Spatial Modeling of Land Cover Change and Watershed Response using Markovian Cellular Automata and Simulation

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A continued challenge in watershed management is information related to future land cover and its impact on watersheds. Changes in land cover can have significant impact on the quality and quantity of water resources, both spatially and temporally. This study evaluates potential implications of land cover change on the hydrology of a regional watershed. Land cover change is evaluated by using Markov Chain analysis and Cellular Automation to assess future land cover based on transitional probabilities and spatial influences. The hydrology of the watershed is simulated using a continuous time simulation model. The land cover change was found to be significant in the watershed with increased urbanization and loss of agricultural and forest cover. Land cover change increased overall surface runoff, stream flow, and sediment loading. Potential land cover changes impact the timing and magnitude of seasonal events. In addition to temporal variation in impacts, spatial impacts varied among subwatersheds and administrative boundaries. Opportunities were identified for mitigating the impacts of land cover change through best management practices and policies that incorporate watershed-scale information to reduce impacts of changing in land cover on water quantity and quality.


1. Introduction

Information on future watershed land cover and its impact on water resources is a major issue in watershed management and policy. Watersheds experience long-term changes in ecosystem processes [Shriver and Randhir, 2006] through changes in land cover. Land cover in watersheds has been changing rapidly during the past two decades. At a global scale, land use changes are transforming land cover at an accelerating pace [Houghton, 1994; Turner et al., 1994] and increasing the scarcity and contamination of water resources. We define land cover as the physical coverage of a watershed landscape, while land use is the human use of the watershed landscape for a specific purpose – for example agriculture, forestry, and urban dwelling. Globally, an estimated 1400 million people live in water-stressed watersheds with runoff less than 1000 m\(^3\)/capita/year [Arnell, 2004]. Changes in land cover could have serious implication on these watershed systems that are already facing pressure from human demands. In addition to runoff, land cover changes have significant environmental impacts [Rindfuss et al., 2004] in watershed systems, especially through habitat loss, eutrophication, acidification, desertification, climate change, and biodiversity loss. This study quantifies the long run impacts of land cover change in a regional watershed system (at a river basin scale) using integrated modeling by incorporating GIS, statistical, and simulation techniques.

Changes in terrestrial ecosystems are closely linked to the sustainability of watersheds and affect the essential parts of natural capital that include climate, soils, vegetation, water resources and biodiversity [Mather and Sdaszyk, 1991; *International Geosphere-Biosphere Programme* (IGBP), 1999]. If not carefully planned, changes in land cover are likely to have negative impacts on ecosystem services provided to a society [Greenwald et al., 2001]. Understanding the trends and impacts of land cover has policy implications, especially relevant to water resources management, open space preservation, and managing urbanization. This is also important to develop approaches to mitigate negative impacts of land cover on watershed systems.

Land cover changes in watershed systems can cause local, measurable changes in watershed health. To quantify such impacts on a watershed system, it is important to use spatially explicit data on land cover changes and their trends into the future [IGBP, 1999]. We evaluate system-wide impacts of land cover change on watershed processes by using a combination of watershed simulation, Geographic Information Systems (GIS), Markovian Chain Analysis (MCA), and Cellular Automation (CA). Specifically, we evaluate the implications of various land cover scenarios on monthly water budget components, and sediment loading. The study is conducted in the Connecticut River watershed of the New England region of the U.S., which drains through four states and is designated as one of the 14 American Heritage Rivers [U.S. EPA, 2003].

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The general objective of this study is to quantify the impacts of long-term land cover change on watershed systems. Specifically, (i) to develop a land cover change model using Markovian Chain Analysis and to evaluate future land cover state in the study watershed; (ii) to simulate watershed processes at varying land cover scenarios; and (iii) to identify various policy options to mitigate the impacts land cover on watershed systems. A major hypothesis is that long-term land cover changes and their effects on watershed systems are significant.

2. Background

In this section, we review past literature in modeling land cover change in watershed systems. *Wood et al.* [1997] reviewed past uses of Markovian models to include: urban land use/land cover (LULC) change modeling [Bell, 1974], forest and vegetation succession modeling [Horn, 1975; Van Hulst, 1979], and more recently in landscape modeling [Baker, 1989; Boerner et al., 1996; Flam and Turner, 1994; Turner, 1990]. Models based on transition probability are particularly useful in spatial analysis in order to predict changing landscape patterns in both natural and human dominated landscapes. This is especially needed when factors causing landscape change are difficult to represent mechanistically. A mechanistic model aims to solve equations based solely on the fundamental laws which govern natural phenomena [Thomas, 1997]. A process model is a mechanistic system of mathematical equations and constants that are used to make quantitative predictions about a real process [Thomas, 1997]. Process-based models are often used to simulate detailed functions of the landscape to combine knowledge of biological responses with a grid-cell based model [Turner et al., 1989].

In developing a land cover model, it is important to build the simplest possible model that can adequately represent the system under study [Parker et al., 2002]. Markovian transition probabilities provide a convenient analytical framework for simulating land cover change using observed transitions developed through remote sensing or GIS technologies. Alternative approaches are typically used for modeling the influence of social and economic drivers on land-use change [Brown et al., 2000]. Markovian models have been used in state-space, change modeling in literature. The MC analysis allows the prediction of a state $L_1$ at a time $t_2$, based on the state $L_1$ of the system at time $t_1$, given a matrix of transition probabilities for each cover class to every other cover class. The 1st-order MC process used for this study is based on the probability that the state of the system through time can be determined by the knowledge of its current state and the probability of transitioning to every other state. The probability of a cell to transition from state $i$ to state $j$ is given by the transition probability ($P_{ij}$) [Pontius, 2000]. Brown et al. [2000] used Markovian modeling to evaluate forest loss in the Upper Midwest region of the U.S. which faces residential and recreational development pressures. *Wood et al.* [1997] used a temporal and spatial MCA to investigate land cover change in the south-central Senegal. Markov analysis has been applied by Lein [1989] to investigate the impacts of land cover change on local climate, and by Howard et al. [1995] to predict changes in organic carbon storage resulting from land cover changes. Logsdon et al. [1996] demonstrated the use of GIS in combination with Markovian analysis to aid analysis and visualization of landscape transitions. Gilruth et al. [1995] developed a Markov model to simulate the dynamics of shifting cultivation in the Guinea Highlands (Futa Djallon). While the use MCA and GIS are present in literature, studies that extend these land cover predictions to future watershed conditions, especially related to the future state of water resources, are limited. This study is unique in filling this gap by extending the land cover predictions to watershed response. The combined of land cover change modeling with watershed simulation is a critical need for watershed managers in the study area. The methods and applications can be used in other watersheds depending on GIS data availability. This spatial and temporal information generated by this integrated model can also be used to evaluate opportunities and policies to mitigate negative implications of land use change.

3. Methodology

The conceptual model of the analysis used in this study is presented in Figure 1. Regional data on spatial land cover in the study watershed is used to model land cover change. A regional scale watershed (less than $10^7$ km$^2$) is appropriate for capturing a variety of land use interactions with the physical, chemical, biophysical, and microbiological processes of the hydrologic cycle along the watershed continuum [IGBP, 1999]. The Markovian analysis uses land cover data sets at discrete time periods, to quantify transition probabilities. These probabilities are then used with CA to predict spatially explicit changes in land cover over a period of time. This information is then used in watershed simulation to evaluate watershed response to these land cover changes. The results of this integrated analysis are
used to evaluate observable trends, issues of concern, and opportunities for mitigation.

3.1. Land Cover Impacts

Land cover change can be defined as the change in each land cover class \( i \) (forest, agricultural, water and urban) represented by \( (L_i) \) at a specified time \( (t_1) \) projected to a future time \( (t_2) \) based on spatial information from a previous time \( (t_0) \). For each land cover class, the state of a land class \( (L_i) \) at a future time \( (t_2) \) is dependent on the spatial changes, which occurred in the land class between the previous time \( (t_0) \) and the specified time \( (t_1) \), which as specified in (1):

\[
L_{i,t_2} = g(L_{i,t_0}, L_{i,t_1})
\]

This can be extended to a probability space, as the probability of land cover state \( (P(L_i)) \) in future time \( (t_2) \) is dependent on the spatial changes, which occurred to the land class between the previous time \( (t_0) \) and the specified time \( (t_1) \) as specified in (2):

\[
P(L_i) = f(L_{i,t_0}, L_{i,t_1})
\]

3.2. Markovian Transition

The MCA uses the Markovian property that probability distribution of future states conditional on current and past states depends upon only the current state and not on past states [Gamerman, 1997]. A Markov chain analysis requires an initial distribution and a transition matrix. The transition matrix is conditional probability of the system to move into a new state given the current state of the system. The MCA is used to predict land cover changes based on a matrix of probabilities for each land class transition. The first order Markovian process used for this study is based on the probability that the system of the state through time can be determined by the knowledge of its current state and the probability of transitioning to every other state. The probability of a cell to change from state \( i \) to state \( j \) is given by its transition probability \( (P_{ij}) \) [Pontius, 2000]. The matrix assumes that the drivers that produce the detectable patterns change the state using a rule that relates the new state to its previous state, and to that of neighboring agents [Singh, 2003]. In comparison with traditional approaches that are based on differential or difference equations, the CA has the advantage of incorporating a spatial component, represented by the transition probability matrix [Baker, 1989]. The matrix defines a cellular movement within the system where the values of the matrix represent the probabilities of one state moving to another state at each time or space increment [Wood et al., 1997].

Using the outputs from the MCA, a CA process is used to apply a contiguity filter to ‘grow out’ land cover from a time \( (t) \) to a later time period \( (t_1) \). The CA filter develops a spatially explicit weighting factor, which is applied to each of the land class suitability, thereby weighing more heavily on areas that proximate to existing land covers. This ensures that land cover change occurs in proximity of similar land cover classes, and not wholly random [Eastman, 2003]. The transition probabilities (Table 1) are weighted to the length of time specified for the final land cover model. The CA makes spatial predictions based on the input of the land cover transition probabilities, the location of previous land cover types, and a collection of raster data sets, which represent the distance-weighted suitability for each cell to transition to a new class [Eastman, 2003]. The CA is run for each of the four states using the transition matrix created by the MCA and using the transition suitability maps. The CA processed the land cover transitions in two iterations for each year in the 15-year trial (30 iterations), assigning land cover at a biannual increment.

3.4. Watershed Simulation Modeling

The response of the watershed to land cover changes is quantified using a regional scale, watershed simulation model, the Soil Water Assessment Tool (SWAT) [Arnold et al., 1993]. The SWAT is a physically based, continuous time model that is capable of predicting water yield, nutrient, and sediment loading under varying watershed conditions [Neitsch et al., 2001]. The SWAT predictions have been found to be acceptable for evaluating the impact of land management practices in large and complex watersheds with varying soils, impacts of land cover and management conditions over longer periods of time [Pontius, 2000; Santhi et al., 2001; U.S. Environmental Protection Agency (EPA), 1999], and modeling watersheds with a mixed

Table 1. Land Cover Transition Probability Matrices of the 4 Administrative Units in the Study Watershed

<table>
<thead>
<tr>
<th>Administrative Unit</th>
<th>FRST</th>
<th>AGRL</th>
<th>URBN</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Hampshire</td>
<td>0.0592</td>
<td>0.1279</td>
<td>0.8128</td>
</tr>
<tr>
<td>FRST</td>
<td>0.0533</td>
<td>0.1158</td>
<td>0.8309</td>
</tr>
<tr>
<td>AGRL</td>
<td>0.041</td>
<td>0.1511</td>
<td>0.8086</td>
</tr>
<tr>
<td>URBN</td>
<td>0.1265</td>
<td>0.0109</td>
<td>0.8627</td>
</tr>
<tr>
<td>Vermont</td>
<td>0.1761</td>
<td>0.016</td>
<td>0.8079</td>
</tr>
<tr>
<td>FRST</td>
<td>0.0575</td>
<td>0.722</td>
<td>0.2205</td>
</tr>
<tr>
<td>AGRL</td>
<td>0.1265</td>
<td>0.0109</td>
<td>0.8627</td>
</tr>
<tr>
<td>URBN</td>
<td>0.1265</td>
<td>0.0109</td>
<td>0.8627</td>
</tr>
</tbody>
</table>
range/complex land covers over a long term [U.S. EPA, 1999]. Erosion and sediment yield for each hydrologic response unit (HRU) are simulated in SWAT using the Modified Universal Soil Loss Equation (MUSLE) [Williams, 1975]. The MUSLE procedure uses runoff volume to simulate erosion and sediment yield. Surface runoff volume is computed using a modification of the Soil Conservation Service (SCS) curve number method [USDA-SCS, 1972]. The potential evapotranspiration (PET) rate in the simulation model is estimated using the Hargreaves equation [Hargreaves et al., 1985; Neitsch et al., 2001].

Rates of channel degradation are determined as a function of two processes, deposition and degradation. Sediment production is modeled using the maximum amount of sediment that can be transported from a reach segment as a function of the peak channel velocity. Available stream power is used to reentrain loose and deposited material until all of the material is removed. Excess stream power causes bed degradation [Neitsch et al., 2001].

In this study, calibration and parameterization of the SWAT model is conducted using methods developed by Neitsch et al. [2001]. The calibration process included the use of a base flow filter program suggested by Arnold and Allen [1999]. The simulation model is calibrated using the USGS streamflow data over a 40 year time period (Figure 1). The calibration parameters include curve number, groundwater coefficient, soil evaporation compensation coefficient, available water capacity of the soil layer, melt factors for snow, and Manning’s n values of the main channel (Table 3). While the calibration used daily values to test simulated and observed time series, we use yearly values to calculate the regression fit. The regression fit showed an $R^2$ of 0.81, indicating a high degree of agreement between simulated and observed data points. The model is calibrated at the outlet of the watershed and the results processed for each subwatershed. The calibration aims at identifying parameter values of the model that minimize the deviation between observed and simulated values through a regression analysis. In addition, an internal validation of the model predictions was also conducted using the USGS gages at Wells River, Vermont (USGS 01138500) and Montague City, Massachusetts (USGS 01170500).

### 3.5. Impact Assessment

The land cover change models in each administrative unit (state) are clipped and merged into a single raster data set that correspond to the extent of the study watershed. The most recent land cover data from each state is used to create the current land cover scenario ($LC_0$). The data from the land cover change model for each of the states is used to create the future land cover scenario ($LC_{15}$). The $LC_{15}$ scenario is used as land cover input to the SWAT model and used to quantify the hydrologic impacts of the land cover transitions from the MCA/CA model. The SWAT model is run for 40 years of forcing data for each land cover scenario - that is, the land cover scenarios ($LC_0$ or $LC_{15}$) are kept static during the respective SWAT model run. The term MCA/CA is used to represent the integrated analysis using MCA and CA methods. The model’s predictive ability is influenced by the variations in input data quality for each state. As in any modeling exercise that are potential sources of error arising from aggregating land cover categories from various classification systems used, variations on data collection and interpretation techniques, resampling of raster data sets, and conversion from vector data sets. Because of the limitations in availability of accurate spatially explicit historical land cover information, the focus is to minimize these errors to the extent possible.

### 3.6. Validation

The first step in land cover modeling is to evaluate the ability to accurately characterize land cover time series [Wood et al., 1997]. In order to evaluate the accuracy of the predictions from the MCA/CA based model, a validation procedure is performed using historical data. The validation is based on a comparative analysis of spatial proximity of land cover classes between the two model-scenarios based

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**Table 2. Transition Land Cover Values for Each of the State Administrative Units in the Study Area (In Number of 60 m Cells)**

<table>
<thead>
<tr>
<th>State</th>
<th>$LC_0$</th>
<th>$LC_{15}$</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>CT</td>
<td>71,050</td>
<td>72,850</td>
<td>2.53</td>
</tr>
<tr>
<td>MA</td>
<td>291,341</td>
<td>498,971</td>
<td>71.27</td>
</tr>
<tr>
<td>NH</td>
<td>30,447</td>
<td>80,142</td>
<td>163.22</td>
</tr>
<tr>
<td>VT</td>
<td>65,600</td>
<td>68,475</td>
<td>4.38</td>
</tr>
</tbody>
</table>

*FRST = Forest, AGRL = Agricultural, and URBN = Urban.

**Table 3. Parameter Values Used in Calibrating the Watershed Simulation Model**

<table>
<thead>
<tr>
<th>Calibration Parameter</th>
<th>SWAT Parameter</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curve number value for the entire watershed</td>
<td>CN2</td>
<td>6</td>
</tr>
<tr>
<td>Groundwater “Revap” Coefficient</td>
<td>GW_REVAP</td>
<td>0.06</td>
</tr>
<tr>
<td>Soil evaporation compensation coefficient</td>
<td>ESCO</td>
<td>6</td>
</tr>
<tr>
<td>Available water capacity of the soil layer</td>
<td>SOL_AWC</td>
<td>0.04</td>
</tr>
<tr>
<td>Melt factor for snow on 21 Jun (mm H2O/C-day)</td>
<td>SMFMX</td>
<td>54</td>
</tr>
<tr>
<td>Melt factor for snow on 21 Dec (mm H2O/C-day)</td>
<td>SMFMN</td>
<td>33</td>
</tr>
<tr>
<td>Manning’s n value for the main channel</td>
<td>Mannings n</td>
<td>0.027</td>
</tr>
</tbody>
</table>
on the Kappa Indices of Agreement (KIAs). The KIAs are statements of the proportional accuracy of the predictions and are adjusted for change agreement [Pontius, 2000]. Two KIA are used for this study, K_{\text{location}} and K_{\text{quantity}}. These KIAs are designed to validate the simulation’s ability to predict location and quantity, respectively. The values of K_{\text{location}} and K_{\text{quantity}} are equal to 1 when the simulation model has perfect predictive success, and are equal to 0 when the simulation’s success rate is equivalent to that from a chance [Pontius, 2000].

Validation of the Markov model’s ability to predict land cover transitions in the study watershed is conducted by using the MC transition estimator to predict the spatially explicit land class change in a subset of the region. The states of Massachusetts and New Hampshire are selected for this because of the higher quality of data available and spatial variation in the land cover. The Massachusetts LC_{15} model estimates land cover in 1999 using a MC transition estimator designed using a transition probability matrix developed using 1975 and 1984 land cover data sets [MassGIS, 2004]. The model predictions are compared to the MassGIS (2004) land cover data set, which is collected and analyzed in a similar manner to the two earlier data sets. The KIA for the Massachusetts LC_{15} model was at 0.8475 for K_{\text{standard}} and 0.9547 for K_{\text{location}}, demonstrating statistical significance in agreement (85% predictive success for quantity, 95% for location) between model predictions and existing data.

A validation for the New Hampshire LC_{15} model estimates the transition from 1995 to 2001 using GRANIT [2004] land cover data set as a comparative data set. This model used a transition probability matrix estimated using 1992 and 1995 data. The KIA for this model iteration is 0.9054 for K_{\text{standard}} and 0.9504 for K_{\text{location}}, demonstrating significance in agreement between model predictions and existing data. The trends in land cover transition estimated for Massachusetts and New Hampshire are also in agreement with observable trends from the U.S. Census Bureau [U.S. Census, 2005].

An internal verification of SWAT model is conducted using monitored data in two separate locations within the study watershed. The monitoring point is at Montague City, MA (USGS 01170500) upstream to the outlet of the watershed. This station is chosen for long-time data availability, and coverage of more than 70% of the study watershed (outflow into subbasin 21). For validation, the observed time series data at the site is compared to the simulated series for that location. It was observed that the model performed well in predicting fluctuations in stream flow. A regression analysis showed an R^2 value of 0.62, indicating an acceptable explanatory power of the simulation model. The correlation coefficient (R) was at 0.79 showing a high positive correlation between observed and predicted. Similar results were obtained in another subbasin (outflow into subbasin 8) located at Wells River, Vermont (01138500) with R^2 of 0.56 and R value of 0.75.

3.7. Study Area

The Connecticut River watershed comprises covers approximately 28,500 km^2 and extends from the U.S.-Canada border in the north to Long Island Sound in the south. The watershed covers parts of New Hampshire (NH), Vermont (VT), Massachusetts (MA), and Connecticut (CT) states. The watershed contains 390 towns and cities, with a population of approximately 2.3 million people. The most recent and aggregated land cover data [USGS, 1992] estimates that the Connecticut River is composed of approximately 85% forests, 9% agriculture, and 7% urban usage.

From the early European settlements in 1700s, a series of modifications to the landscape have dramatically affected the Connecticut River Watershed. The landscape transformations occurred from continuous forestland to farmland in the 18th century. By 1850, widespread farm abandonment allowed the return of native woodland, which developed into predominantly pure white pine stands. By the 1950s urbanization in the southern reaches of the watershed had significantly altered the hydrology through channelization and impoundments. Water quality in the watershed also suffered from significant and unregulated discharges during this period, gaining the watershed reputation of being the nation’s “best landscaped sewer” [U.S. Fish and Wildlife Service, 1995].

3.8. Data

For simulation modeling, the Connecticut River Watershed is divided into subwatersheds. The delineation is using a stream threshold size of 58,000 hectares (580 km^2). The subwatersheds are further divided into hydrologic response units (HRUs) consisting of similar land cover and soil types [Manguerra and Engel, 1998; U.S. EPA, 2001]. The division of subwatersheds enables the model to analyze the effects of the major variables (soil type and land cover) for each HRU separately from the topography and rainfall distribution. Runoff is predicted for each HRU and routed to obtain the total runoff for each of the 27 spatially explicit subwatersheds [U.S. EPA, 2001]. This method increases accuracy over the single HRU method and gives a better physical description of the water balance [Manguerra and Engel, 1998]. The HRUs for the simulation model are defined using a threshold of 10 percent for soil type and a threshold of 5 percent for land cover, and are specified by the model to include 357 individual HRUs within the 27 subbasins. The GIS data used for model inputs are projected to NAD 1983, Lambert Conformal Conic (Massachusetts State Plane, Mainland) to combine with other data sets.

Weather data on precipitation and temperature (Figure 1) are obtained from the National Oceanic and Atmospheric Association’s (NOAA) National Climatic Data Center (NCDC) coop weather station database [National Oceanic and Atmospheric Administration (NOAA), 2004]. Daily precipitation and temperature data for the years 1960 to 2000 are collected from weather stations distributed throughout the watershed (Hartford, CT; Amherst, MA; Keene, NH; Cavendish, VT; Gilman, VT; and Bellows Falls, VT). Daily maximum and minimum temperature data were collected over the same time period for three weather stations, Amherst, Massachusetts (Coop ID No. 190120); Bradley Field in Hartford, Connecticut (Coop ID No. 09706); and Cavendish, Vermont (Coop ID No. 431243). These weather stations were selected based data availability during the time period of interest. The daily climatic conditions are directly input into the SWAT model to run watershed simulations. Precipitation and temperature information varied temporally in the region and thus hydrologic simulations were performed at a daily time step using the SWAT model. For evaluating watershed response under
future land use conditions, we used the same time series of historic climatic conditions. This is reasonable given that future land use faces the temporal variability and trends derived from historic climatic conditions. Spatial changes in temperature and precipitation are interpolated from the three weather stations at each time step of the simulation model.

[27] Land cover data for this study is derived from data sets available throughout the study watershed. Land cover data during past and current time periods (Figure 1) is used in future projections. Data is analyzed in a raster format using a resolution of 60 m. For the purpose of transition modeling, the land cover categories are converted back into Anderson Level I classification system with four land cover types: water, forest, agriculture, and specialized/urban. The GIS data for the entire watershed is compiled from a variety of sources that include MassGIS (MA State); University of Connecticut Map and Geographic Information Center (CT State); Geographically Referenced Analysis and Information Transfer System —GRANIT (NH State); Vermont Center for Geographic Information Inc. (VT State) and U.S. EPA’s BASINS data sets [U.S. EPA, 2001]. Details on modeling and data processing are detailed in Marshall [2005].

4. Results and Discussion

4.1. Land Cover Projection

[28] The LC15 model for New Hampshire, Massachusetts, Vermont, and Connecticut, which comprise 62% of the watershed’s land area, were in agreement regarding the general direction of change for all of the land cover classes. These trends include a decrease in forest and agricultural land, and an increase in urban land (Figure 2). The trend of decreasing agriculture was consistent throughout the watershed, although the magnitude of agricultural loss varied significantly between the administrative boundaries of the four states in the watershed. Changes in land cover within each state are presented in Figure 3. Land cover changes under LC0 and LC15 are presented in Table 2. Agricultural land cover change varied from a loss of almost 14% of the agricultural area in MA, to a loss of only 13% of the agricultural area in Vermont. The model prediction showed increase in agricultural area in Connecticut and New Hampshire regions of the watershed. Urban cover increased in all states ranging from 3% in Connecticut to 163% in New Hampshire regions of the watershed. Increase in urban cover is estimated at 71% in Massachusetts and 4% in Vermont regions of the watershed. Trends in forested area demonstrated the same agreement as agriculture area; the greatest loss was in Massachusetts at 13%, followed by 12% loss in New Hampshire. The loss in forest cover in Connecticut is at 3% and less than 1% in Vermont regions. The

Figure 2. Land cover in the Current scenario (a) and the LC15 scenario (b).

Figure 3. Land cover change within each state boundary within the study watershed.

Figure 4. Land cover of the study watershed under LC0 scenario.
4.3. Spatial Distribution of Surface Runoff

[31] Runoff coefficients (RC) for each subwatershed within the basin are calculated using data on soil characteristics, which varied between LC_0 and LC_15 scenarios. For the 27 total subwatersheds in the study basin, RC increased by an average of 2%, and experienced the greatest increase (11%) in the Connecticut region to a 6% decrease in Vermont region (Figure 5). The mean RC for the study watershed increased from 70.5 to 71.8.

[32] Surface runoff in the SWAT model is calculated using the RC in combination with antecedent moisture conditions and rainfall interception variables. State averages are calculated and presented in discussion. The surface runoff rates under the LC_15 scenario for the state of Vermont showed a decrease of less than 1%. The change in surface runoff state average in New Hampshire is at 2% increase, in Massachusetts at 11% increase, and in Connecticut at 15% increase (Figure 6).

4.4. Spatial Distribution of Sediment Loading

[33] Changes in runoff and sediment discharge were closely related to the changes in RC for each subwatershed. To evaluate the relationship between runoff and sediment production, a regression analysis is used which demonstrate an R^2 value of 0.65, indicating its significance. The greatest change in sediment production occurred in Massachusetts which experienced a 35% and 25% increase in sediment discharge for the watershed and state average in the LC_15 scenario, respectively. Connecticut and New Hampshire experienced increases of 25% and 6%, respectively (Figure 6). Vermont experienced increase in sediment production by 3%. The total change in sediment production for the entire study watershed was an increase of 19.8%. The coefficient of variation for the difference in sediment production was at 0.96. Increasing sediment loads leaving the watershed can impact the quality of the farmland in the watershed, causing fertile soils to be lost downstream and may also impact the watershed’s wetlands.

[34] The surface runoff rate for the watershed as a whole included 21 subwatersheds which experienced an increase in surface runoff; two subwatersheds experienced a decline,
while 4 subwatersheds experienced no change. This pattern of agreement between the subwatersheds is observed in all other analyses except where noted and will be referred to as a typical pattern of agreement. The change in surface runoff experienced by the watershed was an increase of 12%. The greatest increases in surface runoff are experienced in the lower stretches of the watershed in more urbanized areas. The change in surface runoff rates has impact on the volume of sediment transported into waterways, and can cause the overall water yield in the watershed to increase.

4.5. Spatial Distribution of Evapotranspiration

The average simulated ET throughout the study watershed decreased between the LC$_0$ and LC$_{15}$ scenarios. The decrease in ET is largely due to the decline in forest and agricultural transpiration. The state averages for Vermont, New Hampshire, Massachusetts, and Connecticut was a decline in ET of 1%, 2%, 7%, and 11%, respectively (Figure 7). The ET for the watershed as a whole demonstrated a typical pattern of agreement. The total annual change in ET decreased by 8% in the study watershed. The coefficient of variation for the simulated ET was 0.36. Declines in ET produce more surface water contributing to the overall water yield for the basin. Increase in water yield from upstream basins can increase the risk to river-based infrastructure such as dams and bridges.

4.6. Spatial Distribution of Water Yield

The average simulated water yield throughout the study watershed increased between the LC$_0$ and LC$_{15}$ scenarios. The increase in water yield is related to changes in surface runoff, indicating that the changes in RC have a significant impact on the water balance of the study watershed. The change in water yield is greatest during late summer and early fall months coinciding with the simulated decrease in ET. The highest increase in water yield over the study period occurred in the month of August when transpiration rates are highest. This could be attributed to storm events in this month along with temperature regimes at various subwatersheds. The smallest increase was observed in February, a month where the water budget is dominated by snowmelt. Changes in overall water yield demonstrate shifts in the water balance caused by decreases in watershed’s storm water detention functions. Precipitation in the simulation is either consumed by evapotranspiration, allowed to infiltrate into subsurface groundwaters, or allowed to drain over the watershed as surface runoff.

4.7. Temporal Changes in Evapotranspiration

Over the course of the 15-year period, average annual evapotranspiration decreased in all months except for August (Figure 8). The values represent monthly averages over the 15 year time period. Factors impacting the simulated ET include the volume of interception, rates of transpiration, and the amount of water on the land surface available for evaporation. The average monthly change in ET was 5%, with the greatest decrease of 8% occurring in October. The average annual decrease in ET for the study watershed was approximately 5%, and is likely caused by the loss of forest area, which contributes significant amounts of transpiration in the LC$_0$ scenario. Evapotranspiration was observed to have less of an impact on the hydrology of the watershed in the LC$_{15}$ scenario, which is due to the offset of loss from forest transpiration by increased evaporation from urban land cover. The slight increase in ET in August could be because of increase in evaporation component in that month.

4.8. Temporal Changes in Water Yield

Throughout the study watershed, water yield increased in all of the months of the study period (Figure 8). Water yield is related to changes in surface runoff, indicating that the changes in RC have a significant impact on the water balance of the study watershed. Changes in water yield demonstrate shifts in the water balance caused by decreases in watershed’s storm water detention functions. Precipitation in the simulation is either consumed by evapotranspiration, allowed to infiltrate into subsurface groundwaters, or allowed to drain over the watershed as surface runoff.

Figure 7. Change in simulated evapotranspiration and water yield in subwatersheds (subwatershed number increases from north to south).

Figure 8. Change in select components of the simulated water balance of the study watershed by month.
4.9. Temporal Changes in Surface Runoff

The changes in land cover influenced the surface runoff rates at the mouth of the study watershed, increasing by an annual average of 23% over the 15-year study period (Figure 9). The watershed experienced the greatest changes during the summer months, with the highest change occurring in the month of August, which saw a 7% increase. It should be mentioned that summer storm events with heavy precipitation could only be captured as aggregate estimates like that of August when using a daily time step model. The winter months experience the least change in surface runoff; the month of March experienced the smallest increase, amounting to less than 1%. The changes to surface runoff coincide with changes to the overall water yield leaving the study watershed. This indicates surface runoff may be a key component to the water budget of the Connecticut River Watershed as modeled by the LC\textsubscript{15} scenario. Opportunities exist to reduce the impacts of water yield shifts by managing surface runoff regionally for the land cover classes projected to experience transition in the LC\textsubscript{15} model.

4.10. Temporal Changes in Sediment Loading

The study watershed experienced an increase in sediment production for every month of the study period. The average annual sediment production was approximately 72% greater in the LC\textsubscript{15} scenario, with an average monthly increase of 35%. The month with the greatest increase in sediment production occurred in the month of August, and averaged 63; the smallest increase in sediment production occurred in March, which experienced an 11% increase. These temporal trends in sediment production coincide with the monthly trends in surface runoff, where the highest increase was also during the month of August, and the smallest increase was also in the month of March.

5. Conclusions

Watersheds experience long-term changes in the hydrologic processes through shifts in land cover. Information regarding the impacts of land cover change on watershed processes remains limited. The evaluation at the regional scale is important in developing structural and non-structural mitigation strategies to minimize the impacts of land cover change on watershed processes. For this evaluation Markov Chain analysis and cellular automation are used along with watershed simulation modeling.

The simulated patterns and fluxes of water in the study watershed are observed with major influences from snowmelt, surface runoff and evapotranspiration regimes. The impacts of land cover change on the watershed system were observed throughout the study watershed. The simulated impacts of land cover change on the watershed’s water balance included an increase in surface runoff and water yield, and a decrease in evapotranspiration. Changes in water quantity and quality are driven by land cover changes, which include increases in urban areas and decreases in forest and agriculture area. Converting land from forestry to urbanized uses increases pollution. Converting land from agriculture to urbanized uses has a more uncertain effect on water quality. Whether pollution increases or decreases depends on the type of agriculture conducted and the management practices used.

The land cover modeled in the LC\textsubscript{15} scenario produced an increase the impervious area in the watershed, causing in an increase in the average runoff coefficient for the watershed and resulting in higher surface runoff. The decrease in open space in the watershed can slow the rate of groundwater recharge, and negatively impact the amount of water storage available for community supplies. The simulation of the land cover change scenario produced negative impacts on the water quality in the study watershed. Simulated sediment production in the LC\textsubscript{15} model was approximately three times the simulated sediment production in the LC\textsubscript{0} model. The simulation of sediment production is linked to surface runoff, which also increased. The simulated increase in sediment production is partially offset by the gain in the volume of carrying waters; however, these carrying waters also increase channel scour and erosion rate and can offset nutrient delivery to the estuary as well as the estuarine salinity balance.

5.1. Impact Mitigation Strategies

Given the substantial influence of land cover patterns on hydrology, the impacts could be mitigated through watershed restoration activities. These activities can be implemented through appropriate policy and incentive mechanisms that reward use of best management practices (BMPs) and conservation policies targeted to sensitive areas of the watershed. These were identified as having potential to mitigate watershed impacts, and explicit quantification of these mitigation strategies could be done through modeling these practices in the simulation models, which is beyond the scope of this study.

5.2. Water Quality

The results of this study demonstrate the potential increase in sediment production as a concern in the study watershed. The increased production of sediment from land cover can be mitigated through source-level policies that change practices in construction, farms, highway maintenance, gravel operations, logging operations, stream channelization, roads, storm drains and stream banks. The management practices and policies that could be used to protect water quality include zoning bylaws, sediment control standards, floodplain management, regulating impervious surfaces, wetland preservation, land conservation, and BMPs.
The most significant opportunity to protect water quality is through the maintenance and improvement of riparian vegetation along stream banks in urban areas [MADEP, 1993; Palone and Todd, 1998]. The NRCS estimates the average cost of planting a 50-foot-wide buffer of mixed hardwoods and warm season grasses is approximately $200 per acre [U.S. Department of Agriculture-NRCS, 1997]. Focusing mitigation efforts on land-transition areas can be effective. Using current land cover data and National Hydrography Database (NHD) medium-resolution stream network data, approximately 175.4 miles (282.3 km) of river frontage lie in urban areas; 210.3 miles (338.4 km) of river frontage lie in urban areas in the LC15 scenario. Providing the widest buffer and therefore the maximum sediment reduction would use approximately 79 km², or 19,520 acres. Because of the great variation in sediment production between states, further opportunities exist for tradable credits to manage implementation costs [Guerin, 2004].

5.3. Water Quantity

The land cover change scenarios indicated significant temporal changes to the water yield of the watershed, and an overall increase in volume. The use of zoning to encourage the implementation of storm water BMPs can help manage runoff and increase the rates of infiltration in new developments and other land cover activities associated with urban sprawl. The conservation and restoration of wetlands will also provide significant and seasonal water storage. Water harvesting technology implemented with a distributed network of detention storage also provides a quantifiable system to help manage temporal variations in surface runoff rates. Wet detention ponds are water-harvesting structures that provide both storm water quantity and quality benefits and are easily adaptable to existing development. Typical costs for wet detention ponds range from $17.50–$35.00 per cubic meter ($0.50–$1.00 per cubic foot) of storage area [Center for Watershed Protection (CWP), 1998].

In order to mitigate the impacts of land cover change on water yield, restrictions to new development can be applied to require structural water detention systems. The LC15 scenario projects the study watershed to convert an estimated 7700 hectares of forest or agricultural land to urban cover, a cover type which exacerbates issues of sedimentation and imperviousness. By imposing a requirement for approximately 1.3 to 2 m³ of water storage per hectare of new development, the impact of increased water yield can be mitigated. Incentives can be used to implement land cover stewardship and guide the master planning process to account for future impacts among communities. Mitigation should also include smart growth practices that can bring about reductions in the effective imperviousness of the watershed.

In summary, the predicted land cover change demonstrated severe impacts on water quantity and quality. The impacts could be mitigated through appropriate land protection strategies. Examples include targeted application of policies and BMPs in areas sensitive to land cover impacts. Establishment or restoration of riparian buffers is critical to mitigate water quality and storm water impacts. The application of a distributed network of water detention systems can be used to manage water quantity impacts of land cover change. The implementation of mitigation strategies can be incorporated into zoning bylaws. Tax incentives can be provided to encourage the creation of riparian buffers in existing developments, the application of conservation BMPs, and develop distributed, small-scale storm water storage in the watershed. Wet detention basins and constructed wetlands are examples of such storage systems. Understanding the trajectory of the watershed systems and development of long-term strategies to mitigate land cover impacts is an important element of watershed management.

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