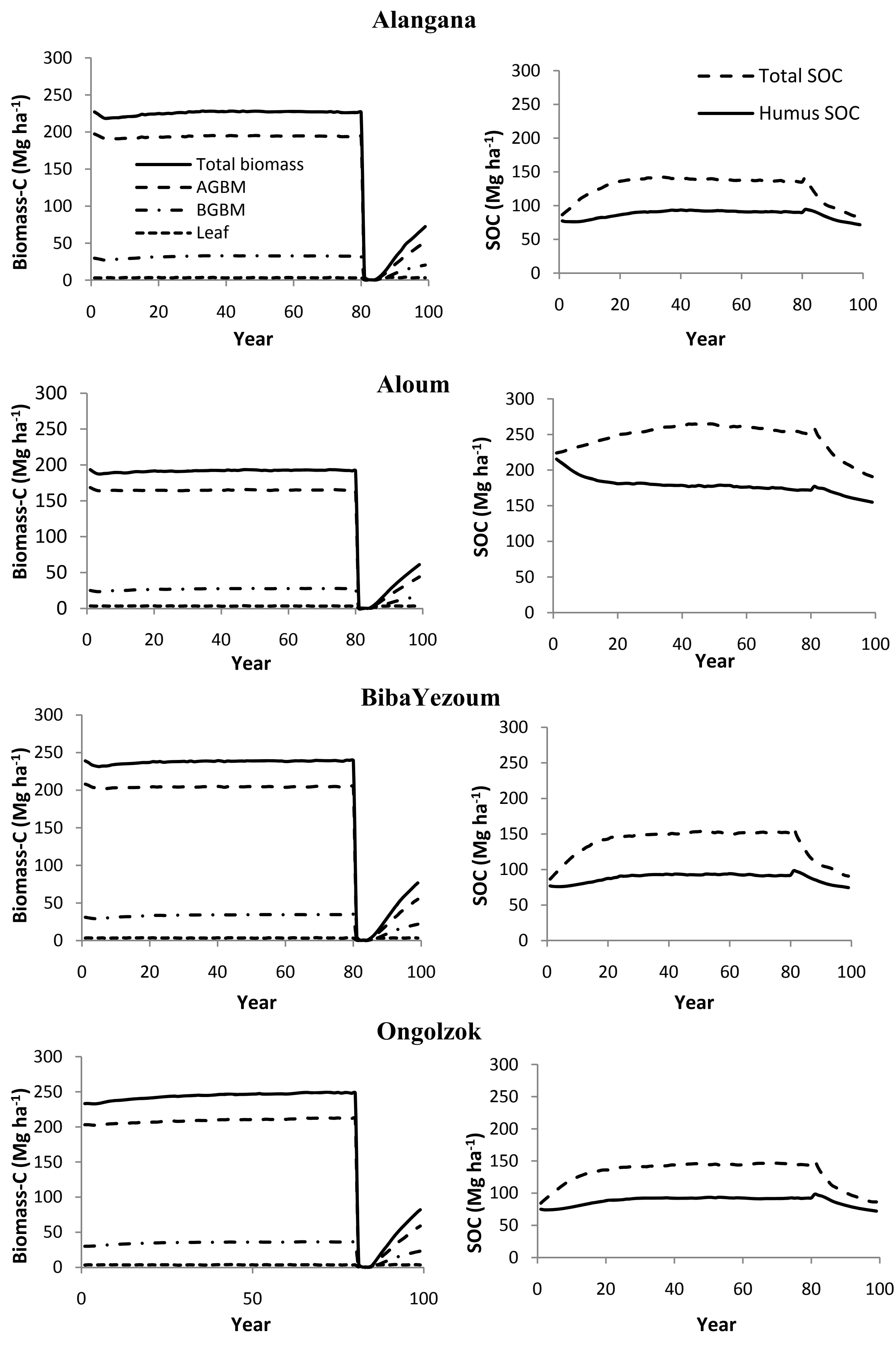


Figure 5. Total, aboveground (AGBM), below-ground (BGBM), leaf biomass and soil organic carbon (SOC) under different land-use transitions: primary forest (PF), maize (MZ) and secondary forest (SF) in Cameroon.

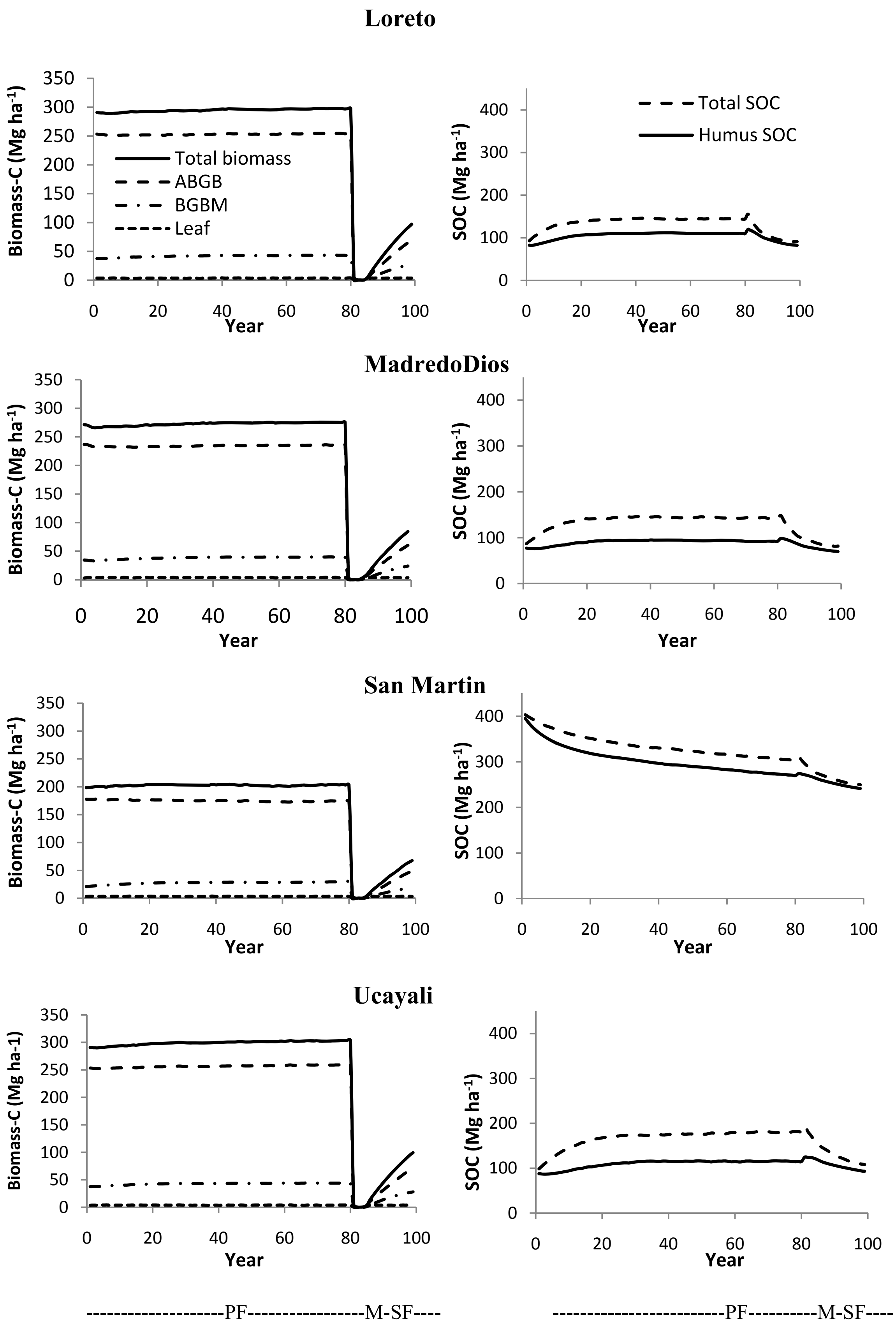


Figure 6. Total, aboveground (AGBM), below-ground (BGBM), leaf biomass and soil organic carbon (SOC) under different land-use transitions: primary forest (PF), maize (MZ) and secondary forest (SF) in Peru.

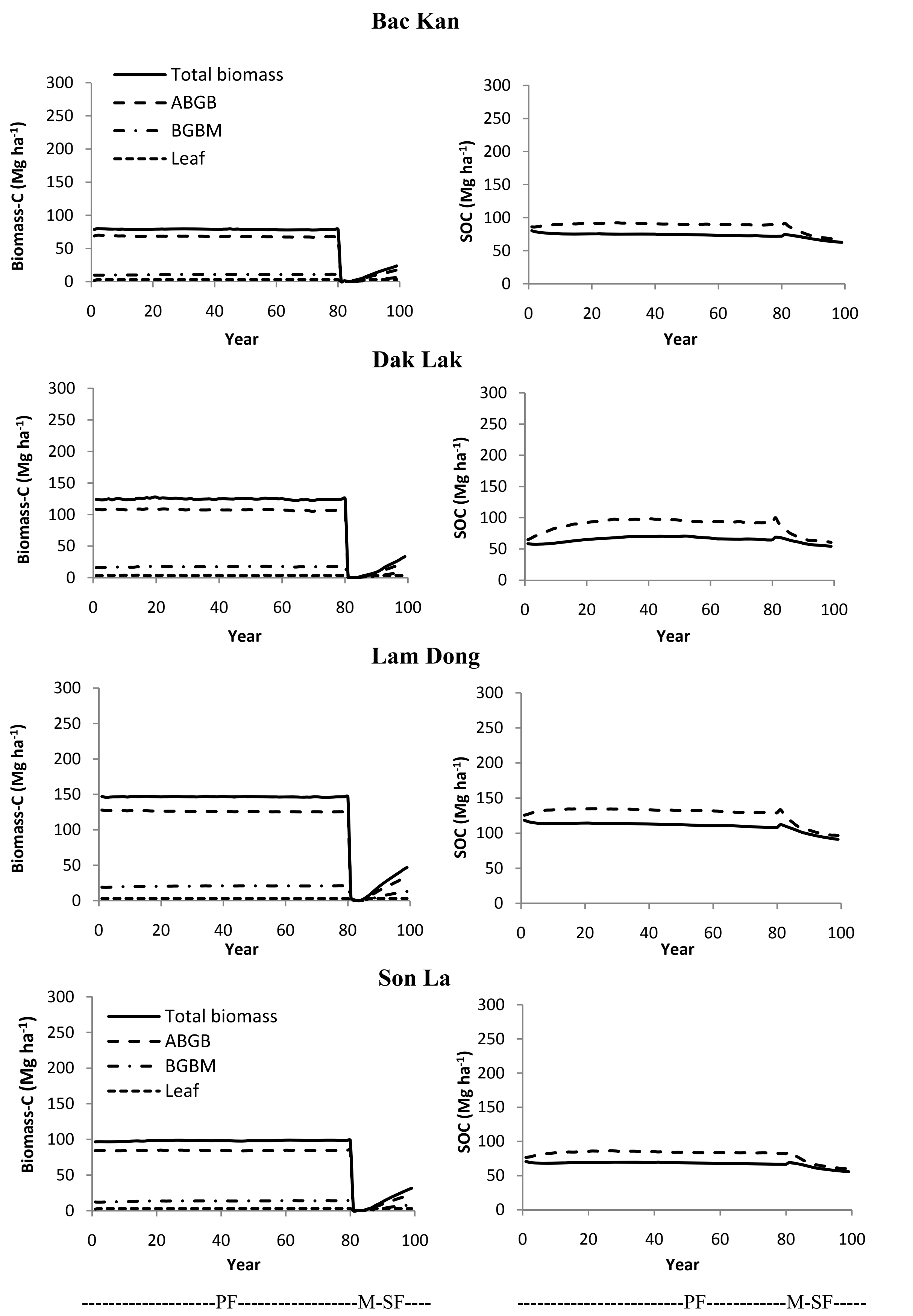


Figure 7. Total, aboveground (AGBM), below-ground (BGBM), leaf biomass and soil organic carbon (SOC) under different land-use transitions: primary forest (PF), maize (MZ) and secondary forest (SF) in Vietnam.

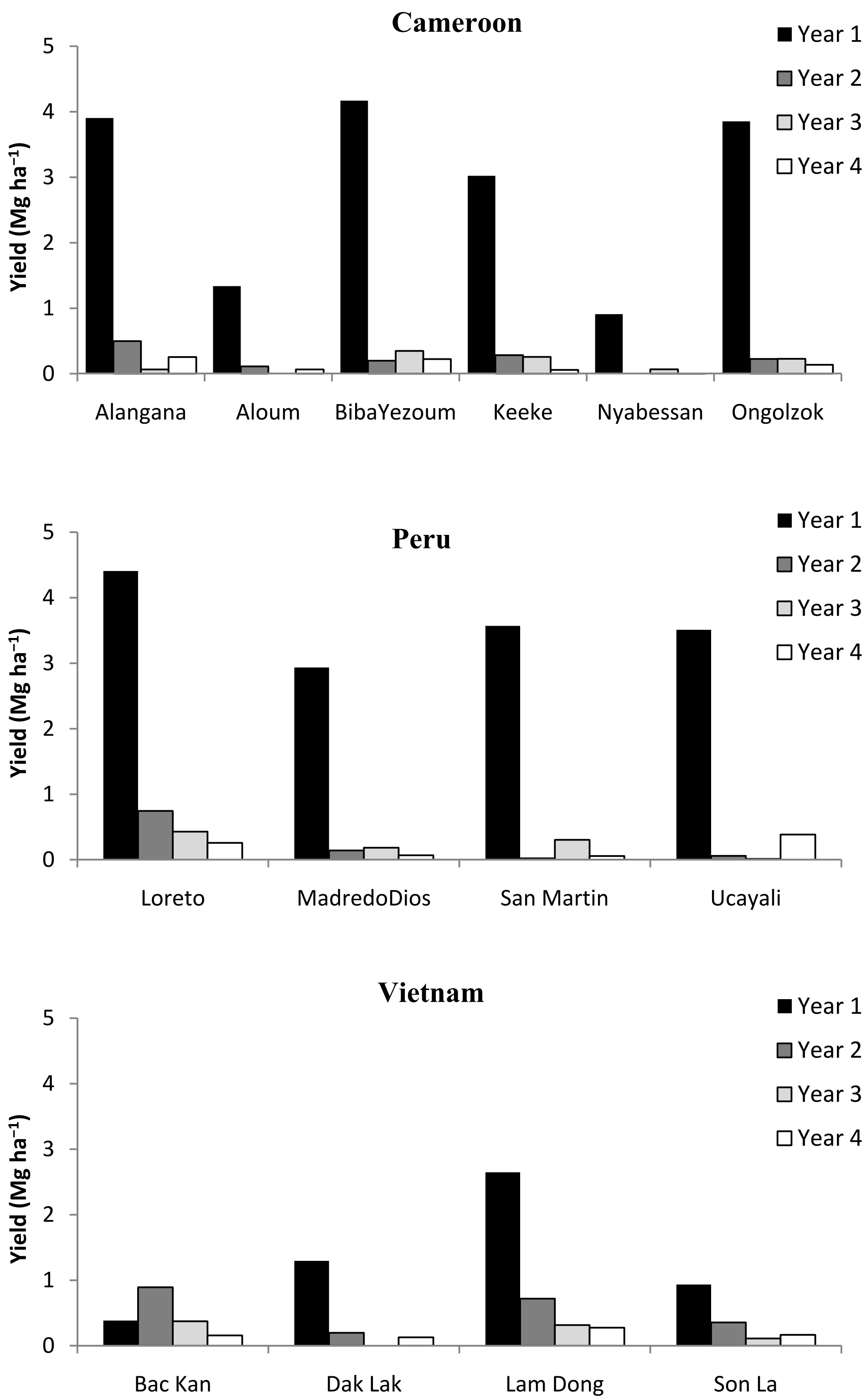


Figure 8. Simulated maize yields over the years following deforestation in various sites in different countries under the study.

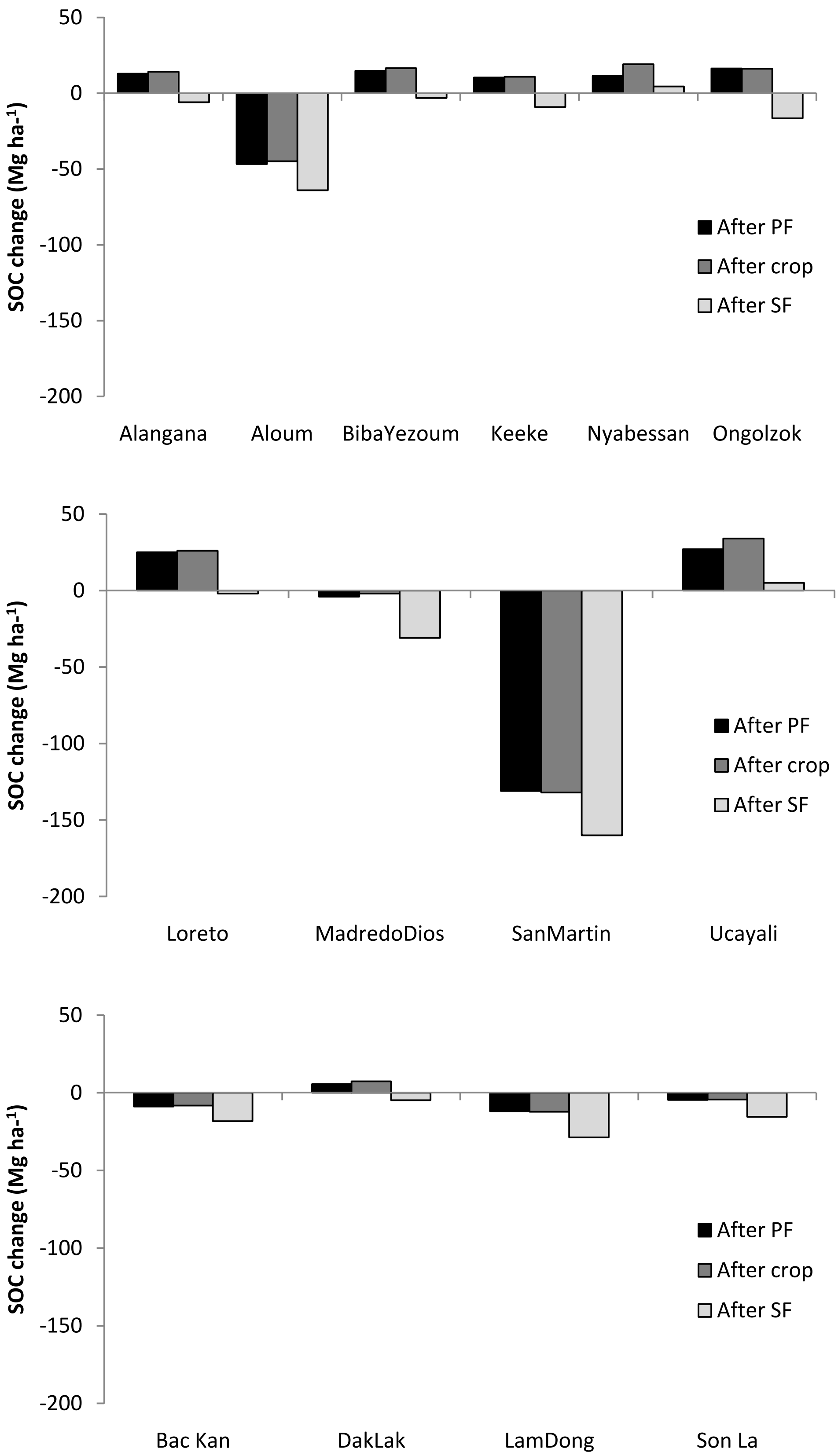


Figure 9. Simulated change in SOC over the land use transition of forest-crop-secondary forest in various sites in different countries under the study.

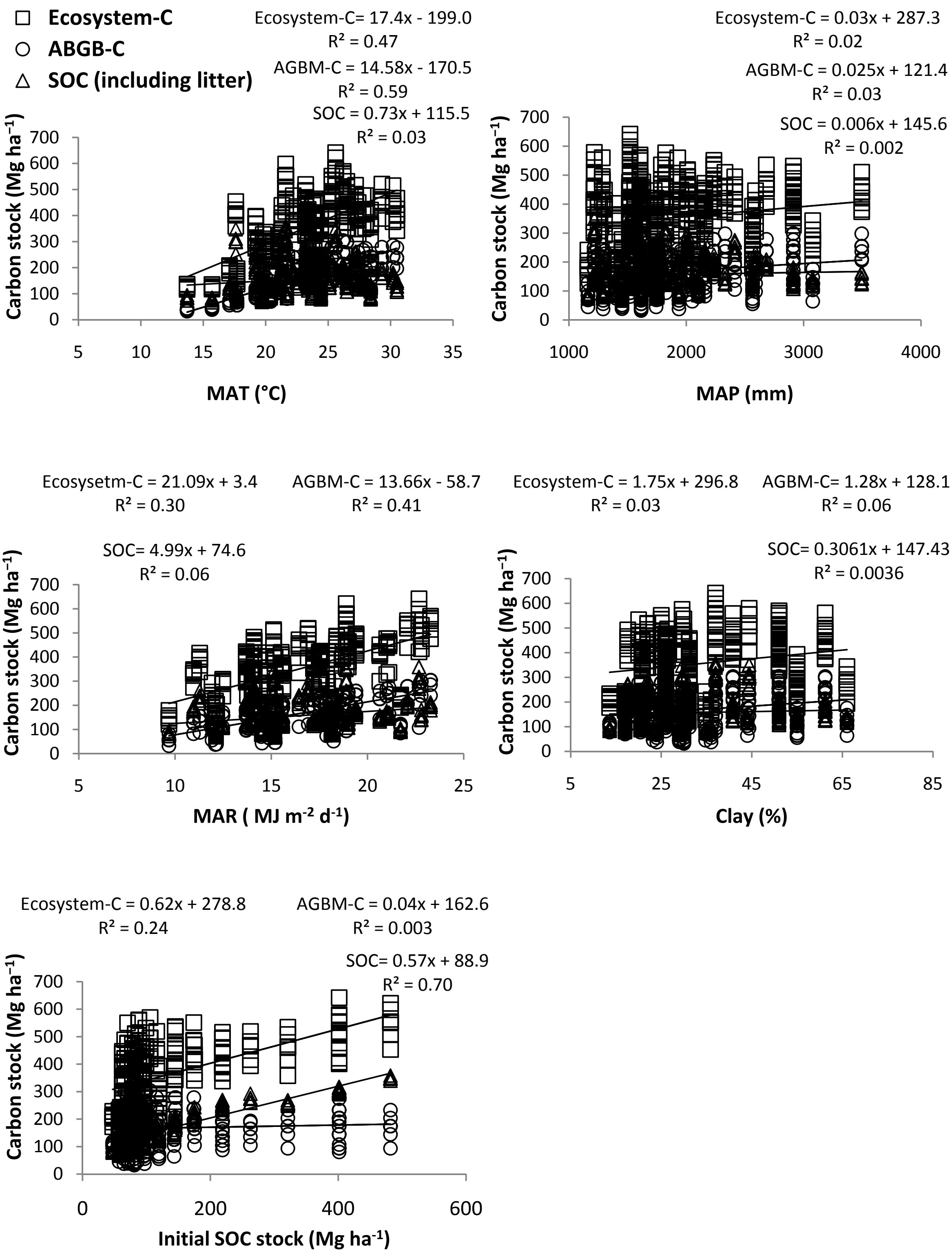


Figure 10. Relation of various carbon pools aboveground (AGBM-C), soil (SOC) and ecosystem-C with the environmental variables such as mean annual temperature (MAT), mean annual precipitation (MAP), mean annual solar radiation (MAR), soil clay content and initial SOC stock under forest for the whole set of model results.

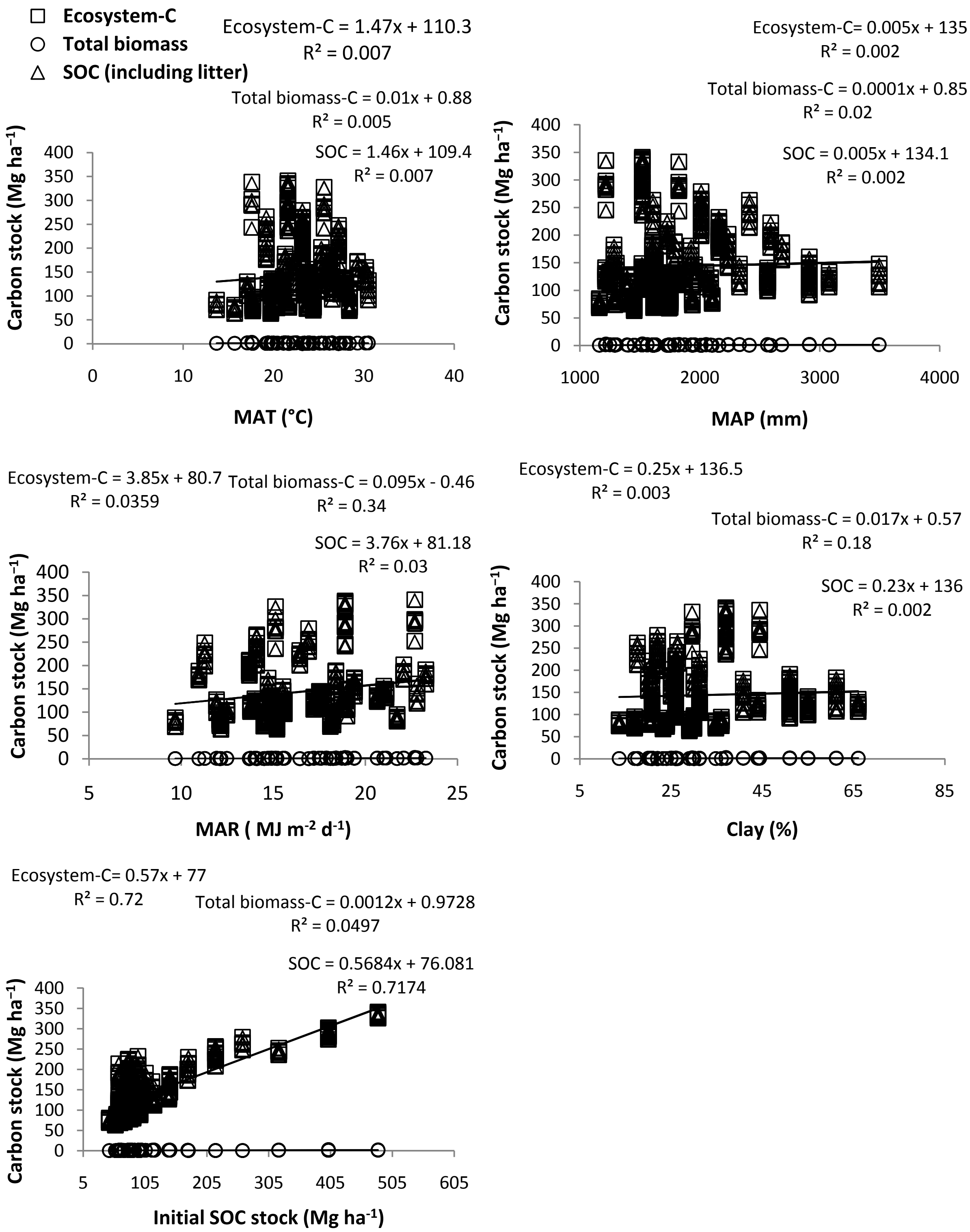


Figure 11. Relation of various carbon pools total biomass-C, soil (SOC) and ecosystem-C with the environmental variables such as mean annual temperature (MAT), mean annual precipitation (MAP), mean annual solar radiation (MAR), soil clay content and initial SOC stock under maize for the whole set of model results.

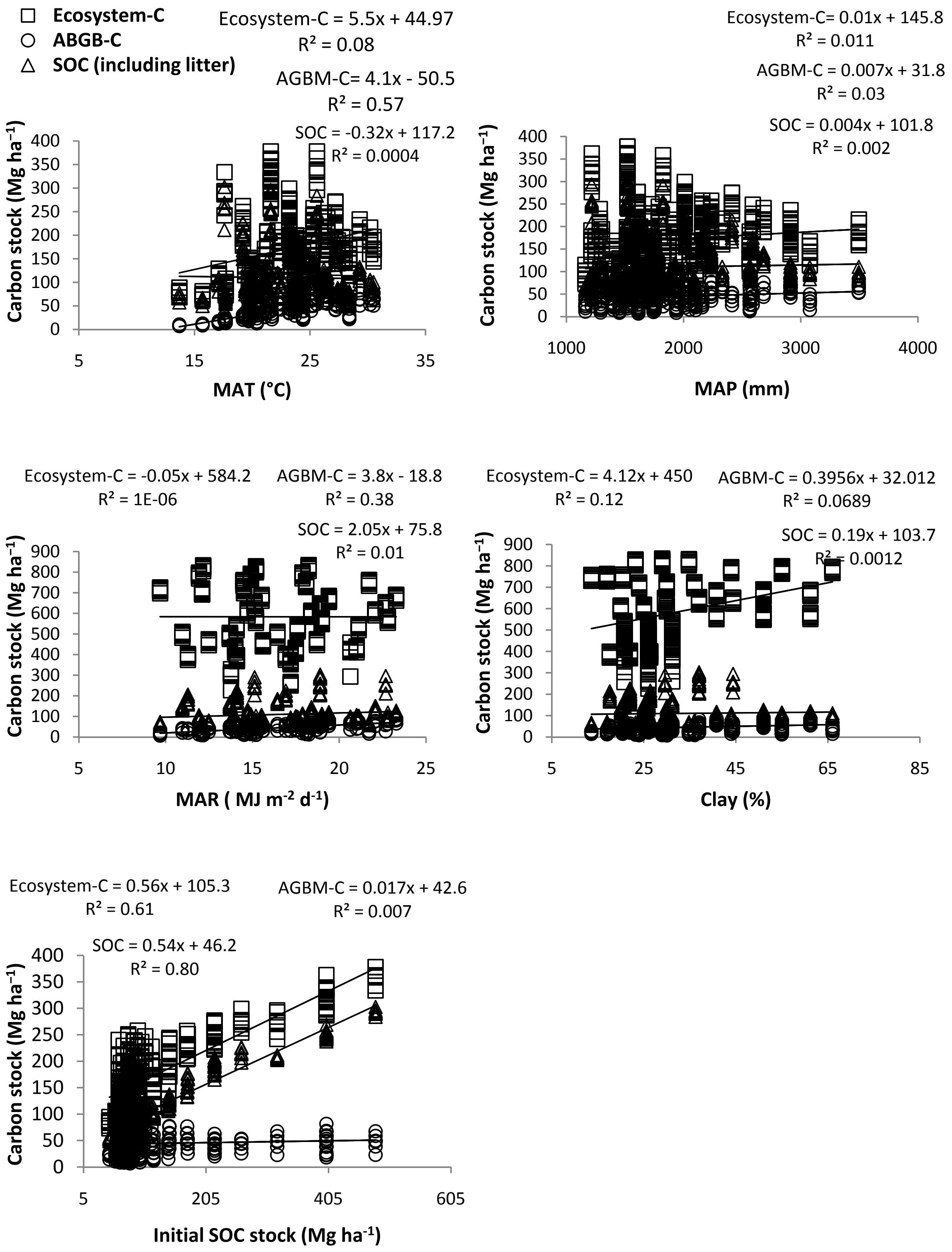


Figure 12. Relation of various carbon pools aboveground (AGBM-C), soil (SOC) and ecosystem-C with the environmental variables such as mean annual temperature (MAT), mean annual precipitation (MAP), mean annual solar radiation (MAR), soil clay content and initial SOC stock under forest for the whole set of model results.

Table 7. Results of the stepwise regression analysis for the different variables in relation to the aboveground biomass carbon, total (above + below) carbon, soil organic carbon and ecosystem carbon under various land-uses for whole set of model results.

	R	R^2	ΔR^2	Coef.	SE	P		R	R^2	ΔR^2	Coef.	SE	P		R	R^2	ΔR^2	Coef.	SE	P
Forest-AGBM-C							**Forest-SOC**							**Forest-Ecosystem-C**						
Constant				-269	9.43		Constant				-26.4	9.61		Constant				-344	18.8	
MAT	0.77	0.60	0.60	11.905	0.38	<0.001	SOCI	0.83	0.69	0.70	0.59	0.01	<0.001	MAT	0.59	0.34	0.34	17.3	0.749	<0.001
MAR	0.86	0.74	0.15	8.059	0.44	<0.001	MAT	0.86	0.74	0.05	3.37	0.38	<0.001	SOCI	0.80	0.65	0.31	0.64	0.026	<0.001
Clay	0.87	0.76	0.02	0.678	0.10	<0.001	MAP	0.86	0.75	0.003	0.01	0.00	<0.001	MAR	0.85	0.72	0.07	11.3	0.835	<0.001
SOCI	0.87	0.76	0.00	0.042	0.01	0.002	Clay	0.86	0.75	0.003	-0.38	0.11	<0.001	MAP	0.85	0.72	0.01	0.02	0.005	<0.001
							MAR	0.87	0.76	0.004	1.52	0.43	<0.001							
Crop-TBM-C							**Crop- SOC**							**Crop-Ecosystem-C**						
Constant				-0.41	0.10		Constant				-0.07	8.8		Constant				0.21	8.82	
MAR	0.58	0.34	0.34	0.093	0.00	<0.001	SOCI	0.84	0.70	0.70	0.59	0.01	<0.001	SOCI	0.85	0.72	0.72	0.59	0.013	<0.001
Clay	0.67	0.45	0.11	0.013	0.00	<0.001	MAT	0.86	0.74	0.05	2.78	0.35	<0.001	MAT	0.86	0.75	0.75	2.8	0.35	<0.001
MAT	0.69	0.48	0.03	-0.022	0.00	<0.001	MAP	0.87	0.75	0.00	0.01	0.00	<0.001	MAP	0.87	0.75	0.004	0.01	0.002	<0.001
SOCI	0.70	0.49	0.01	0.001	0.00	<0.001	Clay	0.87	0.75	0.00	-0.37	0.10	<0.001	Clay	0.75	0.75	0.004	-0.35	-0.10	<0.001
Secondary forest-AGBM-C							**Secondary forest-SOC**							**Secondary forest-Ecosystem-C**						
Constant				-79.8	2.9		Constant				12.6	6.7		Constant				-98	9.8	
MAT	0.75	0.56	0.57	3.39	0.12	<0.001	SOCI	0.90	0.80	0.80	0.55	0.01	<0.001	SOCI	0.78	0.61	0.61	0.56	0.01	<0.001
MAR	0.83	0.70	0.14	2.19	0.13	<0.001	MAP	0.90	0.81	0.01	0.01	0.00	<0.001	MAT	0.86	0.75	0.13	5.73	0.39	<0.001
Clay	0.85	0.73	0.03	0.24	0.03	<0.001	Clay	0.90	0.82	0.01	-0.34	0.08	<0.001	MAR	0.87	0.76	0.01	2.81	0.43	<0.001
SOCI	0.86	0.74	0.01	0.02	0.00	<0.001	MAT	0.91	0.82	0.00	0.85	0.26	0.001	MAP	0.88	0.77	0.01	0.01	0.003	<0.001

R: correlation coefficient; R^2: coefficient of variation; ΔR^2= delta R^2; Coef: coefficients of the different variables in the model; SE: standard error; P: level of significance; MAT: mean annual temperature; MAP: mean annual precipitation; MAR: mean annual solar radiation; SOCI: initial SOC stock.

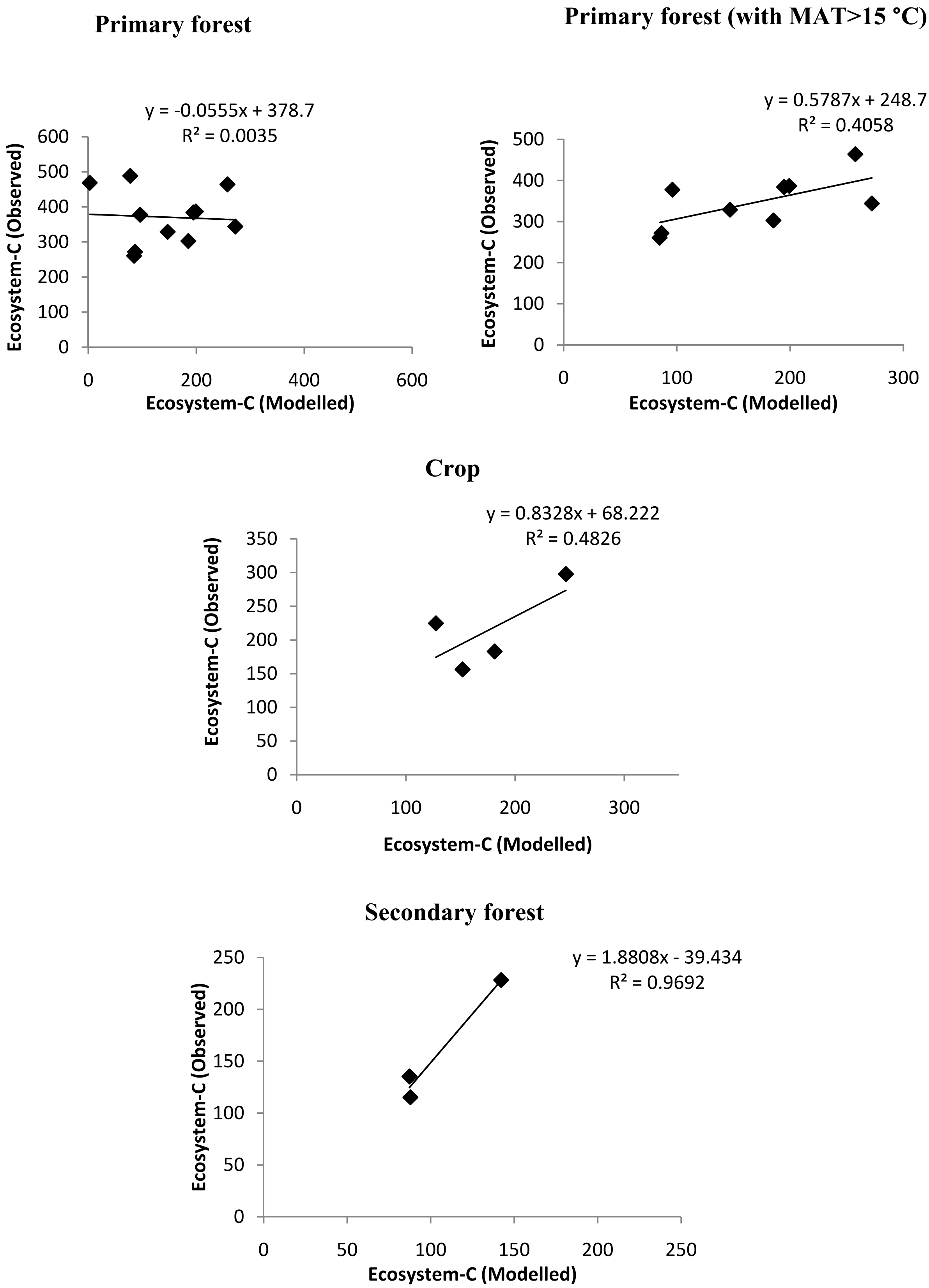


Figure 13. Comparing the modelled and observed ecosystem carbon (for soil, depth >1 m) for primary forest, crop and secondary forest corresponding to the land-uses given in Table 2.

4 Discussion

Carbon exchange between vegetation, soil and the atmosphere occurs through the processes of photosynthesis, respiration, litter production and its decomposition in soil which are controlled by environment and the land-use (Cao and Woodward, 1998). Such a system reaches equilibrium when carbon gain in the form of biomass equals the carbon loss through its decomposition. For a given land-use, this equilibrium carbon at the ecosystem level depends on the environmental (temperature, precipitation, solar radiation, etc) and the soil (nutrient and water availability) factors. Tropical forests, which play an important role in the global carbon cycle, are a good example of such a system, which is in equilibrium. Currently, tropical forests are under high pressure of deforestation and degradation as a consequence of land-use intensification and population pressure. Deforestation and land-use change result in a change in the carbon cycle at the ecosystem level and moves to a new equilibrium level, which is usually at a lower level than under the original forest. Estimating carbon pools and their changes associated with deforestation and land-use change is therefore, important to estimate the loss of carbon and the new equilibrium level. This study reviews the existing literature to collate carbon pools in different land-use and land-use changes occurring in the tropical forest margins to derive simple relations that can describe their quantitative changes in terms of major environmental factors. We collated and reviewed six studies, which span over six countries and cover a number of land-use and land-use change studies mostly in chronosequence. The results of the regression analysis of the variables such as AGBM-C, SOC and ecosystem-C against the two factors (MAT and MAP) could not explain much of its variability (< 20%). However, we need more data to confirm these results since there is a scarcity of such data in the literature estimating the carbon pools covering above and below-ground over a space and time up to a meaningful depth. Measuring carbon especially below a depth of 1 m may not be easy and that would be one of the main reasons for not measuring it below such deeper depths. There is also a lack of detailed information (or data) of the climate and soil characteristics of the studies already published.

Simulated forest transition (PF-crop-SF) in the study represents more or less the slash and burn system in these countries used for the study. The maize crop used in the model represents a food/cash crop (millet, plantain, cocoa, coffee, rubber etc.) which can vary in from place to place and depending on countries. The model simulated results of total, above-and- belowground biomass and SOC content under different land-uses for the various sites show a varying degree of equilibrium forest biomass carbon among different sites depending on the climate and soil conditions. The combination of four or five environmental (MAT, MAP and MAR) and soil (Clay and Initial SOC) factors that were tested in this study were able to explain most of the variation (70-90%) in the results except that for crop total biomass (<50%). The simple regressional model when applied to an independent dataset showed a poor fit to those out of the scope (with MAT > 15 °C) within which the model has been developed. The results show that we need to widen our scope of model simulations by including a wider range of conditions.

5 Conclusions

This study reviews existing literature to collate carbon pools in different land-use and land-use changes occurring in the tropical forest margins along with using models for simulating the forest transition to derive simple relations that can describe their quantitative changes in terms of major environmental and soil factors. The results of the study show only limited studies or data are still available that can estimate the carbon pools at an ecosystem level and we need more field studies to fill the gap. The simple regressional model derived from a few set of parameters are useful to estimate the carbon stock changes associated with the land-use changes in the tropical forest margins provided the models are well tested with a wider range of environmental and soil conditions.

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