Exploring the Effects of Yard Management and Neighborhood Influence on Carbon Storage in Residential Subdivisions

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An Agent-Based Modeling Approach

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Abstract

The dramatic land-use shift from forest and agricultural to exurban residential land uses creates an excellent opportunity for ecosystem restoration and carbon sequestration through yard design and management. Yard management in a residential subdivision is rarely an autonomous endeavor. Cultural and local norms play an important role in how residents design and maintain their yards. Studies show that residents are influenced by the behavior of their neighbors. Yet, social influence has rarely been incorporated into carbon sequestration studies in residential landscapes. Agent-based modeling offers an ideal framework for exploring how social complexities among humans could affect their environment.

An agent-based model called ELMST (Exploratory Land Management and Carbon Storage), was developed to explore how management of individual yards and neighborhood influence could affect carbon storage at the scale of a residential subdivision. The model was run under four scenarios: (tier-0) no management, (tier-1) individual management without influence (tier-2) individual management with opportunity to adapt based on neighbor behaviors, and (tier-3) adaptive management, as in tier-2, but several residents were given an incentive to innovate their yard to a native prairie design upon model start-up. The model was parameterized with interview and fieldwork data from exurban homes Southeast Michigan. Total carbon within the subdivision was compared among scenarios for year 30.

Tier-1 showed a significantly higher quantity of carbon than all others, including tier-0 (no management). Results from tier-2 and tier-3 showed a greater variability of carbon storage at the subdivision level, suggesting that a wide range of outcomes can emerge as a result of neighborhood influence and divergent local norms. Considering model sensitivity of individual management behaviors, the model showed that turfgrass fertilization and mowing the lawn while allowing grass clippings to decompose on-site dramatically increased carbon stored at the parcel level, when compared with the no management scenario. Comparatively, removing grass clippings dramatically decreased carbon stored at the parcel level, when compared with the no management scenario. The native prairie innovation was able to propagate through the subdivision in tier-3 in the ELMST model. Prairie-based parcels were shown to store less carbon overall than the conventional lawn-based parcels that were fertilized or mown while allowing grass clippings to remain on-site, but stored more carbon than if grass clippings were removed all together. Model results imply that trade-off between carbon storage

and other ecosystem services may need to be considered when developing policies for environmentally-friendly residential landscapes.

The ELMST model was developed to be expanded and re-used for a variety of locales, cultures and climates. Results from this study may be used to formulate better research questions and hypothesis, inform data collection, expand intuition of policy makers, and advance the development of agent-based models with regards to coupled human and natural systems.

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Introduction

Climate change due to carbon dioxide and other greenhouse gas accumulations in the atmosphere is a global issue. Between 1850 and 1998, approximately 405 Gt of carbon dioxide was emitted into the atmosphere, increasing the concentration of carbon from 285 ppmv to 366 ppmv (approximately 28 percent) through the burning of fossil fuels, cement production, and land-use/land-cover change (IPCC 2000). While a portion of these anthropogenic emissions are absorbed by oceans and terrestrial ecosystems, at least 40 percent remain in the atmosphere (IPCC 2000).

Addressing the excess atmospheric carbon is an increasing topic of interest. Terrestrial sequestration may be included in a suite of possible solutions to remove excess carbon from the atmosphere. Many programs have been created to explicitly enhance terrestrial carbon sequestration through reforestation programs and agricultural land management practices (Benson & Surles 2006). Policies may take time to implement and could incur unexpected costs and limitations. This thesis investigates a relatively low-cost and convenient means of carbon sequestration through simple yard management practices in residential subdivisions. In 2000, residential areas accounted for 13.4 percent of the conterminous United States and were expanding at a rate of 1.60 percent per year – out-pacing the rate of population growth by roughly 25 percent (Theobald 2005). The distributed land management practices inherent across residential landscapes may offer an opportunity for climate change mitigation through terrestrial carbon storage and other ecosystem services.

Cultural and local norms play an important role in how residents design and maintain their yards. Studies show that residents are influenced by what their neighbors do (Galster 1987; Nassauer, Wang, & Dayrell 2009; Ioannides 2002). However, a current gap in scientific knowledge relates to how neighborhood influence could affect adoption of management regimes and yard types at the parcel level, which are likely to have implications for carbon storage at the subdivision level. An agent-based model, ELMST (Exploratory Land Management and Carbon Storage) was created to compare four yard management scenarios in terms of potential carbon storage at the subdivision level. The model offers an exploration into how social influence among residential neighbors may affect human-ecosystem interactions within individual parcels. The ELMST model operates at the parcel-level, however, measurements are addressed at the subdivision level to show how individual behaviors scale-up to create landscape-level phenomena.

The overarching research question is "how could resident management and neighborhood influence affect carbon storage in the vegetation and soils of a residential subdivision?" The scenarios presented in this study are tier-based: (tier-0) no management, (tier-1) individual management without influence (tier-2) individual management with opportunity to adapt based on neighbor behaviors, and (tier-3) adaptive management, as in tier-2, but several residents were given an incentive to innovate their yard to a native prairie design upon model start-up. Empirical data from homeowner interviews and fieldwork in exurban residential areas of Southeast Michigan were used to parameterize the model whenever possible, otherwise reasonable values from literature were used. As a result, this study is particular to the vegetation, climate and culture of Southeast Michigan exurban residential areas.

This thesis offers a unique contribution to the studies of climate change science, land-use/land-cover change (LUCC), and coupled human and natural systems (CHANS) in that it addresses the social aspects of land management and resulting effects on carbon storage and sequestration. A contribution to the area of complex systems and agent-based modeling is also provided through the development of ELMST, a novel agent-based model created to be re-used for a variety of locales, cultures and climates.

Background

More than three-quarters of the Earth's ice-free land has been altered by humans (Ellis & Ramankutty 2008). Human activities alter the natural carbon stocks and fluxes in terrestrial carbon pools through land-use change, land-cover change and land management. Land-use and land-cover change (LUCC) account for more than 30% of the carbon efflux into the atmosphere – a rate exceeded only by the burning of fossil fuels (Dixon et al. 1994; IPCC 2000). Land-use alterations are largely due to conversion from forests and prairies to farm fields and other agricultural lands (Houghton, Hackler, & Lawrence 1999). Alterations have serious implications on plant and animal communities, soil composition, water quality, and many other ecosystem services (Wu 2002).

The United States has seen dramatic LUCC shifts since 1950 – the most dramatic being the expansion of exurban areas just beyond the urban-rural fringe[1]. A study conducted by Brown et al. (2005) found that between 1950 and 2000, the area of urban land-use increased by one percent while cropland

1 An on-line animation of eastern U.S. patterns of urban, suburban, exurban and rural development from 1980 to 2020: http://www.ecologyandsociety.org/include/getdoc.php?articleid=1390&type=figure11 (Theobald 2005)

decreased by 11 percent. The decrease in agricultural land was primarily due to the development of exurban land uses, which increased sevenfold to tenfold during this same time period (Brown et al. 2005).

Carbon Storage

Agricultural fields are commonly stripped of vegetation, soil organic carbon and other nutrients as a result of intensive row-crop agriculture (Meyer, Baer, & Whiles 2008; Pouyat, Yesilonis, & Golubiewski 2008). The dramatic land-use shift from agricultural to exurban residential land creates an excellent opportunity for ecosystem restoration and carbon sequestration (Brown et al. 2005; Lesch 2010). Developers will typically purchase an agricultural field from a farmer for residential subdivision development. The soil will be graded, homes will be built, and turfgrass will be established. In some cases, small trees may also be planted (Westbrook 2010). When a resident moves into their new home, decisions will be made regarding how to best manage the vegetation in the yard. Management activities include tasks such as mowing the lawn, removing fallen leaves, and yard re-design. Because neighborhood yards are relatively discrete and thought to be managed autonomously by their owners, the carbon dynamics in one parcel may be significantly different from the carbon dynamics in another parcel. The mosaic of individual yard designs and management regimes at the parcel-level are likely to have macro-level impacts at the subdivision level (Kaye et al. 2006). Through distributed land management, residential subdivisions have the potential to be a cost-effective venue for carbon sequestration – especially given the large and expanding areas of exurban development (Brown et al. 2005; Theobald 2005; Bowman & Thompson 2009).

In terrestrial ecosystems, atmospheric carbon is sequestered through the process of photosynthetic growth and stored as biomass in living vegetation, such as grasses and trees. Vegetation will naturally senesce to produce litter which will decompose over time. Decomposition allows a portion of litter carbon (about 20 percent) to be transfered to the soil; the remainder is respired back to the atmosphere in the form of carbon dioxide (Currie & Aber 1997). Carbon stored in soil may respire back to the atmosphere, however soil respiration occurs at a considerably lower rate when compared with litter decomposition (Kucharik et al. 2001). The amount of time carbon spends in each pool (living biomass, litter and soil) is defined as the mean residence time. Mean residence time (MRT) plays a crucial role in the carbon cycle. Grasses, leaves and litter have an MRT of months to years, while woody biomass and soils have an MRT of years, decades or even centuries, making these pools relatively persistent stocks of carbon (IPCC 2000).

Humans participate in the carbon cycle through LUCC and management activities. Neighborhood residents manage the vegetation in their yards, thereby changing the MRT within a given carbon pool. For example, if a resident decides to remove fallen leaves from her yard, carbon is not only removed from the litter pool, but is also denied transfer to the soil pool. When a resident mows her lawn and allows grass clippings to remain on the turfgrass, additional carbon is transferred to the litter pool, and eventually to the soil pool through decomposition. The processes of photosynthetic growth, decomposition and respiration play important roles in net flux of carbon between vegetation, litter, soil and atmosphere. Human-induced management activities may affect the natural carbon flux, thereby changing the way a landscape stores and sequesters carbon (IPCC 2000).

Default Management

Developers play an important role in pioneer resident management practices and local norms. For example, developers understand the importance of turfgrass areas for active families (Westbrook 2010), implying that active families purchase yards with large areas of turfgrass and will manage the turfgrass accordingly. Similarly, developers who create innovative subdivisions with open spaces and conservation features will market these neighborhoods to a particular audience in order to receive the best price (Bowman & Thompson 2009). Initial landscapes not only attract a particular audience, they also suggest aesthetic cues to care (Nassauer 1993), which may have profound effects on future local norms in the subdivision.

Developers invest significant time and resources when developing a new subdivision, and these investments come without a guaranteed payoff (Bowman & Thompson 2009). Risks associated with subdivision design, planning and engineering lead developers to create conventional subdivisions that have historically been known to meet revenue goals (Westbrook 2010; Bowman & Thompson 2009).

According to research conducted by Westbrook (2010), developers acknowledge a value in ecological design alternatives, such as low-impact development or conservation design (Bowman & Thompson 2009). However, these techniques require changes to standard planning and engineering, and have not been consumer tested in specific areas. Changes to standard development and uncertain marketability increase the risk of innovative, ecological designs even further. Home-buyers are also at financial risk when purchasing innovative property, anticipating uncertainty of re-sale and estimated property value.

Thaler and Sunstein describe the concept of "choice architects" in their 2009 book, Nudge. Choice architects organize the context of human decision-making and behavior by creating a "default" designs. The book argues that behavior is predictably altered by default circumstances, and that there is "no such thing as a 'neutral' design" (Thaler & Sunstein 2009, p. 3). Developers may unknowingly be choice architects whose development strategies are likely to effect how future residents will manage their yards. Initial yard design may have a significant impact on local subdivision norms and ultimately carbon storage patterns over time.

The potential to leverage ecologically friendly outcomes through default yard designs is not often practiced – the perceived financial risk may be too great and consumers may be reluctant to buy in. While this paper acknowledges the importance of developers as choice architects with respect to initial yard design and ecosystem services, the depth of this topic is beyond the scope of this thesis. The focus of this paper is placed on conventional subdivisions; subdivisions that developers create with the perceived confidence of meeting revenue goals.

Neighborhood Influence

In 1997, a National Housing Survey conducted by Fannie Mae found that 71 percent of Americans preferred a "single-family detached house with a yard on all sides" (Burchell et al. 2005). Today, more than 55 million single-family homes in the United States occupy the density gradient from urban to exurban to rural (U.S. Census Bureau 2000). While single-family homes provide lodging and security, they also furnish an implicit community structure. Americans spend a great deal of time in residential subdivisions, taking care of their yards and interacting directly or indirectly with their neighbors (Bishop 2008; Ioannides 2002). Perceptions, interactions, and management behaviors among residents provide both the social fabric and ecosystem functionality within a residential subdivision (Cook et al. 2004)

When Americans search for a new home, a number of factors are typically considered: market price, distance to urban centers, distance to good schools and work locations, and recreational opportunities (Brown & Robinson 2006). Qualities associated with particular local norms are also considered, including neighborhood aesthetics and social dynamics (Bishop 2008; Brown & Robinson 2006). People will generally seek out a community where "the cultural ideals fit their values – where they don't have to live with neighbors or community groups that might force them to compromise their principles or their tastes" (Smith, Clurman, & Wood 2005, p. 83). Over the past 30 years, the United States has been sorting itself into homogeneous neighborhoods of similar values and ideals (Bishop 2008). Homophily seems to be a strong driver of resident location (Bishop 2008; Brown & Robinson 2006; Christakis & Fowler 2007), and neighborhood aesthetics are likely to be a reflection of neighborhood norms. Neighborhood norms may bolster individual identity, which may be expressed in the form of individual yard aesthetics, thereby creating an implicit norm in which yard design and management play a fundamental role. Newcomers to a particular subdivision may evaluate the yard types in an effort to understand the neighborhood culture and determine whether or not the perceived culture compliments their concept of who they are, or who they would like to be (Akerlof & Kranton 2010).

Individual yards in residential subdivisions are inherently public spaces. Front yards in-particular, provide an accessible visual area, conceivably placing pressure on an individual to "fit in" with neighborhood expectations and aesthetic norms (Nassauer, Wang, & Dayrell 2009). Not only do yard aesthetics reflect on the identity of an individual resident, but they also reinforce (or challenge) the local norm (Centola, Willer, & Macy 2005; Akerlof & Kranton 2010). This thesis will define a norm as a shared expectation about what is appropriate. The term "neighborhood influence" will be used to describe the conscious or unconscious imitation of neighboring residents' management behaviors or yard designs (Christakis & Fowler 2009).

Residents pay close attention to their neighbors' yards, often resulting in a neighborhood influence effect (Nassauer, Wang, & Dayrell 2009). Neighborhood influence is shown to be a significant factor in resident behavior (Ioannides 2002) where each resident serves as both a source and target of influence (Mason, Conrey, & Smith 2007). Individual residents appear to make autonomous decisions regarding the design and maintenance of their own parcels. However when living within close proximity of their neighbors, it may be difficult to avoid bias toward yard design and management decisions (Christakis

& Fowler 2009; Thaler & Sunstein 2009).

Galster (1987) asserted that the degree to which a resident feels cohesion with his neighbors provides a great deal of explanatory power with regards to upkeep and management of his dwelling. However, most of his neighbors must also feel this same level of cohesion and solidarity in order for management influence to cascade through the subdivision. The tendency to identify closely with neighbors offers greater potential for a more robust local norm. Galster also found that the level of social interaction among neighbors appeared to have little impact on management; positing that identification with neighborhood norms and neighborhood influence may be independent of personal social interaction among residents. However, if social connections are present, then personal social interactions do become an important factor for the diffusion of management behavior (Barabasi 2003; Galster 1987; Christakis & Fowler 2009).

In addition to neighborhood cohesion, Galster encouraged public policy officials to consider neighborhood influence when providing incentives for yard innovation. Residents who do not directly receive incentives but live near those who do, may alter their behavior because of local pressures to conform or boosted optimism for the particular innovation (Galster 1987). An example, relating to the present study, may be if a few residents receive an incentive to replace 25 percent of their turfgrass with native prairie, then the choice of these few residents may be sufficient to spread the native prairie yard style throughout the subdivision, thereby creating a new local norm. However, these types of scenarios are difficult to predict and depend on many known and unknown factors including socioeconomic characteristics of the residents, overall neighborhood cohesion, education for sustainable landscapes, optimism for the new yard design and perceived effect on property value (Galster 1987).

Studies show that neighborhood influence has a substantial effect on the behaviors and preferences of individuals who live in a residential subdivision (Galster 1987; Nassauer, Wang, & Dayrell 2009; Ioannides 2002). True management preferences of individual residents may never be understood, or may be non-existent, given the seemingly pervasive impact of local norms, cultural norms and neighborhood influence. While beyond the scope of this thesis, the emerging science of choice raises similar questions about the rationality of judgment and decision-making (Thaler & Sunstein, 2009).

Agent-Based Models

A pressing challenge in ecological research is to understand the complex feedbacks between human and environmental systems (Cook et al. 2004). Experiments regarding ecological outcomes of socially influenced landscapes are difficult to carry out. For example, Cook et al. (2004) described an adaptive experimental design using in situ human subjects living in a residential subdivision in the Central Arizona - Phoenix Long Term Ecological Research program (CAP LTER). Each section of the neighborhood was fitted with a different landscape design treatment. Residents were permitted to manage and alter the design of their own yards as they pleased, while ecological and social data were collected for many years. Although experimental designs involving actual human subjects could offer "realistic" empirical data, these types of experiments are often not feasible, involving such challenges as ethical limitations, participant bias, long time-frames and budget constraints (Cook et al. 2004).

Models may offer a practical surrogate for in situ human experiments in a variety of different landscapes. Equation-based models have traditionally been used by scientists to gain a better understanding of a particular system and to make predictions about future states of that system (Grimm & Railsback 2005). While equation-based approaches are useful for many natural systems, they are generally unable to account for the stochastic elements inherent in human systems, such as individual identity, decision-making, group dynamics, and social interactions (Cioffi-Revilla 2010). Individual human states and processes are of central importance when studying human-natural systems – small changes in individual behavior may result in unexpected environmental outcomes.

Agent-based models offer a compromise between deterministic, equation-based models and in situ human experimentation by providing a virtual laboratory in which heterogeneous agents interact with one another, and with a changing environment (Cioffi-Revilla 2010). Interactions among agents and environment could lead to large-scale outcomes and/or exhibit emergent properties that cannot be deduced by the simple aggregation of individual agent behaviors (Axelrod & Tesfatsion 2010).

Agent-based models (ABMs) are a computer programs that incorporate assumptions and logic derived from the real world into code. The computer code is then iterated through according to rules embedded in the program (Page 2005). Agent-based models are often run numerous times to generate a distribution of output patterns that may result from stochastic elements built into the model. Datasets may then be analyzed using traditional statistical methods.

Theories of social influence have notably been explored through the use of agent-based models (Xianyu 2010; Cioffi-Revilla 2010; Centola, Willer, & Macy 2005; Epstein 2008; Axelrod 1997; Axelrod & Tesfatsion 2010; Page 2005; Dixon, David S., Reynolds; Mason, Conrey, & Smith 2007). Researchers have also begun to use agent-based models to study the effects of urban sprawl and deforestation on ecosystem services and climate change (Brown & Robinson 2006; Brown et al. 2008; Robinson 2009; Liu et al. 2007; An et al. 2005; Zellner et al. 2009). However, social influence has rarely been incorporated into to LUCC at high resolutions, and particularly in residential landscapes. Thus, in the present study, an agent-based model was developed to explore how individual management and neighborhood influence could affect carbon storage within a residential subdivision.

Summary

Disciplines such as epidemiology, public health, economics, politics, and marketing have used social influence to understand the dissemination of disease, obesity, wealth, voter turn-out, and the latest trends in fashion (Mossel & Roch 2007; Christakis & Fowler 2009; Christakis & Fowler 2007; Thaler & Sunstein 2009). Yet only a handful of studies have examined the effect that neighborhood influence has on resident management behaviors (Galster 1987; Nassauer, Wang, & Dayrell 2009; Ioannides 2002), and none of these studies attempt to model the effect of management decisions on carbon storage and other ecosystem services. An agent-based model offers an ideal framework for exploring the complexities between humans and the environment. Here lies an opportunity to build on the CHANS knowledge-base (Liu et al. 2007), promote the use of agent-based models for exploratory policy analysis (Bankes 1993), and contribute to the study of LUCC and climate change science (IPCC 2000).

The overarching research question addressed in this thesis is "how could resident management and neighborhood influence affect carbon storage in the vegetation and soils of a residential subdivision?" An agent-based model, Exploratory Land Management and Carbon Storage (ELMST), was developed to assist in the exploration of carbon storage in a residential subdivision under four scenarios: (tier-0) no management, (tier-1) individual management without influence, i.e. intrinsic management, (tier-2) individual management with opportunity to adapt based on neighbor behaviors, and (tier-3) adaptive management, as in tier-2, but several residents were given an incentive to innovate their yard to a native prairie design upon model start-up. The model was parameterized with interview and fieldwork data from exurban residential landscapes in Southeast Michigan wherever possible, otherwise values from literature were used. Total subdivision carbon was compared among scenarios.

Research Questions and Hypothesis

To address the overarching research question, three specific questions were formulated that lend themselves directly to each model scenario. Each specific question is associated with one or more hypotheses to help structure testable model scenarios and research experiments.

Q_1 How could intrinsic management affect carbon storage in a residential subdivision after 30 years?

$H_{1.1}$: The total carbon[2] in an managed subdivision without neighborhood influence will be less than the total carbon in an unmanaged subdivision after 30 years.

When residents manage their yards according to their own internal preferences (i.e. without being influenced by their neighbors or adopting new management strategies), some management behaviors encourage carbon storage, while others remove carbon entirely from the subdivision.

Fertilizer may be applied to the lawn, increasing the rate of turfgrass growth and aboveground carbon. Allowing grass clippings and/or fallen leaves to remain on the parcel is expected to keep carbon in the subdivision, transferring a portion to the soil pool through decomposition. Some residents may choose to have yard waste (i.e., grass clippings and/or fallen leaves) picked up by the municipality, thereby completely removing a portion of carbon from the subdivision. Using the distribution of management behaviors derived from interview data in Southeast Michigan (Table 2), total carbon in an intrinsically managed subdivision is expected to be less than the total carbon in an unmanaged subdivision.

2 Here and elsewhere in this analysis, 'total carbon' refers to summed carbon pools in soil and vegetation in residential yards at any point in time. Carbon in residential structures is not considered, nor is carbon from energy use included in the analysis. Carbon that is exported from residential yards, i.e. yard waste, is considered a loss of carbon from the yards.

Q_2 How could neighborhood influence affect carbon storage in a residential subdivision after 30 years?

$H_{2.1}$: The total carbon in a managed subdivision having neighborhood influence will be less than the total carbon in an unmanaged subdivision.

$H_{2.2}$: There will be no significant difference in total carbon between a managed subdivision having neighborhood influence and a managed subdivision absent of neighborhood influence.

When neighborhood influence is applied to a subdivision, it may be reasonable for the distribution of intrinsic management behaviors to evolve into a more homogeneous management culture over time. The majority of management behaviors after 30 years may represent an averaging of management regimes inherent among residents when the subdivision was first developed. Therefore, the total average carbon in a managed subdivision having neighborhood influence is expected to be statistically similar to the total subdivision carbon resulting from intrinsic management behaviors.

Q_3 How could an incentive to innovate to a native prairie yard design[3] in a managed subdivision with neighborhood influence affect carbon storage in a residential subdivision after 30 years?

$H_{3.1}$: The total carbon in a subdivision having incentive to innovate to a native prairie yard will be less than the total carbon in an unmanaged subdivision.

$H_{3.2}$: The total carbon in a subdivision having incentive to innovate to a native prairie yard will be greater than the total carbon in a managed subdivision absent of neighborhood influence.

$H_{3.3}$: The total carbon in a subdivision having incentive to innovate to a native prairie yard will be greater than the total carbon in a managed subdivision having neighborhood influence.

Similar to the hypothesis in Q_2, when neighborhood influence is applied to a subdivision, it may be reasonable for the distribution of intrinsic management behaviors to evolve into a more homogeneous management culture after 30 years' time. With an incentive to innovate to

3 A native prairie yard design is assumed have 25 percent of a one-acre parcel planted with native prairie grasses, such as Little Bluestem (*Schizachyrium scoparium*) and Indian Grass (*Soghastrum nutans*).

a native prairie yard design provided to just a few residents, the innovative design is expected to propagate through the neighborhood. Native prairie is also expected to store more carbon over time than turfgrass because of its relatively high above- and below-ground biomass and its comparably low soil respiration rate (Meyer, Baer, & Whiles 2008). The majority of management behaviors after 30 years may represent an averaging of intrinsic management strategies among residents, this time with the inclusion of native prairie yards. The total carbon in an incentive-based subdivision is, therefore, expected to be greater than those subdivisions without an incentive to innovate (i.e. a subdivision having intrinsic management and a subdivision having neighborhood influence). However, the incentive-based subdivision still considers the same distribution of management behaviors (Table 2), with the additional management option of removing prairie thatch, which may aid in decreasing the overall carbon in the subdivision. Therefore, the total carbon in an incentive-based subdivision is expected to be less than the total carbon in an unmanaged subdivision.

Methods

The Exploratory Land Management and Carbon Storage (ELMST) agent-based model was developed to assist in the exploration of how management behaviors and neighborhood influence could affect carbon storage in a residential subdivision. A four-tier experimental design was developed to assist in hypothesis testing: (tier-0) no management, (tier-1) intrinsic management, (tier-2) adaptive management, and (tier-3) adaptive management with incentive to innovate (Figure 1).

Tier-0 (No Management): The subdivision is developed. Residents do not participate in yard management, allowing vegetation to grow, senesce and decay naturally.

Tier-1 (Intrinsic Management): The subdivision is developed. Each resident manages his yard according to an intrinsic management behaviors derived from Southeast Michigan interview data (Table 2), e.g. fertilizing, mowing the lawn, removing grass clippings, removing fallen leaves. Residents are not influenced by neighboring behaviors, keeping the same management routine throughout the model run.

Tier-2 (Adaptive Management): The subdivision is developed. Each resident begins an intrinsic yard management routine, however a resident is now able to adapt her individual management behaviors based on those of her neighbors.

Tier-3 (Adaptive Management with Incentive to Innovate): The subdivision is developed as usual. However, three residents are randomly selected to receive an incentive to innovate their yards with a native prairie design. Residents are able to adapt their management behaviors based on the behaviors of their neighbors. Residents may also choose to adopt the new prairie design through the process of neighborhood influence.

Model Description

A salient concern with agent-based models is the ability to communicate the complexity inherent in the model effectively. Specifically, how system-level properties emerge from the adaptive behavior of heterogeneous agents (Grimm et al. 2006). The following description of the ELMST model uses the ODD protocol developed by Grimm et al. (2006). This protocol uses three standard blocks (Overview, Design Concepts and Details) to quickly supply information about the focus, resolution and complexity of the model in a format that may be consistent with other ABM descriptions (Grimm & Railsback 2005; Grimm et al. 2006).

Overview

The ELMST (Exploratory Land Management and Carbon Storage) model was developed in the Eclipse Integrated Development Environment (version 3.5), written the Java 1.6 programming language and uses the Recursive Porous Agent Simulation Toolkit (i.e., Repast Simphony) framework and libraries (Eclipse 2000; Java 2002; Repast 2007).

Purpose

The purpose of the ELMST model is to explore the potential effect of yard management and neighborhood influence on carbon storage in a residential subdivision. ELMST implements a simple residential subdivision having a set number of distinct parcels. Individual residents use basic management strategies to alter the vegetation and litter produced by natural ecosystem processes within a parcel. Carbon trajectories at various spatial scales may be observed over time (biomass pool, land-cover type, parcel, and subdivision). The ability to turn on and off model components allows the user to incrementally explore how management behaviors and agent interactions could affect carbon storage at various spatial and temporal scales.

ELMST was designed for re-use and extendability. Virtually any climate, land-cover type and culture may be modeled using different initial parameterizations. The functionality of the model may be programmatically extended to create alternative land-cover types, agent behaviors, social network strategies and influence mechanisms.

The following sections provide a description of the ELMST model used for this study. Whenever possible interview and field data from exurban residential areas of Southeast Michigan were used for initial model parameterization (Project SLUCE2 2009), otherwise values from literature pertaining to a similar biome as Southeast Michigan were used (Table 1, Table 2). Calibrated model parameters include the percentage of living biomass that naturally senesces to produce litter and soil respiration. The ELMST implementation used for this study is specific to conventional exurban subdivisions in Southeast Michigan.

Structure

The subdivision environment houses two distinct modules: the ecosystem module and the resident system module. The ecosystem module provides components and processes related to the annual functionality of distinct biomass pools and land-cover types. The resident system module includes a collection of agents within a lattice-based social network. Agents may interact directly with the ecosystem module and neighboring agents through yard management behaviors and neighborhood influence respectively (Figure 2).

Ecosystem Module Structure

Subdivision parcels are heterogeneous, each containing land-cover areas of varying types and sizes (measured in m^2). Land-covers are represented as a-spatial entities within a parcel and include: (1) impervious surface, e.g., house, driveway, sidewalks, (2) turfgrass, (3) tree cover, and (4) native prairie (Figure 4). Impervious surfaces, turfgrass and tree cover are common to Southeast Michigan residential subdivisions. Native prairie is relatively less common, but offers much in the way of ecosystem services and carbon storage (Meyer, Baer, & Whiles 2008; Nassauer et al. 1997). The model uses native prairie to explore possible outcomes of carbon storage if a few agents are provided with an incentive to install this feature in their own yards. Native prairie is used in the model to demonstrate how neighborhood influence could play a role in the diffusion of uncommon yard designs across a subdivision, creating a new local norm and potentially altering the neighborhood carbon storage over time.

With the exception of impervious surfaces, each land-cover type is composed of four biomass pools: (1) aboveground vegetation, (2) below-ground vegetation, i.e., roots, (3) litter, and (4) soil organic matter (Figure 4). Biomass pools are fundamental model structures, providing temporary containers for carbon as it moves through the ecosystem. Each biomass pool within each land-cover type is uniquely parameterized (Table 1) and validated (Table 3) using data from fieldwork and literature.

Resident Module Structure

One agent (i.e. resident) is assigned to each parcel in the subdivision. Agents are heterogeneous, maintaining their yard according to their own intrinsic management routine (Table 2). Each management routine consists of seven management decisions: (1) when to mow the lawn, (2) blade hight of lawnmower, (3) whether or not to fertilize the lawn, (4) whether or not to leave grass clippings on the lawn, (5) whether or not to remove fallen leaves, (6) whether or not to install native prairie, and if a native prairie has been installed, (7) whether or not to remove thatch from the prairie. Each management decision requires a yes/no value, with the exception of lawn mowing schedule and blade height. Options for lawn mowing include: every week, every other week, once per month and never. Blade height was automatically set to result in a turfgrass biomass density of 40 g/m^2 after a lawn is mowed – a value approximated using a typical three-inch blade height, as determined by interview data (Project SLUCE2 2009). Approximate after-mow biomass was back-calculated using the maximum turfgrass biomass density used in the ELMST model (330.00 g/m^2) and maximum height of Kentucky bluegrass (a two foot estimate) (USDA).

Each agent keeps a list of its immediate von Neuman neighbors for the duration of the model run, creating a static, lattice-based social network (Figure 3). The social network is used to determine which neighbors could influence a particular agent.

The Prairie Incentive Program

In some cases, the model may use a prairie incentive program to encourage installment of native prairie throughout the subdivision. The seasonally wet conditions associated with these land-cover types tend to have a lower respiration rate than turfgrass or tree cover soils, and are likely to store comparatively more carbon over the long-term (Meyer, Baer, & Whiles 2008). Depending upon spatial configuration within the yard, native prairie may also be considered a beautiful focal point of the yard, while promoting a variety of ecosystem services, such as storm water infiltration, biodiversity, and native ecosystem restoration (Nassauer 1993; Nassauer et al. 1997).

Model Component Activation

Several model components may be activated to validate the model and/or compare the effect of a given component on carbon dynamics and outcomes. Components that have the option to be activated (or deactivated) are: the ecosystem module, resident management, resident influence, and the incentive program. Activation of certain components allows the user to incrementally compare model outcomes under different scenarios. This thesis uses the model component activation feature to systematically test hypothesis using a tier-based research approach (Figure 1).

Processes

The model runs on a weekly time-step where one year is equal to fifty-two weeks. Weeks are numbered zero to fifty-one and reset every first week in January. Four seasonal effects typical to Southeast Michigan are represented in the model: (1) start of growing, (2) growing season, (3) end of growing season and (4) dormant season. The growing season is assumed start on week 17 (approximately the first week in May). Ecological processes of photosynthetic growth, litter decomposition and soil respiration begin on week 17 and continue through week 38. On week 39 (approximately the first week in October), foliage and grasses senesce to produce litter. All ecological activity ceases on week 40 and and remains inactive into the following calendar year. Week 17 signals the start of the next growing season, when growth, decomposition and respiration resume (Figure 7).

Agent management routines and neighborhood influence also follow seasonal triggers. Turfgrass fertilization and prairie installation may only occur at the onset of the growing season (week 17).

During the growing season, turfgrass lawns are mowed according to individual mow schedules and grass clippings may (or may not) be removed. Neighborhood influence also occurs over the coarse of the growing season, when residents are more likely to be working in their yards and mingling with neighbors. At the end of the growing season (week 39), after the leaves fall and grasses senesce, agents are triggered to remove leaf and prairie litter, if they so choose. The dormant season prompts inactivity for both yard management and neighborhood influence (Figure 7).

Ecosystem Module Processes

The fundamental ecological mechanisms in the model are the addition, transfer and loss of carbon among the four biomass pools. For example, during the growing season, tree cover produces foliage through the process of photosynthetic growth. At the end of the growing season, leaves senesce, producing leaf litter. As litter decomposes, a proportion (20 percent) of the carbon is transferred to the soil pool while the remainder is respired back to the atmosphere (Aber, Melillo, & McClaugherty 1990; Currie & Aber 1997). Assuming soil respiration to be relatively low, the majority of carbon remains in the soil pool for long periods of time (Kucharik et al. 2001). With the exception of impervious surfaces, each land-cover instance maintains its own carbon-cycle process, allowing for variation of carbon inputs and outputs among biomass pools within each land-cover type (Figure 4, Figure 5).

Resident Module Processes

The ELMST model has an option to activate resident management activity, allowing for alterations of land-cover vegetation and litter pools within each parcel. Agents may choose to take part in or abstain from certain management activities throughout the year. Fertilization results in a higher turfgrass growth rate, resulting in a greater accumulation of above- and below-ground biomass. Lawn mowing removes biomass from aboveground vegetation; the choice to remove grass clippings determines if the discarded biomass is transferred to the turfgrass litter pool, or removed from the system entirely. Similarly, the choice to remove of fallen leaves and/or prairie thatch also eliminates carbon from the system. The choice to install a native prairie at the start of the growing season is an exceptional task in that it replaces a portion of the turfgrass land-cover type with the prairie land-cover type. Aboveground, below-ground and litter biomass belonging to the replaced turfgrass portion are completely removed from the system, leaving the previous soil organic matter (SOM) in place. Initial above- and below-ground prairie vegetation is then installed. If thatch is not removed, the prairie litter pool will accumulate biomass starting from zero (Figure 6).

If neighborhood influence is activated, agents will evaluate the maintenance routines of their immediate von Neuman neighbors every week during the growing season. After evaluation, an agent may decide to adopt a new management behavior based on the management behavior of its neighbors. The more neighbors deciding to practice a particular a behavior, the more likely an agent is to adopt this same decision. Because certain management tasks occur at designated times during the year (e.g. fertilization only occurs only at the start of the growing season), an agent may decide to participate in a behavior before they are actually able to perform the task. For example, an agent may be decide to remove fallen leaves on their property on week 20, however this behavior will not be carried out until week 39. Moreover, an agent could be indecisive about a particular management decision, causing an agent to "change its mind" several times over the coarse of the growing season. The standing decision on the week that the task is scheduled to be performed determines what the agent ultimately does.

Design Concepts

Design concepts, as described in this thesis, illustrate the general approach of complex adaptive systems, including emergence, adaptation, sensing, stochasticity, interaction, collectives and observation (Grimm et al. 2006). Describing the ELMST model in terms of these design concepts explicitly links the general concepts of the model with various properties of complex adaptive systems.

Emergence. – Emergence distinguishes which system-level phenomena emerge from individual model attributes. In tier-0 and tier-1, the resulting total carbon trajectory is deterministic, based on initial model conditions, and emerging from the interaction of ecosystem processes (tier-0) and consistent management behaviors (tier-1). Tiers -2 and -3 include neighborhood influence – individual agents may adapt their behaviors based on the behaviors of their neighbors. Total carbon stored at the subdivision level now becomes an emergent property of adaptive agent management and ecosystem processes. A local norm may emerge as a result of neighborhood influence, creating solidarity among agent management behaviors, and potentially resulting in the lock-in of a particular carbon trajectory.

Adaptation. – Adaptation describes which agent behaviors are modified as a response to the behaviors of neighboring agents. Specific to tiers -2 and -3, agents may adapt their maintenance routine to better "fit in" with their immediate neighbors. Each maintenance routine may be broken down into a set of individual behavioral decisions. Each decision may altered based on the collective decisions exhibited by immediate neighbors; the more neighbors exhibiting a particular maintenance decision, the more likely this same decision will be adopted by an agent. Exactly one behavioral decision may be adopted by an agent at each time-step during the growing season. The likelihood of adopting a particular behavior is a linear function of the number of neighbors exhibiting the behavior. However, fertilization and prairie installation are less likely than all other behaviors because of the additional costs associated with adoption. This concept is discussed more in the sub-models section on neighborhood influence.

Sensing. – Sensing describes how agents and/or the environment are able to identify and respond to certain model attributes. Both ecosystem and agents are able to sense the weekly time-step of the model and the current the season (i.e. onset of the growing season, growing season, end of the growing season, and dormant season). The environment uses seasonal information to trigger photosynthetic growth, litter decay, soil respiration and senescence, while agents in tiers -1, -2, and -3 use seasonal information to manage their yards accordingly (Figure 7). In tiers -2 and -3, agents are also able to sense the management decisions of their immediate, von Neuman neighbors. Neighborhood influence and adaptation are driven by the collective neighbor management decisions perceived by individual agents.

Stochasticity. – Stochasticity characterizes which elements of the model contain stochastic processes. The model offers four stochastic processes: (1) initialization of land-cover areas within a parcel for all tiers, (2) initialization of agent management behavior in tiers -1, -2 and -3, (3) neighborhood influence in tiers -2 and -3, and (4) initialization of agent incentives in tier-3 only. Areas of land-cover types within each parcel are randomly selected from a normal distribution provided by fieldwork data (Table 1). Agent management behavior probabilities were derived from interview data and assigned using a roulette wheel algorithm (Sabar et al.). Neighborhood influence also uses a roulette wheel algorithm to determine which behavior an agent will adopt. If the model offers a native prairie incentive program (i.e. tier-3), all agents are placed in a random lottery, each having an equal chance of being selected to receive the incentive.

Interaction. – Interactions identify the assumed correspondences among individuals. In tiers -1, -2 and

-3, agents interact with the landscape through management of aboveground vegetation and litter. Specific landscape interaction will depend on the type of management behavior performed (Table 2). In tiers -2 and -3, agents also interact indirectly with their immediate neighbors by observing the management decisions of each neighbor, creating a "mental tally" of how many neighbors have decided to participate in a particular management behavior, and randomly choosing one of these behaviors to imitate. Agent-to-environment and agent-to-neighbor interactions occur every week during the growing season.

Collectives. – Collectives denote aggregations in the model that allow for the scaling-up or lock-in of system-level phenomena. Environmental collectives are represented explicitly in the ELMST model through component aggregation. The subdivision is composed of many parcels; a parcel is composed of many land-cover types (i.e. impervious, turfgrass, tree cover and prairie); each land-cover type contains four biomass pools (i.e. aboveground, below-ground, litter and soil); and each biomass pool has a particular biomass density, measured in g/m^2 (Figure 4). Biomass density may be easily converted carbon density (Nowak 1994; Currie 2003). Total carbon within a subdivision is therefore dependent on the many individual biomass pools that comprise the lowest level of collectives in the ELMST model.

Collectives are also found within, and among agents. Each agent contains a management routine which is composed of many separate management decisions. Management decisions include: lawn fertilization, mow schedule, whether or not to remove grass clippings, fallen leaves or prairie thatch, and whether or not to install a native prairie landscape. Concrete behaviors associated with these decisions create an individual management routine for each agent. Individual management routines are likely to alter above-ground and/or litter carbon pools. Alterations to total carbon in aboveground and litter pools due to management behaviors will affect the carbon contained at the biomass pool, land-cover, parcel and subdivision scales (Figure 6).

Individual agents are part of larger agent collectives. Each agent holds an internal list of their immediate von Neuman neighbors. The neighbor list is used to determine the probability of agent adaptation in tiers -2 and -3 through the process of neighborhood influence. Neighborhood influence creates an opportunity for an agent to adopt a new management behavior based on the behaviors of its neighbors. A greater cohesion of management routines may result, wherein agents become more similar to their neighbors over time. The dissemination of management behaviors may create a type of management-based culture (Axelrod 1997). The emergence of a management culture may result in the lock-in of a particular carbon trajectory at the subdivision-level. The stochasticity inherent in neighborhood influence is likely to yield many different solutions for total carbon stored at the subdivision-level for tiers -2 and -3.

Observation. – Observation describes which data are to be collected for analysis, validation and hypothesis testing. The main objective of this study is to compare total subdivision carbon under various management scenarios. Observation of total subdivision carbon is accomplished by summing the total carbon contained in each environmental collective. Each biomass pool maintains a density (measured in g/m^2), which is converted to carbon (g C/m^2) by multiplying the biomass density by 50 percent (Eq. 1a) (Nowak 1994; Currie 2003). Total carbon contained in a single biomass pool within a particular land-cover type may then be calculated by multiplying the carbon density of a biomass pool by the area of the land-cover within a parcel (Eq. 1b). The sum of the total carbon in each biomass pool yields the total carbon within a particular land-cover type (Eq. 1c). Summing the carbon in each land-cover type provides the total parcel carbon (Eq. 1d). Finally, the total carbon in the subdivision is simply by the sum of the total carbon contained in each parcel (Eq. 1e).

$$C = 0.5\mathrm{b} \tag{1a}$$

$$pool_T = C(land_{area}) \tag{1b}$$

$$land_T = pool_T^{aboveground} + pool_T^{below-ground} + pool_T^{litter} + pool_T^{soil} \tag{1c}$$

$$parcel_T = \sum(land_T) \tag{1d}$$

$$subdivision_T = \sum(parcel_T) \tag{1e}$$

A set of aggregations where b is biomass in g/m^2, C is carbon density in g C/m^2, pool_T is total carbon within a biomass pool, land_T is total carbon within a land-cover type, parcel_T is total carbon within a parcel and $\mathrm{subdivision}_T$ is total carbon within a subdivision.

Details

Initialization

The model was initialized with a single subdivision represented as a two-dimensional, 9x9 grid, with each grid-cell representing a one acre (4,046.86 m^2) parcel (Figure 3) such that the entire subdivision comprised a virtual area of approximately 32.78 hectares (327,795.66 m^2). One agent (i.e. resident) was assigned to each parcel and initialized with an intrinsic yard management routine (Table 2). Agents were incorporated into a lattice-based social network, having explicit connections to immediate, von Neuman neighbors (Figure 3). While agents represent nodes of the network; connections between agents create bidirectional edges over which neighborhood influence may travel (Figure 3).

Activation order determines the order of individual model processes within a single time-step. The ELMST model maintains a similar activation order throughout an entire model run. The ecosystem module is processed first, allowing for the natural photosynthetic growth, litter decay, soil respiration and senescence to occur during the appropriate seasonal times (Figure 7). The order to which individual biomass pools are processed is inconsequential since each pool acts independently from all others.

The resident module is processed only after the ecosystem module processes are complete. The resident module processes agent management behaviors before neighborhood influence occurs with respect to the appropriate season (Figure 7). The agents themselves are processed in a random order during each time-step.

The model was run 100 times under each research tier (Figure 1). Each run under a tier was parameterized identically (Table 1, Table 2), with the exception of the random seed, which was systematically incremented for each run. Four component activation parameters may be turned on or off to distinguish under which tier the model should be run (Table 6).

Input

Model input parameters were derived from fieldwork and interview data collected from twenty-six exurban residential homes in Southeast Michigan as part of a larger project, Spatial Land Use Change and Ecological Effects at the Rural-Urban Interface (Project SLUCE2 2009). Where fieldwork or interview data were unavailable, values from literature pertaining to a similar biome as Southeast Michigan were used (Table 1, Table 2).

In a few cases, model parameters needed to be calibrated as a consequence of of model assumptions and lack of definitive data. Calibrated parameters for each land-cover type include percentage of living biomass that naturally senesces to produce litter and soil respiration. Natural litter production was calibrated to (1) permit stable regrowth during the following growing season for turfgrass and prairie based on literature values of maximum biomass (Table 3) and (2) to provide a reasonable amount of soil carbon accumulation given the annual litter decay rate of 0.25 (Currie et al. 2009) also based on literature values (Table 3). ELMST implementation used for this study is specific to conventional exurban subdivisions in Southeast Michigan.

Ecosystem Module Input

Land-Cover Type Distribution. – Categories for the ELMST land-cover types (i.e. impervious, turfgrass, tree cover and prairie) are generalizations derived from fieldwork eco-zone data (Table 11). Land-cover proportion distributions for parcels in the subdivision were created using the mean and standard deviation obtained from spacial fieldwork data associated with parcels having an area equal-to or less-than one acre (4,046.86 m^2, n=16) (Table 12). For each parcel in the model, a random proportion was drawn from an assumed normal distribution for each land-cover type (Table 1). Once proportions had been drawn for each land-cover type for an individual parcel, a normalization algorithm was applied such that the proportions among land-cover types within a parcel summed to one. The actual square-meter area for each land-cover type was calculated from the resulting product of the land-cover proportion and 4,046.86 m^2 (one acre).

Vegetation Biomass Distribution. – Above-ground biomass was initialized to the same value for each type of land-cover in the model (Table 1). Not only does this make for a parsimonious assumption, but the development of a conventional subdivision lends itself to a similar paradigm – developers lay established turfgrass sod and may install a few young trees of roughly the same age (Westbrook 2010; Bowman & Thompson 2009). Below-ground biomass was initialized based upon a root-to-shoot ratio for aboveground biomass within each land-cover type (Smith, Shugart, & Woodward 1997).

Initial Litter Biomass and Soil Organic Matter. – For this study, a conventional subdivision was assumed be built on land previously used for agriculture. Exhausted agricultural fields tend have depleted litter biomass and surface soil organic matter (Pouyat, Yesilonis, & Golubiewski 2008). As a result, each of these pools was simply initialized with a zero biomass (Table 1). Over time, the model accumulated both litter and soil organic matter through ecosystem processes of growth, senescence and decay (Figure 5, Figure 6).

Resident Module Input

Management Routine. – Individual management behaviors assigned to each agent upon model start-up were determined from interview data (Project SLUCE2 2009). Residents from 16 exurban households in Southeast Michigan having a parcel area of one acre or less were asked about their fertilization practices, lawn mowing schedule, if they remove grass clippings and if they remove fallen leaves. Probabilities for each management behavior were derived from an approximate proportion of the number of residents who indicated they participated in a given behavior (Table 2). Respondents were not asked about the removal of prairie thatch; this initialization was assumed to be the same as the probability of applying fertilizer. A roulette wheel algorithm (Sabar et al.) was then used to determine agent initializations for each management decision using the probabilities described in Table 2. Initial probability of prairie installation was set to zero for all modeling tiers. However, tier-3 (adaptive management with an incentive to innovate), used a random lottery process to determine which three agents would receive the incentive to install native prairie yard design. Agents were assumed to always accept the offered incentive.

Sub-Models

This section provides an overview of the design and implementation for each of the primary controlling process in the ELMST model.

Ecosystem Module Sub-Models

Land-cover type proportion normalization algorithm. – Each parcel may contain four land-cover types: impervious surface, turfgrass, tree cover and prairie. Individual land-cover proportions within an each parcel were randomly selected based on an assumed normal distribution provided by SLUCE2 fieldwork (Table 1). A random "raw" parcel proportion value is drawn from a normal distribution for each type of land-cover (Figure 1), and stored in a list. Each item in the list is then divided by the sum of list values. The resulting fraction is the actual proportion of the parcel the land-cover type will be assigned. Actual area is then derived by multiplying the land-cover proportion by 4046.86 m^2 and stored in an instance of the land-cover object (Figure 8).

Carbon Content. – The amount carbon of stored per unit of biomass was determined by multiplying the biomass quantity by a factor of 0.5 (Nowak 1994; Currie 2003). This same factor is applied to all biomass pools (i.e. above-ground, below-ground, litter and soil).

$$c = 0.5\mathrm{b} \tag{2}$$

where c is carbon density b is biomass density.

Photosynthetic Growth. – Richards Growth Model was used to increase the biomass of the aboveground and below-ground vegetation. This model uses a relative growth rate (RGR) which assumes that new growth is proportional to a plant's current biomass (Blackman 1919). Richards Growth Model also assumes a bounded growth, such that the biomass follows sigmoid curve. Parameters for Richards Growth Model include (1) a relative growth rate (RGR), (2) maximum biomass or carrying capacity, and (3) a delta value that determines the shape of the curve (Richards 1959).

$$v'(t) = \frac{k}{(1-\delta)} V(t) \left(\left(\frac{v(t)}{w} \right)^{(\delta-1)} - 1 \right) \quad \delta \neq 1 \tag{3}$$

where v'(t) is equal to the new growth at time t, v(t) is the biomass at time t, k is the relative growth rate (RGR), w is the maximum biomass capacity and δ is a number or fraction indicating the shape of the growth curve (Damgaard 2004; Damgaard; Richards 1959). Individual growth rates, maximum capacities, and delta values were used do parameterize each vegetative land-cover – turfgrass, tree cover and native prairie (Table 1).

Litter Production. – Litter from above- and below-ground biomass pools were combined into the same litter pool at the end of the growing season (Smith, Shugart, & Woodward 1997). While tree cover senesces a small proportion biomass, turfgrass and prairie land-cover types will senesce most of their biomass at the end of the growing season. However, enough above- and below-ground biomass must be left in place for photosynthetic growth to function normally at the onset of the next growing season.

Therefore, the proportion of litter produced by above- and below- ground biomass pools was calibrated to permit stable regrowth during the following growing season for each individual vegetative land-cover type (Table 1).

For turfgrass and prairie, a percentage of the maximum capacity biomass was used, producing a constant biomass starting point for the following year's growth for all grasses. For tree cover, only the foliage on trees will senesce at the end of the growing season. Since tree biomass does not "start over" like grasses, a percentage of the individual tree cover biomass will be converted to litter, allowing the resulting biomass to be variable over time, such that tree cover can continue to grow where it left off during the year prior (Table 1).

Litter Decay. – Litter accumulated at the end of the growing season begins decompositions at the start of the following growing season. A standard exponential decay function is used to model litter decay (Aber, Melillo, & McClaugherty 1990).

$$N(t) = N_0 e^{-k} \tag{4}$$

where N(t) is the resulting litter at time t, N_0 is the quantity at time t-1 and k is the decay rate per year. The decay rate was determined to be 0.25 per year (Currie et al. 2009). The difference between N_0 and N(t) yields the amount of decayed matter produced by the litter pool within a single time-step. Only 20 percent of the carbon in the decayed matter is transferred to the soil, while the remainder is respired back to the atmosphere (Aber, Melillo, & McClaugherty 1990; Currie & Aber 1997).

Soil Respiration. – The proportion decayed matter that is transferred to the soil pool undergoes a second phase of decomposition, resulting in the respiration of carbon from the soil. Soil respiration uses the same standard exponential decay function as litter decomposition (Eq. 4), but with a different decay rate (k). The decay rate for soil organic matter (SOM) was calibrated for each vegetative land-cover type so that the soil organic carbon (SOC) approaches a representative equilibrium within a reasonable time-frame (Simmons et al. 2008; Pouyat, Yesilonis, & Golubiewski 2008) (Table 1).

Resident Module Sub-Models

Prairie Installation. – The prairie installation process replaces 25 percent of the turfgrass area within a parcel with native prairie grasses. A check is performed to ensure the parcel contains 25 percent or greater of the turfgrass land-cover type. If so, a 25 percent (1011.72 m^2) area of the turfgrass aboveground, below-ground and litter biomass are removed completely from the model, leaving the previous soil organic matter (SOM) in place (Figure 6). A new prairie land-cover type is then inserted into the model, equal to the portion of removed turfgrass (1011.72 m^2). Initial above- and below-ground prairie vegetation is also installed (Table 1). The opportunity to install prairie is set to occur once per year, at the start of the growing season.

Fertilization. – Fertilization assumes a one-time application of slow-release methylene urea fertilizer (such as Scotts 41-0-0) at the beginning of the growing season. Fertilizer is assumed to increase the relative growth rate for both above- and below-ground biomass by a factor of 4.83 (Agnew & Christians 1993). Fertilizer must be re-applied at the start of each growing season, otherwise turfgrass growth is assumed to return to its original rate (Figure 6).

Mow Schedule. – Residents may participate in a variety of different lawn mowing schedules during the coarse of a growing season. Applicable mow schedules include: once per week, once every other week and once per month. The option to never mow is also available in the model, but is never used as a result of the interview data (Table 2). The model runs on a weekly time-step. If the agent is set to mow once per week, every time step within the growing season will trigger the agent to mow. To determine when an agent will mow for the every other week or every month schedule, the week number is compared with the agent's mow schedule using the modulus operator.

$$\text{mowThisWeek} = (w \,\%\, x == 0) \tag{5}$$

where w is the week number within the growing season (i.e. a number from 18 to 38), x is equal to 2 for a mow schedule of every two weeks and 4 if the mow schedule is once per month. mowThisWeek is a true/false value that indicates if the agent will mow the lawn on the current week.

An assumed three-inch blade-height is represented as an exogenous after-mow biomass of 40 g/m^2 for all agents. After-mow aboveground biomass was approximated by the back-calculation of maximum turfgrass biomass density used in the ELMST model (330.00 g/m^2, Table 1) and an estimated maximum height of Kentucky bluegrass equal to two feet (USDA). Mowing has no direct effect on below-ground vegetation or soil biomass pools, but may have an effect on the litter pool if grass clippings are allowed to decompose on-site (Figure 6).

Grass Clipping Removal. – After an agent mows, the grass clippings may either be removed completely from the model, or transferred to the turfgrass litter pool (Figure 4).

Leaf Litter Removal: An agent may choose to remove newly senesced leaf litter from his or her parcel once per year at the end of the growing season. Leaf litter is considered to be the aboveground portion of litter produced by tree cover. Since both above- and below-ground vegetation is senesced into the same litter pool, the aboveground portion is determined using the root-to-shoot ratio for tree cover (1:4) (Smith, Shugart, & Woodward 1997).

$$A_{litter} = \frac{b_{litter}}{1+r} \tag{6}$$

where A_{litter} is the aboveground litter biomass for a given year, b_{litter} is the total litter biomass for a given year, and r is the root-to -shoot ratio for a particular land-cover type. The calculated aboveground litter biomass is removed from the total litter produced for the current year.

Prairie Thatch Removal. – If an agent has a prairie yard design, he or she may choose to remove newly senesced prairie thatch once per year at the end of the growing season. Thatch is considered to be the aboveground portion of litter produced by prairie. Since both above- and below-ground vegetation is senesced into the same litter pool, the aboveground portion is determined using eq. 6 and the root-to-shoot ratio for prairie grasses (2:3) (Smith, Shugart, & Woodward 1997).

Neighborhood Influence. – Agents may be influenced by their immediate von Neuman neighbors. Each agent is able to assess the management behaviors of immediate neighbors and keep a count of how many neighbors participate in a particular behavior. The method of neighborhood influence in the ELMST model uses a basic roulette wheel algorithm. Imagine a roulette wheel where each wedge represents a management behavior. The size of the wedge is determined by how many neighbors practice a particular behavior, creating a linear relationship among the number of immediate neighbors practicing a behavior and the likelihood of behavior adoption. During each time-step in the growing season, an agent may assess the behaviors of her neighbors, construct a “mental roulette wheel” and randomly select a behavior to adopt from the roulette wheel.

There are two caveats regarding the likelihood of adopting fertilization and prairie installation behaviors as a result of neighborhood influence. While all other options (i.e. mow schedule, remove grass clippings, remove fallen leaves and remove prairie thatch) are relatively simple behaviors in practice, fertilization and prairie installation have additional associated costs. Fertilization requires the resident to purchase fertilizer, apply it at the start of the growing season and the increased growth rate of fertilized turfgrass remains for the duration of the growing season. Additional fertilization costs were estimated do decrease the likelihood of fertilization adoption as a result of neighbor behaviors by a “willingness to fertilize” factor of 0.50 (Table 2).

A similar situation occurs for the decision to install prairie. If a resident decides to install prairie, a portion of turfgrass is removed and replaced with 1011.72 m^2 of native prairie grasses (25 percent of the parcel). The cost and planning necessary to install prairie is assumed to be higher than that of fertilizer application. Moreover, once a prairie landscape is installed, it is considered permanent, and cannot be reverted back to turfgrass, which bolsters the increased cost of prairie installation. As a result, a “willingness to install prairie” factor is applied to prairie installation, decreasing the likelihood of prairie adoption by a factor of 0.25 as a result of neighborhood influence (Table 2).

Statistical Analysis

The model was run 100 times under each research tier (Figure 1). Each run under a tier was parameterized identically (Table 1, Table 2), with the exception of the random seed, which was systematically incremented for each run. Management and neighborhood influence effects were monitored across tiers. Total subdivision carbon was averaged over year 30 for each of the 100 in-tier runs. Quantitative comparisons of total carbon storage at the subdivision level were made between each tier using descriptive statistics and two-tailed Student's t-tests.

Results

Model Verification and Validation

Verification and validation are the primary processes used to ensure the credibility and usefulness of computational models. Verification is used to ensure that the implementation of the actual model matches the conceptual model intended. Validation is a process used to determine if the model reflects the real-world to the degree that it is useful for its intended use (Thacker et al. 2004).

The ELMST model was verified extensively throughout the development process using repeated unit and functional tests of sub-model components. Validation was based on initial model parameterization using fieldwork and interview data from exurban residential homes in Southeast Michigan (Project SLUCE2 2009). Where fieldwork and interview data were unavailable, values from literature were used. In some cases, parameters were calibrated to produce reasonable model behavior (Table 1). ELMST validation involved frequent comparisons of model output with real-world data provided by literature (Table 3).

Parcel Land-Cover Area Verification

Each parcel may contain four land-cover types: impervious, turfgrass, tree cover and prairie. Individual land-cover proportions within an each parcel were randomly selected based on an assumed normal distribution provided by SLUCE2 fieldwork (Table 1). Random proportion selections were then normalized and converted into actual area values based on a one-acre parcel (4046.86 m^2). Prairie land-cover occurs in tier-3, and only when residents decide to innovate their yards. Yard innovation removes an area of turfgrass equivalent to one-quarter of the parcel, and replaces this area with the prairie land-cover type. Assertions in the code ensure that parcel land-cover areas always sum to 4048.68 m^2. The model was run 100 times for each tier using different random seeds. Land-cover area results conclude that the average areas for each land-cover type follows correct proportions and sum to 4048.68 m^2 (Table 7).

Ecosystem Module Validation

Ecosystem module validation was performed by comparing carbon density results from the unmanaged model scenario (tier-0) with carbon density values found in peer-reviewed literature for various years since vegetation establishment. Densities were compared across vegetative land-cover types (turfgrass, tree-cover and prairie) for each biomass pool (aboveground, below-ground, litter and soil). Results were also compared with SLUCE2 fieldwork data. While not year specific, SLUCE2 field data provides concrete carbon densities for Southeast Michigan exurban residential areas and provides an interesting check across ELMST and literature values (Table 3). Overall results showed that the ELMST model keeps within a reasonable range of both literature and SLUCE2 data values.

Actual carbon dynamics within the model were assessed using graphs of carbon density within each biomass pool for each vegetative land-cover type. Unmanaged turfgrass and prairie offered a stable cycle of aboveground, below-ground and litter carbon after several years (Milesi et al. 2005; Cahill, Kucharik, & Foley 2009), while tree cover rapidly increased in aboveground and below ground biomass for about 30 years before growth slowed and eventually settling at an equilibrium (Hutnik Russell J., Yawney 1961) (Figures 12 - 17).

Resident Module Verification and Validation

Similar to ecosystems, human systems contain a set of rules or heuristics which determine system functionality. However, human systems tend to be highly variable and dynamic, proving validation especially difficult and subjective. Thus, only land management behaviors were verified to function as expected while neighborhood influence validation relied on general theories and case studies from social psychology.

The probability that a resident performs a particular management behavior was determined by SLUCE2 interview data (Table 2). When the model was run 100 times under each tier for 30 years, the ratios of management behaviors remained similar to the original probabilities, with the exception of fertilization and prairie behaviors due to to “willingness to fertilize” and prairie installation incentives respectively (Table 4).

Previous studies have shown that residents pay close attention to their neighbors, often resulting in a neighborhood influence effect, and significantly affecting the behaviors of individual residents (Galster 1987; Nassauer, Wang, & Dayrell 2009; Ioannides 2002). Neighborhood influence in the ELMST model was implemented using a roulette wheel algorithm where the quantity of neighbors performing a management behavior determined likelihood of resident adoption. The probability proportional to the number of neighbors performing a behavior provided a reasonable guess as to the details of the neighborhood influence mechanism. Thus, the roulette wheel algorithm can be used in a computational experiment that reveals how the total subdivision carbon would behave if proportional selection was a correct assumption (Bankes 1993).

Effect of Individual Management Behaviors

The differential effect of each individual management behavior on the outcome of total carbon at the subdivision level was evaluated. Testing the effect of individual behaviors assumed the standard 9x9 subdivision used in this study. All agents were set to perform a single management task consistently for the duration of the model run. Total carbon in the subdivision (measured in Mg C) was recorded for the ten years between year 25 and 35 of the model (Figure 9; Table 5). The effect of individual management behaviors provided insight into outcomes with heterogeneous agents, parcels and neighborhood influence effects.

Model results show that fertilization has the greatest positive effect, increasing the total carbon in an unmanaged subdivision by approximately 40 percent on average, relative to unmanaged parcels. Mowing the lawn and leaving the grass clippings to decompose on-site and may also increase the total carbon in the model by about 17 to 20 percent, relative to the unmanaged scenario, as does having one-quarter of every parcel in native prairie and allowing the thatch to decompose on-site. Removing grass clippings after mowing significantly decreases the amount of carbon in a subdivision by roughly 40 to 44 percent when compared with no management. Removing fallen leaves and prairie thatch has less of an effect, decreasing the modeled carbon storage by approximately 4 to 7 percent relative to the unmanaged scenario.

Model Application

The model was applied using the four tier-based research scenarios as illustrated in Figure 1. In this section, results for each tier are described, followed by a comparison among tiers used to test research hypothesis.

Tier-0 – No Management

When a conventional subdivision is developed and no management takes place over a span of 30 years, the total carbon in the subdivision is deterministic because the rules that determine growth, senescence, litter decay and respiration remain constant. Year 30 model results yield a carbon store range from 234 to 272 Mg C with an average of 255 (± 8.13) Mg C. The low variability in this case is due to annual seasonal shifts in growth, senescence, litter decay and respiration.

Tier-1 – Intrinsic Management

The tier-1 model scenario involves a developed conventional subdivision where residents manage vegetation and litter according to their intrinsic preferences, without adaptation and without neighborhood influence. In this scenario, the total carbon in the subdivision is also deterministic because the rules that determine growth, senescence, litter decay and respiration remain constant as do management behaviors. Year 30 model results yield a carbon store range from 399 to 568 Mg C with an average of 487 (± 31) Mg C. The variability in this scenario is due to the interaction of annual seasonal shifts in natural processes (growth, senescence, litter decay and respiration) and intrinsic land management behaviors of fertilization, lawn mowing, and grass clipping or leaf removal. Prairie is not assumed to be present in this scenario.

Tier-2 – Adaptive Management

In the tier-2 ELMST scenario, a conventional subdivision is developed and residents manage vegetation and litter according to their intrinsic preferences, but also have the ability to influence one another. With the ability to adopt new management behaviors over a 30 year span, the total carbon in the subdivision depended on emergent local norms resulting from neighborhood influence. Year 30 model results yield a carbon store range from 182 to 586 Mg C with an average of 387 (± 75) Mg C. The variability in this case was due to the interaction of annual seasonal shifts in natural processes (growth, senescence, litter decay and respiration), land management behaviors (fertilization, lawn mowing, and grass clipping or leaf removal) and management adaptation based on the behaviors of a resident's immediate von Neuman neighbors. Prairie is not assumed to be present in the tier-2 scenario.

Tier-3 – Adaptive Management with Incentive to Innovate

In tier-3, approximately four percent (three out of eighty-one) residents in a conventional subdivision accept an incentive to innovate their yards from a conventional turfgrass design to a 25 percent native prairie design (Table 7); residents manage their yards and are responsive to the management behaviors and innovative yard designs of their neighbors. Year 30 model results yield a carbon store range between 170 and 586 Mg C with an average of 325 (± 47) Mg C. The variability in this case is due to the interaction of annual seasonal shifts in natural processes (growth, senescence, litter decay and respiration), land management behaviors (fertilization, lawn mowing, and grass clipping or leaf removal), landscape re-design to a native prairie yard, and management adaptation based on the behaviors and yard designs of immediate von Neuman neighbors.

Hypothesis Results: Comparison Among Tiers

Results show that tier-0 had a significantly lower total subdivision carbon than all other tiers ($p<0.01$), while tier-1 had significantly higher total carbon than all other tiers ($p<0.01$). Tier-2 was shown to have a significantly higher subdivision carbon that tier-3. Comparative results of total carbon between each model scenario tier was determined using a two-tailed Student's t-test (Table 10).

Discussion

Effect of Individual Management Behaviors

The model showed that individual management behaviors are likely to affect the way a landscape stores carbon (Figure 9). Fertilization was assumed to increase the relative growth rate by a factor of 4.83 when using a slow-release nitrogen-based fertilizer such as Scotts 41-0-0 (Agnew & Christians 1993). Limiting effects of soil nitrogen on fertilizer function were left out of the model for simplicity. The relatively high increase in turfgrass growth is likely to account for the 40 percent increase in subdivision carbon (Table 5).

Mowing the lawn and allowing grass clippings to decompose on-site accounted for an increase in total subdivision carbon of approximately 20 percent in the ELMST model. Turfgrass was modeled to grow over sigmoid curve, where new growth is proportional to a plant's current biomass (Damgaard 2004; Damgaard; Richards 1959). As biomass approaches maximum capacity, growth rate begins to decrease (Blackman 1919). The removal of aboveground biomass after mowing causes the growth to be set back to a higher growth rate based on the new biomass value (i.e. 40 g/m^2). While lawn mowing may increase the rate at which turfgrass grows in the model, removing grass clippings reduces the amount of carbon stored by over 40 percent from the unmanaged baseline (Table 5).

The relatively small effect of fallen leaf removal is likely due to the small proportion of tree cover area assigned to each parcel in the model (about 0 to 4 percent; Table 7).

Research Question 1: Intrinsic Management and Carbon Storage

Analysis of model results did not support the hypothesis that after 30 years, the total carbon in an intrinsically managed subdivision would be less than the total carbon in an unmanaged subdivision ($H_{1.1}$). Instead, model results found that the total carbon in an intrinsically managed subdivision to be significantly higher than total carbon in an unmanaged subdivision (Figure 11; Table 10).

During model initialization, each agent was assigned a set of intrinsic management behaviors based on approximate probabilities from 2009 SLUCE2 interview data for parcels of one acre (4,046.86 m^2) or less (Table 2). Behaviors included: fertilizer application, mow schedule, grass clipping removal and removal of fallen leaves. The average behavior across the 100 runs for tier-1 were in accordance with the initial parameterization probabilities assigned to each management behavior (Table 4). Upon further examination of Table 2 and Figures 9 and 11, the increase in total subdivision carbon for tier-1 is likely due to the 35 percent of residents fertilizing their lawns and 88 percent of residents who keep grass clippings on the lawn after mowing. A resident average of 43 percent, removed fallen leaves. However, because of the relatively small proportion of tree cover associated with each parcel (about 0 to 4 percent; Table 7), this had little effect on total subdivision carbon (Figure 9).

ELMST land-cover areas were initialized based on 2009 SLUCE2 fieldwork data for parcels of one acre (4046.86 m^2) in area or less (Tables 11 and 12). Turfgrass proved to be the dominant land-cover, ranging between 50 to 80 percent of each parcel area (Table 12). A study by Milesi et al. (2005) found that turfgrass covered roughly 1.9% of the land in the conterminous United States, making it the "single largest irrigated crop in the country." The Milesi et al. study also evaluated the effect of different turf management scenarios on carbon storage, involving different fertilization and irrigation techniques, and removal of grass clippings versus on-site decomposition. Results from the Milesi study were in agreement with results provided by the ELMST model in that: (1) an unmanaged landscape dominated by turfgrass displays the lowest range of carbon flux when compared with other management scenarios for both the Milesi and ELMST study, (2) a well-maintained lawn that is fertilized and mowed, allowing grass clippings to remain on the lawn, acts as a carbon sink and (3) bagging and removing grass clippings reduces overall carbon storage (Milesi et al. 2005)(Figure 9, Figure 11).

Result from the model showed that intrinsic management of residential parcels in conventional exurban subdivisions in Southeast Michigan may store nearly twice the carbon than unmanaged subdivision after 30 years (Table 10). The intrinsic management scenario (tier-1) relies on initial allocation of management behaviors, which do not change over time. The outcome of tier-1 is therefore, deterministic given the initial agent behaviors and ecosystem variables. Model results found that the variability of carbon storage from an intrinsically managed subdivision over year 30 is also greater than that of an unmanaged subdivision. Greater variability is most likely be due to the manual alteration of carbon mean resident time (MRT) within each biomass pool through the various intrinsic management behaviors. Moreover, the greater total carbon in a managed subdivision (tier-1) may be due to the majority of agents mowing their lawns and leaving the grass clippings to decompose on-site. In addition, 35 percent of residents fertilize their lawn, which dramatically increases the affect on total subdivision carbon (Figure 9, Table 5).

Research Question 2: Adaptive Management and Carbon Storage

Model results did not support either hypothesis for a subdivision having neighborhood influence ($H_{2.1}$ and $H_{2.2}$). Results showed that the total carbon in a subdivision having neighborhood influence (tier-2) to be significantly higher than an unmanaged subdivision (tier-0), and significantly lower than a managed subdivision without neighborhood influence (tier-1), however tier-2 had the largest variability of total subdivision carbon over the 100 model runs (Figure 11; Table 10).

Total subdivision carbon among individual model runs varied greatly. This variance is likely due to the assortment of “management cultures” that emerged through the process of neighborhood influence. For example, in one model run, removing leaf litter may have been adopted as a subdivision norm, while another model run may have demonstrated a subdivision where most residents allow leaf litter to remain on their individual parcels. When behaviors were averaged among the model runs over 30 years, results showed overall behaviors to remain relatively stable, with the exception of fertilizer application, which dropped from 35 percent of the residents to zero residents after 30 years.

The zero percent fertilization result in tiers-2 and -3 is due to the willingness to fertilize parameter (Table 2). Willingness to fertilize was set to a best-guess assumption of 0.50 and applied during the neighborhood influence process to reflect a higher cost of adopting the fertilization behavior. For example, switching lawn mowing schedules, or deciding to remove fallen leaves at the end of the growing season are associated with the relatively low costs for adopting the new behavior. Adopting a fertilization regimen, however, accrues the cost of buying fertilizer, applying the fertilizer, and the commitment of always having a fertilized lawn for the remainder of the growing season. External social stigmas regarding the environmental effects of fertilizer application may also play into a resident's willingness to fertilize. The willingness to fertilize parameter was set such that the likelihood of a resident to adopt the fertilization behavior to be half that of other management behavior adoption probabilities in tier-2 and tier-3. Willingness to fertilize was the same for all residents, and remained constant throughout each model run. Sensitivity analysis showed agent adoption of fertilization behavior to be highly sensitive to the willingness to fertilize parameter implementation. Results showed that if willingness to fertilize is less-than one, the number of residents who fertilized their lawn will decrease over time; the lower the willingness to fertilize, the faster the decrease in the number of residents who fertilize. After 30 years, the model showed the number of residents who fertilized their lawns to be zero for all 100 runs at the set willingness to fertilize value of 0.5 (Table 4).

The present model implementation found that when neighborhood influence is applied to a conventional residential exurban subdivision initialized with interview and field data from Southeast Michigan, the subdivision may store either more or less carbon than an unmanaged subdivision after 30 years (Figure 11), depending on the local norms which emerged from neighborhood influence of management behaviors. In most cases, the model found that the subdivision will store more carbon than an unmanaged subdivision, even with infrequent lawn fertilization.

As with tier-1, tier-2 relies on the initial distribution of management behaviors as a starting point for subdivision evolution. Through the process of neighborhood influence, emergent local norms relating to yard management behaviors are likely to cause a carbon trajectory lock-in at the levels of the biomass pools, land-covers and subdivision. Whereas the carbon-trajectory for tiers -0 and -1 were locked-in from the start, the trajectory for tier-2 was erratic for the first few years, before finally stabilizing as resident management converged into a local norm (Figure 32 - 39). The ELMST model showed that neighborhood influence allows for a wide range of carbon trajectory lock-ins as illustrated by Figure 11.

Research Question 3: Adaptive Management with Incentive to Innovate

Model results did not support the three hypothesis for a subdivision having an incentive to install native prairie ($H_{3.1}$, $H_{3.2}$ and $H_{3.3}$). Results showed that the total carbon in a tier-3 subdivision to be significantly higher than a tier-0 (unmanaged) subdivision. However, total carbon in a tier-3 subdivision after 30 years was also found to be significantly lower than both a tier-1 subdivision and a tier-2 subdivision (Figure 11; Table 10). Tier-3 was also found to be less variable than tier-2 for total subdivision carbon over the 100 model runs.

Tier-3 attempts to use the neighborhood influence to hone in on a more environmentally-friendly set of management choices. After the model is initialized with the conventional subdivision, three residents are provided an incentive to innovate their conventional yards to a native prairie yard by converting 25 percent of their turfgrass to native prairie. Residents are assumed to always accept the incentive. Tier-3 investigates neighborhood influence as a tool to transform a conventional subdivision into a more ecologically-friendly subdivision that provides more carbon storage and greater ecosystem services. Similar to tier-2, a willingness to fertilize parameter was set to 0.50 and applied during the neighborhood influence process to reflect the higher cost of adopting the fertilization behavior. A similar result occurred: by year 30, residents in all 100 subdivisions did not apply fertilizer (Table 4).

Similar to fertilization, native prairie installation also accrues a higher cost than most other management behavior adoptions. Prairie installation involves the cost of removing a portion of turfgrass, regrading the land to promote water infiltration, and planting prairie grass plugs. Furthermore, native prairie installations are permanent. There is no option in the ELMST model to uninstall a native prairie in favor of turfgrass or any other land-cover type, also adding to the cost. The willingness to install prairie parameter is set to 0.25, making the likelihood of adoption of prairie by a resident one quarter of the likelihood of most other behaviors. Because prairie installation is permanent and the adoption of prairie is not as likely, the dissemination of prairie throughout the subdivision propagated slowly at first, then increased as more residents installed prairie (Figure 40).

Further Research

The current research assumes an immediate, von Neuman social network. While this type of network provides reasonable assumption for the present study, it may be interesting explore if different network topologies yield similar results. It is often the case that the topology of a network determines the propagation of information, behavior and influence (Barabasi 2003; Christakis & Fowler 2009). While neighborhood residents are shown to pay close attention to their neighbors (Galster 1987; Nassauer, Wang, & Dayrell 2009; Ioannides 2002), is seems reasonable that these neighbors may not always be immediate von Neuman neighbors. Fences, large lots, social ties with neighbors down the block, or resident similarity may drive other neighborhood topologies. If residents adapt their behavior based on their neighbors' behavior, then the total carbon outcome of the influenced-based model scenarios (i.e. tier-2 and tier-3) could be dramatically different based on who the residents are influenced by. Furthermore, residents may choose to pay attention to different neighbors over time, creating a dynamic network topology that changes based on resident preferences. The methods described in this paper could be repeated with different network topologies to discover how robust (or fragile) the total carbon storage is to the social network of its residents.

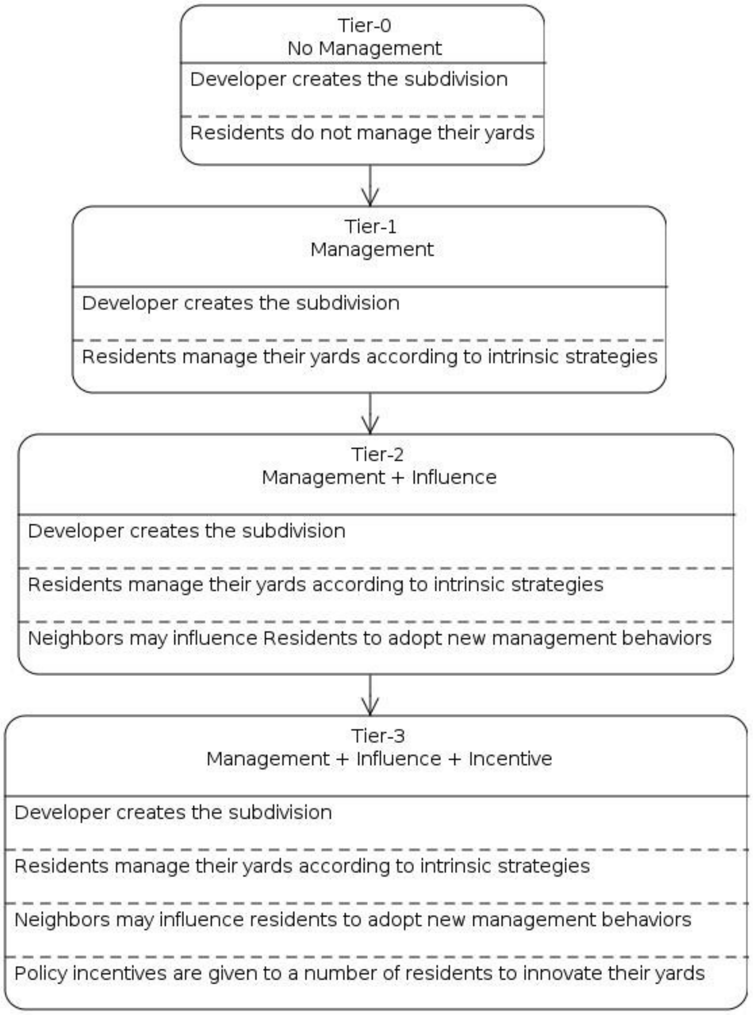
Conclusion

The exploratory, agent-based ELMST model demonstrated how a managed subdivision could store significantly more carbon than unmanaged subdivision after 30 years. The model also showed how a wide range of carbon storage possibilities could arise through neighborhood influence. One experiment considered using social influence among immediate neighbors to propagate a more environmentally friendly prairie-based yard design through a subdivision. The prairie design was able to disseminate to nearly all subdivision parcels within 30 years through the process of social influence. Model results found that a prairie-based subdivision tended to store more carbon than an unmanaged subdivision. However, the model also showed that the prairie-based subdivision stored significantly less carbon than a managed conventional subdivision after 30 years.

Higher carbon storage in a managed conventional residential subdivisions may be associated with turfgrass fertilization and allowing grass-clippings to decompose on-site after mowing the lawn. While the model showed that managed turfgrass may offer the potential to store a significant amount of carbon, turfgrass traditionally offers less in the way of other ecosystem services such as run-off water infiltration, biodiversity and native ecosystem restoration. While fertilization may account for a great deal of carbon storage in residential subdivisions, over-fertilization and lawn chemicals may pose an environmental hazard. From a policy perspective, this research suggests that trade-offs may need to be considered when determining between carbon storage and other ecosystem services in residential landscapes.

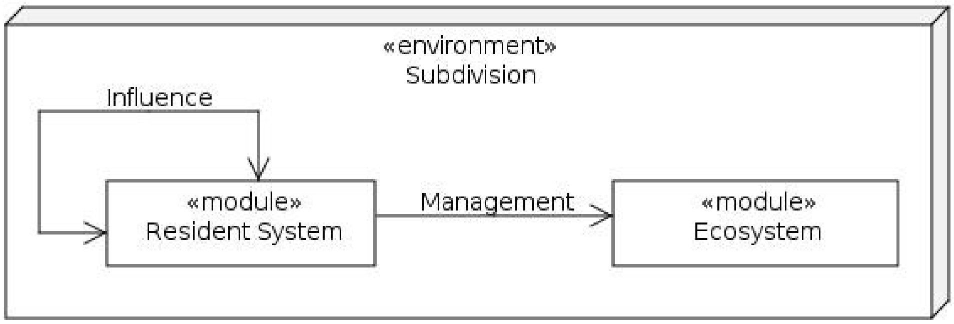
Figures

Figure 1: Tier-Based Research Schematic



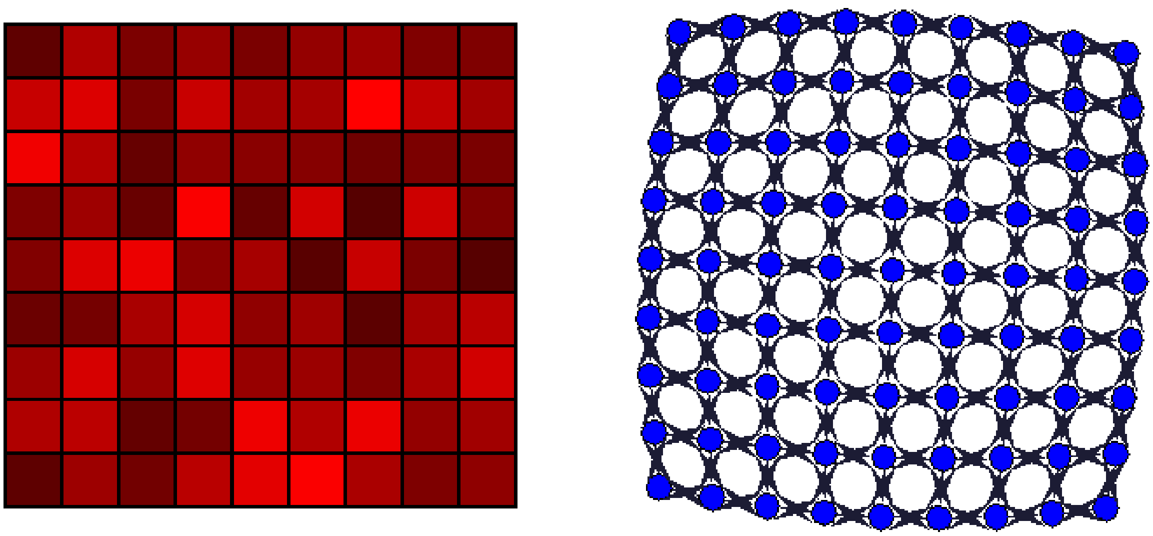
Each tier describes a different social scenario within a residential subdivision. This thesis explored the possible differences in carbon storage among tiers using a conventional exurban subdivision typical to Southeast Michigan.

Figure 2: Conceptual Model Overview



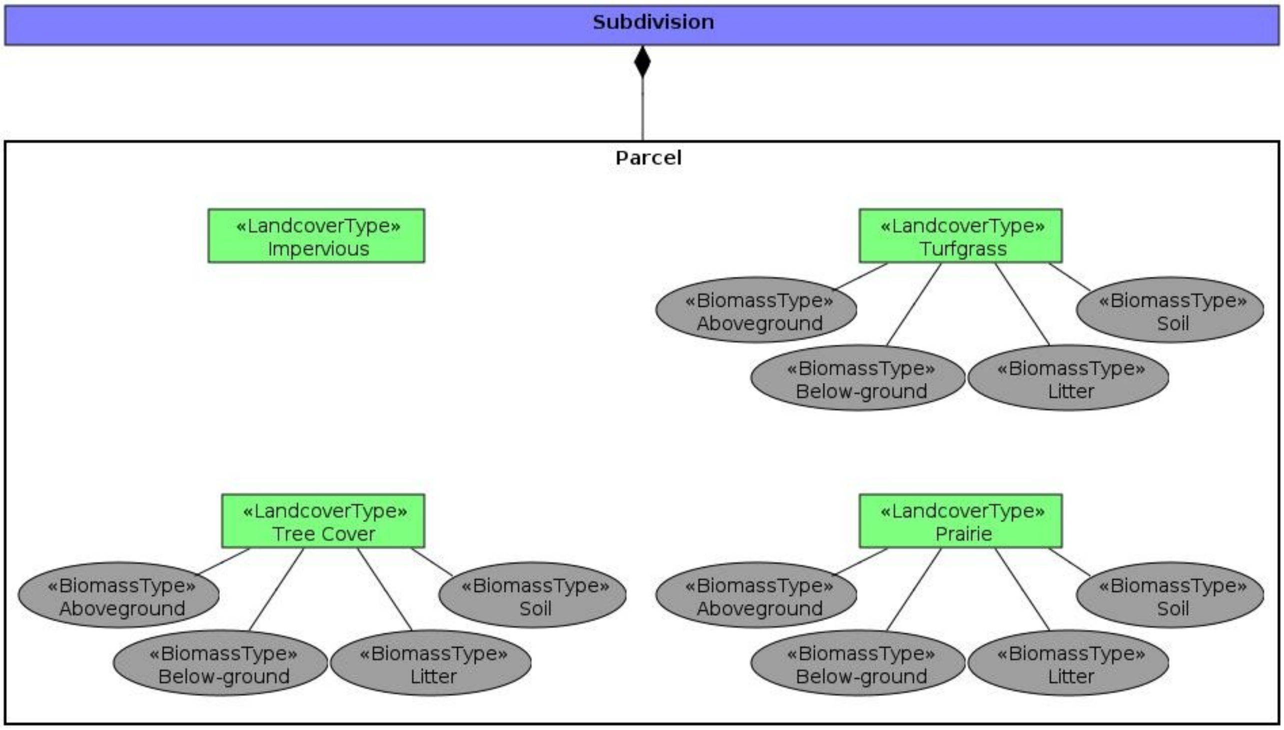
The ELMST model describes a subdivision environment having a simple ecosystem module and resident module. The ecosystem module is a basic carbon-cycling application which includes photosynthetic growth, litter decay and soil respiration. The resident module is responsible for resident management of aboveground vegetation and litter, as well as the process of resident management adaptation through the process of neighborhood influence.

Figure 3: Subdivision Environment and Social Network Structure



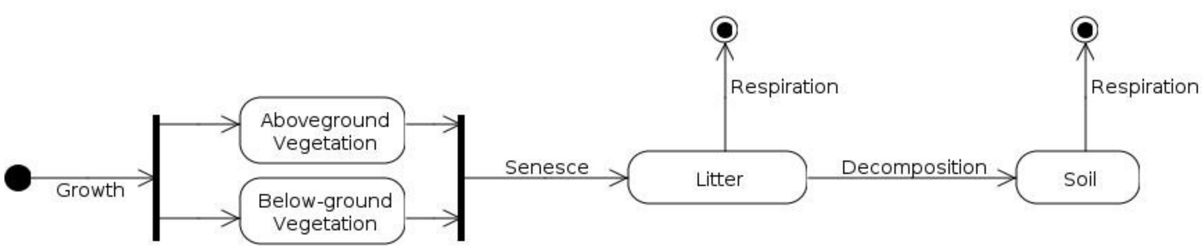
An illustration of the subdivision environment (left) and resident network (right). Each grid cell in the subdivision environment represents a one-acre parcel (4046.86 m^2). Parcels are heterogeneous, containing their own a-spatial land-cover proportions and biomass pools. Each resident is assigned one parcel to manage. In addition to management, each resident maintains a connection with his or her immediate von Neuman neighbors, forming a lattice-based social network. The social network structure determines how neighborhood influence is transferred among subdivision residents.

Figure 4: Ecosystem Components



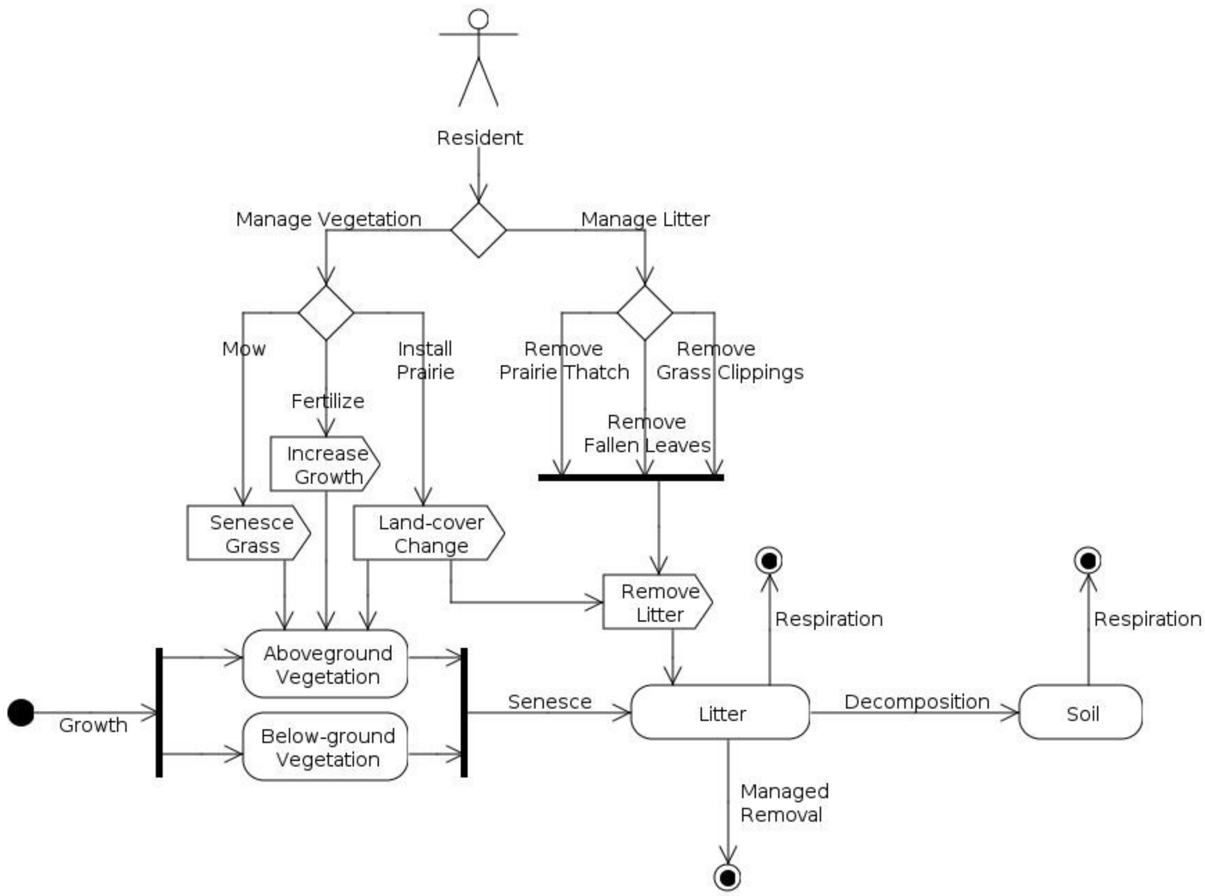
A subdivision contains many parcels. Each parcel contains a given area of each land-cover type. Four land-cover types are considered in the model: impervious surfaces, turfgrass, tree cover and prairie. With the exception of impervious surfaces, each land-cover type contains four biomass pools: aboveground, below-ground, litter and soil.

Figure 5: Unmanaged Carbon-Cycle



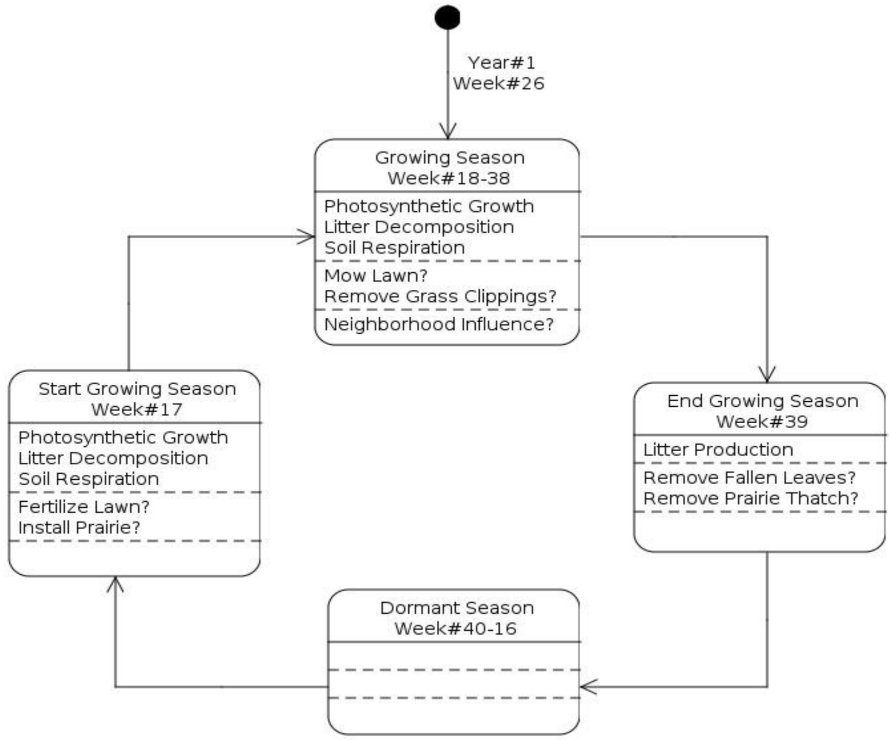
The unmanaged carbon-cycle in the ELMST model is a simplified process, meant to capture only the most fundamental processes and stocks. The cycle begins with growth of aboveground and below-ground vegetation. Vegetation will eventually senesce to produce litter. For simplicity, the model places both aboveground and below-ground litter into the same litter pool. Litter will decompose over time, respiring a majority of the carbon into the atmosphere (about 80%) and transferring rest to the soil pool as soil organic matter (SOM). Over time, soil will slowly respire carbon back into the atmosphere.

Figure 6: Managed Carbon-Cycle



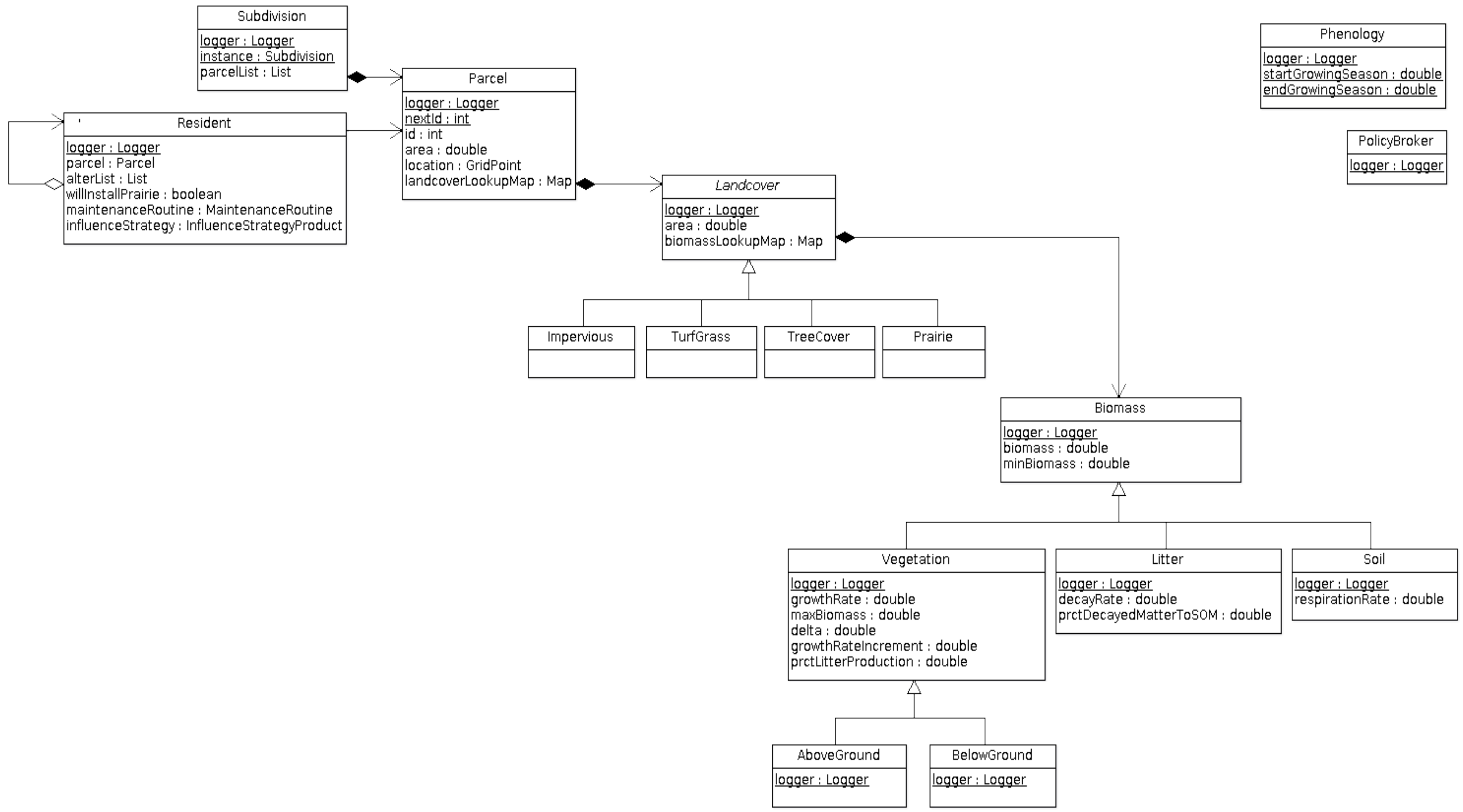
Management manipulates the carbon-cycle by providing additional senescence (mowing), increased growth (fertilizing), land-cover change (installing prairie). Land-cover change removes the current vegetation and litter from the parcel and replaces these pools with new vegetation and litter pool having zero biomass. Residents may gather prairie thatch, fallen leaves and/or grass clippings for pick-up by the local municipality, thereby completely removing carbon from the system.

Figure 7: Seasonal Processes and Agent Activities



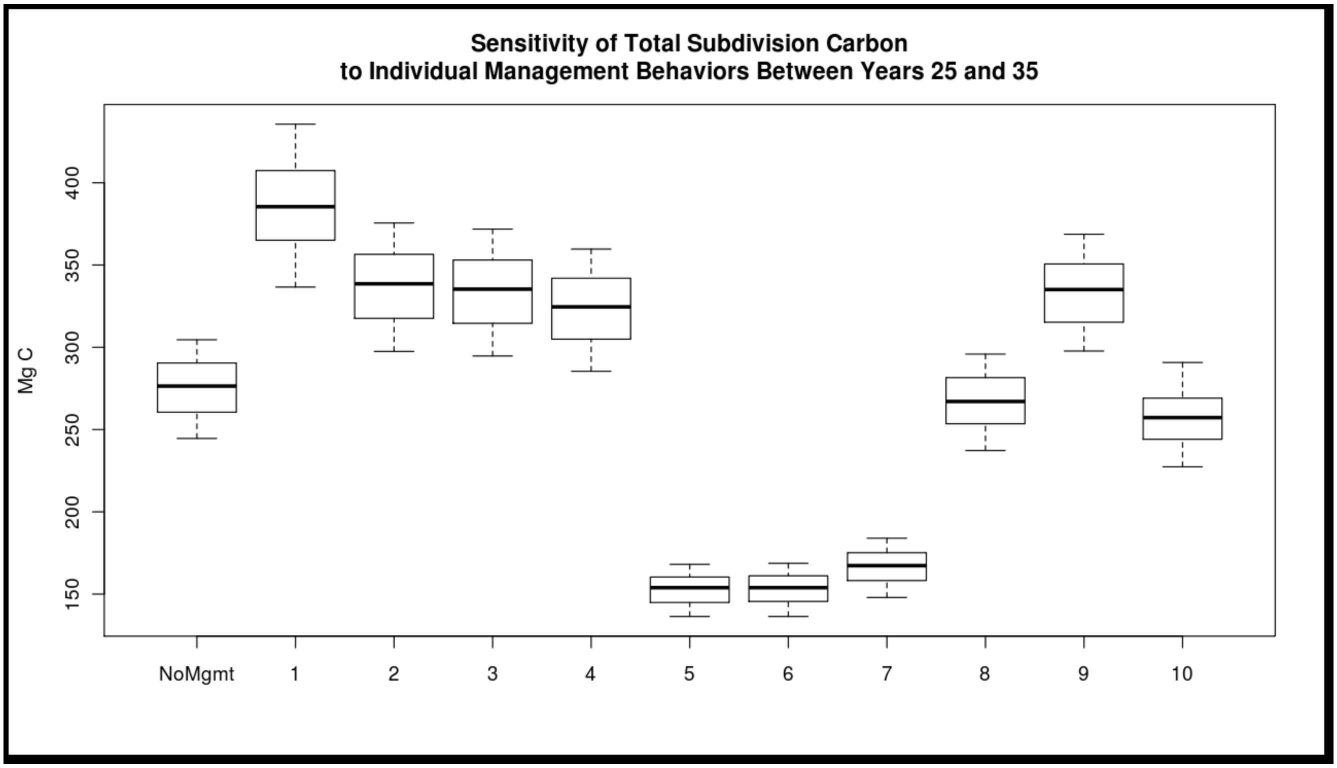
The ELMST model maintains a weekly time-step. Weeks are numbered 0 to 51 and correspond to the first week in January and last week in December respectively. After week 51, week numbers start again from 0. The model was initialized to begin ecosystem, management and neighborhood influence processes on week 26 of the first model year (roughly the first week in July) because the model was initialized with turfgrass and prairie vegetation data gathered from Southeast Michigan in mid-summer of 2009 (Project SLUCE2 2009). Once ecosystem and resident processes begin, they continue for an indefinite length of time as determined by the modeler. Weeks are further divided into four generic seasons: (1) Start of Growing Season, (2) Growing Season, (3) End of Growing Season and (4) Dormant Season. Each season is associated with a set of processes. Some processes may or may not occur depending on the scenario being run, individual resident management decisions, and available land-cover.

Figure 8: ELMST Class Diagram



ELMST class diagram illustrating important relationships among model components.
Note: class methods are not shown

Figure 9: Effect of Individual Management Behaviors on Total Subdivision Carbon



Individual effect of management behaviors assumed the standard 9x9 subdivision used in this study. All agents were set to perform the same management behavior consistently for the duration of the model run. Total carbon in the subdivision (measured in Mg C) was recorded for ten years between year 25 and 35. Each box plot represents an individual run where a single management behavior was performed, illustrating the effect that each management behavior could have on total subdivision carbon. Student's t-test results showed that the mean total subdivision carbon for each behavior was significantly different from all other behaviors ($p<0.01$), with the exception of behaviors 2 and 3 (mowing every week and mowing every other week, while keeping grass clippings on the lawn) which shown to have a less significant difference in means ($p<0.05$). Behaviors that showed no significant difference in carbon storage were 5 and 6 (mowing every week and mowing every other week, while removing grass clippings), which had a p-value of 0.63.

Management behavior key:

NoMgmt = No Management. Equivalent to tier-0.

1 = Fertilize lawn every year.

2 = Mow every week. Keep grass clippings on lawn after each mow.

3 = Mow every other week. Keep grass clippings on lawn after each mow.

4 = Mow every four weeks. Keep grass clippings on lawn after each mow.

5 = Mow every week. Remove grass clippings after each mow.

6 = Mow every other week. Remove grass clippings after each mow.

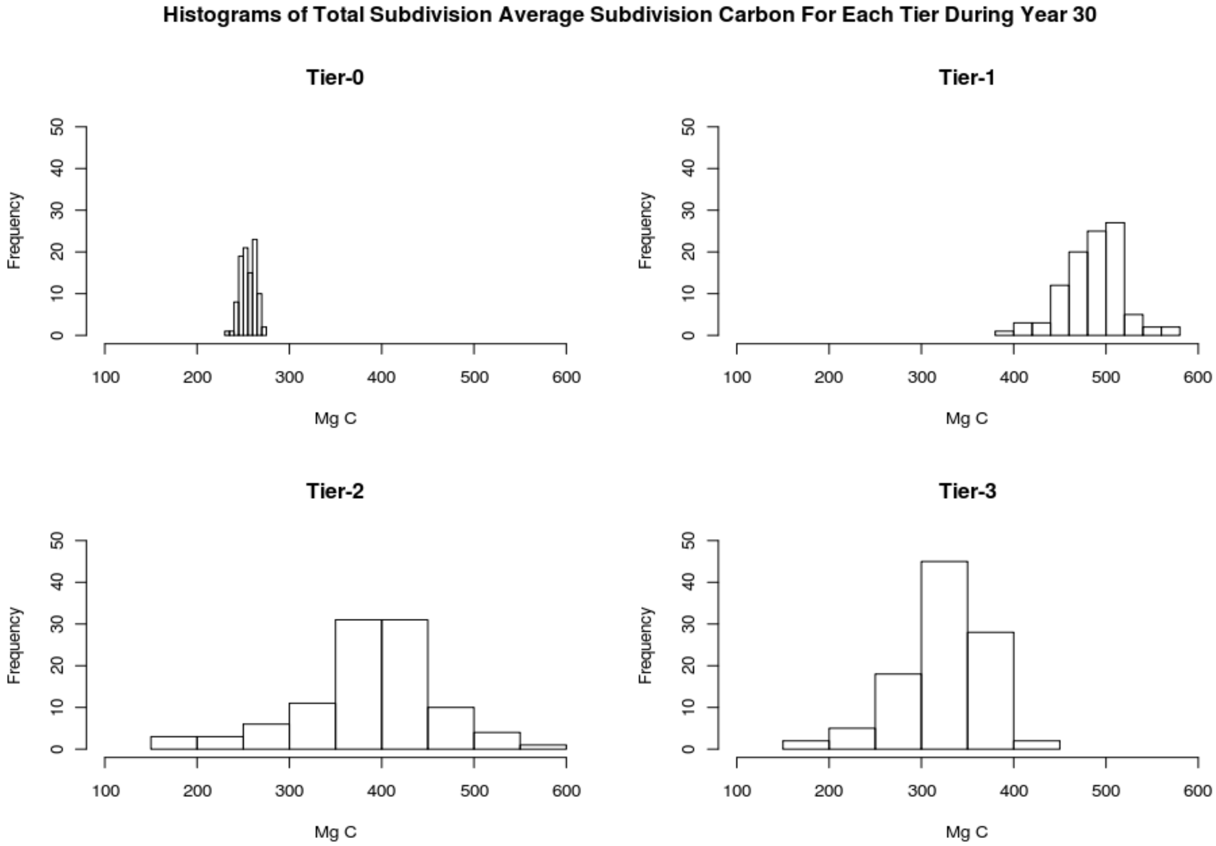
7 = Mow every four weeks. Remove grass clippings after each mow.

8 = Remove fallen leaves every year.

9 = Install prairie. Leave prairie thatch every year.

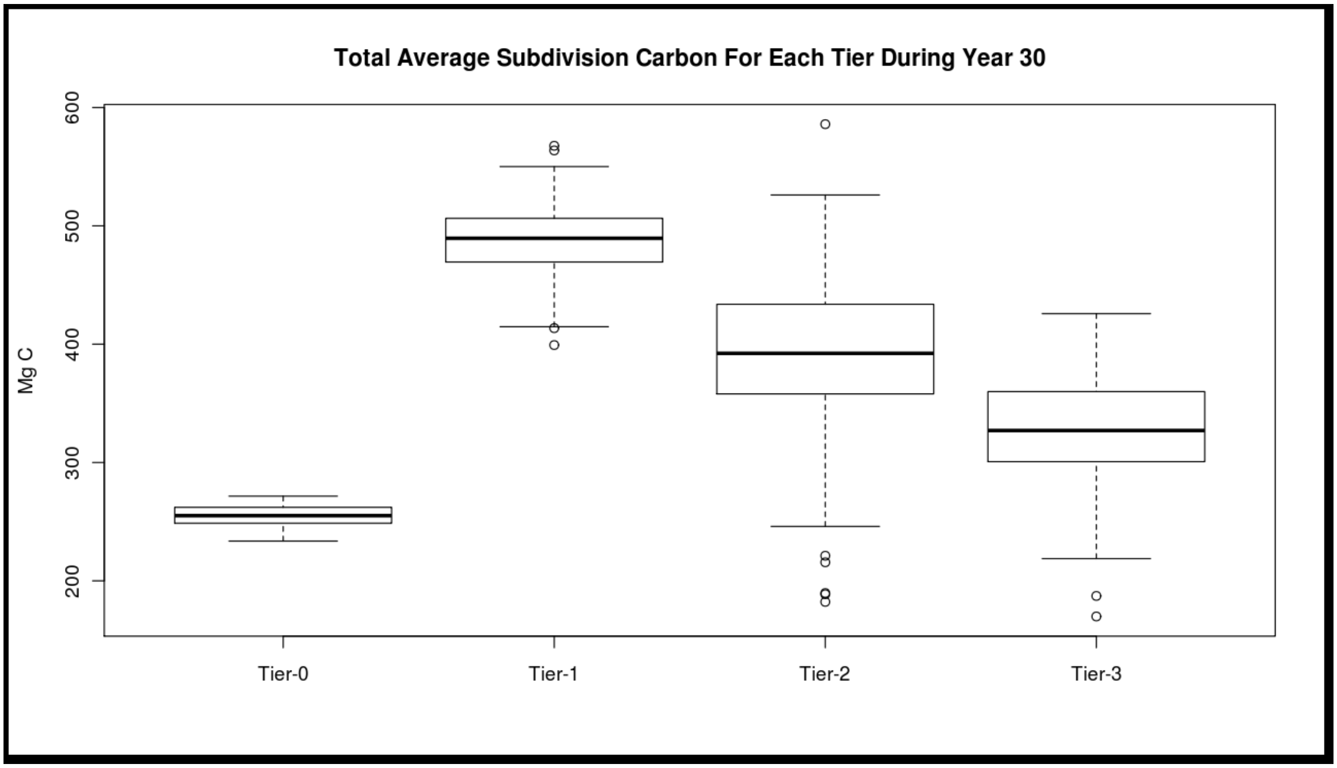
10 = Install prairie. Remove prairie thatch every year.

Figure 10: Model Results: Histograms of Total Average Subdivision Carbon by Tier



Histograms showing the distribution of total average subdivision carbon for model year 30. Each histogram describes the outcomes for 100 model runs within each research tier. Model runs were parameterized identically for each tier except for the random seed, which determined land-cover areas, agent behaviors, neighborhood influence and agent selection for prairie incentive. Land-cover type area and agent behavior probabilities were determined using fieldwork and interview data from exurban residential homes in Southeast Michigan. Neighborhood influence was based on a randomly weighed probability of neighbor behaviors. A random lottery was used to select three agents to participate in the native prairie incentive program. Only tier-3 includes native prairie yard designs.
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate with native prairie.

Figure 11: Model Results: Box Plot of Total Average Subdivision Carbon by Tier



Box plot showing the distribution of total average subdivision carbon for model year 30. Each distribution shows the range of outcomes for 100 model runs within each research tier. Model runs were parameterized identically for each tier except for the random seed, which determined land-cover areas, agent behaviors, neighborhood influence and agent selection for prairie incentive. Land-cover type area and agent behavior probabilities were determined using fieldwork and interview data from exurban residential homes in Southeast Michigan. Neighborhood influence was based on a randomly weighed probability of neighbor behaviors. A random lottery was used to select three agents to participate in the native prairie incentive program. Only tier-3 includes native prairie yard designs.
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate with native prairie.

Tables

Table 1: Ecosystem Initialization Parameters

	Impervious	Turf Grass	Tree Cover	Prairie
Parcel Area				
Proportion of Area	0.34 (0.11)[a]	0.65 (0.12)[a]	0.01 (0.03)[a]	0.00 (0.00)[a]
Initial Biomass (g/m^2)				
Above-ground (M)	0.00	174.15[b]	1,500.00[c]	337.60[b]
Below-ground	0.00	(0.667*M)[d]	(0.25*M)[e]	(0.667*M)[f]
Litter	0.00	0.00[g]	0.00[g]	0.00[g]
SOM	0.00[g]	0.00[g]	0.00[g]	0.00[g]
Growth				
RGR_{Max}	NA	0.20[h]	0.04[i]	0.10[j]
Fertilizer Growth Factor	NA	4.83[t]	NA	NA
$Biomass_{Max}$ (g/m^2)	NA	330.00[k]	20,000.00[l]	1,000.00[m]
Richards Delta (δ)	NA	0.0[n]	2.0[o]	0.0[n]
Litter Senescence and Decay				
Living Biomass to Litter	NA	0.80[p]	0.05[p]	0.45[p]
Decay Rate	NA	0.25[q]	0.25[q]	0.25[q]
Decayed Matter to SOM	NA	0.20[r]	0.20[r]	0.20[r]
Soil Respiration				
Soil Respiration Rate[q]	NA	0.002[s]	0.004[s]	0.0015[s]

[a] *Mean and standard deviation proportion derived from fieldwork parcels (n-16) having an area less-than or equal to 4,046.86 m^2 (1 acre) . Standard deviation values in parenthesis (Project SLUCE2 2009)*

[b] *Initial biomass derived from fieldwork parcels having an area less-than or equal to 4,046.86 m^2 (1 acre). Biomass values represent mean above-ground dry biomass of sampled vegetation (SLUCE, unpublished data)*

[c] *Initial biomass calibrated by back-calculating tree cover growth model and assuming biomass after 100 years is equal to approximately* 3,798 *g/m^2 (Fahey et al. 2010)*

[d] *A function of above-ground biomass and above-to-below ground ratio for cool season grasses and shrubs (Smith, Shugart, & Woodward 1997)*

[e] *A function of above-ground biomass and above-to-below ground ratio for temperate deciduous forest (Smith, Shugart, & Woodward 1997)*

[f] *A function of above-ground biomass above-to-below ground ratio for warm season grasses and shrubs (Smith, Shugart, & Woodward 1997)*

[g] *Subdivision assumed to be built on previous agricultural land with depleted soil and litter densities.*

[h] *Approximate relative growth rate for Kentucky Bluegrass (Poa pratensis) provided by Van Arendonk, J.J.C.M., Poorter (1994)*

[i] *Maximum Relative growth rate for temperate deciduous trees (Portsmuth & Niinemets 2007; Génard, Pagès, & Kervella 1998)*

[j] *Relative growth rate approximated by averaging the relative growth rates of healthy C_4 grass – Big Bluestem (Andropogon gerardii), Little Bluestem (Schizachyrium scoparium) and Indiangrass (Sorghastrum nutans) – 0.10, 0.11 and 0.09 respectively (Levang-brilz & Biondini 2002)*

[k] *Maximum biomass derived from NPP value for proportion of above-ground biomass for cool grass and shrubs (Smith, Shugart, & Woodward 1997)*

[l] *Estimate for pre-European settlement deciduous forest carbon density in Southern Wisconsin (Rhemtulla, Mladenoff, & Clayton 2009) then multiplied by two for biomass estimate (Nowak 1994; Currie 2003)*

[m] *Maximum above-ground biomass estimation for natural wet prairie sloughs (Meyer, Baer, & Whiles 2008, Figure 1)*

[n] *Best fit monomolecular model of turf and prairie grass growth over time as described by Dunn et al.(1988) for Richards Growth Model (Richards 1959)*

[o] *Best fit the logistic model of deciduous tree growth over time as described by Hutnik & Yawney (1961) for Richards Growth Model (Richards 1959)*

[p] *Calibrated to produce reasonable living biomass growth and soil carbon accumulation (Table 3).*

[q] *Litter decay rate per year (Currie et al. 2009, Figure 2.f)*

[r] *The proportion of decayed matter that is transferred to the soil carbon pool (Aber, Melillo, & McClaugherty 1990; Currie & Aber 1997)*

[s] *Calibrated to produce a representative soil organic carbon (SOC) accumulation; settling on a reasonable constant quantity (Table 3).*

[t] *Fertilizer is assumed to increase the relative growth rate for both above- and below-ground biomass by a factor of 4.83 (Agnew & Christians 1993)*

Table 2: Resident Initialization Parameters

Task	Description	Options	Approx.Prob*
Fertilize Lawn *(Turfgrass)*	A resident may decide to apply fertilizer to their lawn once at the beginning of each growing season. The fertilizer will increase the relative growth rate of the lawn by a factor of 4.83 for the duration of that growing season. Growth will return to its original rate the following season unless the resident decides to apply fertilizer again at the start of the growing season. In the scenarios that apply neighborhood influence, the willingness to fertilize factor is applied to reflect the higher cost of adopting the fertilization behavior.	Apply Lawn Fertilizer?	
		APPLY	0.35
		DO NOT APPLY	0.65
		WILLINGNESS TO FERTILIZE	0.50
Mow Schedule *(Turfgrass)*	A resident may choose how often to mow the entire area of turfgrass on his parcel with a lawn mower. All lawn mowers are assumed to have the same blade height and will leave an aboveground biomass of 40 g/m^2 on the lawn after each mow.	Mow Frequency	
		EVERY WEEK	0.31
		EVERY OTHER WEEK	0.54
		EVERY FOUR WEEKS	0.15
Remove Grass Clippings *(Turfgrass)*	When a resident mows his lawn, some of the turfgrass vegetation is removed from the aboveground biomass pool. The removed vegetation may either be bagged and removed from the system, be allowed to remain on the turfgrass as litter.	What Happens To Grass Clippings?	
		REMOVE FROM SUBDIVISION	0.12
		REMAIN ON PARCEL	0.88
Remove Fallen Leaves *(Tree Cover)*	At the end of the growing season, foliage from tree cover will naturally senesce and fall to the ground. The resident may then decide to remove these leaves completely from the subdivision, or allow them remain on the parcel.	Remove Fallen Leaves?	
		REMOVE FROM SUBDIVISION	0.42
		REMAIN ON PARCEL	0.58
Install Native Prairie+ *(Prairie)*	A resident may decide to install a native prairie at the start of the growing season. Once a prairie has been installed, it will remain there for the duration of the model run. In the scenarios that apply neighborhood influence, the willingness to install factor is applied to reflect the higher cost of adopting a native prairie yard design. Once native prairie has been installed, cannot be uninstalled.	Install Prairie?	
		INSTALL	0.00
		DO NOT INSTALL	1.00
		WILLINGNESS TO INSTALL	0.25
Remove Prairie Thatch *(Prairie)*	At the end of the growing season, prairie grass will naturally senesce and form a dense litter layer. The resident may either choose to gather and dispose of this litter, or allow it to remain on the parcel.	Remove Prairie Litter?	
		REMOVE FROM SUBDIVISION	0.12
		REMAIN ON PARCEL	0.88

** Approximate probabilities are derived from Project SLUCEII 2009 interview data (n=16).*

+ Native prairie is used in tier-3 only; assumed to be installed as a result of an incentive program or through the process of neighborhood influence.

Note: A management decision may still be made even if the applicable land-cover type is not present on the parcel. For example, if an agent does not have any tree cover on its parcel, the agent will still have a management decision value associated with the raking of fallen leaves. This may be akin to anticipated management behavior if a certain land-cover type were present on a resident's parcel, but is not currently.

Table 3: Validation of Unmanaged ELMST Carbon Density

	Above-Ground (g C/m^2)	Below-Ground (g C/m^2)	Litter (g C/m^2/yr)	SOC (g C/m^2)	
Turf Grass					
Years	5	5	10	15	1000
ELMST	23.10 – 115.24	15.41–76.86	153.59[c]	392.07 – 418.60	2,997.29 – 3,002.10
ELMST with Fertilization[α]	23.10 – 164.47	15.41 – 109.70	235.67	597.44 – 638.19	4,599.10 – 4,606.47
Literature[+]	22 – 121[a]	15.37–76.85[b]	165[d]	200[e]	3,300[f]
SLUCE2[*]	47.55[1]	95.25[1]	115.20		3,328.00
Tree Cover					
Years	100	100	100	15	1000
ELMST	7,303.94 – 7,688.36	1,825.99 – 1,922.09	480.52[h]	305.13 – 345.87	4,681.71 – 4,696.73
Literature[+]	7,596[g]	1,825.99 – 1,922.09[b]	387.20[i]	520.00[j]	1,333[k]
SLUCE2[*]	11,881.35[2]	3,960.45[2]	802.60		4,828.80
Prairie					
Years	10	10	10	15	1000
ELMST	165.30 – 300.55	110.26 – 200.47	255.46[m]	573.26 – 613.75	5,866 – 5,873
Literature[+]	317[l]	110.26 – 200.47[b]	288.40[n]	971[o]	5,000[p]
SLUCE2[*, 4]	150.58[3]	301.62[3]	95.90		3,399.20

Year rows indicate years since model initialization for each land-cover type. All SOC assume surface soil

[α] *Fertilization assumes a one-time application of slow-release methylene urea fertilizer (such as Scotts 41-0-0) at the beginning of the growing season. Fertilizer is assumed to increase the relative growth rate for both above- and below-ground biomass by a factor of 4.83 (Agnew & Christians 1993) Relative growth rate is assumed to return to its original value at the beginning of the following growing season if fertilizer has not been re-applied.*

[*] *SLUCEII values derived from unpublished field data from Southeast Michigan exurban residential parcels (Project SLUCE2 2009) Data is averaged among 26 managed Southeast Michigan exurban residential parcels developed between 1950 and 2000 on various soil types and various land-use histories. Therefore, these data do not correspond to a particular year.*

[1] *Applied 0.667 root-to-shoot ratio to SLUCEII combined average aboveground-belowground turf grass without woody vegetation value of 142.80 g/m^2 to obtain respective above- and below-ground carbon values for managed turf grass vegetation.*

[2] *Applied 0.25 root-to-shoot ratio to SLUCEII combined average aboveground-belowground dense tree value of 15,841.80 g/m^2 to obtain respective above- and below-ground carbon values for tree cover.*

[3] *Applied 0.667 root-to-shoot ratio to SLUCEII combined average aboveground-belowground old field without woody vegetation value of 452.20 g/m^2 to obtain respective above- and below-ground carbon values for prairie vegetation.*

[4] *Prairie values were derived from old fields found on residential parcels in Southeast Michigan containing a mixture of C_3 and C_4 grasses and forbs. The prairie in the ELMST model represents a wet prairie swell or rain garden containing C_4 grasses such as Indian-grass and Little Bluestem. Therefore these values should only be used to compare carbon storage between unmanaged, voluntary fields with managed, deliberate native prairie land-covers.*

[+] *Literature Values assume no resident management and were derived from a variety of sources for the years indicated.*

Turf Grass

[a] *Identified in Table 2 of Milesi et al. (2005)*

[b] *Above- to Below-ground ratio from Table 15.5 of Smith, T.M., Shugart, H.H., Woodward (1997)*

[c] *During year 15: (212.82 – 59.23) g C/m^2*

[d] *Identified in Table 2 of Milesi et al. (2005) and converted to carbon density (Currie 2003) before including a 0.667 proportion of below-ground litter (Smith, Shugart, & Woodward 1997)*

[e] *Identified in Table 5 of Simmons et al. (2008) for restored grassland on a mined site at the Oe/Oa soil horizons.*

[f] *Turf grass SOC identified by Pouyat, Yesilonis, & Golubiewski (2008)*

Tree Cover

[g] *Carbon density estimate of 100 year-old northern hardwood forest determined to be 9,495 g C/m^2 (Fahey et al. 2010, Figure 1) and multiplied by a factor of 0.8 for urban tree carbon density (Nowak 1994)*

[h] *During year 100 (665.82 – 185.29) g C/m^2*

[i] *Carbon density estimate of 100 year-old northern hardwood forest litter flux. Combined above- and below-ground biomass flux determined to be 484 g C/m^2/yr (Fahey et al. 2010, Figure 1) and multiplied by a factor of 0.8 for urban tree carbon density (Nowak 1994)*

[j] *Identified in Table 5 of Simmons et al. (2008) for a reference forest at the Oe/Oa soil horizons and multiplied by a factor of 0.8 for urban tree carbon density (Nowak 1994)*

[k] *Identified in Figure 1 of Garten (2009) in for surface soils in upland oak-hickory forest.*

Prairie

[l] *Average total above-ground biomass identified as 634 g/m^2 by Meyer, Baer, & Whiles (2008) for natural wet prairie sloughs and converted to carbon*

density (Currie 2003)

[m] *During year 10 (267.99 – 133.39) g C/m^2*

[n] *Biomass litter identified for C_4 grasses in Table 3 of Cahill, Kucharik, & Foley (2009) and converted to carbon density (Currie 2003) before including a 0.667 proportion of below-ground litter (Smith, Shugart, & Woodward 1997)*

[o] *Identified in Meyer, Baer, & Whiles for restored wet prairie sloughs (2008)*

[p] *Maximum SOC identified for natural wet prairie sloughs by Meyer, Baer, & Whiles (2008), Figure 2*

Table 4: Verification of Resident Behavior Across Research Tiers

		Average Behavior Across 100 Runs For Year 30			
Behavior	Initial Parameterization	Tier-0	Tier-1	Tier-2	Tier-3
Fertilize Lawn					
Apply Fertilizer	0.35	NA	0.35	0.00	0.00
Do Not Apply Fertilizer	0.65	NA	0.65	1.00	1.00
Mow Schedule					
Every Week	0.31	NA	0.31	0.29	0.28
Every Other Week	0.54	NA	0.54	0.55	0.55
Every Four Weeks	0.15	NA	0.15	0.16	0.17
Never	0.00	NA	0.00	0.00	0.00
Remove Grass Clippings					
Remove from Subdivision	0.12	NA	0.13	0.12	0.12
Remain on Parcel	0.88	NA	0.87	0.88	0.88
Remove Fallen Leaves					
Remove from Subdivision	0.42	NA	0.43	0.34	0.36
Remain on Parcel	0.58	NA	0.57	0.66	0.64
Install Native Prairie					
Installed	0.00	NA	0.00	0.00	0.99
Not Installed	1.00	NA	1.00	1.00	0.01
Remove Prairie Thatch*					
Remove from Subdivision	0.35	NA	NA	NA	0.37
Remain on Parcel	0.65	NA	NA	NA	0.63

Average behavior proportions among 100 runs for each research tier. Note that each tier maintains the approximate initial parameterization value across model runs except for fertilization. This is due to the "willingness to fertilize factor" which reduces the likelihood of a resident not currently fertilizing to apply fertilizer.

* *Prairie thatch only removed if native prairie has been installed.*

Tier-0: no management

Tier-1: intrinsic management

Tier-2: adaptive management

Tier-3: adaptive management with an incentive to innovate

Table 5: Sensitivity of Management Behaviors on Total Subdivision Carbon

	Sensitivity of Individual Behavior on Total Subdivision Carbon		
Behavior	Approx. Effect*	Confidence Interval	P-Value
Apply Fertilizer to Lawn	+ 40%	107.51 – 112.85	< 0.01
Mow Schedule + Leave Clippings			
Every Week	+ 20%	59.39 – 64.31	< 0.01
Every Other Week	+ 20%	56.12 – 61.05	< 0.01
Every Four Weeks	+ 17%	45.65 – 50.42	< 0.01
Mow Schedule + Remove Clippings			
Every Week	- (44%)	- (124.29 – 120.91)	< 0.01
Every Other Week	- (44%)	- (124.02 – 120.63)	< 0.01
Every Four Weeks	- (40%)	- (110.65 – 107.19)	< 0.01
Remove Fallen Leaves	- (4%)	- (10.77 – 6.65)	< 0.01
Install Native Prairie + Leave Thatch	+ 21%	55.98 – 60.63	< 0.01
Install Native Prairie + Remove Thatch	- (7%)	- (21.01 – 16.99)	< 0.01

Sensitivity analysis conducted assumes the standard 9x9 subdivision used in this study where all agents perform one management behavior consistently for the duration of the model run. Total carbon in the subdivision (measured in Mg C) was recorded for ten years between year 25 and 35 of the model. A two-sample Student's t-test was used to determine significants and confidence intervals between a subdivision with no management (i.e. tier-0) and a subdivision having a single management behavior performed annually by all agents.

* Approximate effect compares the means between an unmanaged subdivision and a subdivision having the given behavior performed consistently on all parcels.

Table 6: Model Component Activation Across Research Tier Scenarios

	Research Scenarios			
Component Activation Parameter	Tier-0	Tier-1	Tier-2	Tier-3
Ecosystem	**ON**	**ON**	**ON**	**ON**
Intrinsic Management	OFF	**ON**	**ON**	**ON**
Neighborhood Influence	OFF	OFF	**ON**	**ON**
Incentive Program	OFF	OFF	OFF	**ON**

Initial values among tiers are assumed to be identical with the exception of model component activation (as shown here) and random seed generation. Model component combinations are used to create the tier-based research design (see: Figure 1). Comparisons between tiers are used to test research hypothesis (See: Table 6)
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate.

Table 7: Model Results: Average Parcel Land-Cover Area Across Research Tiers

	Research Scenarios			
Land-Cover (m^2)	Tier-0	Tier-1	Tier-2	Tier-3
Impervious	1357.69 (345.07)	1357.69 (345.05)	1357.68 (345.05)	1357.69 (345.06)
Turf Grass	2616.81 (345.36)	2616.81 (345.34)	2616.82 (345.35)	1616.27 (359.56)
Tree Cover	72.36 (84.54)	72.36 (84.54)	72.36 (84.54)	72.36 (84.54)
Prairie	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	1000.54 (61.71)
Average Total	4046.86	4046.86	4046.86	4046.86

Average land-cover area within a parcel was gathered for year 30 across 100 runs for each research tier (see: Figure 1).
Average Standard deviation among runs are shown in parenthesis.
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate

Table 8: Model Results: Average Carbon Density Across Research Tiers

	Research Scenarios			
Land-cover (g C/m^2)	Tier-0	Tier-1	Tier-2	Tier-3
Turf Grass				
Aboveground	46.82 (32.35)	24.95 (9.21)	24.25 (6.23)	24.18 (6.00)
Below-ground	31.23 (21.58)	37.06 (30.91)	34.28 (26.81)	33.98 (26.38)
Litter	172.11 (54.97)	308.62 (212.58)	240.64 (151.01)	234.04 (142.13)
Soil	774.94 (9.82)	1756.71 (1244.36)	1357.02 (852.64)	1146.93 (714.77)
Total Average Density	1025.10	2127.34	1656.19	1439.13
Tree Cover				
Aboveground	4301.73 (3243.72)	4301.54 (3243.77)	4301.71 (3243.73)	4301.56 (3243.77)
Below-ground	1075.43 (810.93)	1075.39 (810.94)	1075.43 (810.93)	1075.39 (810.94)
Litter	311.01 (265.91)	198.58 (240.70)	217.66 (203.50)	212.32 (202.33)
Soil	739.27 (557.58)	472.66 (525.02)	510.87 (401.36)	500.35 (396.10)
Total Average Density	6427.44	6048.17	6105.67	6089.62
Prairie				
Aboveground	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	195.36 (4.49)
Below-ground	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	130.30 (32.68)
Litter	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	185.89 (71.18)
Soil	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	727.07 (188.15)
Total Average Density	0.00	0.00	0.00	1238.62

One-hundred run average carbon density results for each for each research tier (see: Figure 1).
Standard deviation among averages is given in parenthesis, and provides an indication of global neighborhood similarity or

cohesion.

Table 9: Model Results: Total Average Subdivision Carbon Across Tiers

	Research Scenarios			
Land-cover (Mg C)	Tier-0	Tier-1	Tier-2	Tier-3
Turf Grass				
Parcel Average	2.68	5.57	4.33	2.33
Subdivision Average	217.28	450.91	351.05	188.41
Tree Cover				
Parcel Average	0.47	0.44	0.44	0.44
Subdivision Average	38.07	35.45	35.79	35.69
Prairie				
Parcel Average	0.00	0.00	0.00	1.24
Subdivision Average	0.00	0.00	0.00	100.38
SUBDIVISION TOTAL AVERAGE	254.95	486.36	386.84	324.48

One-hundred run average total carbon results for each for each research tier (see: Figure 1).
Parcel averages in Mg C were calculated by multiplying average land-cover area (Table 7) by average total carbon density (Table 8).
Subdivision averages were calculated by multiplying the parcel average by the total number of parcels (i.e. 81).
Subdivision total average is the sum of subdivision averages for each land-cover type.
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate

Table 10: Hypothesis Results for Total Subdivision Carbon Over Year 30

	Description	Hypothesis	Outcome	Approx. Effect*	Conf. Interval	P-Value
Q_1	**How could intrinsic management alone affect carbon storage in a residential subdivision after 30 years?**					
$H_{1.1}$	The total area carbon trajectory in a managed subdivision will be lower than the total area carbon trajectory in an unmanaged subdivision.	Tier-1 < Tier-0	Tier-1 > Tier-0	+ 91%	224.95 – 237.84	< 0.01
Q_2	**How could intrinsic management with the addition of neighborhood influence affect carbon storage in a residential subdivision after 30 years?**					
$H_{2.1}$	The total area carbon trajectory in a subdivision having neighborhood influence will be lower than the total area carbon trajectory in an unmanaged subdivision.	Tier-2 < Tier-0	Tier-2 > Tier-0	+ 52%	117.00 – 146.95	< 0.01
$H_{2.2}$	There will be no significant difference in the total area carbon trajectory between an influence-based managed subdivision and a managed subdivision absent of social influence.	Tier-2 == Tier-1	Tier-2 < Tier-1	- (20%)	83.32 – 115.51	< 0.01
Q_3	**How could intrinsic management with the addition of neighborhood influence and a single incentive to install native prairie affect carbon storage in a residential subdivision after 30 years?**					
$H_{3.1}$	The total area carbon trajectory in a managed subdivision with innovation incentives and neighborhood influence could be lower than the total area carbon trajectory in an unmanaged subdivision.	Tier-3 < Tier-0	Tier-3 > Tier-0	+ 27%	59.84 – 78.87	< 0.01
$H_{3.2}$	The total area carbon trajectory in a subdivision with innovation incentives could be higher than the total area carbon trajectory in a subdivision having management, but no neighborhood influence.	Tier-3 > Tier-1	Tier-3 < Tier-1	- (33%)	150.82 – 173.25	< 0.01
$H_{3.3}$	The total area carbon trajectory in a subdivision with innovation incentives and neighborhood influence could be higher than the total area carbon trajectory in a management subdivision with neighborhood influence.	Tier-3 > Tier-2	Tier-3 < Tier-2	- (16%)	45.11 – 80.13	< 0.01

This table provides a summary of the stated hypothesis and results comparing the total subdivision carbon between tiers over model year 30. Results were obtained by running the model 100 times for each tier. Model runs were parameterized identically for each tier except for the random seed, which determined land-cover areas, agent behaviors, neighborhood influence and agent selection for prairie incentive. Land-cover type area and agent behavior probabilities were determined using fieldwork and interview data from exurban residential homes in Southeast Michigan. Neighborhood influence was based on a randomly weighed probability of neighbor behaviors. A random lottery was used to select three agents to participate in the native prairie incentive program. Only tier-3 includes native prairie yard designs.
Results were obtained by running a two-tailed Student's t-test between each pair of model tiers and comparing against their respective alternative hypothesis. None of the hypothesis from this study were confirmed.
* *Approximate effect calculated using percent difference in carbon means between tiers.*
Tier-0: no management
Tier-1: intrinsic management
Tier-2: adaptive management
Tier-3: adaptive management with an incentive to innovate with native prairie.

Table 11: Fieldwork: Eco-Zone Categories Translated to ELMST Land-Cover Types

Eco-Zone Description	Code	Frequency	Notes	ELMST Land-Cover
Home/Building	HO	26	Home or other buildings such as sheds and barns.	Impervious
Pavement	RP	26	Paved areas such as driveways, walkways and pools.	Impervious
Shrubs with mulch and herbs	CMSH	25	Gardens which are often times found around the periphery of a house and classified as impervious in areal photographs.	Impervious
Turf grass without woody vegetation	CTG	25	Includes a mixture of C3 grasses and forbs.	Turf Grass
Turf grass with sparse woody vegetation	CTGW	24	Includes a mixture of C3 grasses, forbs with a scattering of individual trees or shrubs.	Turf Grass
Vegetable garden	CVG	8	Small, infrequent areas often times found within a CTG eco-zone and classified as turf grass on areal photographs.	Turf Grass
Water	WA	4	Small pond on property.	Turf Grass
Deciduous shrub	CDS	1	Dense woody shrubs	Tree Cover
Deciduous Tree	CDT	5	Dense woody trees	Tree Cover
Deciduous shrub and tree	CDST	3	Dense woody shrubs and trees	Tree Cover
Old field	COF	4	Includes a mixture of C4 grasses, C3 grasses ans forbs.	Prairie
Old Field with woody vegetation	CFW	2	Includes a mixture of C4 grasses, C3 grasses, forbs and small clumps of deciduous shrubs or trees.	Prairie

Mapping of eco-zone categories from fieldwork data to ELMST land-cover types.
Source: (Project SLUCE2 2009)

Table 12: Fieldwork: Land-Cover Areas for Parcels of One Acre or Less

Parcel ID	Total Area (m^2)					Proportion of Parcel Area				
	Impervious	Turf Grass	Tree Cover	Prairie	Total	Impervious	Turf Grass	Tree Cover	Prairie	Total
R04	577.35	2642.28	0.00	0.00	3219.63	0.18	0.82	0.00	0.00	1.00
R06	423.71	1800.50	0.00	25.40	2249.61	0.19	0.80	0.00	0.01	1.00
R09	787.54	1246.88	0.00	0.00	2034.43	0.39	0.61	0.00	0.00	1.00
R10	838.17	2658.42	0.00	0.00	3496.59	0.24	0.76	0.00	0.00	1.00
R11	356.90	535.57	0.00	0.00	892.47	0.40	0.60	0.00	0.00	1.00
R12	732.45	1226.50	0.00	0.00	1958.95	0.37	0.63	0.00	0.00	1.00
R13	567.16	1050.17	0.00	0.00	1617.33	0.35	0.65	0.00	0.00	1.00
R15	836.57	1045.18	0.00	0.00	1881.75	0.44	0.56	0.00	0.00	1.00
R16	434.90	464.37	118.35	0.00	1017.62	0.43	0.46	0.12	0.00	1.00
R17	586.07	2203.64	0.00	0.00	2789.71	0.21	0.79	0.00	0.00	1.00
R18	341.77	1155.36	0.00	0.00	1497.13	0.23	0.77	0.00	0.00	1.00
R19	532.94	921.11	0.00	0.00	1454.05	0.37	0.63	0.00	0.00	1.00
R20	537.21	581.30	0.00	0.00	1118.51	0.48	0.52	0.00	0.00	1.00
R21	871.91	1410.21	0.00	0.00	2282.12	0.38	0.62	0.00	0.00	1.00
R22	505.45	431.48	0.00	31.30	968.24	0.52	0.45	0.00	0.03	1.00
R24	400.97	1396.03	0.00	0.00	1797.01	0.22	0.78	0.00	0.00	1.00
Mean	583.19	1298.06	7.40	3.54	1892.20	**0.34**	**0.65**	**0.01**	**0.00**	1.00
StdDev	178.46	711.29	29.59	9.74	778.70	**0.11**	**0.12**	**0.03**	**0.00**	0.00

Bold values used for initial model parameterization.
Source: (Project SLUCE2 2009)

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Appendix I: Visualizations of Select ELMST Model Runs

Figure 12: Validation: Unmanaged Turf Grass Carbon Pools – 200 Years

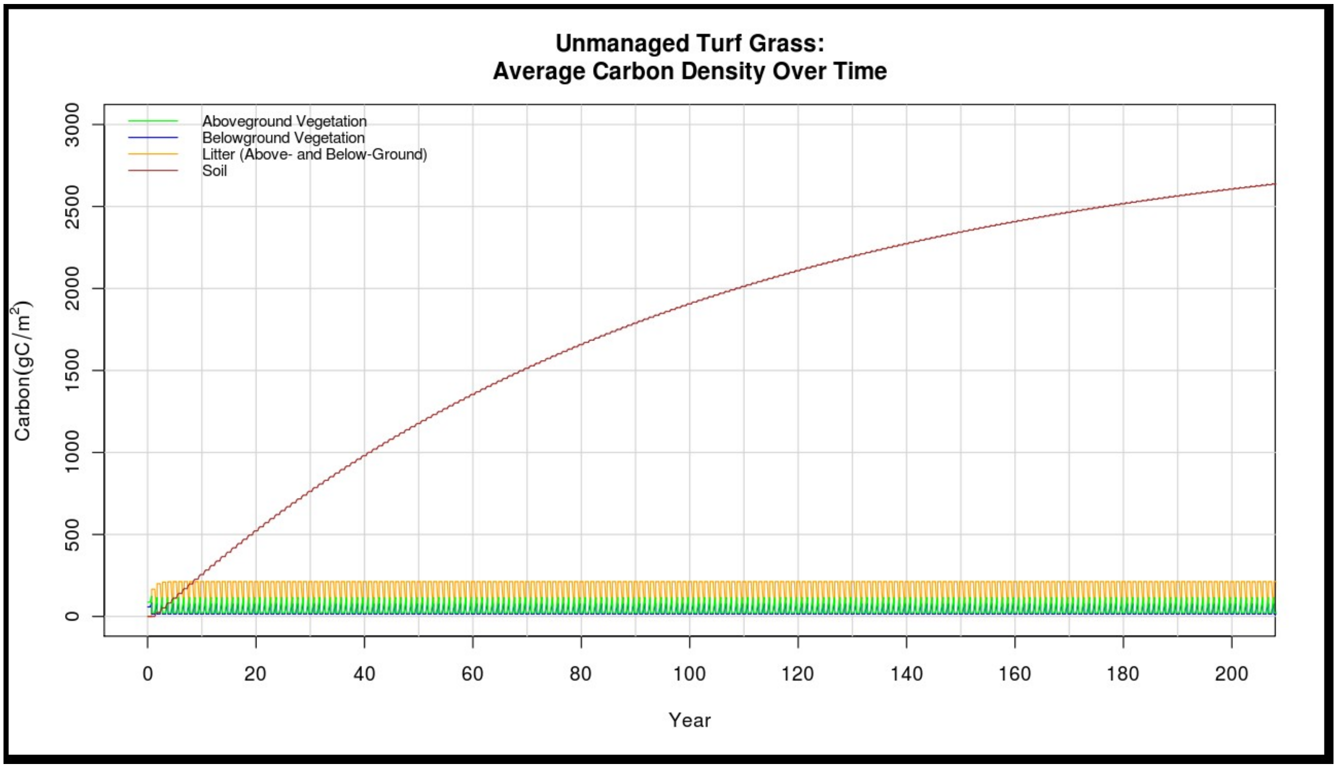


Figure 13: Validation: Unmanaged Turf Grass Carbon Pools – 20 Years

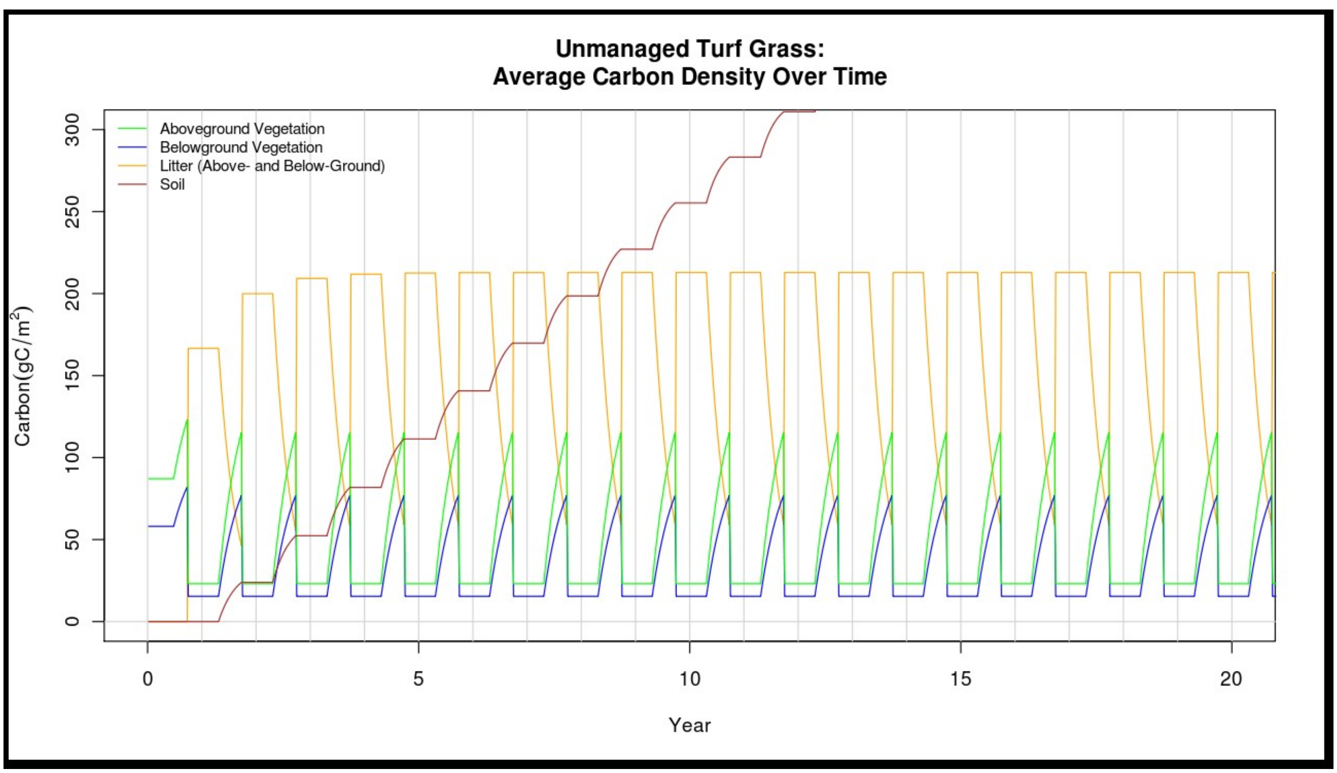


Figure 14: Validation: Unmanaged Tree Cover Carbon Pools – 100 Years

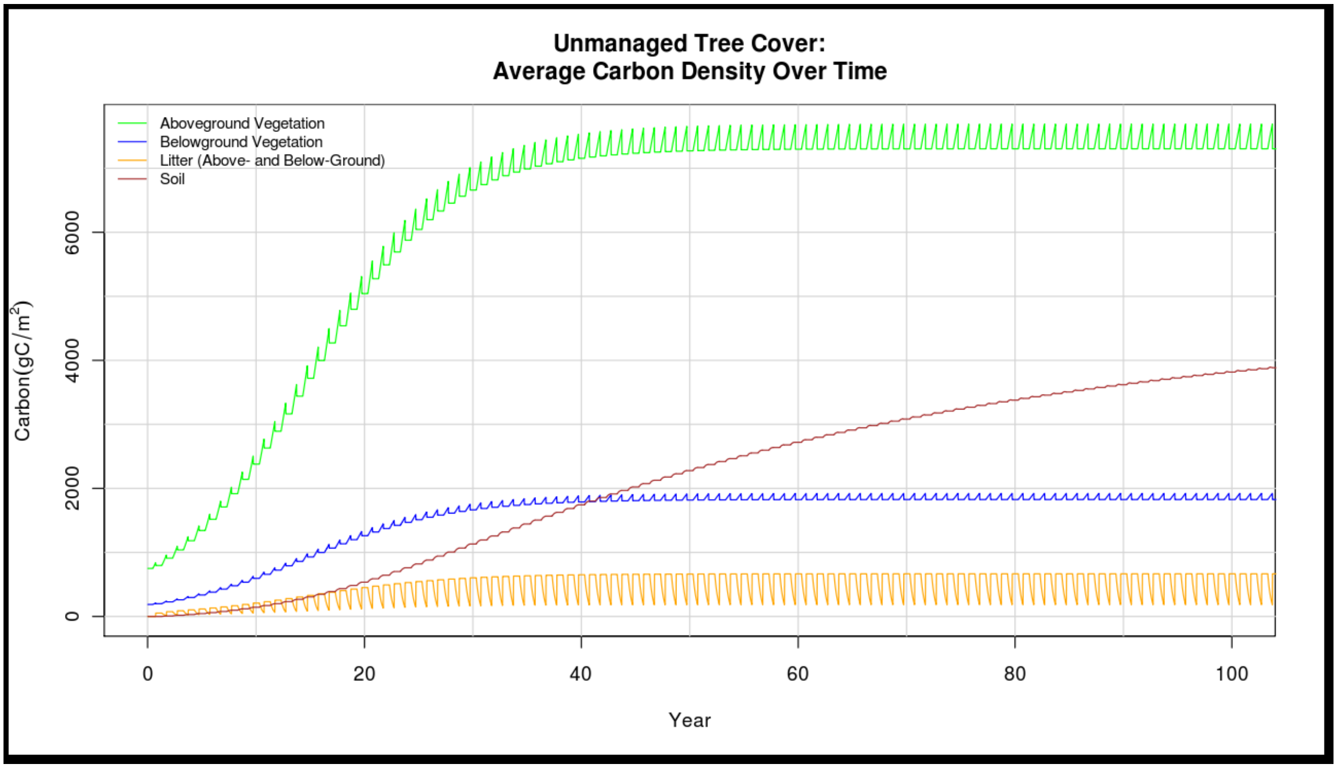


Figure 15: Validation: Unmanaged Tree Cover Litter Pools – 100 Years

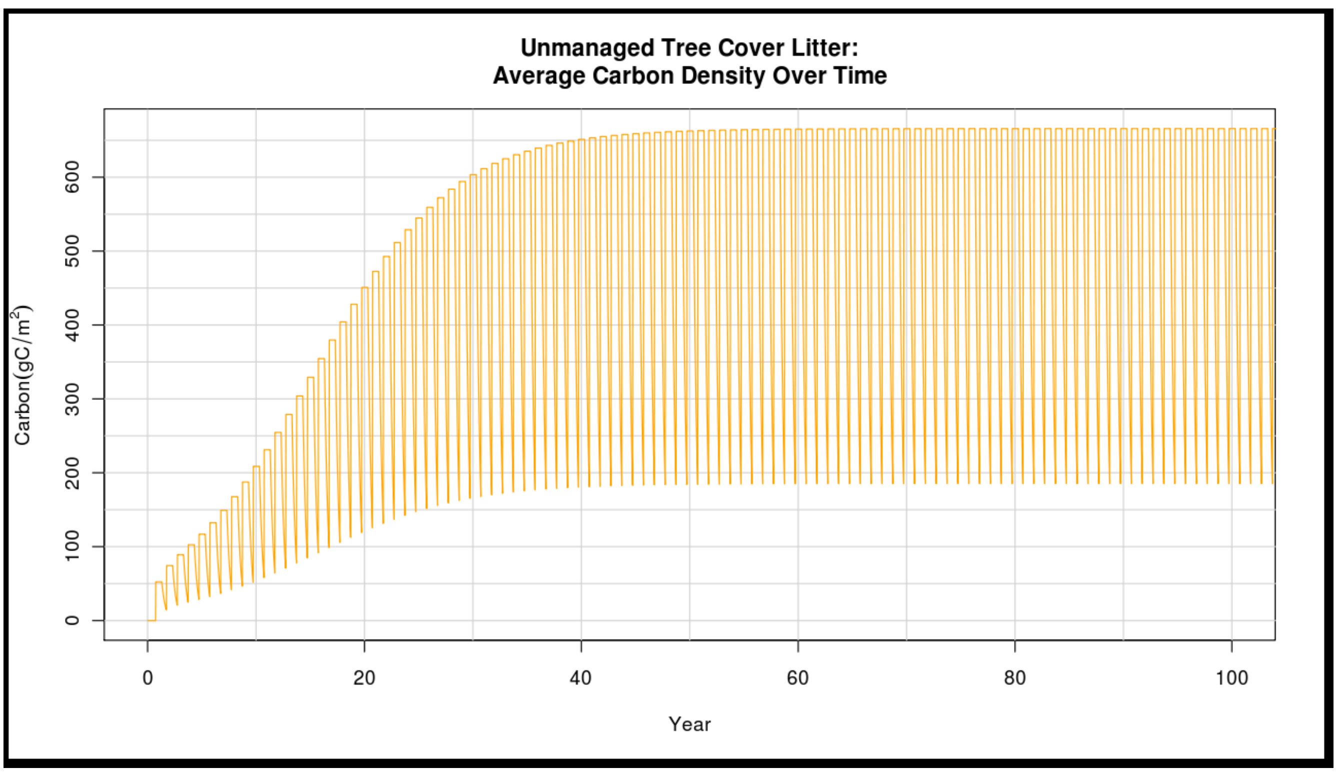


Figure 16: Validation: Unmanaged Prairie Carbon Pools – 1000 Years

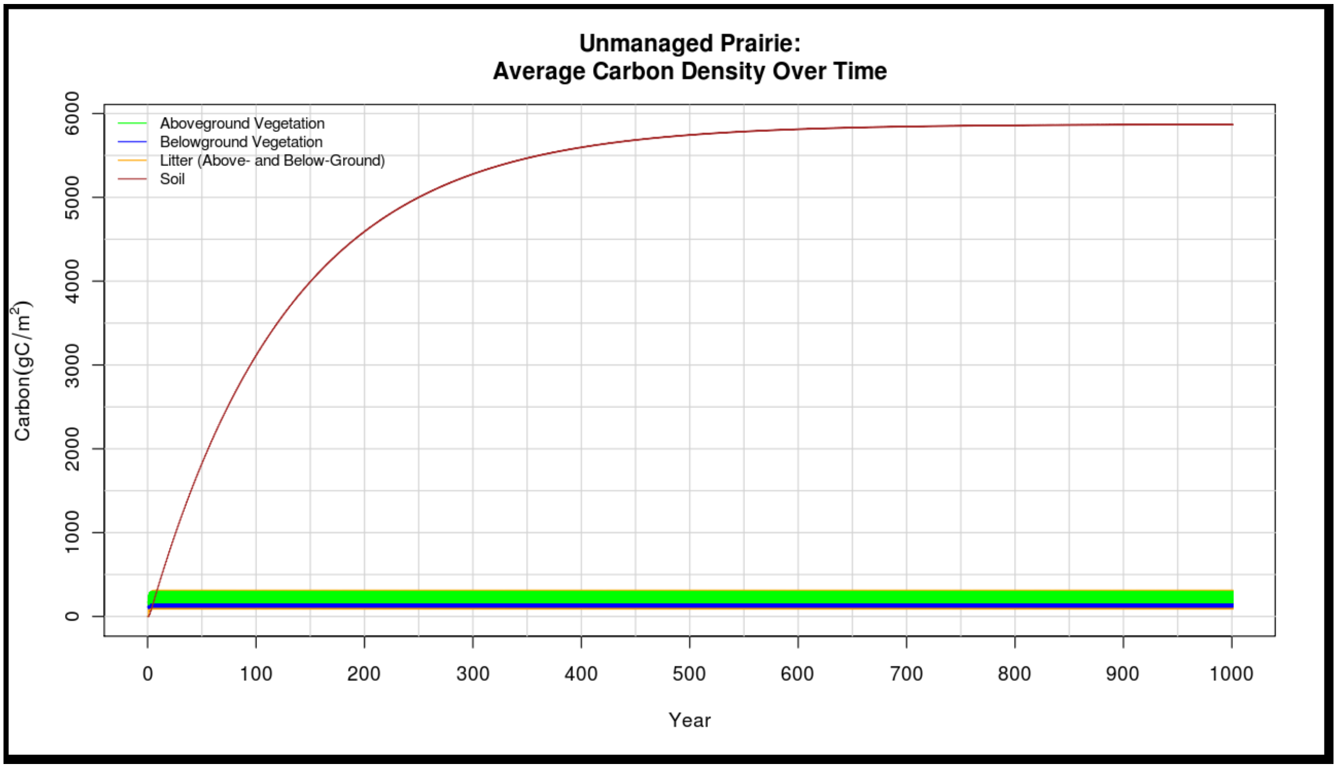


Figure 17: Validation: Unmanaged Prairie Carbon Pools – 20 Years

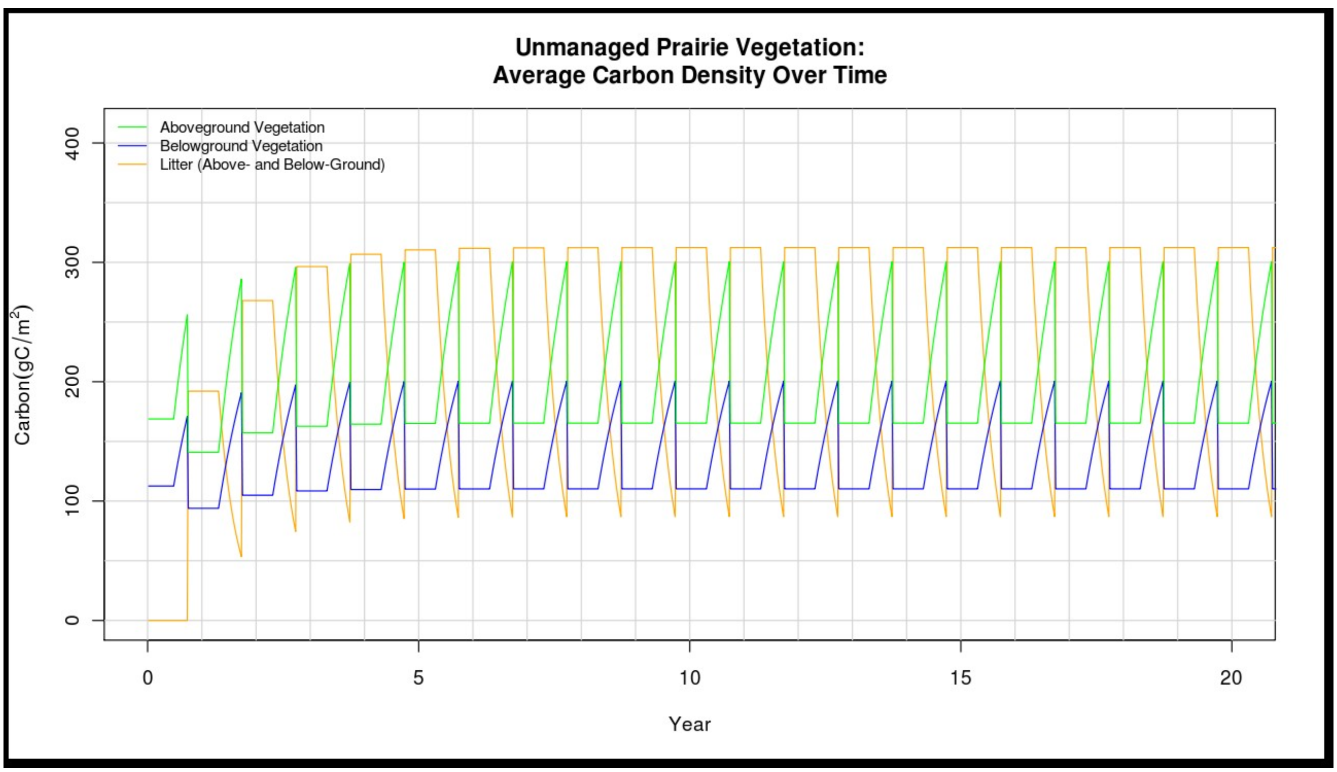
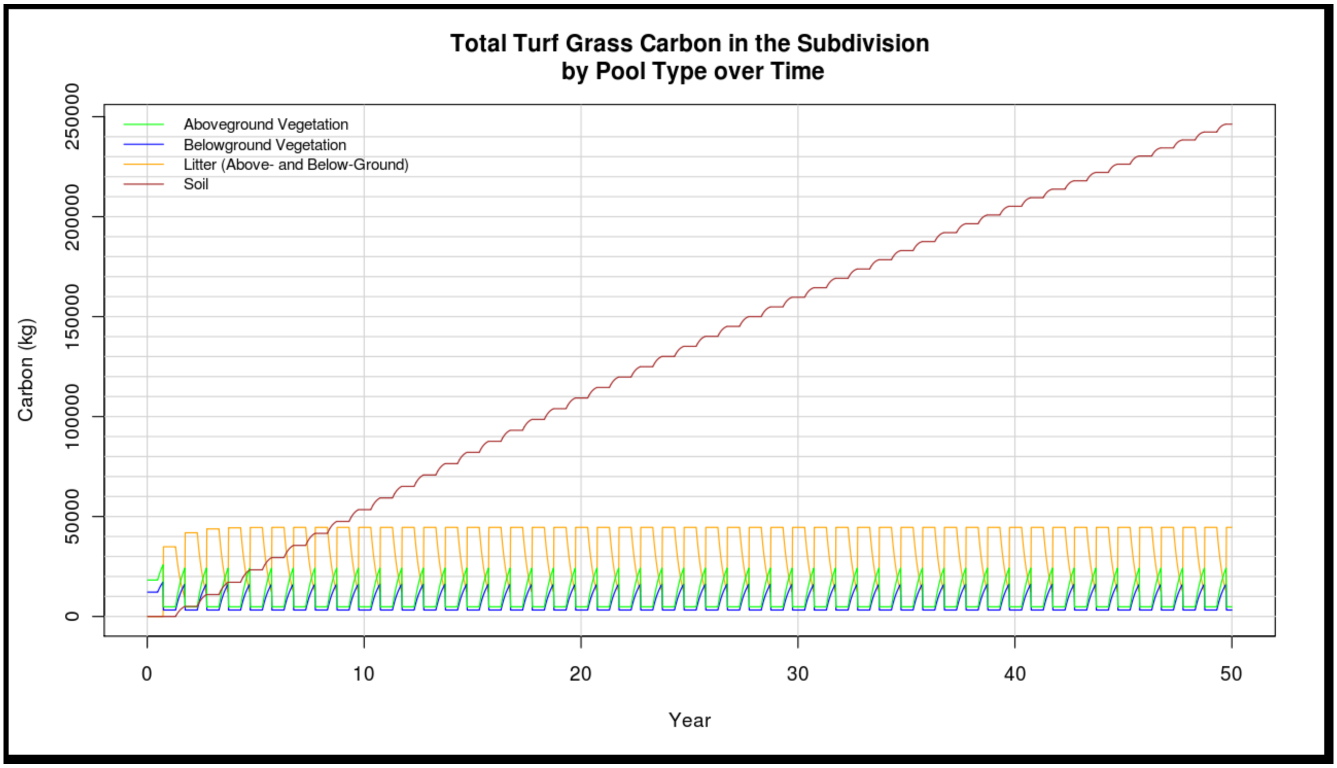
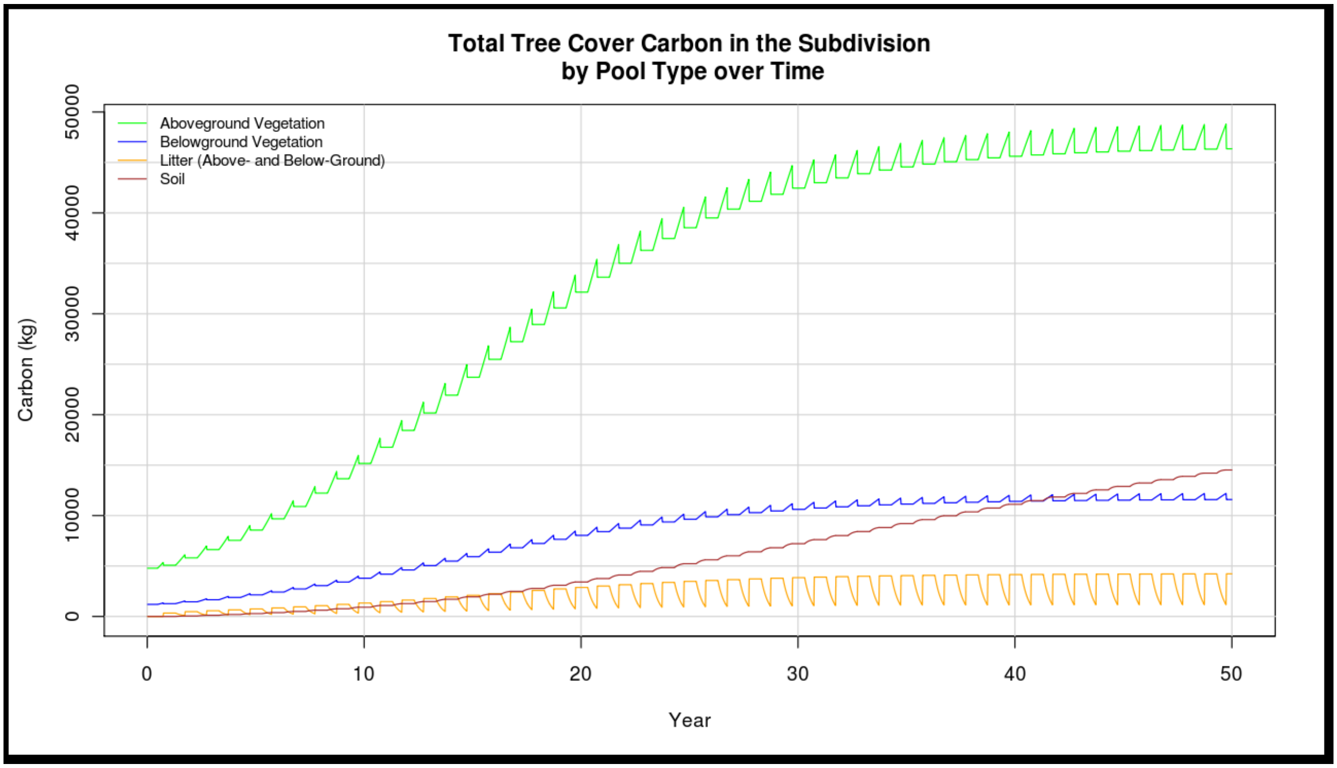


Figure 18: Tier-0 Sample Run: Turfgrass Carbon Pools – 50 Years



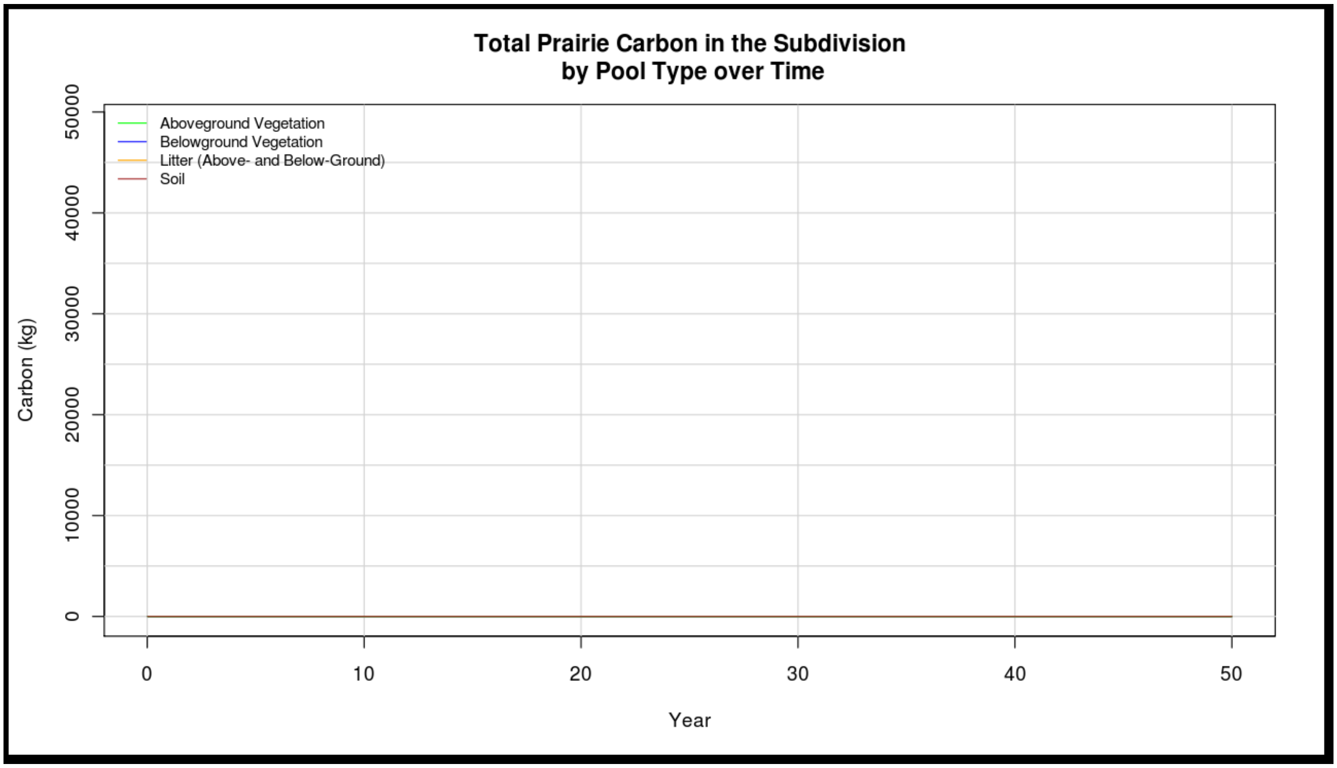
Random Seed: 4390116

Figure 19: Tier-0 Sample Run: Tree Cover Carbon Pools – 50 Years



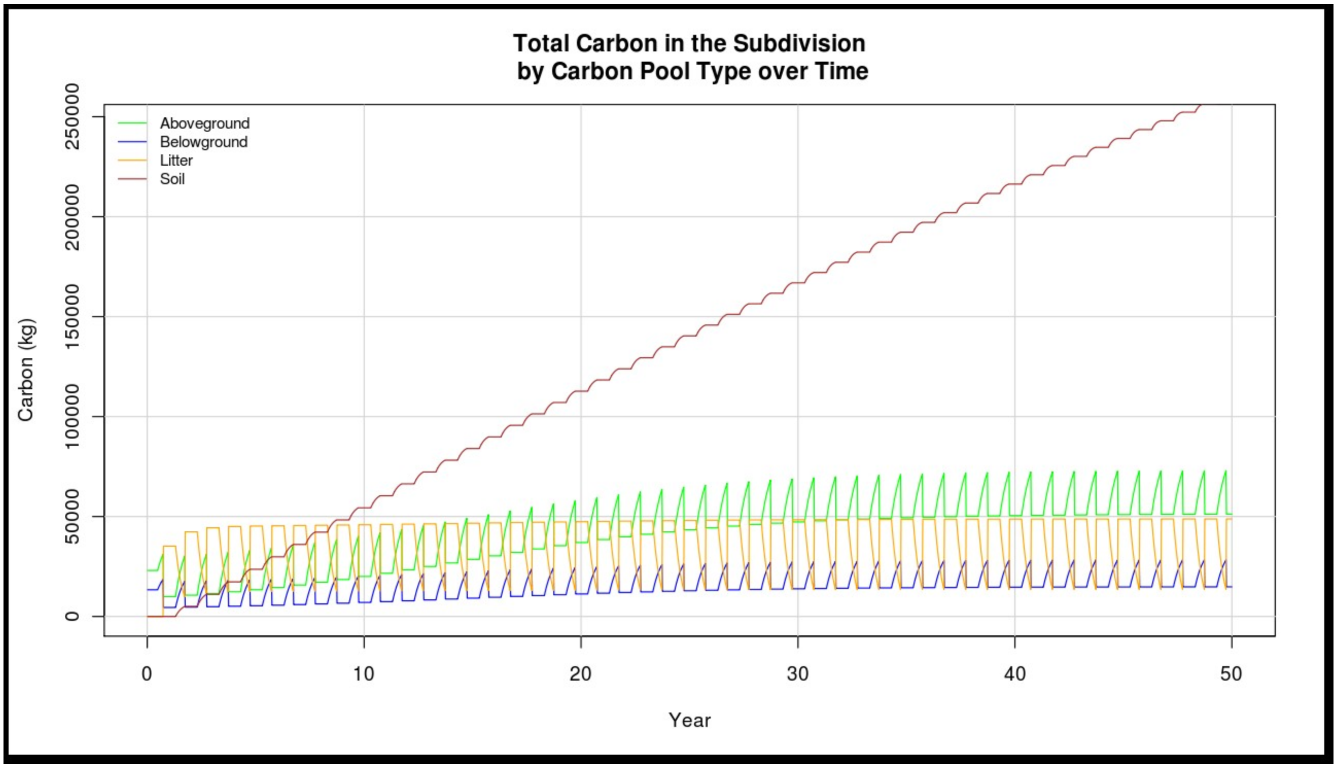
Random Seed: 4390116

Figure 20: Tier-0 Sample Run: Prairie Carbon Pools – 50 Years



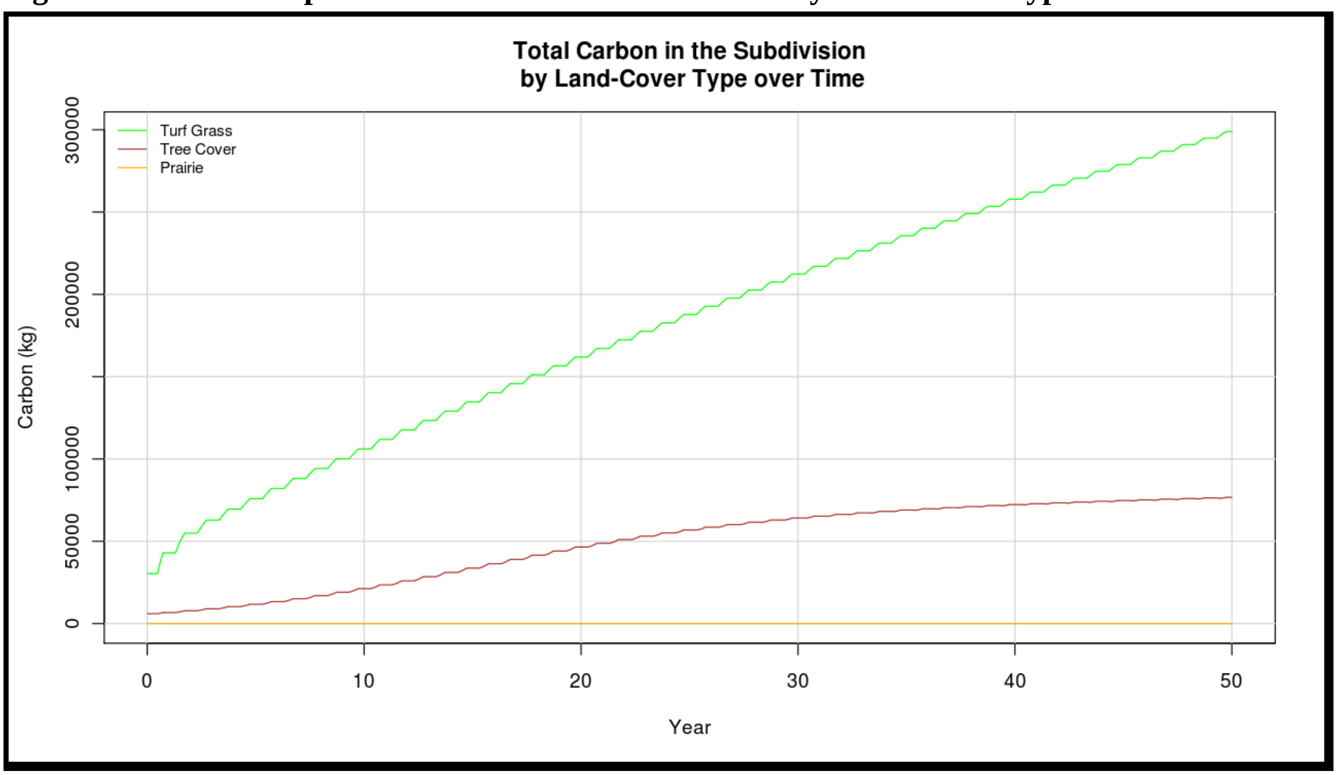
Random Seed: 4390116

Figure 21: Tier-0 Sample Run: Total Subdivision By Carbon Pool – 50 Years



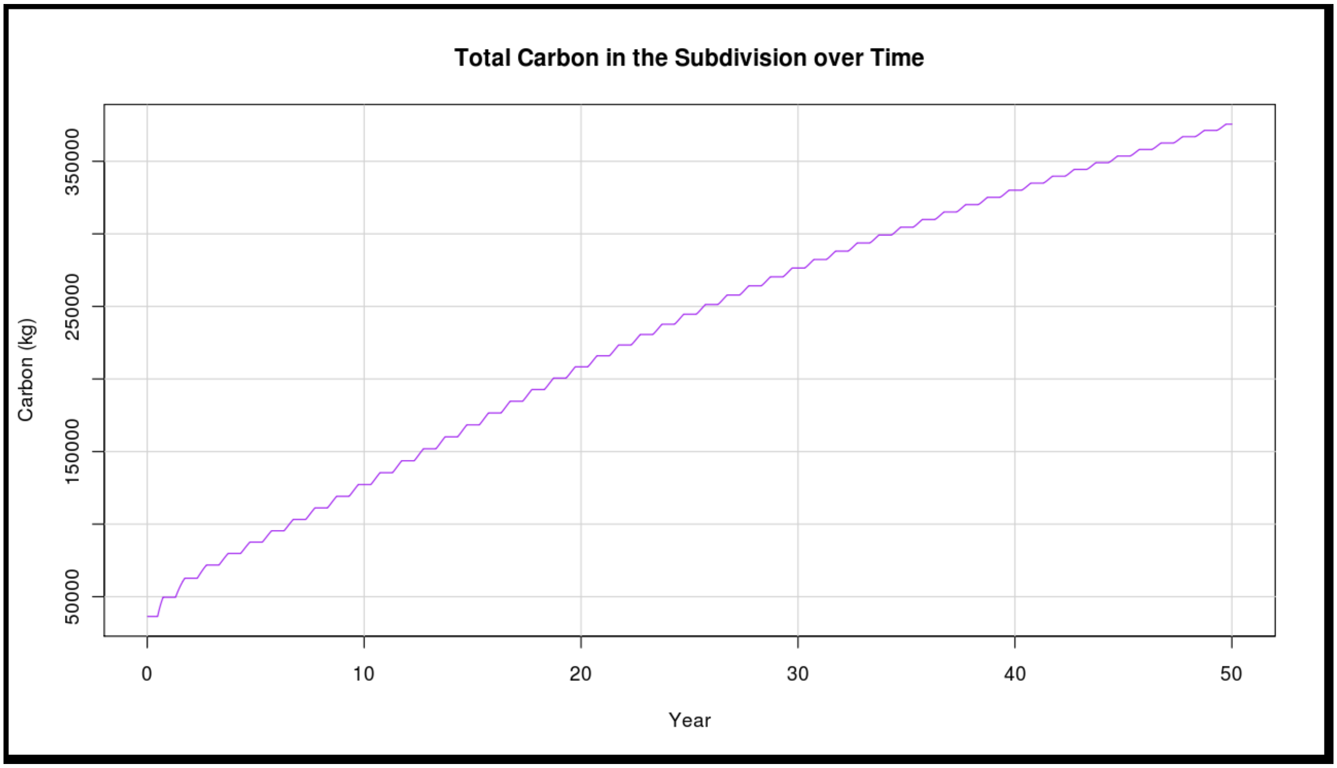
Random Seed: 4390116

Figure 22: Tier-0 Sample Run: Total Subdivision Carbon By Land-Cover Type – 50 Years



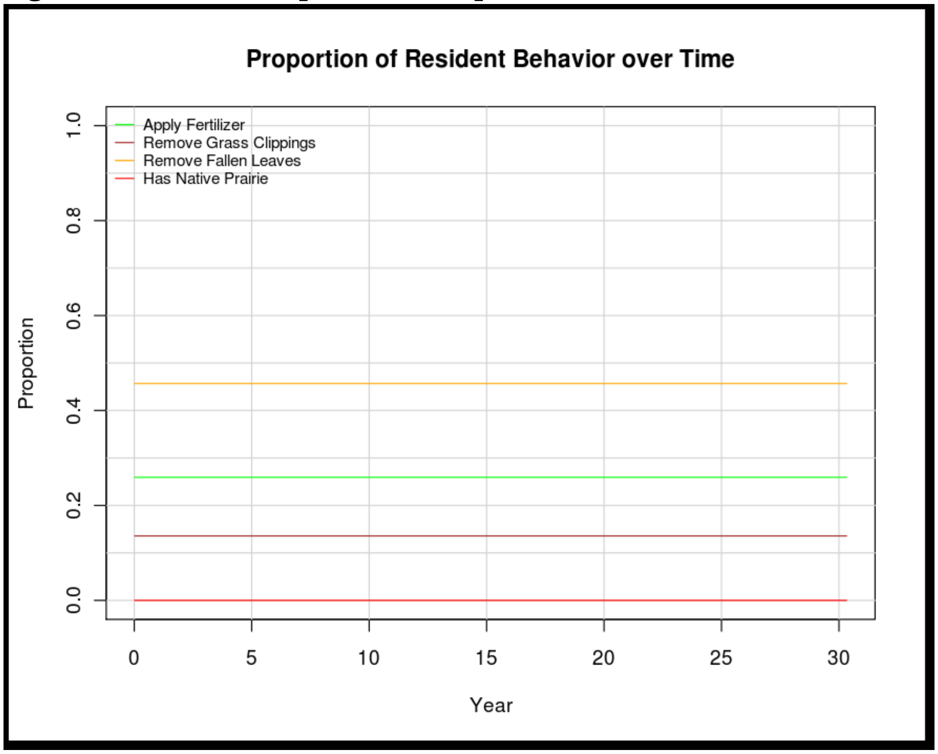
Random Seed: 4390116

Figure 23: Tier-0 Sample Run: Total Subdivision Carbon – 50 Years



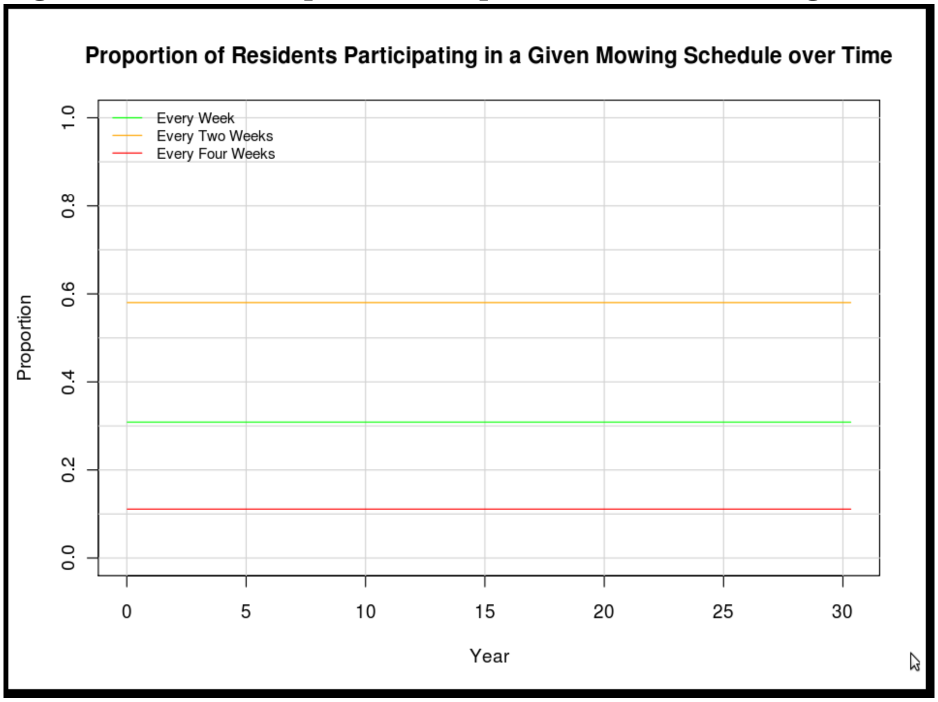
Random Seed: 4390116

Figure 24: Tier-1 Sample Run: Proportion of Resident Behaviors – 30 Years



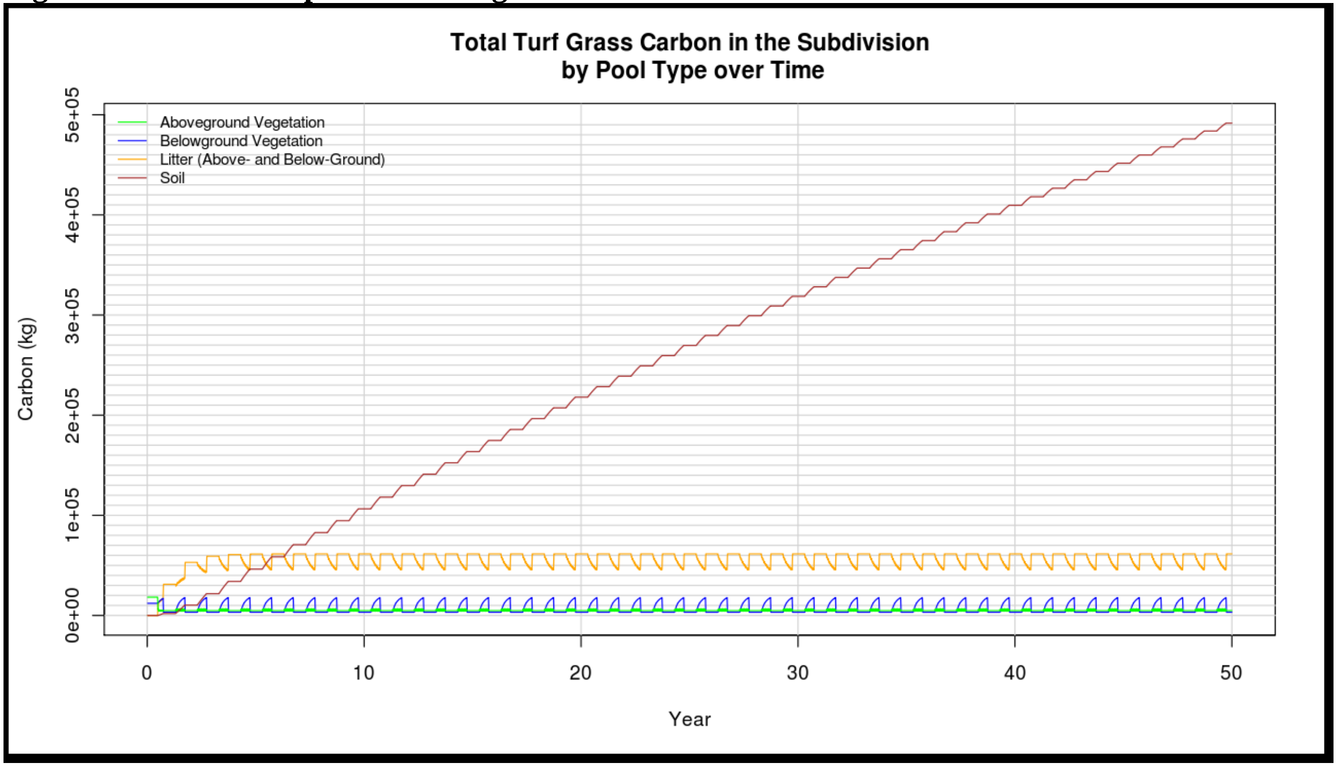
Random Seed: 4390116

Figure 25: Tier-1 Sample Run: Proportion of Lawn Mowing Schedules – 30 Years



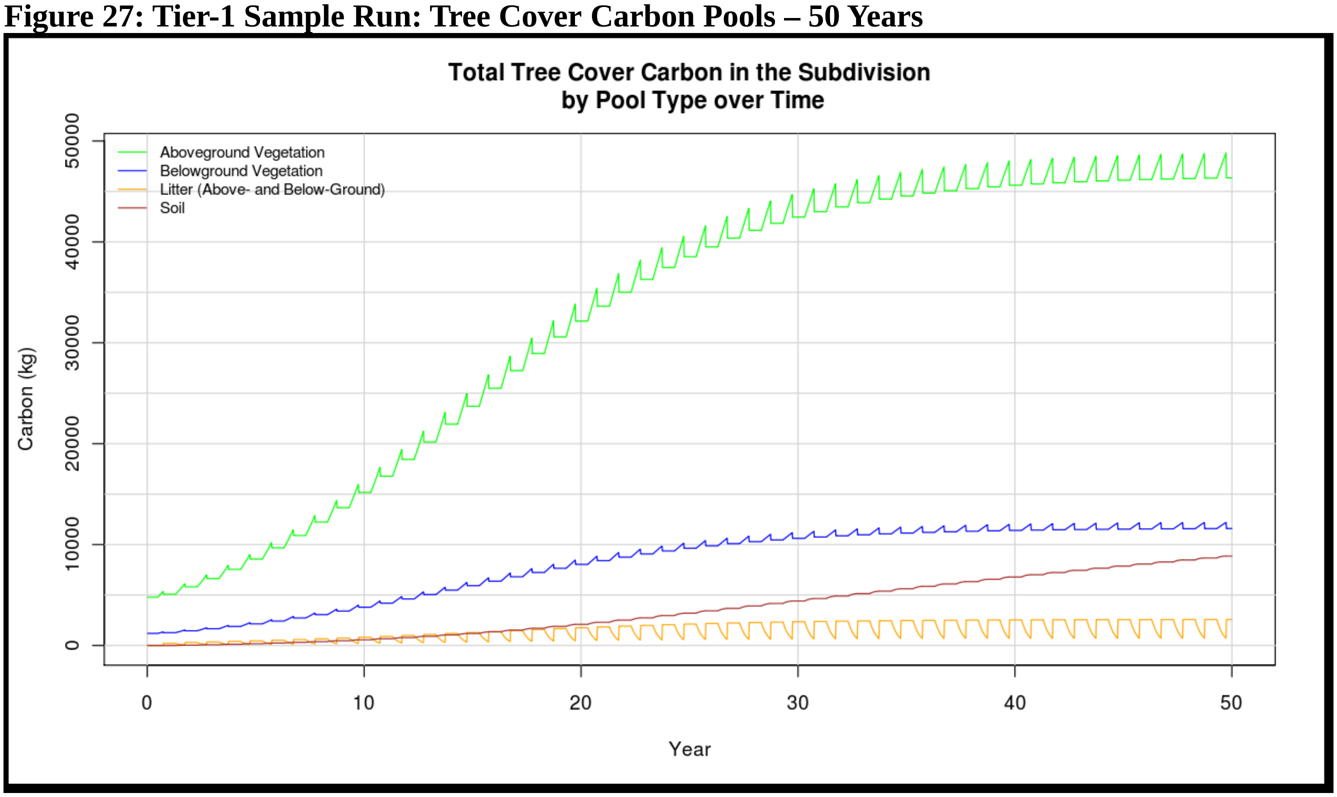
Random Seed: 4390116

Figure 26: Tier-1 Sample Run: Turfgrass Carbon Pools – 50 Years



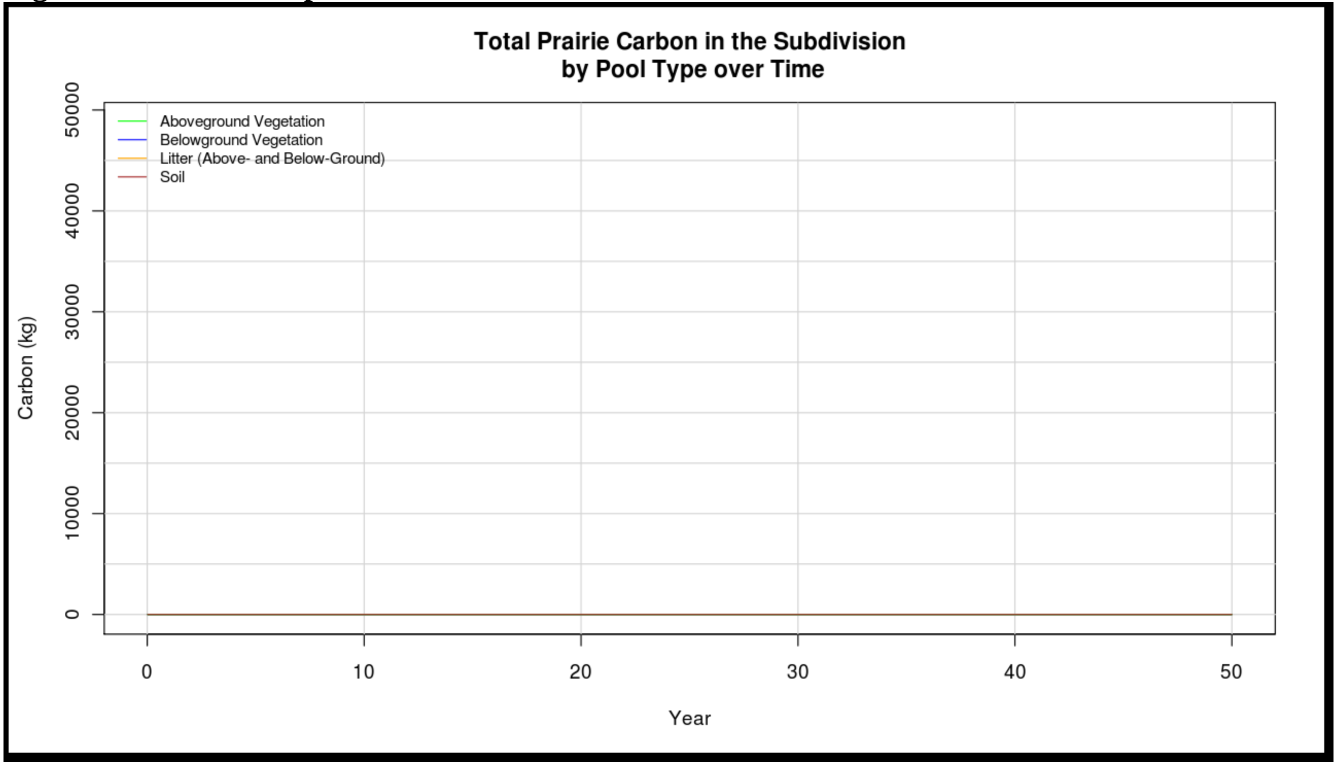
Random Seed: 4390116

Figure 27: Tier-1 Sample Run: Tree Cover Carbon Pools – 50 Years



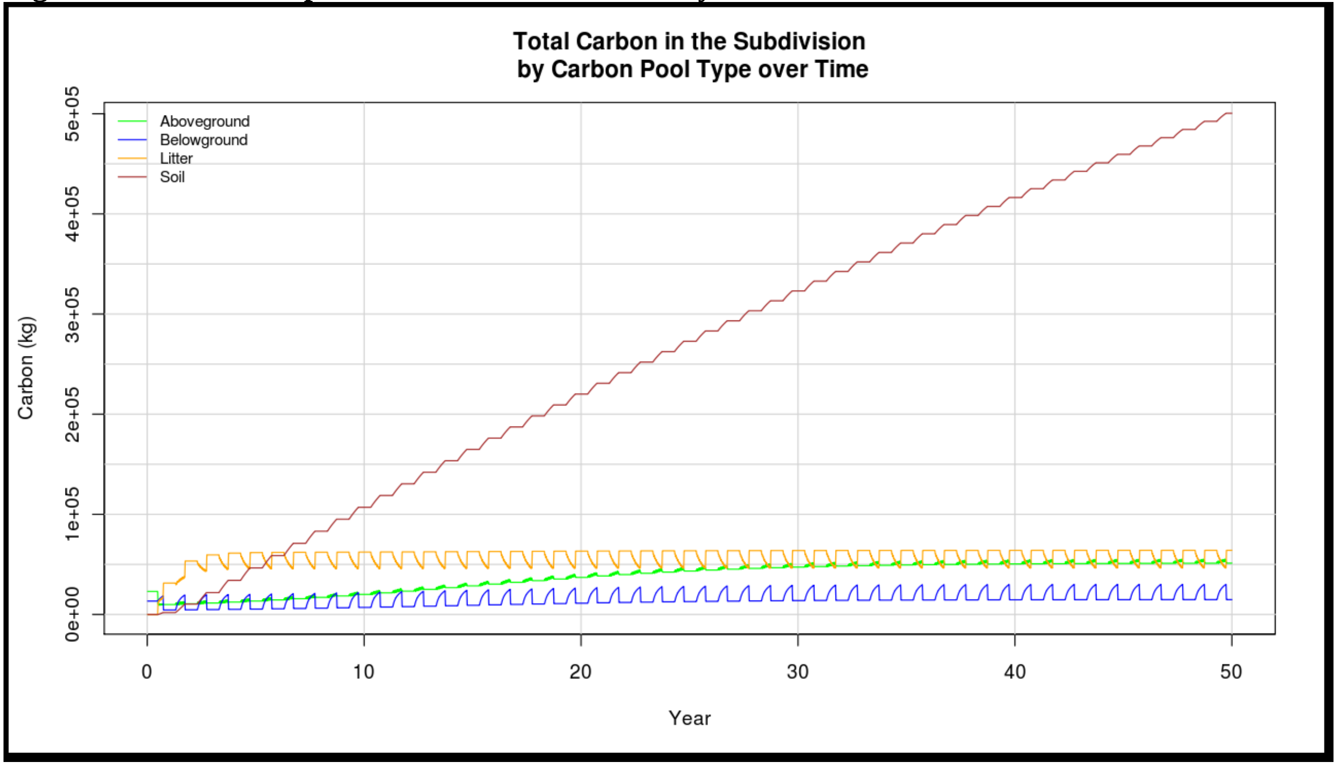
Random Seed: 4390116

Figure 28: Tier-1 Sample Run: Prairie Carbon Pools – 50 Years



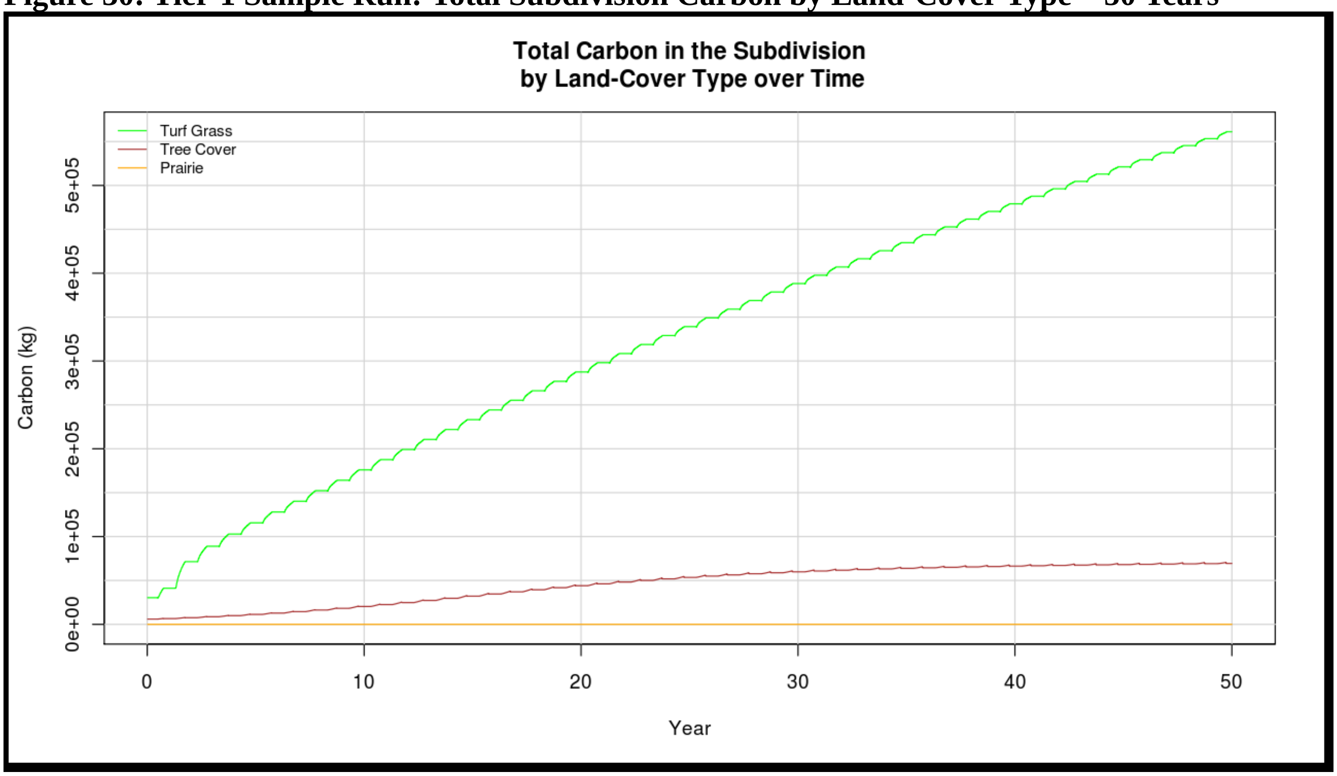
Random Seed: 4390116

Figure 29: Tier-1 Sample Run: Total Subdivision By Carbon Pool – 50 Years



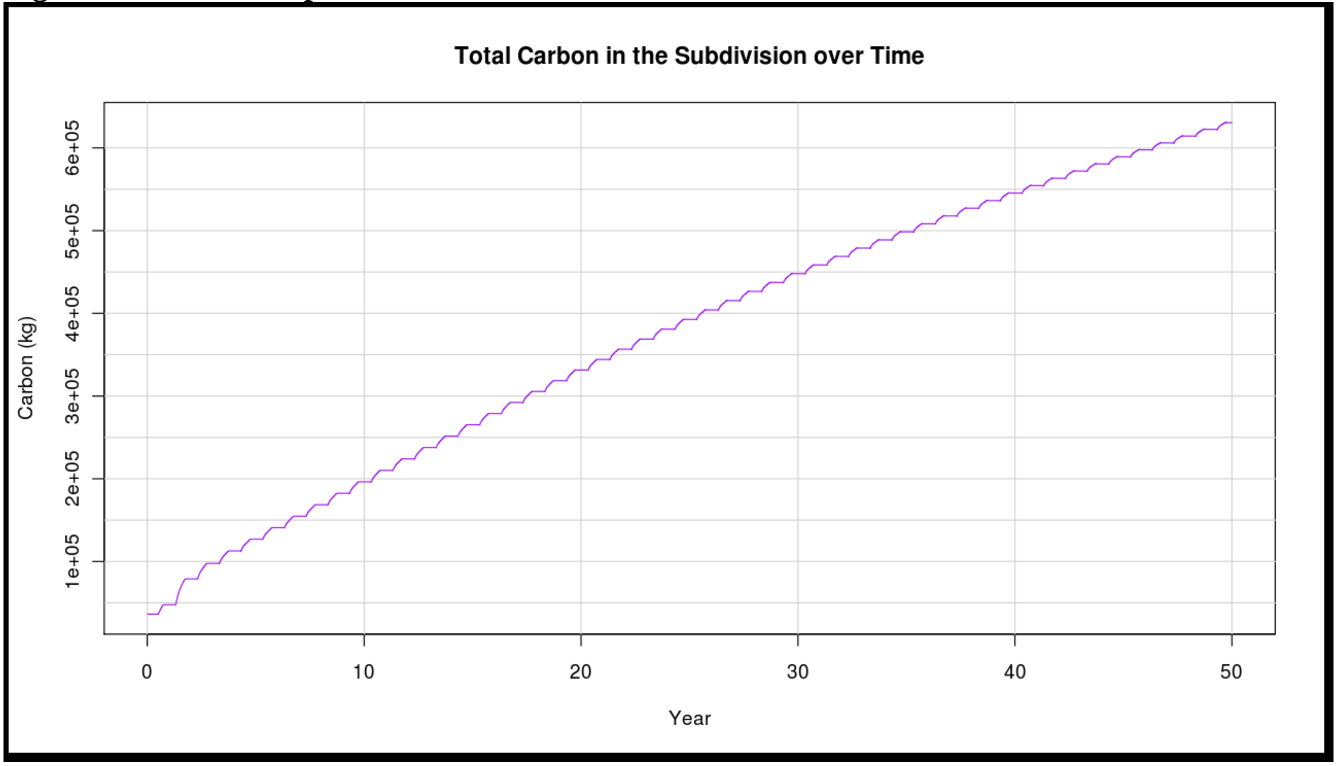
Random Seed: 4390116

Figure 30: Tier-1 Sample Run: Total Subdivision Carbon by Land-Cover Type – 50 Years



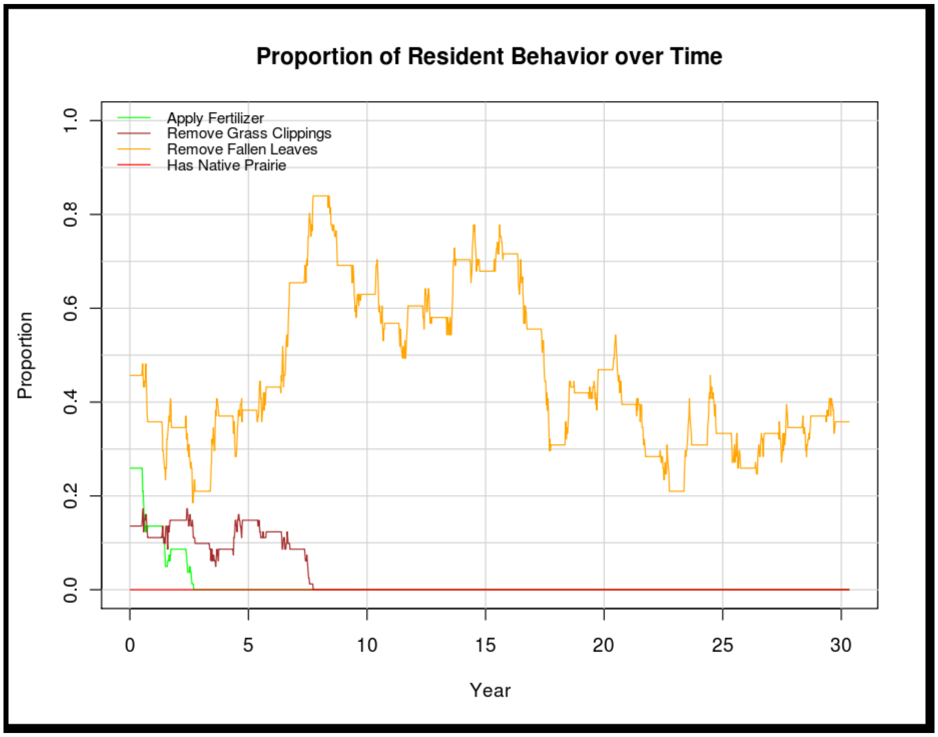
Random Seed: 4390116

Figure 31: Tier-1 Sample Run: Total Subdivision Carbon – 50 Years



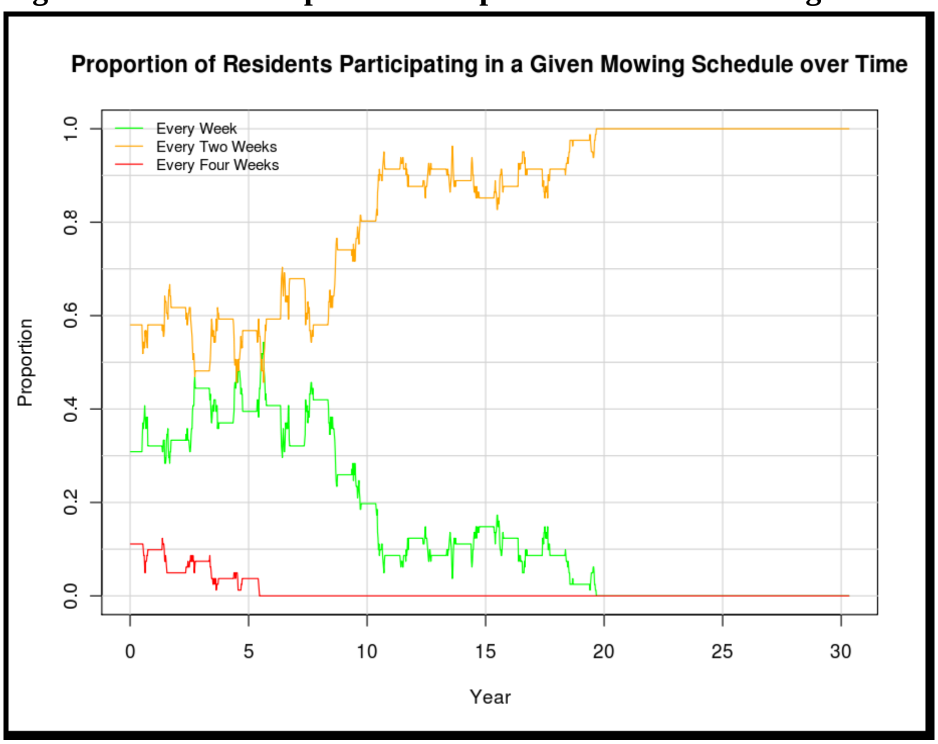
Random Seed: 4390116

Figure 32: Tier-2 Sample Run: Proportion of Resident Behaviors – 30 Years



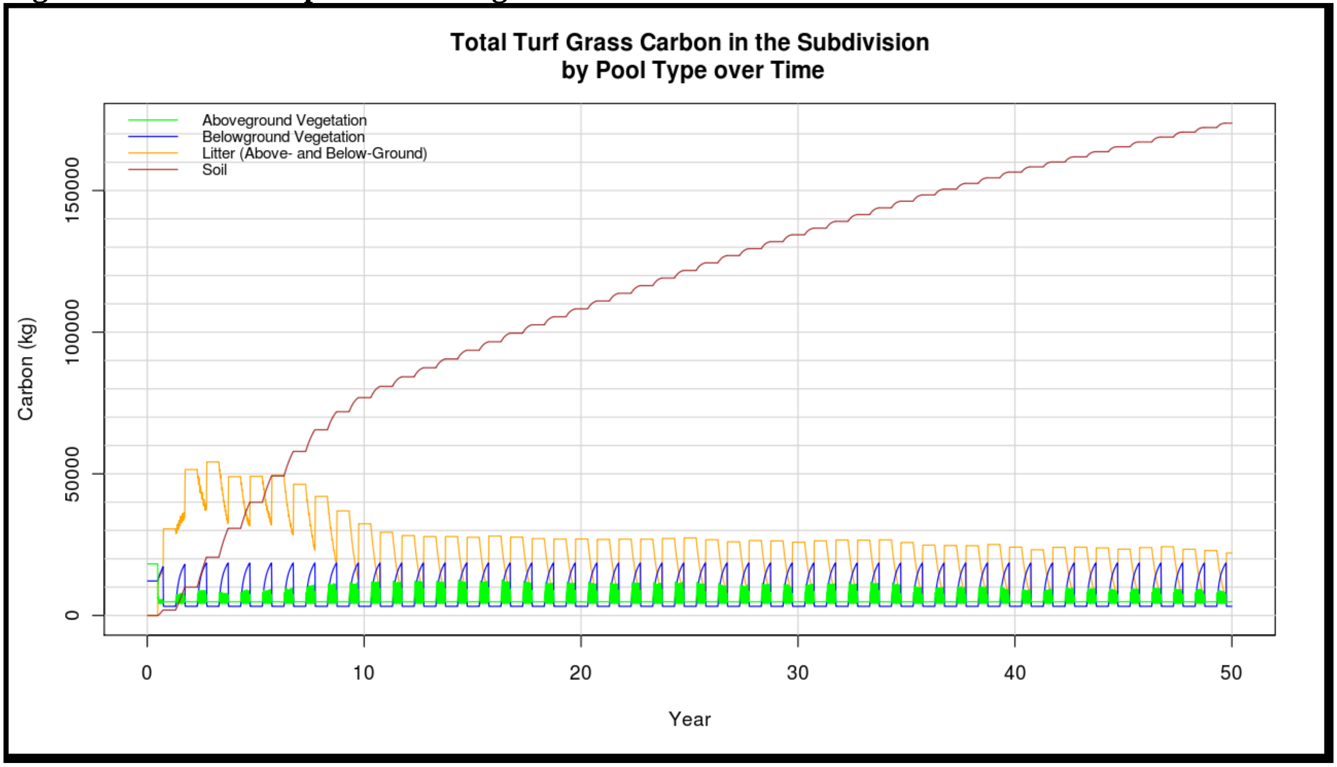
Random Seed: 4390116

Figure 33: Tier-2 Sample Run: Proportion of Lawn Mowing Schedules – 30 Years



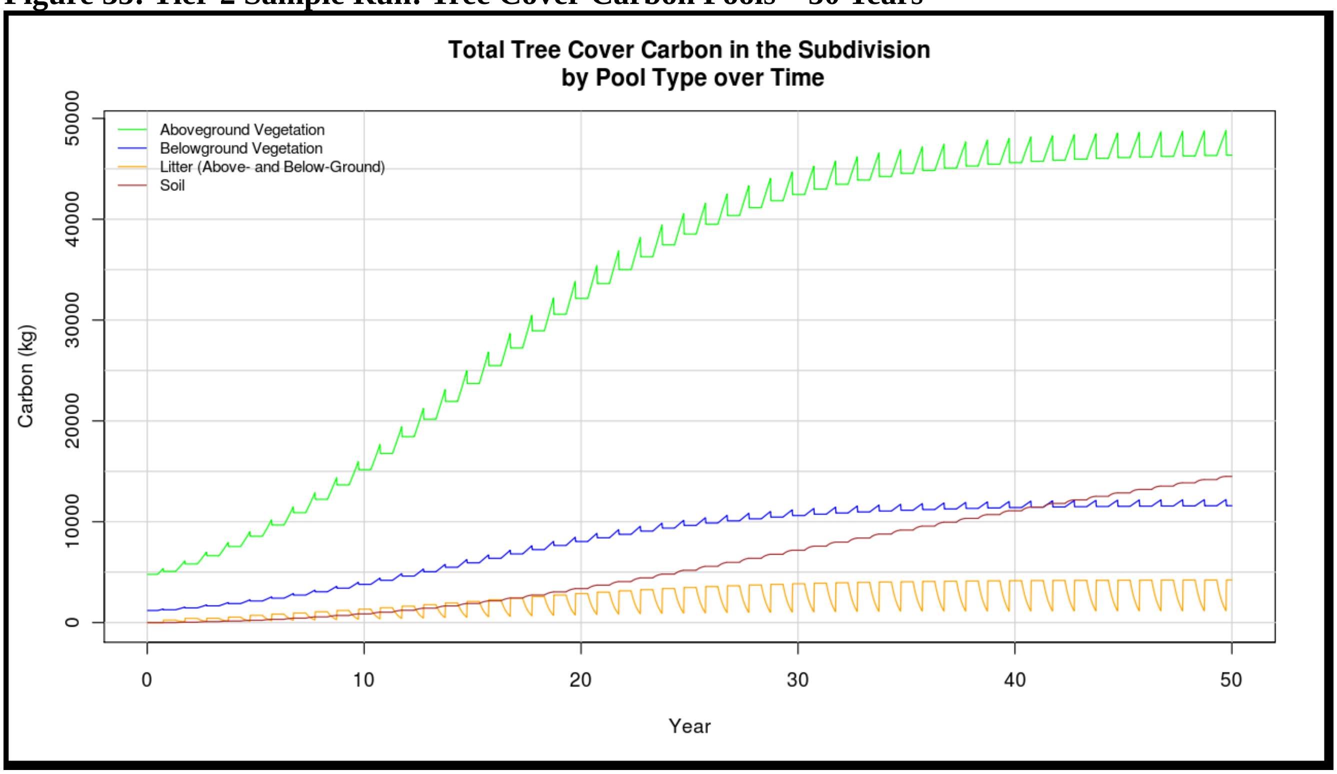
Random Seed: 4390116

Figure 34: Tier-2 Sample Run: Turfgrass Carbon Pools – 50 Years



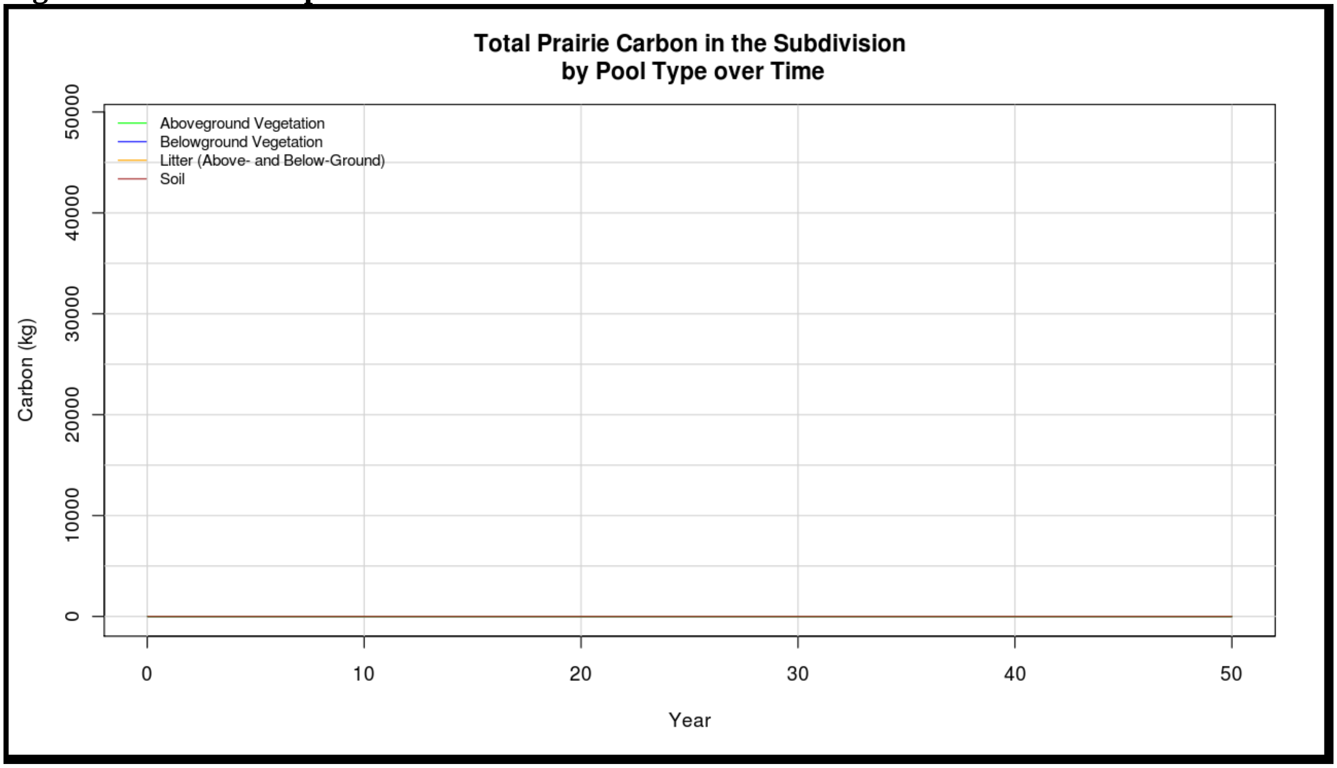
Random Seed: 4390116

Figure 35: Tier-2 Sample Run: Tree Cover Carbon Pools – 50 Years



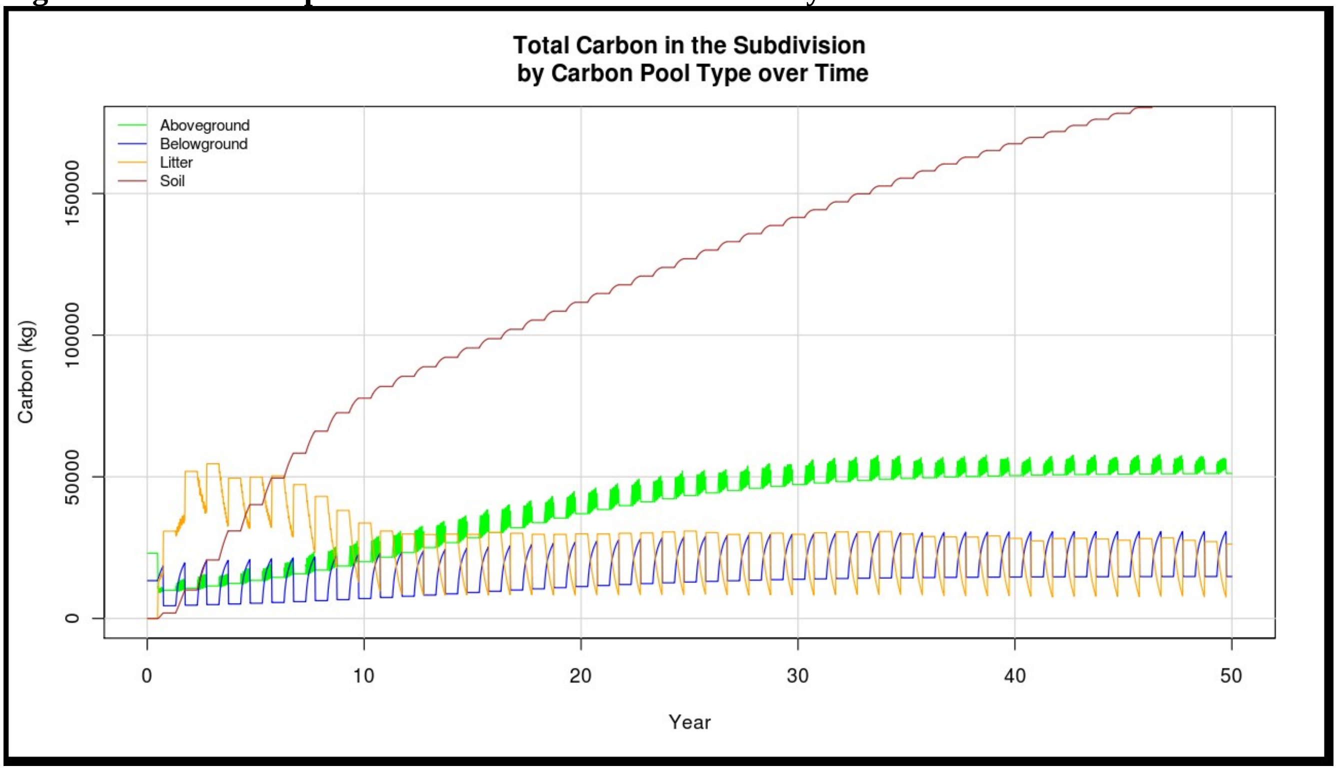
Random Seed: 4390116

Figure 36: Tier-1 Sample Run: Prairie Carbon Pools – 50 Years



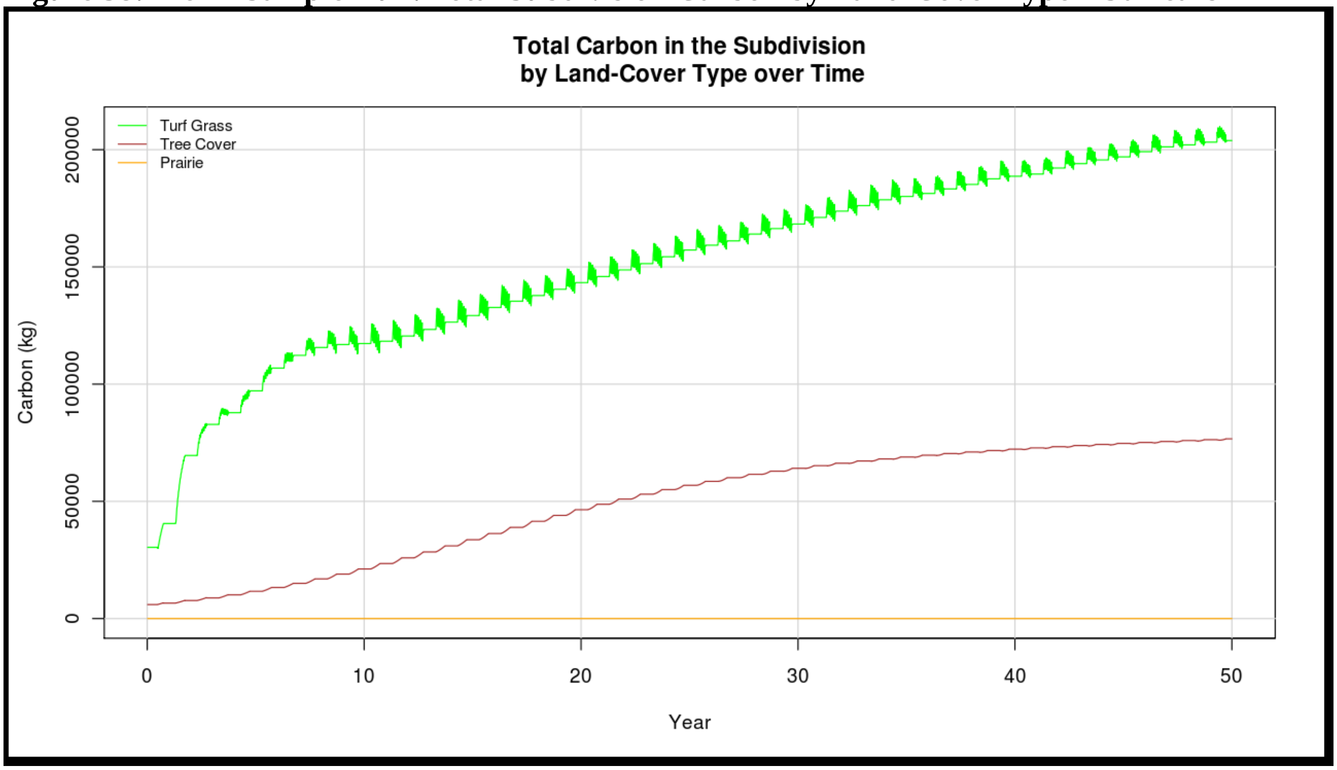
Random Seed: 4390116

Figure 37: Tier-2 Sample Run: Total Subdivision Carbon by Carbon Pool – 50 Years



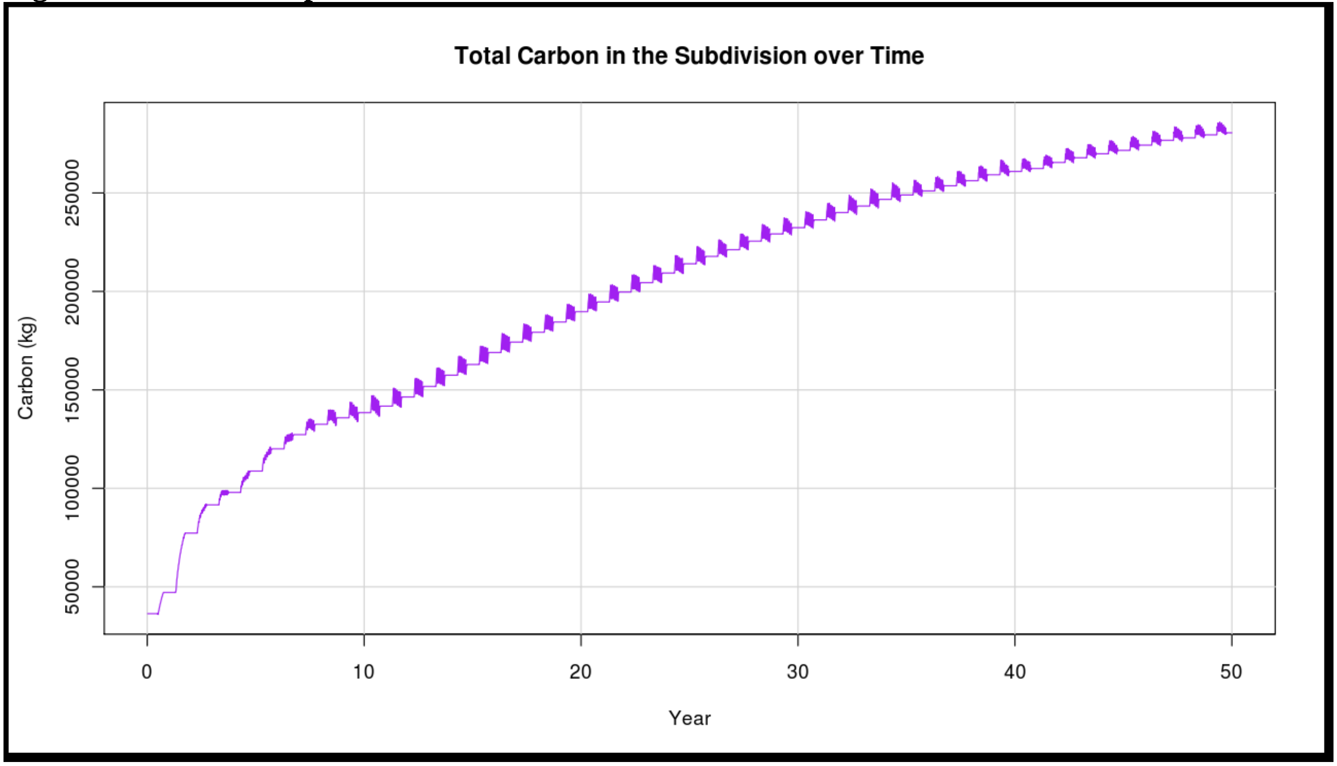
Random Seed: 4390116

Figure 38: Tier-2 Sample Run: Total Subdivision Carbon by Land-Cover Type – 50 Years



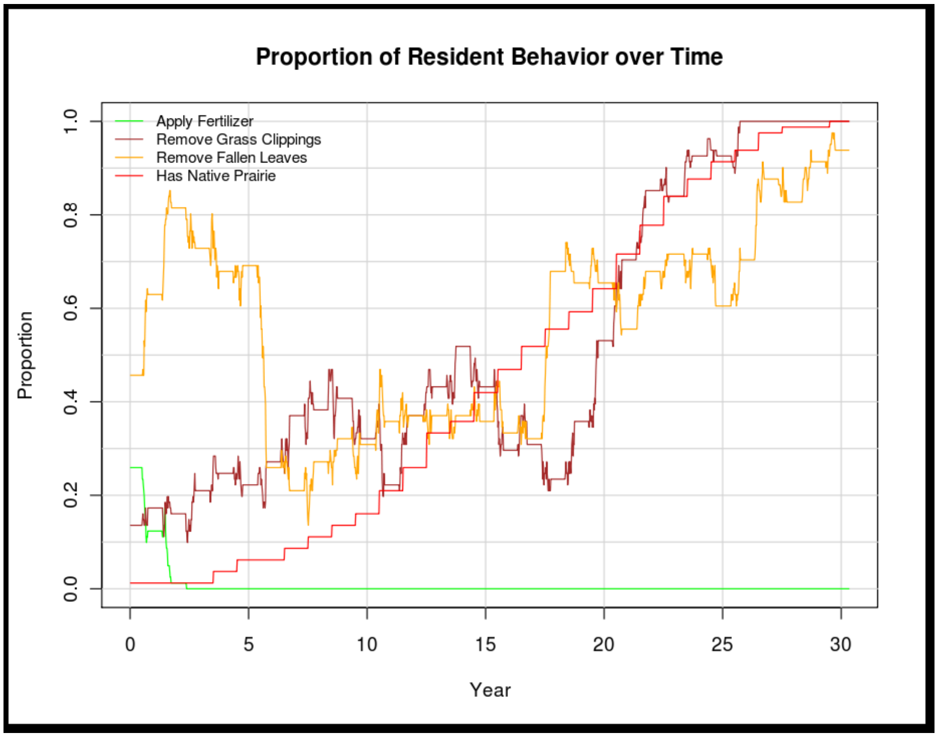
Random Seed: 4390116

Figure 39: Tier-2 Sample Run: Total Subdivision Carbon – 50 Years



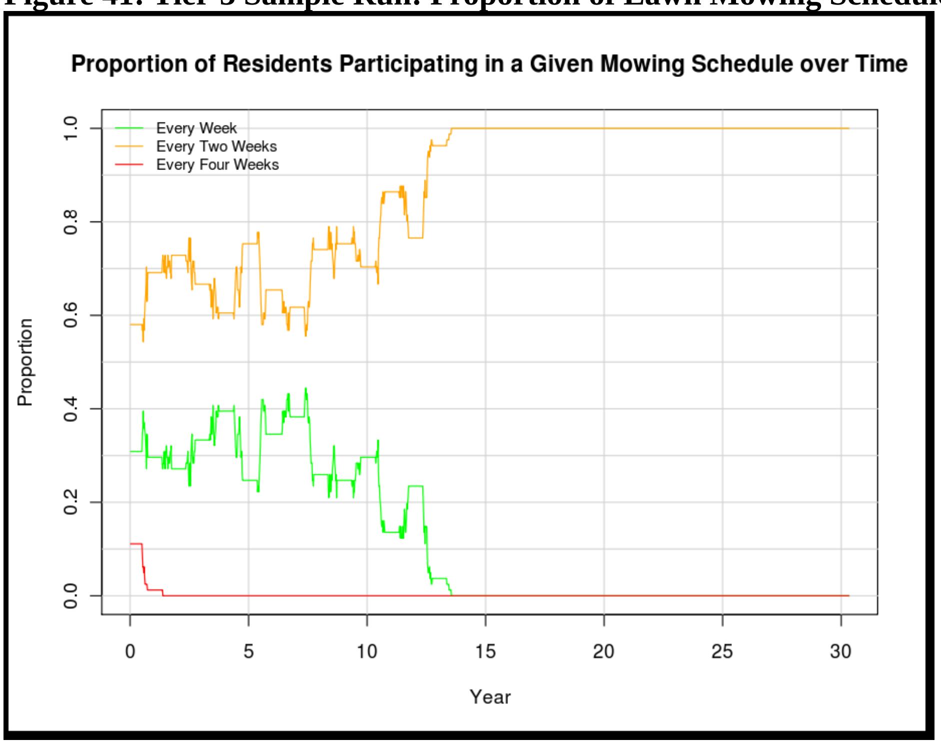
Random Seed: 4390116

Figure 40: Tier-3 Sample Run: Proportion of Resident Behaviors – 30 Years



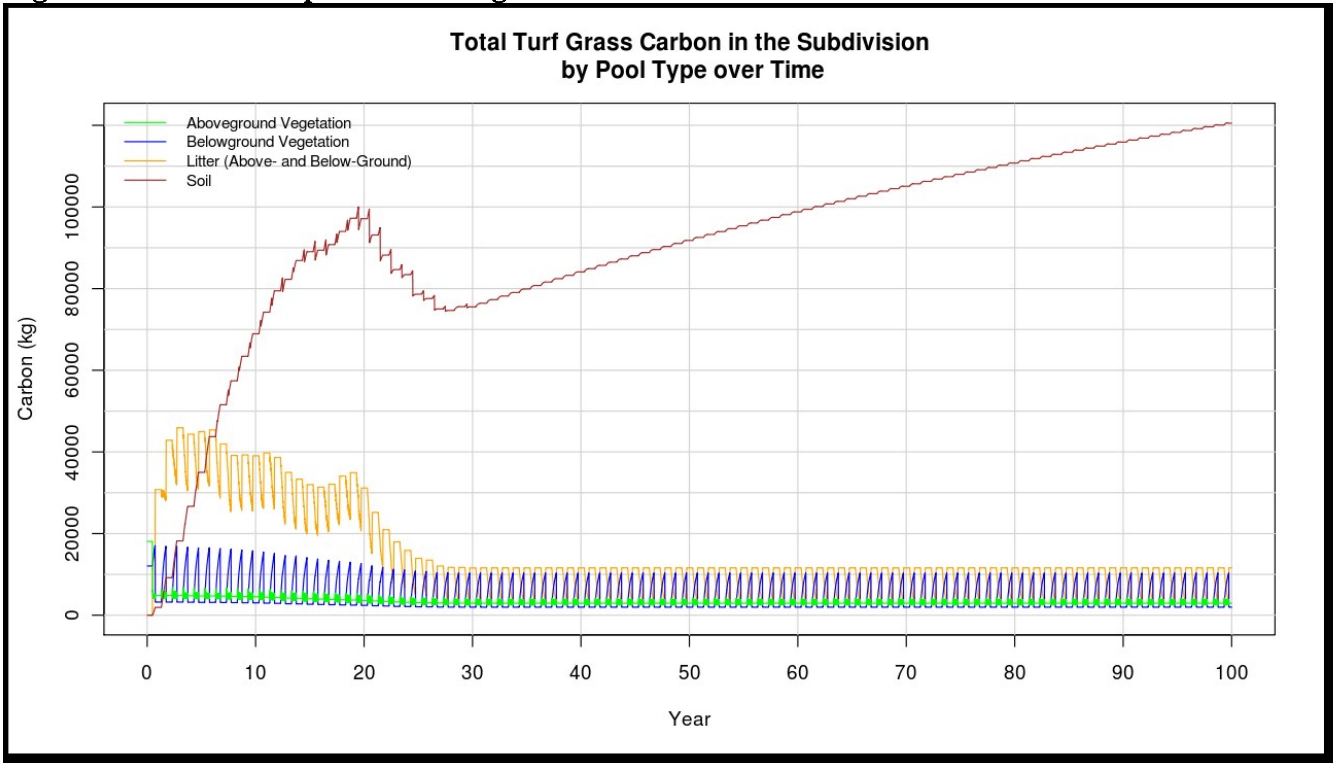
Random Seed: 4390116

Figure 41: Tier-3 Sample Run: Proportion of Lawn Mowing Schedules – 30 Years



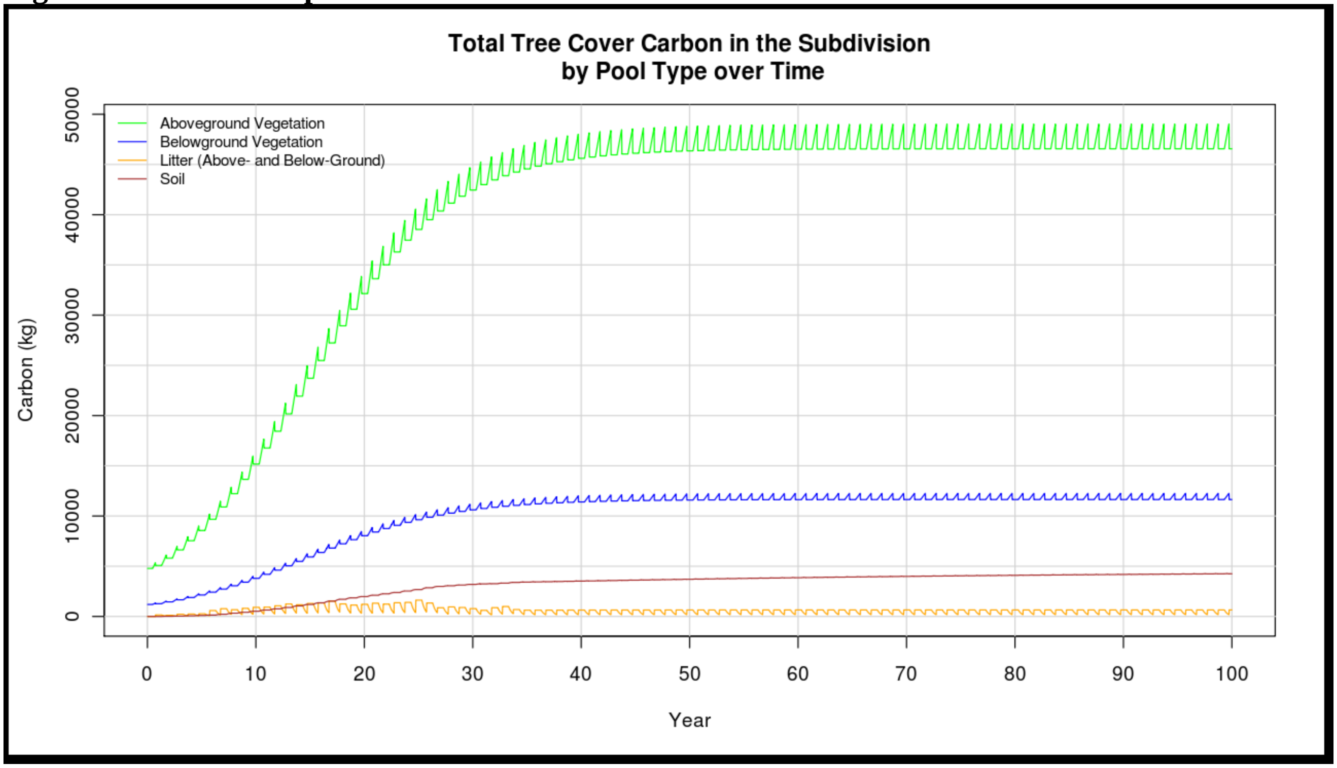
Random Seed: 4390116

Figure 42: Tier-3 Sample Run: Turfgrass Carbon Pools – 50 Years



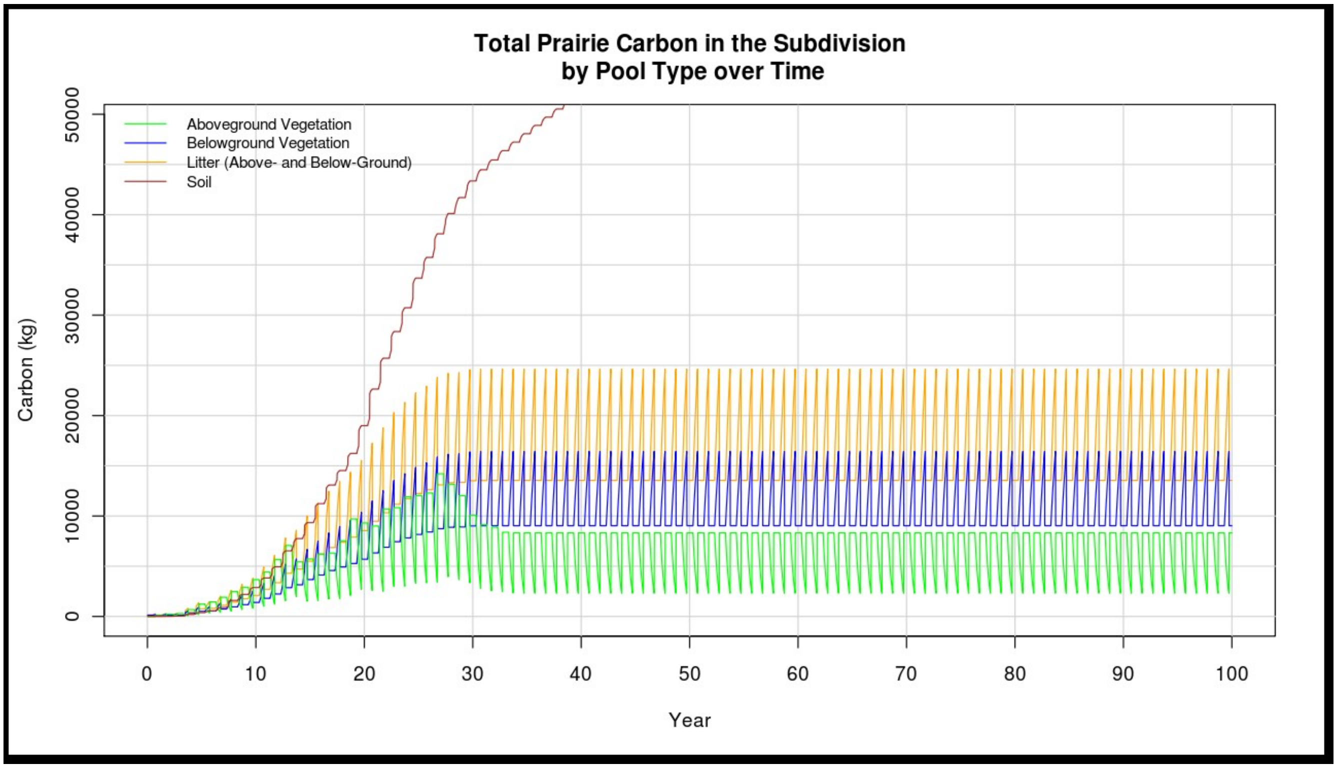
Random Seed: 4390116

Figure 43: Tier-3 Sample Run: Tree Cover Carbon Pools – 50 Years



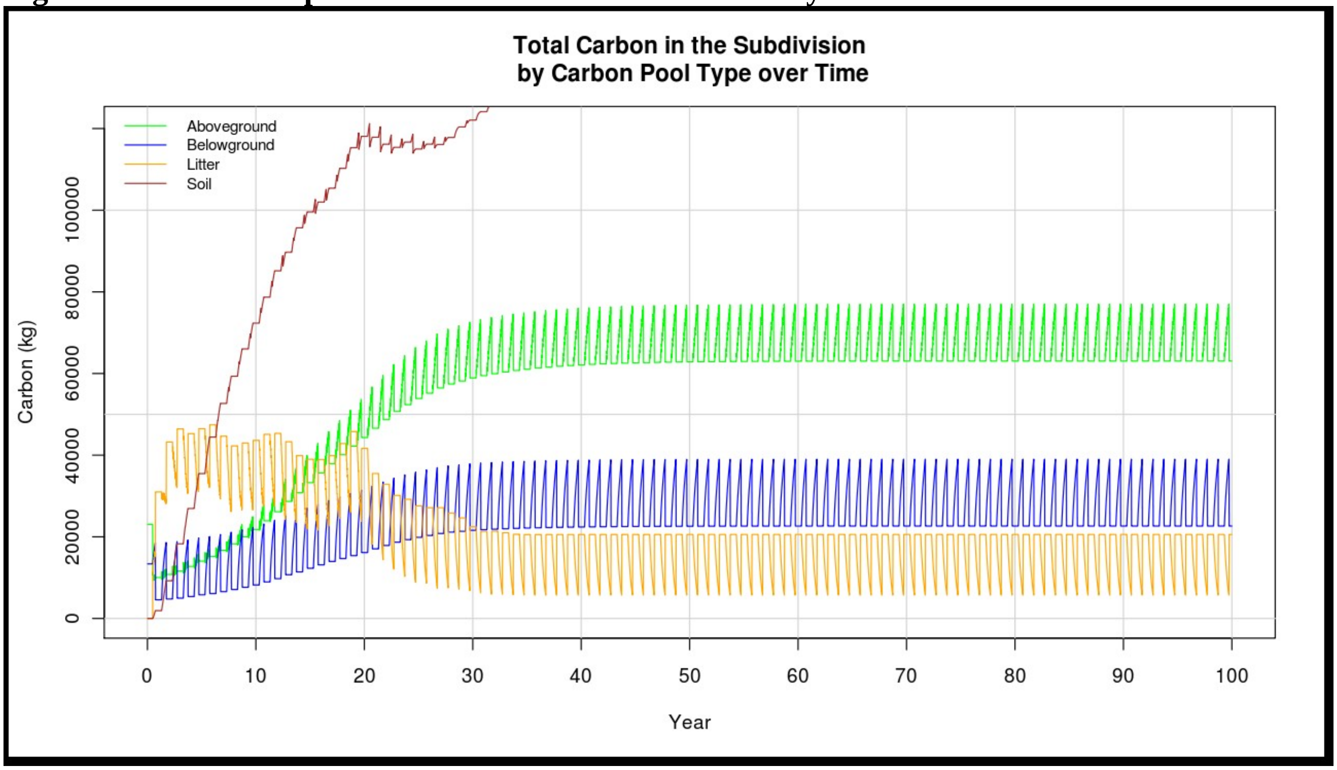
Random Seed: 4390116

Figure 44: Tier-3 Sample Run: Prairie Carbon Pools – 50 Years



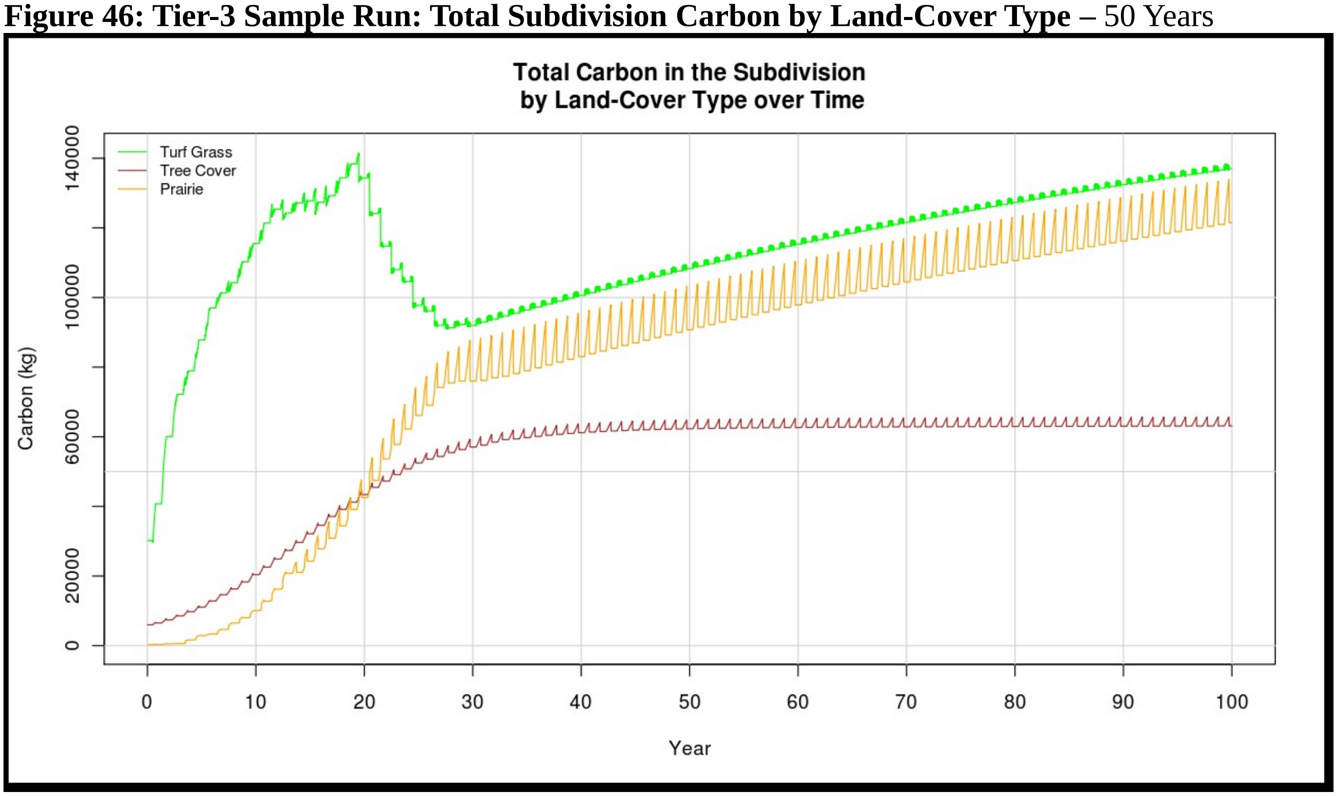
Random Seed: 4390116

Figure 45: Tier-3 Sample Run: Total Subdivision Carbon by Carbon Pool – 50 Years



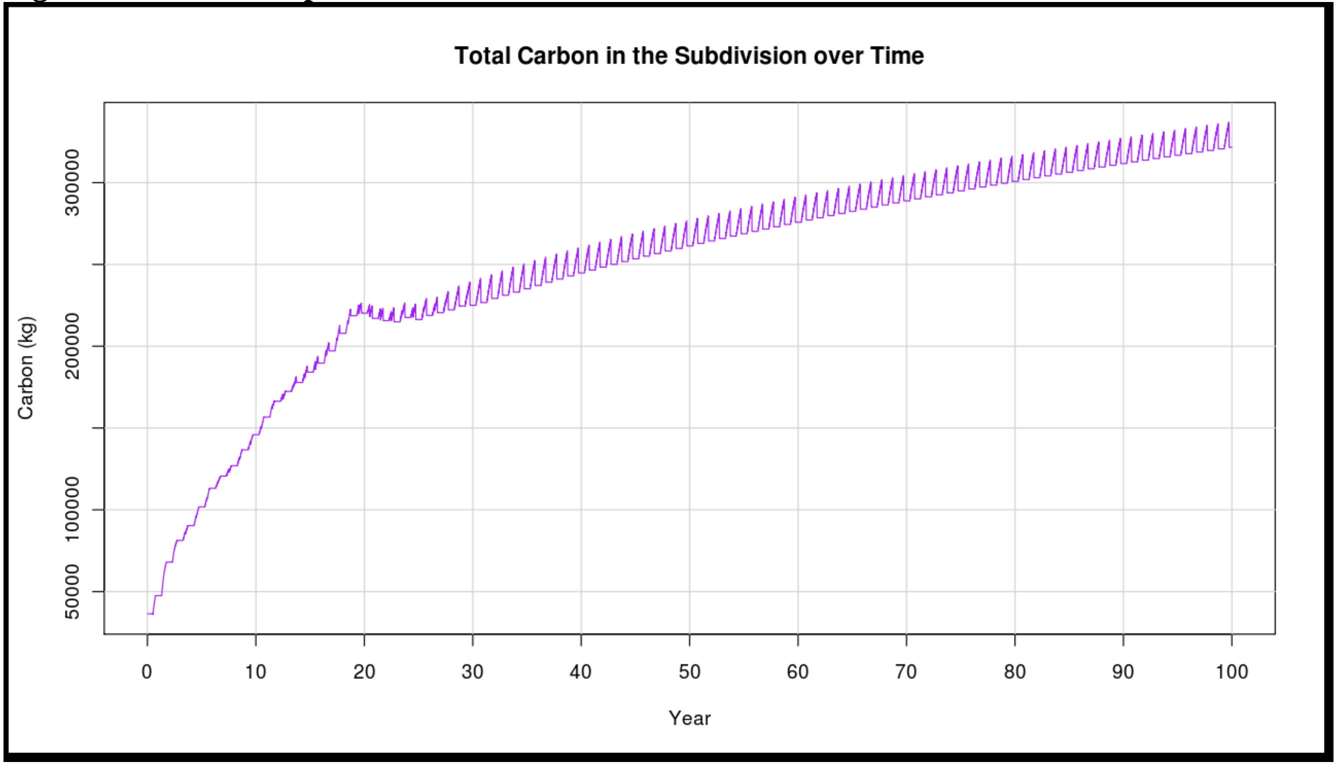
Random Seed: 4390116

Figure 46: Tier-3 Sample Run: Total Subdivision Carbon by Land-Cover Type – 50 Years



Random Seed: 4390116

Figure 47: Tier-3 Sample Run: Total Subdivision Carbon – 50 Years



Random Seed: 4390116