

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

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4 Paul C. Selman^{1,6}, Benjamin M. Sleeter², Jinxun Liu¹, Tamara S. Wilson¹,
5 Parker C. Trauernicht³, Abby G. Frazier⁴, Gregory P. Asner⁵

6 **Affiliations:**

7 ¹U.S. Geological Survey, Moffett Field, CA, USA

8 ²U.S. Geological Survey, Seattle, WA, USA

9 ³University of Hawai'i at Mānoa, Honolulu, HI, USA

10 ⁴The East-West Center, Honolulu, HI, USA

11 ⁵Arizona State University, Tempe, AZ, USA

12 ⁶Author to whom correspondence should be addressed

13 **Email:** pselmants@usgs.gov

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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 CO₂ 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 CO₂ will be essential to better constraint 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). 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. Simulations were run for 90 years at an annual timestep, using initial conditions corresponding to the year 2010. All simulations were repeated for 30 Monte Carlo realizations.

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 km². 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.

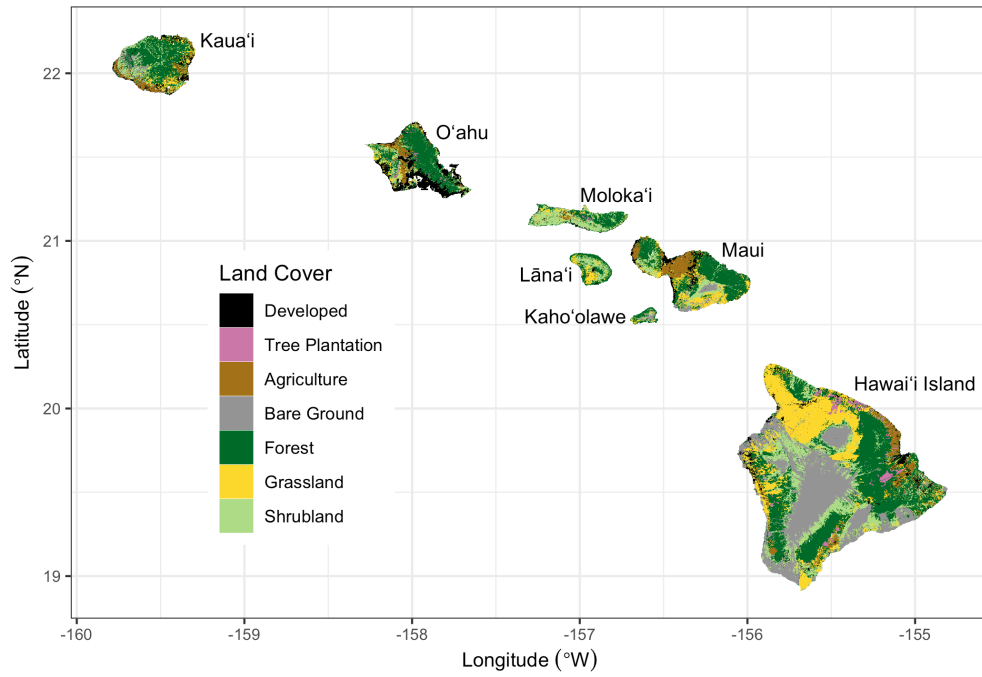


Figure 1: Land cover classification of the seven main Hawaiian Islands, adapted from Jacobi et al (2017). Agriculture in this map combines herbaceous and woody crops, but these two crop types are treated as separate land cover classes in the simulation model. Water and Wetland land cover classes are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

Water and wetland state types remained static throughout the simulation period.

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 Hawaii (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 Hawai'i fire 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. 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). 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 the mean value for each combination of moisture zone and state type (Sleeter *et al* 2019) calculated using empirical relationships between total 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 RCPs 4.5 and 8.5 (Timm *et al* 2015, Timm 2017). For each RCP, temporal growth multipliers were calculated using empirical equations relating NPP to climate (Schuur 2003, Del Grosso *et al* 2008) and temporal decay multipliers were calculated using Q10 functions (Sleeter *et al* 2019). 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).

Initial conditions

Scenario simulations

Results

Discussion

Conclusion

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Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Data Availability

Tabular model output data are available from the USGS ScienceBase data repository at: <https://doi.org/10.5066/P9AWLKFZ>. Model input data and R code used to format input data, summarize output data, and compile this manuscript are available from the HI_Model GitHub repository at: https://github.com/selmants/HI_Model.

ORCID

Paul C. Selman <https://orcid.org/0000-0001-6211-3957>

Benjamin M. Sleeter <https://orcid.org/0000-0003-2371-9571>

Jinxun Liu <https://orcid.org/0000-0003-0561-8988>

Tamara S. Wilson <https://orcid.org/0000-0001-7399-7532>

Abby G. Frazier <https://orcid.org/0000-0003-4076-4577>

Gregory P. Asner <https://orcid.org/0000-0001-7893-6421>

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