Integrating continuous stocks and flows into state-and-transition simulation models of landscape change

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Abstract
1. State-and-transition simulation models (STSMs) provide a general framework for forecasting landscape dynamics, including projections of both vegetation and land-use/land-cover (LULC) change. The STSM method divides a landscape into spatially referenced cells and then simulates the state of each cell forward in time, as a discrete-time stochastic process using a Monte Carlo approach, in response to any number of possible transitions. A current limitation of the STSM method, however, is that all of the state variables must be discrete.

2. Here we present a new approach for extending a STSM, in order to account for continuous state variables, called a STSM with stocks and flows (STSM-SF). The STSM–SF method allows for any number of continuous stocks to be defined for every spatial cell in the STSM, along with a suite of continuous flows specifying the rates at which stock levels change over time. The change in the level of each stock is then simulated forward in time, for each spatial cell, as a discrete-time stochastic process. The method differs from the traditional systems dynamics approach to stock-flow modelling in that the stocks and flows can be spatially explicit, and the flows can be expressed as a function of the STSM states and transitions.

3. We demonstrate the STSM-SF method by integrating a spatially explicit carbon (C) budget model with a STSM of LULC change for the state of Hawai‘i, USA. In this example, continuous stocks are pools of terrestrial C, whereas the flows are the possible fluxes of C between these pools. Importantly, several of these C fluxes are triggered by corresponding LULC transitions in the STSM. Model outputs include changes in the spatial and temporal distribution of C pools and fluxes across the landscape in response to projected future changes in LULC over the next 50 years.

4. The new STSM-SF method allows both discrete and continuous state variables to be integrated into a STSM, including interactions between them. With the addition of stocks and flows, STSMs provide a conceptually simple yet powerful approach for characterizing uncertainties in projections of a wide range of questions regarding landscape change.

KEYWORDS
carbon budget, land use change, landscape dynamics, Markov chain, modelling, spatial, stochastic, ST-Sim software, systems dynamics
1 INTRODUCTION

We live in a world of spatially heterogeneous and temporally dynamic landscapes. One class of models—simulation models—are commonly used to forecast the fate of such landscapes (Baker, 1989; Sklar & Costanza, 1991; Veldkamp & Lambin, 2001), including models of vegetation/forest dynamics (Keane et al., 2004; Scheller, 2013) and land-use/land-cover (LULC) change (Agarwal, Green, Grove, Evans, & Schweik, 2002; Brown, Verburg, Pontius, & Lange, 2013; Verburg, Kok, Pontius, & Veldkamp, 2006).

A major limitation of most landscape simulation models is that they have been developed for specific questions or regions, resulting in a proliferation of landscape modelling approaches (Keane et al., 2004; National Research Council, 2014). Hence, most existing models are not suitable for use as a general landscape modelling framework (Wimberly, Sohl, Liu, & Lamsal, 2015). There are a few exceptions, including SELES (Fall & Fall, 2001) and the state-and-transition simulation model (STSM) approach for forecasting landscape change (Daniel, Frid, Sleeter, & Fortin, 2016). The STSM method is a general, stochastic, spatially explicit approach for projecting landscape dynamics. Unlike most other approaches to landscape simulation modelling, the STSM method can be applied to a wide range of questions, including both vegetation dynamics and land-use change (Kerns, Shlisky, & Daniel, 2012; Wilson, Costanza, Smith, & Morisette, 2014). In the STSM approach, space is represented as a set of discrete spatial units, time is represented in discrete steps and the change in discrete state of each spatial unit over time is modelled as a stochastic process. Examples of questions for which STSMs have been developed include forest management (Costanza, Terando, McKerrow, & Collazo, 2015; Daniel, Ter-Mikaelian, Wotton, Rayfield, & Fortin, 2017), rangeland management (Provencher, Frid, Czembor, & Morisette, 2016) and LULC change (Daniel et al., 2016; Wilson, Sleeter, & Cameron, 2016).

A current limitation of STSMs, however, is that all of the state variables must be discrete, making it challenging to model processes that do not lend themselves well to discretization (Daniel et al., 2016). Examples of situations in which spatially explicit continuous state variables are often required include landscape projections of ecosystem carbon (Boisvenue, Smiley, White, Kurz, & Wulder, 2016), tracking of continuous tree attributes such as density or biomass across forested systems (Scheller et al., 2007; Wang et al., 2014), and spatially explicit population models (Turner et al., 1995). While it is already possible to track certain continuous variables in a STSM, this approach will only work when the continuous variables can be expressed as a direct function (i.e. as a “lookup”) of the STSM discrete state variables. There are other continuous variables, however, for which a lookup approach is not appropriate—these are typically variables for which there are spatial or temporal lags between changes in the STSM discrete state of each spatial unit and the corresponding change in the continuous variable (e.g. forest soil carbon).

To overcome this limitation, we present here a new approach for incorporating continuous state variables into STSMs. Our extension to the STSM method is based on the “systems dynamics” approach to modelling, as first articulated by Forrester (1961), and popularized since through software products such as Vensim and STELLA (Richmond, 2001; Sterman, 2000). This method extends a STSM as follows: (1) any number of continuous stocks are defined as additional state variables for each spatial unit in a landscape; (2) flows are also specified, for each spatial unit, that update the levels of stocks every timestep; and (3) the change in the levels of each stock over time, for each spatial unit, is represented as a discrete-time stochastic process.

There are a number of other modelling approaches that share some features with our STSM-SF approach. For example coupled map lattices (Kaneko, 1992), the continuous variable equivalent of cellular automata (Fonstad, 2006), are also able to model a continuous random variable in discrete space and time; however, unlike the STSM-SF approach, they only track one state variable at a time. Matrix population models (Caswell, 2001) are a widely used approach for modelling the dynamics of structured continuous variables (e.g. population cohorts). Like STSM-SFs, these models operate in discrete time, allow for multiple continuous state variables (i.e. as cohorts), and can be run stochastically. Their limitation in landscape simulation modelling applications, however, is that they are not readily spatially referenced. Finally, both differential and difference equations have been used to represent continuous state variables in discrete space (e.g. Canham et al., 2004; Gravel, Mouquet, Loreau, & Guichard, 2010); unlike the approach outlined here, however, these approaches are generally designed to work with a relatively small number of spatial units (i.e. patches).

In this paper we present the details of our stock-flow extension to the STSM method, including a case-study example demonstrating some of the key features of the new stock-flow approach. Specifically, the case study will show how terrestrial carbon dynamics can be integrated into a STSM of LULC change for the state of Hawai‘i, USA. We conclude with a brief discussion of the strengths and limitations of the STSM-SF method.

2 APPROACH

With the STSM method, a landscape is divided spatially into a set of simulation cells, typically as a regular raster grid. A number of discrete state variables are then tracked for each cell, each of which is represented as a discrete-time stochastic process. The first of these state variables is the state type, $X_t$, of the cell at time $t$, such that $(X_t; t \geq 0)$. For example, in a simple model of forest vegetation the state type might represent the cell’s dominant vegetation community, such as coniferous, deciduous and mixed (Figure 1). A set of $u$ matrices of one-step transition probabilities between states, $P_{u,t} = \begin{pmatrix} a_{ij,t} \end{pmatrix}$, is defined for each cell, the elements of which specify the probability that the cell will transition from state type $i$ to state type $j$ due to transition type $u$ $(u \in U$, where $U$ is the set of all possible transition types) in timestep $t$. For example continuing our forest model example of Figure 1, the transition types could include processes such as succession, fire and timber harvest. Because STSMs are space and time heterogeneous, the entries for $P_{u,t}$ are themselves random variables that are allowed
to vary by cell and timestep, and which can be expressed as a function of the current state of all cells in the landscape. A simulated realization of a STSM begins by setting initial values for \( X_0 \) for each cell and then sequentially applying the \( u \) transition probability matrices for the first timestep, \( P_{u,1} \), in order to generate \( d^{(u)}_{u,t} \) for all \( u \in U \) in the first timestep, where \( d^{(u)}_{u,t} \) represents a random variate of the Bernoulli distribution \( D_{u,t} \), such that \( D_{u,t} \) takes on a value of 1 if transition \( u \) occurs in timestep \( t \) and 0 otherwise. Based on the realized transitions, \( d^{(u)}_{u,t} \), that occur in the first timestep, a random variate for the resulting state type, \( x_1 \), is then updated at the end of the first timestep. This update process is repeated for each subsequent timestep in order to generate random variates \( d^{(u)}_{u,t} \) and \( x_t \) for all \( u \in U \) and \( t > 0 \). In addition to the state type, a STSM can also include two optional forms of “counters” as state variables: \( \{ A_t : t \geq 0 \} \), where \( A_t \) is a positive integer random variable representing the discrete age of the cell (in units of timesteps) at time \( t \), and \( \{ Y_{u,t} : u \in U, t \geq 0 \} \), where \( Y_{u,t} \) represents a set of positive integer random variables of the number of timesteps since the last transition of type \( u \) for the cell as of time \( t \) (referred to as time-since-transition or TST). Additional details on the STSM approach can be found in Daniel et al. (2016).

Because the STSM method only tracks discrete state variables, it can be challenging to model processes that do not lend themselves well to discretization. For example in a simple model of forest vegetation such as that shown in Figure 1, discrete state types may be well suited for characterizing the vegetation composition of each cell over time; on the other hand, a variable such as terrestrial carbon might be better represented as a continuous quantity. To overcome this limitation, we have developed an approach for adding continuous random variables—which we refer to as stocks—as state variables to a STSM, and, in turn, continuous flows to update the level of these stocks over time. The result is what we refer to as a *state-and-transition simulation model with stocks and flows* (STSM-SF).

Converting a STSM into a STSM-SF begins by defining a set \( V \) of possible stock types; these stock types define the suite of continuous state variables that are to be tracked for each cell. Once again, continuing our forest model example of Figure 1, four stock types are defined representing the amount of carbon in each of four carbon (C) pools: Atmosphere, Living Biomass, Dead Wood and Soil Organic Matter. As with the discrete STSM state variables for each cell, the value of each cell’s continuous stocks are also represented as discrete-time stochastic processes \( Z_{v,t} \), where \( Z_{v,t} \) is a random variable representing the amount of stock type \( v \) at time \( t \). The one-step change in the level of each cell’s stocks, \( z_{v,t} \), is then defined using a matrix of flows, \( B_{v,t} = \{ b_{v,g}^{(v,t)} \} \), the elements of which are random variables specifying the amount of stock type \( g \) that moves to stock type \( h \) due to flow type \( w \) in each timestep \( t \). Continuing our simple forest model of Figure 1, the flow types could represent all of the possible fluxes of carbon between the C pools of each cell in a timestep: for example Growth, Mortality, Decomposition and Fire Emission. Simulating the fate of each stock over time involves setting initial values for the level of each stock type (i.e. \( z_{v,0} \) for all \( v \in V \)), and then sequentially applying the first timestep’s \( w \) flow matrices, \( B_{w,t} \), in order to generate random variates for the stock types \( z_{v,t} \) for all \( v \in V \) for the first timestep. This one-step update process is then repeated for each subsequent timestep of a simulated realization in order to generate random variates, \( z_{v,t} \), for all \( v \in V \) and \( t > 0 \). As multiple types of flows can occur within each timestep, the order in which the flow matrices are applied within each timestep can be specified, as this order can be important.

### 2.1 Calculating flows

The flow amounts in a stock-flow model, as defined by the elements \( b_{v,g}^{(v,t)} \) in the flow matrix \( B_{v,t} \), are random variables that can vary by cell and timestep in a STSM-SF. While these flow amounts can be calculated, for each cell and timestep, as a function of the current state (i.e. \( X_t, A_t, Y_{u,t}, Z_{v,t} \)) of any of the cells in the landscape at time \( t \), in practice they are most commonly specified as a proportion of a stock—either as a proportion of the source stock (i.e. \( b_{v,g}^{(v,t)} = c Z_{g,t} \), where \( 0 \leq c \leq 1 \)) or the target stock (i.e. \( b_{v,g}^{(v,t)} = c Z_{h,t} \)). For example in the model of Figure 1, the Mortality flow could be expressed as a proportion of the source stock (i.e. as a mortality rate for Living Biomass); the same might be true for the Decomposition flow (i.e. as a decomposition rate for Dead Wood). The Growth flow—that is the annual flux of C...
from the Atmosphere to Living Biomass—could be modelled as a function of the size of the target stock (i.e. Living Biomass). Alternatively, flow amounts could also be modelled to be independent of any of the stocks. Note, however, that while the flow amounts might be independent of current stock levels, they are often still a function of one or more of the other discrete STSM state variables. Returning to the example model of Figure 1, instead of modelling the Growth flow as a function of the Living Biomass stock, it could alternatively be modelled as a function of the current state type (i.e. vegetation community) and age of each cell. This linkage between the flow rates and the state variables of a STSM is an important feature of the STSM-SF approach. Finally, another key feature of the STSM-SF approach is that any flows can be made a function of the realized transitions, \( d^{(u)} \), that occur on the STSM side of the simulation (i.e. \( b^{(u)} \)). For example in the model of Figure 1, emissions of \( C \) to the atmosphere could be defined to occur only in response to a fire; in other words, a Fire Emission flow in the stock-flow portion of the model can be triggered by the occurrence of a Fire transition in the STSM portion of the model. Additionally, because transitions can change the state type and age of a cell, the flow amounts for a cell that incurs a transition will change in future timesteps to match the new flow parameters associated with the cell’s new STSM state.

3 | CASE-STUDY EXAMPLE

To illustrate the STSM-SF method, we present a model of the interaction between LULC change and terrestrial carbon for the state of Hawai‘i, USA. The intent of this model is to demonstrate how potential future changes in LULC, including shifts in vegetation communities due to climate change, might alter the spatial and temporal terrestrial carbon balance for Hawai‘i. Note that this model is an extension of the STSM presented in Daniel et al. (2016); readers are thus referred to this paper for additional details regarding the LULC change portion of the model.

As the purpose of the case study is to demonstrate the STSM-SF method, we consider here only two future scenarios: (1) a “LULC change” scenario, in which we assume that historical patterns of LULC change and disturbances (including wildfire), combined with projections of future shifts in moisture zones, continue into the future; and (2) a “fire only” scenario, in which the only disturbance we allow is wildfire, and no other LULC change or moisture zone shifts occur. All of the STSM parameters for both scenarios are the same as those in the case-study model of Daniel et al. (2016), with the “fire only” scenario including only the Wildfire transitions shown in Figure 2. All the simulations were generated using the ST-Sim software version 3.0.44 (ApexRMS, 2017), with model inputs and outputs prepared using the R software version 3.2.4 (R Core Team, 2017).

3.1 | State variables and scales

As with the case-study model of Daniel et al. (2016), the spatial extent of our model was 16,416 km², representing the terrestrial portion of the state of Hawai‘i, which we divided into a grid of 1 × 1 km simulation cells. Our simulations were run for two time periods: (1) a “spin-up” period, in which we ran simulations for 500 annual timesteps, in order to estimate the equilibrium distributions of ages and carbon stock sizes for each cell as of the year 2011; and (2) a “future” period, in which we ran the model forward at an annual timestep for 50 years, starting in 2011, and using the final conditions from the spin-up period as our new initial conditions. All simulations, for both the spin-up and future periods, were repeated for 100 Monte Carlo realizations.

A number of state variables were tracked for each cell and timestep. Firstly, we used all three of the traditional discrete state variables available for STSMs—that is the state type, age (from 0 to 250) and time-since-transition (TST). As in Daniel et al. (2016), a total of 21 possible state types were included here, consisting of all possible combinations of seven LULC classes (Agriculture, Grassland, Shrubland, Forest, Eucalyptus Plantation, Developed and Barren), crossed with three moisture zones (Wet, Mesic, Dry). In addition to these discrete state variables, we also defined eight carbon (C) pools as continuous state variables for each cell, with each pool defined as a stock type using the new STSM-SF approach. The C pools, all in units of \( 10^3 \) kg of C per km² (equivalent to kg/m²), included the following six terrestrial carbon components: Live Biomass, Dead Wood, Litter, Soil Organic Matter, Atmosphere and Harvest Products. Two of these pools—Atmosphere and Harvest Products—were included strictly to

![FIGURE 2](image-url)
enforce a mass balance of C in our model. The Dead Wood and Litter C pools were each further divided into two separate stock types (i.e. Dead Wood Age 1, Dead Wood Age 2+, Litter Age 1, Litter Age 2+) in order to separate the recent (i.e. 1 year old) C from the older C in each of these pools; in doing so we demonstrate how the stock-flow approach can be used to create age-structured cohorts within stocks.

### 3.2 Model structure

Our STSM-SF model is structured around two pathway diagrams: one for the transitions between states (as in all STSMs), and a second for the flows between stocks (Figure 2). In the stock-flow portion of our model, the flows represent fluxes of C between our C stocks, including: (1) growth, mortality, litterfall and harvest of living biomass; (2) the decay of dead wood; (3) the decomposition of litter; and, (4) emissions from living biomass, dead wood, litter and soil organic matter.

The first step in quantifying each of our flow pathways was to generate estimates of the mean fluxes between all possible C pools, for every possible state type and age tracked by our STSM, in the absence of any transitions; we refer to these as the "baseline" flow amounts. These baseline flow amounts were estimated separately for each of the model’s 21 state types and 250 age classes. For the state types associated with the Barren, Developed and Agriculture LULC classes, the baseline flow amounts were all assumed to be zero (i.e. no net annual C fluxes between any of the C pools). For the remaining state types—which we refer to as the “dynamic” C state types—the baseline flow amounts were estimated for Hawai‘i (Sleeter et al., 2017) using the Integrated Biosphere Simulator (IBIS), a process-based biogeochemical model (Foley et al., 1996; Kucharik et al., 2000). The IBIS simulation provided projections for the average size of both C pools and fluxes for every possible combination of state type and age in our STSM, which allowed us to reproduce the dynamics of the biogeochemical model within the STSM-SF without requiring the two models to be linked. With the exception of the Growth flow type, all of the baseline flow amounts were expressed in our model as proportions of their respective source stocks (i.e. as flow rates). For the Growth flow type, we assumed that this annual C flux was equivalent to the total Net Primary Productivity (NPP; Chapin et al., 2006) projected by IBIS, again for every possible combination of STSM state type and age.

We represented this baseline flow amount as being independent of any of the stocks in the model—that is we assumed that the Growth flow type represented a fixed amount of C each year, and that the size of this flux, for each cell in our model, is a function only of the cell’s current state type and age.

In addition to these baseline flow amounts, we also estimated the rates at which C moves between stocks in response to each of the possible transition types shown in Figure 1 (i.e. transition-triggered flows); estimates of these rates were derived using default values provided the Intergovernmental Panel for Climate Change (IPCC) for preparing terrestrial national greenhouse gas inventories (Eggleston, Buendia, Miwa, Ngara, & Tanabe, 2006), with all of the rates expressed as proportions of the size of the source stock. Additional details regarding the stock-flow model structure are provided in Appendix S2.

### 3.3 Spatial and temporal variability in flows

A key feature of the STSM-SF approach is the ability to vary stocks and flows across cells and over time. We used two data sources to characterize the spatial variability in C flows in our simulations. The first of these was a state-wide map for Hawai‘i, at a resolution of 1 × 1 km, estimating the average annual NPP (in kg C m⁻² year⁻¹) of each simulation cell in our landscape based on MODIS satellite imagery (Sleeter et al., 2017). The second was a map estimating the soil C (in kg C m⁻²), at 1 × 1 km resolution, using data from the Soil Survey Geographic Database (SSURGO) for the state of Hawai‘i (Natural Resources Conservation Service, 2016). We used these two spatial data sources to scale the baseline flow amounts for each cell in our landscape according to the following constraints: (1) each cell’s growth flow amount, relative to all other cells on the landscape with the same state type and age (and thus the same baseline flow amount), is proportional to the estimated NPP from the MODIS-generated map; (2) each cell’s soil stock size, relative to all other cells on the landscape with the same state type and age, is proportional to the estimated soil C from the SSURGO map and (3) the IBIS-generated baseline flow amounts for each state type and age, when averaged over all cells in the landscape, are respected. To accomplish this we scaled our baseline flow amounts up and down for the growth and soil emission flows of each cell, such that our model respected the relative spatial variability observed in the NPP and soil C, yet also continued to respect the baseline (i.e. mean) flow rates generated by IBIS for each dynamic C state type and age.

Finally, we used a third data source—a time series of historical global maps estimating NPP, at a resolution of 1 × 1 km, for the years 2002–2011 (U.S. Geological Survey, 2016) —in order to characterize the temporal variability in our growth flows over time for future simulations (i.e. years 2011–2061). We scaled our baseline growth flow amounts for each cell and timestep such that: (1) the simulated temporal variability in growth across future years, by state type, matches the temporal variability in the time series of historical NPP; (2) the simulated spatial variability in growth across cells matches the spatial variability in the MODIS NPP map and (3) the expected values for the simulated growth flow amounts for each state type/age match the baseline flow amounts generated by IBIS. Note that we also used the same sampled historical year, for each realization and timestep, to select historical fire probabilities in our LULC change fire model, thus capturing any covariance that might exist between the variation in historical NPP and area burned.

### 3.4 Initialization

For the future period simulations, the initial state type and TST values for each cell were set using the same approach as in Daniel et al. (2016); (1) for state type, by combining existing 30 m resolution maps of the LULC class and moisture zone (for all realizations); and (2) for initial time-since-fire, sampling the values, for each cell and realization, from a uniform distribution bounded by 0 and the historical fire cycle corresponding to the cell’s state. Because no data existed in Hawai‘i
regarding the initial age of each cell, nor the initial level of any of the carbon pools, these initial values were all treated as random variables and initialized using the 100 realizations for projections of the 500-year spin-up simulations (Figure 3). Realized values for the future period’s initial age and carbon stocks were generated by sampling, without replacement, one of the spin-up period’s realizations, and then setting the future period’s initial age and carbon stocks to the corresponding spin-up period’s realized final timestep maps for age and carbon stocks. Additional details regarding the model initialization are provided in Appendix S2.

4 | RESULTS

In addition to the two traditional forms of model output associated with STSMs—that is transition output and state output—a STSM-SF provides two additional forms output: (1) flow output, which records the amount of each flow type; and (2) stock output, which records the level of each stock type. As with the transition and state output, the flow and stock output is provided for every cell, timestep and realization of a simulation, which in turn can be summarized in various ways.

Our case-study provides a sample of the type of flow and stock output that can be generated using a STSM-SF. Figure 4, for example, shows a time-series summary of the flow output for two of the model’s C fluxes—growth of living biomass, and total emissions—along with projections for the two largest C stocks in our case-study example—living biomass and soil organic matter. These results show firstly that, as we would expect given our spin-up procedure, the growth and emission fluxes appear to be in equilibrium for the “fire only” scenario, as do the living biomass and soil organic matter stocks. Second, we see that most of the C flux and stock is found in the Forest LULC, both in living biomass and soil. Finally, the differences in projections between the “LULC change” and “fire only” scenarios highlight the role of LULC change in shifting the C fluxes over time. For example the C emissions from shrubland areas are projected to increase in the future under the “LULC change” scenario, due to conversions into shrubland from other LULC classes, whereas the emissions from the other LULC classes are all projected to decline. Furthermore, there is considerable additional variability introduced into our projections of C fluxes and stocks once we include uncertainties regarding future LULC change.

Figure 5 summarizes the spatial pattern of the growth and emission flow types, along with maps summarizing the Net Biome Production (NBP; Chapin et al., 2006), where NBP is calculated as the difference between the Growth flow and the sum of the Harvest and all Emission flows. Under the “LULC change” scenario, the areas with highest projected increases in NBP are generally agricultural areas, as these cells are frequently converted to other LULC classes (e.g. Forest) with greater C storage potential. Note the higher level of uncertainty in the flow projections for some cells in the landscape; these are the cells that, in general, are most likely to incur LULC transitions. We also see that there is considerably more variability in the projections for changes in living biomass stocks than for soil organic matter, with the greatest increases in projected living biomass C occurring in agricultural areas (Figure 6).

Figure 7 summarizes the projections for our case study. For the “fire only” scenario we see that the NBP is projected, on average, to be zero, yet with considerable variability between realizations due to the uncertainties regarding the timing and amount of wildfire each year; this is what we would expect for a system in equilibrium. On the other hand, for the “LULC change” scenario we see that the system is projected to have a negative mean NBP over the entire simulation period; as a result, the landscape is projected to be a net source of C to the atmosphere, although because of the steady flux of C into harvest products, the net flux of C to the atmosphere is projected to eventually decline.

5 | DISCUSSION

While the STSM method has been shown to be a general approach for representing a wide range of models of landscape dynamics (Daniel...
FIGURE 4  Total carbon flux and stock each year in each of four LULC classes, as projected by the case-study STSM-SF for the entire state of Hawai‘i. (a) Carbon flux for growth of living biomass and total emissions. (b) Carbon stock for living biomass and soil organic carbon pools. Red line indicates the mean amounts for the “fire only” scenario, blue line indicates the mean amount for the “LULC change” scenario; coloured zones indicate the corresponding 95% Monte Carlo confidence intervals over 100 Monte Carlo realizations. Only those LULC classes with dynamic carbon are displayed.

FIGURE 5  Maps of carbon fluxes due to growth of living biomass, total emissions and net biome production (NBP), as projected by the case-study STSM-SF for the “LULC change” scenario. Left column shows the mean fluxes for each simulation cell, averaged over 50 years and 100 Monte Carlo realizations; right column shows the width of the 95% Monte Carlo confidence interval for the corresponding means. All values are in kg m$^{-2}$ year$^{-1}$. Results are shown only for the Island of Hawai‘i.
et al., 2016; Kerns et al., 2012; Wilson et al., 2014), a major limitation of the method was its inability to track continuous state variables. The integration of continuous stocks and flows into the STSM approach, in the manner outlined in this paper, overcomes this limitation. Any number of continuous stocks, each a spatially-referenced random variable that changes over time in response to corresponding flows, can now be integrated into a STSM. As evidenced by the widespread use of the stock-flow approach in the field of systems dynamics (Ford, 1999; Sterman, 2000), we believe that the stock-flow paradigm will prove to be an equally general and intuitive extension to the STSM method for conceptualizing and modelling continuous variables in a stochastic, spatially explicit context.

The case-study model for Hawai‘i presented here demonstrates some of the key features of the STSM-SF approach. In this example, which follows the general approach recommended by the IPCC for preparing terrestrial national greenhouse gas inventories (Eggleston et al., 2006), our continuous state variables are pools of terrestrial carbon, some of which are age-structured, whereas the flows are the fluxes of carbon between these pools. The case study shows how the continuous state variables of a stock-flow model can be integrated with the discrete state variables from the STSM. More specifically, some fluxes (i.e., growth of living biomass) can be made a function of the STSM state variables (i.e., state type and age), whereas any flux can be triggered to occur in response to the realized transitions generated by the STSM. Note that the case-study model shown here could also have been developed by representing growth fluxes as a function of the standing stock of living biomass; however, we chose to model growth as a function of age in order to demonstrate this additional integrative capability. The case-study model also highlights how the complex dynamics of a biogeochemical model can be abstracted and integrated into a STSM. The advantage of abstracting and integrating, rather than linking the two models, is that the resulting STSM-SF is much faster to run, providing the opportunity to do hundreds of Monte Carlo realizations, for multiple scenarios, over large (e.g., >10^7 cell) landscapes.

Through the integration of discrete and continuous variables into a single, stochastic modelling framework, we are able to reflect the effects of uncertainties in LULC change through to our projections of C dynamics. Note that, while we did not consider it in our case-study example, with the STSM-SF method it would also be possible to express the effects of uncertainties in the other direction—that is, the feedback effect of changes in C stocks on future rates of LULC transitions (e.g., the effect of reduced soil C on changes in land cover). Note also that, while our case-study demonstrates how some uncertainties could be incorporated into our projections, including the rates of future LULC transitions, the initial age of our landscape and the covariance between interannual NPP and fire frequency, there are many more parameter uncertainties that we did not consider, including: (1) uncertainties in past and future C flux rates, including the effects of LULC transitions on these rates; (2) the potential effects of climate change on vegetation change, NPP and C fluxes and (3) the initial distribution of C pool sizes. As a result, the confidence intervals attached to our case-study projections are likely much narrower than they would be if a broader, more complete suite of uncertainties were to be considered.

FIGURE 6 Maps of the change in carbon stocks, for the living biomass and soil organic carbon pools, as projected by the case-study STSM-SF for the “LULC change” scenario. Left column shows the mean change in each stock between 2011 and 2061 for each simulation cell, averaged over 50 years and 100 Monte Carlo realizations; right column shows the width of the 95% Monte Carlo confidence interval for the corresponding means. All values are in kg/m^2. Results are shown only for the Island of Hawai‘i.
Our case-study highlights one of the benefits of developing landscape simulation models within a general modelling framework, namely the ability to explore the effects of not only parameter uncertainties, as we have demonstrated in our case-study example, but also to explore questions of structural uncertainty—that is uncertainty in the structure of the models themselves (Morgan & Henrion, 1992; Walker et al., 2003). Unlike many existing landscape simulation models, in which the model structure is pre-defined, with the STSM-SF framework one is able to include any number and configuration of states, transitions, stocks and flows, and to subsequently alter the structure of the model as part of a scenario-based sensitivity analysis. For example in our case study we developed specific forms for our LULC and C budget models, with a particular set of LULC classes/transitions and C pools/fluxes. However, we could quite easily generate new scenarios in the future, in which we added or removed certain LULC classes/transitions and C pools/fluxes, in order to further assess the sensitivity of our projections to our assumptions regarding the model’s structure.

While adding stocks and flows overcomes a key limitation of STSMs, this new approach still has a few limitations. First, at present stocks are always defined as state variables at the level of a cell; there are applications for which it might be more appropriate for some stocks to be defined and tracked at a coarser resolution than the cell—for example the Atmosphere and Harvest Products stocks in our case-study example might be better tracked at the resolution of the entire landscape. Extending our framework to allow state variables to be defined at varying, hierarchical spatial resolutions would accomplish this. Second, as outlined in Daniel et al. (2016), there is still no capability for STSMs to integrate agent/individual-based models (Grimm & Railsback, 2005; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007); this, however, is an area of research we are actively pursuing. Finally, like all models of landscape dynamics, it can be challenging to parameterize a STSM-SF. An important feature of the STSM-SF method, however, is its ability to use the output of other models—such as the biogeochemical model used here in the case-study example—to assist with its parameterization. Due to the empirical nature of the STSM-SF method, whereby dynamics are expressed through probabilities (for transitions) and rates (for flows), the method offers a common language through which various models, operating at different scales, can be readily integrated.

To summarize, the addition of continuous stocks and flows to state-and-transition simulation models further extends the generality of the STSM method. When combined with the ST-Sim software, STSM-SFs provide a flexible new framework for developing a wide range of stochastic, spatially explicit models of landscape dynamics.

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AUTHORS’ CONTRIBUTIONS

C.D., B.S., L.F. and M.-J.F. conceived the ideas and designed methodology; C.D. and B.S. collected and analysed the data; C.D. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

DATA ACCESSIBILITY

All model inputs used in this manuscript are available from the DRYAD Digital Repository https://doi.org/10.5061/dryad.6939c (Daniel, Sleeter, Frid, & Fortin, 2017).
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