Environmental Science

http://www.aimspress.com/

Volume 2, Issue 3, 577-606.
DOI: 10.3934/environsci.2015.3.577
Received date 23 February 2015,
Accepted date 14 June 2015,
Published date 16 June 2015

Research article

An integrated approach to modeling changes in land use, land cover, and disturbance and their impact on ecosystem carbon dynamics: a case study in the Sierra Nevada Mountains of California

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Abstract: Increased land-use intensity (e.g. clearing of forests for cultivation, urbanization), often results in the loss of ecosystem carbon storage, while changes in productivity resulting from climate change may either help offset or exacerbate losses. However, there are large uncertainties in how land and climate systems will evolve and interact to shape future ecosystem carbon dynamics. To address this we developed the Land Use and Carbon Scenario Simulator (LUCAS) to track changes in land use, land cover, land management, and disturbance, and their impact on ecosystem carbon storage and flux within a scenario-based framework. We have combined a state-and-transition simulation model (STSM) of land change with a stock and flow model of carbon dynamics. Land-change projections downscaled from the Intergovernmental Panel on Climate Change's (IPCC) Special Report on Emission Scenarios (SRES) were used to drive changes within the STSM, while the Integrated Biosphere Simulator (IBIS) ecosystem model was used to derive input parameters for the carbon stock and flow model. The model was applied to the Sierra Nevada Mountains ecoregion in California, USA, a region prone to large wildfires and a forestry sector projected to intensify over the next century. Three scenario simulations were conducted, including a calibration scenario, a climate-change scenario, and an integrated climate- and land-change scenario. Based on results from the calibration scenario, the LUCAS age-structured carbon accounting model was able to accurately reproduce results obtained from the process-based biogeochemical model. Under the climate-only scenario, the ecoregion was projected to be a reliable net sink of carbon, however, when land use and disturbance were introduced, the ecoregion switched to become a net source. This research demonstrates how an integrated approach to carbon accounting can be used to evaluate various drivers of ecosystem carbon change in a robust, yet transparent modeling environment.

Keywords: land use; carbon; modeling; scenarios; California; state-and-transition simulation model; stock and flow model; IBIS

1. Introduction

Land-use change is a first-order driver of global change [1–3]. It is estimated that approximately half of the land area on earth has been transformed or degraded to meet human needs [4]. Changes in land use, particularly intensification of activities, may have far reaching impacts on the ability of ecosystems to provide goods and services [5]. At the global scale, greenhouse gas emissions resulting from land-use change are estimated to account for 23% of all global emissions [6]. Additionally, conversion of forests and other native vegetation to land uses may result in the permanent and semi-permanent loss of biomass, fluxes of carbon from soils, and a decline in carbon storage capacity; an important counterbalance to rising concentrations of atmospheric CO_2 from increased fossil fuel emissions. At the global scale forests are estimated to sequester 2.4 Pg C yr^{-1}; however, in the tropics, intensive land-use practices result in forested ecosystems acting as a net annual source of atmospheric carbon at a rate of 1.3 Pg C yr^{-1} [6]. On the other hand, reductions in land-use intensity have the potential to increase carbon stocks and the annual rate of net carbon uptake through biomass growth and increased accumulation in soils.

Within the U.S. there is considerable variability in the rate at which ecosystems store and emit carbon. The U.S. Environmental Protection Agency estimated ecosystems sequestered 218.2 Tg C in 2012, with an additional 18.1 Tg C yr^{-1} stored in wood products [7], while Pan et al. similarly estimated that U.S. forests store an additional 240 Tg C yr^{-1} [6] with reforestation and fire suppression activities sequestering an additional 2 Pg C in terrestrial ecosystems since 1945 [2]. Using historical estimates of changes in land use and cover for the state of California [8], Liu et al. estimated that California's ecosystems were a net source of carbon between 1951 and 2000 at an average rate of 0.55 Tg C yr^{-1} with 126 Tg C lost due to logging and an additional 50 Tg C due to wildfires [9]. Furthermore, upper canopy tree biomass decreased by 10% during this period while understory vegetation biomass increased, indicating a shift in age structure due to ecosystem disturbance. Brown et al [10] estimated during the 1990s, forests and rangelands in California sequestered 2.52 Tg C yr^{-1} while Birdsey and Lewis [11] estimated a net sequestration rate on forest lands of 2.68 Tg C yr^{-1}.

In California, it is expected that land use will continue to intensify in response to increased demands for food, fiber, and housing for a population expected to surpass 50 million by 2060 [12]. However, considerable uncertainty exists regarding the magnitude and types of land-use change expected to occur. Drivers, such as technological change, energy sector developments, societal choices regarding environmental conditions, and local to federal level policies, all play an important role in determining the evolution of land-use. To address these uncertainties, scenario-based projections are often utilized and have been the basis for several global-scale change assessments [13–15]. To utilize these global-scale scenarios at local to regional scales, numerous efforts have been undertaken to downscale results [16–20].

Modeling the effects of land-change processes on ecosystem carbon dynamics often results in the loose coupling of multiple, highly complex models, each focused on excelling in one particular aspect of the modeling effort (e.g. biogeochemical cycling with process-based ecosystem models, or land-use change with a land-based model). As an example, the U.S. Geological Survey's ecosystem carbon assessment used a modeling framework consisting of a land-use scenario downscaling model, a spatially explicit land allocation model, a fire model, two biogeochemical models, and a carbon "bookkeeping" model to estimate change in baseline and projected carbon stocks and fluxes [21]. In some cases model inputs were shared across models, however, due to structural differences within the models, this was not always achieved. Furthermore, there was a lack of integration between models, and generally the integration was the simple linear flow of outputs from one model to another (e.g. the land change model passed output maps to the biogeochemical model). While the individual models used for this assessment were each robust, the lack of integration reduced transparency, made sensitivity analysis difficult, and prohibited the analysis of feedback effects between model projections (e.g. feedbacks between land-use change and wildfire).

The goal of this study was to develop an integrated, regional-scale terrestrial carbon model, which can project changes in ecosystem carbon dynamics resulting from both changing biophysical conditions (e.g. CO_2 fertilization, changes in climate) and land-change processes (e.g. urbanization, agricultural intensification, wildfire, harvest). Our objective was to develop a modeling framework which could reliably reproduce estimates of carbon stocks and fluxes from a process-based biogeochemical model while increasing transparency and achieving significant computational and parameterization efficiencies. Using this integrated framework, we conducted simulations for a calibration scenario, and two future projections (climate only, climate and land change) based on the A1B scenario from the IPCC's Fourth Assessment Report [22]. Additionally, we conducted a simple sensitivity analysis of key model parameters, in an effort to demonstrate the usefulness of the integrated structure of the model. For each of the future scenarios we analyzed the impact on forest carbon storage and flux in the Sierra Nevada Mountains Ecoregion. Below we describe the linkages between these modeling components, as well as the calculation of key model parameters, and summarize the results of our modeling simulations. We conclude with a discussion of the results and the key uncertainties associated with this effort.

2. Materials and Methods

2.1. Model overview

Here we provide an overview of the modeling framework used for this research. Collectively, we refer to this as the Land Use and Carbon Scenario Simulator (LUCAS). The motivation behind development of LUCAS was to have an integrated modeling platform capable of efficiently and robustly evaluating the effects of land-use and management actions on regional carbon dynamics. Within LUCAS, a STSM was used to project land use, land cover, and ecosystem disturbance based on future global change scenarios. Integrated within the STSM, a stock and flow (SF) model was developed to calculate carbon storage and fluxes. The SF projects "automatic" fluxes, such as those associated with biomass growth, litterfall, and decomposition, as well as "event-based" fluxes, which can occur when a simulation cell within the STSM experiences an abrupt change, such as wildfire, harvest, or conversion into a new land use. To parameterize the SF portion of LUCAS, we ran a series of simulations using the process-based IBIS [23] ecosystem model to generate carbon flux coefficients.

2.1.1. State-and-transition simulation model (STSM)

STSM's are a form of a time-inhomogeneous Markov chain model, where the landscape is partitioned into a discrete set of simulation cells, each cell is assigned a discrete state, and transitions are defined to move cells between states at any point in time [24]; For a thorough review of STSM models, see Daniel and Frid [25]. We use the ST-Sim software package [26] as the framework for our STSM modeling. In addition to tracking the state of each cell in a simulation, an STSM also tracks its age and time-since-transition. This enables us to model specific age-dependent transitions with more parsimonious model formulation than a traditional Markov chain.

2.1.2. Stock and flow model (SF)

In addition to the STSM modeling capability, we used a stock and flow (SF) approach to track changes in in carbon stocks and fluxes over time. The SF portion of the model tracks the amount of material in any number of carbon stocks (i.e. pools) over time for each simulation cell, consistent with the approach recommended by the IPCC for national terrestrial greenhouse gas inventories [27]. Within each timestep of the model, carbon can flow from one stock to another within a simulation cell at specified rates. Flows can occur for any simulation cell and timestep in the simulation, and are either triggered in response to an STSM transition (e.g. fire or harvest), or occur automatically (e.g. above ground biomass growth).

2.1.3. IBIS ecosystem model

The IBIS model is a physically consistent modeling framework that follows basic rules of physics, plant physiology and biogeochemistry [23,28]. The original model combined features of a mechanistic model of canopy photosynthesis [29], a semimechanistic model of stomatal conductance [30], an algorithm on phenology [31], and several soil biogeochemical models [32–34] in a single application[1]. IBIS has the ability to simulate major land surface processes, canopy physiology, vegetation phenology, long-term vegetation dynamics, ecosystem productivity and carbon cycling. A modified version of IBIS includes the nitrogen (N) cycle [35], land-use and land-cover change and wild-land fire effects [9], and methane (CH_4) emission [36]. For this research, we use IBIS to generate carbon flux proportions by forest age class between a set of simplified carbon pools. The stocks and fluxes simulated in LUCAS are illustrated in Figure 1, which match closely with the simplified stocks output from IBIS [9]. Structurally, we use the same version of IBIS developed by Liu et al. [9], however, we have made important changes required for this research, such as the use of a constant CO_2 level, average historical climate, no land use change or disturbance, and initiation of starting biomass levels.

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[1] The IBIS model source code can be obtained from the University of Wisconsin-Madison SAGE Center for Sustainability and the Global Environment at: http://www.sage.wisc.edu/download/IBIS/ibis.html.

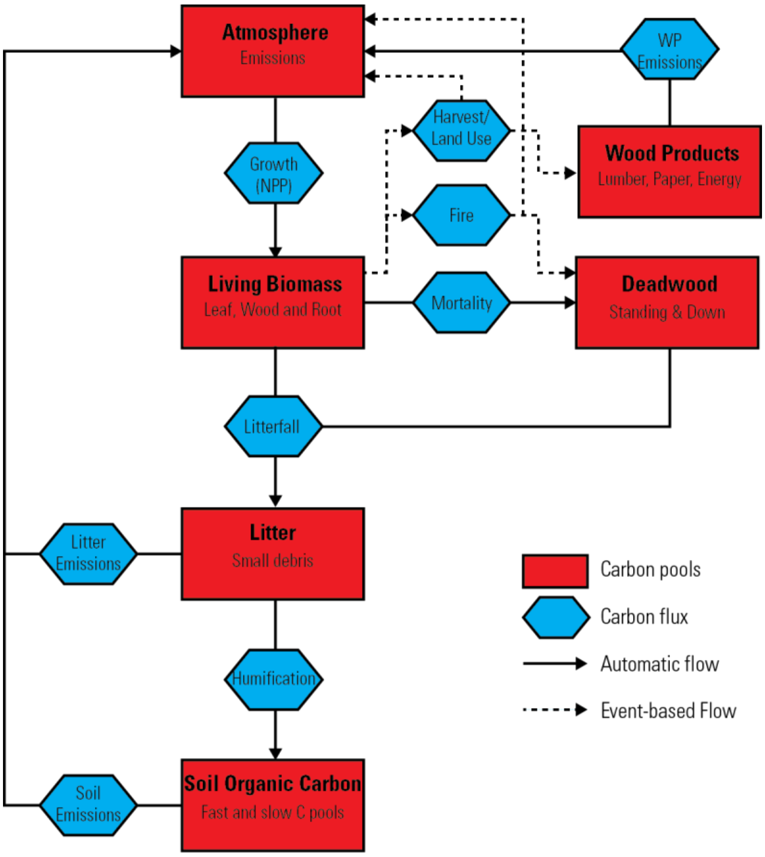

Figure 1. Conceptual diagram of the LUCAS Stock and Flow model used to simulate the flow of carbon between pools.

2.1.4. Model integration

The three models discussed above are integrated in two ways. The SF and STSM models are structurally integrated within the ST-Sim software. The STSM model produces projections of land change, while the SF model tracks the changes in carbon stocks over time, either as automatic flows, which occur at every successive timestep, or as event-based flows triggered when a transition occurs within the STSM model.

The IBIS model was used to generate three types of parameters for the LUCAS model: 1) projections over time of the amount of carbon in each pool, structured by age, 2) rates of carbon flux between pools, and 3) an annual projection of net primary production (NPP) of the entire study area to represent forest growth. A calibration scenario was run in IBIS (“IBIS-CALIB”) to generate the age-structured carbon pool estimates and flux rates. An additional IBIS scenario was simulated to derive future growth rates consistent with climate change projections associated with the IPCC’s A1B emission scenario [13]. Figure 2 shows a conceptual diagram of how the three models are linked together.

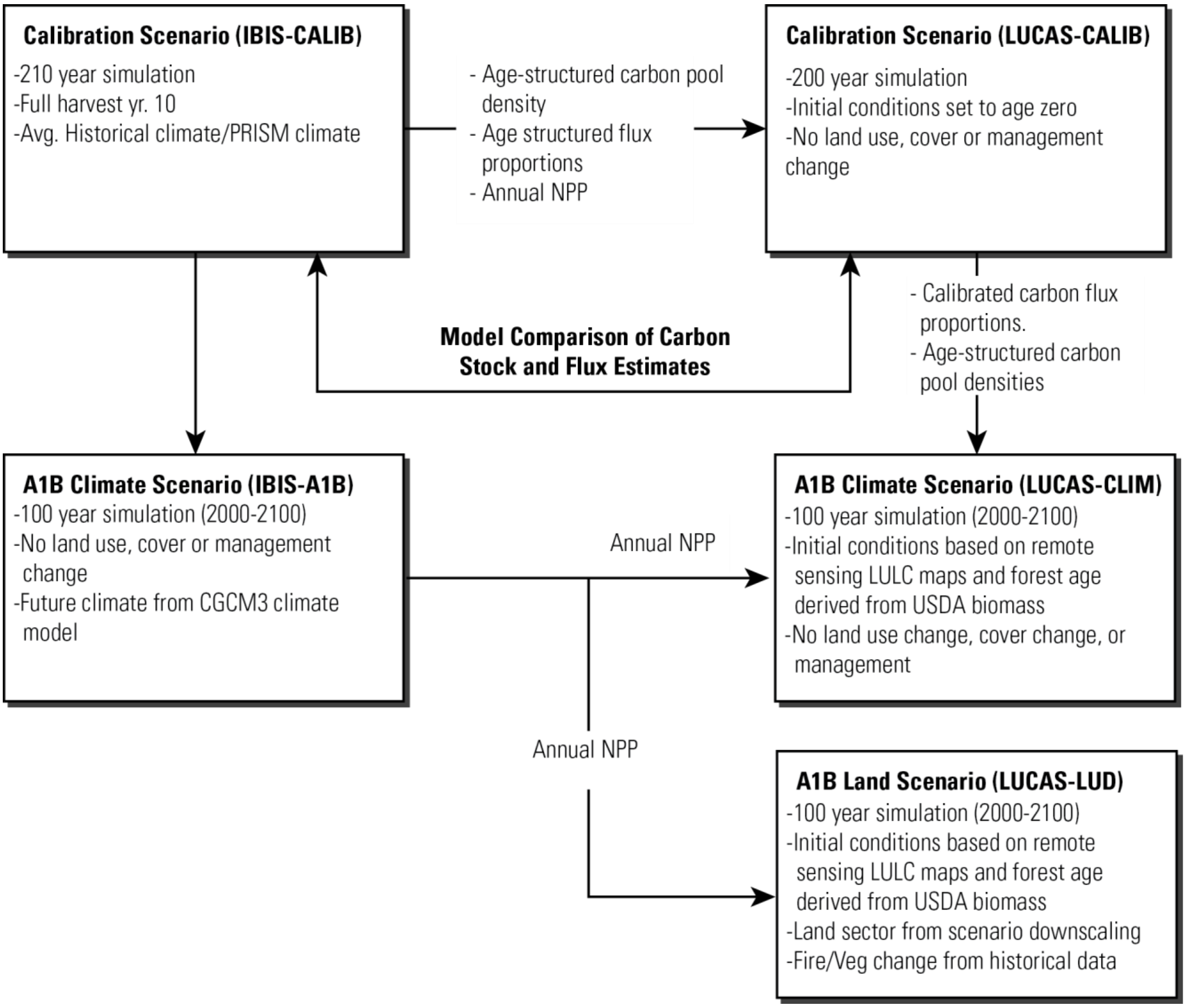

Figure 2. Conceptual diagram of the integration of the LUCAS model and the IBIS ecosystem model within a scenario modeling framework.

2.2. State classes and transitions

We represented nine possible states in our model: agriculture, barren, development, forest, grassland, shrubland, snow/ice, water, and wetland (see section 2 in Supplementary for state class descriptions). These nine categories generally correspond to an Anderson level I classification scheme, which was developed for use with satellite remote sensing data [37] and is readily transferable to the IPCC's recommended classification scheme [27]. A similar scheme was used by Loveland et al. [38] and Sleeter et al. [39] to project changes in recent historical land use and land cover for the conterminous U.S. Transitions defined for this study are shown in Table 2. For state classes with no defined transitions (i.e. water, barren, snow/ice) we assumed there was no change over time.

Table 2. Transitions between state classes used within the LUCAS model.

Transition Group	Transition Type
Agricultural Intensification	Forest to Agriculture Grassland to Agriculture Shrubland to Agriculture Wetland to Agriculture
Agricultural Extensification	Agriculture to Forest Agriculture to Grassland Agriculture to Shrubland Agriculture to Wetland
Management	Forest Clearcut Forest Thinning
Natural Disturbance	Forest Wildfire Grassland Wildfire Shrubland Wildfire
Urbanization	Agriculture to Developed Forest to Developed Grassland to Developed Shrubland to Developed Wetland to Developed
Vegetation Change	Forest to Grassland Forest to Shrubland Grassland to Forest Grassland to Shrubland Shrubland to Forest Shrubland to Grassland

2.3. Study area

The study area defined for this research is the Sierra Nevada Mountains ecoregion (SNM) [40], located in eastern California, USA (Figure 3). The ecoregion is a granitic batholith which divides the low lying Central Valley to the west and the Basin and Range to the east. Roughly 62% of the 53,160 km^2 region is classified as forest, with much of the remaining area classified as shrubland (25%), barren (6%), grassland (3%), and water (2%). Developed and agricultural land uses in the ecoregion are rare and confined to a few small regions. The most common forms of land-cover change are the result of wildfire and timber harvesting activities, both of which have important implications for carbon storage and cycling in California. The region also contains a large number of protected lands, including Yosemite National Park, Kings Canyon National Park, Ansel Adams Wilderness, and John Muir Wilderness, among others.

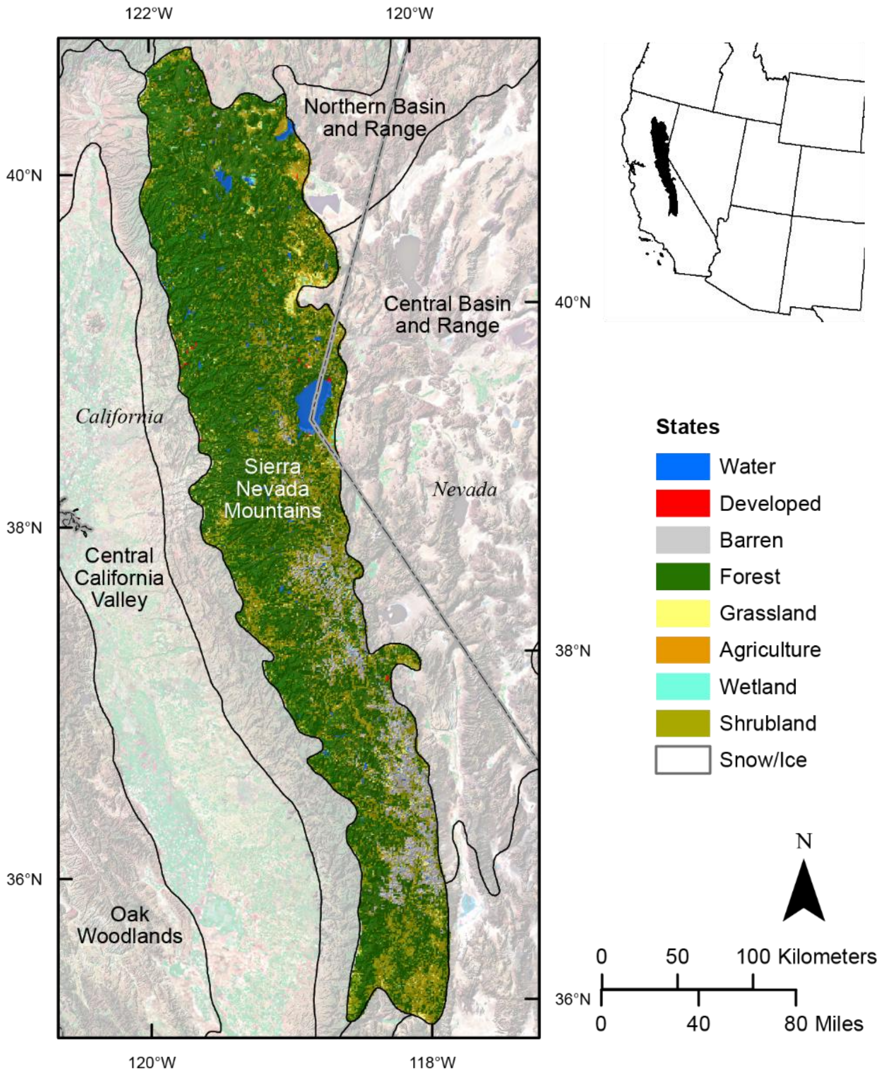

Figure 3. Study area map and distribution of STSM states in the year 2001 within the Sierra Nevada Mountains ecoregion.

2.4. Scenarios

Below we describe the three basic scenarios developed for this study. The scenarios were primarily developed with the goal of parameterizing and calibrating the LUCAS model, and secondly, to demonstrate how the modeling approach could be used to evaluate the relative effect of climate and land-use/disturbance on ecosystem carbon for the Sierra Nevada Mountains ecoregion.

2.4.1. Calibration scenario

A calibration scenario was run in IBIS ("IBIS-CALIB") to provide age-structured carbon pool densities and flux estimates at the ecoregion scale, which in turn were used to parameterize the LUCAS model. The first step in the calibration process was to run the IBIS model over 300 years in a "cold-start" mode where in the first year of the simulation all forest pixels had their biomass set to that of a one year old forest. The result was the production of a 300 year forest growth curve. IBIS estimates of biomass and NPP were calibrated against plot-level and remotely-sensed observations [9]. For this simulation we used the average climate from 1960–1990 and fixed CO_2 at 332 ppm, consistent with the same period in time. Assuming no change in climate or CO_2, both of which may potentially alter growth rates, we were able to derive flux rates under a temporally consistent set of assumptions. For additional detail on initialization of the IBIS model see section 4 of the Supplementary.

The 300 years of regrowth from IBIS-CALIB were used to generate age-structured carbon pool densities and flux rate parameters for the LUCAS model. To evaluate whether the LUCAS model could reproduce carbon stock and flux rates similar to those of IBIS, we conducted a 300 year simulation using parameters developed from the IBIS-CALIB simulation. NPP derived from the IBIS-CALIB scenario was used to drive growth rates in the LUCAS model, ensuring consistency between approaches. We then compared the results of the two scenarios to ensure that LUCAS was capable of replicating the IBIS carbon pool and flux estimates (section 3.1).

2.4.2. Climate change scenario

A future climate change scenario (IBIS-CLIM) was simulated in IBIS to generate projected growth (i.e. NPP) on an annual time-step for the Sierra Nevada Ecoregion. For the IBIS-A1B scenario, monthly climate data from the Canadian Centre for Climate Modelling and Analysis Coupled Global Climate Model (CGCM3) [41–43] downscaled by the Canadian Forest Service and updated in 2009 (ftp.nofc.cfs.nrcan.gc.ca) [44], were used within IBIS to generate a time-series of projected biomass growth (i.e. NPP) for the Sierra Nevada Mountains ecoregion for the period 2000–2100. Using the base SF model parameters (age-structured carbon pool densities and flux rates) developed under the CALIB scenario, and the future biomass growth projections from the IBIS-A1B simulation, we used LUCAS to project changes in ecosystem carbon storage and flux under a climate-only scenario (“LUCAS-CLIM”).

2.4.3. Land-use and disturbance scenario

The LUCAS land use and disturbance (LUCAS-LUD) scenario used the same growth rate (i.e. NPP) projection as generated by IBIS for the CLIM scenario; in addition the LUD scenarios also incorporated coherent projections of land use, land-use change, and disturbance under the same A1B storyline. Projected land use and land-use change for the Sierra Nevada Ecoregion were obtained from Sleeter et al., which used an integrated assessment model, regional-scale land-use histories, and expert knowledge, to downscale land-use projections to ecoregions of the conterminous U.S. [16].

Within the STSM we used a combination of transition probabilities and transition targets (i.e. explicitly defined targets for the area to be transitioned) to drive the land-use change associated with the LUD scenario. Transition probabilities were used to characterize natural disturbance (wildfire) and vegetation change pathways, and were based on recent historical data. Land use and land-use change transitions were based on area targets from downscaled future projections. See section 3 in Supplementary for additional information on transition targets and probabilities used in the LUD scenario.

2.4.4. Sensitivity tests

A strength of the LUCAS approach is the ability to quickly test the sensitivity of specific model parameters which may have high uncertainties. For this paper we conducted a simple experiment by altering key model parameters associated with timber harvest and wildfire.

For forest harvest we tested the effect of altering the flux rates which occur when a stand experiences a clear cut event. Base flux rates (see Table 7) between living biomass, atmosphere, and wood products were modified to demonstrate the effect of increased emissions and reduced long-term wood product storage. For wildfire events we tested the impact of reducing the impact of wildfire on direct emissions as well as loss of biomass to deadwood. Results of these simple tests are shown in section 3.1.1.

2.4.5. Initial conditions

The LUCAS model requires a set of initial conditions to be specified characterizing the distribution of state classes, carbon stock density, and forest age structure at the start of each simulation. Ideally, we would use an internally consistent dataset to specify all three of these elements. For example, remote sensing can be used to determine whether a pixel is a forest, how old that forest pixel is by analyzing a time series of observations and/or evaluating the degree of canopy closure [45], and the above-ground biomass based on empirical methods using optical and active remote sensing and inventory data [46]. However, to date, no such comprehensive dataset exists. To overcome this, we used a combination of methods and datasets to derive our suite of initial conditions, including remote sensing-based maps of land use and cover [47], an imputed spatially explicit map of living biomass [48], and the IBIS models projections of age-structured carbon stocks. For details on IBIS model initialization, see section 4 of the Supplementary.

2.4.6. State classes

For all three LUCAS simulations (LUCAS-CALIB, LUCAS-CLIM, and LUCAS-LUD) the initial state class of each simulation cell was established by using a circa 2000 LULC dataset that was created by harmonizing existing multi-temporal LULC datasets [47]. The methodology relied on the principle of convergence of evidence to reclassify areas mapped by multiple national-scale LULC datasets. Raster maps were summarized for the Sierra Nevada Mountains ecoregion for input into the STSM (Table 3). For the LUCAS-CALIB simulation, all cells classified as forest were set to an age of 1 to match the IBIS-CALIB simulation.

Table 3. Distribution of the LUCAS initial conditions across state classes for the climate (LUCAS-CLIM) and land-use (LUCAS-LUD) scenarios. For the calibration (LUCAS-CALIB) scenario, all forest cells were set to the age 0–5 bin to match the IBIS calibration simulation. All non-forest cells were unchanged.

State Class	Age Min	Age Max	Area (km^2)	Proportion (%)
Agriculture			164	0.1
Barren			3213	6.0

Developed			647	1.2
Grassland			1508	2.8
Shrubland			13,104	2.5
Snow/Ice			22	0.0
Water			1058	2.0
Wetland			195	0.4
Forest	0	5	136	0.3
Forest	6	10	447	0.8
Forest	11	15	659	1.2
Forest	16	20	1200	2.2
Forest	21	25	1617	3.0
Forest	26	30	2095	3.9
Forest	31	35	2056	3.9
Forest	36	40	2075	3.9
Forest	41	45	1975	3.7
Forest	46	50	1850	3.5
Forest	51	55	1531	2.9
Forest	56	60	1330	2.5
Forest	61	65	1182	2.2
Forest	66	70	1066	2.0
Forest	71	75	848	1.6
Forest	76	80	763	1.4
Forest	81	85	633	1.2
Forest	86	90	542	1.0
Forest	91	95	58	0.1
Forest	96	100	103	0.2
Forest	101	105	0	0.0
Forest	106	110	0	0.0
Forest	111	115	0	0.0
Forest	116	120	0	0.0
Forest	121	125	52	0.1
Forest	126	130	52	0.1
Forest	131	135	493	0.9
Forest	136	140	141	0.3
Forest	141	145	63	0.1
Forest	146	150	10,282	19.3
Total			53,160	100

2.4.7. Carbon stocks

Initial age-structured carbon stock estimates for the living biomass, soil, litter, and deadwood pools were estimated from IBIS: using the results of the IBIS-CALIB simulation, we calculated the average forest carbon pool density for each age class for input into LUCAS (Table 4). For the

LUCAS-CALIB simulation, all forest cells were parameterized with their age 1 values. For the LUCAS-CLIM and LUCAS-LUD scenarios, we used a forest age map, which was calculated using a biomass-to-age look-up approach, to initialize forest carbon stocks based on present-day forest age structure (see Supplementary section 5).

Table 4. Initial carbon stock attributes used within the LUCAS model for LUCAS-CALIB, LUCAS-CLIM-LUCAS-LUD scenarios and derived from the IBIS-CALIB scenario. Units are in kg C/m^2. Soil carbon values represent 0–2 meters of depth.

Age min	Age max	Living Biomass	Soil Organic Carbon	Litter	Deadwood
1	1	1.13	11.09	0.19	1.87
2	2	1.36	10.93	0.35	1.75
3	3	1.59	10.83	0.51	1.63
4	4	1.80	10.77	0.64	1.54
5	5	2.01	10.75	0.75	1.45
6	6	2.20	10.75	0.83	1.38
7	7	2.39	10.78	0.89	1.32
8	8	2.57	10.81	0.94	1.26
9	9	2.75	10.86	0.98	1.22
10	10	2.92	10.92	1.00	1.18
11	11	3.08	10.98	1.02	1.15
12	12	3.25	11.05	1.03	1.13
13	13	3.41	11.12	1.04	1.11
14	14	3.56	11.19	1.05	1.09
15	15	3.71	11.26	1.05	1.08
16	16	3.86	11.34	1.05	1.08
17	17	4.01	11.41	1.05	1.08
18	18	4.15	11.48	1.05	1.08
19	19	4.28	11.55	1.04	1.08
20	20	4.42	11.63	1.04	1.09
21	25	4.80	11.83	1.03	1.11
26	30	5.40	12.16	1.02	1.18
31	35	5.93	12.46	1.03	1.25
36	40	6.41	12.74	1.06	1.32
41	45	6.84	12.99	1.10	1.38
46	50	7.22	13.22	1.14	1.42
51	60	7.73	13.52	1.20	1.47
61	70	8.30	13.87	1.26	1.51
71	80	8.77	14.17	1.32	1.54
81	90	9.15	14.42	1.36	1.58
91	100	9.45	14.64	1.40	1.63
101	120	9.81	14.94	1.44	1.71
121	140	10.14	15.30	1.50	1.79
141	160	10.37	15.63	1.55	1.85

161	180	10.51	15.93	1.58	1.88
181	200	10.61	16.22	1.61	1.91
201	9999	10.73	16.99	1.66	1.94

2.4.8. Forest age

To establish a modern day forest age structure for the LUCAS-CLIM and LUCAS-LUD scenarios, we combined spatially explicit maps of land use and cover with spatially explicit imputed estimates of biomass based on forest inventory data [48]. For each pixel classified as forest in the state class map, we extracted a corresponding living biomass value from the carbon map. In cases where there was no biomass value associated with a mapped forest pixel, we assumed the value from that cells nearest neighbor. The resulting map of biomass was then used to determine forest age using a biomass to age look-up approach and several scalars (see section 5 of the Supplementary).

For the LUCAS-CALIB scenario, all forest cells had their age reset to 1 yr. For the LUCAS-CLIM and LUCAS-LUD scenarios, we used the forest age structure shown in Table 3 to initialize the model. Initial carbon stocks are thus established by multiplying Tables 3 and 4 to derive total, regional-scale ecosystem carbon at the beginning of the scenario simulation. For soil carbon we used estimates from SSURGO to initialize the model. Figure 4 shows carbon stocks for the scenarios initiating in year 2000 (LUCAS-CLIM and LUCAS-LUD), along with a comparison to other published estimates of carbon stock density for the Sierra Nevada Mountains ecoregion (Figure 4), including those of Wilson et al. (USDA) [48], Liu et al. (EDCM-LC) [49], Kellendorfer et al. (NBCD) [46], Blackard et al. [50], and to the USDA's SSURGO dataset [51]. Generally, our estimates of carbon stock correspond well with other research; the living biomass pool was estimated at an average of 8.07 kg C/m^2, higher than Liu et al. (4.38 kg C/m^2) and Blackard et al. (7.25 kg C/m^2), while slightly lower than Wilson et al. (9.22 kg C/m^2). Estimates from NBCD were considerably higher than all other estimates at 16.95 kg C/m^2.

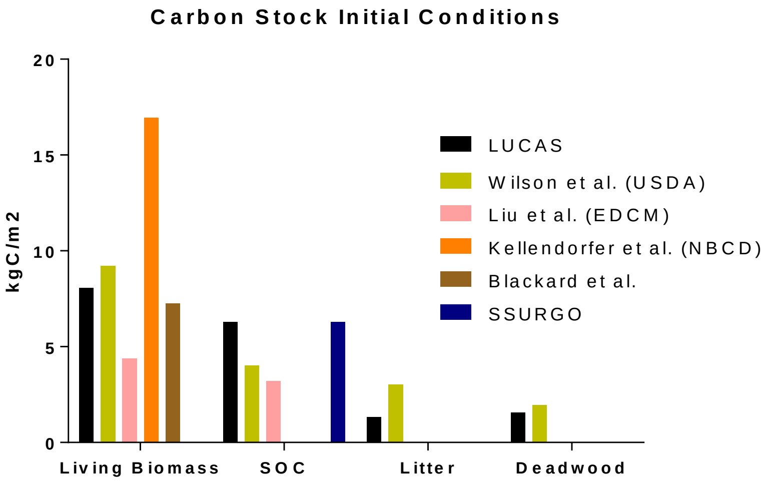

Figure 4. Estimated initial carbon stocks for the Sierra Nevada Mountains Ecoregion for the LUCAS-CLIM and LUCAS-LUD scenarios and estimates from other studies. The CLIM/LUD initial conditions represent "modern day" (circa yr. 2000) forest carbon stock size in the Sierra

Nevada ecoregion based on our calculation of forest age structure. We used the average soil organic carbon estimate derived from SSURGO to initialize these simulations.

2.5. Stock and flow calibration

2.5.1. Climate variability and net primary production (NPP)

The LUCAS model does not directly use climate data within the model, but does require an annual estimate of biomass growth to drive the flux of carbon from the atmosphere to the living biomass pool in the SF model. To estimate living biomass growth we use a region-wide estimate of net primary productivity (NPP) for mature forest stands, as predicted by the IBIS model. For young and regenerating stands, NPP is scaled to reflect reduced productivity. In LUCAS, NPP projections from the IBIS-CALIB and IBIS-CLIM simulations were used to reflect short- and long-term changes in climate and the impact on biomass growth.

For the LUCAS-CALIB simulation we used annual NPP based on IBIS-CALIB NPP estimates. This period reflects the use of average historical climate within IBIS (Table 5), and the growth rate of a mature forest. An average NPP value was used for the first 100 years of the simulation to avoid using NPP estimates for young and regenerating forests which would have resulted in artificially suppressed growth rates. In analyzing the IBIS output, NPP was relatively stable once forests reach 40 years old. For years 101–200 of the LUCAS-CALIB simulation we used the annual NPP estimate from IBIS, which was driven by observed climate for the years 1900–2010 using the Parameter-elevation Regressions on Independent Slopes Model (PRISM) [52]. LUCAS simulations for the LUCAS-CLIM and LUCAS-LUD scenarios used NPP estimates produced from the IBIS-CLIM simulation.

Table 5. Climate data and NPP parameters used in LUCAS model simulations.

Temporal Period	Scenario	Source of climate/CO_2 data used in IBIS	LUCAS NPP Parameter
Timestep 1–300	CALIB	PRISM Average historical climate (1960–1990); fixed 332 ppm CO_2 concentration	IBIS CALIB NPP
Years 2000–2100	CLIM/LUD	CGCM3 Climate projection; increasing trend (see Liu et al. 2011 for detail) [9]	IBIS A1B NPP

2.5.2. Flow parameterization

Flow pathways within the SF model move carbon between various pools (i.e. fluxes). We have simplified the flux estimates from IBIS to represent the major pathways between primary carbon pools. Detailed calculations for each flux can be found in section 6 of the Supplementary.

2.5.2.1. Automatic flows

Automatic flows describe the flux of carbon which occurs annually between pools, without any occurrence of land-use change, management, or disturbance. Automatic flows include growth, litterfall (from live and deadwood), humification, and emission (from litter and soil) (Figure 1).

Using the output from the IBIS-CALIB scenario we calculate the proportion of carbon transferred from one pool to another, i.e. the flux rate. Individual-aged flux proportions are then averaged into 2–10 year age bins for input into the SF model (Table 6). Within the SF model, the flux rates serve as a set of coefficients which get multiplied against the carbon stock for a cell with a defined age.

Table 6. Age-structured flow proportions derived from IBIS-CALIB scenario for use in SF model.

Age Min	Age Max	NPP Scalar	Litterfall (Biomass)	Litterfall (Deadwood)	Humification	Emission (Litter)	Emission (Soil)	Mortality
1	1	0.5267	0.1039	0.0822	0.1784	0.1351	0.0198	0.0089
2	2	0.7059	0.1438	0.0796	0.1384	0.1073	0.0188	0.0088
3	3	0.7915	0.1637	0.0771	0.1768	0.1513	0.0177	0.0094
4	4	0.8492	0.1674	0.0742	0.1994	0.1776	0.0172	0.0094
5	5	0.8804	0.1654	0.0716	0.2112	0.1912	0.0167	0.0100
6	6	0.9053	0.1605	0.0689	0.2169	0.1976	0.0164	0.0100
7	7	0.9256	0.1546	0.0661	0.2206	0.2016	0.0161	0.0101
8	8	0.9427	0.1487	0.0633	0.2223	0.2043	0.0159	0.0101
9	9	0.9567	0.1428	0.0599	0.2246	0.2062	0.0157	0.0106
10	10	0.9645	0.1372	0.0576	0.2255	0.2066	0.0156	0.0106
11	11	0.9754	0.1320	0.0548	0.2272	0.2086	0.0155	0.0107
12	12	0.9863	0.1275	0.0524	0.2294	0.2101	0.0154	0.0108
13	13	0.9863	0.1227	0.0506	0.2291	0.2109	0.0152	0.0109
14	14	0.9910	0.1183	0.0485	0.2307	0.2126	0.0152	0.0110
15	15	0.9972	0.1142	0.0462	0.2333	0.2143	0.0153	0.0110
16	16	1.0000	0.1108	0.0445	0.2355	0.2164	0.0153	0.0111
17	17	0.9988	0.1071	0.0437	0.2366	0.2176	0.0153	0.0112
18	18	1.0000	0.1040	0.0428	0.2383	0.2191	0.0153	0.0113
19	19	1.0000	0.1009	0.0417	0.2402	0.2200	0.0153	0.0114
20	20	1.0000	0.0980	0.0414	0.2411	0.2228	0.0154	0.0113
21	25	1.0000	0.0906	0.0409	0.2450	0.2255	0.0154	0.0117
26	30	1.0000	0.0809	0.0427	0.2483	0.2283	0.0156	0.0120
31	35	1.0000	0.0736	0.0466	0.2479	0.2268	0.0159	0.0123
36	40	1.0000	0.0681	0.0509	0.2455	0.2229	0.0163	0.0125
41	45	1.0000	0.0639	0.0553	0.2412	0.2176	0.0167	0.0126
46	50	1.0000	0.0603	0.0590	0.2368	0.2119	0.0171	0.0127
51	60	1.0000	0.0564	0.0639	0.2311	0.2053	0.0176	0.0129
61	70	1.0000	0.0525	0.0690	0.2239	0.1983	0.0181	0.0130
71	80	1.0000	0.0497	0.0726	0.2179	0.1926	0.0184	0.0131
81	90	1.0000	0.0476	0.0734	0.2136	0.1886	0.0185	0.0131
91	100	1.0000	0.0460	0.0733	0.2101	0.1854	0.0185	0.0132
101	120	1.0000	0.0444	0.0733	0.2058	0.1814	0.0185	0.0133
121	140	1.0000	0.0429	0.0736	0.2005	0.1763	0.0185	0.0133
141	160	1.0000	0.0420	0.0737	0.1965	0.1723	0.0184	0.0134

161	180	1.0000	0.0414	0.0738	0.1932	0.1693	0.0182	0.0134
181	200	1.0000	0.0411	0.0739	0.1905	0.1669	0.0181	0.0134
201	9999	1.0000	0.0406	0.0740	0.1856	0.1623	0.0174	0.0134

Flow proportions are calculated as a percentage of the “from pool” transitioning to the “to pool” annually. The “NPP Scalar” moves carbon from an Atmosphere pool to living biomass; “Litterfall (biomass)” moves carbon from living biomass to the litter pool; “Litterfall (deadwood)” moves carbon from the deadwood pool to the litter pool; “Humification” moves carbon from the litter pool to the soil pool; “Emission (litter)” moves carbon from the litter pool to the atmosphere; “Emission (soil)” moves carbon from the soil pool to the atmosphere; “Mortality” moves carbon from the living biomass pool to the deadwood pool. All values represent the average values from IBIS output across their respective age ranges.

2.5.2.2. Event-based flows

Event-based flows in the SF model are triggered by transitions within the STSM. When a transition occurs for a simulation cell within the STSM, one or more additional flows are invoked to represent the flux of carbon due to land use, land-use change, or disturbance. Event-based flows were invoked for the following transitions: forest harvest, urbanization and agricultural intensification, and wildfire. Table 7 shows the event-based flow proportions used for this study, which were generally derived from literature or expert judgment, and designed to match the assumptions used within IBIS [9]. It is important to note that these values were generally derived from literature and represent major sources of uncertainty within the model. To evaluate their relative contribution to changes in ecosystem carbon balance we conducted a series of sensitivity tests, which are discussed in detail in section 3.1.1.

Table 7. Event-based flow proportions used within the LUCAS SF model.

STSM Event	From Stock	To Stock	Proportion
Clearcut Harvest	Living Biomass	Wood Products	0.50
	Living Biomass	Atmosphere	0.20
	Living Biomass	Deadwood	0.28
Urbanization	Living Biomass	Wood Products	0.70
	Living Biomass	Atmosphere	0.20
Deforestation	Living Biomass	Wood Products	0.80
	Living Biomass	Atmosphere	0.20
Wildfire	Living Biomass	Atmosphere	0.50
	Living Biomass	Deadwood	0.50
	Soil	Atmosphere	0.10
	Litter	Atmosphere	0.90
	Deadwood	Atmosphere	0.70

3. Results

We present two sets of modeling results. First we compare the calibration scenarios from both IBIS and LUCAS; the goal of this comparison was to confirm that the LUCAS model was able to adequately reproduce the IBIS projections of carbon dynamics, the primary objective of this research. Second, we compare results from LUCAS simulations of the climate-only (LUCAS-CLIM) and land-use (LUCAS-LUD) scenarios, the goal of which is to gain insight into how changes in climate, land use, land cover, and disturbance may impact ecosystem carbon storage and flux. Lastly, we demonstrate how sensitivity analysis can be done by modifying basic carbon flux parameters.

3.1. Calibration scenarios

The purpose of the CALIB scenario was to develop a basic set of carbon stock and flow parameters for the Sierra Nevada Mountains ecoregion, which could be used within the LUCAS framework to reproduce output from a process-based biogeochemical model. Here we compare carbon stock and flux estimates from LUCAS to those of IBIS for the CALIB scenario. Results are shown from the initial clearing of all forest cells (year 10 in the IBIS simulation) forward for 200 years.

In general, the LUCAS age-structured accounting approach is able to closely replicate estimates produced by IBIS, particularly for the living biomass and soil pools (Figure 4). LUCAS projects an increase of total forest carbon stock density in the Sierra Nevada from 1.126 kg C/m^2 in the beginning of the simulation to 10.63 kg C/m^2 at the end of the 300 year simulation, compared to IBIS which projected forest carbon at 10.73 kg C/m^2 at the end of the simulation (Figure 5). Soil carbon projections between the two models are very similar. Soil carbon was projected to increase from 11.09 kg C/m^2 to 17.59 kg C/m^2 in both models (Figure 5). A comparison of carbon fluxes is shown in Figure 6.

Projections of NPP, net ecosystem production (NEP; growth minus heterotrophic respiration), and net biome production (NBP; NEP minus losses from land change and disturbance) are used to ensure the LUCAS approach can reliably project changes in various measures of ecosystem productivity at the regional scale. Because no land use or disturbances were included in the CALIB scenarios, NEP and NBP were the same. For NPP, LUCAS is able to replicate closely the NPP projection from IBIS, however, this is expected since IBIS NPP is used as an input to drive the SF model. Regardless, we can confirm the general model structure works as expected by comparing the raw output NPP projections from each model (Figure 7). Projected NBP was also similar between models. We compared the estimates of NBP between the two models for the last 200 years of the simulations (after carbon stocks and fluxes began to stabilize) which resulted in an r^2 value of 0.96, indicating the two methods show a strong positive correlation (Figure 8).

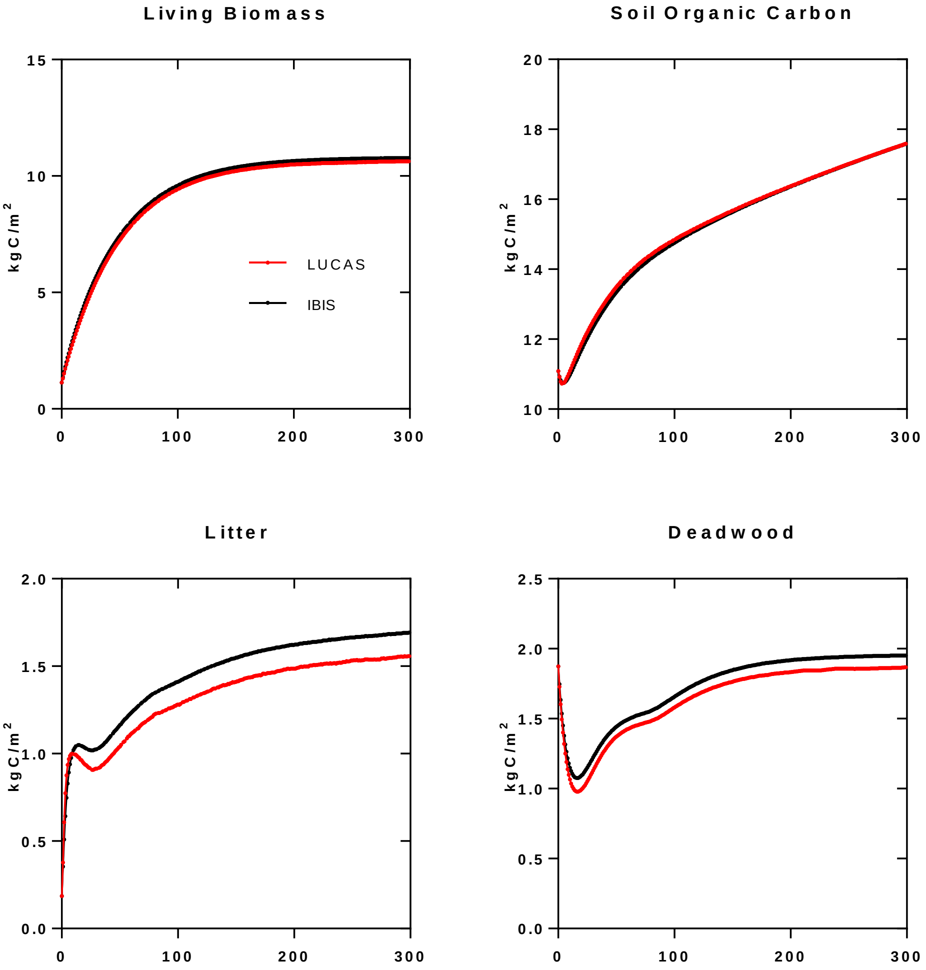

Figure 5. Comparison of carbon stock estimates between the IBIS (black lines) and LUCAS (red lines) models over the 300 year calibration simulation. In both model simulations, living biomass carbon stocks were initialized at densities representing a new regenerating forest.

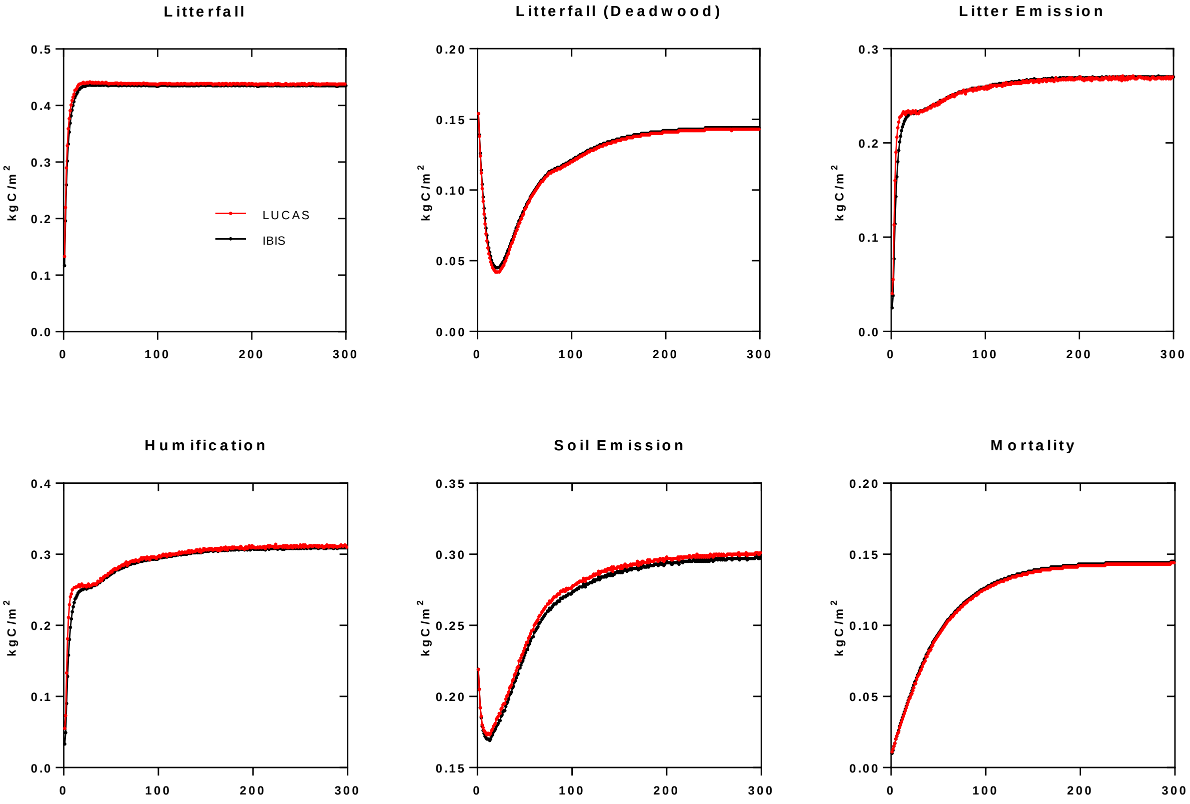

Figure 6. Comparison of carbon fluxes between LUCAS and IBIS models for the calibration scenarios.

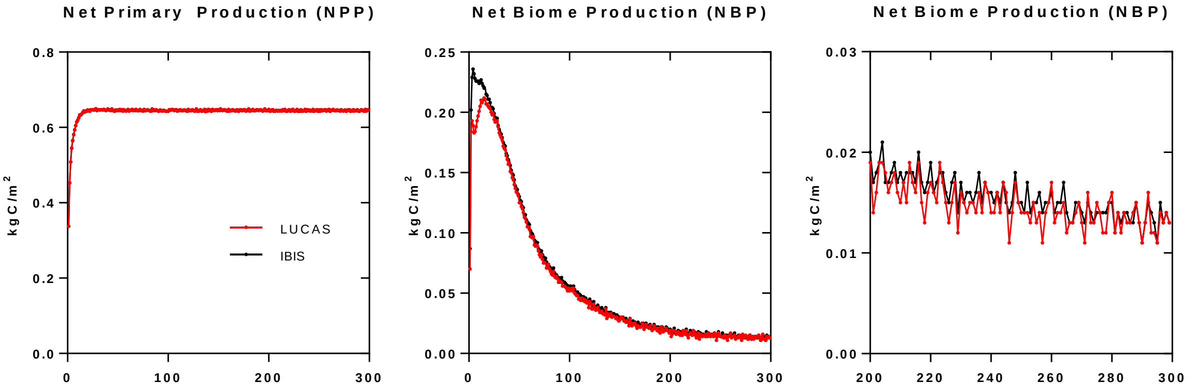

Figure 7. Comparison of IBIS and LUCAS calibration scenario projections of NPP and NEP/NBP. The third panel shows NBP for the last 100 years of the calibration scenario.

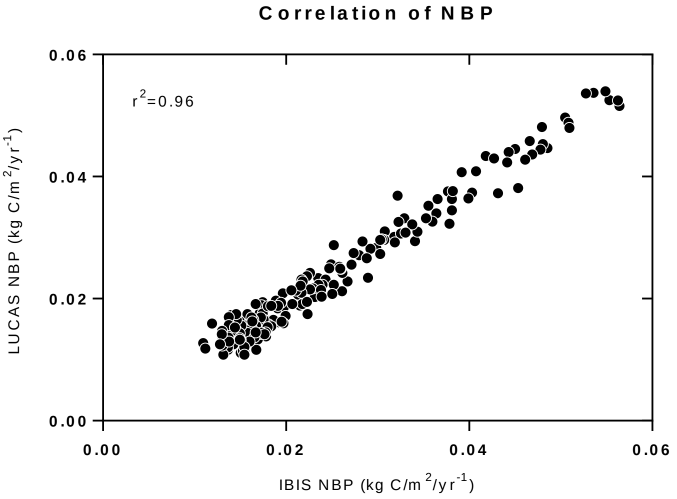

Figure 8. Correlation between IBIS and LUCAS NBP estimates for the last 200 years of the calibration simulations.

3.2. Climate and land-change scenarios

Under the LUCAS-CLIM scenario, total ecosystem carbon increased from 535.3 Tg C to 604.2 Tg C in 2100, an increase of 13% (Figure 9). Of the total ecosystem carbon in 2100, soils accounted for approximately 45% of the stored carbon, biomass accounted for 42%, deadwood accounted for ~ 7%, and litter ~ 6%. In 68% of the years, Sierra Nevada Forests were a net sink of carbon (Figure 10).

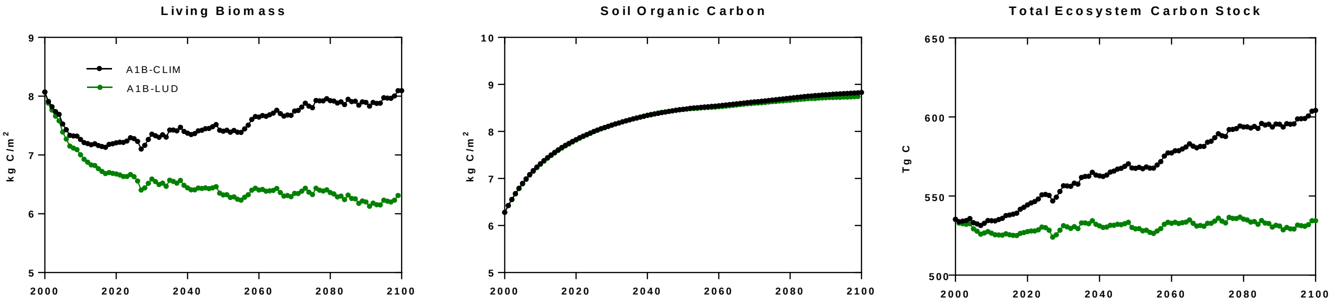

Figure 9. Projection of living biomass, soil organic carbon, and total ecosystem carbon stock, under the A1B-CLIM (black lines) and A1B-LUD (green lines) scenarios.

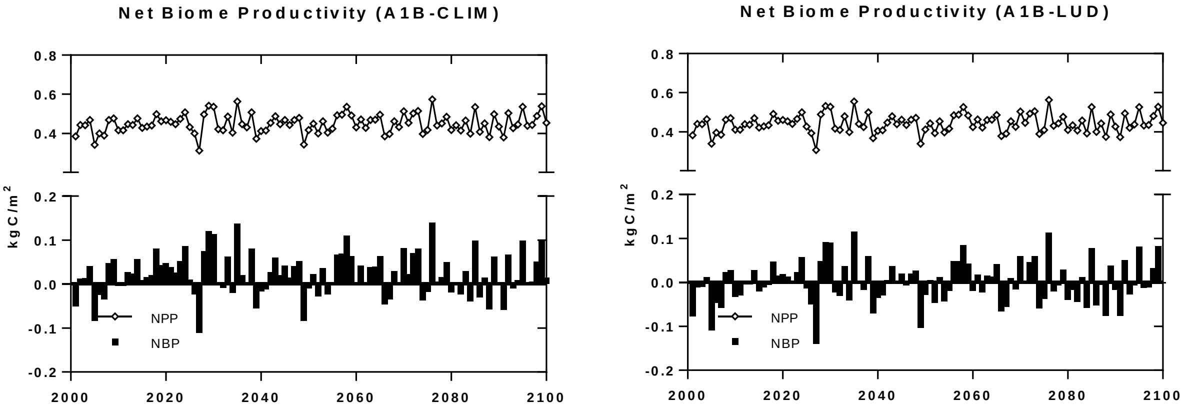

Figure 10. Comparison of net biome productivity under two LUCAS generated scenarios. The left panel shows projected annual NBP for the climate-only (LUCAS-CLIM) scenario, and the right panel shows projected annual NBP for the climate and land change (LUCAS-LUD) scenario. Under the A1B-LUD scenario, LULC change and wildfire disturbance result in the region shifting from being predominately a carbon sink to a net source of atmospheric carbon.

Under the LUCAS-LUD scenario, the major land changes were associated with wildfire and harvest, and to a lesser degree, vegetation change and urbanization (Figure 11). Projections of forest wildfire were consistent over the projection period and averaged 78 km^2/yr^{-1}. Forest harvest averaged 122 km^2/yr^{-1}, while vegetation change was projected at 12 km^2/yr^{-1}. Urbanization was rare, averaging less than 1 km^2/yr^{-1}. In total, forest area in the Sierra Nevada Mountains Ecoregion was projected to decline by 1.1% (350 km^2) between 2000 and 2100.

When land change was included in the A1B simulation (LUD scenario), total ecosystem carbon was projected to decline by 0.2% by 2100, to 534.4 Tg C (Figure 9). Living biomass was projected to decline from 250.9 Tg C to 193.6 Tg C while soil carbon was projected to increase from 195.2 Tg C to 268.8 Tg C. Figure 10 shows the annual projected carbon density for living biomass, soil organic carbon stocks, and total ecosystem carbon stock; the projected area of wildfire, harvest, vegetation change, and urbanization is shown in Figure 11. When land use and disturbance (fire) was incorporated, average annual NBP was 0.0 Tg C yr^{-1}. There was almost a complete reversal from the climate only scenario where only 47% of the time the ecoregion was projected as a carbon sink (Figure 9).

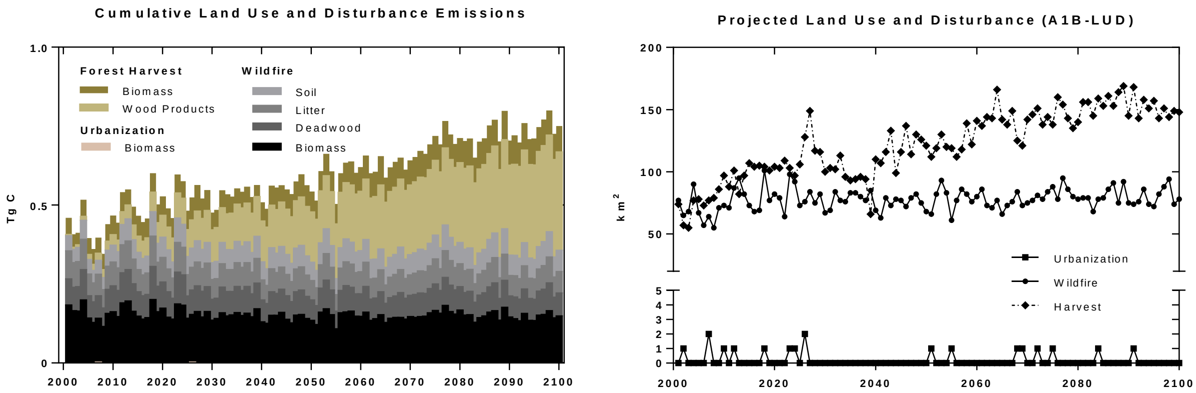

Figure 11. For the A1B-LUD scenario, cumulative emissions associated with land use, land use change, and disturbance (left) and projected land use, land cover, and disturbance area (right).

The largest drivers of carbon change in the LUCAS-LUD scenario were forest harvest and wildfire (Figure 11). Harvest of wood products resulted in the loss of 0.54 Tg C yr^{-1}; of that, 87%, or 0.47 Tg C yr^{-1} was transferred to the wood products pool. The remainder was lost as the result of emissions. For wildfire, we projected an average annual emission of 0.36 Tg C yr^{-1} from biomass, soil, litter, and deadwood combustion, with an additional 0.25 Tg C yr^{-1} transferred from the living biomass pool to the deadwood pool (Figure 11). Combined, we estimate the total emissions from land use and disturbance at 42.9 Tg C between 2000–2100, with an additional 37.8 Tg C transferred to the deadwood pool.

Carbon stored in wood products under the LUD scenario was projected at 31.2 Tg C by 2100, which accounts for a continual 1% emission rate from the wood products pool. In 2000, we estimated total ecosystem carbon storage to be 505.9 Tg C. Over the 100 year scenario we projected a 0.2% decrease in total ecosystem carbon storage (i.e. the sum of living biomass, soil, litter, and deadwood) (493.3 Tg C) and a 1.1% increase when including harvested wood products (518.8 Tg C).

3.2.1. Sensitivity analysis

To demonstrate the usefulness of the LUCAS approach for understanding model uncertainty we tested the sensitivity of parameters associated with forest harvest, wood product emission, and wildfire and their impact on long-term carbon storage. For forest harvest we modified the base flux rates from Table 7 to decrease fluxes to deadwood, reduce the flux to the wood products pool, and increase the direct emissions to atmosphere. Second, we modified the rate of emission of the harvested wood products pool. Lastly, we reduced all wildfire base flux rates by 50%. Modified flux coefficients are shown in Table 8.

Table 8. Flux rates used to modify fluxes associated with forest harvest, HPW decomposition, and wildfire.

Scenario Name	Description	From Stock	To Stock	Base Proportion	Modified Proportion
Harvest	Harvest coefficients	Living Biomass	HWP	0.50	0.35
		Living Biomass	Atmosphere	0.20	0.60
		Living Biomass	Deadwood	0.28	0.05
HWP005	Longer lived HWP pool	HWP	Atmosphere	0.01	0.005
HWP02	Shorter lived HWP pool	HWP	Atmosphere	0.01	0.02
Wildfire50	Wildfire Flux coefficients reduced by 50%	Living Biomass	Atmosphere	0.30	0.15
		Living Biomass	Deadwood	0.70	0.35
		Soil	Atmosphere	0.10	0.05
		Litter	Atmosphere	0.90	0.45
		Deadwood	Atmosphere	0.70	0.35

Under the A1B-LUD scenario, net ecosystem carbon balance (NECB; the change in the sum of all ecosystem pools between 2000 and 2100) was −0.9 Tg C. The four alternative scenarios provide an indication as to how model parameters, often with high levels of uncertainty, may impact NECB (Figure 12). Under the "Harvest" scenario, NECB was lowest, the result of a large decrease in the storage of deadwood. Conversely, the "Wildfire50" scenario resulted in the region becoming a sizable sink of carbon over the 100 year projection (+5.4 Tg C), the result of reducing all fire-related fluxes by 50%. The HWP pool increased by 21% under the "HWP005" scenario where the longevity of the HWP pool was increased to ~ 200 years with a decay coefficient of 0.005. Under the "Harvest" and "HWP02" scenarios the HWP pool declined by 29% compared to the A1B-LUD scenario.

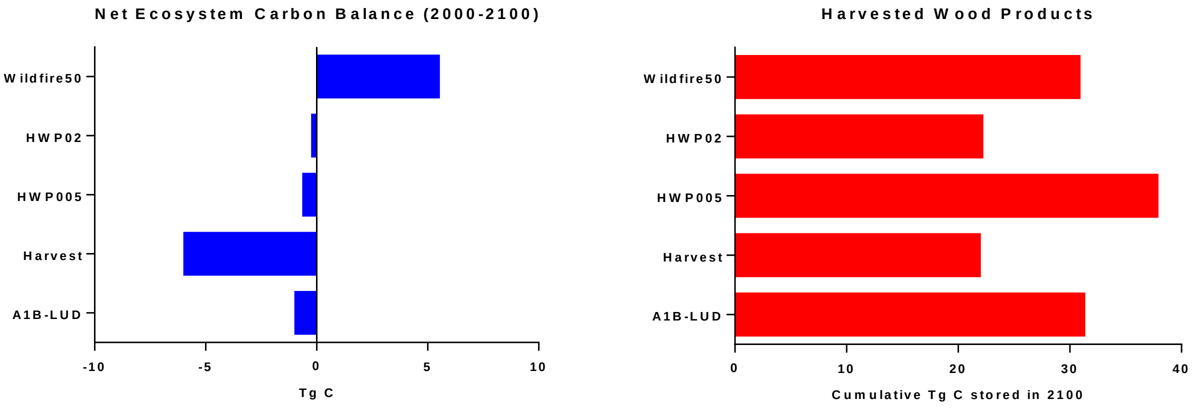

Figure 12. Net ecosystem carbon balance (NECB) and harvested wood products (HWP) under the A1B-LUD scenario and the four sensitivity tests.

4. Discussion

With this study we have demonstrated a method for using a process-based biogeochemical model to parameterize an integrated state-and-transition/stock and flow simulation model to produce projections of regional-scale carbon stocks and fluxes in response to changes in climate, land use, land cover, and disturbance. There are some clear advantages and disadvantages which must be considered when evaluating the choice of a terrestrial carbon model. Process-based models such as IBIS are advantageous when representation of detailed ecological processes are needed. IBIS is able to simulate plant physiology (e.g. leaf photosynthesis), environmental physics (e.g. energy and moisture exchange), and biogeochemical cycling (e.g. soil carbon and hydrological processes), processes not readily available in LUCAS. IBIS also includes more detailed carbon pools and fluxes along with additional input data and parameter controls, whereas LUCAS relies on a basic set of carbon flux rates to drive the exchange of carbon between pools. In general, IBIS is capable of simulating highly detailed responses to model inputs and parameter settings typically requiring considerable in-depth analysis. However, IBIS regional simulations are typically computationally intensive and time consuming, thus making it not suitable for extensive uncertainty testing. Given its complexity, IBIS also lacks a certain degree of transparency, with many model parameters not generally exposed for modification. Conversely, the LUCAS model is an ideal tool for sensitivity analysis, uncertainty assessment, and evaluation of alternative management options due to its relative ease-of use, transparency, scalability, underlying stochastic foundation, and efficient computational requirements. For example, LUCAS runs as a standard desktop application utilizing common spreadsheet software applications for management of model inputs and outputs. Virtually all model parameters are exposed for modification by the user, often with the ability to characterize uncertainties around specific inputs. The LUCAS model can be set up at any spatial, temporal, or thematic scale. We demonstrated an application at a regional scale using broad LULC categories and a basic set of carbon pools, however, LUCAS can just as easily be run at a local scale using specific vegetation types, more detailed land management and use characteristics, and a more refined set of carbon pools.

The approach described here utilizes the more detailed process-based model to supply parameters for the integrated model, and corresponds to an IPCC Tier 3 approach for carbon accounting [27]. However, it is likely that in many applications such an approach will not be feasible, due to the high degree of complexity associated with parameterizing and running a complex process-based model such as IBIS. In such cases, the LUCAS approach can be implemented using default parameters, either obtained from literature or from other experiments. Furthermore, the LUCAS modeling approach is highly scalable; we demonstrated how this model can be implemented at an ecoregional scale, however a similar approach could be applied at continental to global scales using default carbon stock and flux parameters available from the IPCC [27]. Similarly, the LUCAS model could be applied in highly detailed settings with an expanded set of carbon pools and fluxes, such as an expansion of the number of soil pools, or greater resolution in the wood products pool to represent pulp/paper, fuel wood, hardwood, and their unique decomposition and emission rates. The LUCAS models flexibility allows virtually any scale of analysis across spatial, temporal, and thematic domains.

The LUCAS model uses a growth-curve based carbon accounting method, similar to that of the Canadian Carbon Budget Model [53,54]. Here we utilized a single growth curve for the Sierra Nevada Mountains ecoregion, based on projections using the IBIS model which were calibrated with data from the U.S. Forests Service's Forest Inventory and Analysis (FIA) program. However, this approach can be modified to accept growth curves from a range of sources, including plot level data directly (e.g. FIA growth curves), ecosystem models such as CENTURY [32], or other dynamic global vegetation models such as MC2 [55]. Growth curves can also be obtained from standard lookup Tables, such as those available from the IPCC. Conducting simulations based on a range of available growth parameters would allow us to better reflect the variability and uncertainties associated with projecting changes in ecosystem carbon stocks and fluxes.

Climate data are not used directly within the LUCAS model. To evaluate the impacts of future changes in climate, LUCAS relies on an NPP parameter generated from either an exogenous model or recent historical data to drive annual growth. The benefit of this approach is the large reduction in input data (e.g. IBIS utilizes monthly temperature and precipitation data whereas LUCAS relies on a single annual average NPP value) which results in significant computational efficiencies. For example, the IBIS 300 year simulation conducted to derive flux parameters for LUCAS was modeled at 5 km resolution and took ~ 14 hours, whereas the comparable simulation in LUCAS took approximately 80 seconds at 1km resolution. However, by not directly utilizing climate inputs within LUCAS it becomes difficult to represent the range of variability across various climate models without first conducting those simulations in IBIS or a similar process-based model. Research should be done to explore alternative methods of generating regionally specific NPP projections across a range of climate scenarios so as to address uncertainties in future growth production.

Large uncertainties exist in our projections of climate-driven changes in land cover and disturbance. For this paper we assumed fire disturbance would continue based on a recent historical distribution obtained from remotely-sensed data. This approach decouples the future climate derived from the CGCM3 model with future projections of wildfire. For future studies, research should be done to more closely couple these factors. One such method would be to incorporate projections from an exogenous fire model which has simulated change based on a range of climate futures [56]. Lacking this capability, research can be undertaken to better understand how climate influences fire frequency, and develop modified historical distributions to reflect these relationships. Similarly, changes in vegetation, which would be characterized as a change in broad land-cover class, should also be considered in relation to future changes in climate. Climate induced change in vegetation is reflected in DGVMs such as IBIS and MC2. Future work should be undertaken to evaluate these projections and incorporate them into the LUCAS framework where possible.

For the purposes of this research we used a very basic set of event-based fluxes within the LUCAS model. Each event (i.e. transition) triggered one or more carbon fluxes, which were generically specified to match general assumptions within IBIS. There is significant room for improvement in this regard and the LUCAS framework is ideal for evaluating the uncertainties associated with these flux rates. For example, when harvest occurs, we estimated that 50% of the living biomass would be transferred to the wood products pool, while 28% was transferred to deadwood and 20% assumed to be emitted to the atmosphere from the burning of slash (2% was left as remaining biomass). While this approach mimics assumptions used within IBIS, it does not reflect the potential reduction in emissions due to increased efficiencies likely to be realized under the IPCC SRES A1B scenario (e.g. high rates of technological innovation, particularly within the energy sector). Due to its low computational overhead, the LUCAS framework is a useful platform to evaluate how alternative assumptions about carbon flux proportions would impact overall ecosystem carbon dynamics.

A major strength of the LUCAS approach is the integration of a robust LULC change model (STSM) with a stock and flow (SF) carbon accounting approach. Having an integrated modeling platform allows for the rapid testing of how land-change projections impact ecosystem carbon dynamics. For example, a land manager could quickly evaluate, through simple changes in basic STSM model parameters, how changing the minimum harvest age, protection of old growth forest, or reducing rates of deforestation would change the amount of carbon stored in living biomass. This capability, combined with the relative ease-of-use and transparency in underlying model assumptions, lends itself well to policy and decision making applications. Furthermore, because the land and carbon models are structurally linked, feedbacks between the two can be analyzed, such as the relationship between urbanization, fire size and frequency, and the distribution and accumulation of carbon pools.

The LUCAS model provides a highly transparent and computationally efficient means of conducting sensitivity analysis. We provided an example of a simple sensitivity test by adjusting model parameters known to have higher levels of uncertainty and showing how they can impact the storage and flux of carbon. Although outside the scope of this paper, LUCAS is designed around the capability of representing uncertainty through stochastic Monte Carlo simulations. Future work should explore development of more robust measures of uncertainty around various input parameters by combing sensitivity analysis within a Monte Carlo framework. As such, the modeling framework will be able to better characterize the true range of variability in ecosystem carbon storage and flux across multiple regions and temporal domains.

5. Conclusion

We have presented a method for producing regional-scale projections of carbon dynamics resulting from climate, land-use and land-cover change, and disturbance, using an integrated modeling approach. By linking the IBIS process-based ecosystem model with a state-and-transition simulation model (STSM) and stock and flow (SF) model, we are able to produce robust calibrated projections of carbon flux between major carbon stocks. This approach, termed the LUCAS model, is able to closely replicate results produced independently using the IBIS model for a calibration scenario. Additionally, LUCAS was used to produce projections of carbon stock change under two future scenarios, one driven by climate only, and another which further integrated land use, land cover, and disturbance. Additionally, we demonstrate the ability to conduct a simple sensitivity test to evaluate the effect of model assumptions on regional carbon balance. Due to it transparent approach, relative ease-of-use, and minimal computational demand, the LUCAS model is an ideal tool for evaluating a range of scenarios which explore how changes in land use and management can be used to affect increases in carbon storage and/or rates of sequestration.

Acknowledgments

We would like to thank Brad Reed of the USGS and two blind peer reviewers for their constructive reviews and recommendations on this manuscript.

Conflict of Interest

The authors state no conflict of interest.

Supplementary

Supplementary material is attached and describes various aspects of this modeling effort in additional details, including the IBIS ecosystem model, descriptions of state classes, development of land change projections, initialization of the IBIS simulations, the calculation of forest age, and detailed calculations for all carbon fluxes used within the stock flow model.

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