Ecosystem carbon balance in the Hawaiian Islands under different scenarios of future climate and land use change

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Abstract

The State of Hawai‘i passed legislation in 2018 setting a goal to be carbon neutral by 2045. Meeting this goal will partly depend on carbon sequestration by terrestrial ecosystems, yet the future direction and magnitude of the land carbon sink in the Hawaiian Islands is highly uncertain. We used simulation modeling to assess how projected future changes in climate and land use will influence ecosystem carbon balance in the Hawaiian Islands under four unique scenarios over a 90-year timespan. Net ecosystem carbon balance declined under all four scenarios. Moving from a high to a low radiative forcing scenario reduced net ecosystem carbon loss by ~21%, and net carbon losses were reduced by a total of ~55% under the combined scenario of low radiative forcing and low rates of land-use change. A sensitivity test of the CO_2 fertilization effect on plant productivity revealed it to be a major source of uncertainty in projections of ecosystem carbon balance. Reconciling this uncertainty in how net photosynthesis will respond to rising atmospheric CO_2 will be essential to better constrainment of models used to evaluate the effectiveness of ecosystem-based climate mitigation strategies.

Introduction

The main Hawaiian Islands are a complex mosaic of natural and human-dominated landscapes,

Methods

We used the Land Use and Carbon Scenario Simulator (LUCAS), an integrated landscape change and carbon gain-loss model, to project changes in ecosystem carbon balance for the seven main Hawaiian Islands under all combinations of two land-use scenarios (low and high) and two radiative forcing scenarios (RCP 4.5 and RCP 8.5). We also developed a separate set of scenarios to test model sensitivity to different levels of a CO_2 fertilization effect (CFE). The landscape change portion of LUCAS is a state-and-transition model that applies a Monte Carlo approach to track the state type and age of each simulation cell in response to a pre-determined set of transitions (Daniel *et al* 2016). The carbon gain-loss portion tracks carbon stocks within each simulation cell over time as continuous state variables, along with a pre-defined set of continuous flows specifying stock level rates of change over time (Daniel *et al* 2018, Sleeter *et al* 2019). We parameterized the Hawai‘i LUCAS model to estimate annual changes in carbon stocks and fluxes in response to land use, land use change, wildland fire, and long-term climate variability for the time period 2010-2100.

Study area

The spatial extent of this study was the terrestrial portion of the seven main Hawaiian Islands (Figure 1), a total land area of 16,554 km^2. We subdivided this landscape into a grid of 264,870 simulation cells, each of which was 250 x 250 m in size. Each simulation cell was assigned to one of 210 possible state types based on the unique combination of three moisture zones (dry, mesic, and wet; Figure S1), seven islands, and ten discrete land cover classes (Figure 1).

States and transitions

We developed two land-use scenarios (low and high) with transition pathways modified from Daniel *et al* (2016). Transitions between state types were pre-defined to represent urbanization, agricultural contraction, agricultural expansion, harvesting of tree plantations, and wildfire. Agriculture, forest, grassland, tree plantation, and shrubland state types each had multiple transition pathways, while the barren state type could only transition to developed (i.e., urbanization). There was no transition pathway out of an urbanized (developed) state. Water and wetland state types remained static throughout the simulation period.

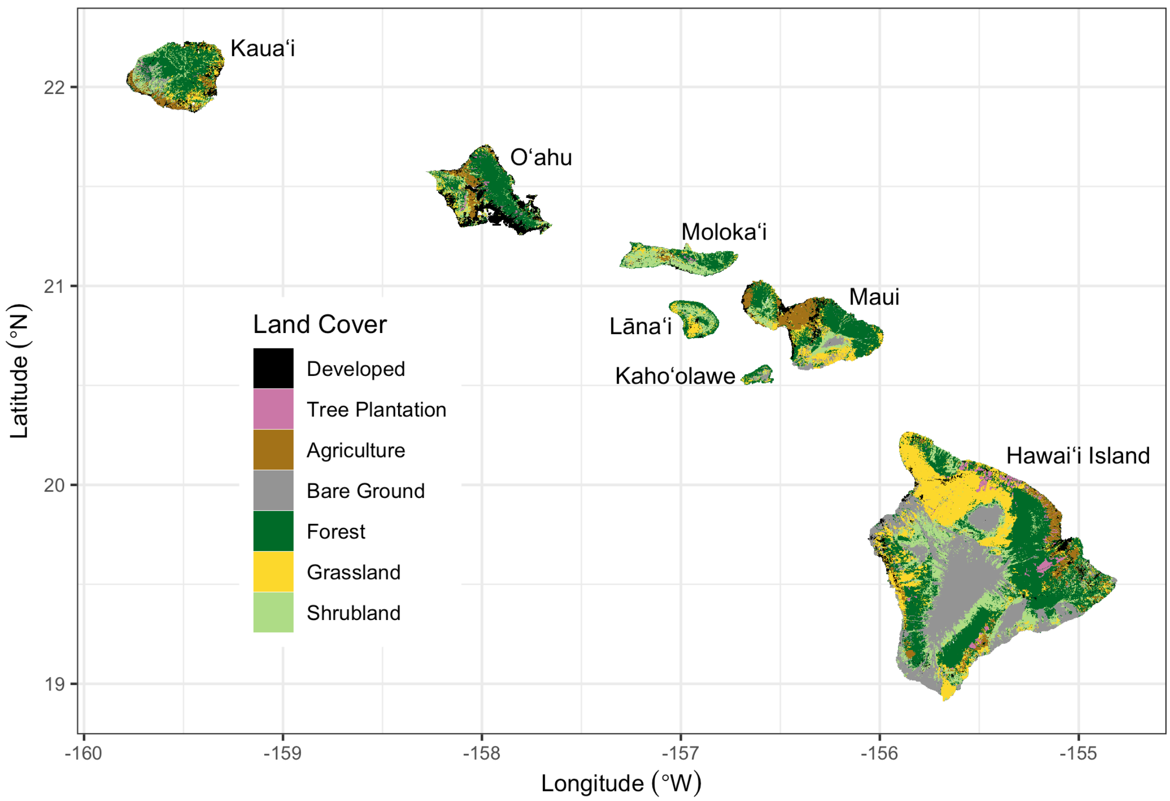

Figure 1: Land cover classification of the seven main Hawaiian Islands, adapted from Jacobi et al (2017). Agriculture in this map combines herbaceous and woody crops, but these two crop types are treated as separate land cover classes in the simulation model. Water and Wetland land cover classes are not shown.

Transition targets were based on historical trends of land use change in the Hawaiian Islands from 1992-2011 (NOAA 2020) and on population projections for the State of Hawai‘i (Kim and Bai 2018). For the high land-use scenario, transition rates for each timestep and Monte Carlo realization were sampled from uniform distributions bounded by the median and maximum historical rates of agricultural contraction, agricultural expansion, and urbanization for each island. For the low land-use scenario, rates of agricultural contraction and expansion were sampled from uniform distributions bounded by zero and the minimum historical rates for each island. Urbanization rates in the low land-use scenario were based on island-level population estimates and projections at five year intervals from 2010-2045 (Kim and Bai 2018). We converted population projections into urbanization transition targets following Sleeter *et al* (2017) by calculating population density for each island and then projecting future developed area based on the five-year incremental change in island population. The spatial extent of agricultural contraction, agricultural expansion, and urbanization was constrained in both land-use scenarios based on existing zoning maps (Daniel *et al* 2016). Transition targets for tree plantation harvest were set at ~75% of recent historical rates in the high land-use scenario and ~40% of recent historical rates in the low land-use scenario (Daniel *et al* 2016). In both land-use scenarios, approximately 60% of tree plantation harvests were replacement harvests resulting in conversion to agriculture. The remaining 40% were rotation harvests replanted to *Eucalyptus* spp.

The wildfire transition sub-model was modified from Daniel *et al* (2016) by incorporating a new 21-year historical wildfire spatial database of the Hawaiian Islands (Figure S2). We used this new spatial database to calculate historical wildfire size distribution and ignition probabilities for each unique combination of moisture zone (Figure S1), island, and state type (Figure 1) for the years 1999-2019. Starting in 2020, the number and size of fires was randomly drawn from one of these historical year-sets for each timestep and Monte Carlo realization, using burn severity probabilities from Selmants *et al* (2017). Wildfire in the low land-use scenario was sampled from the subset of historical fire years at or below the median area burned statewide from 1999-2019. The high land-use scenario sampled from historical fire years above the median area burned over the same 21-year period (Fig. S2a).

Carbon stocks and flows

The fate of carbon stocks was tracked for each simulation cell based on a suite of carbon flows (i.e., carbon fluxes) specifying the rates of change in these carbon stocks over time (Daniel *et al* 2018, Sleeter *et al* 2019). We defined carbon stocks as continuous state variables for each simulation cell, including live biomass, standing dead wood, down dead wood, litter, and soil organic carbon. We also included and tracked carbon in atmospheric, aquatic, and harvest product pools to enforce carbon mass balance (Daniel *et al* 2018). To transfer carbon between stocks, we defined baseline carbon flows as continuous variables resulting from growth, mortality, deadfall, woody decay, litter decomposition, and leaching (which includes runoff). We also defined carbon flows resulting from land use, land use change, and wildfire (Selmants *et al* 2017, Daniel *et al* 2018).

Initial carbon stocks and baseline carbon flows were estimated based on the moisture zone (Figure S1), state type, and age of each simulation cell using a lookup table derived from the Integrated Biosphere Simulator (IBIS; Foley *et al* 1996, Liu *et al* 2020), a process-based dynamic global vegetation model. We initiated IBIS with minimal vegetation and simulated forward for 110 years using 30-year climate normals for the Hawaiian Islands (Giambelluca *et al* 2013, 2014). We calibrated IBIS carbon stocks with statewide gridded datasets of soil organic carbon (Soil Survey Staff 2016) and forest aboveground live biomass (Asner *et al* 2016). We also calibrated gross photosynthesis in IBIS using a Hawai‘i-specific gridded dataset derived from MODIS satellite imagery (Kimball *et al* 2017).

Carbon flow rates for each state type and moisture zone were estimated as the ratio of the IBIS-derived flux to the size of the originating carbon stock at each age (Sleeter *et al* 2018). A spatially explicit stationary growth multiplier was applied to each simulation cell to reflect local variations in net primary productivity (NPP) driven by microclimate. This spatial growth multiplier was the NPP anomaly for each cell relative to mean values for each combination of state type and moisture zone (Sleeter *et al* 2019) calculated using empirical relationships between total annual NPP and mean annual rainfall or temperature (Schuur 2003, Del Grosso *et al* 2008). Climate change impacts on carbon flows were represented by temporal growth and decay multipliers applied to each simulation cell based on statistically downscaled CMIP5 climate projections for the Hawaiian Islands under each of the two radiative forcing scenarios (RCP 4.5 and RCP 8.5; Timm *et al* 2015, Timm 2017). The impact of future changes in rainfall and temperature on NPP were represented by annual growth multipliers calculated using empirical NPP models (Schuur 2003, Del Grosso *et al* 2008) and climate model projections of temperature and rainfall for each radiative forcing scenario. The effect of future warming on turnover rates of dead organic matter were represented by temporal decay multipliers calculated using Q10 functions and climate model temperature projections for each radiative forcing scenario. We applied a Q10 of 2.0 for wood and soil organic matter decay flows (Kurz *et al* 2009, Sleeter *et al* 2019) and a Q10 of 2.17 for litter decay flows (Bothwell *et al* 2014). Transition-triggered carbon flows resulting from disturbances associated with land use change, timber harvesting, and wildfire were based on values from Don *et al* (2011), Selmants *et al* (2017), and Daniel *et al* (2018).

CO_2 fertilization effect

Increasing atmospheric CO_2 concentrations stimulate leaf-level photosynthesis, potentially increasing NPP as well. However, the magnitude and persistence of this effect is highly uncertain, particularly across a range of climatic conditions and over long time spans. Following Sleeter *et al* (2019), we developed a separate set of scenarios designed to test the sensitivity of LUCAS model ecosystem carbon balance projections to the influence of differing rates of a CO_2 fertilization effect (CFE). We incorporated a NPP CFE multiplier representing the percent increase in NPP for every 100 ppm increase in atmospheric CO_2 concentration under the high land use and high radiative forcing (RCP 8.5) scenario. We tested five CFE levels ranging from 5% to 15%, which is within the range of CFEs observed in free air CO_2 enrichment (FACE) experiments. For all levels, we assumed CFEs reached saturation at an atmospheric CO_2 concentration of 600 ppm, with no further increase in NPP despite a continued increase in CO_2 concentration to 930 ppm by 2100. This 600ppm threshold generally coincides with the upper limit from FACE experiments and is reached by the year 2060 under RCP 8.5.

Scenario simulations and analysis

Each of the four unique scenarios were run for 90 years at an annual timestep and repeated for 30 Monte Carlo realizations, using initial conditions corresponding to the year 2010. All simulations were performed within the SyncroSim (version 2.2.4) software framework with ST-Sim (version 3.2.13) and SF (version 3.2.10) add-on modules (Daniel *et al* 2016, 2018). Model inputs and outputs were prepared with the R statistical computing platform (R Core Team 2019) using the tidyverse (Wickham *et al* 2019), raster (Hijmans 2020), and rsyncrosim (Daniel *et al* 2020) packages.

Results

Terrestrial ecosystems of the seven main Hawaiian Islands stored an estimated 316 Tg of carbon at the beginning of the simulation period in 2010, with 58% in soil organic matter, 22% in living biomass, and 20% in surface dead organic matter (litter and dead wood; Fig. 2). By the end of the simulation period in 2100,

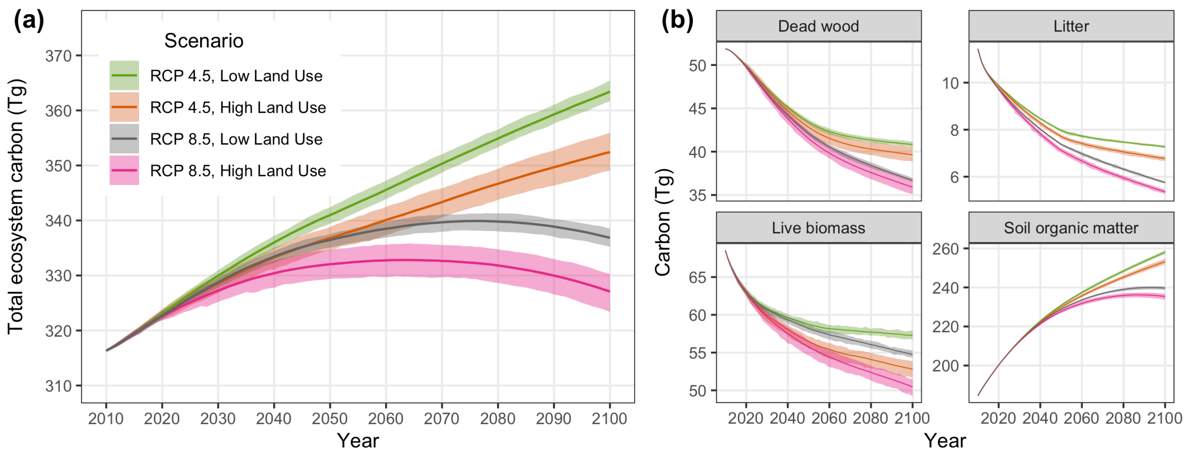

Figure 2: Projected changes in total ecosystem carbon storage (a) and individual carbon stocks (b) for the seven main Hawaiian Islands. Solid lines indicate the mean of 30 Monte Carlo realizations for each scenario, with shaded areas indicating the minimum and maximum range of Monte Carlo realizations.

Discussion

Conclusion

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Data Availability

Tabular model output data in machine readable format are available from a USGS ScienceBase data repository: https://doi.org/10.5066/P9AWLFKZ. Model input data and R code used to format input data, summarize output data, and compile this manuscript are available from a GitHub repository: https://github.com/selmants/HI_Model.

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