Adapting an Ecosystem Process Model to Estimate Ecosystem Services in Exurban Ecosystems

by

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Dedication

To my family,

Dan, Nicholas, and Josie

Acknowledgements

During the time it has taken me to complete this dissertation my life has seen the highest of highs and the lowest of lows. Words cannot express my gratitude for all of the family, friends, and colleagues who have stayed by me for this wild ride and have helped me achieve this milestone. The most important lesson this journey has taught me is that being successful mother, partner, colleague, or scientist doesn't happen in a vacuum - letting others in will allow you to flourish.

I can still remember the first time I talked to my advisor, Bill Currie, on the phone for an informal interview before I applied to UM. I had seen a job posting on a listserv that led to an hour-long conversation about ecological modelling, integrating models across disciplines, and systems thinking. Up to this point I didn't know where my next step would take me, but after we talked, I immediately applied to the program. Bill's shared enthusiasm for modelling and perspectives on integrating humans into ecological systems has driven my research. I cherish all of our long office meetings where we discussed not only science but our lives. He has been an amazing advisor and mentor. I know I have made it this far because of all the behind the scenes battles he fought on my behalf and I'm lucky to have him in my corner.

The origin of my dissertation research came out of the SLUCE project, which was led by three of my committee members – Bill Currie, Dan Brown, and Joan Nassauer. SLUCE project meetings were the highlight of my first years at UM. Being able to witness the integration of all of my research interests in one room was inspiring. I learned so much from meetings and classes with Dan Brown that I will continue to use in the future. Joan Nassauer is a superstar.

Collaborating and sitting on committees with her has taught me to how to manage ownership of my work and how to stand up for myself in a room full of colleagues. The research she has done on social-ecological systems continues to broaden my understanding of social science beyond economics. I also appreciate my other colleagues on the SLUCE project including Derek Robinson, Megan Hutchinson, Shipeng Sun, Dawn Parker, and the late Rick Riolo.

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Over the years I've had the pleasure of meeting countless grad students and postdocs in Currie Lab and our lab mates from the Ibáñez lab. A special thank you to Currie Lab members Stephanie Hart who supportive of me when I was dealing with everything life decided to throw at me; Kyle Wittinghill who took me under her wing at ESA meetings; Liza Jenkins, who could empathize with my work-life struggles; Jason Martina who always was there to answer my questions; and Stephanie Hart former lab manager who motivated me when things were tough. Thanks to Ben Conner-Barrie, Daniel Katz, and Ben Lee from the Ibáñez lab for fostering great conversations about science and life.

My research could not have been accomplished without the following sources that allowed me to pursue the work on this dissertation: The Rackham Graduate School dissertation fellowship and travel grants, the School of Environment and Sustainability fellowship and travel grants and The National Science Foundation Coupled Human and Natural Systems Program. I

would like to acknowledge that the University of Michigan resides on the traditional Territories of the Three Fire Peoples - the Ojibwe, Odawa, and Bodewadmi. As I work, live, and learn on these territories I resolve to acknowledge that myself and my research has benefited from access to land originally gained through exploitation of others. I also am grateful for the services provided by the SNRE/SEAS staff, especially all the help offered by Jennifer Taylor and Diana Woodworth. Many other SNRE/SEAS members were instrumental to my success including faculty - Michael Moore, Michaela Zint, Don Zak; postdocs - Ginger Allington; and PhDs - John Graham, Dan Obenour, Laura Smith, Irem Daloglu. I also owe appreciation to my former advisors and mentors from The Ohio State University, especially Fred Hitzhusen, Richard Moore, and Maria Miriti.

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I am full of gratitude for my girlfriends who have been there for me through it all, never have let me give up, and always offer to help. Sara Hadavi's thoughtfulness always amazes me and her research on the benefits of natural spaces always reminds me to get out from behind the desk and back outdoors. Silvia Cordero-Sancho was the first friend I made at UM and today is one of my closest. She offers advice on science, plays fun auntie for my kids, and is always there when I need a coffee break. M'Lis Bartlett always has an ear available for listening and letting me talk out what I'm working through. Preeti Rao got me across the finish line by reading drafts, helping me formulate cohesive arguments, watching my kids, and feeding me. I will be forever grateful she everything these women have done for me these last few months and for the happy memories they have given me and my family.

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Finally, my eternal thanks to my husband, Dan, whose encouragement brought me to Michigan and whose wisdom helped me get through the end. And, to my two kids, Nicholas and Josie, I love them dearly and think them for being amazingly patient with me during my writing days. For them dissertation meant "mom stares at the computer for hours" and graduation means "cake and a puppy" and that mom will officially be a "nature doctor". I hope someday they will truly understand the real meaning of this endeavor.

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Abstract

Ecosystem services (ES) are the physical goods and associated benefits that are provided to humans by ecological systems. Assessment of ES requires knowledge of ecology and ecosystem processes, and ES estimates can be improved when they include knowledge of nonlinearities, feedbacks, and interactions within ecosystems. A variety of assessment tools have been proposed to estimate the provision of ES. However, they fail to acknowledge interconnectedness of services or connections between ecosystem processes and services.

This dissertation examines connections of ecosystem processes and ES with the assumption that knowledge of ecosystem ecology and ecosystem processes can be applied to improve estimates of ES capacity over time and under a variety of management scenarios. To investigate this connection, I modified the ecosystem process model Biome-BGC to simulate the provision of ES in exurban Southeastern Michigan. The modification resulted in a new version of the model, Biome-BGC-Ex, and involved detailed changes to the source code. The modified model included the ability to model competition between turfgrass and open grown trees in a single grid cell, to incorporate residential management practices, and to translate model outputs into well-defined, quantitative estimates of ES.

My research was conducted as part of a larger collaboration, the SLUCE (Spatial Land Use Change and Ecological Effects) project and addresses the exurban residential landscape as a coupled human-natural system. It references and builds on previous elements of the SLUCE project including an empirical ecological field study, developer and homeowner interviews, web-based surveys, and modeling in a coupled human-natural system framework. My contributions to

the project, specifically modifying Biome-BGC and linking it to ES, can be applied to future research on coupled human-natural systems in exurban residential landscapes.

Chapter two describes how Biome-BGC was modified for the exurban landscape and then calibrated and parameterized for Southeastern Michigan. It examined which yard management practices have the greatest effect on carbon sequestration and model results suggested N fertilization was the strongest driver across three major vegetation types. Chapter three describes how Biome-BGC-Ex was modified to estimate ES capacity of ten services and evaluated the impact of yard management practices on ES capacity. Model simulations showed trade-offs between ES relating to high amounts of carbon or biomass and freshwater recharge. Chapter four took a broader approach and evaluated ecosystem process models as a potential tool for ES assessment and discussed how the integration of Biome-BGC-Ex with other tools could improve ES assessment. I found that while process models can improve understanding of interconnected ecosystem processes and biophysical feedbacks that affect the production of ES, they require more detailed data and complex knowledge to run. These chapters also discuss limitations of Biome-BGC-Ex and its ability to adequately address ecological complexities of exurban landscapes. One major limitation was accurately modelling N dynamics of exurban tree cover and model simulations likely overestimating C sequestration under high levels of fertilization.

My dissertation research is the first to modify Biome-BGC to measure ES in a residential ecosystem. It is also novel because the work focuses on how human management of the landscape affects ES production as opposed to land use or land cover change. My dissertation research can likely be replicated in similar ecosystems to inform more complex ES modelling frameworks that rely on ES production modelling grounded in the understanding of ecosystem processes and their feedbacks.

Chapter 1
Introduction

1.1 Background & Overview

Broadly, this dissertation examines the connection of ecosystem processes and ecosystem services (ES) with the belief that knowledge of ecosystem ecology and ecosystem processes can be applied to the field of ES and improve the estimates of ES capacity over time and under a variety of management scenarios. To investigate this connection, I have modified the widely-used ecosystem process model, Biome-BGC, which was designed to represent primarily wildland terrestrial biomes, to simulate the provision of ES in the exurban residential landscape (Running and Hunt 1993, White et al. 2000, Thornton et al. 2002, Thornton and Rosenbloom 2005). The modification resulted in a new version of the model, Biome-BGC-Ex, and involved detailed changes to the source code of the original model. The modified version includes the ability to model the competition between turfgrass and open grown trees in a single grid cell, the introduction of residential management practices, and the translation of model outputs into well-defined, quantified estimates of ES.

Ecosystem services (ES) are the physical goods and associated benefits that are provided to humans by the ecosystems of the planet. ES assessment requires knowledge of ecology and ecosystem processes and estimates of ES can be improved when they include knowledge of nonlinearities, feedbacks, and interactions within ecosystems (Cumming et al. 2005). A variety of ES assessment tools and methods have been proposed to estimate the provision of ES and the goods and benefits they provide to society (see reviews and comparisons by Eigenbrod et al.

2010, Bagstad et al. 2013, Boerema et al. 2017, Sharps et al. 2017, Mandle et al. 2020 for further details). However, they neglect to acknowledge the interconnectedness of services or the connection between ecosystem processes and services (Seppelt et al. 2011, Bruins et al. 2017, Bennett 2017, Lavorel et al. 2017). Ecosystem process models are tools that simulate the storage and flux of energy, water, carbon (C), and nutrients that functionally link biotic and abiotic components within an ecosystem. ES assessment tools can be improved by including methods rooted in ecosystem science including ecosystem process modelling. This dissertation aims to fill this gap by taking a model that includes interconnected ecosystem processes and their biophysical feedbacks and using it to measure the provision of a suite of ES which fall into the supporting, provisioning, and regulating categories of ES. This approach allows for two main outcomes; first, it allows us to rely on our extensive knowledge of ecosystem processes, which we acknowledge give rise to ES. Second, it gives us the opportunity to understand how different drivers of ES capacity including ecosystem structure and human management affect outcomes.

Exurban development occupies a significant portion of developable land in the United States (Theobald 2005, Brown et al. 2005) and the exurban population is projected to continue growing in the future (Golding and Winkler 2020). This land includes developer-designed subdivisions with large lots as well as individually-developed rural properties, often built on preexisting agricultural land or in remnant patches of forest (An et al. 2011). While the definitions of exurban land use may vary, the work in this dissertation defines exurban residential land use as one housing unit per 0.2 to 16.2 ha (Brown et al. 2005). It is important to improve understanding of the ES provided by this landscape as well as how human management affects their provision. Suburban and exurban residential developments in the North American temperature forest ecosystem are dominated by a human-managed vegetation cover, characterized by maintained turfgrass growing under open grown trees (Luck et al. 2009, Fissore et al. 2012, Cook et al. 2012, Huyler et al. 2014a, Groffman et al. 2014a, Currie et al. 2016). Additional vegetation cover including standalone turfgrass and remnant forest patches (Currie et al. 2016) combined with variable yard management practices (Nassauer et al. 2014) create a range of possible C and ES outcomes across the landscape. Ecosystem process models are a tool that can be used to simulate large numbers of possible input scenarios and evaluate potential outcomes. Simulation results can also be used to inform homeowners, planners, and local policy makers on how changes in management can lead to desired ecological outcomes. This dissertation uses an ecosystem process model to evaluate how thousands of combinations of yard management practices affect C sequestration outcomes as well as a suite of ten ES in the residential exurban landscape of Southeastern Michigan.

This dissertation has five chapters, an introductory chapter followed by three research papers as three separate chapters and the final concluding chapter. The first paper (Chapter 2) is in the process of being revised and resubmitted to *Ecological Modelling.* The second paper (Chapter 3) will be submitted to *Ecological Applications.* The journal for the third paper (Chapter 4) is to be determined. This introductory chapter provides a description of the three papers and their results. Chapter 2 describes how Biome-BGC-Ex was modified for the exurban landscape and then calibrated and parameterized for exurban residential land in Southeastern Michigan. The modified model was then used to answer the following question: How do individual and combinations of yard management practices affect C sequestration? Chapter 3 describes how Biome-BGC-Ex was modified to provide outputs that can be used to estimate ES capacity of ten services in the residential landscape. The main questions of this component of the study, which focused on exurban Southeastern Michigan were: How do individual and combinations of yard management practices affect ES capacity? As well as what are the trade-offs and synergies found between the modelled services? Chapter 4 takes a broader approach to evaluate terrestrial ecosystem process models as a tool for ES assessment. The main questions this paper addressed were: Are ecosystem process models a useful tool for estimating ES capacity? Along with, how can ecosystem process models be integrated with other tools to improve ES assessment?

While I solely completed the research presented in this d-issertation (unless otherwise cited), it was conducted as part of a larger collaboration, the SLUCE project (Spatial Land Use Change and Ecological effects (Brown et al. 2008)), which was funded by the National Science Foundation's Program on the Dynamics of Coupled Human and Natural Systems and conducted at the University of Michigan. This project addresses the exurban residential landscape as a coupled human-natural system. My research references and builds on previous elements of the SLUCE project including an empirical ecological field study (Currie et al. 2016), developer and homeowner interviews (Nassauer et al. 2014, Nassauer 2017), web-based surveys (Nassauer et al. 2009, Wang et al. 2012, Visscher et al. 2014, 2016), and modeling in a coupled human-natural system framework (Robinson et al. 2013). My contributions to the project, specifically modifying Biome-BGC and linking it to ES, can be applied to future research on coupled human-natural systems. The conclusion chapter provides some insight into the future direction of this research including how Biome-BGC-ES could be coupled with agent-based models and economic models developed in the SLUCE project to further explore how landscape management decisions affect the provision of ecosystem services.

1.2 Adapting a widely used ecosystem process model (Biome-BGC) for the Exurban Residential Landscape

Terrestrial ecosystem process models simulate the stocks and flows of energy, carbon, nutrients and water in vegetation and soil. Widely used examples of this type of model include, but are not limited to CENTURY (Parton et al. 1993b), Biome-BGC (Running and Hunt 1993, Thornton et al. 2002), TEM (McGuire et al. 1992) and PnET (Aber et al. 1996, 1997). Although these models were originally designed for wildland ecosystems (e.g. Biome-BGC for forests, Running and Hunt 1993; CENTURY for grasslands, Parton et al., 1993), they can be modified to understand fluxes of C and N across a range of wildland and human-dominated ecosystems including agriculture (Parton and Rasmussen 1994, Foereid and Høgh-Jensen 2004, Wang et al. 2005, Stehfest et al. 2007), managed forests (Tatarinov and Cienciala 2006, González-Sanchis et al. 2015), managed grasslands (Qian and Follett 2002, Bandaranayake et al. 2003, Hidy et al. 2012), and urban ecosystems (Milesi et al. 2005, Zhang et al. 2012, Trammell et al. 2017).

In this dissertation I have created a modified version of an "off the shelf" ecosystem process model designed for wildland systems (Biome-BGC) for use in the human-dominated exurban landscape, hereafter referred to as Biome-BGC-Ex. Modifying an existing model has two main benefits; first we are providing adaptations to a model that is already widely regarded and used in the scientific community and second, by drawing on extensively validated model dynamics we did not spend time having to model a system from scratch, which would have required more resources than were available for the scope of this project.

In the past five years Biome-BGC has been adapted for a variety of human managed forest, agricultural, and grassland ecosystems (González-Sanchis et al. 2015, Mao et al. 2016, 2017, Hidy et al. 2016). Previously, Biome-BGC had been modified to estimate turfgrass (lawn) pools and fluxes in the US (Milesi et al. 2005). Another similar ecosystem process model, CENTURY, has been applied to residential ecosystems (Trammell et al. 2017). However, the only other available literature on Biome-BGC being modified for or applied to urban or residential ecosystems with more extensive tree and turfgrass management is in research completed by myself in my first and second paper and previous work by myself and my colleagues (Robinson et al. 2013).

Two limitations of applying Biome-BGC to the residential landscape are that it can only simulate a single layer of vegetation and that it does not include yard management practices. This dissertation addresses both limitations by creating a modified version of the model, Biome-BGC-

Ex that allows for competing layers of tree and turfgrass vegetation (

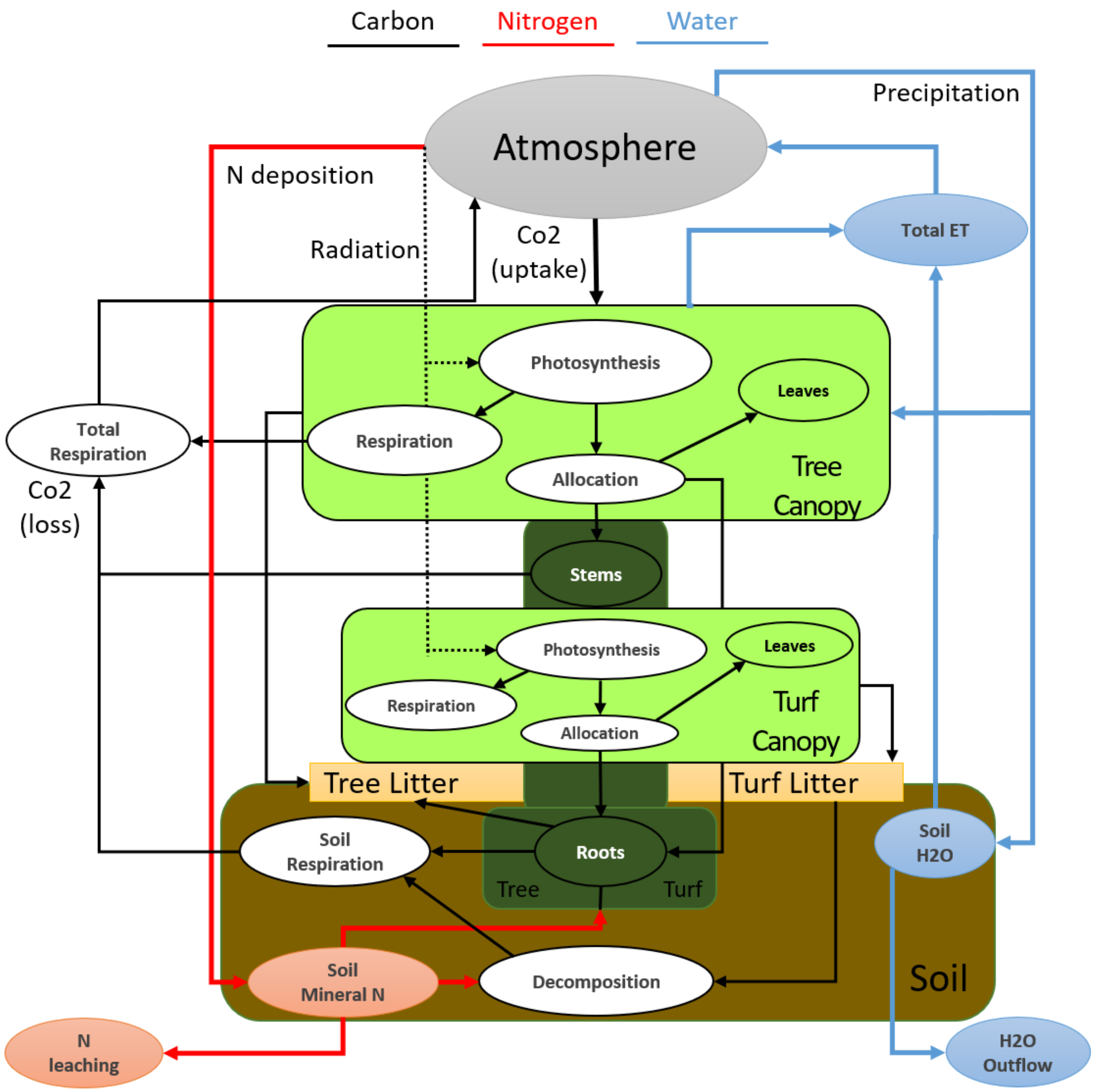

Figure 1-1) and includes the following residential yard management practices: fertilization, irrigation, mower blade height, mulch mowing, pruning intensity and frequency, raking, coarse woody debris (CWD) removal, tree planting, and tree removal. This process required extensive changes to the model source code including adding a new subroutine to

simulate competition between trees and turfgrass for light (radiation), creation of pools and fluxes for all vegetation and litter C, nitrogen (N), and water processes for each vegetation layer, and modification of existing subroutines to simulate yard management. All modifications were carried out in Microsoft Visual Studio using C++ language. A more detailed description of changes can be found in Appendix -A.

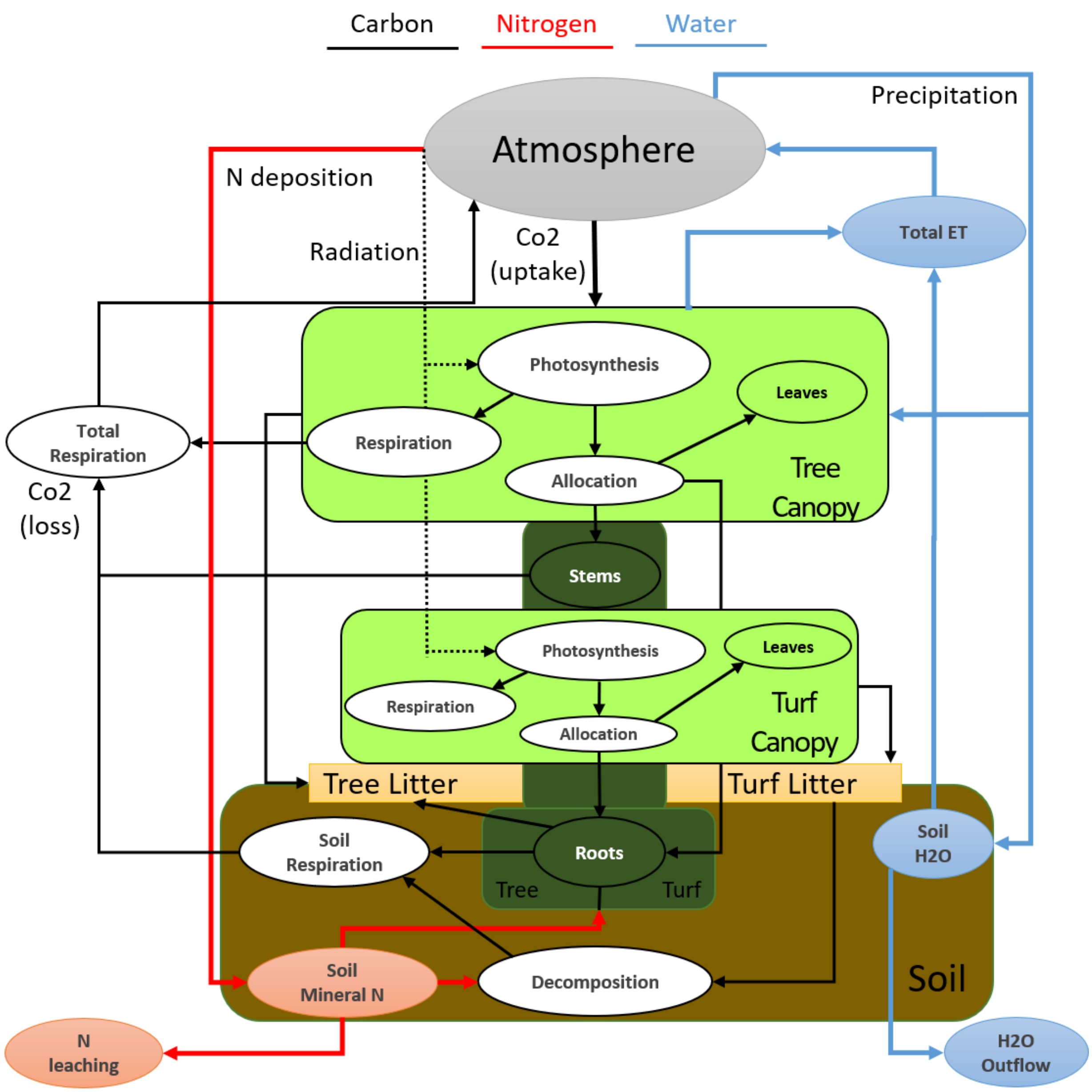

Figure 1-1: Conceptual diagram of Biome-BGC-Ex detailing C, N, and water fluxes and pools.
Compared to the original version of Biome-BGC this figure shows the addition of turf vegetation and litter pools and the fluxes of radiation, C, N, and water to these pools.

1.3 Evaluating the Effect of Exurban Yard Management Practices on C Sequestration with Biome-BGC-Ex

The residential landscape has the potential to store C in vegetation and soils over time (Raciti et al. 2011, Currie et al. 2016). This potential is limited or enhanced by a variety of social and environmental factors including climatic drivers (Boisvenue and Running 2006), land development patterns and vegetation choices (Westbrook 2010, Magliocca et al. 2014, Nassauer 2017), time since development (Golubiewski 2006, Raciti et al. 2011, Huyler et al. 2014a, Campbell et al. 2014), neighbor influence (Nassauer et al. 2009, 2014), parcel size (Robinson et al. 2009, Huang et al. 2013, Visscher et al. 2014), and the amounts and ages of vegetation, particularly trees (Currie et al. 2016). In addition, homeowners' practices and behaviors affect vegetation and soil C pools on their properties. For example, turfgrass management practices such as fertilization, irrigation, and mulch mowing have been found to increase soil C pools (Pouyat et al. 2002, 2009, Qian et al. 2003, Townsend-Small and Czimczik 2010, Huyler et al. 2014b). Planting and retaining trees in residential yards can increase soil C accumulation (Huyler et al. 2017) and ecosystem C accumulation (Fissore et al. 2012). Tree pruning has not been shown to improve C storage, unless it is able to increase tree longevity, while irrigating young trees can improve C storage by increasing tree longevity (Nowak et al. 2002).

Research in exurban and urban landscapes has given us insight into the intensity, frequency, and combinations of homeowner yard management practices (Law et al. 2004, Zirkle et al. 2011, Nassauer et al. 2014, Currie et al. 2016). It has also led to the realization that this landscape includes three dominant vegetation cover types in exurban residential landscape, *turfgrass, dense woody,* and *turfgrass with sparse woody* (Figure 1-2); referred to in italics to correspond with naming and definitions found in Currie et al. 2016. *Turfgrass with sparse woody* is a novel ecosystem, characterized by maintained turfgrass growing under open grown trees in temperate forest ecosystems of North America (Luck et al. 2009, Fissore et al. 2012, Cook et al. 2012, Huyler et al. 2014a, Groffman et al. 2014a, Currie et al. 2016). However, there are many limitations to collecting adequate field data and designing field experiments to explore how management decisions on each of these vegetation types affects C sequestration. Ecosystem process models are a tool that can be used to simulate how management and vegetation structure affects ecosystem processes and functions on the landscape and estimate C outcomes over extended periods of time. The first paper (Chapter 2) presents the ecosystem process model Biome-BGC-Ex as a tool designed to estimate C sequestration under a range of homeowner management and vegetation structure conditions.

As mentioned above (Section 1.2), Biome-BGC-Ex was designed to address two main limitations of the original Biome-BGC model. First, to simulate *turfgrass with sparse woody* and have tree and turfgrass vegetation compete for light, water, and nutrients. Second, to incorporate yard management practices. This model was then initialized, parameterized and calibrated for the exurban residential landscape using data previously collected from field studies (Currie et al. 2016), previous iterations of applying the model to residential land (Milesi et al. 2005, Robinson et al. 2013), and MODIS NPP (NTSG, 2014; Zhao et al., 2005; Zhao and Running, 2010).

Biome-BGC-Ex was used in three separate analyses to evaluate which individual and combinations of management practices have the largest effects on C sequestration in the exurban residential landscape of Southeastern Michigan over a 50-year time period. In the first analysis Monte Carlo methods were used to explore the potential range of combinations of management practices currently in use on exurban residential land (Nassauer et al. 2014, Visscher et al. 2014, 2016). This method allowed us to quantify the full range of C sequestration in residential parcels and to identify which management practices are likely to be the strongest drivers of C sequestration or loss. Second, we simulated C sequestration for a typology of six different exurban homeowner types and their associated management practices (Homeowner Agent Typology, HAT) developed by Nassauer and others (2014). C sequestration was compared across each homeowner type for each vegetation cover type to determine which was able to store the most C. For the third analysis these results were scaled up to the landscape based on current landscape vegetation coverage proportions found in our study region (Currie et al. 2016). Results from these analyses showed fertilizer was the strongest driver of C sequestration in *turfgrass* and *turfgrass with sparse woody* vegetation cover types and homeowner types with the highest rates of fertilization sequestered the most carbon at the scale of the parcel and the landscape.

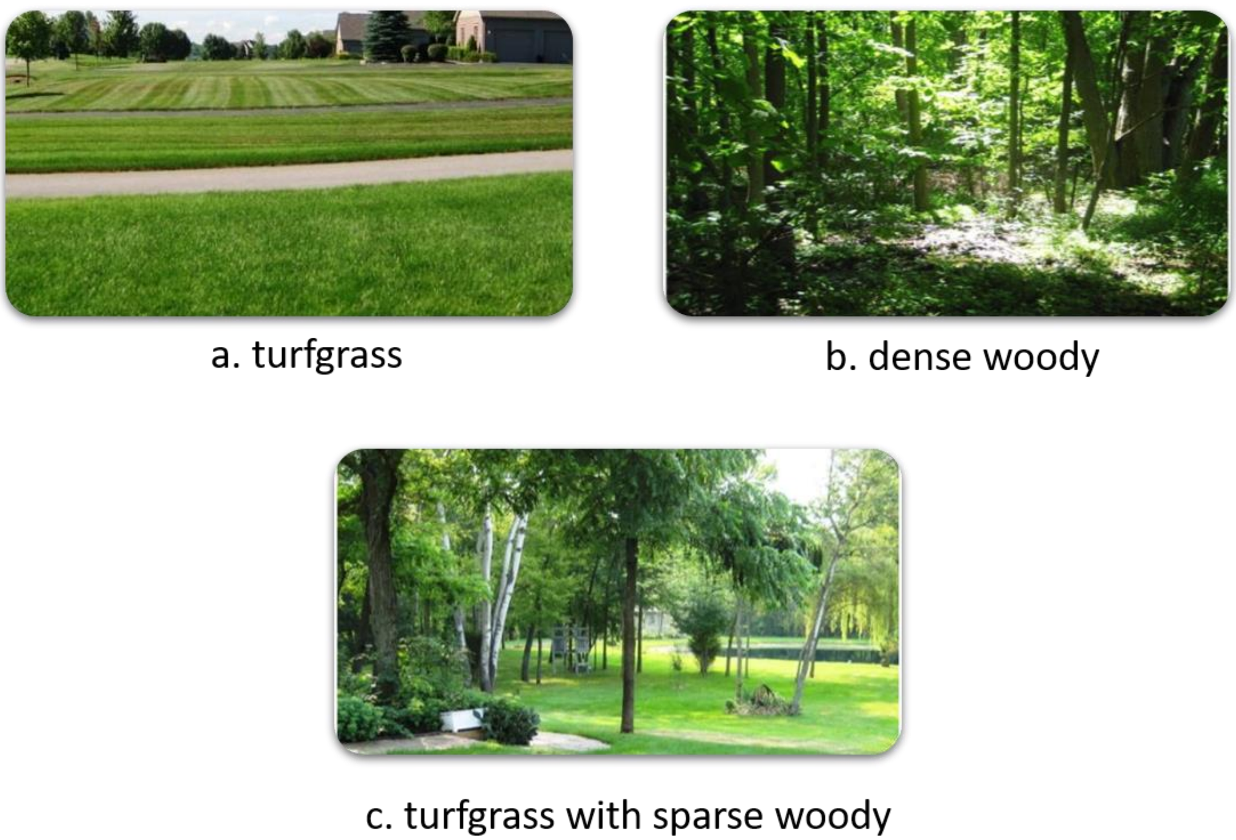

Figure 1-2: Examples of the three dominant vegetation cover types found in exurban residential landscape a) *turfgrass,* b) *dense woody, c) turfgrass with sparse woody.*

1.4 Linking Ecosystem Processes to Ecosystem Services with Biome-BGC-Ex

Ecosystem services (ES) are the physical goods and associated benefits that are provided to humans by the ecosystems of the planet. Ecosystem processes along with ecosystem composition and structure give rise to the production of ES (Fu et al. 2013). When ecosystem processes are impacted by human management or other human-caused changes to ecosystem structure, feedbacks within biophysical systems and between human and biophysical systems occur that impact the production of ES (Figure 1-3) (Fu et al. 2013, Potschin-Young et al. 2018). Despite the acknowledgement that ecosystem processes are vital to service production, there is a documented but unfulfilled need to bring our knowledge of ecosystem processes to ES science (Bennett 2017, Lavorel et al. 2017, Broszeit et al. 2019).

Assessment of ES contains three main components (Figure 1-3) (Tallis et al. 2012, Villamagna et al. 2013, Tomscha et al. 2016): 1) ES capacity (also referred to as ecological production function or ES supply) is the potential of an ecosystem to produce and deliver services based on biophysical and social properties and functions, 2) ES flow is the realized flow of services for which there is demand, 3) ES demand, which includes ES valuation, is the amount of services required or desired by society. One limitation of existing ES estimation tools is that they neglect to include a functional treatment of the ecological processes that, from a causal understanding, produce ES (Seppelt et al. 2011, Currie 2011, Bruins et al. 2017, Lavorel et al. 2017), which may lead to misunderstanding the mechanisms underlying the effects of management decisions on ES (Bennett 2017, Boerema et al. 2017).

Ecosystem process models are a tool that reflect complexities, such as biophysical feedbacks, among processes and with some modification can be used to provide users with dynamic and quantitative measures of ES that can be integrated with other types of models and tools. Previous studies have used modified ecosystem process models (e.g., PnET-CN, CENTURY, Biome-BGC) to estimate ES capacity. This has included linking Biome-BGC with a hydrology model to estimate ES in a watershed (Xu et al. 2016), linking a modified version of Biome-BGC (Biome-BGCMuSo) with a crop simulation model (Pokovai et al. 2020), and modifying Biome-BGC to estimate ES in a managed forest (Turner et al. 2011). The CENTURY model has been applied to residential ecosystems but not with the goal of modeling the provision of ecosystem services (Trammell et al. 2017). The second paper (Chapter 3) of this dissertation is one of the first analyses that uses Biome-BGC-Ex to examine ES capacity in a residential landscape and examine trade-offs and synergies in those ES. This study is also novel because it focuses on how human management of the landscape affects ES production as opposed to land use or land cover change.

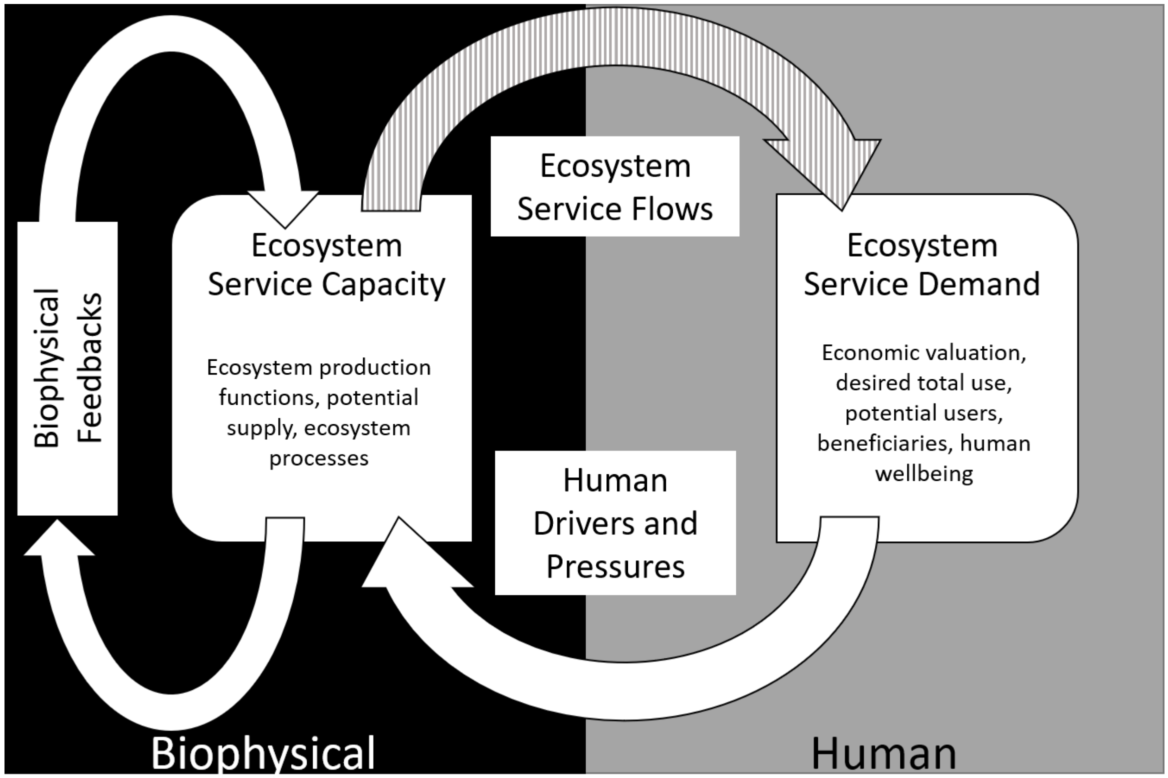

Figure 1-3: Simplified ES framework conceptualizing capacity, flow, demand, biophysical feedbacks, and human drivers and pressures.
Based on similar simplified frameworks by Tomscha and others (2016) and Tallis and others (2012).This dissertation focuses on how human drivers and pressures in the form of management behaviors affect ES Capacity and the biophysical feedbacks occurring in the ecosystem (solid white arrows). While this work acknowledges that ES flows affect ES demand (shaded arrow), this relationship is beyond the scope of the methods presented in this dissertation.

Biome-BGC-Ex was used in two separate analyses to examine how yard management behaviors affect the ES capacity of a suite of ten ES including NPP, soil fertility, firewood production, nitrogen retention, freshwater recharge, spring soil water recharge, summer soil water retention, climate regulation, microclimate regulation, and air pollution abatement. These services were estimated within three vegetation cover types identified as dominant in the exurban residential landscape *turfgrass*, *turfgrass with sparse woody*, and *dense woody* (Currie et al.

2016). The first analysis used Monte Carlo simulation methods to explore the combined effects of interacting, variable values of yard management practices on ES. This allowed us to determine which management practices were the strongest influence on each service. The second analysis simulated each ES for each of the six exurban homeowner type defined in our Homeowner Agent Typology (Nassauer et al. 2014) and allowed us to evaluate how specific management behavior combinations drove biophysical feedbacks within and between ecosystem processes and ES capacity led to trade-offs and synergies between services and how demand for different cultural ecosystem services affected ES Capacity outcomes. Results from these analyses showed fertilizer, irrigation, raking. and pruning were the strongest drivers of modeled ES. While most services were synergistic, there were trade-offs between many of the services and freshwater recharge.

1.5 Evaluating Ecosystem Process Models as a Tool for Estimating ES Capacity

Despite the proliferation of ES assessment tools, most do not consider mechanistic feedbacks within ecosystems, e.g. feedbacks among biogeochemical cycles, or other biophysical interactions among ES; each service is typically estimated independent of other services (Currie 2011, Bruins et al. 2017, Lavorel et al. 2017). The tools most referred to in the literature and used in studies on trade-offs and synergies of ES typically use lookup tables and regression equations to simulate ES capacity individually and overlay these results to determine trade-offs and synergies (ESTIMAP (Zulian et al. 2018); InVEST (Sharp et al. 2016); LUCI (Trodahl et al. 2017); EBI (Van der Biest et al. 2014)). Many studies have determined that by not considering interactions and biophysical feedbacks between ES or between ecosystem processes and ES, scientists and managers may improperly estimate ES capacity and misunderstand the mechanisms underlying the effect of management decisions on service outcomes (Villa et al. 2014, Bruins et al. 2017, Bennett 2017, Boerema et al. 2017).

The third paper (Chapter 4) of this dissertation evaluates ecosystem processes models as a tool for estimating ES capacity of supporting, regulating, and provisioning ES. This paper has three main objectives. First, it reviews how current ES assessment tools estimate ES and concludes that although some consider multiple aspects of ES including capacity, flow, and demand (Figure 1-3), they do not consider interactions or biophysical feedbacks between processes and services. Second, it analyzes benefits and limitations of applying ecosystem process models to study ES. Benefits of this approach include: the ability to simulate a variety of management, policy, and climate scenarios; the fact that these models have already been verified, calibrated, and applied across a range of geographic areas and ecosystems; and the fact that ecosystem process models are designed with dynamic flows and biophysical feedbacks in mind. Limitations of this approach include the fact that ecosystem process models have significant complexity, require large amount of input data collection, require additional modification for human-dominated ecosystems or ES output, and may need to link to additional spatial frameworks to include a spatial component. Finally, this paper discusses how ecosystem process models could be integrated with other methods to provide improved estimation of ES and incorporate feedbacks between the human and biophysical systems.

1.6 Conclusions

The model Biome-BGC-Ex addresses two of the main limitations of applying off-the-shelf ecosystem process models to human-dominated, residential ecosystems. It allows for simulation of multiple layers of competing vegetation and incorporates yard management practices. Further, this model addresses one of the limitations of current ES assessment tools by linking estimates of ES capacity to an ecosystem process model. The methods and results presented in this dissertation advance our understanding of how homeowner management practices affect ecosystem processes and how these influence C sequestration and ES outcomes.

The approaches described in this dissertation have the potential to inform more complex ES modelling frameworks that rely on ES capacity modelling grounded in the understanding of ecosystem processes and biophysical feedbacks. As improved estimation of ES and C sequestration continues to be of importance to ES scientists, land managers, and policy makers, these methods can further be integrated withing existing modelling and decision-making frameworks. While the methods and model shown in this dissertation were applied to the exurban landscape of Southeastern Michigan, they can also be applied to other suburban and exurban residential development across broader temperate regions.

1.7 References

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Chapter 2
Modelling the Effect of Exurban Residential Landscape Management Practices on Carbon Sequestration in a Temperate Forest Biome

ABSTRACT

Vegetation and soils in the residential exurban landscape have the potential to store significant amounts of carbon (C). However, a variety of human factors and decisions can affect C outcomes by altering ecosystem processes and functions on the landscape. Ecosystem process models are an important tool that can be used to understand these dynamics and to predict C storage outcomes over extended periods of time. In this study we present Biome-BGC-Ex, a new version of the ecosystem process model Biome-BGC, that we have modified to include competition between trees and turfgrass and residential landscape management practices in the exurban landscape. In a series of analyses, we evaluate individual and combinations of residential management practices to compare their effect on carbon sequestration in the temperate exurban region of Southeastern Michigan, USA over a fifty-year time horizon. For the first two analyses we ran Biome-BGC-Ex simulations for three predominant vegetation cover types identified in our study region, and model results suggested that N fertilization was the strongest driver of C sequestration in two of the cover types *turfgrass* and *turfgrass with sparse woody* vegetation, however further empirical research is needed to address these findings. At the landscape scale, homeowner type with the highest fertilizer rate had the largest increase in total ecological C over 50 years while the type that did not fertilize and pruned annually resulted in a loss of total ecological C. These outcomes were driven by gains and losses of tree biomass and

soil C. The main limitation of the modified model involves lack of validation in its ability to adequately simulate N dynamics in the exurban landscape. As is, the current model likely overestimates C sequestration under high levels of N fertilization. Biome-BGC-Ex can potentially be used to measure C dynamics across similar temperate exurban residential landscapes, but future work must address limitations in the model's simulation of N dynamics.

2.1 INTRODUCTION

The residential landscape functions as a coupled human–natural system (Liu et al. 2007) that has the potential to sequester carbon (C) in vegetation and soils over time (Raciti et al. 2011, Currie et al. 2016). The rate of C sequestration in this environment depends on a variety of social and ecological factors and their interactions. Homeowner choices and behaviors, which we refer to as 'management practices' include activities such as mowing, fertilizing, irrigation, and pruning. Homeowner management preferences are motivated by a variety of factors including aesthetics, safety, leisure provision, neighborhood norms, and environmental concerns (Nassauer et al. 2009, Cook et al. 2012, Larson et al. 2016, Locke et al. 2018). Although residential homeowners may not fully recognize the impacts of their choices, management practices alter the ecological processes that affect vegetation and soil C cycling. The complex interactions between homeowner management practices and ecosystem processes produce heterogeneous patches of C storage outcomes across the landscape (Rao et al. 2013, Polsky et al. 2014, Currie et al. 2016).

Potential C sequestration in the residential environment is driven by social and ecological factors including: climatic drivers (Boisvenue and Running 2006, Pickett and Cadenasso 2008), land use history (Raciti et al. 2011, Ziter and Turner 2018, Peach et al. 2019), land development patterns and vegetation choices (Magliocca et al. 2014, Nassauer 2017), time since development

(Raciti et al. 2011, Huyler et al. 2014a, Campbell et al. 2014), neighbor influence (Nassauer et al. 2009, 2014), parcel size (Robinson et al. 2009, Huang et al. 2013, Visscher et al. 2014), and the amounts and ages of vegetation, particularly trees (Currie et al. 2016). In addition, homeowners' practices and behaviors affect vegetation and soil C pools on their properties. For example, turfgrass maintenance practices such as fertilization, irrigation, and the return of mowed turfgrass clippings into the lawn can increase soil C pools (Pouyat et al. 2002, 2009, Qian et al. 2003, Huyler et al. 2014b). Tree planting and retaining existing trees can increase soil C accumulation (Huyler et al. 2017) and ecosystem C accumulation (Fissore et al. 2012). Research in residential landscapes has given us insight into the frequency of and variation within each management practice (Zirkle et al. 2011, Nassauer et al. 2014, Visscher et al. 2014, 2016, Currie et al. 2016).

This study focuses on exurban residential development, which increasingly determines patterns of land use and vegetation at the urban-rural fringe throughout the U.S. (Brown et al. 2005, 2008, Churkina et al. 2010, Berger and Kotkin 2017). Exurban land area increased from about 5 % (270,608 km^2) of total land area of the conterminous US in 1950 to about 25 % (1.39 million km^2) in 2000 (Brown et al. 2005) and is projected to increase in future decades (Golding and Winkler 2020). This land includes developer-designed subdivisions with large lots as well as individually-developed rural properties, often built on preexisting agricultural land or in remnant patches of forest (An et al. 2011). Exurban residential land use is defined for this study as one housing unit per 0.2 to 16.2 ha (Brown et al. 2005). Compared to suburban land use, Exurban development is composed of lower-density settlements that may lie adjacent to more densely populated suburban areas. In contrast to suburban areas, exurban parcels are larger, farther from city or town centers, and are typically disconnected from municipal services of sanitary sewer and water (An et al. 2011). Exurban landscapes contain a heterogeneous mix of impervious surfaces and vegetation patches, including maintained *turfgrass*, and remnant forest patches, which we refer to as *dense woody*, scattered throughout the landscape (Brown et al. 2008, An et al. 2011, Currie et al. 2016). Exurban and suburban development creates a novel ecosystem, characterized by maintained turfgrass growing under open grown trees in temperate forest ecosystems of North America (Luck et al. 2009, Fissore et al. 2012, Cook et al. 2012, Huyler et al. 2014a, Groffman et al. 2014a, Currie et al. 2016), which we will refer to as *turfgrass with sparse woody* vegetation in this study.

Given the significance of exurban residential land use in the United States and its growing spatial footprint, it is important to understand the full extent heterogenous vegetation structure and human management has on potential C sequestration in this landscape. Historically, global C models and C inventories have not accurately identified exurban residential land, typically misidentifying it as forest, agriculture or denser urban (Schneider et al. 2009, Friedl et al. 2010), which may lead to over or under estimation of C stored. The effects of human management on this land are not considered in coarse-scale studies of C storage, likely resulting in inaccurate estimates of soil and vegetation C in landscapes that contain significant areas of exurban settlement (Pataki et al. 2006, Churkina 2008, Raciti et al. 2012). Since residential landscapes are managed differently from wildland or agricultural systems, in ways that affect C cycling, they should also be modelled differently if we wish to capture the major drivers of landscape C storage. The exurban landscape falls on a gradient between wildland and dense urban landscapes in many respects. It contains open grown trees and grasses, but it is not a wildland forest or grassland. It contains impervious surfaces and built structures, but at much lower densities than those in urban or suburban land. The effects of these factors and their interaction with ecosystem processes and function can be explored with ecological models.

Carbon sequestration in vegetation and soil is driven by net ecosystem flows of C, which in turn are strongly governed by available water and nitrogen (N). Terrestrial ecosystem biogeochemical models simulate nutrient cycling and biogeochemical processes based on soil and climate characteristics. Unlike demographic or gap models, which are focused succession and individual tree dynamics within a forest patch, these ecosystem process models do not include competition and can only simulate the dynamics of a single homogeneous layer of a plant functional type (e.g., deciduous tree, C3 grass) at a given point in space. Compared to other models of urban and residential C sequestration (e.g. UFORE, Nowak et al. 2008; InVEST, Polasky et al. 2011) that predict C sequestration empirically based on ecosystem structure and aboveground biomass, ecosystem process models consider the mechanistic relationships and biogeochemical feedbacks between pools and fluxes of C, water, and nutrients. This allows users to estimate C sequestration under a variety of scenarios and to determine which factors are limiting and driving C sequestration, but with a limited ability to model vegetation dynamics. Ecosystem process models have been calibrated, validated, and applied to global simulations as well as for local, site specific conditions. Although these models were originally designed for wildland ecosystems (e.g. Biome-BGC for forests, Running and Hunt 1993; CENTURY for grasslands, Parton et al., 1993), they can be modified to understand C/N fluxes across a range of wildland and human-dominated ecosystems including agriculture (Parton and Rasmussen 1994, Foereid and Høgh-Jensen 2004, Wang et al. 2005, Stehfest et al. 2007), managed forests (Tatarinov and Cienciala 2006, González-Sanchis et al. 2015), managed grasslands (Qian and Follett 2002, Bandaranayake et al. 2003, Hidy et al. 2012), and urban ecosystems (Milesi et al. 2005, Zhang et al. 2012, Trammell et al. 2017).

Our primary objective in the present analysis was to model how residential landscape management practices lead to increased or decreased C sequestration through uptake in soil and vegetation in the exurban landscape. Specifically, we were interested in the dynamics of C sequestration on the three dominant vegetation cover types in exurban residential landscape, *turfgrass, dense woody,* and *turfgrass with sparse woody* (referred to in italics to correspond with naming and definitions found in Currie et al. 2016). We modified Biome-BGC, a widely used ecosystem process model to determine which management practices would affect C sequestration. The key additions to the model, now referred to as Biome-BGC-Ex, were creating a "biome" to simulate *turfgrass with sparse woody* vegetation and adding residential yard management practices. We then parameterized and calibrated the model based on results from our field survey of the exurban landscape and social surveys of exurban homeowners (Nassauer et al. 2014, Visscher et al. 2014, 2016, Currie et al. 2016). By expanding on an existing model framework, we hope to contribute to a broad understanding of ecosystem processes and C sequestration in human-dominated exurban systems that could potentially be applied globally in temperate forest biomes.

We applied Biome-BGC-Ex in three separate analyses to address the question of how do individual and combinations of residential yard management practices influence C sequestration over a 50-year time horizon? First, at the parcel scale we used a Monte Carlo simulation that explores the potential range of combinations of management practices currently in use on exurban residential land in our study region, Southeastern Michigan, USA. This method allowed us to quantify the full range of C sequestration in residential parcels and to identify and compare which management practices are likely to be the strongest, weakest, or insignificant drivers of C sequestration or loss. Our first hypothesis was that C sequestration would differ with different management activities and that fertilizer would have the largest influence on C sequestration. Second, to account for heterogeneity in management practices among different types of homeowners (homeowner agent typology analysis), we analyzed and compared C sequestration of different specific sets of management practices found to co-occur in our study region (Nassauer et al. 2014) within three predominant vegetation cover types at the scale of the parcel. Our second hypothesis was that all homeowner types would have net positive C sequestration in *turfgrass with sparse woody*, with the highest amount found in the homeowner type with the highest fertilization rate. Third, we scaled the results of the second analysis to that of residential exurban neighborhoods (i.e., subdivisions) found in Southeastern Michigan to compare how homeowner agent type influenced C sequestration at this scale. Our third hypothesis was that the homeowner types with medium to high fertilization and low amounts of woody biomass removal would lead to the largest net C sequestration.

2.2 METHODS

2.2.1 MODIFYING BIOME-BGC

2.2.1.1 OVERVIEW OF BIOME-BGC

Biome-BGC is a mechanistic biogeochemical model that is used to measure the storage and flux of carbon (C), nitrogen (N) and water within and between the atmosphere, vegetation, and soil of terrestrial ecosystems (Running and Hunt 1993, White et al. 2000, Thornton et al. 2002, Thornton and Rosenbloom 2005). We obtained Biome-BGC 4.2 (Thornton et al. 2002) from the Numerical Terradynamic Simulation group at the School of Forestry, University of Montana (http://www.ntsg.umt.edu), and this is the version we will be referring to unless otherwise noted. A newer version of the model is available (Biome-BGC-MuSo, Hidy et al.

2016), model modifications for this study were completed prior to its release. This ecosystem model provides a suitable platform for this work because it has been widely used and modified to quantify ecosystem C balance in a variety of biomes worldwide, including wildland or natural forests and grasslands (Bond-Lamberty et al. 2005, Goetz et al. 2012, Lombardi et al. 2016, Sun et al. 2017), managed forests (Tatarinov and Cienciala 2006, Migliavacca et al. 2009, González-Sanchis et al. 2015, Mao et al. 2017), managed grasslands (Hidy et al. 2012), and urban lawns (Milesi et al. 2005) Biome-BGC is a one dimensional model and represents a point in space with all fluxes and stocks scaled to a per square meter basis (Golinkoff 2010). Within this point in space the model is designed to simulate dynamics of single plant functional type (PFT) e.g., deciduous broadleaf forest or C3 grassland.

Biome-BGC requires multiple forms of input data including drivers (weather and climate data), initial conditions (soil conditions, initial C and N stocks, N deposition), and parameters (ecophysiological conditions of vegetation and soil). The model includes detailed daily interactions among light, water availability, soil properties, and N cycling, capturing differences among biomes. Carbon is accumulated through photosynthesis and removed during autotrophic (maintenance and growth) and heterotrophic (decomposition) respiration. Biome-BGC can provide output for a variety of daily, monthly, or yearly data including C, N, and water pools and fluxes, NPP, and evapotranspiration.

Biome-BGC can simulate changes in detrital and soil organic C pools over time resulting from temporal dynamics in production and decomposition. Biome-BGC assumes a uniform layer of soil (not divided into soil horizons) that is comprised of four soil organic matter (SOM) pools (fast, medium, slow, and recalcitrant). It has several pools that store the C and N of dead and decaying wood and leaves. Dead coarse roots and stem wood enter the coarse woody debris

(CWD) pool and as they are broken down join fine roots and leaves in four separate litter pools (labile, shielded cellulosic, unshielded cellulosic, and lignin). The litter pools decompose and enter SOM and as SOM decomposes it is transferred into successively slower decomposing pools. The rate of decomposition and heterotrophic respiration is informed by the empirical studies that show rates are limited by soil water (Orchard and Cook 1983, Andren and Paustian 1987) and temperature (Lloyd and Taylor 1994). C allocation and decomposition are limited by N limitation in the system and the model assumes that microbes and plants have equal weight when competing for soil N and that plant and soil C:N ratios (provided by the user) are constant across each model run.

A limitation for the purposes of modeling the residential landscape is that it represents each vegetation cover type (referred to as a biome in the model) by a single plant functional type, e.g., woody vegetation, tundra plants, or grasses. To represent residential landcover, much of which includes lawns of turfgrass mixed with trees (*turfgrass with sparse woody),* we created a modified version of Biome-BGC, hereafter referred to as Biome-BGC-Ex. This new version allowed more than one plant functional type (turfgrass and trees) in vertical layers and simulated management practices that directly affect soils and vegetation (Figure 2-1).

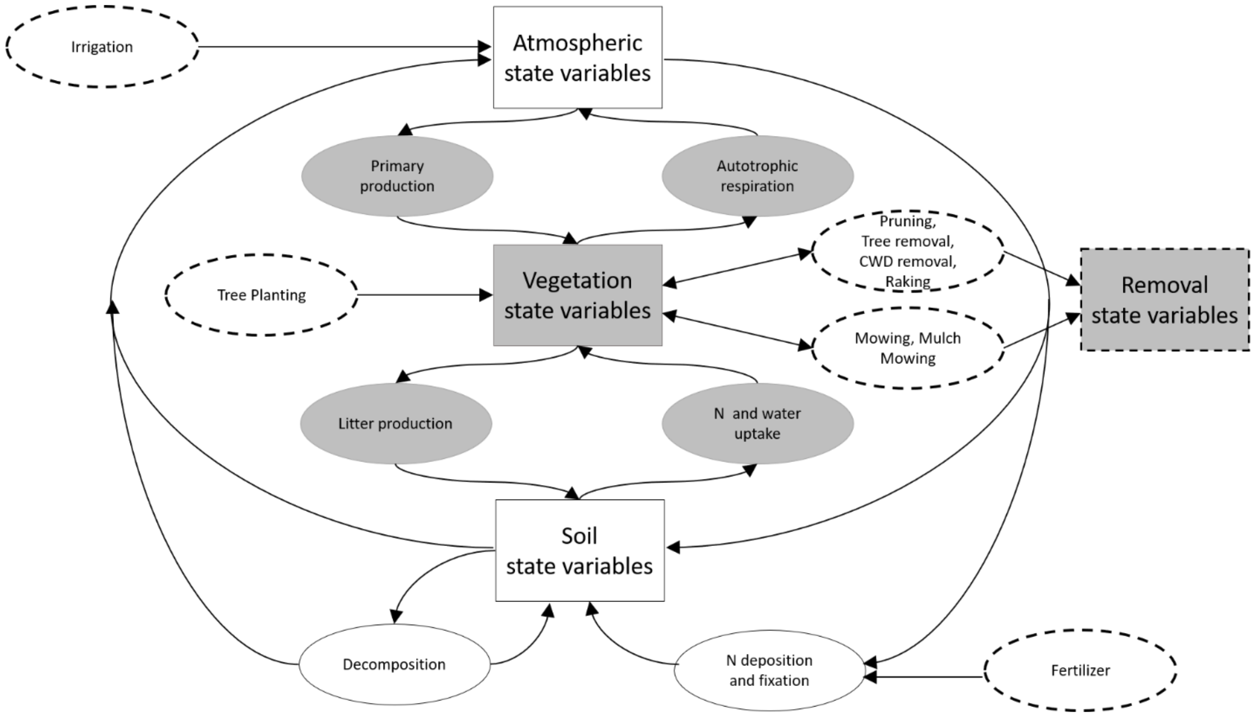


Figure 2-1: Conceptual diagram of Biome-BGC-Ex carbon (C), nitrogen (N), and water dynamics.
Dashed outlines indicate management practices. Grey filled shapes indicate pools and fluxes with potential for multiple vegetation layers. Decomposition refers to fluxes of soil C and N including formation of soil organic C, N mineralization, N immobilization, and N volatilization. Removal state variables are the C and N that is removed from the system (i.e., N and C pools stored here are not considered to be retained in the system).

2.2.1.2 Multiple Plant Functional Types

The key modification of Biome-BGC-Ex allows a vegetation cover type with two distinct layers of vegetation in which two plant functional types can exist in the same grid cell and to compete for resources including light, water, and nitrogen. This allowed us to simulate *turfgrass with sparse woody* vegetation (Currie et al. 2016) as a distinctive vegetation community with a layer of trees above a layer of turfgrass. To simulate *turfgrass* and *dense woody vegetation* we were able to use the existing capabilities of Biome-BGC. Following Bond-Lamberty et al. (2005), we divided Biome-BGC functionality into site-level variables (meteorology, soil C and N) not needing modification from vegetation-level variables that did require changes to the source code. In Biome-BGC-Ex, vegetation-specific processes, such as photosynthesis, respiration, and C allocation and daily updates of C, N, and water state variables, are simulated separately for each plant functional type. Litter and coarse woody debris variables are considered vegetation-specific variables until they enter soil pools.

Biome-BGC-Ex includes additional modifications to processes where plant functional types compete for resources. Competitive advantage for light and precipitation interception is determined by vegetation height, which is controlled by two new variables describing the relationship between biomass and height for each plant functional type. This relationship is modelled following an equation from Bond-Lamberty and others (2005):

> "An exponential equation of the form:
>
> $$h = h_{max}(1 - e^{-\frac{5}{m_{hmax}}m}) \quad (1)$$
>
> was chosen to describe this relationship. The two parameters supplied for each vegetation type are h_{max}, the maximum vegetation height, and m_{hmax}, the vegetation mass at which this height is attained… At the beginning of each simulation year Biome-BGC computes the height of each vegetation type based on current stem (for woody plants) or leaf (for grasses) mass and determines a height order. All light and precipitation interception for the subsequent year occurs using this height order, with the tallest vegetation intercepting first; light or precipitation that is not intercepted becoming available to the next tallest vegetation type".

In Biome-BGC-Ex, competition between the trees and turfgrass for belowground resources of N and soil water is size symmetric (based on plant biomass in each layer). These processes follow the pre-existing logic in Biome-BGC (Hara 1993, Bond-Lamberty et al. 2005, Pretzsch and Biber 2010). For N, Biome-BGC-Ex assesses total demand for soil available N from plant uptake, litter decomposition and soil processes of each layer; if demand is greater than the soil mineral N pool, every potential demand flux is reduced by the same proportion, such that all available N is used.

2.2.1.3 Simulating the Effects of Residential Yard Management Practices on Ecosystem Processes

Biome-BGC-Ex tracks the effects on ecosystem function of inputs, removals, storage, and transformations of vegetation and detrital C and N, as well as water inputs, associated with residential landscape management practices. In Biome-BGC-Ex an additional input file was created to supply values for a new set of model drivers representing residential yard management practices. The input file includes new variables describing the intensity and frequency of each management practice including fertilization, irrigation, mower height, mulch mowing, pruning intensity, pruning frequency, raking, coarse woody debris (CWD) removal, tree planting, and tree removal.

Our source code modification for management typically involved adding new management practices to similar ecological processes already present in Biome-BGC. Fertilizer use was added daily to the soil mineral N pool during the growing season (May 1 – Oct. 1). For irrigation, a user-provided weekly water target was compared to precipitation on a weekly basis and if not met the difference was added as irrigation (this assumes less irrigation when rainfall is adequate for turf management). Raking was represented as a proportional removal of leaf litter. The addition of tree planting to the model required additional modification so that additional tree biomass was added to above-and below-ground C and N stocks for woody vegetation.

Tree removals, pruning, coarse woody debris (CWD) removal and mowing were all incorporated as separate processes within the daily mortality function, which simulates the fraction of vegetation biomass to be moved to CWD and litter pools. For all mortality removals, we made the parsimonious assumption that belowground vegetation mortality was proportional to aboveground removals and all belowground mortality was transferred to appropriate litter pools; this follows existing Biome-BGC logic. For tree removals, the appropriate proportion of C and N from aboveground vegetation was removed from the ecosystem, while a corresponding proportion of belowground woody C and N entered litter pools. For tree pruning the amount to be removed is assumed to be a combination of foliar biomass, small branches, and twigs (Currie et al. 2016, unpublished). Because Biome-BGC does not differentiate between fine and coarse woody vegetation structures, we made the assumption that 38% of woody biomass is made of small branches and twigs (Whittaker et al. 1974) and deducted our pruning removals on that proportion of the woody C pool. For mowing of turfgrass, we used LAI as a proxy for height of the mower blade. Each day a LAI threshold value was compared to the projected LAI based on turfgrass growth; if higher than the threshold, 20 percent of the above ground turfgrass biomass was cut and a corresponding 20% of the belowground turfgrass biomass was assumed to senesce and enter litter as a result (Milesi et al. 2005). When mulch mowing was simulated, aboveground biomass cut during mowing was transferred to litter pools, but when clipping removal was simulated, the cut aboveground biomass was removed from the ecosystem. Belowground turfgrass litter (root litter) always remained in the ecosystem, transferred to litter. Biomass removals were considered to be transferred outside the boundary of the modeled system. A detailed list of modifications to Biome-BGC source code can be found in Appendix Table B-1.

2.2.2 Study Region and Broader Context

Our research was conducted as part of a larger collaboration, the SLUCE project (Spatial Land Use Change and Ecological effects, (Brown et al. 2008), which addressed the exurban residential landscape as a coupled human-natural system. The empirical context is a study region comprising ten counties in Southeastern Michigan that contain the Detroit, Ann Arbor, and Flint metropolitan areas (Figure 2-3a) with an estimated total regional population of 5.3 million (U.S.

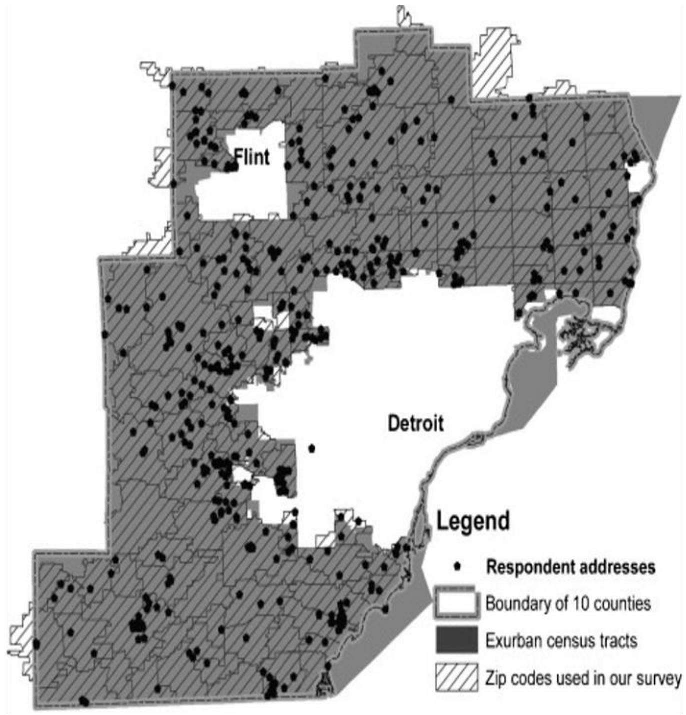
Census Bureau 2021) that are dominated by exurban residential development (Zhao et al. 2007, Brown et al. 2008, Huang et al. 2013). In this system we demonstrated individual and collective choices about landscape management that affect ecosystem structure and function, which then affect C sequestration and the delivery of other ecosystem services to society (Robinson et al. 2009). This study references and builds on previous elements of the SLUCE project including an empirical ecological field study (Currie et al. 2016), developer and homeowner interviews (Nassauer et al. 2014, Nassauer 2017), online surveys (Nassauer et al. 2009, Wang et al. 2012, Visscher et al. 2014, 2016), and modeling in a coupled human-natural system framework (Robinson et al. 2013).

2.2.3 MODEL INPUT DATA

A detailed field study conducted in 2009 in exurban residential neighborhoods of nine townships within the study region collected data on C and N present in foliage, wood, litter, and soil of 26 parcels sampled to exhibit a range of soil conditions (Figure 2-3b; Currie et al. 2016). In the current study, results of that prior research were used to parameterize and determine the initial conditions for our ecosystem model (Figure 2-1, section 2.2.4). This study simulates three predominant vegetation cover types identified in our 2009 field study: *dense woody* vegetation, *turfgrass*, and *turfgrass with sparse woody* vegetation. *Dense woody* vegetation has a closed to mostly closed canopy and no managed turfgrass. It was present in 8 of the 26 parcels in the 2009 study and made up the second largest proportion (22.1%) of land cover in investigated subdivisions (Currie et al. 2016). *Turfgrass with sparse woody* contains managed turfgrass and trees, but with gaps present between canopies. This vegetation cover type was identified in 24 of the 26 parcels and typically made up the largest proportion (26.3 %) of land cover in investigated subdivisions (Currie et al. 2016). *Turfgrass* is managed turfgrass or lawn with no woody vegetation. This was present on 24 of the 26 parcels and made up 16.6% of land cover in investigated subdivisions.

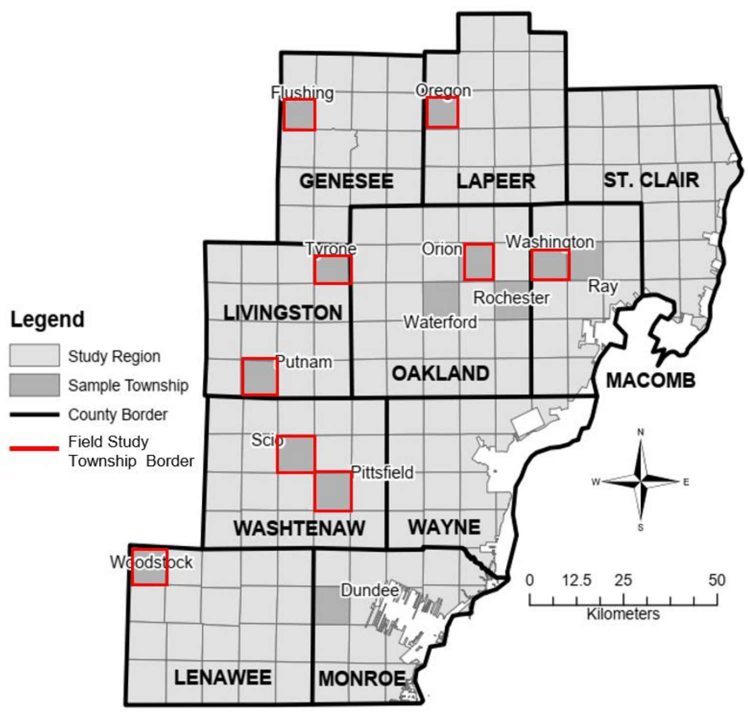
All analyses used inputs based on in-person interviews of the same 26 parcels as above, which surveyed homeowners on frequency and application amounts for a variety of management practices (listed in Table 2-2; Nassauer et al. 2014). Results from these interviews were also used by Nassauer and others (2014, unpublished data) to construct the Homeowner Agent Typology used in our analysis (Table 2-3). Management input probabilities for the Monte Carlo Analysis (section 2.2.5.1 , Table 2-2) took into account results from the online surveys conducted in the 207 zip codes of our study region (Figure 2-3a, reported in Visscher et al. 2104 and Visscher et al. 2016). Recommendations by the Michigan State Extension were used to improve our management distribution ranges for fertilizer (Frank 2015) and irrigation (Frank 2015) inputs and national standards of woody plant maintenance were used to improve estimates of pruning biomass removal (ANSI 1995). Literature on residential land management was also used to confirm ranges of fertilizer and irrigation (Law et al. 2004, Zirkle et al. 2011) and to translate mowing height to leaf area index (LAI) at time of mowing (Milesi et al. 2005).

Figure 2-2: Study Region Extent



a. Zip code boundary

a. Map displays the ten-county study region of Southeastern Michigan, exurban census tracts and zip codes boundaries of online surveys from Visscher et al. 2014, 2016 (reproduced with permission from Nassauer et al. 2009).



b. Township boundary

b. Map displays 13 sample townships dominated by exurban land use selected for focus by the SLUCE project. Red bordered townships were the location of field surveys in Currie et al. 2016 and field interviews in Nassauer et al. 2014

Table 2-1: Initial carbon pools for each vegetation cover type.
Values are used in both the Monte Carlo analysis and Homeowner Agent Typologies analyses. Carbon pool values are based on average values for each vegetation type measured in the 26 exurban yards sampled in the study region (Currie et al. 2016).

	Carbon Pool (kg C m^{-2})				
Vegetation cover type	**Aboveground tree vegetation**	**Aboveground turfgrass vegetation**	**Litter**	**Coarse woody debris**	**Soil to 1 m depth**
Turfgrass with sparse woody (TGW)	6.17	0.08	0.12	0.0	12.85
Dense woody (DW)	14.18	NA	0.62	0.18	20.41
Turfgrass (TG)	NA	0.15	0.107	0.0	12.64

Table 2-2: Description of management practices and their distributions and probability frequencies (from field data and other research studies) used in the Monte Carlo analysis. Abbreviations: turfgrass with sparse woody (TGW), turfgrass (TG), dense woody (DW), standard deviation (SD)

Management practice	**Description**	**Vegetation cover type**	**Probability of occurrence**[1]	**Distribution type**	**Distribution range**[1]
Fertilizer	Nitrogen added (kg N m^{-2} yr^{-1})	TGW TG	0.7	Uniform	0.0048 – 0.024[2]
Irrigation	total weekly water amount (cm)	TGW TG	0.75	Normal	Mean: 2.54[3] SD: 0.5
Mow height	Leaf Area Index (LAI) at time of mowing	TGW TG	1.0	Uniform	1.0 - 4.5[4]
Mulch mowing	If yes, grass clippings stay on lawn	TGW TG	0.7	NA	NA
Pruning intensity	Percent of foliar and fine woody biomass removed	TGW DW	0.75	Uniform	5 - 25%[5]
Pruning frequency	If pruning occurs, yearly or every three years	TGW DW	Yearly: 0.6 Every 3 years: 0.4	NA	NA
Raking	Percent of aboveground tree litter biomass removed	TGW DW	0.55	Uniform	5 - 100%
Coarse woody debris (CWD) removal	Percent of CWD removed (for TGW all CWD is always removed)	TGW DW	TGW: 1.0 DT: NA	TGW: NA DT: Uniform	TGW: 100% DT: 0 – 100
Tree planting	Aboveground tree biomass added (kg C m^{-2}) in random year from 14-38	TGW DW	0.7	Uniform	0.1 - 3.0
Tree removal	Percent of tree biomass removed in random year from 14 to 38	TGW DW	1.0	Uniform	0 - 100

[1] Probabilities and distributions are based on homeowner interviews conducted across the study region (Nassauer et al. 2014) and supplemented with additional sources as follows.
[2] (Law et al., 2004, Zirkle et al. 2011, MSU Extension 2014a)
[3] (Zirkle et al., 2011, MSU Extension 2014b)
[4] (Milesi et al. 2005)
[5] (ANSI 1995)

Table 2-3: Quantification of management practices for each separate Homeowner Agent Typology (HAT) in Biome-BGC-Ex simulations for each vegetation cover type. (LAI: Leaf Area Index). Further information on how Homeowner Agent Types were defined by Nassauer et al. 2014 can be found in Appendix B.

	Homeowner Agent Type					
Management Practice	**Neat Neighbor**	**Lakeshore Owner**	**Nature Neighbor**	**Tree Planters**	**Impro ver**	**View er**
Turfgrass with sparse woody (TGW)						
Fertilizer ($kg\ N\ m^{-2}\ yr^{-1}$)	0.01863	0.00782	0	0.00782	0	0.007 82
Irrigation ($cm\ week^{-1}$)	2.877	2.203	2.203	2.877	2.203	2.203
Mow height (LAI)	2.3	2.3	2.3	2.3	2.3	2.3
Mulch mowing	Yes	Yes	Yes	Yes	Yes	Yes
Pruning intensity (%)	10	10	10	10	10	10
Pruning frequency	Every 3 years	Every 3 years	Every 3 years	Yearly	Yearly	Yearl y
Raking (%)	100	100	0	0	0	0
Coarse woody debris (CWD) removal (%)	100	100	100	100	100	100
One-time tree planting ($kg\ C\ m^{-2}$)	0.8251	0	0	2.275	0.8251	2.275
Year of tree planting	15	NA	NA	15	15	15
One-time Tree Removal (%)	25	25	25	25	25	25
Year of tree removal	35	35	35	35	35	35
Dense Woody (DW)						
Coarse woody debris (CWD) removal (%)	60	60	60	60	60	60
Tree planting ($kg\ C\ m^{-2}$)	0.8251	0	0	2.275	0.8251	2.275
Year of tree planting	15	NA	NA	15	15	15
Tree Removal (%)	0.25	0.25	0.25	0.25	0.25	0.25
Year of tree removal	35	35	35	35	35	35
Turfgrass (TG)						
Fertilizer ($kg\ N\ m^{-2}$)	0.01863	0.00782	0	0.00782	0	0.007 82
Irrigation (cm)	2.877	2.203	2.203	2.877	2.203	2.203
Mow height (LAI)	3.3	3.3	3.3	3.3	3.3	3.3
Mulch mowing	Yes	Yes	Yes	Yes	Yes	Yes

2.2.4 Calibration and Parameterization of Biome-BGC

Initialization of Biome-BGC-Ex followed the original protocol of running the model in what is called the spin-up mode until a dynamic equilibrium among vegetation ecophysiology, nutrient pools and fluxes, and climate was met (Thornton et al. 2002). The spin-up was run separately for each vegetation cover type (*dense woody*, *turfgrass*, and *turfgrass with sparse woody*) and provides a set of initial C, N, and water state variables based on this equilibrium. Following the method described by Robinson et al. 2013, once equilibrium was reached, we augmented the resulting spin-up variables for vegetation and soil C and N based on results of our 2009 field study (Table 2-1, Currie et al. 2016). The results of the initialization became the initial C, N, and water state variables for the calibration.

We calibrated the model for each vegetation cover type separately with the aim of producing a baseline scenario that, with minimal management (discussed below), exhibited constant total NPP over a 50-year period. This represents a hypothetical baseline based on the site, climate (including moisture), soils, and N availability present in residential parcels in our study region. This stable baseline allowed us to assess departures in ecosystem C storage due to management practices. Further information on site, soil, and climate and final ecophysiological (EPC) parameters can be found in Appendix B.

To provide an approximate representation of the *dense woody* vegetation cover type in exurban Southeastern Michigan, we began by using a set of model ecophysiological parameters for a deciduous broadleaf forest previously modified for our study region (Robinson et al. 2013). The baseline scenario was run with a management strategy of 60% CWD removal. This is based on the ratio of the CWD present in the 2009 field study (183 g C m^{-2}) and the amount found in a mature temperate deciduous forest at a similar latitude (Hubbard Brook Experimental Forest, 468 g C m^{-2}; Fahey et al. 2005). We also modified the model parameters for leaf water potential, described below for *turfgrass with sparse woody*. This set of conditions produced a relatively constant total NPP over 50 years of 730 g C m^{-2} y^{-1} (aboveground average 418 g C m^{-2} y^{-1}). This value falls in the expected range for a temperate deciduous forest in the lower peninsula of Michigan (Brown and Schroeder 1999, Curtis et al. 2002).

To provide an approximate representation of the exurban *turfgrass* vegetation cover type in Southeastern Michigan, we chose a baseline management strategy based on the lowest ranges found in homeowner interviews and surveys (Nassauer et al. 2014, Visscher et al. 2014, 2016). There was mulch mowing when Leaf Area Index (LAI) was greater than 3.1 m^2 m^{-2}; no fertilizer or irrigation occurred. We modified the default model parameters for C3 grasses (Thornton and Rosenbloom 2005) by changing the lignin, cellulose, and labile portions of fine roots to 12%, 52%, and 36% respectively and the canopy average specific leaf area (SLA) to 70 m^2 kg^{-1} C to represent turfgrass (Milesi et al. 2005). Calibration increased the C:N ratios of leaves, litter and roots over Biome-BGC default values by 20% to 28.8, 58.8, and 50.4 respectively, which lie within an accepted range of C3 grasses (White et al. 2000). For the *turfgrass* baseline scenario we were unable to meet the goal of a constant NPP, possibly from a lack of fertilizer in our hypothetical baseline. Instead of constant NPP, we were able to establish a constant value of turfgrass vegetation C stock that matched the initial condition of 148 g C m^{-2} measured in our prior field study.

To provide an approximate representation of the *turfgrass with sparse woody* vegetation cover type in exurban Southeastern Michigan, we used a baseline management strategy of 100% CWD removal and mulch mowing when LAI is greater than 1.5 m^2 m^{-2}, based on the minimal range of management observed in our study region (Nassauer et al. 2014, Visscher et al. 2014, 2016). We began by using the model parameters described above for *dense woody* and *turfgrass* and initial conditions for *turfgrass with sparse woody* vegetation. Next, we simulated the growth of *turfgrass with sparse woody* for 50 years with the goal of producing a constant NPP that is relatively close to the five year (2009-2013) average MODIS NPP (MOD17) of 570 g C m^{-2} y^{-1}, which was calculated from nine predominantly exurban townships in our study region (NTSG, 2014; Zhao et al., 2005; Zhao and Running, 2010). To calibrate the two-layer model for a good fit with observed data we made the parsimonious assumption that the effect of water stress on stomatal conductance was the same for both trees and grasses (per unit area) in this environment. For trees and grasses we assigned the initial reduction of stomatal conductance to be at a leaf water potential of -0.5 (MPa) and the final reduction of stomatal conductance to be at a leaf water potential of -2.5 (MPa). These new values fall within the acceptable ranges of values for a parameter that is not well informed empirically (White et al. 2000). This set of initial conditions produced a relatively constant total NPP of 564 g C m^{-2} y^{-1}.

While the objective of this study is to forecast the space of possibilities in carbon sequestration resulting from extensive combinations of management practices over a 50-year time horizon, we do not have empirical data available from our study region to validate our modifications. In the discussion we address how model results compare with empirical data from residential landscapes and urban forests to provide a soft validation of the model to assess if carbon sequestration results fall into expected ranges and trends.

2.2.5 Model Analyses

Following our model changes and calibrations, we performed three sets of model simulations. The first was a Monte-Carlo approach designed to randomly sample the space of numerous potential interactions among multiple management practices co-occurring at differing frequencies and intensities for each vegetation cover type. The second simulated specific, coordinated sets of management practices carried out by different types of homeowners at the scale of the individual parcel. We refer to the coordinated sets of management as a Homeowner Agent Typology (HAT), which represents observed combinations of behaviors among groups of residential land managers as determined by our homeowner interviews and validated by our subsequent online survey (Nassauer et al. 2014, Visscher et al. 2014, 2016). The third analysis expanded the results of the prior HAT simulation to the landscape scale.

2.2.5.1 Monte Carlo Simulation

We used Monte Carlo simulation to explore the effects of variable, random combinations residential landscape management practices on model outputs, represented by probability distributions (Currie and Nadelhoffer 1999). For each model run, different randomly selected sets of values from the input probability distributions were used to simulate a particular outcome; together a large set of model runs produces a distribution of outcomes. Plausible ranges for model parameters were used to ensure that the distribution of outcomes represents a realistic expectation of ranges in carbon cycling (Table 2-2). Management input values are static for the duration of each model run. Each simulation run had a Biome-BGC-Ex management input file was filled with randomly selected values, using the Latin hypercube sampling technique (R package 'lhs'; Carnell 2016), from the probability distributions. Each simulation was run for fifty years. For *turfgrass* and *dense woody*, which had four and five management practices respectively, we performed 3000 simulation runs and for *turfgrass with sparse woody*, which had nine management variables, we performed 7000 simulation runs.

To investigate which management practices led to positive or negative changes in C sequestered in vegetation and soil over time, C values in year fifty were subtracted from year zero, the baseline condition, to determine the change in C over time. For each vegetation type, we first predicted the probability of net C sequestration across all simulations. Then, after testing for non-linearity and constant variance of residuals, we used multiple linear regression analysis to compare the effect of each management practice on total ecosystem C sequestration and individual C pools. For easier comparison of independent variables, we include regression results where management practices have been normalized on a zero to one scale (the full set of normalized and non-normalized results for all C pools can be found in Appendix Table B-5). All statistics were conducted in R version 3.3.2 (R Core Team 2019) using the packages: ggplot2 (Wickham 2016) and rms (Harrell 2020).

2.2.5.2 Homeowner Agent Typology (HAT) Analyses

In prior work based on homeowner interviews and subsequent web surveys, Nassauer et al. (2014) developed a typology of homeowners, each associated with distinct regimes of residential landscape management practices. See Appendix B for additional information on how these typologies were defined. Each type describes a group of homeowners based on characteristics of the properties where they tended to live and management practices they tended to use. These six types were: *neat neighbor, lakeshore owner, nature neighbor, tree planter*, *improver*, and *viewer*. We refer to these six types as a Homeowner Agent Typology (HAT), while retaining the previously published names for each type. We assigned explicit values (Table 2-3) for each management practice in each vegetation cover type based on the raw interview data that were originally used to define the types (Nassauer et al. 2014). Each type differs in the combination of fertilizer and irrigation intensity, pruning frequency, and whether raking, tree planting, and tree removal occur. Some practices varied little such as mowing amount, mulch mowing, pruning intensity, and removal of CWD. For the first HAT analysis, at the scale of the parcel, we separately simulated each combination of homeowner type and vegetation cover type for 50 years and report the resulting change in C stored in vegetation and soil pools from the initial condition.

For the second HAT analysis, the prior results for each HAT type were scaled up from the parcel to a hypothetical neighborhood (i.e., subdivision) surrounding the parcel based on vegetation coverages found in our study region. Then we compared changes in C sequestration assuming each HAT was the sole agent type for the neighborhood. This allowed us to examine how C is affected by the interaction between homeowner type and current landscape vegetation coverage proportions in exurban neighborhoods. For upscaling, we used the average areal proportion of each vegetation cover type found in exurban neighborhoods in our region: 14.0% for *turfgrass*, 26.3% for *turfgrass with sparse woody*, and 24.1% for *dense woody* (Currie et al. 2016) and assumed these proportions were the same for all HATs. In upscaling, we used these proportions to calculate landscape-scale, area-weighted values of C sequestration in vegetation and soil pools for each HAT. Other vegetation categories (old field, gardens, impervious, water) represent 35.7% of exurban residential landscapes (Currie et al. 2016) but are excluded from this analysis since we are focusing on the dominant vegetation cover and we have only modified Biome-BGC to measure effects of management in these vegetation types.

2.3 Results

2.3.1 Monte Carlo Simulation: Overall C Trajectories By Vegetation Cover Type

Net ecosystem C sequestration varied significantly among vegetation cover types. Considering the full set of model runs, which included the full ranges of all the human management choices and activities, ecosystem C was sequestered in 65% of the simulations of the vegetation cover type *turfgrass with sparse woody* over the 50-year simulation period. In this vegetation cover type, ecosystem C storage increased by 25% or more in 36% of the simulations and increased by 50% or more in 14% of the simulations. In the *dense woody* vegetation cover type, C was net sequestered in 19% of the simulations over the 50-year period, while in the pure *turfgrass* vegetation cover type ecosystem C was net sequestered in 31% of the simulations. Trajectories of increases in C storage in *turfgrass with sparse woody* and *dense woody* were driven by increases in live tree biomass, while those in *turfgrass* were driven by increases in soil C pools. Of all model runs that did show positive C sequestration over 50 years, *turfgrass with sparse woody* saw on average an increase of 3.17 kg C m^{-2} (32% increase), *dense woody* saw on average an increase of 3.77 kg C m^{-2} (11% increase) and pure *turfgrass* saw on average an increase of 1.72 kg C m^{-2} (13% increase).

Considering the frequency distributions of the numbers of model runs that produced each value of ecosystem C balance, pure *turfgrass* and *dense woody* vegetation types each followed a quasi-normal, unimodal frequency distribution (not shown). In contrast, *turfgrass with sparse woody* had a distinct bimodal frequency distribution (Figure 2-3). Further analysis found this distribution was related to a decline in tree productivity and biomass, driven by a variety of management strategies (explained further in 3.2). This decline typically improved turfgrass productivity due to increased availability of light, nutrients, and water. In the left mode of Figure 2-3 (n=1856), the average turfgrass NPP in years 45 to 50 was greater than 200 g C m^{-2} y^{-1} while the ecosystem overall exhibited large amounts of C loss due to the decline of trees over time, with 97% of simulations exhibiting a loss of tree C over fifty years. In the right, mostly positive C mode (n=5144 model runs), tree survival and growth were greater, while the average turfgrass NPP was less than 200 g C m^{-2} y^{-1} (Figure 2-3). Tree removals, pruning and fertilizer affected the productivity and biomass of trees and drove the ecological dynamics between trees and turf, resulting in the bimodal distribution in the frequencies of model runs with varying levels of carbon sequestration (Figure 2-3).

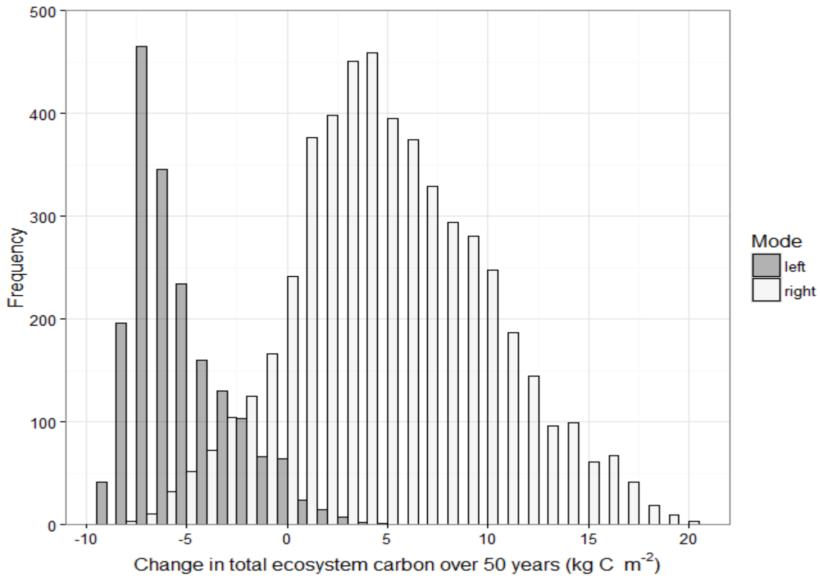


Figure 2-3: Frequency distribution of change in total ecosystem C over fifty years in vegetation cover type *turfgrass with sparse woody* from Mote Carlo Simulations. The bimodal distribution was divided based on the average turfgrass NPP in years 45 to 50 and simulations where the turfgrass NPP was greater than 200 g C m-2 y-1 placed in the left mode and simulations turfgrass NPP was less than 200 g C m-2 y-1 were placed in the right mode.

2.3.2 Monte Carlo Simulation: Effects of Residential Management Practices

Recall that among the 13,000 model runs in the Monte Carlo analysis, management practices varied randomly through defined ranges, and in stochastic combinations. Multivariate regressions were performed on the database of model results to evaluate which management practices correlated with ecosystem C sequestration. Regression results indicated all management practices significantly influenced C sequestration (Table 2-4). Fertilization, tree removal, and tree pruning had the strongest effects, whether positive or negative, on total ecosystem C sequestration over the 50-year period.

Turfgrass with sparse woody was significantly impacted by fertilizer addition, which had the largest positive and overall effect on the change in total ecosystem C (Table 2-4). Maximum application rates resulted in gains of up to 9.8 kg C m^{-2} over 50 years, relative to the full ranges of other management actions and their combinations using the Monte Carlo approach (Figure 2-4 a). Pruning at an annual frequency had the largest negative effect on total C followed by tree removal and pruning every three years (Figure 2-4b, c).

Table 2-4: Normalized multiple linear regression results for total ecosystem carbon in turfgrass with sparse woody, dense woody, and turfgrass.

	Turfgrass with sparse woody	Dense Woody	Turfgrass
Intercept	3.514^{***} (0.137)	5.816^{***} (0.099)	-5.385^{***} (0.034)
Fertilizer	12.325^{***} (0.097)		4.590^{***} (0.032)
Irrigation	5.254^{***} (0.126)		-0.573^{***} (0.039)
Mow height	-1.754^{***} (0.112)		2.889^{***} (0.037)
Mulch mowing	0.713^{***} (0.070)		2.148^{***} (0.023)
Pruning intensity	-5.937^{***} (0.161)	-8.000^{***} (0.148)	
Prune yearly	-3.784^{***} (0.126)	-5.536^{***} (0.115)	
Prune every 3 years	-0.303^{**} (0.130)	-0.871^{***} (0.121)	
Raking	-4.442^{***} (0.097)		
Tree planting	1.383^{***} (0.097)	-3.141^{***} (0.103)	
Tree removal	-4.819^{***} (0.112)	-6.471^{***} (0.103)	
Coarse woody debris removal		1.443^{***} (0.089)	
Observations	7,000	3,000	3,000
R^2	0.819	0.905	0.923
Adjusted R^2	0.818	0.905	0.923
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; SE in parentheses			

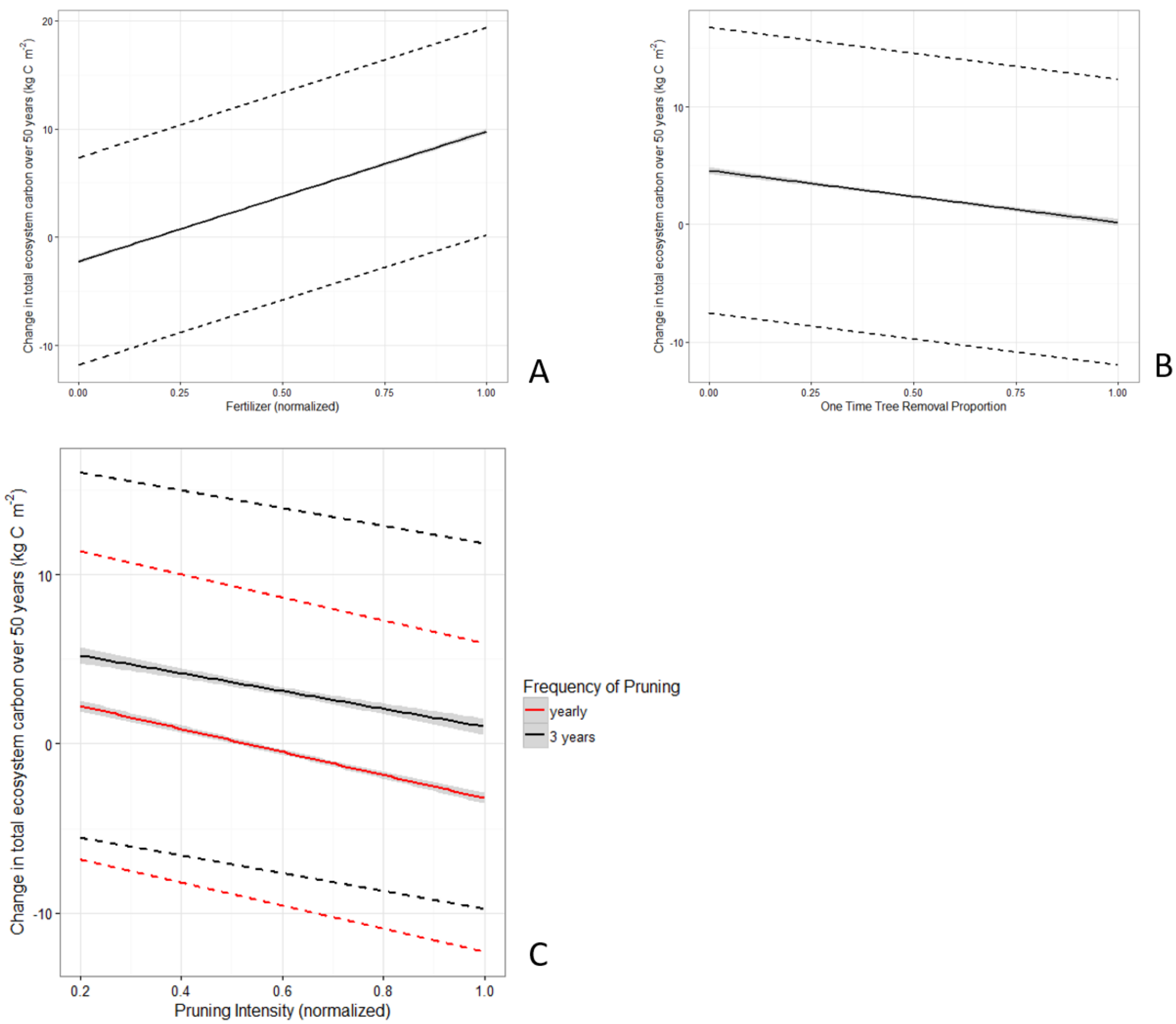


Figure 2-4: Partial linear regression fits of a) fertilizer, b) tree removal, c) pruning from multiple linear regression for *turfgrass with sparse woody*.
Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

Pruning biomass annually was found to be the strongest overall and strongest negative predictor of total ecosystem C sequestration in *dense woody* (Table 2-4a). In our results, maximum pruning intensity (25%) at a yearly interval reduced total C by up to 12.69 kg C m^{-2} over 50 years, relative to the full ranges of other management actions and their combinations (a).

The only human management activity that resulted in a positive C trajectory for all carbon pools in the *dense woody* vegetation category was tree planting (Figure 2-5b).

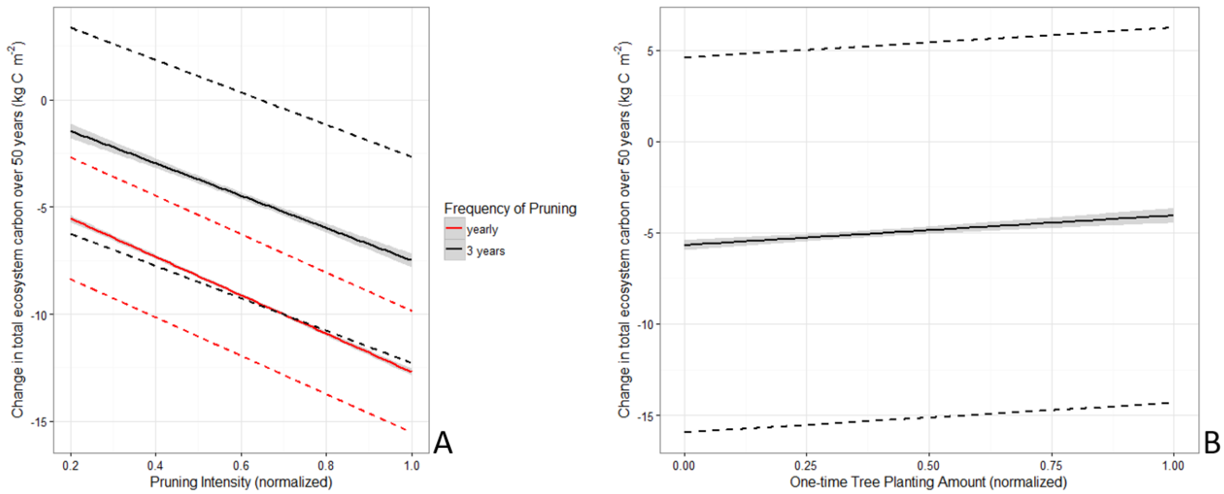


Figure 2-5: Partial linear regression fit of a) pruning and b) tree planting from multiple linear regression for *dense woody*.
Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

For the *turfgrass* vegetation cover type fertilization was found to have the largest positive and overall effect on total ecosystem C. Simulation results showed that a combination of fertilizer and mulch mowing was required in all instances of positive carbon gain and a combination of maximum application and mulch mowing provides a gain of 3.07 kg C m^{-2} over 50 years relative to the full ranges of other management actions and their combinations using the Monte Carlo approach (Figure 2-6). Irrigation was the only management practice in this vegetation type that produced, on average, a loss of ecosystem C over the 50-year period relative to the baseline case, although the loss of C was very slight compared to the high range of variability in the Monte Carlo set of model results (data not shown). Even though irrigation increased grass NPP and grass litter production slightly it increased soil C decomposition even more, leading to a slight, net negative ecosystem C balance.

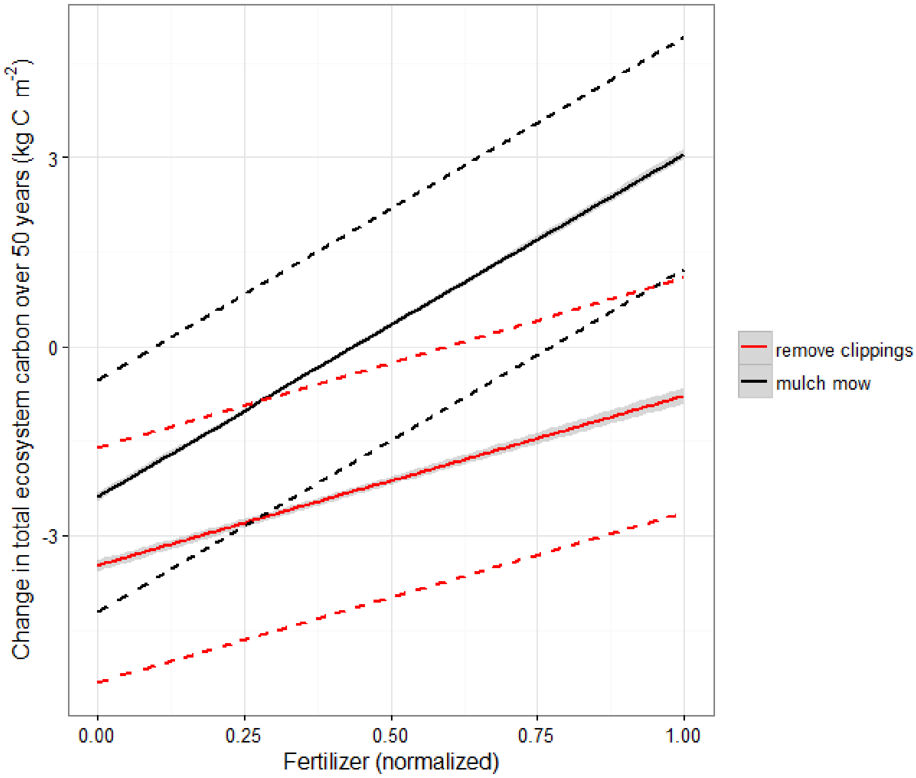


Figure 2-6: Partial linear regression fit of fertilizer from multiple linear regression for *turfgrass*.
Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

2.3.3 Homeowner Agent Typology (HAT)

In our first HAT analysis, which measured the effects of management behaviors associated with each of the homeowner agent types on C sequestration within each vegetation cover type, human activities most often led to positive changes in total C sequestration relative to the baseline (Table 2-5). For *turfgrass with sparse woody*, homeowners that had the highest fertilizer rate and planted trees (*Neat Neighbors*, Table 2-3) resulted in the greatest increase in ecosystem C storage at 8.51 kg C m^{-2} due to increases in tree and litter C. They were followed by homeowners with a medium fertilizer rate and no raking (*Tree Planters* and *Viewers*) with 6.61 kg C m^{-2} and 5.162, respectively (Table 2-5). This C increase was driven by tree litter C and soil C, as the lack of raking increased leaf litter and led to a readily accessible source of soil C. Homeowners that pruned annually and did not fertilize (*Improvers*) were the only type in *turfgrass with sparse woody* to result in a loss of ecosystem C.

All HAT types had positive outcomes for C sequestration in the *dense woody* cover type (Table 2-5). Homeowners with the highest amount of tree planting (*Tree Planters* and *Viewers*, Table 2-3) resulted in the greatest ecological C increase at 3.97 kg C m^{-2} over 50 years. In contrast, for *turfgrass*, only homeowners with the highest fertilization rate (*Neat Neighbors*) produced a substantial increase in C over 50 years, the majority of which was in soil C (Table 2-5). Non-fertilizers (*Improvers* and *Nature Neighbors*) had combinations of management practices resulting in the greatest losses of C in the *turfgrass* cover type.

The second HAT analysis, which upscaled changes in C for each homeowner type from the scale of the parcel to the neighborhood, found the type with the highest fertilizer rate (*Neat Neighbors*, Table 2-3) had the largest effect on C sequestration, increasing total C stored by 3.0 kg C m^{-2} over 50 years (Figure 2-7). Homeowners with a medium fertilizer rate and no raking (*Tree Planters* and *Viewers*) also provided large increases in C at 2.7 and 2.31 kg C m^{-2}, respectively. These increases were predominantly due to growth in tree biomass and accumulation of litter from trees over the 50-year period. Homeowners that did not fertilize and pruned annually (*Improvers*) are the only HAT category that resulted in a loss of total ecological C at the landscape scale, which was driven by a loss of tree biomass and soil C.

Table 2-5: Simulation results from the Homeowner Agent Typology (HAT) analysis for each HAT and for each vegetation cover type.
In dense woody and turfgrass with sparse woody types, tree litter pools include foliar, fine root, and woody litter from above and below ground pools.

		Change in carbon over 50 years within each Homeowner Agent Type (kg C m-2)					
Vegetation Cover Type	Carbon Pool	Neat Neighbor	Lakeshore Property	Nature Neighbor	Tree Planters	Improver	Viewer
Turfgrass with sparse woody (TGW)	Tree Vegetation	6.920	1.815	0.163	2.412	-3.696	1.271
	Turf Vegetation	-0.080	-0.025	-0.025	-0.076	-0.007	-0.055
	Tree Litter	1.953	1.203	1.077	2.503	0.759	2.250
	Turf Litter	-0.030	0.064	0.081	-0.021	0.094	0.025
	Soil	-0.256	-0.342	-0.261	1.790	-0.711	1.671
	Total Ecosystem	8.507	2.715	1.035	6.608	-3.560	5.162
Dense woody (DW)	Vegetation	0.718	0.359	0.359	1.345	0.718	1.345
	Tree Litter	3.182	3.064	3.064	3.389	3.182	3.389
	Soil	-0.822	-0.856	-0.856	-0.765	-0.822	-0.765
	Total Ecosystem	3.077	2.567	2.567	3.969	3.077	3.969
Turfgrass (TG)	Vegetation	0.027	0.013	-0.047	-0.003	-0.047	0.013
	Turf Litter	0.113	0.084	0.031	0.072	0.031	0.084
	Soil	2.516	0.028	-2.108	-0.001	-2.108	0.028
	Total Ecosystem	2.655	0.124	-2.125	0.069	-2.125	0.124

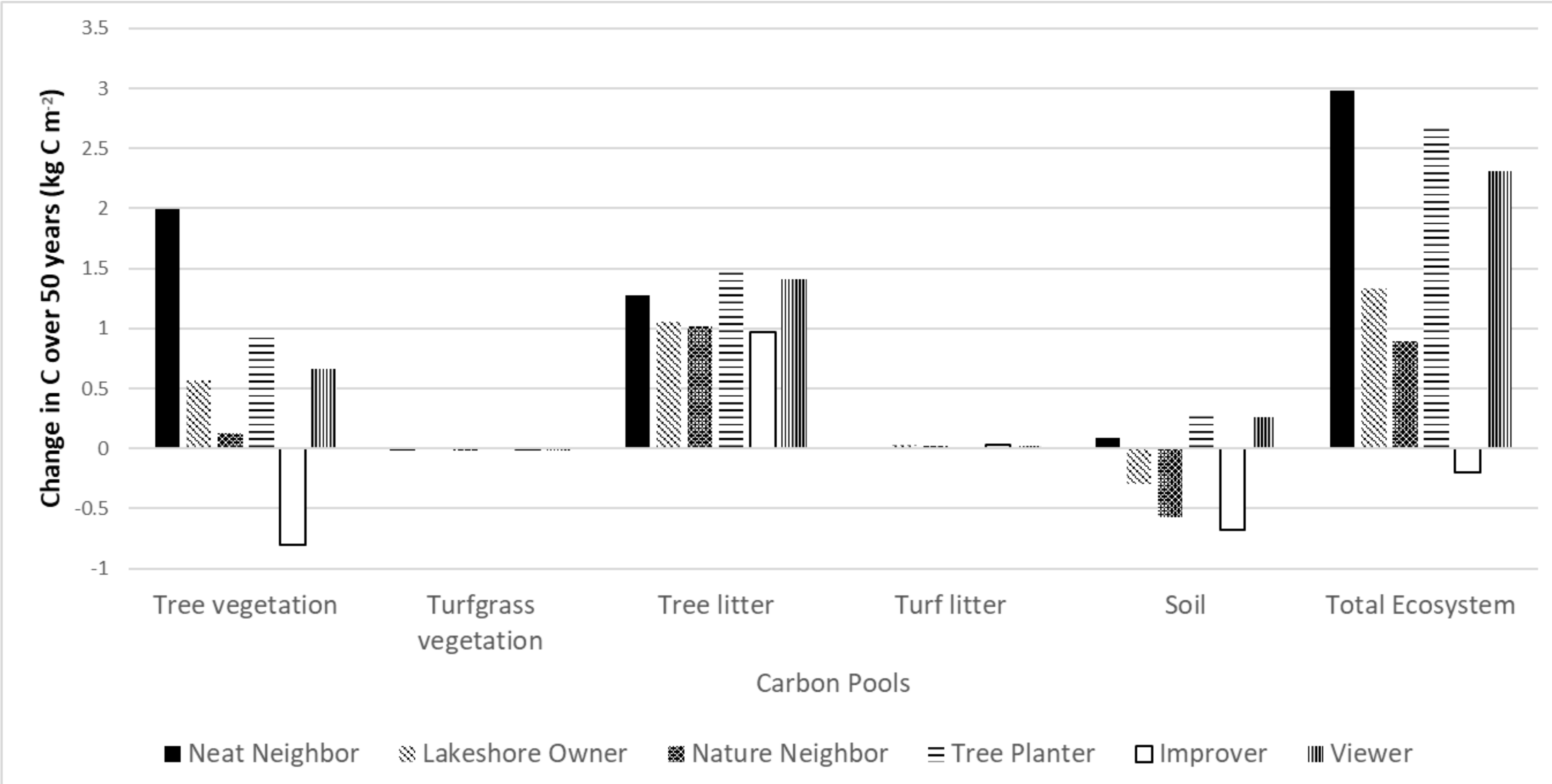


Figure 2-7: Changes in C pool sizes over 50 years for each HAT is scaled up to the neighborhood based on the proportion of each vegetation cover type in the exurban residential study region.
Tree litter carbon pools include above and below ground fine and coarse woody debris (CWD) litter. Soil refers to mineral soil organic matter, excluding surface litter pools.

2.4 Discussion

2.4.1 C sequestration in exurban residential landscapes

2.4.1.1 Turfgrass with sparse Woody

Results of both our Monte Carlo and Homeowner Agent Typology (HAT) analyses confirmed our first hypothesis and showed that fertilizer, pruning, and tree removals had the largest impacts, whether positive or negative, on the outcome of ecosystem C sequestration. *Turfgrass with sparse woody*, which we modeled here using a new approach and is the main vegetation cover type in residential yards in our exurban landscape (Currie et al. 2016), has a high likelihood of sequestering C given that many homeowners follow a management regime of little to no pruning, few tree removals and medium to high levels of fertilization. While not considered in this analysis, this suggests that the relative frequency of the different HAT types among the population has the potential to have a large influence on the carbon storage potential of the region. Neighborhoods dominated by types that fertilize, plant trees, and remove less biomass from the system (*Neat Neighbor*, *Tree Planter* and *Viewer*, Table 2-3) have the greatest potential for C sequestration. These types tend to associate with a different parcel size (small, medium, and large respectively) and are known to coexist on the landscape (Nassauer et al. 2014). These types averaged a net accumulation rate of 0.09 and 0.11 kg C m^{-2} yr^{-1} in the last five simulation years, which is similar to rates found in urban tree cover, but less than the 0.22 kg C m^{-2} yr^{-1} estimated for Michigan (Nowak et al. 2013).

These three management practices also drove the bimodal distribution of C sequestration. In the left mode, yearly pruning occurred in 60%, zero fertilization occurred in 73%, and tree removals were greater than 25% in 77% of simulations. In Biome-BGC-Ex these particular management practices made it difficult for trees to not only increase biomass but to harvest enough light and to acquire enough N to maintain the biomass already established in the initial conditions, resulting in increased tree mortality over time relative to the baseline case. Tree mortality, by allowing more light to reach the grass layer, subsequently allowed turfgrass to increase in productivity, thus increasing turfgrass vegetation and litter C pools, although not at a high enough level to make up for the loss of C from tree mortality. In the right mode (Figure 2-3) 85.5% of simulations had fertilizer application and only 40% had yearly pruning. Thus, in Biome-BGC-Ex, in the *turfgrass with sparse woody* vegetation type, increased fertilizer and decreased pruning frequency allowed trees to increase in biomass giving them an increased competitive advantage over turfgrass for light, water and N, which resulted in decreased NPP and carbon sequestration for turfgrass.

Fertilizer addition was found to have a significant effect on tree vegetation C sequestration in our modeling simulation results. However, the model's N dynamics, especially at high levels of N addition, likely do not adequately simulate the dynamics of plant N assimilation and N immobilization by decomposers. Following the same process as Biome-BGC, Biome-BGC-Ex calculates N demand based on the C:N ratios for different plant, litter and soil pools that are established as constants for the system prior to running the simulations (Appendix B). When N demand exceeds available N, actual N assimilation and N immobilization are reduced proportionally to their demand. Studies on N cycling in forested ecosystems have consistently shown that gross immobilization by decomposers far exceeds root N uptake (Nadelhoffer et al. 1999). In our model simulations, when soil C makes up the majority of total C combined with soil's lower C to N ratios, this relationship is reflected (data not shown). However, when tree vegetation C increases (typically due to fertilization) N demand increases in tandem resulting in proportionally less N available for immobilization. The model has no mechanism in place to adjust how N demand and N uptake may change based on relative biomass pools and N fertilization in the system. This results in Biome-BGC-Ex likely overestimating the amount of tree C storage when fertilization occurs. Future model versions should consider additional dynamics of N uptake and demand when fertilization is present including incorporating dynamics informed by N fertilization studies in forest and grassland ecosystems.

2.4.1.2 TURFGRASS

In our study region, *turfgrass* is unlikely to lead to increases in C sequestration over time, unless it is heavily nitrogen enriched. Of the simulation runs where *turfgrass* resulted in an increase in C over time, 100% had fertilizer inputs and 97% had mulch mowing. This is consistent with other modeling studies which found positive relationships between fertilizer and soil C in turfgrass (Campbell et al. 2014) as well as those that found established turfgrass grown without nitrogen inputs results in a loss or negligible gain of ecosystem C (Milesi et al. 2005) and soil C (Qian et al. 2003). The HAT results further verify this relationship, as the only substantial increases in C occurred with the highest level of fertilizer inputs (*Neat Neighbor*, Table 2-3), which averaged a net soil accumulation rate of 0.04 kg C m^{-2} yr^{-1} averaged across the last five simulation years. This rate falls within the range of empirical residential turfgrass studies and is lower than surface soil accumulation measured in residential turfgrass in Baltimore, MD of 0.08 kg C m^{-2} yr^{-1} (Raciti et al. 2011), but higher compared to 0.026 kg C m^{-2} yr^{-1} in Alabama (Huyler et al. 2014b) or 0.029 (Smith et al. 2018) in Utah.

Based on other studies we hypothesized that irrigation would increase C sequestration in our simulations (Qian et al. 2010, Zirkle et al. 2011). However, we found irrigation to lower ecosystem C storage overall in the *turfgrass* cover type. This echoes the results of Milesi et al. (2005), which used Biome-BGC to model turfgrass across the United States and found irrigation was not necessary for turfgrass growth in southeastern Michigan. The negative relationship between irrigation and C is due to increased soil organic matter decomposition and heterotrophic respiration in Biome-BGC-Ex when soil moisture and evapotranspiration increases (data not shown). This is an ecological process known to factor into residential carbon storage (Kaye et al. 2005, Groffman et al. 2009, Qian et al. 2010), and has been validated by empirical studies demonstrating that increases in evapotranspiration (as a proxy for increases soil temperature and soil moisture) are positively related to increases in decomposition (Meentemeyer 1978, Currie et al. 2009).

The effect of fertilizer and irrigation on carbon sequestration may have also been impacted by the initial conditions we used and the baseline we established. As previously mentioned (section 2.2.3 2.2.4), although our baseline conditions did not include fertilizer management, the ecophysiological parameters describing C:N ratios and initial pools of vegetation and soil C and N were established based on results of the 2009 field study (Currie et al. 2016), where 65% of the sites had been fertilized for at least one growing season. These conditions assumed that turfgrass was already established and that initial soil C and N reflected the relatively high values we observed in the field in exurban yards in our region (Table 2-3). The combination of these high observed initial values and constant C:N ratios over the simulations led to a high demand for N in the processes of vegetation C allocation and decomposition. Simulation runs with lower levels of N inputs were not able to sustain these initial C and N pools due to a higher demand for N than available, resulting in C losses from soils over the 50-year period. However, our modeling results are consistent with empirical studies of turfgrass in residential landscapes that show a declining relationship between turfgrass carbon and time since development, typically leveling out or decreasing between 40 and 50 years (Qian and Follett 2002, Pouyat et al. 2009, Huyler et al. 2017).

Our results for *turfgrass* illustrate the limitations of our project design and the model's N dynamics in multiple ways. First, by having constant C to N ratios and initializing the model with high N concentrations in soil and vegetation we made additional high levels of fertilization necessary to meet plant and soil N demands. Second, plant N demand and microbial N demand are calculated based on the C:N ratios of vegetation, litter, and soil pools that are established as constants for the system prior to running the model simulations (Appendix B). Based on these values and the system's potential assimilation and immobilization, N demand is calculated. If N demand can't be met, N assimilation and N immobilization are reduced proportional to their total demand. Under differing levels of fertilization, the relationships between assimilation and immobilization may no longer represent what is found in real world systems. For example, studies showing that microbes are more competitive for mineral N than plant roots over short-term period (Kuzyakov and Xu 2013, Ouyang et al. 2016), studies showing microbes typically assimilate an order of magnitude more mineral N than plant roots (Nadelhoffer et al. 1999), and studies on how plants and soils adapt to N limitations (Shi et al. 2006, Yao et al. 2011). Third, by having management practices remain constant over the duration of the simulation managers were unable to respond to biomass loss on the landscape by adjusting their management strategy. The results for *turfgrass* illustrate while this model can simulate similar patterns to other empirical and modelling studies of turfgrass, there are still important limitations that must be addressed and verified when modelling human management of turfgrass systems.

2.4.1.3 Dense Woody

The *dense woody* vegetation cover type tends to increase in C sequestration over time, unless pruning occurs. A majority of the *dense woody* simulations had a net loss of carbon relative to the baseline due to high rates of pruning. The HAT results, which did not include pruning as a *dense woody* management strategy, all resulted in net C sequestration gains. The lack of pruning within *dense woody* patches is consistent with the "zone of care" concept (Nassauer et al. 2014), in which residents on large parcels more actively manage only a portion of their yards that sits closer to their homes, generally not including *dense woody* cover. While residents responding to the study are survey indicated some intermittent management outside the zone of care (Nassauer et al. 2014), actual rates were highly variable.

2.4.2 Importance of Fertilizer as a Management Practice

Fertilizer addition is considered standard practice in turfgrass management by residential homeowners (Milesi et al. 2005). In addition, most native and construction-disturbed urban soils cannot supply adequate amounts of nutrients for normal growth of landscape plants and turfgrass, so fertilizers are often used (Carey et al. 2012). Our simulation results found similar results to other empirical (Campbell et al. 2014) and modelling (Qian et al. 2003, Milesi et al. 2005) studies, showing nitrogen enrichment was necessary for C sequestration in *turfgrass*. In *turfgrass* and *turfgrass with sparse woody* our initial hypothesis that fertilizer would be the strongest influence on C sequestration was observed in our model simulations. As previously mentioned (2.4.1), while the positive relationship between fertilization and C sequestration shown in our simulations results match those found in empirical studies, the strength of the relationship estimated in the simulations may be greater than what is found in reality, especially at the highest levels of fertilization.

In *turfgrass with sparse woody* simulations fertilizer additions also drove C sequestration, typically through increased tree productivity. Biome-BGC-Ex assumed size-symmetric competition for N between trees and turfgrass, meaning that the model determines the daily N need for both trees and turfgrass and then allocates the available N proportionally (Hara 1993). Although homeowners may fertilize to affect turfgrass, fertilizer added to our *turfgrass with sparse woody* simulations was available to both tree and turfgrass vegetation. In Biome-BGC-EX trees competed for and obtained much of the added N leading to a positive response in tree NPP and woody biomass growth, driving the C increases we observed in many model results (Figure 2-3). In simulations where nitrogen was added, tree vegetation carbon increased on average by 37%. In model simulations increases in tree biomass contributed to increases in belowground litter C from dead roots leading to soil C increases over time, which is a process also observed in empirical residential field studies (Huyler et al. 2017).

The relationship between tree carbon and fertilizer addition is difficult to evaluate in the context of the exurban landscape, since there is a lack of studies evaluating the effect of nitrogen enrichment explicitly in this landscape. In a study region overlapping our study's, Kahan and others (2014) found that vegetation and soil in protected areas bordering residential development had increased concentrations of N and lower C to N ratios as housing density increased. Compared to other temperate deciduous forests in the US they found higher foliar N concentrations in protected areas bordering development, indicating that urban tree cover does respond to N enrichment. In denser urban environments, trees on streets, in parks, and on residential property often receive additional nutrients and water, whether applied directly or indirectly (McHale et al. 2009, Shober et al. 2010). Recommendations for urban tree fertilization geared toward land managers and arboriculturists do exist, with values falling within the range applied in the *turfgrass with sparse woody* scenarios (Scharenbroch and Lloyd 2004). However, the response of urban trees to fertilization across species may not be uniform (Ferrini and Baietto 2006).

While the vegetation structure of *turfgrass with sparse woody* may be more like urban parks or forest patches (McPherson et al. 1997), temperate forests also provide an opportunity for comparison. Studies on nitrogen deposition in North American temperate forests have found evidence of added nitrogen leading to increases in living and dead wood of around 10% (Magill et al. 2004, Pregitzer et al. 2008). However, other studies have shown trees take up limited amounts of additional nitrogen and show only minor increases in C (Nadelhoffer et al. 1999, Currie et al. 2004). Further field and empirical research on the application and effects of fertilizer in managed vegetation mixtures of grasses and open trees within the exurban landscape would be useful in further assessing the N dynamics and ecological competition in this unique vegetation community.

Our simulations found mulch mowing significantly reduced the amount of fertilizer necessary for C sequestration in both *turfgrass* and *turfgrass with sparse woody*. In the pure *turfgrass* vegetation cover scenarios we found that the amount of fertilizer necessary for carbon sequestration is more than double when grass clippings are removed compared to when they are mulch mowed. This relationship has been observed in empirical turfgrass studies which found that grass clippings increase soil C pools in N limited ecosystems (Kaye et al. 2005, Huyler et al. 2014a, Peach et al. 2019). Our simulations showed that mulch mowing increased the amount of soil C in *turfgrass* soil by 40%, which is consistent with other modelling studies that have found mulch mowing increases the amount of soil C sequestered in turf by 11 to 59% over a 10- to 50-year period (Qian et al. 2003, Milesi et al. 2005).

2.4.3 Modeling Exurban Residential landscape and future research

Our study found that different realistic sets of management practices, as examined in the HAT analysis, have differential effects on C sequestration, and these differences can have significant impacts when scaled up to the landscape. Our study shows that increases in woody biomass are the strongest driver of C increases in the residential landscape, which is consistent with empirical studies (Golubiewski 2006, Fissore et al. 2012, Huyler et al. 2017). Our colleagues have found that a homeowner's preference for trees is driven by many factors including: aesthetic preferences (neatness, views), a desire for privacy, neighborhood norms, and parcel size (Nassauer et al. 2014, Visscher et al. 2016). Efforts to increase exurban carbon storage should consider these preferences along with the coinciding management practices that encourage tree growth.

One of the major contributions of Biome-BGC-Ex is the ability for the user to model and simulate the dynamics of multiple plant functional types in two distinct vertical layers in the same grid cell. This gave us the ability to evaluate the dominant vegetation cover type found in the exurban residential landscape of our study region, *turfgrass with sparse woody.* The *turfgrass with sparse woody* landcover is a product of human management, in which turfgrass is planted and maintained on residential property along with an overstory of sparse tree cover. In our study region, *turfgrass with sparse woody* cannot be maintained without human intervention, as turfgrass cannot outcompete increased tree cover that would occur under natural or non-managed conditions. The new exurban "biome" introduced in this model could be used to investigate C dynamics in residential landscapes found in similar temperate forest biomes, assuming they display a similar ecosystem structure and function (Groffman et al. 2014, 2017). There is also potential for Biome-BGC-Ex to be used in other landscapes with sparser, open grown tree cover caused by human intervention such as temperate agroforestry ecosystems which experience size asymmetric competition for light above ground and size symmetric competition for soil water and nutrients below ground (Jose et al. 2009). The ability of Biome-BGC-Ex to measure how management practices affect C dynamics across a variety of vegetation covers means it can be used as a tool by scientists and policy makers to target which landscape management practices will produce desired C outcomes.

This study assumes model variables such as C:N ratios and management practices are constant over the 50-year period. As mentioned previously (2.4.1.2), constant C:N ratios may limit the model's ability to accurately simulate N dynamics. It is a common limitation of models like Biome-BGC, that are not individual-based or species-specific, and that are not meant to capture tree species change or community change over time, to have constant C:N ratios in plant tissues over time and across species. In reality, in a forest or tree community, species composition, tree size, and tree management might change over time resulting in changes to C:N ratios. The assumption of a constant tree community composition and average tree size over the 50-year modelling period is one of many simplifying assumptions in our simulation of exurban vegetation. It is also likely that homeowners will adjust their behavior when resulting changes in the appearance of a residential landscape do not fit into the norms of their neighborhood or fit their preferences, and these norms and preference may also change over time (Nassauer et al. 2014). While this study examined the question of which practices drive carbon sequestration, it does not follow how humans might respond to or provoke changes in the landscape leading to feedbacks between the human and ecological system. The second HAT analysis also does not account for different combinations and locations of HATs within the neighborhood. This study contributes to these considerations in our larger project (SLUCE), which aims to understand how social-ecological drivers on the landscape impact C balance by explicitly simulating developers and residents as human agents with environmental decision-making functions (Robinson et al. 2013). Future models that combine Biome-BGC-Ex with an Agent Based Model would be one strategy for understanding how dynamic homeowner preferences and behaviors affect C outcomes and how feedbacks both within an ecosystem and between humans and the ecosystem affect C.

Our results show the importance of management practices affecting nitrogen availability in exurban land. While these practices positively affect the ecosystem service of C sequestration, they are also linked to outcomes of other ecosystem services that are not explored in this analysis (Groffman et al. 2009, Carey et al. 2012). Excessive lawn fertilizer use is known to have negative effects on the landscape such as decreased water quality (Carey et al. 2012, Hobbie et al. 2017). Hobbie and others (2017) estimated that 8% of residential N inputs were lost via runoff in a mixed density urban watershed, which is an important ecosystem loss of N that Biome-BGC-Ex does not account for. The current version of Biome-BGC-Ex is limited in its ability to simulate surface loss of N or fertilizer and in its soil hydrology sub-models. This could be addressed by linking Biome-BGC-Ex with a spatially explicit model such as SWAT (Francesconi et al. 2016), watershed models (Samal et al. 2017), or surface waterflow models (Xu et al. 2016). Additionally, a new version of Biome-BGC, Biome-BGCMuSo, was released after modifications of Biome-BGC-Ex were complete and includes a multilayer soil model that has improved the simulation of soil hydrology including runoff (Hidy et al. 2012, 2016). These factors along with other observations on the model's N dynamics (2.4.1.2 could be considered in future versions of Biome-BGC-Ex.

The small sample of data available from our 26 sampled parcels for model parameterization and calibration along with an overall lack of long term or chronosequence data from exurban land did not allow for a robust validation of Biome-BGC-Ex as a tool for simulating ecosystem processes in exurban ecosystems. However, a comparison of trends shown between our model results and empirical studies of other urban ecosystems indicate our model is performing as expected. Fissore and others (2012) estimated C accumulation in mixed tree and turfgrass residential yards across a density gradient and found it ranged between 0 - 1.1 kg C m^{-2} yr^{-1}, with higher values found with increased parcel size and tree density. This study, which accounted for tree and turfgrass NPP, heterotrophic respiration, and leaf management, underscored the wide span of potential C accumulation in the residential landscape. Nowak and others (2013) estimated C accumulation in urban tree cover across the US and found temperate regions to vary between 0.08 - 0.3 kg C m^{-2} yr^{-1}. For Michigan they estimated a rate of 0.22 kg C m^{-2} yr^{-1}. In this study, for *turfgrass with sparse woody* the HAT C accumulation range is between 0.08 - 0.68 kg C m^{-2} yr^{-1} when averaged across the last five simulation years (data not shown). For *dense woody* the HAT results range between 0.21 to 0.23 kg C m^{-2} yr^{-1} when averaged across the last five simulation years (data not shown). As previously mentioned, (2.4.1.2) *Neat Neighbor*, the only HAT that sequesters carbon in *turfgrass,* averaged a soil C accumulation rate of 0.04 kg C m^{-2} yr^{-1}. This falls within the range (0.026 - 0.08 kg C m^{-2} yr^{-1}) measured in urban residential yards (Raciti et al. 2011, Huyler et al. 2014b, Smith et al. 2018). As discussed in the previous section (2.4.2), the dynamics of nitrogen in exurban ecosystems are not well studied and the response of urban trees to fertilizer varies across species (Ferrini and Baietto 2006). Future research specifically investigating competition dynamics between open grown trees and turfgrass, particularly regarding nitrogen, would improve confidence in the model.

We acknowledge that this study is not a full-scale carbon budget. We are only considering the C in soils and vegetation and are not accounting for C losses that arise from the application of these management practices (e.g., gas-powered lawn mowers, running sprinklers, production of N fertilizer) or losses that may occur due to people living away from urban centers (e.g. transportation), which are known to have significant impacts on urban C and N fluxes (Fissore et al. 2011). Selhorst and Lal (Selhorst and Lal 2013) estimated the average C equivalent (Ce) emissions for lawn mowing as 0.019 g Ce m-2 y-1 and 0.006 g Ce m-2 y-1 for fertilizer application (including production, packaging, storage, and distribution). Using these values applied across all Monte Carlo simulation results, 10% fewer *turfgrass with sparse woody* simulations and 40 % fewer in *turfgrass* would have sequestered carbon. We also did not consider the fate of any C removed from the system, when in many cases homeowner may keep collected woody biomass on their property (Currie et al. 2013). If the full C costs of each management practice were considered it may produce different outcomes (Selhorst and Lal 2013, Contosta et al. 2020). Future studies could use Biome-BGC-Ex in conjunction with other tools to estimate residential carbon budgets.

2.5 Conclusion

In this study we adapted an ecosystem process model designed for wildland systems to the human-dominated exurban landscape. Models such as Biome-BGC-Ex can give insight into the mechanisms of growth and decay within a system and can be used to simulate potential variation in ecosystem states and fluxes given sets of assumptions, drivers, and initial conditions (Tatarinov and Cienciala 2006, Robinson et al. 2009, 2013, Lei et al. 2015). Models are not meant to be perfect predictors of future outcomes; however, for our study they allow us to compare how C sequestration could respond to a range of input scenarios under a constrained set of site and climate conditions. Through simulations with Biome-BGC-Ex we found that homeowners' management practices can have significant impact on outcomes of C sequestration in the residential exurban environment. These simulations suggested that N fertilization in the *turfgrass with sparse woody* and *turfgrass* vegetation cover types was necessary for C sequestration. In *turfgrass with sparse woody* fertilizer was assumed to be applied uniformly to both trees and turf, which maintained and increased tree biomass leading to C sequestration. In *turfgrass* fertilizer was necessary for C sequestration in order to meet the vegetation and soil nitrogen demands, however mulch mowing can significantly reduce the amount of fertilizer needed. In the *dense woody* vegetation cover type pruning and tree removals had the largest impact on C sequestration and should be minimized to improve C outcomes. At the landscape scale, management that increases woody biomass is the strongest driver of C sequestration in exurban residential land and efforts to increase C should consider homeowner preferences and management practices that encourage tree growth. Overall, our study results illustrate the strength of assessing the effects of human management by using an ecosystem process model with C, N, and water dynamics in vegetation and soil linked through functional ecosystem processes.

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Chapter 3
Simulating the Effects of Yard Management Practices on Ecosystem Service Capacity in Residential Landscapes

ABSTRACT

Ecosystem process models can be adapted to represent the complex interactions among social and ecological processes in human-dominated ecosystems. We adapted the Biome-BGC-Ex model to estimate the ecological production of a suite of ten supporting, regulating, and provisioning services in exurban ecosystems of Southeastern Michigan. Using Monte Carlo simulation methods, we simulated potential combinations of ten separate yard management practices and found that the ES capacity for each service varies with the management activities. All services across all vegetation types have significant changes in capacity due to at least one yard management practice. Fertilizer is an important driver for almost all ES explored here. Our analysis of trade-offs and synergies between the modeled services under six different homeowner agent types (HATs) found that differences and trade-offs in ES capacity between HATs can be explained by biophysical feedbacks modelled within the ecological system. Our study shows trade-offs between ES relating to high amounts of carbon or biomass and freshwater recharge. Our results indicate that homeowner efforts to improve locally beneficial services have the potential to positively affect those with benefits at a coarser scale. Our methodology is an advance toward fully anticipating the consequences of homeowner yard management choices.

3.1 INTRODUCTION

Ecosystem services (ES) are the physical goods and associated benefits provided to humans by the ecosystems of the planet. The Millennium Ecosystem Assessment (MA, 2005) highlighted the importance of nonlinearities, feedbacks, and interactions within ecosystems and in the provision of ES (Cumming et al. 2005). This highlights the importance of the dynamics of integrated social-ecological systems (SES) in which interactions exist within and between human and ecological systems (Carpenter et al. 2009; Ostrom et al., 2007). By addressing these interactions, ES science can support decision-making that recognizes how landscape ecological functions affect the provision of ES and how land management practices might affect future provision and trade-offs among ES (Villamagna et al. 2013, Bennett 2017).

A full analysis of ES requires that both ecological and socio-economic aspects and their relationship need to be considered. A variety of overarching frameworks have evolved from the original framework proposed by the MA report (2005) that attempted to identify the relationships between goods and services provided by ecosystems and improvements to human wellbeing (e.g., ES supply chain (Tallis et al. 2012), ES cascade model (Haines-Young and Potschin 2010), ES delivery process (Villamagna et al. 2013)). The key components of these frameworks can be distilled to ES capacity, ES flow, and ES demand. ES capacity is the potential of an ecosystem to produce and deliver services based on biophysical and social properties and functions (Villamagna et al. 2013). ES flow is the realized flow of services for which there is demand. ES demand is the amount of services required or desired by society. These frameworks recognize that ES demand generates human pressures on ecological systems that drive changes in ES capacity. This study focuses on how these human pressures, in the form of residential homeowner management behaviors, affect ES capacity in the exurban residential landscape.

ES capacity is reliant on interactions between the ecological processes of ecosystems and human drivers and pressures on those ecosystems, including design, planning, and management actions (Termorshuizen et al. 2009, Fu et al. 2013, Bruins et al. 2017). Ecosystem processes are flows of energy, water, carbon (C), and nutrients that link biotic and abiotic factors within an ecosystem; they are interconnected by direct and indirect biophysical feedbacks (Currie 2011). Although human activity tends to modify these processes one at a time (e.g., irrigating lawns, adding N fertilizer), alteration of one process nearly always induces alteration of other processes (Finzi et al. 2011). As a result of human activity there are complex feedbacks between ecosystem processes and ES capacity. These feedbacks are described as balancing (negative) when they dampen change or reinforcing (positive) when they stimulate change. These dynamics lead to trade-offs and synergies in the production of ES, where trade-offs describe losing capacity of one service in return for the gain of another and synergies describe the positive response of multiple ES to change in a driver (Bennett et al. 2009). Despite the proliferation of ES assessment tools, most do not consider mechanistic biophysical feedbacks, e.g. feedbacks among biogeochemical cycles, or other mechanistic interactions among ES; each service is typically estimated independent of other services (Nicholson et al. 2009, Seppelt et al. 2011, Currie 2011, Bruins et al. 2017, Lavorel et al. 2017). If knowledge of ecosystem processes and functions, including interactions with human actions and behaviors, is not adequately incorporated into ES models, scientists, managers, and other practitioners may misunderstand the mechanisms underlying the effects of management decisions on ES capacity, improperly estimate the production of services, and possibly take actions that have consequences that could have been better anticipated (Bruins et al. 2017, Bennett 2017, Boerema et al. 2017).

Ecosystem process models are tools that have been designed to simulate biogeochemical processes and feedbacks within ecosystems. They have been verified, calibrated, and applied to global simulations as well as for local, site specific conditions across a range of wildland and human-dominated ecosystems including agriculture (Parton and Rasmussen 1994, Stehfest et al. 2007, Wang et al. 2012), managed forests (Tatarinov and Cienciala 2006, González-Sanchis et al. 2015), managed grasslands (Qian and Follett 2002, Bandaranayake et al. 2003, Hidy et al. 2012), urban ecosystems (Milesi et al. 2005, Zhang et al. 2012, Trammell et al. 2017), and exurban residential landscapes (Chapter 2). These models can provide quantifiable outputs of ecosystem C, N, and water pools and fluxes that can be used to estimate ES capacity. Because ecosystem process models can reflect complexities such as feedbacks among processes occurring in an ecosystem, they can provide users with dynamic and quantitative measures of ES that can be integrated with other types of models and tools. Such models can provide robust measures of ES capacity, and they have the potential to be adapted to include human management because they employ transparent assumptions to extrapolate beyond known conditions (Cuddington et al. 2013a).

In this study, we applied a generalizable method to improve estimates of the provision of ES in the exurban residential landscape. We used the model Biome-BGC-Ex to estimate a suite of ES which fall into the supporting, provisioning, and regulating categories defined by the MA report (2005). Biome-BGC-Ex is a version of the ecosystem process model Biome-BGC (Running and Hunt 1993, Thornton and Rosenbloom 2005) that has been modified to simulate ecosystem processes in the residential exurban landscape (Chapter 2). Previous studies have used Biome-BGC to estimate ES capacity. This has included linking Biome-BGC with a hydrology model to estimate ES in a watershed (Xu et al. 2016), linking a modified version of Biome-BGC

(Biome-BGCMuSo) with a crop simulation model (Pokovai et al. 2020), and modifying Biome-BGC to estimate ES in a managed forest (Turner et al. 2011). Although other ecosystem process models have been modified for urban residential land (Trammell et al. 2017), this study will be the first that uses one to examine ES capacity in a residential landscape and focus on how homeowner yard management affects ES.

Exurban residential land use is low-density settlement characterized by relatively large yards or private gardens for individual residences. Exurban land area increased from about 5 % (270,608 km^2) of total land area of the conterminous US in 1950 to about 25 % (1.39 million km^2) in 2000 (Brown et al. 2005) and the exurban population is projected to increase in future decades (Golding and Winkler 2020). In the US, exurban land use includes subdivisions, typically established by a single developer, as well as individually-developed properties, typically subdivided parcels on prior agricultural or forest land (An et al. 2011). Exurban residential land use is defined for this study as one housing unit per 0.2 to 16.2 ha (Brown et al. 2005). Exurban development is composed of lower-density settlements that may lie adjacent to more densely populated suburban areas. In contrast to suburban areas, exurban parcels are larger, farther from city or town centers, and are typically disconnected from municipal services of sanitary sewer and water (An et al. 2011). Exurban landscapes are also known as peri-urban landscapes (Geneletti et al. 2017), and sometimes, characterized pejoratively as urban sprawl (Berger and Kotkin 2017). The yards that characterize this land use can provide ES, especially in comparison with conventional agriculture or dense urban areas (Nassauer et al. 2004, Raudsepp-Hearne et al. 2010, Radford and James 2013, Visscher et al. 2016).

Although exurban residents affect ES in many ways, this study is specifically concerned with yard management behaviors that may affect ecosystem processes and drive differences in ES capacity. We focus on two behaviors that have pervasive effects. The first behavior relates to vegetation choices made by developers or residents, particularly the creation of a novel ecosystem characterized by maintained turfgrass growing under open grown trees (Cook et al. 2012, Groffman et al. 2014b, Currie et al. 2016). We refer to this vegetation community as *turfgrass with sparse woody*. The second behavior involves, vegetation and soil management practices, which directly affect water, carbon, and nitrogen flows. These include fertilization, irrigation, mowing, pruning, raking, tree removals, and tree planting. Developer and resident behaviors are driven by a variety of factors including parcel size (Nassauer et al. 2014), neighborhood norms (Nassauer et al. 2009, Visscher et al. 2014, Sisser et al. 2016)and ease of maintenance (Carrico et al. 2013). These behaviors may also be directly or indirectly motivated by a demand for ES or avoidance of ecosystem disservices. This includes cultural ES, such as aesthetic services of beauty, neatness, safety, relaxation, and leisure provision; provisioning services of food and firewood production; and regulating services such as habitat for wildlife, biodiversity, and soil stability (Visscher et al. 2016, Larson et al. 2016, Barnes et al. 2020). Ecosystem disservices include as aesthetic unpleasantness, high-cost maintenance, and nuisances (e.g., allergenic plants, mosquitoes, rodents) (Wang et al. 2012, Nassauer 2017, Barnes et al. 2020). While homeowners may choose a behavior in response to their demand for an individual ES, the behavior is likely to induce either a synergistic or trade-off response in one or more ES. This project simulates human pressures, in the form of homeowner management behaviors, that result from these ES demands. It then analyzes their effect on ecological processes with the goal of expanding our understanding of how human pressures and ecological feedbacks affect ES capacity in the exurban landscape, specifically residential land uses characterized by trees and turfgrass landcover. t

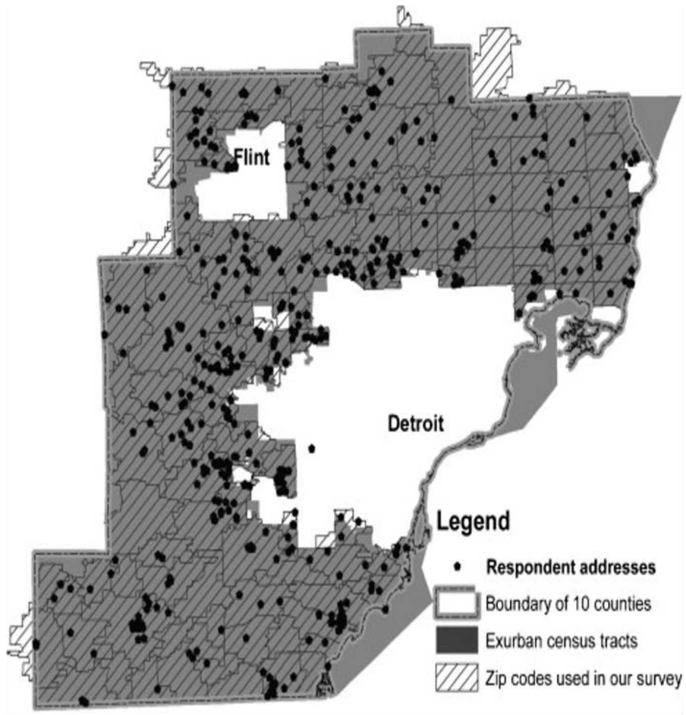
This study uses the ecosystem process model, Biome-BGC-Ex, to estimate the ecological production of a suite of ten supporting, regulating, and provisioning services in the exurban residential landscape of Southeastern Michigan, USA: NPP, soil fertility, firewood production, nitrogen retention, freshwater recharge, spring soil water recharge, summer soil water retention, climate regulation, microclimate regulation, and air pollution abatement. The main questions of this study were: 1) how do individual and combinations of yard management practices affect ES capacity? 2) what are the trade-offs and synergies between the modelled services? First, we used a Monte Carlo simulation that explores the potential range of combinations of management practices to analyze how management practices affect the ES capacity of each service. Our first hypothesis was that, for each service, the capacity of the ecosystem to provide that service would differ among different management practices. Next, we compared trade-offs and synergies between the modeled services under different homeowner agent types (HATs), each characterized by different management intensities, combinations, and motivations reflective of those reported by interviewees in our study region. Our second hypothesis was that most simulated services would have synergistic responses to management, although the magnitude of response would vary between combinations. These analyses allow us to consider how different management practices drive ES capacity individually and in combination.

3.2 METHODS

3.2.1 STUDY REGION AND BROADER CONTEXT

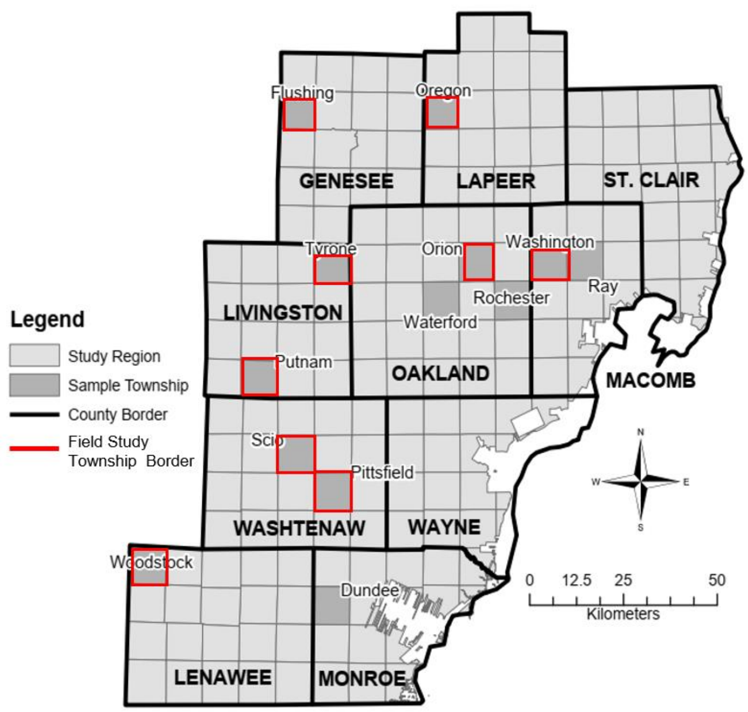
This study was conducted as part of a larger collaboration, the SLUCE project (Spatial Land Use Change and Ecological effects (Brown et al. 2008), which addressed the exurban residential landscape as a coupled human-natural system. The empirical context is a 1.7 million ha study region (Figure 3-1) comprising ten counties in Southeastern Michigan that contain the Detroit, Ann Arbor, and Flint metropolitan areas with an estimated total regional population of 5.3 million (U.S. Census Bureau 2021) that is dominated by exurban residential development (Zhao et al. 2007, Brown et al. 2008, Huang et al. 2013). Here we draw on products of a larger interdisciplinary project including an empirical ecological field study (Currie et al. 2016), developer and homeowner interviews (Nassauer et al. 2014, Nassauer 2017), online surveys (Nassauer et al. 2009, Wang et al. 2012, Visscher et al. 2014, 2016), modeling in a coupled human-natural system framework (Robinson et al. 2013), and adapting Biome-BGC to represent exurban vegetation cover types and management practices in Biome-BGC-Ex (Kiger et al. Chapter 2).

Figure 3-1: Study Region Extent



a. Zip code boundary

a. Map displays the ten-county study region of Southeastern Michigan, exurban census tracts and zip codes boundaries used in online surveys from Visscher et al. 2014, 2016 (reproduced with permission from Nassauer et al. 2009).



b. Township boundary

b. Map displays 13 sample townships dominated by exurban land use selected for focus by the SLUCE project. Red bordered townships were the location of field surveys in Currie et al. (2016) and field interviews in Nassauer et al. (2014).

3.2.2 Model Input Data

In 2009 our detailed field study gathered social and ecological data in exurban residential neighborhoods of nine townships within the study region (Figure 3-1b). This study collected data on C and N present in foliage, wood, and litter of tree and turfgrass vegetation and soil of 26 parcels (Currie et al. 2016) and on homeowner landscape management preferences and practices within these parcels (Nassauer et al. 2014). These parcels were selected from a pool of 600 respondents to an internet-based survey of exurban residential landscape preferences conducted in prior work in the study region (Nassauer et al. 2009, Figure 3-1a). A subset of 53 respondents from this pool was invited to participate in an on-site interview and biophysical site survey. The subset was selected to represent stages (i.e., parcels that had been converted to residential land in each decade from the 1960s to the 2000s) and types (i.e., across the four types of exurban developments in our study region defined by An et al. 2011) of residential development in the region (based on aerial photos) and typical soils in the region (clay-rich soils were excluded based on STATSGO data) (Currie et al. 2016). Of this subset 26 households agreed to participate (Currie et al. 2016).

This study simulates three predominant vegetation cover types identified as being the dominant cover types in the exurban residential neighborhoods of our study area: *dense woody* vegetation, *turfgrass*, and *turfgrass with sparse woody* vegetation (Currie et al. 2016). These landcover types occur on land that was historically forest or been cultivated or grazed crop or pasture. The current vegetation composition depends on active human management (tree and stump removal and turfgrass seeding, together with continued mowing). *Dense woody* vegetation has a closed to mostly closed canopy and no managed turfgrass. It was present in 8 of the 26 parcels in the 2009 study and made up the second largest proportion (22.1%) of land cover in investigated subdivisions (Currie et al. 2016). *Turfgrass* is managed turfgrass or lawn with no woody vegetation. This was present on 24 of the 26 parcels and made up 16.6% of land cover in investigated subdivisions. *Turfgrass with sparse woody* contains managed turfgrass and trees, but with gaps present between canopies. This vegetation cover type was identified in 24 of the 26 parcels and typically made up the largest proportion (26.3 %) of land cover in investigated subdivisions (Currie et al. 2016).

All analyses used inputs based on in-person interviews of the same 26 households as above, which surveyed homeowners on frequency and application amounts for a variety of management practices (listed in Table 3-1; Nassauer et al. 2014). Management input probabilities for the Monte Carlo Analysis (section 3.2.5.1) took into account results from the online surveys conducted in the 207 zip codes of our study region (Figure 3-1a, reported in Visscher et al. 2104 and Visscher et al. 2016). Recommendations by the Michigan State Extension were used to improve our management distribution ranges for fertilizer (Frank 2015) and irrigation (Frank 2015) inputs and national standards of woody plant maintenance were used to improve estimates of pruning biomass removal (ANSI 1995). Literature on residential land management was also used to confirm ranges of fertilizer and irrigation (Law et al. 2004, Zirkle et al. 2011) and to translate mowing height to leaf area index (LAI) at time of mowing (Milesi et al. 2005). Results of the 2009 field study were also used to parameterize and determine the initial conditions of the model simulations (see 2.2.4 Appendix C; Currie et al. 2016).

Results from the 26 household interviews were also used by Nassauer and others (2014) to construct the Homeowner Agent Typology used in our analysis (section 3.2.5.2 Table 2-3). As part of our larger project, Nassauer et al. (2014) developed a typology of exurban homeowners in our study area, each with distinct yard management regimes. The six types were:

neat neighbor, lakeshore owner, nature neighbor, tree planter, improver, and *viewer (*Figure 3-2*)*. We refer to these six types as a Homeowner Agent Typology (HAT). HATs are based on a combination of parcel size, parcel characteristics and homeowner behaviors. These behaviors are related to many factors including neighborhood norms and parcel size, but for the purpose of this study we are most interested in which ES they desire from their yards. *Neat neighbors* were small parcel owners with turf-dominated yards that were fertilized and planted with trees. They noticed their neighbors' yards and expected their neighbors to notice theirs. Their behaviors were related to an ES demand of a yard that is aesthetically neat. *Lakeshore property owner* owned small lake front or adjacent parcels. They fertilized but did not plant new trees. They desired aesthetic water views and low maintenance tree management. *Nature neighbors* lived on small parcels adjacent to large woodlands. They did not fertilize. They managed to maintain aesthetic woodland views. *Tree planters* owned medium parcels with large amounts of *turfgrass with sparse woody* vegetation cover. They planted trees on their property and used fertilizer. They were influenced by neighbors' perceptions and aspiring to a "more natural" approach to property maintenance. *Improvers* own large parcels with large amounts of *dense woody* vegetation cover. They tended to not fertilize but did manage tree vegetation. They managed their properties with a desire for recreation and relaxation as well as wildlife viewing. *Viewers* owned large parcels that included large patches turfgrass either open or under woody vegetation. Their behaviors were related to interest in wildlife viewing and aesthetic characteristics of turf lawns beneath canopy trees. While these interviews qualitatively assessed motivations for management behaviors that the current study translated to ES demand, it was not designed to assess whether residents' demands had been met or how satisfied residents were with the resulting ES flow.

Table 3-1: Description of management practices and their distributions and probability frequencies used in the Monte Carlo Analysis.
Abbreviations: TGW = turfgrass with sparse woody, TG = turfgrass, DW = dense woody, SD = standard deviation; NA = not applicable.

Management practice	Description	Vegetation cover type	Probability of occurrence††	Distribution type	Distribution range[1]
Fertilizer	Nitrogen added (kg N m^{-2} yr^{-1})	TGW TG	0.7	Uniform	0.0048 – 0.024‡‡
Irrigation	total weekly water amount (cm)	TGW TG	0.75	Normal	Mean: 2.54§§ SD: 0.5
Mow height	Leaf Area Index (LAI) at time of mowing	TGW TG	1.0	Uniform	1.0 - 4.5***
Mulch mowing	If yes, grass clippings stay on lawn	TGW TG	0.7	NA	NA
Pruning intensity	Percent of foliar and fine woody biomass removed	TGW DW	0.75	Uniform	5 - 25%†††
Pruning frequency	If pruning occurs, yearly or every three years	TGW DW	Yearly: 0.6 Every 3 years: 0.4	NA	NA
Raking	Percent of aboveground tree litter biomass removed	TGW DW	0.55	Uniform	5 - 100%
Coarse woody debris (CWD) removal	Percent of CWD removed (for TGW all CWD is always removed)	TGW DW	TGW: 1.0 DT: NA	TGW: NA DT: Uniform	TGW: 100% DT: 0 – 100
Tree planting	Aboveground tree biomass added (kg C m^{-2}) in random year from 14-38	TGW DW	0.7	Uniform	0.1 - 3.0
Tree removal	Percent of tree biomass removed in random year from 14 to 38	TGW DW	1.0	Uniform	0 - 100

†† Probabilities and distributions are based on homeowner interviews conducted across the study region (Nassauer et al. 2014) and supplemented with additional sources as follows.
‡‡ (Law et al., 2004, Zirkle et al. 2011, MSU Extension 2014a)
§§ (Zirkle et al., 2011, MSU Extension 2014b)
*** (Milesi et al. 2005)
††† (ANSI 1995)

Table 3-2: Quantification of management practices for each separate Homeowner Agent Typology (HAT) in Biome-BGC-Ex simulations for each vegetation cover type.
For all vegetation cover types: If tree planting is stated to occur it is applied one-time at the start of year 15. If tree removals are stated to occur this is applied one time at the end of the growing season in year 35. Terminology for HATs is from (Nassauer et al. 2014) and photo representations of the HATs can be found in **Figure 3-2**. *Neat Neighbor* and *Lakeshor Owner* were not included in the *dense woody* analysis as this vegetation cover type was not found in these yards. (LAI: Leaf Area Index, m2 m-2).

	Homeowner Agent Type					
Management Practice	**Neat Neighbor**	**Lakeshore Owner**	**Nature Neighbor**	**Tree Planters**	**Improver**	**Viewer**
Turfgrass with sparse woody (TGW)						
Fertilizer (kg N m^{-2} yr^{-1})	0.01863	0.00782	0	0.00782	0	0.00782
Irrigation (cm $week^{-1}$)	2.877	2.203	2.203	2.877	2.203	2.203
Mow height (LAI)	2.3	2.3	2.3	2.3	2.3	2.3
Mulch mowing	Yes	Yes	Yes	Yes	Yes	Yes
Pruning intensity (%)	10	10	10	10	10	10
Pruning frequency	Every 3 years	Every 3 years	Every 3 years	Yearly	Yearly	Yearly
Raking (%)	100	100	0	0	0	0
Coarse woody debris (CWD) removal (%)	100	100	100	100	100	100
One-time tree planting (kg C m^{-2})	0.8251	0	0	2.275	0.8251	2.275
Year of tree planting	15	NA	NA	15	15	15
One-time Tree Removal (%)	25	25	25	25	25	25
Year of tree removal	35	35	35	35	35	35
Dense Woody (DW)						
Coarse woody debris (CWD) removal (%)	NA	NA	60	60	60	60
Tree planting (kg C m^{-2})	NA	NA	0	2.275	0.8251	2.275

Year of tree planting	NA	NA	NA	15	15	15
	Neat Neighbor	**Lakeshore Owner**	**Nature Neighbor**	**Tree Planters**	**Improver**	**Viewer**
Tree Removal (%)	0.25	0.25	0.25	0.25	0.25	0.25
Year of tree removal	35	35	35	35	35	35
Turfgrass (TG)						
Fertilizer (kg N m^{-2})	0.01863	0.00782	0	0.00782	0	0.00782
Irrigation (cm)	2.877	2.203	2.203	2.877	2.203	2.203
Mow height (LAI)	3.3	3.3	3.3	3.3	3.3	3.3
Mulch mowing	Yes	Yes	Yes	Yes	Yes	Yes
Main ES Demand(s)	Aesthetic – neatness;	Aesthetic – lake views; low maintenance	Aesthetic - wooded views	Aesthetic – turf lawns beneath canopy trees.	Recreation, wildlife viewing	Aesthetics – large lawn area; wildlife viewing
Parcel size[‡‡‡]	small	small	small	medium	large	large
Sample size (n = 26)	6	3	2	7	4	4

[‡‡‡] Parcel sizes defined as large (>1.1 acre), medium (0.5-1.1 acre) and small (<0.5 acre).

1. Neat Neighbor (small parcel)
2. Lakeshore Property Owner (small parcel)
3. Nature Neighbor (small parcel)
4. Tree Planter (medium parcel)
5. Improver (large parcel)
6. Viewer (large parcel)

Figure 3-2: Typical backyards of each of the six homeowner agent types (HATs).
Used with permission from Nassauer et al. 2014.

3.2.3 THE MODEL: BIOME-BGC-EX

This study simulates ecosystem processes and services with Biome-BGC-Ex, a version of the ecosystem process model Biome-BGC 4.2 (Thornton et al. 2002) modified by our team to simulate carbon storage in the exurban landscape (Chapter 2). Biome-BGC was chosen for adaptation because it has been widely used to quantify detailed ecosystem processes and interactions including light, water availability, soil properties, and N and C cycling in a variety of biomes worldwide, including forest and grassland biomes (Thornton et al. 2002, Turner et al. 2006, Hidy et al. 2012, Goetz et al. 2012, González-Sanchis et al. 2015). It also included enough detail in soil processes to allow it to realistically capture changes in soil organic C and mineral N pools over time, related to changes in Net Primary Production (NPP) or leaf litter treatments resulting from yard management practices.

Biome-BGC-Ex augments Biome-BGC with the ability to model multiple vertical layers of vegetation within a single spatial grid cell and the ability to simulate yard management practices that directly affect soils and vegetation (Chapter 2). Biome-BGC-Ex can model *turfgrass* and *dense woody* as a single vegetation cover type along with *turfgrass with sparse woody vegetation,* which is comprised of two distinct layers of vegetation (turfgrass and deciduous woody). Thus, it embodies different vegetation cover types competing for above and belowground resources (e.g., light, water, nitrogen) within the same grid cell. It also gives the user the ability to simulate a suite of management practices: nitrogen (N) fertilization, irrigation, mowing and fate of clippings, pruning, raking, coarse woody debris (CWD) removal, tree planting, and tree removal. Further detail on Biome-BGC-Ex can be found in Chapter 2.

Operating Biome-BGC-Ex begins by supplying ecophysiological parameters and initial carbon and nitrogen pools for each vegetation cover type. Our initial carbon (C) and N pools were based on results of our field study (Currie et al. 2016). Ecophysiological parameters were modified from default Biome-BGC parameters for C3 grasses (Appendix Table C-2, Thornton and Rosenbloom 2005) and deciduous broadleaf forests (Appendix Table C-3) in our study region based on results of the field study and our model calibration (Robinson et al. 2013). We calibrated the model for each vegetation cover type separately with the aim of producing a baseline scenario for each that, with minimal yard management, exhibited constant total NPP over a 50-year period. These represent hypothetical baselines based on the site, climate (including moisture), soils, and N availability present in residential parcels in our study region (greater detail provided in Chapter 2, Appendix C). D*ense woody* assumed removal of 60% of coarse woody debris (CWD). *Turfgrass* assumed mulch mowing when turf Leaf Area Index (LAI) is greater than a 3.1 m^2 m^{-2}; no fertilizer or irrigation occurred. For *turfgrass with sparse woody* we assumed a baseline management strategy of 100% CWD removal and mulch mowing when turf LAI is greater than 1.5 m^2 m^{-2}. These stable baselines for each vegetation cover type allowed us to assess differences in ES due to management practices.

3.2.4 Description of Services Modelled

Using Biome-BGC-Ex, we simulated a suite of ecosystem services. These included NPP, soil fertility, firewood production, nitrogen retention, freshwater recharge, spring soil water recharge, summer soil water retention, climate regulation, microclimate regulation, and air pollution abatement. The ecological production of these services was calculated directly or indirectly using outputs from Biome-BGC-Ex (Table 3-3Table 3-3: Description of ecosystem services and their calculation from Biome-BGC-Ex model results.).

Table 3-3: Description of ecosystem services and their calculation from Biome-BGC-Ex model results.
NPP = net primary productivity; SOC = soil organic carbon.

Ecosystem Service	Description	Calculation/Indicator
NPP	Carbon fixed by plants above and belowground after autotrophic respiration is accounted for.	Annual NPP (kg C m^{-2} y^{-1}) of the full vegetation community in year 50.
Soil Fertility	Soil must have sufficient nutrients and organic matter to provide an optimal growing environment for plants. Soil organic carbon (SOC) retains water and nutrients and supports soil microbes. Soil mineral nitrogen (N) is directly available for plant uptake.	Index (0-100) based on SOC and soil mineral N in year 50. Each variable was normalized and then weighted evenly (0.5) to create the index (Maes et al. 2011).
Firewood	Wood that is harvested and can be used as fuelwood	Woody biomass (kg C m^{-2} yr^{-1}): CWD collected in year 50 plus firewood available from tree removals. Tree removal firewood is expressed as an annual average.
Nitrogen Retention	Avoided nitrogen pollution from leaching & volatilization – two processes which contribute to air and water pollution	Proportion of nitrogen retained in year 50. Calculated as[§§§]: 1 – (N exports [leaching + volatilization]/N inputs [deposition + fixation + fertilization)
Freshwater Recharge	Water that moves through system into a groundwater pool, aquifer, or surface water pool.	Measured as soil water outflow (mm yr^{-1}) in year 50.
Spring Soil Water Recharge	Additional water the soil retains over the winter months, which is available to plants at the start of the growing season	Measured as additional water retained (mm yr^{-1}) in the soil water pool over the non-growing season (Nov in year 49-April in year 50). Calculated as: water inputs [precipitation] - water exports [evapotranspiration + soil water outflow + snow sublimation]

[§§§] note: we are not considering N contained in biomass removed from the system.

Summer Soil Water Retention	Proportion of incoming water the soil retains at height of growing season, indicates soil moisture during growing season	Proportion of water retained in July of year 50. Calculated as:[****]: 1 – (water exports [evapotranspiration + soil water outflow]/water inputs [precipitation + irrigation])
Climate Regulation	Carbon sequestration and storage – Carbon sequestration regulates global climate by taking up carbon that may have otherwise contributed to atmospheric CO_2 (Nowak 1994, McPherson 1998)	Net change in total carbon stored in vegetation and soils (kg C m^{-2}) over 50-year period.
Microclimate Regulation	Potential for the system to reduce air temperature. Cooling effects are the result of evapotranspiration (Taha 1997, Bolund and Hunhammar 1999, Qiu et al. 2013)	Total evapotranspiration (mm yr^{-1}) in year 50.
Air pollution Abatement	Potential to capture and remove air pollutants. The reduction is primarily caused by foliage filtering pollution and particles from the air, which can be measured with Leaf Area Index (Bolund and Hunhammar 1999, Maes et al. 2011, Andersson-Sköld et al. 2018)	Leaf Area Index in year 50 – a higher value indicates a greater potential to remove pollutants.

[****] note: this number can be less than zero due to export of water stored previously in soil water pool.

3.2.5 Model analyses

We performed two sets of model simulations for each vegetation cover type, each of which aimed to meet one of our two research objectives. For the first objective, we used a Monte-Carlo approach to randomly sample the space of numerous potential interactions among multiple management practices co-occurring at differing frequencies and intensities. For the second objective, we simulated specific, coordinated sets of management practices carried out by different types of homeowners. We refer to the coordinated sets of management practices as a Homeowner Agent Typology (HAT), which represents observed combinations of behaviors among exurban land developers and homeowners, as determined by our homeowner site visits and interviews and subsequently validated by our survey (Nassauer et al. 2014, Visscher et al. 2014, 2016).

3.2.5.1 Monte Carlo Simulation

We used Monte Carlo simulation methods (Currie and Nadelhoffer, 1999) to explore the combined effects of interacting, variable values of yard management practices on ES, each represented by probability distributions (Table 3-1) sampled with the Latin hypercube technique (R package ‘lhs’; Carnell 2016). Each vegetation cover type had a corresponding set of plausible homeowner management practices (Table 3-1). These realistic ranges of yard management practices helped to ensure that the distribution of model outcomes represents a realistic expectation of ranges for each ES.

We ran each simulation for fifty years with the value of each ES in year fifty reported in the results. For *turfgrass* and *dense woody,* which had four and five management practices respectively, we performed 3000 simulation runs. For *turfgrass with sparse woody*, which had nine management variables, we performed 7000 simulation runs. Together, these large sets of model runs produced distributions of ES outcomes for each vegetation cover type.

To investigate which management practices led to positive or negative changes in each ES, we used multiple linear regression analysis for each ES within each vegetation cover type. For easier comparison of independent variables, we include regression results where regression coefficients for each management practice have been normalized on a zero to one scale (the full set of normalized results, regression coefficient plots, and additional partial linear regression figures can be found in Appendix Table C-5, Figure C-1, and Figure C-2, respectively). Pearson coefficient of correlation was calculated for relationships between carbon and nitrogen pools, management practices and ecosystem services. All statistics were conducted in R version 3.3.2 (R Core Team 2019) on RStudio (RStudio Team 2016), using the packages: ggplot2 (Wickham 2016), rms (Harrell 2020), and corrplot (Wei and Simko 2017).

3.2.5.2 Homeowner Agent Typology Analysis (HATs)

While the Monte Carlo analysis allows us to see a full range of potential outcomes, the HAT analysis is designed to simulate ES capacity for coordinated sets of management practices known to be carried out by homeowners at the scale of the individual parcel in our study region. Based on the raw interview data that Nassauer, et al. (2014) used to define the HATs, we assigned explicit values (Table 3-2) for each HAT's management practice in each vegetation cover type. Each HAT differed in the combination of fertilizer and irrigation intensity, pruning frequency, and whether raking, tree planting, and tree removal occurred. Some practices varied little among HATs, e.g., mowing, pruning intensity, and removal of CWD. Each combination of HAT and vegetation type (*turfgrass, woody, and turfgrass with sparse woody*) was simulated in Biome-BGC for 50 years, except for the combinations of *Neat Neighbor* and *Lakeshore Owner* and *dense woody* as these combinations were not found in our study region. The results across HATs and within each service were normalized (0 - 100) and displayed in a radar chart to assess the trade-offs and synergies among ecosystem services. A higher score within each ES is interpreted as, relative to other management types, more ES capacity for that service.

3.3 Results

3.3.1 Monte Carlo Simulation

3.3.1.1 Turfgrass with sparse woody

Across all ecosystem services (ES) in this vegetation cover type, fertilization, irrigation, raking, and pruning were the strongest drivers of differences in ES capacity among model runs (Figure 3-3), with fertilizer as the strongest driver for eight of ten modeled ES. NPP, soil fertility, climate regulation, and air pollution abatement are services directly related to above or belowground biomass and fertilizer were shown to be strongly positively correlated with tree vegetation and litter C and soil C and N (Figure 3-4). In this vegetation cover type, nitrogen was the most limiting factor to biomass increases in Biome-BGC-Ex and higher fertilizer application was strongly linked to increased availability of above and belowground biomass.

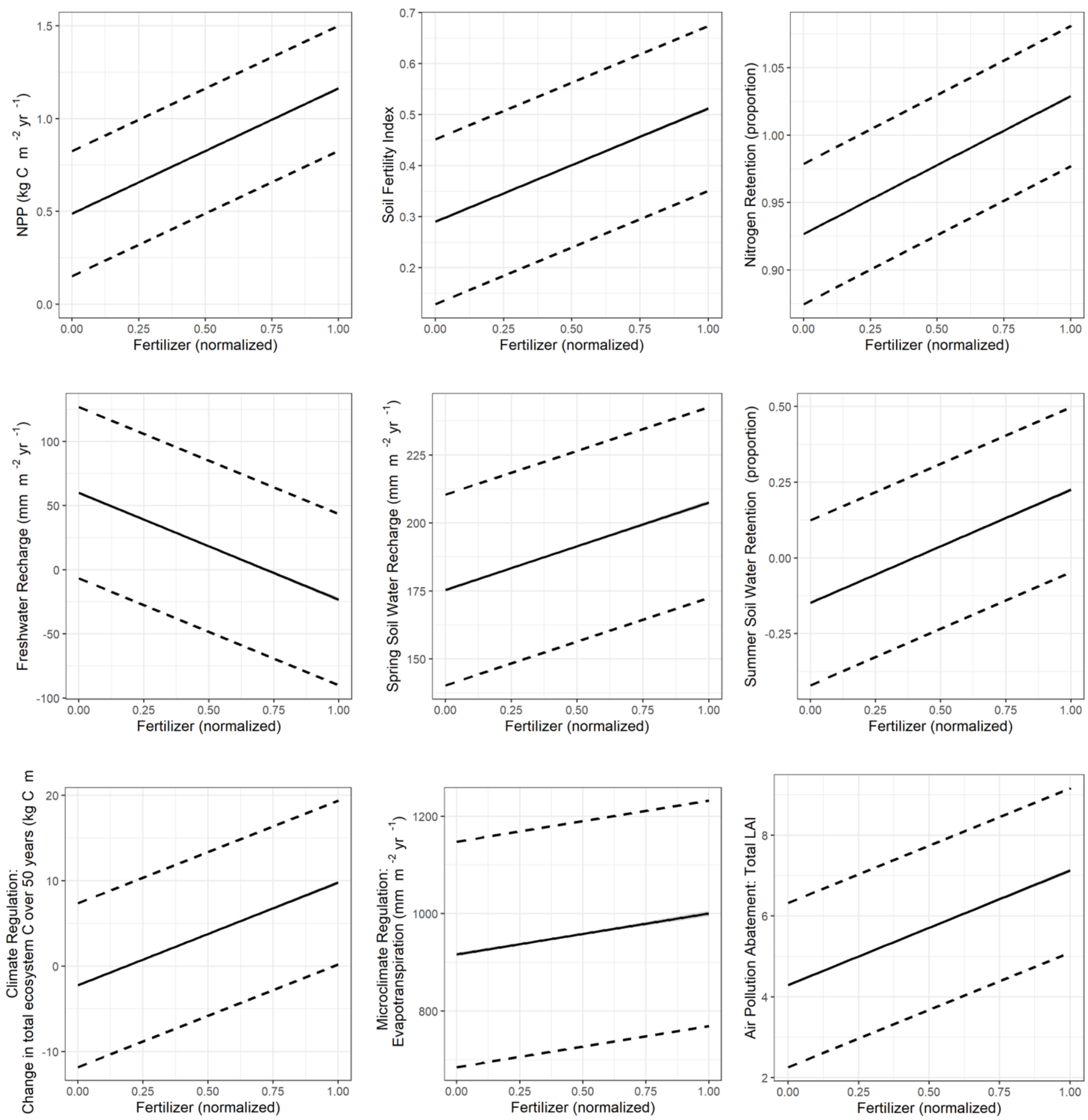


Figure 3-3: Partial linear regression results from the Monte Carlo analysis for ecosystem services where fertilizer is the strongest driver of the given ecosystem service in the t*urfgrass with sparse woody* vegetation cover type.
Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

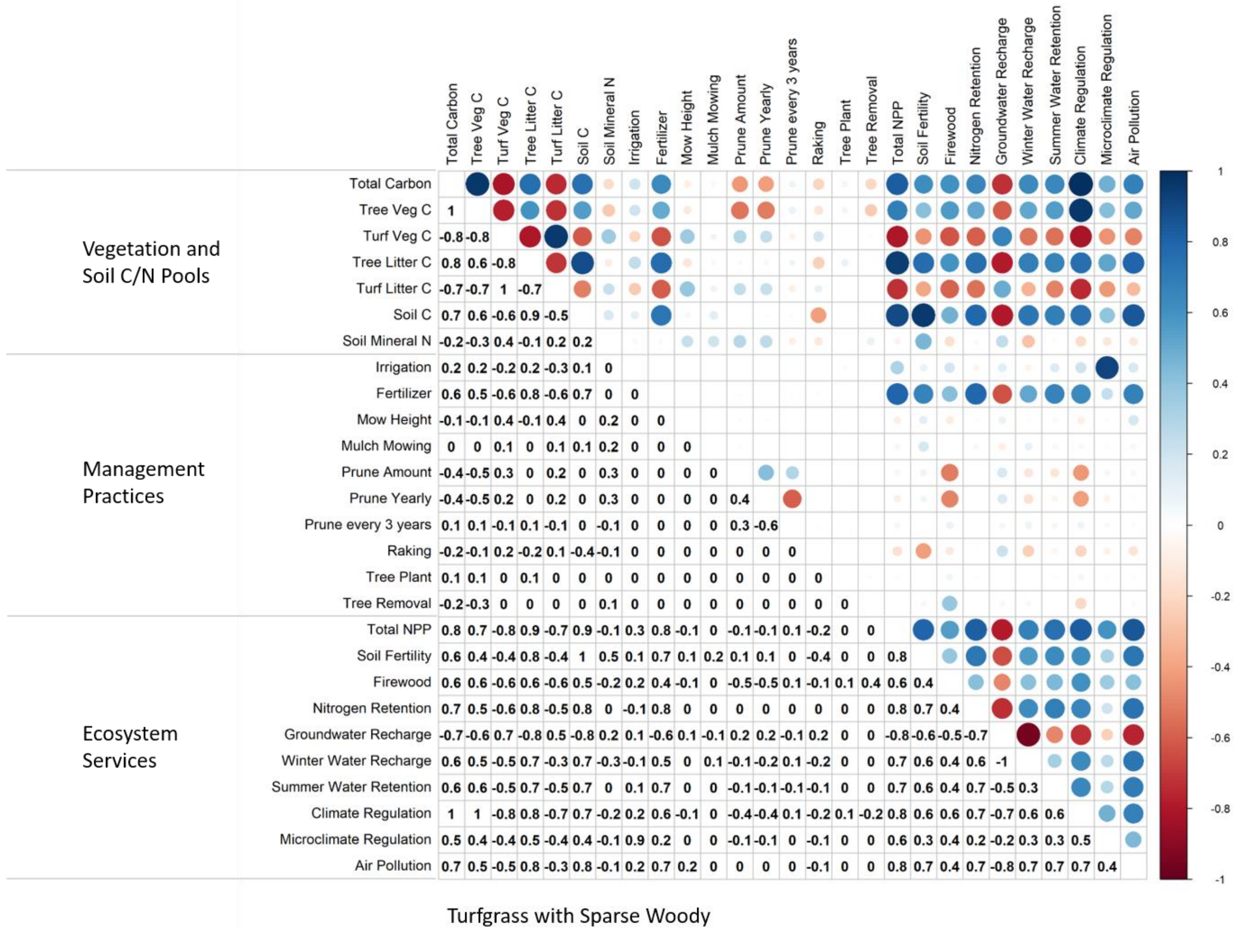


Figure 3-4: Results from the Monte Carlo analysis on correlation between carbon and nitrogen pools, management practices, and ecosystem services for *turfgrass with sparse woody*. Positive correlations are displayed in blue and negative correlations in red color. Color intensity and the size of the circle are proportional to the correlation coefficients.

Fertilizer addition also led to significant increases in nitrogen retention, spring soil water recharge and summer soil water retention (Figure 3-3). Nitrogen retention was strongly linked to the presence of fertilizer, with small amounts of fertilizer providing large gains that level off with additional increase. This relationship was driven by Biome-BGC-Ex requiring nitrogen additions to maintain growth in this vegetation cover type. If fertilizer was not added simulated vegetation mortality began to increase as nitrogen demands could not be met which led to an overall loss of nitrogen. Without fertilizer, irrigation provided significant negative impacts on nitrogen retention due to increased nitrogen leaching. Fertilizer led to increases in spring soil water recharge and summer soil water retention due to biomass in vegetation and soil preventing loss of water through soil water outflow. Fertilizer addition led to a significant decrease in freshwater recharge because fertilizer resulted in greater NPP and greater water demand and uptake by plants. Without fertilizer applied, greater rates of raking led to an increase in freshwater supply because reduced leaf litter results in lower soil organic carbon (SOC) and soil water holding capacity, which led to decreased water retention in soil.

After fertilization, the next strongest driver varied among the ES. For NPP, irrigation was the next strongest driver, however this effect interacted with the amount of fertilization. When fertilizer was not applied, water and NPP were strongly positively linked. The ES of climate regulation was negatively correlated with pruning intensity and frequency. For the ES of soil fertility, increased raking of plant litter resulted in lower soil fertility because it lessened the amount of C and N that was incorporated in soil organic pools over time.

There were trade-offs between many services due to how these services responded to fertilizer and tree removals. Soil fertility and firewood increased with fertilizer application and tree removals. Fertilizer increased tree biomass for firewood and directly improved soil mineral

N increasing soil fertility. The model assumed all aboveground biomass is removed from the system with tree removal, which can directly provide firewood. Belowground biomass remained in the system as litter, which increased soil fertility as it decomposed. Climate and microclimate regulation, NPP, and air pollution abatement increased with fertilizer but declined with tree removals because they are all strongly linked to either total biomass production or leaf biomass. In contrast, freshwater recharge decreased with fertilizer but increased with tree removals. Fertilization increased biomass leading to increased plant water uptake and less water available to leave the system while tree removals decreased biomass and total plant water uptake.

Microclimate regulation was the only service driven primarily by irrigation. Increased irrigation resulted in increased evapotranspiration, which can lower the local temperature through evaporative cooling and thus improving the microclimate service. Fertilizer had a small but significant positive impact on evapotranspiration because increased biomass increased plant transpiration in our simulations.

3.3.1.2 TURFGRASS

For the *turfgrass* vegetation cover type, fertilizer and irrigation were significant for all services. Fertilizer addition was the strongest driver of services that are directly impacted by fluxes of carbon and nitrogen in vegetation and soil: NPP, soil fertility, nitrogen retention, and climate regulation (Figure 3-5). Mulch mowing also increased available nitrogen. Soil fertility, climate regulation, and NPP are all services strongly related to the system's ability to increase carbon stored in ecosystem pools and fertilizer was shown to positively correlate to soil C and N (Figure 3-6). In the case of simulations, nitrogen limited growth in the Biome-BGC-Ex model, and thus increasing additions of fertilizer and mulch mowing increased those services. Nitrogen retention was also strongly related to the presence of fertilizer, as zero fertilizer addition led to turfgrass mortality in our simulations, which resulted in an overall loss of nitrogen.

In the *turfgrass* vegetation cover type mow height and irrigation were significant drivers for freshwater recharge, spring soil water recharge, microclimate regulation, summer oil water retention, climate regulation, and air pollution abatement. There were trade-offs between microclimate regulation, climate regulation, and freshwater recharge. due to how these services responded to irrigation and mow height. Irrigation presence and amount were strong positive drivers of microclimatic cooling via evapotranspiration. There was also a strong interaction between irrigation and mow height. When there was no irrigation a higher mow height had little effect on microclimatic regulation, likely because there is not enough irrigation to allow for the additional leaf area to greatly increase transpiration. However, when there was irrigation, there was additional water available for transpiration in proportion with the additional leaf area in model runs where mow height was greater. In the case of climate regulation, irrigation had a negative effect because irrigation increased decomposition which released carbon in our simulations. However, mow height was positively related to vegetation biomass increases leading to increased climate regulation. For freshwater recharge, irrigation had a positive effect and mow height had a negative effect. Increased biomass from higher mow heights results in more plant water uptake reducing water available for recharge. Irrigation directly increases the pool of soil water available for recharge.

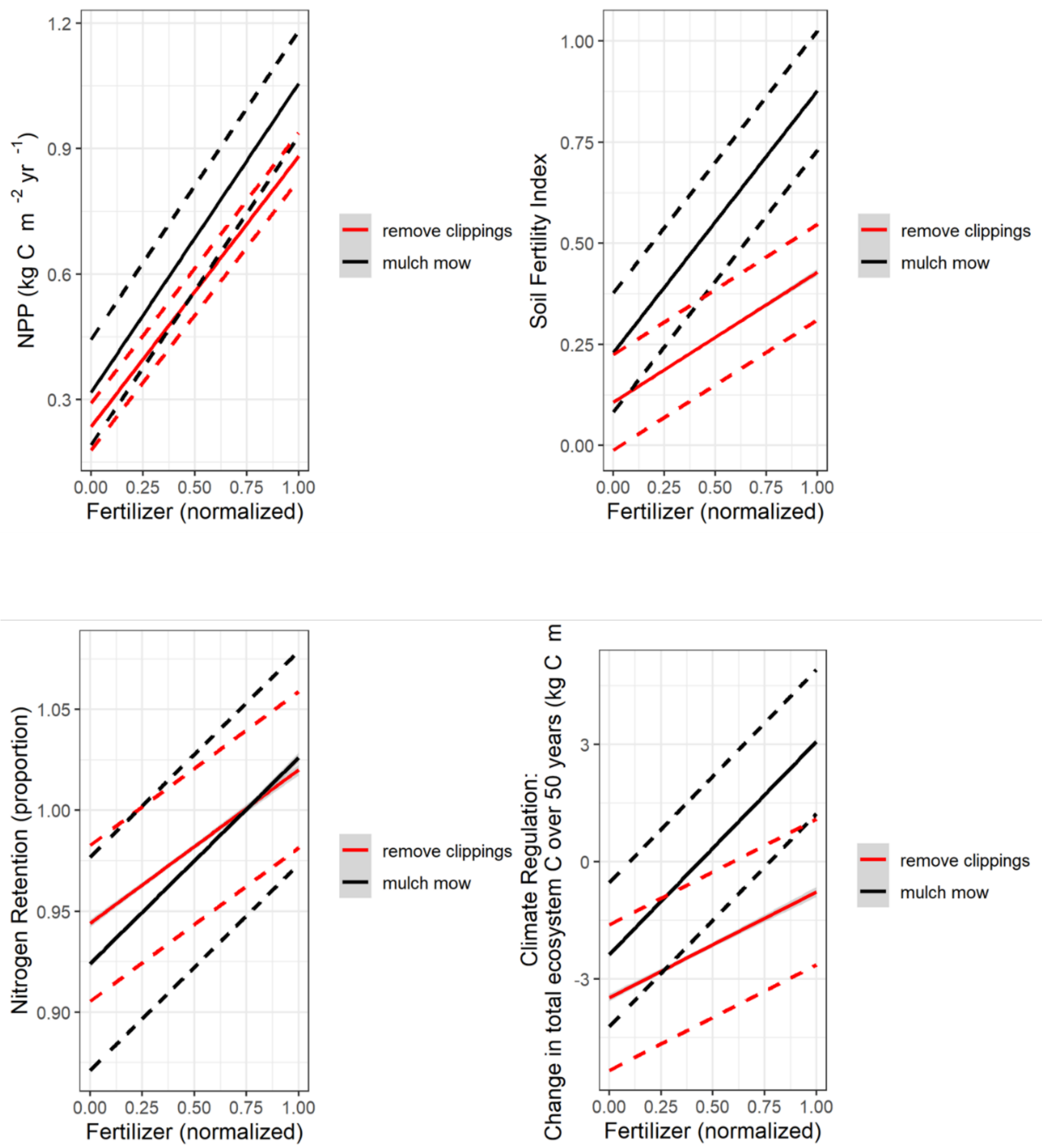


Figure 3-5: Partial linear regression for ecosystem services where fertilizer is the strongest driver of the given ecosystem service in the *turfgrass* vegetation cover type.
The impact of mulch mowing is shown in black, while scenarios where clippings are removed are shown in red. Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

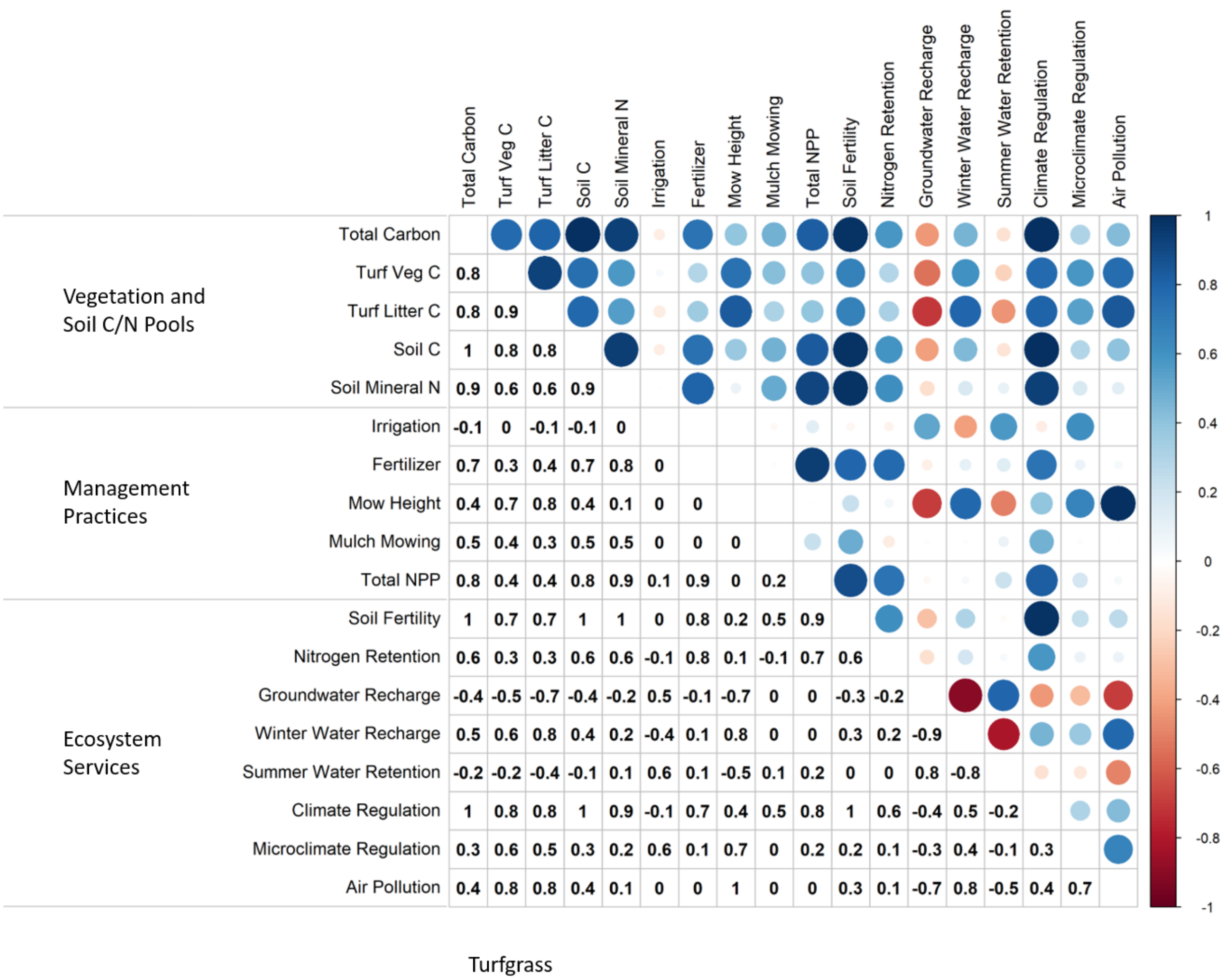


Figure 3-6: Results from the Monte Carlo analysis on correlation between carbon and nitrogen pools, management practices, and ecosystem services for *turfgrass*.

Positive correlations are displayed in blue and negative correlations in red color. Color intensity and the size of the circle are proportional to the correlation coefficients.

3.3.1.3 Dense Woody

Simulations for the *dense woody* vegetation cover type did not include fertilization and irrigation(Nassauer et al. 2014, Visscher et al. 2014).. In *dense woody* pruning was the strongest driver for four of the ten modeled services: NPP, soil fertility, climate regulation, and air pollution regulation (Figure 3-7). Coarse woody debris (CWD) removal and tree removals also resulted in decreases to these services, but to a lesser degree. Yearly pruning was the strongest driver of biomass loss in *dense woody* and yearly pruning was found to have a strong negative correlation with vegetation and soil C (Figure 3-8). The loss of biomass led to decreases in NPP and climate regulation (ecosystem C storage). Since pruning disproportionately favors the loss of leaves and small branches, LAI of the woody vegetation is reduced, leading to reductions in air pollution abatement.

Coarse woody debris (CWD) removal poses a trade-off between services as firewood and nitrogen retention benefited from the CWD removals while the other services saw losses due to CWD removal (Figure 3-8). Most variability within nitrogen retention relates to nitrogen volatilization, and this is most strongly driven by a positive relationship with CWD removal as the removal of dead biomass decreases potential volatilization. Firewood increased with tree removals used as firewood.

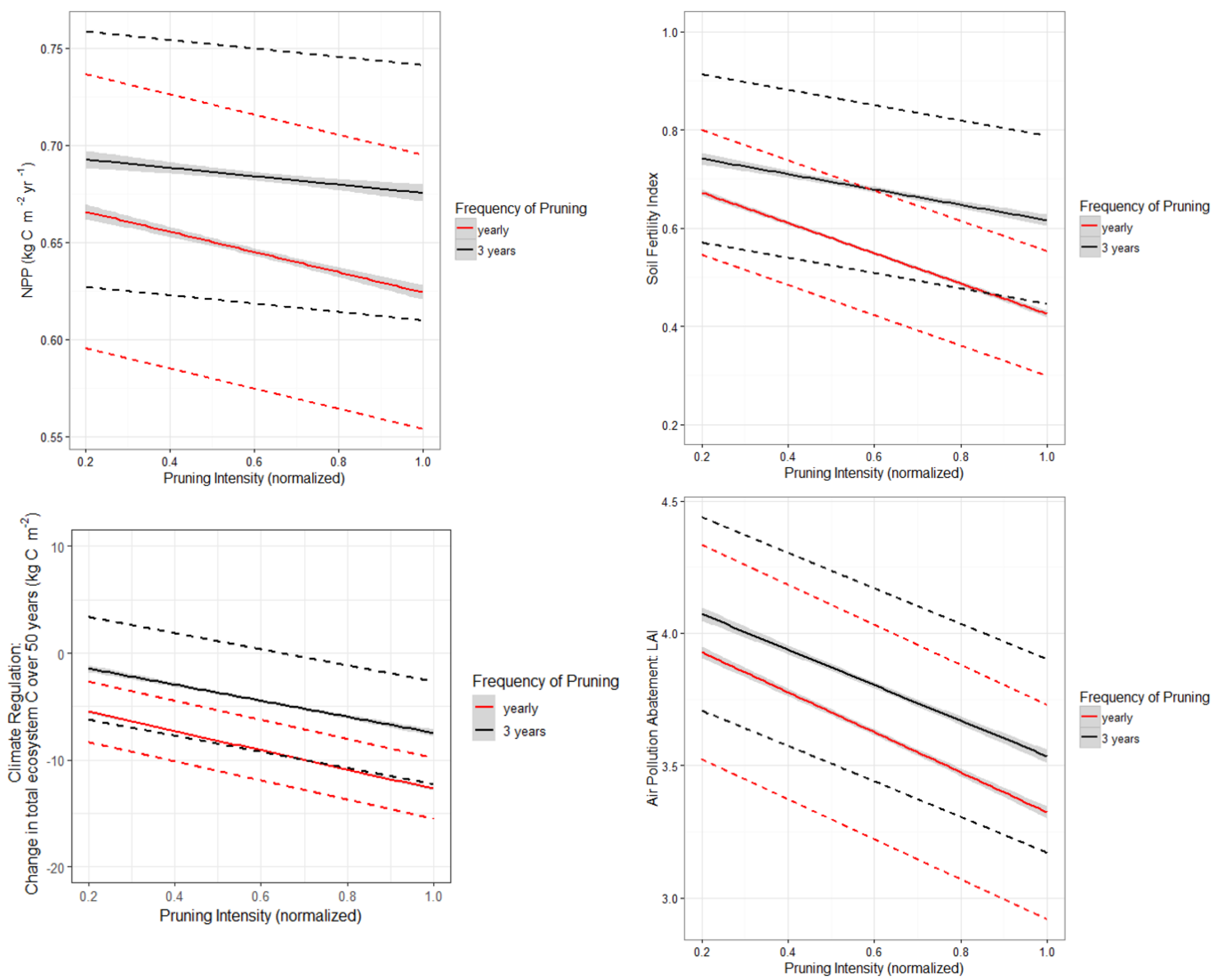


Figure 3-7: Partial linear regression for ecosystem services where pruning is the strongest driver of the given ecosystem service in the *dense woody* vegetation cover type.
The impact of pruning yearly is shown in red, while scenarios where pruning is every three years are shown in red. Solid lines show the partial regression fit for the coefficient bounded in grey by the 95% confidence interval (based on the standard error of the coefficient). This is the expectation of the effect of given independent variable, while all other independent variables vary stochastically and in combination. The dashed lines represent the 95% prediction interval; the area where 95% of the data points are expected to fall given the variation of all other independent variables.

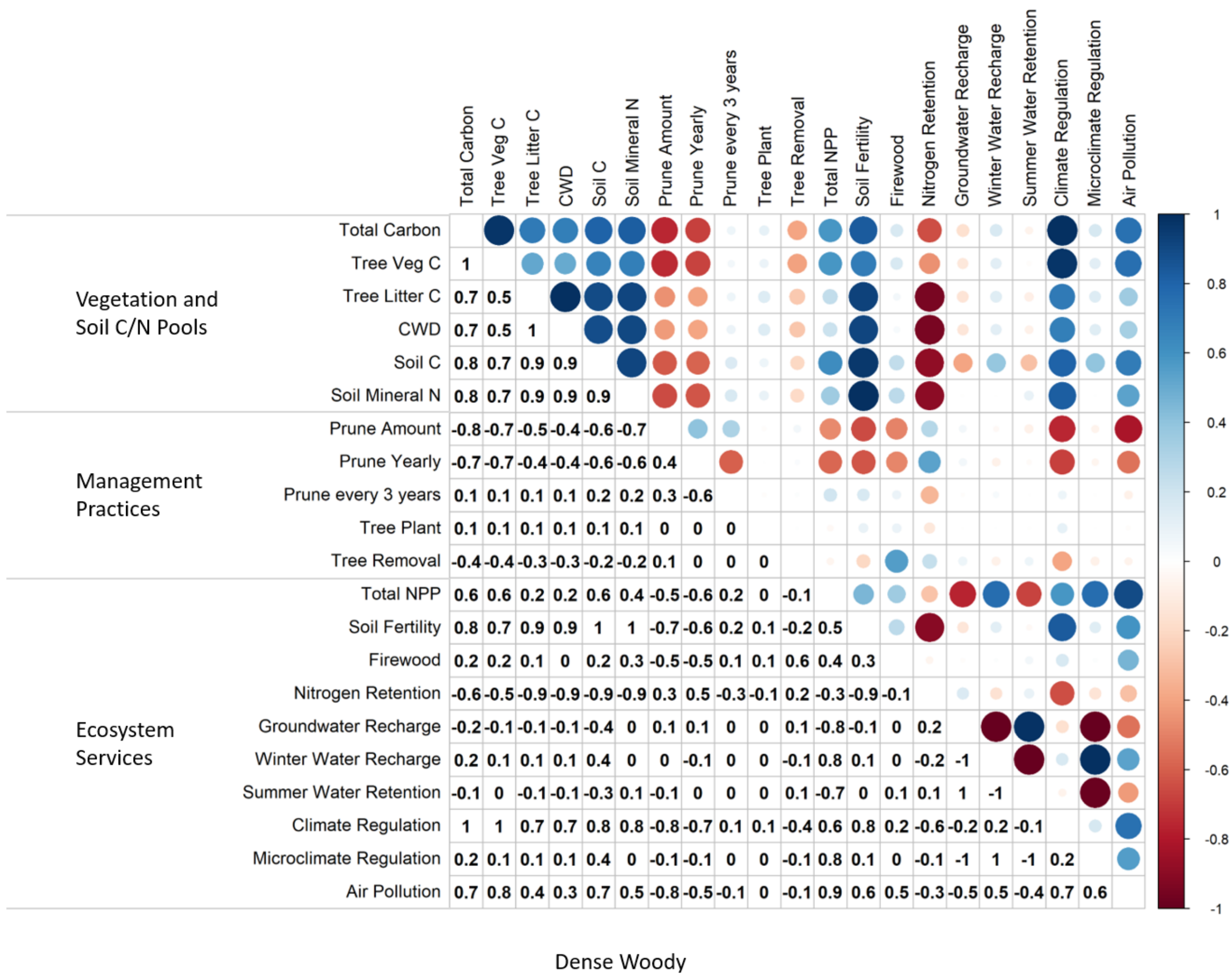
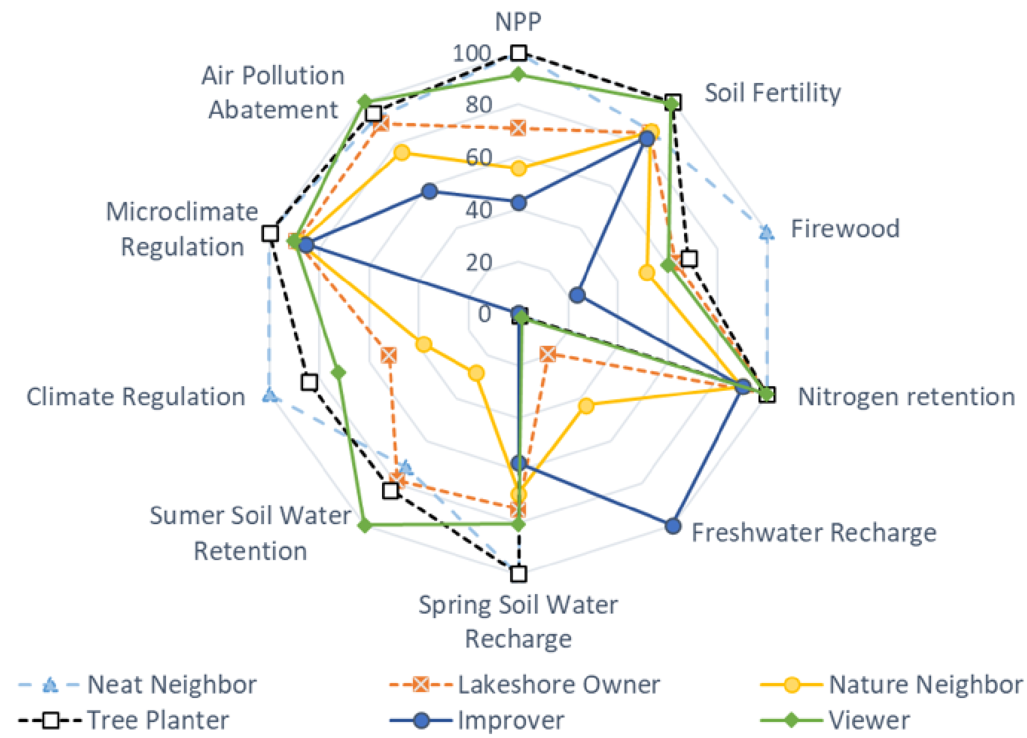


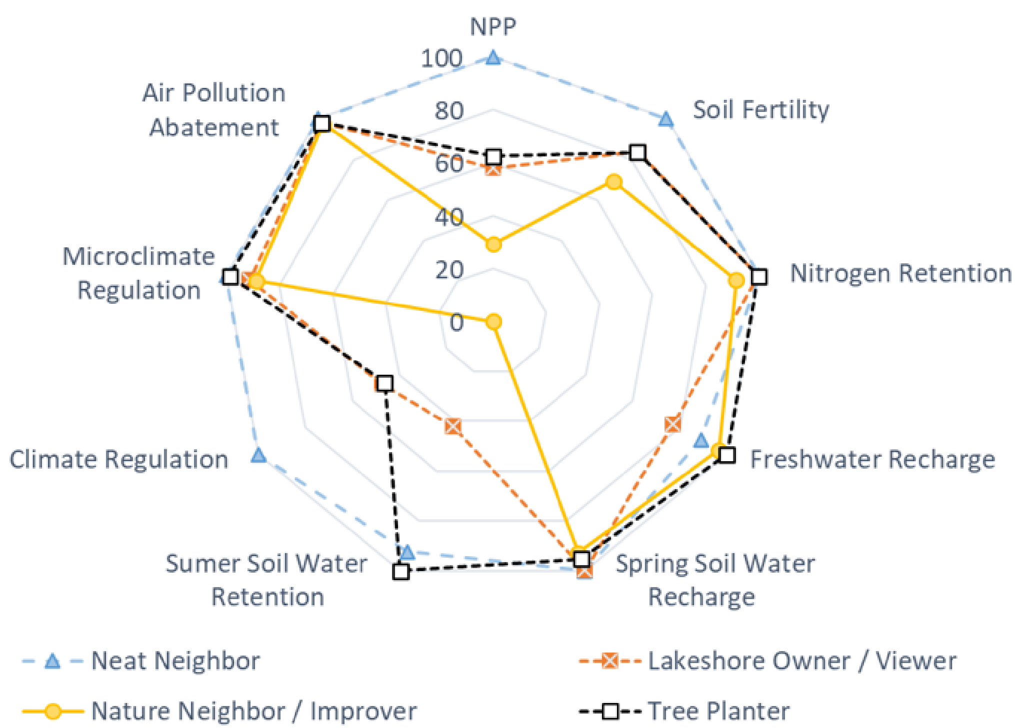
Figure 3-8: Results from the Monte Carlo analysis on correlation between carbon and nitrogen pools, management practices, and ecosystem services for *dense woody*. Positive correlations are displayed in blue and negative correlations in red color. Color intensity and the size of the circle are proportional to the correlation coefficients.

3.3.2 Homeowner Agent Typology (HAT)

Our HAT analysis examined the effect of management behaviors associated with each HAT on trade-offs and synergies of ES within each vegetation cover type. Synergies arise when multiple services are enhanced simultaneously by a given HAT, while trade-offs arise when one service is improved at the expense of another service's production. For *turfgrass with sparse woody* management by HATs varied for fertilizer, irrigation, pruning intensity and frequency, raking removals, and tree planting (Figure 3-9a). *Neat neighbor* (light blue triangles) management behavior was related to neighborhood norms and a desire of aesthetic neatness, which they manage for with high fertilizer, irrigation and raking along with infrequent pruning. This type scores highest in four ES: firewood, N retention, spring soil water recharge and climate regulation, but the lowest in freshwater recharge. This contrasts with *Tree Planter* (black outlined squares) whose management behavior was related to neighbor perception along with a desire for an aesthetic view of horticultural trees and plantings. Compared to *Neat Neighbors* they applied less fertilizer, pruned more frequently, and planted more trees. They scored similarly for many services, but we found they trade off in soil fertility, firewood, summer soil water, and climate regulation. *Viewer* (green diamond) had low values of fertilizer and irrigation but high values of pruning and tree planting, and a desire for the aesthetic characteristics of turf lawns beneath canopy trees. *Viewer* scored close to or slightly lower than *Neat Neighbor* and *Tree Planter* for all ES except for summer soil water retention and air pollution abatement. *Improver* (dark blue circles) management behavior was related to wanting a yard suited for recreation and wildlife viewing. They managed less than *Neat Neighbor* by applying no fertilizer and lower amounts of irrigation but pruned yearly, which results in the lowest scores for all ES except for freshwater recharge where they scored the highest. *Nature Neighbor* (yellow circles) behaviors were influence by a desire for aesthetic views of woodlands and their management was comparatively minimal. Their results followed the same pattern as *Improver*, but with slightly higher scores for all ES except for freshwater recharge where they scored lower. *Lakeshore Owner* (orange squares) had management behaviors that were related to lake views and low maintenance. Their results followed the pattern of *Nature Neighbor* with higher values in all ES except for freshwater recharge.



A. Turfgrass with Sparse Woody



B. Turfgrass

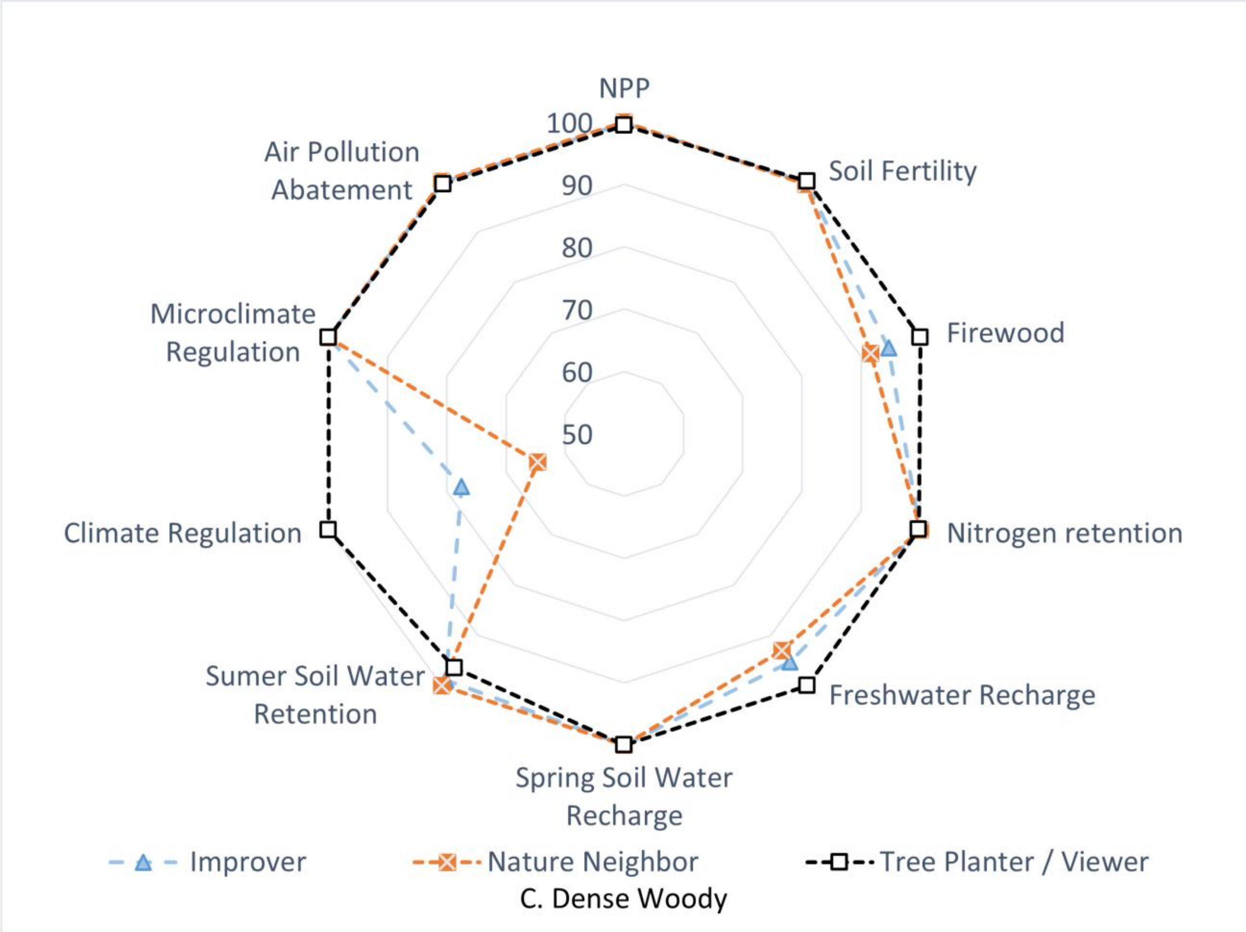


Figure 3-9: Comparison of ecosystem service production across Homeowner Agent Typologies (HATs) for *a. turfgrass with sparse woody b. turfgrass, c. dense woody*. Simulation results for each HAT have been normalized within each service for comparison.

For *turfgrass* (Figure 3-9b) synergies and trade-offs tended to vary based on homeowner agent types. *Neat Neighbor* (blue triangle), which managed for property neatness with high fertilizer and irrigation rates, had the highest score for seven ES: NPP, soil fertility, nitrogen retention, spring soil water recharge, climate regulation, microclimate regulation, and air pollution abatement. High production of these services came at the expense of production in freshwater recharge and summer soil water retention, relative to other HATs. *Nature Neighbor* and *Improver* (yellow circle) types, which managed for recreation and adjacent wooded views with no fertilizer and low irrigation, scored the lowest for all services but freshwater recharge.

Tree Planter (black outlined square), which managed for the aesthetics of horticultural plantings, fertilize at a lower rate than *Neat Neighbor* but had similar scores for many of the ES except for climate regulation, NPP and soil fertility, which were lower. *Tree Planter* also had higher production of freshwater recharge and summer soil water retention compared to *Neat Neighbor* because the resulting lower plant biomass required less water uptake leaving more water available to the soil pool. HATs with lower levels of both fertilizer and irrigation (*Lakeshore Owner, Viewer)* had overall lower production of services compared to those with high fertilizer and irrigation and showed positive relationships between nitrogen retention, spring soil water recharge, microclimate regulation and air pollution abatement. These services showed a trade-off with NPP, soil fertility, freshwater recharge, and summer soil water retention. *Nature Neighbor* and *Improver* (yellow circle) types, which managed for recreation and adjacent wooded views with no fertilizer and low irrigation, scored the lowest for all services but freshwater recharge.

In the *dense woody* vegetation type, all HATs show synergies between NPP, soil fertility, N retention, spring soil water recharge, microclimate regulation, and air pollution abatement (Figure 3-9c). The HATs with the most tree planting (*Tree Planter, Viewer*) show additional synergies among firewood, freshwater recharge, and climate regulation, but a slight trade-off with summer soil water retention. The other HATs show trade-offs with firewood, freshwater recharge, and climate regulation, with the trade-off strongest for HATs that do not plant trees (*Lakeshore Owner* and *Nature Neighbor)*. Under the conditions established for these scenarios, homeowners that desire woodland views or the aesthetic characteristics of turf lawns beneath canopy trees and periodically add large amounts of additional biomass to the system – in the form of tree planting - realize many enhanced ecosystem services.

3.4 Discussion

Results of our Monte Carlo simulation confirmed our first hypothesis that for each service ES capacity would differ with management activities. All services across all vegetation types had significant changes in ES capacity due to at least one individual yard management practice. In *turfgrass with sparse woody* most management practices had significant influence on ES estimates and multiple linear regressions of the management practices explained high amounts of variation for most services, except for those focused on soil water recharge and retention. In *turfgrass* all ES estimates were significantly impacted by at least three of the four management practices and regression models explained most of the variation within each service. In *dense woody* all services were found to be significantly influenced by at least one management practice. However, management practices were less likely to explain ES estimate, especially for services related to water storage and flow.

Results of our Homeowner Agent Typology (HAT) give us the ability to probe how trade-offs and synergies vary between common resident behavior combinations and how feedbacks within the ecosystems drive these relationships. This analysis also provided an opportunity to evaluate how cultural ES demands, which are one factor that can affect resident management behavior, related to ES estimated by Biome-BGC-Ex. We found that the two HATs with the highest overall scores across ES in *turfgrass with sparse woody* trade-off in soil fertility, firewood, summer soil water, and climate regulation that are a result of their varying management behaviors. High levels of fertilization in *Neat Neighbor*, which were related to cultural neighborhood norms and the desire for an aesthetically neat yard, resulted in greater climate regulation and firewood ES. However, lower fertilization and high levels of tree planting in *Tree Planter*, which were related to neighborhood norms that followed a desire for aesthetic views of turf lawns beneath canopy trees, were able to still score high in these categories while also having higher soil fertility and summer soil water retention. As in the Monte Carlo Analysis, the HAT results also displayed trade-offs between freshwater recharge and other services. Within HATs most services followed synergistic patterns except for freshwater recharge, which traded-off with the other services. The *Improver* type desired a property suitable for recreation and wildlife viewing, but their management combination of no fertilizer and frequent pruning led to the lowest values for all ES except for freshwater recharge.

3.4.1 Role of fertilizer and Nitrogen in the ecological production of residential ecosystem services

Fertilizer was an important driver for almost all ES explored in this paper. Biome-BGC-Ex allows us to explore the complex ways of how fertilizer application affects ecosystem function and resulting ecosystem services. While fertilizer addition directly impacts the N cycle, reinforcing feedbacks between the N and C cycle drove many of the ES explored in this study. Fertilizer increased N availability in Biome-BGC-Ex, which drove increased NPP because the model considers the N limitations of plant production. As more biomass was produced, greater amounts of C were stored in above and belowground vegetation, which led to greater climate regulation, microclimate regulation and air pollution abatement. As the resultant increased biomass died and flowed into litter and soil organic matter, soil fertility was boosted along with soil water holding capacity, which led to improved spring soil water recharge and summer soil water retention along with decreased freshwater supply. Increased aboveground tree biomass also provides a greater amount of wood that can potentially be harvested for firewood.

The role of fertilizer plays in the flux and storage C, N, and water has been a focus of studies of urban ecosystems, although most of this focus is on parcels and developments that are denser and closer to city centers than those considered for this analysis. However, there are fewer studies that examine the relationship between ES and fertilizer in urban environments. Fertilizer addition is known to increase soil C in residential yards (Townsend-Small and Czimczik 2010, Huyler et al. 2014a). and studies have shown positive relationships between fertilizer and soil quality and NPP (Acosta-Martínez et al. 1999, Kaye et al. 2005, Campbell et al. 2014). Our results indicate a strong positive relationship between *turfgrass* NPP and fertilizer application (Figure 3-5), which was also shown in previous applications of Biome-BGC (Milesi et al. 2005). However, Lilly and others (2015) found that while fertilizer was correlated with increased C allocation in turfgrass it had no effect on NPP.

The linkages between fertilizer and water related ecosystem services in residential landscapes have not been as thoroughly explored with empirical studies. Easton and Petrovic (2004) found that fertilizer application leads to lower soil moisture levels in urban turfgrass vegetation due to the increase in biomass. Urban turfgrass grown in the western US was shown to increase ET with increased mowing height and increased fertilizer (Feldhake et al. 1983). Across ecosystems types increased soil organic matter increases the water holding capacity of soils, which leads to a reduction in water moving into groundwater (Libohova et al. 2018). Our simulations found that fertilizer is a negative driver of freshwater recharge and summer soil water retention (water that enters and is retained by the system). In this study, freshwater recharge is measured as the water that moves through soil solum into groundwater or surface water pools. In our simulations, fertilizer addition increased NPP and ecosystem C which led to two balancing feedbacks that decreased freshwater recharge. First the increase in above and belowground biomass required greater plant water uptake to meet model requirements for evapotranspiration. Second, higher amounts of litter and soil organic matter led to increases in soil water holding capacity, which decreased the amount of water moving through the soil. Fertilizer caused a similar decline in summer soil water retention due to increased evapotranspiration. Freshwater recharge and summer soil water retention traded off with spring soil water recharge and microclimate regulation because these services had the opposite response to fertilizer additions. Microclimate regulation increased with the increased evapotranspiration required by additional biomass from fertilization. Spring soil water recharge increased with improved soil quality and litter biomass that is provided by fertilizer.

The prevalence of fertilizer application in residential landscapes is well documented (Carey et al. 2012, Cook et al. 2012, Visscher et al. 2014), and interviews with residents in our study region found that 65% fertilize their lawns (Nassauer et al. 2014). Homeowners most commonly cite concern for social and neighborhood appearance norms and aesthetics as their reasoning for fertilizer application (Cook et al. 2012, Carrico et al. 2013, Fraser et al. 2013, Visscher et al. 2014, Martini et al. 2015). Although our study showed that fertilizer use can enhance a suite of ES, given the assumptions of our model, Biome-BGC-Ex, these outcomes are subject to inherent limitations of our model, which we describe below.

The negative ecological effects of management practices such as fertilizer application in the residential landscape have been addressed in many urban ecological studies. This literature focuses predominantly the relationships between fertilizer application and nitrogen pollution including increased stream nitrate concentrations (Groffman et al. 2004), increased storm water N levels (Hobbie et al. 2017), increased N concentrations in lechate (Petrovic 1990, Chen et al. 2018), and increased nitrous oxide emissions (Townsend-Small and Czimczik 2010, Livesley et al. 2010, Braun and Bremer 2018). Although our model was able to simulate pools and fluxes of N from fertilizer within the boundaries of our modelled system, it was not designed to incorporate the surface flow of fertilizer out of the yard or the full carbon costs of mowing and fertilization in the system. Including these costs would directly impact estimates of N retention and C sequestration, while indirectly affecting the other services. Hobbie and others (2017) found that an estimated 8% of N inputs are lost runoff in a mixed density urban watersheds. This loss is not insignificant and should be taken into consideration, especially in relation to where the property is situated in the landscape and its potential for water runoff. As shown in the previous chapter (Chapter 2), including emissions from lawn mowing and fertilizer application would reduce climate regulation across all Monte Carlo simulations, and in the case of the HAT analysis, would decrease the gap between Climate Regulation scores for those that fertilize (*Neat Neighbor, Lakeshore Owner, Tree Planter, Viewer)* versus those that do not (*Nature Neighbor, Improver)*.

Our simulations found that fertilizer application was positively linked to nitrogen retention, which was defined as avoided nitrogen pollution from leaching and volatilization. This could be due to a several factors. First, although Biome-BGC-Ex simulates N exports from leaching and volatilization, as mentioned above it does not take into account surface losses of N. Inclusion of this export could potentially lead to larger losses of N in heavily fertilized yards. Second, primary production in Biome-BGC is assumed to be nitrogen limited and this aspect was not adjusted for in Biome-BGC-Ex. Even with the highest level of fertilizer additions nitrogen demand is typically not met in our simulations, which needs further investigation as our study region is known for being N saturated (Kahan et al. 2014)f. Third, the temporal design of the model has nitrogen demand and uptake being assessed daily and taken up immediately by biomass, while in reality fertilizer may be sitting on vegetation or soil surface for a longer period and thereby subject to runoff and export from the system. Older established lawns, like those in our simulations, have been shown to retain a high proportion of nitrogen and function as nitrogen sinks with high gross immobilization and root nitrogen uptake (Groffman et al. 2004, Raciti et al. 2008, Weitzman and Kaye 2016). Since our study was at the scale of the vegetation cover type it only focused on avoided nitrogen pollution from leaching and volatilization and did not consider the fate of N in vegetation removed from the system. However, Hobbie and others (2017) found that removal of resident yard waste was a significant N export at the watershed scale, and estimated removals from mowed and raked litter to be 25% of N export in their least dense urban site. Future applications of this model might consider a more complex fertilizer model that accounts for additional complexity in the temporal and spatial dynamics of fertilizer in the residential landscape.

3.4.2 Ecosystem Service Capacity in the Exurban Residential Landscape

The main advantage of our study is the ability to look beyond simple linkages and correlations to demonstrate the effects of management practices on ES as they manifest in exurban ecosystems. The approach of using an ecosystem process model such as Biome-BGC-Ex allows the user to consider how ecosystem processes and functions can be affected directly and indirectly and how these relationships lead to trade-offs and synergies. Overall, our study shows trade-offs between ES relating to high amounts of carbon or biomass (NPP, soil fertility, N retention, climate regulation, microclimate regulation, air pollution abatement) and freshwater recharge. These services also typically trade off with firewood production. Other studies of urban or residential landscapes have found similar synergies and trade-offs between services. Similar to our study, increased urban greenery and plant biomass have been found to show synergies between nutrient pollution reduction (nitrogen retention), improvements in air quality (air pollution abatement), and increases in evapotranspiration that lead to local cooling (microclimate regulation) (Livesley et al. 2016a). Studies have also reported on a trade-off between carbon sequestration (climate regulation) and water yield (freshwater recharge) (Qin et al. 2015) as well as trade-offs between regulating services and provisioning services (firewood) (Raudsepp-Hearne et al. 2010).

One benefit of the ecosystem process model approach to ES is that we can gain a better understanding of how underlying ecosystem feedbacks lead to trade-offs and synergies of ES. For example, the underlying ecological feedbacks that drive the trade-offs between soil fertility, firewood, and climate regulation between *Neat Neighbor* and *Tree Planter* in *turfgrass with sparse woody*. NPP scores were similar despite lower fertilizer and frequent pruning in the *Tree Planter* type, but *Neat Neighbor* had higher climate regulation, which means it sequestered more carbon. This was likely driven by the frequent pruning of *Tree Planter* removing proportionally more fine woody biomass. This frequent biomass removal also caused a reinforcing feedback of less woody biomass being built up over time leading to less coarse woody biomass available for firewood. Comparatively, soil fertility was higher for *Tree Planter* because there was no raking and a reinforcing feedback in response to pruning led to increased root mortality which eventually decomposed and contributed to soil fertility.

In the *turfgrass* HAT analysis we found that *Neat Neighbors,* who managed for aesthetically neat lawns with high levels of fertilization and irrigation, had the highest scores for all ES but summer water retention and freshwater recharge. However, *Tree Planters* fertilized at a lower rate and still scored very close to *Neat Neighbor* for most services, except climate regulation, NPP and soil fertility. This demonstrates that while lower fertilizer rates decreased some services, it did not necessarily provide losses for all of them because many of services rely on water processes that were still being maintained.

As discussed above, homeowner yard management practices are determined and influenced by a variety of factors. Larson et al. (Larson et al. 2016) found that cultural services, which include aesthetics, low-maintenance, and personal enjoyment, drive homeowner behaviors. For the HATs in our analysis, we measured only ES that could be modeled in Biome-BGC-Ex. However, many of the HAT types were initially characterized in part by homeowner preferences for certain aesthetics or maintenance (Nassauer et al. 2014). For example, *Improvers* did not fertilize and enjoyed wildlife viewing and recreation on their property while *Viewers* fertilized, planted relatively more trees, enjoyed wildlife viewing, and the preferred the aesthetic characteristics of turf lawns beneath canopy trees. The management behaviors associated with these preferences led to lower scores for *Improvers* all services except for freshwater recharge.

This can be interpreted as the cultural service preferences for wildlife viewing and recreation of *Improvers* trading off with most of the modelled services, while the *Viewers* cultural service preferences of wildlife viewing and aesthetics have a synergistic relationship with these same services. This difference is driven by their lack of fertilizer application, which as discussed above is positively correlated to many services. In this case if we consider the full framework cycle of ES) we expect that *Improvers* may change their behaviors if ES flows do not meet their demands. While this project uses static resident behaviors for model inputs and did not consider whether residents' ES demands had been met, future research could allow for dynamic behaviors that responds to ES flows).

Investigations into homeowner management behavior have shown a mismatch between the spatial scale of a services ecological production and its societal demand (García-Nieto et al. 2013, Baró et al. 2017). Homeowners are typically motivated to manage for ES they directly benefit from such as aesthetic value, soil fertility, microclimate regulation, and water regulation. Homeowners may be less likely to manage for ES with a demand at a regional to global scale (climate regulation, freshwater recharge). However, the results of our study indicate that efforts to improve locally beneficial services have the potential to positively affect those with benefits at a coarser scale. For example, practices that increase vegetation biomass such as fertilization, irrigation, and no raking or pruning can increase locally beneficial services such as microclimate regulation, air pollution abatement, and soil fertility while also increasing more widely beneficial services such as nitrogen retention and climate regulation.

Biome-BGC-Ex was designed with the intention of estimating ecological processes occurring on exurban residential land (Chapter 2) and the ranges and combinations of resident behavior in this study are distinct from behavior on smaller urban parcels (Nassauer et al. 2014). Within the exurban landscape there is variation in parcel size and development configuration (An et al. 2011), which has been linked with different types of resident behaviors and ecological outcomes (Nassauer et al. 2014, Visscher et al. 2014, Currie et al. 2016). If results of the HAT analysis were scaled from per unit area in each vegetation cover type to the area of the parcel or development different HATs may be found to have a larger impact on ES Capacity. For example *Neat Neighbor* was defined as occurring on smaller parcels in denser developments dominated by turfgrass (Nassauer et al. 2014). While it scores high in many ES for *turfgrass with sparse woody,* its main impact on the landscape will be in relation to *turfgrass* ES. In contrast, *Tree Planter* was defined as occurring on medium sized parcels with vegetation cover predominantly in *turfgrass with sparse woody* (Nassauer et al. 2014). Its high scores in this vegetation cover type indicate that is a relatively positive combination of management behaviors (low fertilizer and high tree planting) to promote ES in this landscape. Nassauer and others (2014) found that homeowners of large parcels, which typically follow management combinations found in *Viewer* and *Improver*, manage a smaller proportion of their total property (referred to as the zone of care) than homeowners on small and medium parcels. They also tend to have a larger proportion of their property as *dense woody* vegetation and include *turfgrass with sparse woody* (Currie et al. 2016). Our HAT analysis found *Viewer* scored relatively high, but typically lower than *Tree Planter* and *Neat Neighbor* for ES in *turfgrass with sparse woody* and had highest score for most ES in *dense woody.* The *Viewer* management combination is the same as *Tree Planter* except for a lower amount of irrigation and indicates that a combination of low fertilizer, high planting, frequent pruning, and no raking can lead to a synergistic combination of ES in the exurban landscape.

Biome-BGC-Ex is a modelling tool that can estimate ES capacity across a suite of provisioning, supporting, and regulating services. In addition to the ES included in this study, Biome-BGC has also been used to estimate provisioning services not as common in residential land such as timber or agricultural production. However, it has limitations in the breadth of ES it can include. Other ES assessment tools (e.g., InVEST (Tallis and Polasky 2009), LUCI (Jackson et al. 2013)) include estimates of regulating services such as biodiversity, pollination, and habitat quality that Biome-BGC-Ex is not equipped to address. While vegetation cover or land use could be used as a proxy for these services, more robust estimates would require linking or combining Biome-BGC-Ex with additional models. One ES assessment tool, ARIES, has proposed an approach that gives users the ability to create a network of ecological process models to improve the accuracy and breadth of estimates (Villa et al. 2014).

3.5 Conclusion

This study shows how ecosystem process models can be adapted to include human-dominated ecosystems, allowing us to consider how human management behaviors drive interactions and feedbacks within ecological processes and between processes and ES. To explore exurban ecosystems, we used Biome-BGC-Ex, a dynamic ecological model that we adapted from Biome-BGC to estimate a suite of ecosystem services while linking their production to the interaction of ecosystem process and human management behaviors. Compared to other approaches, this methodology accounts for the interconnected processes that produce ecosystem services on the landscape and allows projection of ecosystem services produced over time and across a variety of management behaviors occurring on the landscape. Importantly, results of our investigation demonstrate the wide variability in ES capacity that is driven by landscape management decisions. We suggest that our method is an advance toward fully anticipating the consequences of our management choices.

3.6 Acknowledgements

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Chapter 4
Evaluating Ecosystem Process Models as a Tool for Ecosystem Service Assessment: A Review of Current Methods for Assessing Ecosystem Service Capacity

ABSTRACT

Ecosystem services (ES) are the physical goods and associated benefits that are provided to humans by the ecosystems of the planet. This study addresses the need for ES assessment and estimation tools that can address limitations in current methods including the ability to estimate supporting and regulating ES capacity and to include interactions and biophysical feedbacks between ES and ecosystems. I propose that ecosystem process models be used as a tool to estimate ES capacity, as they are already designed with many of the desired attributes of ES capacity or ecological production function. In this chapter, I first review current assessment tools and their methods for estimating ES capacity. ES assessment tools vary in which services they model, how they estimate the capacity of ES, and the type and scope of input data they require to estimate capacity. However, they still fall short of addressing the complex biophysical dynamics inherent in estimating ES capacity. Next, I analyze the benefits and shortcomings of applying ecosystem process models to study and estimate ES. The ecosystem process model approach gives users the ability to estimate and predict quantifiable ES outcomes across a variety of management, policy, and climate scenarios (i.e., pressures). The main limitation for usability of these models is the amount and difficulty of acquiring input data on the initial conditions, ES drivers and ecosystem parameters. Lastly, I discuss how ecosystem process models can be integrated with other methods to provide improved estimation of ES. For instance, our model

Biome-BGC-Ex can be linked to agent-based models of human management to study the dynamics between ES capacity, flow, and demand.

4.1 INTRODUCTION

Ecosystems are comprised of biotic and abiotic components that are linked through nutrient cycles and energy flows. Our knowledge of wildland ecosystems is well documented and in recent decades the field has grown to incorporate human-dominated ecosystems through research in urban, agricultural, managed forests, and managed grassland ecosystems. Ecosystem services (ES) are the physical goods and associated benefits that are provided to humans by the ecosystems of the planet. The Millennium Ecosystem Assessment (MA) report (2005) highlighted the role ecosystems play in the assessment of ES. Specifically, it highlighted the importance of understanding how nonlinearities, feedbacks, and interactions within ecosystems affect the production ES (Cumming et al. 2005). Many computer-based tools exist to analyze and quantify ES (hereafter, ES assessment tools), however most do not consider biophysical feedbacks or interactions between ecosystem processes and ES. In this chapter, I address the question of whether ES assessment tools currently in use are capable of capturing nonlinearities, biophysical feedbacks and interactions in ecosystem processes, and whether a stronger foundation from ecosystem process modeling could be used to improve ES assessment tools.

4.1.1 CLASSIFICATION, CONCEPTUAL FRAMEWORKS, & ASSESSMENT OF ES

ES have traditionally been divided into four categories: supporting, provisioning, regulating, and cultural. Supporting services are functions that underpin the production of all other services. Provisioning services are physical products and goods directly obtained from the ecosystem (e.g., food, fiber, timber). Regulating services include those that both directly (e.g., pollution regulation, carbon sequestration) and indirectly (e.g., regulation of climate and water flows) sustain environmental quality. Cultural services encompass tangible uses (e.g., recreation) and less tangible benefits (e.g., spiritual, aesthetic, educational). In this article I focus on supporting, provisioning, and regulating services.

A full analysis of ES requires that ecological, social, and economic (or other measure of human well-being) aspects and their relationship need to be considered. A variety of overarching frameworks have evolved from the original framework proposed by the MA report (2005) that attempted to identify the relationships between goods and services provided by ecosystems and the improvements to human wellbeing including the ES supply chain (Tallis et al. 2012), the ES cascade model (Haines-Young and Potschin 2010), the Economics of Ecosystems and Biodiversity Framework (Braat and de Groot 2012), and the ES delivery process (Villamagna et al. 2013). The key components of these frameworks can be distilled to ES capacity, ES flow, and ES demand (**Error! Reference source not found.**). ES capacity, also referred to in the literature a s the ‘ecological production function' (Tallis and Polasky 2009), is the potential of an ecosystem to produce and deliver services based on biophysical and social properties and functions (Villamagna et al. 2013). ES flow is the realized flow of services for which there is demand. ES demand is the amount of services required or desired by society. These frameworks also recognize that ES demand may result in pressures that drive changes in ES capacity. For the purposes of this chapter, I focus on discussing biophysical feedbacks occurring within and between ecosystems processes and ES capacity as well as the human drivers and pressures that may alter both. These feedbacks are described as balancing (negative) when they dampen change or reinforcing (positive) when they stimulate change. In many cases these human drivers and pressures are part of their own feedback loops within social (human) systems or between social-ecological systems, but consideration of these feedbacks is beyond the scope of this chapter.

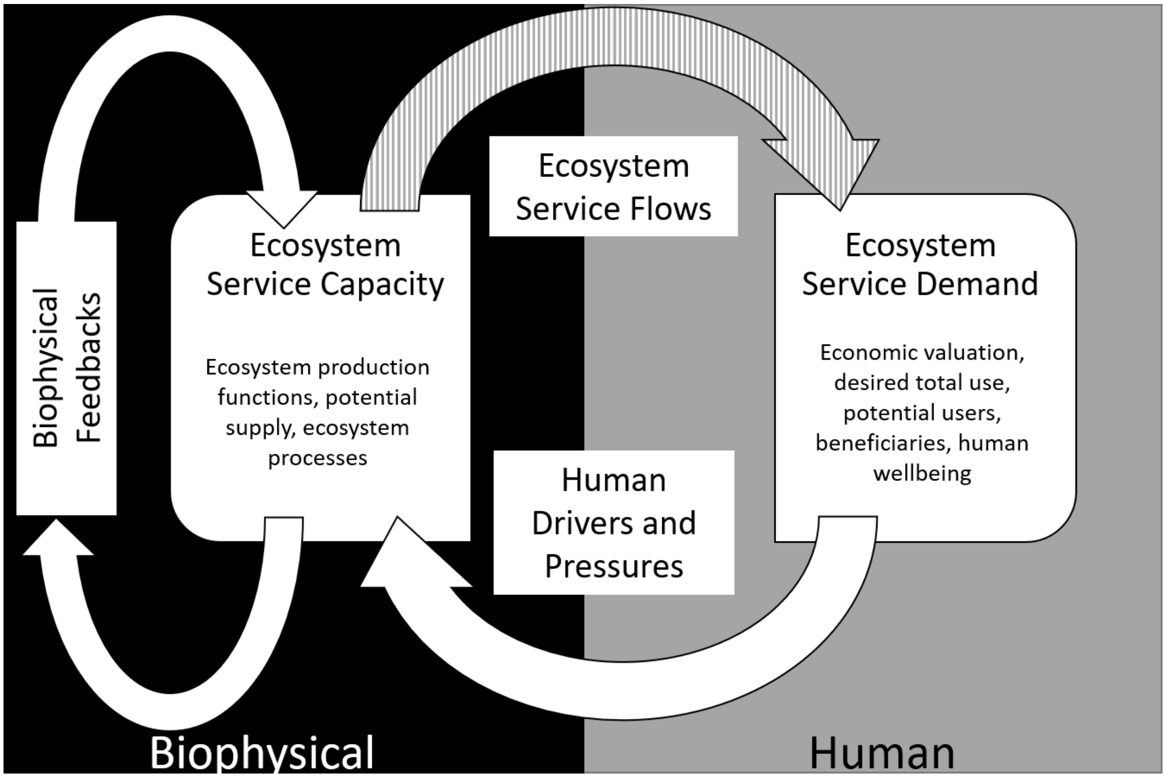

Figure 4-1: Simplified ES framework conceptualizing capacity, flow, demand, biophysical feedbacks, and human drivers and pressures.
Based on similar simplified frameworks by Tomscha and others (2016) and Tallis and others (2012).This chapter focuses on how human drivers and pressures in the form of management behaviors affect ES Capacity and the biophysical feedbacks occurring in the ecosystem (solid white arrows). While this work acknowledges that ES flows affect ES demand (shaded arrow), this relationship is beyond the scope of the methods presented in this paper.

In addition to ES frameworks, a variety of methods and tools for assessment have been created to quantify ES capacity, flow, and demand (Table 1). Many have been comparatively reviewed in the literature including how assessment tools measure or consider different aspects of ES delivery (Villamagna et al. 2013), their suitability and classification as decision-support tools (Bagstad et al. 2013b, Vorstius and Spray 2015, Hugé et al. 2020), their ability to forecast changes in ES due to land degradation and restoration (Turner et al. 2016), their sensitivity to land use and land cover change (LULCC) and ability to accurately provide output data (Sharps et al. 2017), and their ability to adequately quantify biological and economic aspects of ES (Boerema et al. 2017).

Despite the proliferation of ES assessment tools, most do not consider mechanistic biophysical feedbacks, e.g. feedbacks among biogeochemical cycles, or other mechanistic interactions among ES; each service is typically evaluated independent of other services (Nicholson et al. 2009, Seppelt et al. 2011, Currie 2011, Bruins et al. 2017, Lavorel et al. 2017). If knowledge of ecosystem processes and functions, including interactions with human actions and behaviors, is not adequately incorporated into ES models, scientists, managers, and other practitioners may misunderstand the mechanisms underlying the effects of management decisions on ES capacity, improperly estimate the production of services, and possibly take actions that have consequences that could have been better anticipated (Bruins et al. 2017, Bennett 2017, Boerema et al. 2017).

As pointed out by Sutherland and others (2018), there has been an underemphasis on regulating and supporting ES classes in ES quantification, ES valuation, and decision-making tools partially due to the difficulty in measuring or estimating them. The difficulties in quantifying regulating ES capacity are due to their dynamic nature regarding their temporal and spatial variability as well as their response to ecological pressures. These services are key to maintaining the environmental quality of the ecosystem and the provision of other ES. There is a demonstrated need for ES modelling and estimation tools that can address limitations in current methods including the ability to estimate supporting and regulating ES capacity and to include interactions and feedbacks between ES capacity and ecosystem processes.

4.1.2 Ecosystem Process Models

Ecosystem processes include nutrient cycling and flows of energy, water, and carbon that link biotic and abiotic factors within an ecosystem; they are interconnected, and feedbacks exist both directly and indirectly among them (Currie 2011). Ecosystem processes along with ecosystem composition and structure give rise to the production of ES (Fu et al. 2013). When ecosystem processes are impacted by human management or other human-caused changes to ecosystem structure, biophysical feedbacks occur that impact the production of ES (**Error! Reference source not found.**) (Fu et al. 2013, Potschin-Young et al. 2018).

Ecologists use ecosystem process models to represent integrated understanding of ecosystem dynamics and stability, and how flows of carbon (C), nitrogen (N), water, and energy move and interact within a system. Over time, ecosystem process models have become more sophisticated and generalizable, applied to multiple biomes (Running and Hunt 1993); used and compared in local (Robinson et al. 2009), regional (McGuire et al. 1992) and global level analyses (Churkina et al. 1999, Cramer et al. 1999); and linked to biogeography (Sitch et al. 2003) and climate models (Bachelet et al. 2001, Randerson et al. 2009). These models can provide quantifiable outputs of ecosystem C, N, and water pools and fluxes that can be translated into ES frameworks, especially regarding supporting and regulating services.

This chapter focuses on ecosystem process models that simulate terrestrial nutrient cycling and biogeochemical processes based on soil and climate characteristics. Widely used examples of this type of model include, but are not limited to CENTURY, Biome-BGC, TEM and PnET (Table 2). This class of models was considered for this review for two reasons. First, potential applications range from finer scale site-level analyses up to continental scale analyses, which aligns with other tools used to estimate ES capacity. This is compared to other ecological models such as dynamic global vegetation models (DGVMs), which are aimed at regional to global analyses. Second, the focus on biogeochemical processes in vegetation and soil aligns with many regulating services that are based on stocks and flows of carbon, nitrogen, and water. This contrasts with demographic models which are focused on growth, mortality, and recruitment of individual plants or physiological models which are focused on plant photosynthesis and biomass accumulation (Peters 2011).

4.1.3 Objectives

I propose that when considering methods for estimating ES capacity of supporting, regulating, and provisioning services, scientists should consider the use of ecosystem process models for many reasons. First, ecosystem processes could provide a foundation for understanding mechanisms giving rise to the production of ES and these models are based on extensive knowledge of ecosystem processes. Second, current tools for estimating ES capacity often conceptualize ES as discrete entities as opposed to integrated or interdependent suites of ES. Third, ecosystem process models give us the opportunity to understand how different ecological pressures and drivers of ecological change such as climate, human management, and ecosystem structure mechanistically affect the production of ES. This chapter will discuss these factors in more detail by first reviewing current assessment tools and their methods for estimating ES capacity. Second, by providing analysis on benefits and shortcomings of applying ecosystem process models to study ES. Third, by discussing how ecosystem process models could be integrated with other methods to provide improved estimation of ES.

4.2 Characteristics of ES Assessment Tools

The ES assessment tools, also referred to in the literature as ES modeling tools, most often cited for estimating ES typically contain multiple submodules for individual services or are comprised of multiple pre-existing models. These assessment tools often contain separate models that estimate the potential capacity for services, the flow of services, the desired amount of service, and in some cases the economic value of that service (Table 2). The goal of using ecosystem process models to quantify ES is not to compete with these tools, but to better inform the aspects that lead to their estimation of ES capacity. This section will first broadly explain some of the assessment tools, explain in more detail how they estimate the production of ES, and what the benefits and limitations of these methods are compared to ecosystem process models.

4.2.1 ES Assessment Tool Overview

The growing need for understanding the connections for all stages of ES including capacity, flow, demand, and economic valuation has led scientists to develop tools that can assess ES across these stages. Among some of the emerging tools for quantifying ES are the: Multi-scale Integrated Model of Ecosystem Services (MIMES, (Boumans et al. 2015)), Artificial Intelligence for Ecosystem Services (ARIES, (Villa et al. 2014)),Integrated Valuation of Ecosystem Services and Trade-offs (InVEST, (Tallis and Polasky 2009, Doug et al. 2020)), Land Utilization and Capability Indicator (LUCI, (Jackson et al. 2013)), Ecosystem Service Mapping Tool (ESTIMAP, ((Zulian et al. 2013, 2018)), and Ecosystem Service Bundle Index (EBI (Van der Biest et al. 2014)). See Appendix Table D-1 for more detailed descriptions. Many of these tools have been compared in the literature for different ecosystems (e.g., marine ecosystems (Lavorel et al. 2017)), geographic areas (e.g., UK watersheds (Sharps et al. 2017), African Biosphere Reserves (Hugé et al. 2020)), and user types (Waage et al. 2008, Balvanera et al. 2017, Kienast and Helfenstein 2018). Resources from academic and governmental institutions are also available to help users identify which tool is right for them such as ValuES (Schmidt and Seppelt 2018), the US Climate Resilience Toolkit (Gardiner et al. 2019), and the

Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services' Policy Support Tool (Krug et al. 2020). While these tools require different inputs and integrate ecosystem and socio-economic processes through distinct approaches, they find commonality in that they can estimate multiple services, provide spatially explicit results, and simulate the effects of development and land management on ecological and human systems (Francesconi et al. 2016, Sharps et al. 2017).

ES assessment tools have been designed and tested for different geographical locations and extents. At the large scale, tools such as InVEST have received broad attention and been applied to a range of landscapes across the globe. Other tools have been applied mostly at the national or continental level such as ESTIMAP in the EU (Zulian et al. 2018). Others have determined that despite their usefulness at relatively large scales, most of these approaches lack the level of spatial and thematic detail required to conduct assessments at the regional and local level (Derkzen et al. 2015, Martínez-López et al. 2019). Customizable ES tools such as ARIES provide a useful solution to this issue, but have a similar limitation to ecosystem process models (see section 3.4) in that accurate estimation requires readily available local data or models that can be parameterized with local data (Martínez-López et al. 2019, Paulin et al. 2020).

4.2.2 How Do ES Assessment Tools Estimate ES Capacity?

For the purposes of discussion regarding the use of ecosystem process models to estimate the production of ES, I focus here on methods ES assessment tools use to estimate ES capacity. These methods along with the type and scope of input data they require vary widely. ES assessment tools vary according to the services they model, how they estimate the capacity of ES, and the type and scope of input data they require to estimate capacity.

The simplest approach, used by ESTIMAP, is a statistical modelling approach that uses individual regressions to estimate each service that are based on ecological indicators that can be accessed in GIS layers (Zulian et al. 2018). Similarly, the EBI modelling tool does not rely on ecological processes, but instead uses biophysical indicator variables to calculate ES potentials (Van der Biest et al. 2014). This approach does not consider ecosystem processes, biophysical feedbacks, or interactions between processes and services. However, there are benefits to this approach in that input data is easily accessible and understandable and can be found for most geographic areas.

A step-up in complexity is the approach InVEST takes by creating individual empirical production functions for each service. These functions were created with knowledge of ecosystem processes, but are simplistic and do not incorporate biophysical feedbacks or interactions between processes and services (Tallis and Polasky 2009, Doug et al. 2020). Each service is also estimated independently of other services. For example, C sequestration is estimated with an equation assuming linear change in C sequestration over time based on initial land use/land cover (LULC) and current C pools provided by the user. Additionally, any ES that may be linked to C sequestration, such as urban cooling, are calculated by separate models and the only shared data is LULC. Similarly, the LUCI tool simulates biophysical processes such as nutrient loading that can feed into hydrological models, but they only use simple lookup tables and regression models (Sharps et al. 2017). The main benefit of this approach is that the required input data can still be easily acquired from available GIS data layers and LULC maps while providing a production function grounded in the knowledge of ecosystem processes.

The MIMES modelling tool takes an ecosystem accounting approach that simulates changes in biophysical conditions due to human impacts over space and time (Altman et al.

2014, Boumans et al. 2015). In theory this approach allows for dynamics and interactions among services and between processes and services. However, the creation of the ecosystem production function is left in the hands of the user, as opposed to a preestablished model being provided (Boumans et al. 2015). The main disadvantage of this approach is that the framework requires specialized knowledge and training and there have been few studies following the model's initial introduction.

The ARIES modelling tool is more complex in two main ways. First, the platform was developed to allow the building and integration of various kinds of models based on what data are available for the site in question (Villa et al. 2014, Sharps et al. 2017). The eventual goal of this framework is to allows users to couple models such as an ecosystem process model to estimate carbon and nutrient services with a hydrology model to estimate flooding and erosion (Villa et al. 2014). Second, it has been designed to use probabilistic or Bayesian methods to estimate any insufficient local data for the biophysical equations (Bagstad et al. 2014); this aspect is also used by the EBI modelling tool (Van der Biest et al. 2014). Probabilistic methods also give users the ability to estimate the uncertainty for each service outcome. While this increases the complexity of knowledge needed to understand how services are being quantified, it also allows for more complex modelling that can potentially include interconnected ecosystem processes and biophysical feedbacks. However, at this time most analyses are focused more on the probabilistic methods while choosing the best individual model for each service (Martínez-López et al. 2019, Domisch et al. 2019). This may allow for the potential inclusion of interaction between process and services but does not rely on truly interconnected process modelling.

Compared to ecosystem process models, many ES assessment tools have the advantage of considering multiple aspects of ES, usually estimating capacity along some aspects of flow or demand (i.e., valuation). However, they still fall short of addressing the complex biophysical dynamics inherent in estimating ES capacity. The benefits of reduced complexity and ease of use in these tools have come at the expense of being able to dynamically model ecosystem processes and ES capacity. Access to improved information on ES capacity would give scientists and land managers more information to aid in maximizing potential capacity and meeting demand. However, this addition to modelling frameworks could increase the cost and time of assessment and limit the potential users.

4.3 Why Should Process Models be Considered for Estimating ES Capacity?

4.3.1 Ecosystem processes give rise to the production of ecosystem services

Within the context of biophysical or ecological systems, ES capacity relies on both ecosystem structure and ecosystem processes (Fu et al. 2013). Frameworks of ES (**Error! Reference source not found.**) acknowledge that understanding ecosystem structure and function is integral to estimating ES capacity (Haines-Young et al. 2012, Villamagna et al. 2013) and that ecosystem properties including ecosystem processes and dynamics drive the capacity of an ecosystem to provide a given service (Bastian et al. 2012, 2013). As mentioned above (section 4.2.2), most ES assessment tools do not consider integrating ecosystem processes and ES and a review of the literature found that only 26% of studies that evaluate more than one ES investigate the relationships between those ES (Boerema et al. 2017).

ES capacity, also referred to as 'ecological production function' or EPF (Tallis and Polasky 2009), is the quantification of the ability for an ecosystem to supply ecosystem services (Villamagna et al. 2013). When ecosystem structure and function is altered by natural disturbances or human modification, ES capacity adjusts the amount of various services that can potentially be produced. Bruins et al. (2017) proposed a nine-point list of "desired attributes of

EPFs" which includes: quantified ES outcomes, ability to predict the outcome of management scenarios, ability to reflect ecological complexities such as nonlinearities and biophysical feedbacks, and an ability to perform well across a broad range of geographic areas. I propose that ecosystem process models can be used as a tool to estimate ES capacity, as they are already designed with many of these attributes in mind.

4.3.2 How have process models been used to estimate ecosystem services?

Although most ecosystem process models were originally designed for wildland systems, in their original form they may be limited in their ability to include human interactions with the ecological system (Cuddington et al. 2013b). However, it has been common for researchers to modify models for their desired questions and needs. This can include, as shown in Table 4-1, adding additional processes, increasing complexity of existing pools and flows, integrating effects of climate change including changes to temperature and precipitation, or expanding the model to include human managed ecosystems (agriculture, managed forest, urban environments). While initial modification can be time consuming to code, calibrate and test, the resulting modified models are typically available for future use. These models can also be modified to incorporate human pressures and drivers on ES capacity such as human management or changes in land cover or ecosystem type. While ecosystem process models are typically not spatially distributed, some ecosystem process models have been linked with models that incorporate spatial relationships across a landscape. However, there are countless other studies that have used ecosystem process models to estimate factors that are closely aligned with key ES (NPP, C sequestration, biomass yields, nitrogen retention, etc.) even though the ES terminology and concepts were not explicitly used. The following studies have explicitly stated the use of ecosystem process models as a tool to estimate ES.

Table 4-1: Ecosystem process model comparison.
A comparison of terrestrial ecosystem process models used for productivity, carbon, and nitrogen cycling. Scale (cell resolution) refers to the range of scales over which the model has been applied in the literature. Abbreviations: C = carbon, W = water, N = nitrogen, P = phosphorus, S = sulfur

Model	Scale (cell resolution)	Layers of Plant Functional Types (PFTs)	Typical Biomes / Ecosystem Types	Cycles	Notes	Timestep / Temporal Resolution	Options included for human management or impacts	Key Citations
Biome-BGC	Plot to 0.5° grid	Original version: one layer Modified version: Multiple – can have an overstory and understory	Wildland: Forest, grassland, shrubland Managed: forest (Tatarinov and Cienciala 2006) (González-Sanchis et al. 2015), agriculture (Wang et al. 2005), grassland (Hidy et al. 2012), urban residential (Milesi et al. 2005, Kiger Chapter 2, 3)	C, W, N	Can be integrated with remote sensing input data Has LAI as an output variable – can be used to validate	Daily (photosynthesis and evapotranspiration) and Annual (allocation, decomposition, N cycle)	Fertilizer, irrigation, mowing, mulch mowing, pruning, tree planting, tree removal, raking, CWD removal	(Running and Hunt 1993, Thornton et al. 2002) modifications: (Bond-Lamberty et al. 2005, Kiger Chapter 2, 3)

CENTURY	Plot to 0.5° grid	Two – can have shading and nitrogen competition between forest and grassland	Wildland: Grassland, forest & savanna Managed: turfgrass (Qian and Follett 2002, Bandaranayake et al. 2003), agriculture (Parton and Rasmussen 1994, Foereid and Høgh-Jensen 2004, Stehfest et al. 2007), urban residential (Trammell et al. 2017)	C, W, N, P, S	Does allow easy integration of management Plant production does not include a photosynthesis model – just uses a simple net primary production model No LAI output	CENTURY is monthly, but companion model DAYCENT is daily (Parton et al. 1998)	Fertilizer irrigation, cultivation, grazing, harvesting, biomass removal & addition, climate, elevated CO2	(Parton et al. 1987, 1993b)
PnET-CN	Stand to watershed	single	Wildland: Temperate and boreal forest Managed: temperate forest Other biomes are in the progress (Thorn et al. 2015)	C, W, N	No grassland biome Has been linked with SWAT to model water availability (Kirby and Durrans 2007)	Daily and monthly – set of nested models where canopy flux is daily but other functions and allocations are monthly	Fertilizer, biomass removal, elevated CO2	(Aber et al. 1995, 1996, 1997)

TEM	Plot to 0.5° grid	single	Wildland: boreal, temperate, and tropical forest; grassland; tundra	C, W, N	Only one carbon pool for vegetation and one pool for soil Includes a dynamic soil thermal (permafrost) model (Zhuang et al. 2003)	monthly	Climate, elevated CO2	(Raich 1991, McGuire et al. 1992, Felzer et al. 2009)

The Photosynthesis and Evapotranspiration (PnET) model has been coupled with other models to study the effects of climate change and land use change on ES capacity in forested ecosystems. Samal and others (2017) linked PnET-CN to an aquatic ecosystem model to estimate a suite of environmental indicators representing provisioning and regulating water ES for a forest-dominated watershed in New Hampshire. Further iterations of this project incorporated ES demand models into the framework and allowed researchers to estimate trade-offs between a mix of ten ES (Borsuk et al. 2019). ForeSAFE, a model that integrates PnET with three other biogeochemical models, was used to simulate trade-offs between a suite of five forest provisioning and regulating services in a Swedish spruce forest (Zanchi and Brady 2019).

The CENTURY model has been used to estimate supporting, regulating, and provisioning ES in agricultural, grassland, and rangeland ecosystems. Belem and Saqalli (2017) integrated CENTURY with agent-based models (ABMs) to estimate the impact of farming practices and settlement development on ES capacity (soil fertility, crop yields) in West Africa at multiple scales (plot to region). Iravani and others (2019) proposed an innovative approach to parameterize CENTURY using an inverse modelling approach in order to aid in estimating C related services in native grasslands of Alberta, Canada. G-Range, a version of the CENTURY model that has been modified to simulate plant population dynamics and competition between plant functional types at a coarse resolution (0.5 degree × 0.5 degree or coarser) than the original model, was used to estimate global changes in rangeland ES capacity (NPP, herbaceous NPP, carbon storage) under varying climate scenarios (Boone et al. 2018). Other studies have used an off-the-shelf version of CENTURY to estimate differences in carbon related ES due to ecosystem restoration in China's Grain to Green Program (Feng et al. 2013), LULCC scenarios in a subtropical region of India (Liu et al. 2018), and in agricultural ecosystems under varying crop management scenarios in the Pampas of Argentina (Caride et al. 2012) and the Campos Gerais region of Brazil (Potma Gonçalves et al. 2018).

Biome-BGC has been adapted to simulate ES capacity of supporting, provisioning, and regulating ES within mixed-use, urban, and forest ecosystems. The Procedure for Ecological Tiered Assessment of Risk (PETAR) framework uses Biome-BGC alongside models of LULCC and surface water flow to estimate water and C related ES in a mixed-use watershed of the Yangtze River Delta in China (Xu et al. 2016). Biome-BGCMuSo, a version of Biome-BGC with a multilayered soil module and management modules for croplands, grasslands, and forests (Hidy et al. 2012, 2016), was linked to a crop simulation model to estimate crop yields and nitrate leaching under a range of fertilization and climate scenarios in Hungary (Pokovai et al. 2020). Othoniel and others (2019) used an integrative modelling approach that links a land cover change model with Biome-BGC (C sequestration) and InVEST (crop yields and pollination) to investigate ES trade-offs at the local and country scale in Luxembourg. A version of Biome-BGC that has been modified for managed forests in the Pacific Northwest region of the US was used to consider relationships between carbon sequestration, wood production, and biodiversity (Turner et al. 2011). The previous chapters of this dissertation use Biome-BGC-Ex, which I modified to simulate homeowner management practices and ecosystem structure specific to residential areas (turfgrasses, dense woody patches, and open grown trees over turfgrass) to simulate a suite of ten provisioning, regulating, and supporting services in exurban Southeast Michigan.

4.3.3 Benefits of a process model approach

The ecosystem process model approach to estimating ES capacity has many benefits. It gives users the ability to estimate and predict quantifiable ES outcomes across a variety of management, policy, and climate scenarios (i.e., pressures). Ecosystem process models can already simulate dynamic relationships and biogeochemical feedbacks between pools and fluxes of carbon, water, and nutrients, which can be extended to the ES they are able to inform. Ecosystem process models have been verified, calibrated, and applied to global simulations as well as for local, site specific conditions across a range of wildland and human-dominated ecosystems including agriculture (Parton and Rasmussen 1994, Foereid and Høgh-Jensen 2004, Wang et al. 2005, Stehfest et al. 2007), managed forests (Tatarinov and Cienciala 2006, González-Sanchis et al. 2015), managed grasslands (Qian and Follett 2002, Bandaranayake et al. 2003, Hidy et al. 2012), urban ecosystems (Milesi et al. 2005, Zhang et al. 2012, Trammell et al. 2017), and the exurban residential landscapes (BIOME-BGC-Ex, Chapter 3). With current computing power these models can run thousands of times in a short span of time which gives users the ability to simulate a multitude of scenarios and assess the impacts on ES.

Although ecosystem process models were not originally designed for ES quantification, many models directly output ES capacity estimates, output variables that are indicators of ES, or can be modified to estimate production of supporting, provisioning, and regulating ES. For example, Biome-BGC-Ex estimated residential ES using all three methods (Chapter 3). NPP (supporting), freshwater recharge (regulating) and C sequestration (regulating) were estimated directly from model outputs. Microclimate regulation (regulating), air pollution abatement (regulating) and soil fertility (supporting) were estimated from indicators based on model output. Firewood (provisioning), water retention (regulating & supporting) and nitrogen retention (regulating) required some model modification and were calculated based on multiple model outputs. However, one challenge of this task is determining which model outputs and processes might translate into services that are valued by either by users or society. Although there are frameworks which identify lists of potential ES (e.g., (Maes et al. 2016)), the user must decide for themselves based on their question, study system, and model ability. For example, in Chapter 3 I determined two water retention ES that would be valued by homeowners. The first, spring soil water recharge estimated the amount of water retained over winter that would be available to support spring plant growth. This growth would underpin many of the other services (e.g., C sequestration, microclimate regulation). The second, summer soil water retention, measured the proportion of water retained in the soil at the height of the growing season. In a residential system this service can relate to localized water flow regulation and also availability of water to maintain a lush lawn.

One of the major benefits of the ecosystem process model approach to quantifying ES capacity is that it can simulate dynamic biophysical feedbacks that affect ES Capacity and the trade-offs and synergies between the services that are rooted in ecosystem processes. These models rely on the understanding of how nutrient, C, and water flows occur within an ecosystem and how they rely on each other for an ecosystem to function. For example, in most ecosystems C (biomass) accumulation is dependent on nitrogen availability, water availability, or a combination of both. Plants will take up water and nitrogen (N) until growth is limited, and any remaining water and nitrogen will either remain in soil or flow from the system. As shown in Chapter 3, three potential services that result from this simple relationship are carbon sequestration, nitrogen retention (reduced water pollution), and freshwater provision. These services are all interconnected due to their underlying processes. Our study found (Chapter 3) that in model simulations of mixed turf and trees fertilizer increased N availability, which drove increased NPP because growth is limited by N. As more biomass was produced, greater amounts of C were stored in above and below ground vegetation, which led to greater climate regulation. Since all additional N was taken up for growth nitrogen retention remained high. Water was also limited and led to most water inputs being taken up for growth which led to declining freshwater provision. However, when irrigation was added to fertilized simulations climate regulation decreased, due to increased soil decomposition. This method also allowed us to examine how ES Capacity compared across different realistic combinations of management behavior. I compared ES Capacity in a mixed tree and turfgrass vegetation cover (*turfgrass with sparse woody)* for six different realistic combinations of management behaviors (Homeowner Agent Typology Analysis Chapter 3, based on (Nassauer et al. 2014). We found that homeowners who demanded an aesthetically neat lawn (referred to as *Neat Neighbors)* managed with a combination of high fertilizer, irrigation and raking and infrequent pruning, which led to the comparatively highest ES capacity in firewood, N retention, spring soil water recharge and climate regulation. Homeowners who demanded an aesthetic view of horticultural trees and plantings applied less fertilizer (referred to as *Tree Planters)*, pruned more frequently, and planted more trees. While *Tree Planters* also resulted in comparatively high ES capacity for many services, the two types of managers experienced trade-offs between soil fertility, firewood, and climate regulation. Both types had similar NPP, despite lower fertilizer and frequent pruning in the *Tree Planter* type, but *Neat Neighbor* had higher climate regulation, which means it sequestered more carbon. This is likely driven by frequent pruning of *Tree Planters,* which removed proportionally more fine woody biomass. This frequent biomass removal caused a balancing feedback of less woody biomass being built up over time there leading less coarse woody biomass available for firewood. Comparatively, soil fertility was likely higher for *Tree Planters* because there was no raking and another reinforcing feedback caused by pruning led to increased root mortality which eventually is decomposed and contributes to soil fertility. An ecosystem process model is designed to include the dynamic relationships between these processes and can simulate how the processes are dependent on each other. It can simulate how a change in one pool or flux feeds into the others. This is also true of the services estimated with this method, as it can show how different climate or management scenarios lead to services having a synchronous response or trading off.

Similar to some ES assessment tools, ecosystem process models also allow for multiple management, climate, and other pressures to be modelled as scenarios, which allows for the user to determine the full scope of potential outcomes. This could be in the form of a sensitivity analysis to see how the range of management affects ES capacity or by considering uncertainty in the form of running multiple proposed climate scenarios. Biome-BGC-Ex was run 13,000 times to examine how the combination of a range of management and ecosystem structure variables affected ES capacity outcomes (Chapter 3). This comparative approach allowed us to see the full range of possible outcomes based on our knowledge of homeowner management and provided a way to examine which management practices were the most important for service production. From this analysis we found that human drivers and pressures in the form of yard management practices led to significant ES capacity variation across the modelled services. We also determined that fertilizer application was a significant driver of most of the ES and that trade-offs exist between freshwater regulation and all other ES we modelled, Caride and others (2012) used CENTURY to model the combined impacts of crop sequence, fertilization, and tillage system on future agricultural ES across multiple scenario combinations. The advantage of running scenarios of different pressures in ecosystem process models is, as described in the previous paragraph, that they simulate the effect of pressures on the underlying processes that support the suite of modelled services.

Biophysical and socio-economic patterns and processes occur over a wide range of interrelated spatial and temporal dimensions. Depending on the model, aspects of scale that affect these dynamic relationships may be predetermined or adjustable by the user. Most models can be run for short time periods such as one growing season to long-term simulations that run for hundreds of years. Within the model, processes themselves run on predetermined time scales with processes such as photosynthesis and evapotranspiration accounted for on a daily timestep and other aspects addressed on a weekly, monthly, or yearly timestep (Table 1). Ecosystem process models applied in a spatial framework often assume homogeneous vegetation coverage within a grid cell, and the spatial resolution for each cell can be from the size of a plot or yard up to a 0.5 ° latitude and longitude. Chapter 3 shows an example that simulated ES capacity in residential yards of Southeastern Michigan at the scale of vegetation cover type and landscape scale with Biome-BGC-Ex over a period of 50 years. The model G-Range, which was developed based on CENTURY, tracked global rangeland ES at a 0.5 degree x 0.5 degree resolution for 120 year simulations (Boone et al. 2018). Although process models do not consider flows of C, nutrients, and water between cells (see section 3.4), they can represent heterogeneity across a landscape due to differences in ecosystem structure, ecosystem type, and differences in ecosystem pressures such as heterogenous management practices. CENTURY has been used to measure agricultural related ES in West Africa at multiple scales from farm to country over a period of 30 years (Belem and Saqalli 2017). This study was able to model heterogeneity in C related ecosystem services and crop yields across the landscape.

4.3.4 Limitations or shortcomings of ecosystem process modelling approach to estimating ES

While one benefit of ecosystem process models is that they allow users to simulate complex interactions and feedbacks, the downside of this complexity is that it may create barriers to their use for modelling ES (Paruelo et al. 2016, Rieb et al. 2017). Typically, these models are designed for scientists and researchers as opposed to land managers and planners. They require knowledge of ecological specific terminology, ecophysiology, and how ecological processes occur and interact. The user-interface of some of these models are also outdated and not designed with a non-specialist user in mind. A conceptual limitation to ecosystem process models is their inability to model the entire chain of ES from capacity to flow to demand. However, I do see an opportunity for ES modelling frameworks to incorporate some of the important aspects of these models into a more user-friendly format.

The main limitation for usability of these models is the amount and difficulty of acquiring input data. Typically, these models require multiple forms of input data including initial conditions (current biomass, soil conditions, nitrogen availability, etc.), drivers (weather and climate data, management scenarios), and parameters (ecophysiological conditions of vegetation and soil). Information on initial site conditions and drivers needs to be provided for the given research question. In many cases this can be select from a standardized set of parameters based on the given ecosystem.

As mentioned previously, most of these models have been designed for wildland ecosystems as opposed to ecosystems with a major human component. If parameter sets for human-dominated ecosystems are not available, then substitutions for the affected variables need to be acquired. This can be accomplished through surveying the literature, field data collection, or remote sensing. In the case of modifying Biome-BGC for measuring exurban residential ES, existing exurban field research and literature on urban and exurban applications of Biome-BGC were used to adjust the model parameters (Chapter 3). However, there was a long decision-making process for determining how to calibrate the model, which values from the study region to use as initial C and N stocks, and how to parameterize C to N ratios of vegetation and soil. Iravani and others (2019) have proposed an inverse modelling approach that can be used to aid in parameterizing ecosystem process models, in their case they applied this method to estimate grassland C ES in grasslands using the CENTURY model.

An additional issue of models designed for wildland system is that changes to processes impacted by humans may be not reflected in the model code. One issue with Biome-BGC-Ex that was not fully rectified was how the model estimated N demand and N saturation. Biome-BGC in its original form was always meant to be N limited, as it was originally designed for a region that was known to have N as a limiting factor for growth (Running and Gower 1991). Despite initializing the model with soil C and N pools which represented a N saturated study region, N demand was never met in the simulations even with the highest level of fertilizer additions. It was later determined that since Biome-BGC-Ex limits plant growth and decomposition as opposed to adjusting C:N ratios when nitrogen is limited the low plant C:N ratios required high levels of N inputs to maintain living biomass. In reality, we would expect plant growth to be limited in the short-term with C:N ratios adjusting in plant matter over time.

Although decision making and policy aimed at ES can be improved with accurate and defendable quantification, spatially explicit units are needed to quantify ES because supply and demand for ecosystem services are spatially explicit (Crossman et al. 2013). Ecosystem process models are best able to estimate ES capacity at the local to regional scale and a resolution of less than 0.5 degrees. If users are interested in modelling at a coarser scale, models such as DGVMs may be a better choice. One of the main limitations of the models discussed in this chapter is that they are nonspatial within a grid cell. Each simulation is spatially bound to an area with homogeneous vegetation, soil, and climate conditions. This can especially limit the understanding of services that relate to flow across space such as water flow services. In some cases, there may be other ecological models better suited to measuring the movement of services across a landscape, but they also have their own limitations. For example, the Soil and Water Assessment Tool (SWAT) is a spatially explicit model that has been used as a tool to model water quantity and sediment regulation, but is limited in its ability to model services involving C and N in terrestrial ecosystems (Francesconi et al. 2016). LANDIS-II is a model that combines terrestrial ecosystem processes (from PnET and CENTURY), forest succession, and disturbances across forested landscapes (Scheller et al. 2007). While this model includes a spatial component, it designed for large landscape tracts (>1 million ha) and is limited in its ability to estimate services in nonforest ecosystems or landscape types. This limitation can also be addressed by linking an ecosystem process model to other models with spatial components such as linking with a watershed model (Samal et al. 2017), surface waterflow models (Xu et al. 2016), or plant dynamics (Boone et al. 2018).

Usability may also be limited by the user-interfaces of these models. For example, it may be difficult to know where and how to provide input data. Data output may not be in a format that is instantly beneficial to the user, such as in a large table of values. Since these models are nonspatial, results would need to be put through an additional step of mapping to see results over the project's spatial extent. This contrasts with models designed specifically for ES that are spatially explicit and can provide map-based outputs.

Ecosystem process models would need to be considered as part of a broader modelling framework, as shown in Figure 4-2, to address the full conceptual model of ES capacity, flow, and demand. While in some cases they can measure the realized use of some provisioning services through management scenarios (e.g., forest harvest, crop yield), ecosystem process models are best suited for estimating ES capacity and are not designed to consider human demand or valuation of services. In addition, while ecosystem process models are suitable for modelling services classified as production, regulation and supporting, they would need to be used in conjunction with other models or information to measure the capacity of cultural services and the regulating services of pollination, habitat quality, and biodiversity. In Chapter 3 we showed how it is possible to consider cultural ecosystem services including aesthetics as part of what drives human management behavior. However, the project was not designed with dynamic management behavior that could change based on the resulting ES flows or simulate feedbacks between the human to the ecological system. In the next section I will explore how the strengths of ecosystem process models can address limitations of existing modelling frameworks and vice versa.

4.4 Next Steps: Integrating Ecosystem Process Models with Other Tools to Improve ES Assessment

Ecosystem process models are a tool that can improve our ability to understand the complex dynamics of ES capacity. Based on our knowledge of ES assessment tools, there are a few ways which these methods can be reconciled. First, ecosystem process models could be considered as one part of an assemblage of models. For example, the MIMES and ARIES assessment tools consider the dynamics of ecosystem processes. ARIES chooses the best models available in its database for each user's question and service choices (Villa et al. 2014), however at this time the only ecosystem model included is LPJ-Guess a DGVM model designed for regional to global scale analysis. Ecosystem process models could be added to such databases and given preference if more than one service could be estimated with the model or if the users are estimating services at the local scale. While this may increase the complexity of modelling, including feedbacks and interactions between ecosystem processes could give users more accurate estimates of service trade-offs and synergies. Although this option could increase data input demands, most models have default parameters based on ecosystem type and the Bayesian methods in the ARIES tool could be used for parameters where uncertainties exist.

A second option would be to use ecosystem process models to estimate ES capacity and link this with other existing models to create an integrated model ES assessment tool that can estimate ES flow, ES demand, and ecological pressures (Figure 4-2). Belem and Saqalli (2017) demonstrate this by linking the CENTURY model with agent-based models that represent household decisions and livestock management to assess the impacts of climate change and agro-ecosystem management on ES in West Africa. Biome-BGC has previously been linked with agent-based models to estimate differences in carbon storage under varying land management and policy scenarios (Robinson et al. 2013).

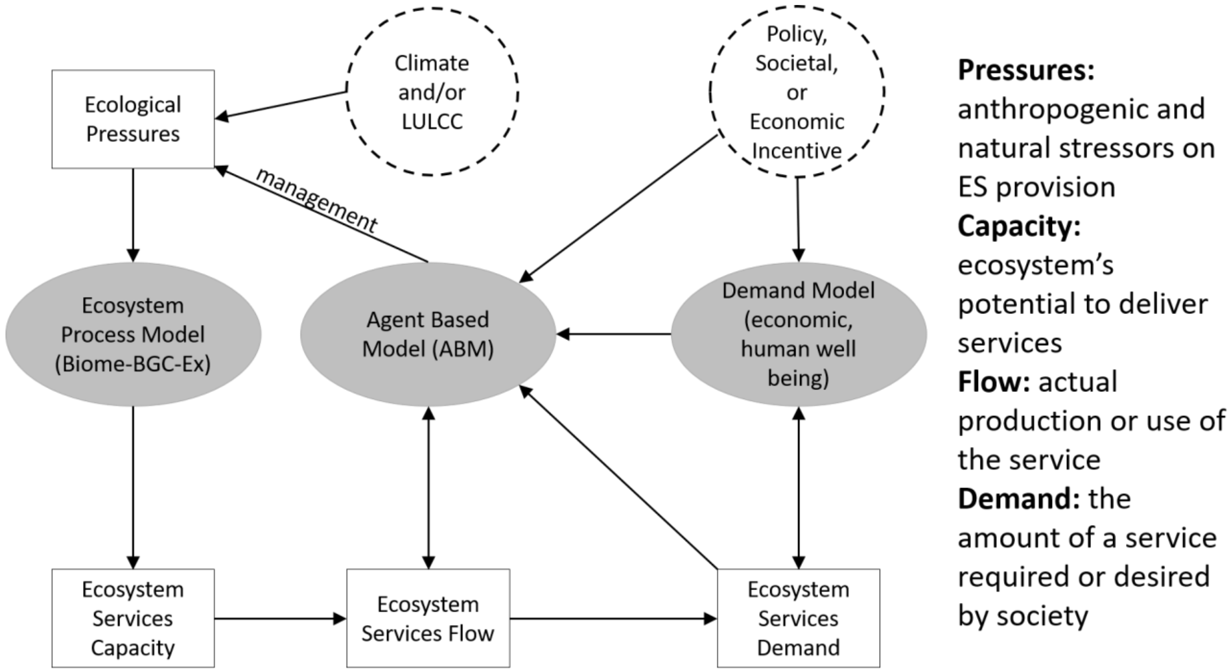

Figure 4-2: Proposed process-informed integrated modelling framework.
This framework would link multiple models to estimate ES capacity, flow, and demand in a given ecosystem. The linked models (gray ovals in diagram) would represent a process-informed ES analysis framework. Abbreviations: LULCC = land use and land cover change.

Following this strategy Biome-BGC-Ex (Chapter 3) could be linked to an agent-based model of human management to study the dynamics between ES capacity, flow, and demand and simulate feedbacks that exist between human and ecological systems. At a higher resolution (parcel level) this could consider how homeowners or land managers are making decisions. For example, agent type could be determined based on their ES demands (e.g., lush lawn, views of surrounding nature, cooler microclimate) which could be based on social and economic factors (e.g. Homeowner Agent Types from previous chapters, Nassauer et al. 2014). Agent management practices (e.g., fertilization, biomass removal, irrigation) would change over time to best meet their demands. At a coarser resolution (neighborhood or city level) this could consider local government decisions on environmental quality (e.g., fertilizer reduction initiatives), developer economic incentives (e.g., payments or tax benefits for not removing large trees) or federal economic incentives (e.g., carbon credits). This type of dynamic framework could allow agents to change their behavior over time based on what is occurring within their site or community and have that behavior create feedbacks between the human and biophysical system (Figure 4-1: Simplified ES framework conceptualizing capacity, flow, demand, biophysical feedbacks, and human drivers and pressures.Figure 4-1).

A third and final option that addresses the issue of data acquisition would be to simplify the input parameter sets of ecosystem process models to what can easily be accessed from remote sensing or spatial databases. For example, with Biome-BGC-Ex, future users could use the parameter sets proposed in Chapter 3 or the default parameters of the model, but site level initial soil conditions could be supplemented with a geographic soil database (e.g., SSURGO-30), vegetation initial conditions could be based on MODIS outputs or NDVI, and ecosystem structure could be informed by land cover and land use maps.

Scientists have continued to call for tools that can model the complex relationship between and within ecosystem processes and ES (Cuddington et al. 2013b, Paruelo et al. 2016). The need for assessment tools that integrate knowledge of ecosystem processes and services will continue to grow as governments begin to require estimation and monitoring of ecosystem services. For example, the European Union 2020 Biodiversity Strategy called for EU Member States to map, assess, and enhance ecosystem services within national territories, to promote and integrate these values into national accounting and reporting at the national and EU level (EC 2011, 2019). This will require standardization and harmonization of data, indicators, and methods to assess ecosystem services (Paulin et al. 2020). By including our knowledge of interactions and biophysical feedbacks that affect ecosystem processes and ES in the models and tools that predict ES, users will be better equipped to recognize how ecosystems affect the provision of services, trade-offs associated with environmental management decisions, and how changes in land management might affect the future provision of ES.

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Chapter 5
Conclusion

Assessment of ecosystem services (ES) and the effect of pressures and feedbacks on them requires knowledge of ecosystem ecology and ecosystem processes. Despite acknowledgement that ecosystem processes are vital to service production, there is a documented but unfulfilled need to bring our knowledge of ecosystem processes to ES science (Bennett 2017, Lavorel et al. 2017, Broszeit et al. 2019). Current assessment tools are limited in their ability to estimate ES capacity as they do not include interactions and biophysical feedbacks between ES and ecosystem functions. The overarching goal of this dissertation was to evaluate how ES assessment can be improved by applying ecosystem process models modified for human-dominated ecosystems as a tool to improve estimates of supporting, regulating, and provisioning ES. This dissertation provides an example of such an improved tool by modifying a widely used ecosystem model, Biome-BGC, and assessing the methods and results in that example in the broader context of ES assessment tools currently in use in the field. I summarize here the findings of the three research papers presented in this dissertation, addresses limitations of this project, and proposes future research directions.

5.1 Summary of Dissertation Objectives and Conclusion

This study applies ecosystem ecology theory and ecosystem process models to human-dominated ecosystems, specifically to residential yards in exurban Southeastern Michigan. The main products of this dissertation are: 1) the creation of a new version of the ecosystem process model Biome-BGC, referred to as Biome-BGC-Ex, that can simulate processes in vegetation cover types and yard management practices found in residential yards; 2) the conversion of Biome-BGC-Ex model outputs to a suite of ten ES; and 3) an evaluation of ecosystem processes models as a tool for estimating ES capacity. The primary goals and findings of each chapter are detailed below.

In the first paper of the dissertation (Chapter 2) I focus on addressing two limitations of current ecosystem process models for human-dominated residential ecosystems 1) inability to model multiple layers of competing vegetation, such as combined layers of trees and turfgrass in residential yards and 2) lack of management practices found in residential yards. The study introduces Biome-BGC-Ex, a new version of the ecosystem process model Biome-BGC, that I have modified to include competition between trees and turfgrass as well as residential landscape management practices including fertilization, irrigation, mower blade height, mulch mowing, pruning intensity and frequency, raking, coarse woody debris (CWD) removal, tree planting, and tree removal. Following these modifications, the model was calibrated and parameterized for exurban residential land in Southeastern Michigan. It was then used to answer the following question: How do individual and combinations of yard management practices affect C sequestration?

In a series of analyses, we evaluated the impact of individual and combinations of residential management practices on carbon sequestration in the temperate exurban region of Southeastern Michigan, USA over a fifty-year time horizon. For the first two analyses we ran Biome-BGC-Ex simulations for three predominant vegetation cover types identified in our study region *turfgrass with sparse woody, turfgrass,* and *dense woody* and model results suggested that

N fertilization was the strongest driver of C sequestration. Our analysis of Homeowner Agent Types (HAT) at the scale of the parcel and the landscape, found that different realistic sets of management practices have differential effects on C sequestration, and these differences can have significant impacts when scaled up to the landscape. The HAT with the highest fertilizer rate had the largest increase in total ecological C over 50 years, while the HAT that did not fertilize and that pruned trees annually resulted in a loss of total ecological C over the same time period.

Across vegetation cover types, my simulations predicted that fertilization, pruning and tree removals have the largest impacts on C due to biophysical feedbacks that impact tree biomass and soil C. In the *turfgrass with sparse woody* cover type, fertilization was the primary positive driver of C storage while pruning and tree removals drove decreases in C. These practices significantly affected the ecological dynamics between trees and turfgrass in this cover type and led to significant declines of both trees and overall C storage when tree removals, frequent pruning, and the absence of fertilization occurred together. In the *turfgrass* cover type, ecosystem C increases required fertilizer in 100 percent of simulations and mulch mowing in 97 percent. The *Dense woody* cover type had the highest occurrence of ecosystem C increase when pruning and tree removals were lowest.

Overall, the study results illustrate the strength of assessing the effects of human management by using an ecosystem process model with C, N, and water dynamics in vegetation and soil linked through functional ecosystem processes. Biome-BGC-Ex can potentially be used to measure C dynamics across similar temperate exurban residential landscapes. One limitation of this study is that it simplifies management practices to be constant over the 50-year period, as opposed to using realistic dynamic decision making. To address this limitation the model could be linked with other tools such as Agent Based Models, such as those proposed in the SLUCE project (Robinson et al. 2013), to further investigate how dynamic residential management behaviors affect C outcomes.

The second paper of this dissertation (Chapter 3) addresses two limitations of current ES assessment tools: 1) that they neglect to consider mechanistic ecosystem feedbacks, e.g. feedbacks among biogeochemical cycles, or other mechanistic interactions among ES (Nicholson et al. 2009, Seppelt et al. 2011, Currie 2011, Bruins et al. 2017, Lavorel et al. 2017); and 2) the underemphasis on regulating and supporting ES classes (Sutherland et al. 2018). This chapter describes how Biome-BGC-Ex was modified to provide outputs that can be used to estimate ES capacity for a suite of services in the residential landscape. The main questions of this study, which focused on exurban Southeastern Michigan were: 1) which individual and combinations of yard management behaviors have the greatest effect on ES capacity? and 2) what are the trade-offs and synergies found between the modelled services?

In a series of analyses, we estimated ES capacity of ten services: NPP, soil fertility, firewood production, nitrogen retention, freshwater recharge, spring soil water recharge, summer soil water retention, climate regulation, microclimate regulation, and air pollution abatement. Based on these results, we evaluated which individual and combinations of residential management practices have the largest effect on carbon sequestration in the temperate exurban region of Southeastern Michigan, USA over a fifty-year time horizon. Using Monte Carlo simulation methods, we simulated potential combinations of ten yard management practices and found that the ES capacity for each service varies with the management activities. All services across all vegetation types have significant changes in capacity due to at least one yard management practice. Fertilizer was the strongest driver for many of the modelled services. Our analysis of trade-offs and synergies between the modeled services under six different homeowner agent types (HATs) found that differences and trade-offs in ES capacity between HATs can be explained by feedbacks within the ecological system. Our study shows trade-offs between ES relating to high amounts of carbon or biomass and freshwater recharge.

The approach of using an ecosystem process model such as Biome-BGC-Ex allows the user to consider how homeowner management behaviors affects ecosystem processes and functions directly and indirectly through biophysical feedbacks. For example, we were able to show that in model simulations of mixed turf and trees (*turfgrass with sparse woody)* fertilizer additions increased N availability, which drove increased NPP because growth is limited by N. As more biomass was produced, greater amounts of C were stored in above and below ground vegetation, which led to greater climate regulation. As all additional N was taken up for growth nitrogen retention remained high. Water was also limited and led to most water inputs being taken up for growth which led to declining freshwater provision. However, when irrigation was added to fertilized simulations climate regulation decreased, due to increased soil decomposition.

The main advantage of this study is the ability to look beyond simple linkages and correlations among ES to demonstrate the effects of management practices on ES as they manifest, through causal ecosystem interactions, in exurban ecosystems. Results of our investigation demonstrate that analysis of ecological processes in novel ecosystems underscore the complexity of landscape management decisions. One limitation of our current version of Biome-BGC-Ex is how N dynamics are simulated in the model. First, surface N loss is not adequately considered in this model; N loss is primarily represented by N leaching through the soil water exports and through N volatilization. Second, C to N ratios are constant in the model and do not adjust with management. Future research should include additional field components to inform better N dynamics in the model. A second limitation of this method as an approach to estimating ES is that Biome-BGC-Ex is aspatial and does not include flows of inputs or outputs across the landscape. This could be addressed by linking Biome-BGC-Ex with a spatially explicit model such as SWAT (Francesconi et al. 2016), watershed models (Samal et al. 2017), or surface waterflow models (Xu et al. 2016).

The third paper of this dissertation (Chapter 4) evaluated terrestrial ecosystem process models as a potential tool for ES assessment. This paper is framed around the principle that ecosystem processes along with ecosystem composition and structure give rise to the production of ES (Fu et al. 2013). Current assessment tools do not include mechanistic biophysical feedbacks or interactions between ES or between ecosystem processes and ES, which may lead to incorrect estimates of ES capacity. The main questions this paper addressed were: Are ecosystem process models a useful tool for estimating ES capacity? Also, how can ecosystem process models be integrated with other tools to improve ES assessment?

This paper first reviews the most cited and referred to ES assessment tools and evaluates their ability to model ES capacity. It then provides a detailed synthesis of the benefits and limitations of the proposed approach of using ecosystem process models as a tool to estimate ES capacity. We find that while process models increase the complexity of knowledge needed to understand how services are being quantified, it also allows for more complex modelling that includes interconnected ecosystem processes and feedbacks. Compared to ecosystem process models, ES assessment tools have the advantage of considering all areas of ES including capacity, flow, and demand. However, they fall short of addressing the complex biophysical dynamics inherent in estimating ES capacity. The benefits of reduced complexity and ease of use in these tools have come at the expense of being able to dynamically model ecosystem processes and ES capacity that incorporates greater ecological understanding. We conclude the paper by offering future steps for integrating ecosystem process models with other tools to improve ES assessment.

5.2 Limitations and Future Research Directions

The results of both the first and second paper highlighted the importance of N availability in model simulations. Ecosystem processes that affect C accumulation (photosynthesis, plant growth, decomposition) are limited by a combination of light, water, and N availability. In our simulations, N limitation was the driving factor in C sequestration and ES that were directly related to biomass. Further examination of the model revealed that it may need additional modifications to represent the dynamics of N more accurately in human-dominated systems with a large influx of N imports and competition between trees and turfgrass. First, there is a lack of empirical data on competition between trees and turfgrass for N. Urban trees have been shown to take up excess N (Livesley et al. 2016b) and have higher LAI on high fertility sites (Groffman et al. 2006). Studies on savanna ecosystems, where trees and grasses also coexist, do not show definitively that trees and grasses have balanced competition for water and N (Donzelli et al. 2013), as we have chosen to assume in Biome-BGC-Ex. Further studies on the competitive dynamics between trees and turfgrass in managed ecosystems are necessary to improve this aspect of the model. In addition, if we want Biome-BGC-Ex to become a widely used ecological model for residential ecosystems, applications to other similar geographic areas need to be completed and compared.

Second, the original Biome-BGC model assumes that that microbes and plants have equal weight when competing for soil N. This assumption does not consider studies showing that microbes are more competitive for mineral N than plant roots over short-term period and that (Kuzyakov and Xu 2013, Ouyang et al. 2016). In addition, by reducing N demand fluxes for each process by the same proportion when N demand is not met, we may not be accurately simulating how plants and soils adapt to N limitations (Shi et al. 2006, Yao et al. 2011). There are also complex interactions between plant roots, soil microbes, human management and seasonality that may drive important N dynamics in residential yards that are not addressed by the model (Yao et al. 2011, Jacoby et al. 2017). In the absence of empirical data on N assimilation by roots and microbes in residential yards, future versions of Biome-BGC-Ex could consider creating a new parameter that allows the user to adjust the proportion of N assimilated between plants and soil microbes.

A third limitation of our model simulations was that we adjusted the parameters for plant C:N ratios based on results of our empirical field study (Currie et al. 2016). Since our study region is N enriched (Kahan et al. 2014) we used low C:N ratios, or a higher proportion of N per unit of C. However, since this ratio is a constant for the duration of model simulations it caused N to constrain plant growth in simulations where no additional N fertilizer was added. This led to large amounts of mortality, especially for trees that could not meet their N demand. Ideally, C:N ratios would be dynamic based on management inputs and while mortality may still occur, we would also expect C:N ratios to adjust for management over time.

As mentioned in the second and third papers (Chapters 3 & 4), one limitation of ecosystem process models as a tool for estimating ES is that they do not consider the full conceptual model of ES capacity, flow, and demand. While in some cases they can measure the realized use of some provisioning services through management scenarios (e.g., forest harvest, crop yield), ecosystem process models are best suited for estimating ES capacity and are not designed to consider human demand or valuation of services. Ecosystem process model limitations are similar within the context of Coupled Human and Natural Systems (CHANS) or socio-ecological systems. Process models can dynamically simulate impacts of drivers and pressures on natural systems as well as exports of ES and benefits to human systems. However, they do not have the capability to dynamically model how human or social processes change due to ES or how these changes affect pressures and drivers that feed into natural systems.

One way to address this limitation is through coupling ecosystem process models with agent-based models (ABM) that can dynamically simulate agent behavior and their resulting changes in management based on their demand for ES. This approach was originally proposed by the SLUCE project as a way to integrate an ABM based on homeowner yard management decisions with an ecosystem process model to estimate C sequestration in the exurban landscape(Robinson et al. 2013). For example, agent types could be determined based on the desire to sequester carbon and they could make management decisions based on current C stored in the landscape. These decisions would affect C storage (simulated in the ecosystem process model) and then this would feed back to the agents again. A similar method can be followed for a greater variety of ES, where agent types could be created based on their ES demands.

Finally, we acknowledge that this study does not address the full ecological impacts of human management and development of exurban residential areas. To do this we would need to move beyond models solely of ecosystem processes and dynamics and include life-cycle analysis of C, N, and water in the exurban landscape. This study only considers the pools and fluxes of ecosystem processes and ES in soils and vegetation and does not account for gains and losses that arise from the application of these management practices (e.g., gas-powered lawn mowers, electric-powered sprinklers) or losses that may occur due to people living away from urban centers (e.g., transportation). We also did not consider the fate of any C or N removed by homeowners from the system, when in many cases homeowner may keep collected woody biomass on their property or burn firewood collected (Currie et al. 2013). If the full ecological costs of each management practice were considered it may produce different outcomes (Fissore et al. 2012, Lerman and Contosta 2019).

5.3 Final Thoughts

This dissertation presented a novel approach to improving our understanding of ecosystem processes and ES in the residential exurban landscape. It focused on understanding how human management behaviors drive changes in ecological systems but altering the flux and storage of carbon, nitrogen, and water on the landscape. This research proposes that one approach to improving ES assessment is by utilizing ecosystem process models to improve our estimates ES Capacity. It is also novel because its focus is on how human management of the landscape affects ES production as opposed to land use or land cover change. I hope that the tools and methods presented in this research can be replicated in similar ecosystems to inform more complex ES modelling frameworks that rely on ES production modelling grounded in the understanding of ecosystem processes and their feedbacks.

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Appendices

Appendix A Supplementary Information for Chapter 1

Appendix -A-1

Detailed modifications for a multi-layer vegetation layer model that includes residential yard management practices. Brackets indicate the corresponding name of the function or subroutine in the Biome-BGC(-Ex) code. All code was modified in Visual Basic Studio using C++.

1. [bgc_struct.h, bgc_io.h] hold and define **data structures** for bgc
    a. Data Structures and model variables that are vegetation dependent now have multiple "subsets" (used to be just x but now x_1, x_2, x_3).
        i. [cinit] – carbon state initialization variables
        ii. [phenarray] – phonological control arrays
        iii. [phenology] – daily phonological data arrays
        iv. [mgmt] – management variables (this is a new structure for this version)
        v. [epconst] – canopy ecophysiological constants
        vi. [psn] – photosynthesis routine variables
        vii. [pment] – photosynthesis routine meteorological variables
        viii. [restart_data] – restart file variables
    b. For data structures that contain both site and vegetation dependent variables, vegetation variables are tracked by separate sub-structures, site level variables are calculated, and then all variables are encompassed in a site level "super-structure".
        i. [metvar] – meteorological variables
        ii. [wstate] – water state variables
        iii. [wflux] – water flux variables
        iv. [cstate] – carbon state variables
        v. [cflux] – carbon flux variables
        vi. [nstate] – nitrogen state variables
        vii. [nflux] – nitrogen flux variables
        viii. [ntemp] – temporary nitrogen variables for reconciliation of decomposition immobilization fluxes and plant growth N demands
        ix. [epvar] – ecophysiological variables
        x. [summary] – summary variables
    c. Some structures have no changes
        i. [control] – simulation control variables
        ii. [co2control] – annual co2 concentration
        iii. [ndepcontrol] – annual nitrogen deposition
        iv. [metarr] – meteorological variable arrays
        v. [siteconst] – soil and site constants
2. [bgc_func.h, pointbgc_func.h] header file for **function prototypes** for bgc and pointbgc
    a. These files basically lay out which structures and variables the functions need to have access to when they are run.

b. If a function needs to be run for each vegetation type, the variable 'nvegtypes' was added to the code here.
c. Structure names are also changed to reference changes addressed above.
d. All new functions for competition were added to [bgc_func] here
    i. [prioritize_light], [prioritize_rain], [prioritize_soilwater], [prioritize_nutrients], [competition_init] – these are all grouped into one main function [competition]

3. [bgc, pointbgc] files are the **functions for core model logic**
    a. [pointbgc] – front-end to Biome-BGC, calls up and organizes all data from the INI files and then passes this information into [bgc], which does the ecology, and then takes information back from [bgc] and puts it into output file for user.
        i. Reorganized how some of the data structures are initialized because we need to know how many vegetation types there before they can be called up.
    b. [bgc] – this function preforms all ecological processes and calls up all ecological functions.
        i. Main changes were updating code to include new structure names and adding in loops to run functions for multiple vegetation types or to adjust array sizes to accommodate multiple vegetation layers.
        ii. The competitive ability of vegetation layers are compared (using height functions) and re-resorted yearly, at the start of the annual loop.
4. Individual functions – these functions carry out ecological processes as well as other operations necessary for the logic of Biome-BGC
    a. Some functions were updated to run for each individual layer and/or to include the new structure names but no changes were made to the functions themselves.
        i. [baresoil_evap] – daily bare soil evaporation (run once for the site)
        ii. [check_balance] – daily test of mass balance for water, carbon, and nitrogen state variables (run for each vegetation layer and then once for the site)
        iii. [daymet] – transfer one day of meteorological data from [metarr] structure to [metv] structure (run once for the site)
        iv. [maint_resp] – daily maintenance respiration routine (run separate for each vegetation layer)
        v. [mortality] – daily mortality fluxes (run for each vegetation layer)
        vi. [nleaching] – daily nitrogen leaching flux (run once for the site)
        vii. [outflow] – daily hydrologic outflow (run once for the site)
        viii. [make_zero_flux_struct, precision_control, presim_state_init, zero_srcsnk] – forces water, carbon, nitrogen, and/or summary flux and/or state structure values to zero for multiple reasons depending on function
        ix. [phenology] – daily phenology fluxes (run once for each vegetation layer)
        x. [photosynthesis] – daily c3/c4 photosynthesis model (run once for each vegetation layer)

xi. [snowmelt] – daily snowmelt and sublimation (run once for the site)
xii. [state_update] – resolve the fluxes in the daily loop to update state variables
xiii. [summary] – summary variables for potential output (run for each vegetation layer and the for the site)
xiv. [output_ctrl] – reads output control information from the INI file (produces one output file per vegetation layer and just repeats any of the site-level variables in each of the files).
xv. [restart_init] – initialize restart parameters (run for each vegetation layer)

b. Some functions were updated to run for each individual layer and/or to include the new structure and had changes to their internal function due to having multiple vegetation layers.
   i. [canopy_et] – canopy evapotranspiration
      1. For each individual vegetation layer no changes were made (no change in the ecological process). However, this function has a built-in check to make sure transpiration is not greater than available soil water. Code was added so transpiration for all vegetation layers is summed and compared to soil water in order for the model to continue forward.
   ii. [daily_allocation] – daily allocation of carbon and nitrogen, as well as the final reconciliation of N immobilization by microbes.
      1. Updated so demands and allocation could be completed for all vegetation layers and the site. First the N demand for each vegetation layer is determined and then summed along with decomposition immobilization (from [decomp]). This is compared to N supply and if it is not limiting processes can proceed at potential rates. If N is limiting it is divided up with a proportion going to immobilization and the remaining divided size-symmetrically between vegetation types.
   iii. [decomp] – daily decomposition fluxes
      1. No change to processes but updated to do litter decomposition for each vegetation layer first and then move on to soil decomposition.
   iv. [prcp_route] – routing of daily precipitation to canopy, soil, snowpack
      1. Canopy routing of precipitation is determined by which vegetation layer is determined to be the “highest” layer in the canopy. This layer intercepts precipitation routed to the canopy based on all-sided LAI and user defined interception rate. The precipitation remaining after interception is available for the next layer of vegetation to intercept and so on until all layers of vegetation have intercepted precipitation or there is none remaining. Any precipitation remaining after canopy interception moves to soil water.

v. [rad_trans] – calculates canopy radiation interception and transmission
    1. [bgc] determines which layer of vegetation has access to light first and then runs that layer through this function. The first layer has access to all available shortwave radiation and PAR for that day and absorption values are determined based on that layer's LAI and other variables. The remaining shortwave radiation and PAR (that would be filtered through this layer of this canopy) is then calculated and made available for the next layer of vegetation.

vi. [epc_init] – reads in the EPC file and calculates any variables needed from this data
    1. Changes file to read in multiple EPC files depending on the number of vegetation layers specified in the INI file. Adds in code to read new variables for maximum vegetation height and mass at max height.

vii. [state_init] – initialize water, carbon, and nitrogen state variables for pointbgc simulation
    1. In this function we now initialize the data structure for [wstate, cstate, nstate]. This was previously done by the function [presim_state_init] very early in [pointbgc] but it is now done here when we know how many vegetation types are present.

c. New functions were added to Biome-BGC to adapt the model for competition with multiple layers of vegetation.
    i. [mgmt_init] – added a function that initializes management parameters supplied in the input file
    ii. [competition] - added functions that initialize data structures, calculate vegetation height, and prioritize vegetation access to light and water.

Model changes to modify for management – these changes were added to the model after the model was tested to successfully run the multi-layer version.

5. Added new management variables to necessary **Data Structures** found in [bgc_struct.h]
    a. [cstate, nstate, cflux, nflux] – carbon and nitrogen state and flux structures
        i. tree removal pool variables for leaf, live and dead stems
        ii. raking removal pool variables for all litter pools
        iii. cwd removal pool variable
        iv. pruning removal pool variables for leaf, live and dead stems
        v. mower clipping removal pools
        vi. For all above variables: flux variables were added to move C/N from the original (ecosystem) pool to the removal pool
        vii. tree planting addition pool variables for leaf, live and dead stems
        viii. Tree planting C/N flux variables to move from addition pool to the ecosystem pool

b. [summary] – new summary variables describing the management practices were added to this structure
c. [mgmt] – A new structure was added to the model that includes all the management variables that the user supplies to the model. This structure defines all the variables in the user supplied management file.

6. Added new management function definitions to the **function prototype files** [bgc_func.h, pointbgc_func.h] for the functions [tree_plant_init, tree_plant, mgmt_init]
7. Modifications to functions
   a. [bgc] – This function includes core model logic. However, it also includes some sub-routines that might have been better off in their own functions such as nitrogen deposition.
      i. I added fertilizer to the model through the nitrogen deposition subroutine during the growing season (May 1 to Sept 30). I add the 'daily fertilizer' variable to the 'daily N deposition' variable to determine the total amount of outside N added to soil mineral N for that day.
   b. [metarr_init] – this function reads in the meteorological data and creates an array of meteorological for every day the model is run
      i. I added in an irrigation subroutine to this function. During the growing season (May 1 to Sept 30) it measures precipitation on a weekly basis and compares it to the user supplied irrigation amount. If the irrigation amount isn't met by the weekly precipitation, extra precipitation is added to the model on the first day of the week to meet the user requirement.
   c. [check_balance] – daily test of mass balance
      i. Even though the C/N is removed from the ecological processes the model still needs to achieve mass balance so all the new C/N pool variables for removals are still counted in the mass balance equations (follow same methodology as other mortality pools)
   d. [morality] – daily morality fluxes
      i. CWD removal was added as a subroutine to this function within the current tree specific mortality C/N flux routine.
      ii. Tree Removals were added as a separate routine in this function that occurs if the model flags it as a year for tree removals. This code basically follows the tree morality code but uses different C/N flux and pool variables. It transfers aboveground removals into removal pools and equivalent belowground removals into litter pools.
      iii. Pruning was added as a separate routine and first determines if it is the correct year to prune. For pruning the user provides a percent removal value. However, Since Biome-BGC doesn't differentiate between woody vegetation structures, for all woody biomass fluxes we multiplied the removal value by .38 to determine the total removal flux. This is based on research that states 38% of woody biomass is made of small branches and twigs (Whittaker et al. 1974). Aboveground removals are transferred into

removal pools and equivalent belowground removals turnover into litter pools.

iv. Mowing was added as a separate routine in which mowing is signaled if the user supplied LAI reaches the models ‘projected LAI’. If mulch mowing occurs, 20% of the leaf and fine root C/N pools turnover into litter pools. If mower clippings are removed 20% of aboveground C/N pools are transferred to a removal pool while 20% of roots turnover into litter pools.

e. [phenology] – daily phenology fluxes

i. Raking was added as a subroutine to the leaf litterfall routine. The user supplies a percentage of aboveground leaf biomass that is removed from the system. In the model we take the daily fluxes of leaf C/N to litter pools and multiply them by this number and then subtract this value out of the model into raking removal pools.

8. New Functions

a. [tree_plant_init] – This function was added to initialize data structures for tree planting, if it is chosen by the user to occur. It determines how to divide up the user supplied biomass value into the C pools required by Biome-BGC and also determines proportional N values. (Abbreviations: Tree Planting Biomass (TP), aboveground (AG), belowground (BG)

i. The user supplies an aboveground biomass value for tree planting (TPAG). The proportional belowground amount (TPBG) is determined based on the proportion of belowground to aboveground biomass currently in the tree vegetation layer.

$$TPBG = \frac{TPAG}{(current\ AG/current\ BG)} \quad (1)$$

ii. The tree planting aboveground total is divided into carbon pools for leaf, live stem, and dead stem carbon based on the proportions of these pools in current biomass.

$$TP\ leafC = \frac{current\ leafC}{current\ AG} * TPAG \quad (2)$$

$$TP\ livestemC = \frac{current\ livestemC}{current\ AG} * TPAG \quad (3)$$

$$TP\ deadstemC = \frac{current\ deadstemC}{current\ AG} * TPAG \quad (4)$$

iii. The belowground total is divided into carbon pools for fine roots, life roots, and dead roots

$$TP\ finerootC = \frac{current\ finerootC}{current\ BG} * TPBG \quad (5)$$

$$TP\ liverootC = \frac{current\ liverootC}{current\ BG} * TPBG \quad (6)$$

$$TP\ deadrootC = \frac{current\ deadrootC}{current\ BG} * TPBG \quad (7)$$

iv. The accompanying nitrogen pools are determined based on the C:N ratios supplied in the ecophysiology parameter file.

b. [tree_plant] – This function was added to carries out the flux of C and N from the pools determined in the tree_plant_init function to the C/N pools in the ecosystem. [
c. [mgmt_init] – This function was added to initialize the simulation management parameters; basically reads the management input file into the model.

Appendix B Supplementary Information, Tables, and Figures for Chapter 2

Table B-1 Summary of Biome-BGC functions changed in Biome-BGC-Ex modification
Summary of Biome-BGC functions whose logic was fundamentally changed by modifying the model for multiple vegetation types and residential management practices for the exurban environment version Biome-BGC-Ex. The list will be of most use when working with the model source code.

Existing Functions		
Function Name	**Purpose**	**Description of Changes**
bgc	Core model logic	All code is updated to include new structure names that represent separate vegetation and site level variables. Loops are added to run functions for multiple vegetation layers and adjust array sizes to accommodate multiple layers Competition indices are recalculated annually. Fertilizer is added to the soil mineral nitrogen pool daily during the growing season (May 1 - Oct 1). Tree planting occurs the first day of the given year.
canopy_et	Calculate canopy evapotranspiration	Transpiration calculated for each vegetation layer, summed to site level, and checked against soil water to make sure sufficient water is available.
check_balance	Daily test of mass balance	Even though C/N is removed from the ecological processes, the model still needs to achieve mass balance so all the new C/N pool variables for removals are still counted in the mass balance equations (following same pattern as other mortality pools).
daily_allocation	Daily allocation of C/N; reconciliation of microbial N immobilization	Total N demand across all vegetation layers is summed with demand from litter and soil processes in [decomp] below. This is compared to N supply and if not limiting processes can proceed at potential rates. If N is limiting, this function assesses allocation with a proportion going to immobilization and the remaining divided size symmetrically between vegetation layers.
decomp	Calculate daily decomposition fluxes	Immobilization potential demand calculated for each vegetation layer and soil processes and then summed to the site level.

metarr_init	Generates an array of daily meteorological data	An irrigation subroutine was added to this function. During the growing season (May 1 to Sept 30), precipitation is measured on a weekly basis and compared to user supplied irrigation amount. If irrigation isn't met by weekly precipitation, extra precipitation is added to the model on the first day of the week to meet the user requirement.
mortality	Calculate daily mortality fluxes	CWD removal was added as a subroutine within the current tree mortality C/N flux routine. Tree removals were added as a separate routine that runs if the model flags it as a year for tree removals. It transfers user defined amounts of C/N from aboveground vegetation into tree removal specific pools and equivalent belowground removals into litter pools. Pruning was added as a separate routine. If flagged, it first determines if it is the correct year to prune. Then it transfers user defined amounts of C/N from above ground vegetation into pruning removal specific pools and equivalent belowground removals into litter pools. Mowing was added as a separate routine which is signaled if the user supplied LAI reaches the model's 'projected LAI'. If mulch mowing is flagged, 20% of the leaf and fine root C/N pools turnover into litter pools. If mower clippings are removed 20% of aboveground C/N pools are transferred to mowing removal pools while 20% of roots turnover into litter pools.
phenology	Calculates daily phenology fluxes	Raking was added as a subroutine to the leaf litterfall routine. The proportion of litter removed supplied by the user is subtracted from the daily fluxes of leaf C/N to litter pools and moved to the raking removal pools.
prcp_route	Routing of daily precipitation to canopy, soil, and snowpack	Called for each vegetation layer in order of height. Each layer intercepts and stores water separately and precipitation remaining after interception is available for each successive layer until no layers are remaining. Any remaining precipitation moves to soil water.
radtrans	Calculates canopy radiation interception and transmission	Called for each vegetation layer in order of height. The highest layer has access to all available shortwave radiation for interception. The remaining radiation (that would be filtered through this layer of the canopy) is then calculated and made available for the subsequent layers.

New Functions	
Function Name	**Purpose**
competition	Calculates vegetation height and prioritizes vegetation access to light and water Two new variables were added to describe the relationship between biomass and height in the ecophysiological (EPC) input file. Following a similar method used in Bond-Lamberty et al. (2005): "An exponential equation of the form: $h = h_{max}(1 - e^{-\frac{5}{m_{hmax}}m})$ (1) was chosen to describe this relationship. The two parameters supplied for each vegetation type are h_{max}, the maximum vegetation height, and m_{hmax}, the vegetation mass at which this height is attained… At the beginning of each simulation year Biome-BGC computes the height of each vegetation type based on current stem (for woody plants) or leaf (for grasses) mass and determines a height order. All light and precipitation interception for the subsequent year occurs using this height order, with the tallest vegetation intercepting first; light or precipitation that is not intercepted becoming available to the next tallest vegetation type."
mgmt_init	Reads the new management input file into the model and initializes the new management parameters for the model.
Tree_plant_init	Calculates how the user supplied tree biomass value is translated into the C pools required by the model and then determines proportional N values. (Abbreviations: Tree Planting Biomass (TP), aboveground (AG), belowground (BG) 1. The user supplies an aboveground biomass value for tree planting (TPAG). The proportional belowground amount (TPBG) is determined based on the proportion of belowground to aboveground biomass currently in the tree vegetation layer. $TPBG = \frac{TPAG}{(current\ AG/current\ BG)}$ (2) 2. The tree planting aboveground total is divided into carbon pools for leaf, live stem, and dead stem carbon based on the proportions of these pools in current biomass. $TP\ leafC = \frac{current\ leafC}{current\ AG} * TPAG$ (3) $TP\ livestemC = \frac{current\ livestemC}{current\ AG} * TPAG$ (4) $TP\ deadstemC = \frac{current\ deadstemC}{current\ AG} * TPAG$ (5)

	3. The belowground total is divided into carbon pools for fine roots, life roots, and dead roots $TP\ finerootC = \frac{current\ finerootC}{current\ BG} * TPBG$ (6) $TP\ liverootC = \frac{current\ liverootC}{current\ BG} * TPBG$ (7) $TP\ deadrootC = \frac{current\ deadrootC}{current\ BG} * TPBG$ (8) 4. The accompanying nitrogen pools are determined based on the C:N ratios supplied in the ecophysiology parameter file.
Tree_plant	Carries out the flux of C/N from the pools determined in tree_plant_init function to the C/N pools in the ecosystem.

Description of Homeowner Agent Types

Homeowner Agent Types (HATs) were developed by Nassauer et al. (2014) based on interviews with 26 exurban homeowners in our project's study region. HATs are based on a combination of parcel size, parcel characteristics and homeowner behaviors. Parcel sizes defined as large (>1.1 acre), medium (0.5-1.1 acre) and small (<0.5 acre).

1. *Neat neighbors* (n = 6) were small parcel owners who lived in newer homes with turf-dominated yards. They had no mature indigenous trees on their property, some planted trees and all fertilized. They noticed their neighbors' yards and expected their neighbors to notice theirs.
2. *Lakeshore property owners* (n = 3) owned lake front or adjacent parcels. They had mature indigenous trees but did not plant new trees. Most fertilized but other practices varied. They were influenced by neighbors' perceptions, access to water views, and a desire for low tree maintenance.
3. *Nature neighbors* (n = 2) lived on small parcels with mature indigenous trees and were adjacent to large woodlands. They did not fertilize. They were influenced by enjoying and maintaining aesthetic woodland characteristics.
4. *Tree planters* (n = 7) owned medium parcels with large amounts of turfgrass with sparse woody vegetation cover. They did not have mature indigenous trees, but most had mature horticultural trees and had planted trees on their property. Most used fertilizer. They were influenced by neighbors' perceptions and aspiring to a "more natural" approach to property maintenance.
5. *Improvers* (n = 4) own large parcels with large amounts of low-maintenance old field and dense woody vegetation cover. Management practices for fertilization and tree planting

varied. All were interested in watching wildlife on their properties and having autonomy in their management decisions.

6. *Viewers* (n=4) owned large parcels that included patches of turfgrass with sparse woody. All viewers had planted trees and most fertilized. All enjoyed watching wildlife on their properties and having nature in their view.

Table B-2 Biome-BGC-Ex *Dense Woody* ecophysiology (EPC) parameters.
Default values from the Biome-BGC deciduous tree biome are used unless specified. The Keywords are parameter names predefined in Biome-BGC. The 'Type' abbreviations DIM implies the parameter is dimensionless.

Keyword	Value	Type	Description	Source (if not default value)
WOODY_FLAG	1	flag	1 = woody 0 = non-woody	
EVERGRN_FLAG	0	flag	1 = evergreen 0 = deciduous	
C3_FLAG	1	flag	1 = C3 photosynthesis 0 = C4 photosynthesis	
MODEL_PHEN_FLAG	1	flag	1 = model phenology 0 = user-specified phenology	
ONDAY	0	yday	Year-day to start new growth (when phenology flag = 0)	
OFFDAY	0	yday	Year-day to end litterfall (when phenology flag = 0)	
TRNS_GR_PROP	0.2	proportion	transfer growth period as fraction of growing	
LIT_FALL_PROP	0.2	proportion	litterfall as fraction of growing season	
LFR_TURNOVER	1	1/yr	annual leaf and fine root turnover fraction	
LWOOD_TURNOVER	0.7	1/yr	annual live wood turnover fraction	
MORT_FRAC	0.02	1/yr	annual whole-plant mortality fraction	Robinson et al. 2013
FIRE_MORT_FRAC	0	1/yr	annual fire mortality fraction	We are assuming no fire in this system
ALLOC_FR_LEAF	1.2	ratio	ratio of new fine root C to new leaf C	
ALLOC_STEM_LEAF	2.2	ratio	ratio of new stem C to new leaf C	
ALLOC_LWOOD_ TOTWOOD	0.16	ratio	ratio of new live wood C to new total wood C	
ALLOC_CROOT_STEM	0.22	ratio	ratio of new root C to new stem C	
GR_PROP	0.5	proportion	current growth proportion	
LEAF_CN	19.8	kgC/kgN	C:N of leaves	2009 Field Data
LLITTER_CN	48	kgC/kgN	C:N of leaf litter, after retranslocation	2009 Field Data
FR_CN	84.6	kgC/kgN	C:N of fine roots	2009 Field Data

LWOOD_CN	84.6	kgC/kgN	C:N of live wood	Same as fine roots, based on White et al. 2000
DWOOD_CN	550	kgC/kgN	C:N of dead wood	
SOIL1_CN SOIL2_CN	12.0	kgC/kgN	C:N of fast and medium decomposition soil pools	Included in a separate constants file
SOIL3_CN SOIL4_CN	10.0	kgC/kgN	C:N of slow and recalcitrant decomposition soil pools	Included in a separate constants file
LIT_LAB_PROP	0.38	proportion	leaf litter labile proportion	
LIT_CEL_PROP	0.44	proportion	leaf litter cellulose proportion	
LIT_LIG_PROP	0.18	proportion	leaf litter lignin proportion	
FR_LAB_PROP	0.34	proportion	fine root labile proportion	
FR_CEL_PROP	0.44	proportion	fine root cellulose proportion	
FR_LIG_PROP	0.22	proportion	fine root lignin proportion	
DWOOD_CEL_PROP	0.77	proportion	dead wood cellulose proportion	
DWOOD_LIG_PROP	0.23	proportion	dead wood lignin proportion	
CANOPYW_INT_ COEF	0.045	1/LAI/d	canopy water interception coefficient	
CANOPY_LT_EXT_ COEF	0.54	DIM	canopy light extinction coefficient	
LEAF_AREA_RAT	2	DIM	all-sided to projected leaf area ratio	
AVG_SLA	32	m^2/kgC	canopy average specific leaf area (projected area basis)	
SHADE_SUN_SLA_ RAT	2	ratio	ratio of shaded SLA to sunlit SLA	
FLNR	0.07	DIM	fraction of leaf N in Rubisco	Robinson et al. 2013
GS_MAX	0.006	m/s	maximum stomatal conductance (projected area basis)	
GC_MAX	0.00006	m/s	cuticular conductance (projected area basis)	
GB	0.01	m/s	boundary layer conductance (projected area basis)	
PSI_MIN	-0.5	MPa	leaf water potential: start of conductance reduction	Calibrated (see methods)
PSI_MAX	-2.5	MPa	leaf water potential: complete conductance reduction	Calibrated (see methods)
VPD_MIN	1100	Pa	vapor pressure deficit: start of conductance reduction	
VPD_MAX	3600	Pa	vapor pressure deficit: complete conductance reduction	

Table B-3 Biome-BGC-Ex *Turfgrass* ecophysiology (EPC) parameters.
Default values from the Biome-BGC C3 grass biome are used unless specified. The Keywords are parameter names predefined in Biome-BGC. The 'Type' abbreviations DIM implies the parameter is dimensionless.

Keyword	*Value*	*Type*	*Description*	*Source* (if not default value)
WOODY_FLAG	0	flag	1 = woody 0 = non-woody	
EVERGRN_FLAG	0	flag	1 = evergreen 0 = deciduous	
C3_FLAG	1	flag	1 = c3 psn 0 = c4 psn	
MODEL_PHEN_FLAG	1	flag	1 = model phenology 0 = user-specified phenology	
ONDAY	0	yday	Year-day to start new growth (when phenology flag = 0)	
OFFDAY	364	yday	Year-day to end litterfall (when phenology flag = 0)	
TRNS_GR_PROP	1	proportion	transfer growth period as fraction of growing	
LIT_FALL_PROP	1	proportion	litterfall as fraction of growing season	
LFR_TURNOVER	1	1/yr	annual leaf and fine root turnover fraction	
LWOOD_TURNOVER	0	1/yr	annual live wood turnover fraction	
MORT_FRAC	0.01	1/yr	annual whole-plant mortality fraction	
FIRE_MORT_FRAC	0	1/yr	annual fire mortality fraction	
ALLOC_FR_LEAF	1	ratio	ratio of new fine root C to new leaf C	Robinson et al. 2013
ALLOC_STEM_LEAF	0	ratio	ratio of new stem C to new leaf C	
ALLOC_LWOOD_ TOTWOOD	0	ratio	ratio of new live wood C to new total wood C	
ALLOC_CROOT_STEM	0	ratio	ratio of new root C to new stem C	
GR_PROP	0.5	proportion	current growth proportion	
LEAF_CN	28.8	kgC/kgN	C:N of leaves	20% higher than the default value
LLITTER_CN	58.8	kgC/kgN	C:N of leaf litter, after retranslocation	20% higher than the default value
FR_CN	50.4	kgC/kgN	C:N of fine roots	20% higher than the default value

LWOOD_CN	0	kgC/kgN	C:N of live wood	
DWOOD_CN	0	kgC/kgN	C:N of dead wood	
SOIL1_CN SOIL2_CN	12.0	kgC/kgN	C:N of fast and medium decomposition soil pools	Included in a separate constants file
SOIL3_CN SOIL4_CN	10.0	kgC/kgN	C:N of slow and recalcitrant decomposition soil pools	Included in a separate constants file
LIT_LAB_PROP	0.39	proportion	leaf litter labile proportion	
LIT_CEL_PROP	0.44	proportion	leaf litter cellulose proportion	
LIT_LIG_PROP	0.17	proportion	leaf litter lignin proportion	
FR_LAB_PROP	0.36	proportion	fine root labile proportion	Milesi et al. 2005
FR_CEL_PROP	0.52	proportion	fine root cellulose proportion	Milesi et al. 2005
FR_LIG_PROP	0.12	proportion	fine root lignin proportion	Milesi et al. 2005
DWOOD_CEL_PROP	0	proportion	dead wood cellulose proportion	
DWOOD_LIG_PROP	0	proportion	dead wood lignin proportion	
CANOPYW_INT_ COEF	0.01	1/LAI/d	canopy water interception coefficient	
CANOPY_LT_EXT_ COEF	0.6	DIM	canopy light extinction coefficient	
LEAF_AREA_RAT	2	DIM	all-sided to projected leaf area ratio	
AVG_SLA	70	m^2/kgC	canopy average specific leaf area (projected area basis)	Milesi et al. 2005
SHADE_SUN_SLA_ RAT	2	ratio	ratio of shaded SLA to sunlit SLA	
FLNR	0.3456	DIM	fraction of leaf N in Rubisco	Calculated based on leaf C:N ration from equation in White et al. 2000
GS_MAX	0.005	m/s	maximum stomatal conductance (projected area basis)	
GC_MAX	0.0000 1	m/s	cuticular conductance (projected area basis)	
GB	0.04	m/s	boundary layer conductance (projected area basis	
PSI_MIN	-0.5	MPa	leaf water potential: start of conductance reduction	Calibrated (see methods)
PSI_MAX	-2.5	MPa	leaf water potential: complete conductance reduction	Calibrated (see methods)
VPD_MIN	930	Pa	vapor pressure deficit: start of conductance reduction	
VPD_MAX	4100	Pa	vapor pressure deficit: complete conductance reduction	

Table B-4 Site and atmospheric initial conditions for all vegetation cover types.

Model Parameter		Value
Effective Soil Depth[a]		1 m
Soil Texture[b]	Sand	63%
	Silt	20.4%
	Clay	16.6%
Site Elevation		200 m
Site Latitude		41.98 degrees
Atmospheric CO_2[c]		396.48 ppm
Total Nitrogen Deposition[c]		0.000979 kg N m^{-2} yr^{-1}

[a](Currie et al. 2016)

[b] NOAA 2014

[c] Based on a five-year average of 2008-2012. Wet and dry inorganic N deposition from EPA CASNET. Atmospheric organic nitrogen was calculated as fifty percent of total inorganic deposition (Neff et al. 2002).

Description of Climate Parameters

Identical climate files were used for each year so that variations in climate would not mask the effects of management. We created the climate file based on fifty years (1956-2006) of past daily climate data in the study region from the National Climatic Data Center (NCDC). For each month, we randomly created precipitation events to be equal to the mean number of historical precipitation days in that month, with the distribution of rainfall amounts chosen from an exponential decay model. We used the MTCLIM model (Running et al. 1987, Thornton and Running 1999) to produce daily values of short-wave radiation (W m^{-2}), vapor pressure deficit (Pa), average daylight temperature, and day length.

Table B-5 Additional results tables for normalized linear regression C pools analyses (1-3) and non-normalized linear regression C pool analyses (4-6).

Additional results tables for normalized linear regression C pools analyses (1-3) and non-normalized linear regression C pool analyses (4-6). Standard errors are in parentheses.

1. Turfgrass with sparse woody vegetation (TGW) – Normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.						
	Total ecosystem carbon	**Tree vegetation carbon**	**Turf vegetation carbon**	**Tree litter carbon**	**Turf litter carbon**	**Soil carbon**
Intercept	3.514*** (0.137)	3.685*** (0.113)	-0.046*** (0.001)	0.658*** (0.019)	0.037*** (0.002)	-0.899*** (0.032)
Fertilizer	12.325*** (0.097)	7.953*** (0.080)	-0.072*** (0.001)	1.702*** (0.013)	-0.105*** (0.001)	2.847*** (0.023)
Irrigation	5.254*** (0.126)	4.074*** (0.105)	-0.031*** (0.001)	0.717*** (0.017)	-0.058*** (0.002)	0.553*** (0.030)
Mow height	-1.754*** (0.112)	-1.759*** (0.093)	0.045*** (0.001)	-0.336*** (0.015)	0.075*** (0.001)	0.220*** (0.026)
Mulch mowing	0.713*** (0.070)	0.264*** (0.058)	0.005*** (0.001)	0.068*** (0.010)	0.008*** (0.001)	0.369*** (0.017)
Pruning intensity	-5.937*** (0.161)	-5.693*** (0.134)	0.034*** (0.001)	-0.256*** (0.022)	0.043*** (0.002)	-0.064* (0.038)
Prune yearly	-3.784*** (0.126)	-3.889*** (0.105)	0.004*** (0.001)	0.130*** (0.017)	0.008*** (0.002)	-0.036 (0.030)
Prune every 3 years	-0.303** (0.130)	-0.508*** (0.107)	-0.009*** (0.001)	0.215*** (0.018)	-0.013*** (0.002)	0.012 (0.031)
Raking	-4.442*** (0.097)	-2.232*** (0.081)	0.023*** (0.001)	-0.571*** (0.013)	0.020*** (0.001)	-1.682*** (0.023)
Tree planting	1.383*** (0.097)	1.086*** (0.080)	0.0003 (0.001)	0.219*** (0.013)	0.0003 (0.001)	0.077*** (0.023)
Tree removal	-4.819*** (0.112)	-4.755*** (0.093)	0.006*** (0.001)	-0.091*** (0.015)	0.005*** (0.001)	0.016 (0.026)
Observations	7,000	7,000	7,000	7,000	7,000	7,000
R^2	0.819	0.804	0.715	0.746	0.671	0.753
Adjusted R^2	0.818	0.804	0.715	0.746	0.670	0.752
Note:	***p<0.1; **p<0.05; ***p<0.01; SE in parentheses**					

2. Dense woody (DW) - Normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.				
	Total ecosystem carbon	**Tree vegetation carbon**	**Tree litter carbon**	**Soil carbon**
Intercept	5.816*** (0.099)	1.020*** (0.092)	4.724*** (0.026)	-0.198*** (0.013)
Pruning intensity	-8.000*** (0.148)	-5.980*** (0.138)	-1.145*** (0.039)	-0.875*** (0.019)
Prune yearly	-5.536*** (0.115)	-4.728*** (0.107)	-0.519*** (0.031)	-0.289*** (0.015)
Prune every 3 years	-0.871*** (0.121)	-1.167*** (0.112)	0.110*** (0.032)	0.186*** (0.016)
Tree planting	-3.141*** (0.103)	0.374*** (0.095)	-2.565*** (0.027)	-0.950*** (0.013)
Coarse woody debris removal	1.443*** (0.089)	0.927*** (0.083)	0.418*** (0.024)	0.098*** (0.012)
Tree removal	-6.471*** (0.103)	-5.279*** (0.095)	-0.888*** (0.027)	-0.304*** (0.013)
Observations	3,000	3,000	3,000	3,000
R^2	0.905	0.873	0.835	0.837
Adjusted R^2	0.905	0.872	0.834	0.837
Note: *p<0.1; **p<0.05; ***p<0.01; SE in parentheses				

3. Turfgrass (TG) - Normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.				
	Total ecosystem carbon	**Turf vegetation carbon**	**Turf litter carbon**	**Soil carbon**
Intercept	-5.385*** (0.034)	-0.143*** (0.001)	-0.099*** (0.001)	-5.140*** (0.033)
Fertilizer	4.590*** (0.032)	0.037*** (0.001)	0.061*** (0.001)	4.492*** (0.031)
Irrigation	-0.573*** (0.039)	0.008*** (0.001)	-0.021*** (0.001)	-0.561*** (0.037)
Mow height	2.889*** (0.037)	0.109*** (0.001)	0.171*** (0.001)	2.609*** (0.036)
Mulch mowing	2.148*** (0.023)	0.039*** (0.001)	0.041*** (0.001)	2.068*** (0.022)
Observations	3,000	3,000	3,000	3,000
R^2	0.923	0.828	0.923	0.923
Adjusted R^2	0.923	0.827	0.923	0.923
Note: *p<0.1; **p<0.05; ***p<0.01; SE in parentheses				

4. Turfgrass with sparse woody vegetation (TGW) – Non-normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.						
	Total ecosystem carbon	**Tree vegetation carbon**	**Turf vegetation carbon**	**Tree litter carbon**	**Turf litter carbon**	**Soil carbon**
Intercept	4.016*** (0.152)	4.187*** (0.126)	-0.059*** (0.001)	0.754*** (0.021)	0.015*** (0.002)	-0.962*** (0.036)
Fertilizer	78436.070*** (615.713)	50613.160*** (510.837)	-460.524*** (4.600)	10830.310*** (84.864)	-667.030*** (7.582)	18120.160*** (145.448)
Irrigation	1.136*** (0.027)	0.881*** (0.023)	-0.007*** (0.0002)	0.155*** (0.004)	-0.013*** (0.0003)	0.119*** (0.006)
Mow height	-0.501*** (0.032)	-0.503*** (0.026)	0.013*** (0.0002)	-0.096*** (0.004)	0.022*** (0.0004)	0.063*** (0.008)
Mulch mowing	0.713*** (0.070)	0.264*** (0.058)	0.005*** (0.001)	0.068*** (0.010)	0.008*** (0.001)	0.369*** (0.017)
Pruning intensity	-23.750*** (0.644)	-22.774*** (0.534)	0.134*** (0.005)	-1.024*** (0.089)	0.171*** (0.008)	-0.257* (0.152)
Prune yearly	-3.784*** (0.126)	-3.889*** (0.105)	0.004*** (0.001)	0.130*** (0.017)	0.008*** (0.002)	-0.036 (0.030)
Prune every 3 years	-0.303** (0.130)	-0.508*** (0.107)	-0.009*** (0.001)	0.215*** (0.018)	-0.013*** (0.002)	0.012 (0.031)
Raking	-4.442*** (0.097)	-2.232*** (0.081)	0.023*** (0.001)	-0.571*** (0.013)	0.020*** (0.001)	-1.682*** (0.023)
Tree planting	0.461*** (0.032)	0.362*** (0.027)	0.0001 (0.0002)	0.073*** (0.004)	0.0001 (0.0004)	0.026*** (0.008)
Tree removal	-4.819*** (0.112)	-4.755*** (0.093)	0.006*** (0.001)	-0.091*** (0.015)	0.005*** (0.001)	0.016 (0.026)
Observations	7,000	7,000	7,000	7,000	7,000	7,000
R^2	0.819	0.804	0.715	0.746	0.671	0.753
Adjusted R^2	0.818	0.804	0.715	0.746	0.670	0.752
Note: *p<0.1; **p<0.05; ***p<0.01; SE in parentheses						

5. Dense woody (DW) – Non-normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.				
	Total ecosystem carbon	**Tree vegetation carbon**	**Tree litter carbon**	**Soil carbon**
Intercept	5.546*** (-0.099)	1.020*** (-0.092)	4.724*** (-0.026)	-0.198*** (-0.013)
Pruning intensity	-32.010*** (-0.593)	-23.928*** (-0.551)	-4.580*** (-0.158)	-3.502*** (-0.077)
Prune yearly	-5.536*** (-0.115)	-4.728*** (-0.107)	-0.519*** (-0.031)	-0.289*** (-0.015)
Prune every 3 years	-0.871*** (-0.121)	-1.167*** (-0.112)	0.110*** (-0.032)	0.186*** (-0.016)
Tree planting	-3.141*** (-0.103)	0.374*** (-0.095)	-2.565*** (-0.027)	-0.950*** (-0.013)
Coarse woody debris removal	0.481*** (-0.030)	0.309*** (-0.02)	0.139*** (-0.008)	0.033*** (-0.004)
Tree removal	-6.471*** (-0.103)	-5.279*** (-0.095)	-0.888*** (-0.027)	-0.304*** (-0.013)
Observations	3,000	3,000	3,000	3,000
R^2	0.905	0.873	0.835	0.837
Adjusted R^2	0.905	0.872	0.834	0.837
Note: *p<0.1; **p<0.05; ***p<0.01; SE in parentheses				

6. Turfgrass (TG) – Non-normalized Multiple Linear Regression results for total, vegetation, litter, and soil carbon.				
	Total ecosystem carbon	**Turf vegetation carbon**	**Turf litter carbon**	**Soil carbon**
Intercept	-6.211^{***} (0.041)	-0.174^{***} (0.001)	-0.148^{***} (0.001)	-5.886^{***} (0.040)
Fertilizer	29215.890^{***} (203.895)	232.573^{***} (6.114)	387.318^{***} (5.763)	28596.000^{***} (196.229)
Irrigation	-0.134^{***} (0.009)	0.002^{***} (0.0003)	-0.005^{***} (0.0003)	-0.131^{***} (0.009)
Mow height	0.826^{***} (0.011)	0.031^{***} (0.0003)	0.049^{***} (0.0003)	0.746^{***} (0.010)
Mulch mowing	2.148^{***} (0.023)	0.039^{***} (0.001)	0.041^{***} (0.001)	2.068^{***} (0.022)
Observations	3,000	3,000	3,000	3,000
R^2	0.923	0.828	0.923	0.923
Adjusted R^2	0.923	0.827	0.923	0.923
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; SE in parentheses				

Appendix C Supplementary Information, Tables, and Figures for Chapter 3

Appendix C-1

Table C-1 Initial carbon pools for each vegetation cover type, used in both the Monte Carlo analysis and Homeowner Agent Typologies analyses.
Carbon pool values are based on average values for each vegetation type measured in exurban yards of the study region (Currie et al. 2016).

	Carbon Pool (kg C m^{-2})				
Vegetation cover type	**Aboveground tree vegetation**	**Aboveground turfgrass vegetation**	**Litter**	**Coarse woody debris**	**Soil to 1 m depth**
Turfgrass with sparse woody (TGW)	6.17	0.08	0.12	0.0	12.85
Dense woody (DW)	14.18	NA	0.62	0.18	20.41
Turfgrass (TG)	NA	0.15	0.107	0.0	12.64

Table C-2 Biome-BGC-Ex *Dense Woody* ecophysiology (EPC) parameters.
Default values from the Biome-BGC deciduous tree biome are used unless specified. The Keywords are parameter names predefined in Biome-BGC. The 'Type' abbreviations DIM implies the parameter is dimensionless.

Keyword	Value	Type	Description	Source (if not default value)
WOODY_FLAG	1	flag	1 = woody 0 = non-woody	
EVERGRN_FLAG	0	flag	1 = evergreen 0 = deciduous	
C3_FLAG	1	flag	1 = C3 photosynthesis 0 = C4 photosynthesis	
MODEL_PHEN_FLAG	1	flag	1 = model phenology 0 = user-specified phenology	
ONDAY	0	yday	Year-day to start new growth (when phenology flag = 0)	
OFFDAY	0	yday	Year-day to end litterfall (when phenology flag = 0)	
TRNS_GR_PROP	0.2	proportion	transfer growth period as fraction of growing	
LIT_FALL_PROP	0.2	proportion	litterfall as fraction of growing season	
LFR_TURNOVER	1	1/yr	annual leaf and fine root turnover fraction	
LWOOD_TURNOVER	0.7	1/yr	annual live wood turnover fraction	
MORT_FRAC	0.02	1/yr	annual whole-plant mortality fraction	Robinson et al. 2013
FIRE_MORT_FRAC	0	1/yr	annual fire mortality fraction	We are assuming no fire in this system
ALLOC_FR_LEAF	1.2	ratio	ratio of new fine root C to new leaf C	
ALLOC_STEM_LEAF	2.2	ratio	ratio of new stem C to new leaf C	
ALLOC_LWOOD_ TOTWOOD	0.16	ratio	ratio of new live wood C to new total wood C	
ALLOC_CROOT_STEM	0.22	ratio	ratio of new root C to new stem C	
GR_PROP	0.5	proportion	current growth proportion	
LEAF_CN	19.8	kgC/kgN	C:N of leaves	2009 Field Data
LLITTER_CN	48	kgC/kgN	C:N of leaf litter, after retranslocation	2009 Field Data
FR_CN	84.6	kgC/kgN	C:N of fine roots	2009 Field Data

LWOOD_CN	84.6	kgC/kgN	C:N of live wood	Same as fine roots, based on White et al. 2000
DWOOD_CN	550	kgC/kgN	C:N of dead wood	
SOIL1_CN SOIL2_CN	12.0	kgC/kgN	C:N of fast and medium decomposition soil pools	Included in a separate constants file
SOIL3_CN SOIL4_CN	10.0	kgC/kgN	C:N of slow and recalcitrant decomposition soil pools	Included in a separate constants file
LIT_LAB_PROP	0.38	proportion	leaf litter labile proportion	
LIT_CEL_PROP	0.44	proportion	leaf litter cellulose proportion	
LIT_LIG_PROP	0.18	proportion	leaf litter lignin proportion	
FR_LAB_PROP	0.34	proportion	fine root labile proportion	
FR_CEL_PROP	0.44	proportion	fine root cellulose proportion	
FR_LIG_PROP	0.22	proportion	fine root lignin proportion	
DWOOD_CEL_PROP	0.77	proportion	dead wood cellulose proportion	
DWOOD_LIG_PROP	0.23	proportion	dead wood lignin proportion	
CANOPYW_INT_ COEF	0.045	1/LAI/d	canopy water interception coefficient	
CANOPY_LT_EXT_ COEF	0.54	DIM	canopy light extinction coefficient	
LEAF_AREA_RAT	2	DIM	all-sided to projected leaf area ratio	
AVG_SLA	32	m^2/kgC	canopy average specific leaf area (projected area basis)	
SHADE_SUN_SLA_ RAT	2	ratio	ratio of shaded SLA to sunlit SLA	
FLNR	0.07	DIM	fraction of leaf N in Rubisco	Robinson et al. 2013
GS_MAX	0.006	m/s	maximum stomatal conductance (projected area basis)	
GC_MAX	0.00006	m/s	cuticular conductance (projected area basis)	
GB	0.01	m/s	boundary layer conductance (projected area basis)	
PSI_MIN	-0.5	MPa	leaf water potential: start of conductance reduction	Calibrated (see methods)
PSI_MAX	-2.5	MPa	leaf water potential: complete conductance reduction	Calibrated (see methods)
VPD_MIN	1100	Pa	vapor pressure deficit: start of conductance reduction	
VPD_MAX	3600	Pa	vapor pressure deficit: complete conductance reduction	

Table C-3 Biome-BGC-Ex *Turfgrass* ecophysiology (EPC) parameters.
Default values from the Biome-BGC C3 grass biome are used unless specified. The Keywords are parameter names predefined in Biome-BGC. The 'Type' abbreviations DIM implies the parameter is dimensionless.

Keyword	*Value*	*Type*	*Description*	*Source* (if not default value)
WOODY_FLAG	0	flag	1 = woody 0 = non-woody	
EVERGRN_FLAG	0	flag	1 = evergreen 0 = deciduous	
C3_FLAG	1	flag	1 = c3 psn 0 = c4 psn	
MODEL_PHEN_FLAG	1	flag	1 = model phenology 0 = user-specified phenology	
ONDAY	0	yday	Year-day to start new growth (when phenology flag = 0)	
OFFDAY	364	yday	Year-day to end litterfall (when phenology flag = 0)	
TRNS_GR_PROP	1	proportion	transfer growth period as fraction of growing	
LIT_FALL_PROP	1	proportion	litterfall as fraction of growing season	
LFR_TURNOVER	1	1/yr	annual leaf and fine root turnover fraction	
LWOOD_TURNOVER	0	1/yr	annual live wood turnover fraction	
MORT_FRAC	0.01	1/yr	annual whole-plant mortality fraction	
FIRE_MORT_FRAC	0	1/yr	annual fire mortality fraction	
ALLOC_FR_LEAF	1	ratio	ratio of new fine root C to new leaf C	Robinson et al. 2013
ALLOC_STEM_LEAF	0	ratio	ratio of new stem C to new leaf C	
ALLOC_LWOOD_ TOTWOOD	0	ratio	ratio of new live wood C to new total wood C	
ALLOC_CROOT_STEM	0	ratio	ratio of new root C to new stem C	
GR_PROP	0.5	proportion	current growth proportion	
LEAF_CN	28.8	kgC/kgN	C:N of leaves	20% higher than the default value
LLITTER_CN	58.8	kgC/kgN	C:N of leaf litter, after retranslocation	20% higher than the default value
FR_CN	50.4	kgC/kgN	C:N of fine roots	20% higher than the default value

LWOOD_CN	0	kgC/kgN	C:N of live wood	
DWOOD_CN	0	kgC/kgN	C:N of dead wood	
SOIL1_CN SOIL2_CN	12.0	kgC/kgN	C:N of fast and medium decomposition soil pools	Included in a separate constants file
SOIL3_CN SOIL4_CN	10.0	kgC/kgN	C:N of slow and recalcitrant decomposition soil pools	Included in a separate constants file
LIT_LAB_PROP	0.39	proportion	leaf litter labile proportion	
LIT_CEL_PROP	0.44	proportion	leaf litter cellulose proportion	
LIT_LIG_PROP	0.17	proportion	leaf litter lignin proportion	
FR_LAB_PROP	0.36	proportion	fine root labile proportion	Milesi et al. 2005
FR_CEL_PROP	0.52	proportion	fine root cellulose proportion	Milesi et al. 2005
FR_LIG_PROP	0.12	proportion	fine root lignin proportion	Milesi et al. 2005
DWOOD_CEL_PROP	0	proportion	dead wood cellulose proportion	
DWOOD_LIG_PROP	0	proportion	dead wood lignin proportion	
CANOPYW_INT_ COEF	0.01	1/LAI/d	canopy water interception coefficient	
CANOPY_LT_EXT_ COEF	0.6	DIM	canopy light extinction coefficient	
LEAF_AREA_RAT	2	DIM	all-sided to projected leaf area ratio	
AVG_SLA	70	m^2/kgC	canopy average specific leaf area (projected area basis)	Milesi et al. 2005
SHADE_SUN_SLA_ RAT	2	ratio	ratio of shaded SLA to sunlit SLA	
FLNR	0.3456	DIM	fraction of leaf N in Rubisco	Calculated based on leaf C:N ration from equation in White et al. 2000
GS_MAX	0.005	m/s	maximum stomatal conductance (projected area basis)	
GC_MAX	0.0000 1	m/s	cuticular conductance (projected area basis)	
GB	0.04	m/s	boundary layer conductance (projected area basis	
PSI_MIN	-0.5	MPa	leaf water potential: start of conductance reduction	Calibrated (see methods)
PSI_MAX	-2.5	MPa	leaf water potential: complete conductance reduction	Calibrated (see methods)
VPD_MIN	930	Pa	vapor pressure deficit: start of conductance reduction	
VPD_MAX	4100	Pa	vapor pressure deficit: complete conductance reduction	

Table C-4 Site and atmospheric initial conditions for all vegetation cover types.

Model Parameter		Value
Effective Soil Depth[a]		1 m
Soil Texture[b]	Sand	63%
	Silt	20.4%
	Clay	16.6%
Site Elevation		200 m
Site Latitude		41.98 degrees
Atmospheric CO_2[c]		396.48 ppm
Total Nitrogen Deposition[c]		0.000979 kg N m^{-2} yr^{-1}

[a](Currie et al. 2016)

[b] NOAA 2014

[c] Based on a five year average of 2008-2012. Wet and dry inorganic N deposition from EPA CASNET. Atmospheric organic nitrogen was calculated as fifty percent of total inorganic deposition (Neff et al. 2002).

Description of climate parameters

Identical climate files were used for each year so that variations in climate would not mask the effects of management. We created the climate file based on fifty years (1956-2006) of past daily climate data in the study region from the National Climatic Data Center (NCDC). For each month, we randomly created precipitation events to be equal to the mean number of historical precipitation days in that month, with the distribution of rainfall amounts chosen from an exponential decay model. We used the MTCLIM model (Running et al. 1987, Thornton and Running 1999) to produce daily values of short-wave radiation (W m^{-2}), vapor pressure deficit (Pa), average daylight temperature, and day length.

Table C-5 Additional results tables for normalized linear regression ES analyses for 1) turfgrass with sparse woody, 2) turfgrass, and 3) dense woody.

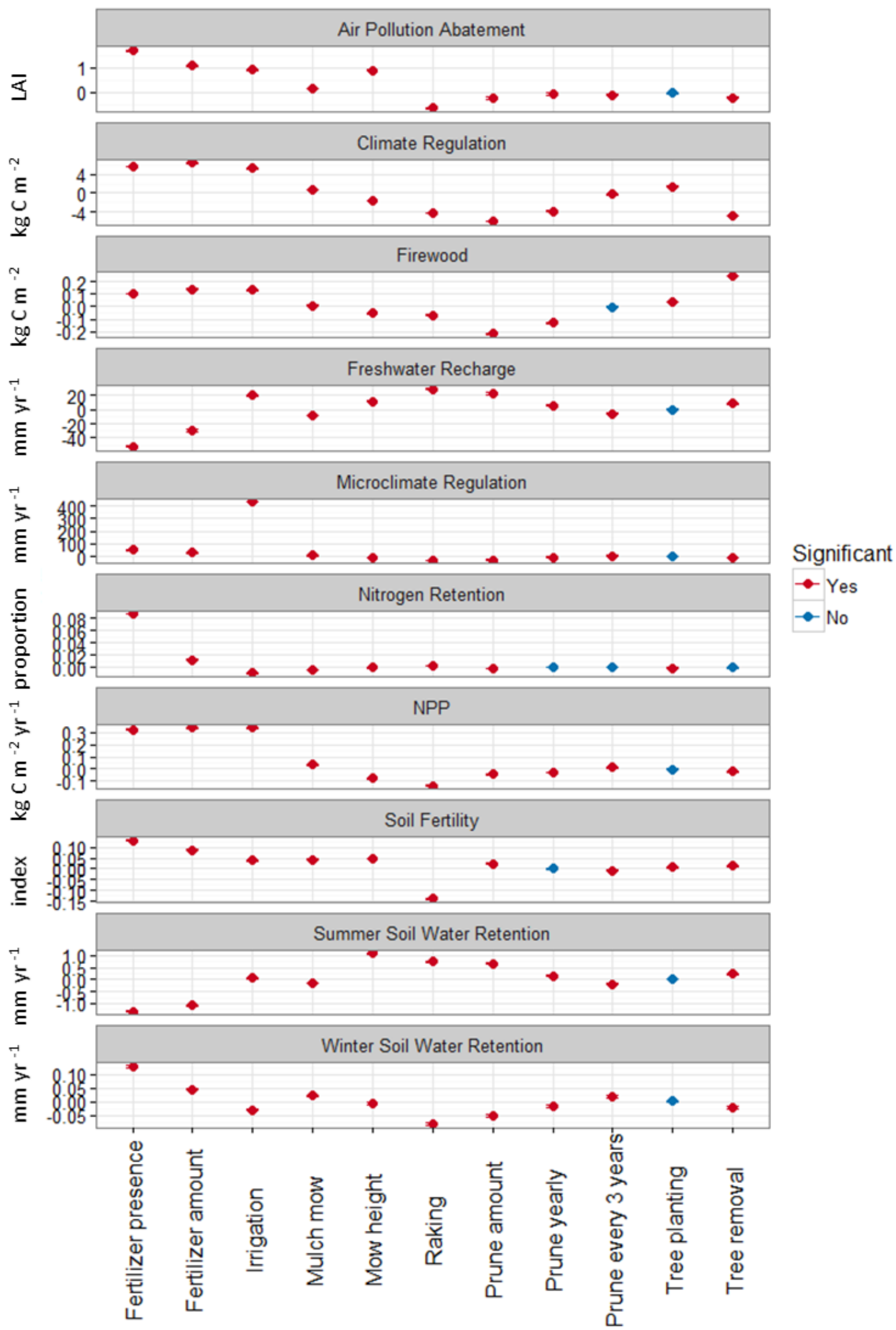
Standard errors are in parentheses.

	1. Ecosystem Services normalized regression results for *turfgrass with sparse woody vegetation* (TGW)									
	Total NPP	**Soil Fertility**	**Firewood**	**Nitrogen Retention**	**Freshwater Recharge**	**Spring Soil Water Recharge**	**Summer Soil Water Retention**	**Climate Regulation**	**Microclimate Regulation**	**Air Pollution Abatement**
	(kg C m^{-2} y^{-1})	Index (0-1)	(kg C m^{-2} yr^{-1})	Prop. (0-1)	(mm yr^{-1})	(mm yr^{-1})	Prop. (0-1)	(kg C m^{-2})	(mm yr^{-1})	(m^2 m^{-2})
Intercept	0.448*** (-0.007)	0.244*** (-0.003)	0.181*** (-0.005)	0.935*** (-0.001)	28.657*** (-1.534)	185.516*** (-0.835)	-0.133*** (-0.007)	3.514*** (-0.137)	761.527*** (-1.928)	3.822*** (-0.048)
Fertilizer	0.681*** (-0.005)	0.226*** (-0.002)	0.246*** (-0.004)	0.102*** (-0.001)	-84.633*** (-1.087)	32.779*** (-0.591)	0.377*** (-0.005)	12.325*** (-0.097)	84.685*** (-1.366)	2.864*** (-0.034)
Irrigation	0.339*** (-0.006)	0.038*** (-0.003)	0.132*** (-0.005)	-0.010*** (-0.001)	20.843*** (-1.416)	-5.605*** (-0.77)	0.103*** (-0.006)	5.254*** (-0.126)	433.565*** (-1.779)	0.893*** (-0.044)
Mow height	0.037*** (-0.004)	0.044*** (-0.002)	0.010*** (-0.003)	-0.004*** (-0.001)	-8.852*** (-0.789)	4.394*** (-0.429)	0.022*** (-0.003)	0.713*** (-0.07)	8.816*** (-0.992)	0.172*** (-0.025)
Mulch mowing	-0.087*** (-0.006)	0.044*** (-0.003)	-0.055*** (-0.004)	-0.002** (-0.001)	12.537*** (-1.253)	-1.683** (-0.682)	-0.022*** (-0.005)	-1.754*** (-0.112)	-12.690*** (-1.575)	0.856*** (-0.039)
Pruning intensity	-0.151*** (-0.005)	-0.143*** (-0.002)	-0.070*** (-0.004)	-0.001 (-0.001)	30.660*** (-1.093)	-15.558*** (-0.595)	-0.040*** (-0.005)	-4.442*** (-0.097)	-30.194*** (-1.374)	-0.697*** (-0.034)
Prune yearly	-0.040*** (-0.008)	0.024*** (-0.004)	-0.217*** (-0.006)	-0.0003 (-0.002)	21.690*** (-1.809)	-8.847*** (-0.984)	-0.065*** (-0.008)	-5.937*** (-0.161)	-24.802*** (-2.273)	-0.197*** (-0.056)
Prune every 3 years	-0.029*** (-0.006)	0.001 (-0.003)	-0.128*** (-0.005)	0.001 (-0.001)	5.144*** (-1.415)	-2.517*** (-0.77)	-0.015** (-0.006)	-3.784*** (-0.126)	-4.142** (-1.779)	-0.06 (-0.044)
Raking	0.011* (-0.006)	-0.009*** (-0.003)	-0.003 (-0.005)	0.0001 (-0.001)	-5.385*** (-1.456)	3.165*** (-0.792)	-0.024*** (-0.006)	-0.303** (-0.13)	6.475*** (-1.83)	-0.112** (-0.045)
Tree planting	-0.002 (-0.005)	0.008*** (-0.002)	0.038*** (-0.004)	-0.001 (-0.001)	-0.298 (-1.088)	0.423 (-0.592)	-0.004 (-0.005)	1.383*** (-0.097)	-0.47 (-1.367)	-0.016 (-0.034)
Tree removal	-0.023*** (-0.006)	0.013*** (-0.003)	0.246*** (-0.004)	0 (-0.001)	7.890*** (-1.253)	-3.608*** (-0.682)	-0.014*** (-0.005)	-4.819*** (-0.112)	-7.435*** (-1.575)	-0.204*** (-0.039)
Observations	7,000	7,000	7,000	7,000	7,000	7,000	7,000	7,000	7,000	7,000
R^2	0.775	0.692	0.74	0.628	0.526	0.377	0.498	0.819	0.902	0.547
Adjusted R^2	0.775	0.691	0.74	0.627	0.525	0.376	0.497	0.818	0.902	0.547
Note:	*p<0.1; **p<0.05; ***p<0.01; SE in parentheses									

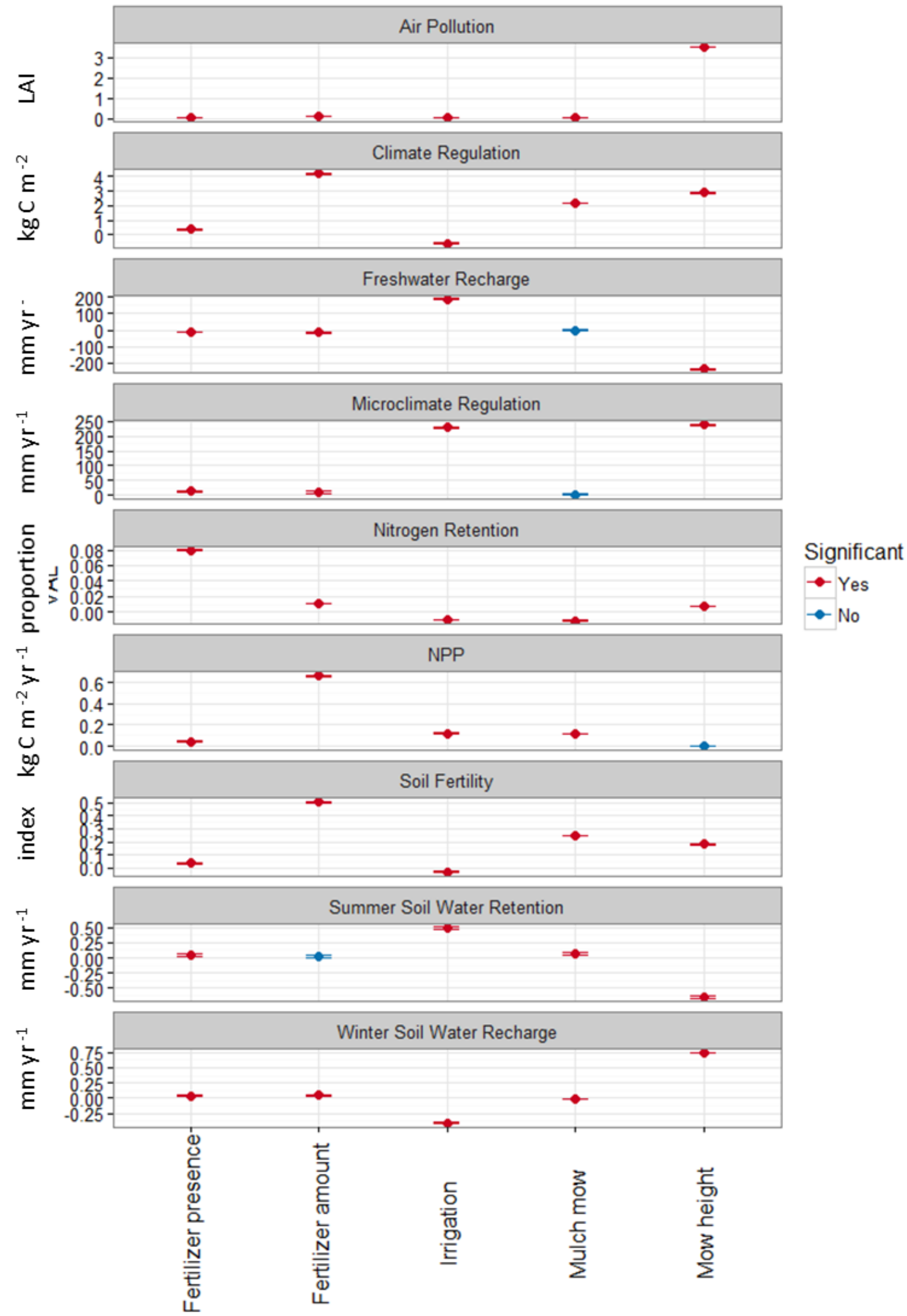
	2. Ecosystem Services normalized regression results for turfgrass (TG)								
	Total NPP	Soil Fertility	Nitrogen Retention	Freshwater Recharge	Spring Soil Water Recharge	Summer Soil Water Retention	Climate Regulation	Microclimate Regulation	Air Pollution Abatement
	(kg C m^{-2} y^{-1})	Index (0-1)	Prop. (0-1)	(mm yr^{-1})	(mm yr^{-1})	Prop. (0-1)	(kg C m^{-2})	(mm yr^{-1})	m^2 m^{-2}
Intercept	0.155*** (-0.003)	-0.058*** (-0.004)	0.938*** (-0.001)	186.425*** (-2.872)	15.182*** (-0.222)	-0.140*** (-0.009)	-5.385*** (-0.034)	604.624*** (-2.556)	1.014*** (-0.002)
Fertilizer	0.710*** (-0.003)	0.547*** (-0.004)	0.094*** (-0.001)	-24.525*** (-2.673)	2.505*** (-0.206)	0.103*** (-0.008)	4.590*** (-0.032)	24.983*** (-2.379)	0.118*** (-0.001)
Irrigation	0.122*** (-0.003)	-0.027*** (-0.005)	-0.009*** (-0.002)	189.975*** (-3.216)	-12.377*** (-0.248)	0.503*** (-0.01)	-0.573*** (-0.039)	229.453*** (-2.863)	0.006*** (-0.002)
Mulch mowing	0.119*** (-0.002)	0.248*** (-0.003)	-0.010*** (-0.001)	-0.922 (-1.943)	-0.364** (-0.15)	0.049*** (-0.006)	2.148*** (-0.023)	2.375 (-1.729)	0.025*** (-0.001)
Mow height	-0.0004 (-0.003)	0.183*** (-0.004)	0.007*** (-0.002)	-237.997*** (-3.081)	22.457*** (-0.238)	-0.420*** (-0.01)	2.889*** (-0.037)	237.569*** (-2.743)	3.526*** (-0.002)
Observations	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000
R^2	0.965	0.914	0.617	0.762	0.795	0.613	0.923	0.824	0.999
Adjusted R^2	0.965	0.914	0.617	0.761	0.794	0.612	0.923	0.824	0.999
Note:	*p<0.1; **p<0.05; ***p<0.01; SE in parentheses								

	3. Ecosystem Services normalized regression results for dense woody (DW)									
	Total NPP	**Soil Fertility**	**Firewood**	**Nitrogen Retention**	**Freshwater Recharge**	**Spring Soil Water Recharge**	**Summer Soil Water Retention**	**Climate Regulation**	**Microclimate Regulation**	**Air Pollution Abatement**
	(kg C m^{-2} y^{-1})	Index (0-1)	(kg C m^{-2} yr^{-1})	Prop. (0-1)	(mm yr^{-1})	(mm yr^{-1})	Prop. (0-1)	(kg C m^{-2})	(mm yr^{-1})	m^2 m^{-2}
Intercept	0.699*** (-0.002)	0.931*** (-0.002)	0.161*** (-0.006)	0.858*** (-0.0002)	-2.039* (-1.11)	32.477*** (-0.063)	0.144*** (-0.001)	5.546*** (-0.099)	810.639*** (-1.109)	4.220*** (-0.011)
Pruning intensity	-0.041*** (-0.003)	-0.238*** (-0.003)	-0.217*** (-0.009)	0.004*** (-0.0002)	1.404 (-1.663)	0.04 (-0.095)	-0.006*** (-0.001)	-8.000*** (-0.148)	-1.828 (-1.662)	-0.727*** (-0.016)
Prune yearly	-0.034*** (-0.002)	-0.083*** (-0.002)	-0.128*** (-0.007)	0.005*** (-0.0002)	2.005 (-1.291)	-0.184** (-0.074)	0.003*** (-0.001)	-5.536*** (-0.115)	-1.768 (-1.291)	-0.188*** (-0.013)
Prune every 3 years	0.004* (-0.002)	0.049*** (-0.003)	-0.004 (-0.007)	-0.003*** (-0.0002)	0.431 (-1.353)	-0.039 (-0.077)	0.003*** (-0.001)	-0.871*** (-0.121)	-0.797 (-1.353)	-0.01 (-0.013)
CWD removal	0.017*** (-0.002)	-0.258*** (-0.002)	0.124*** (-0.006)	0.018*** (-0.0002)	0.519 (-1.152)	-0.023 (-0.066)	0.001 (-0.001)	-3.141*** (-0.103)	-0.511 (-1.151)	0.105*** (-0.011)
Tree planting	-0.005*** (-0.002)	0.031*** (-0.002)	0.044*** (-0.005)	-0.003*** (-0.0001)	-0.051 (-1.000)	0.002 (-0.057)	-0.0002 (-0.001)	1.443*** (-0.089)	0.047 (-0.999)	-0.032*** (-0.01)
Tree removal	-0.003* (-0.002)	-0.076*** (-0.002)	0.374*** (-0.006)	0.006*** (-0.0002)	4.858*** (-1.153)	-0.277*** (-0.066)	0.003*** (-0.001)	-6.471*** (-0.103)	-4.832*** (-1.152)	-0.020* (-0.011)
Observations	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000
R^2	0.424	0.933	0.731	0.877	0.011	0.011	0.016	0.905	0.011	0.728
Adjusted R^2	0.423	0.933	0.731	0.877	0.009	0.009	0.014	0.905	0.009	0.728
Note:	*p<0.1; **p<0.05; ***p<0.01; SE in parentheses									

1) Results from the Monte Carlo analysis for *turfgrass with sparse woody*. Regression coefficient plots for each ecosystem service showing the coefficient estimate for each management practice, with lines that indicate the 95% confidence interval (based on the standard error of the coefficient).



2) Results from the Monte Carlo analysis for *turfgrass*. Regression coefficient plots for each ecosystem service showing the coefficient estimate for each management practice, with lines that indicate the 95% confidence interval (based on the standard error of the coefficient). Note that firewood is not included for this vegetation cover.



3) Results from the Monte Carlo analysis for *dense woody.* Regression coefficient plots for each ecosystem service showing the coefficient estimate for each management practice, with lines that indicate the 95% confidence interval (based on the standard error of the coefficient). Note that firewood is not included for this vegetation cover

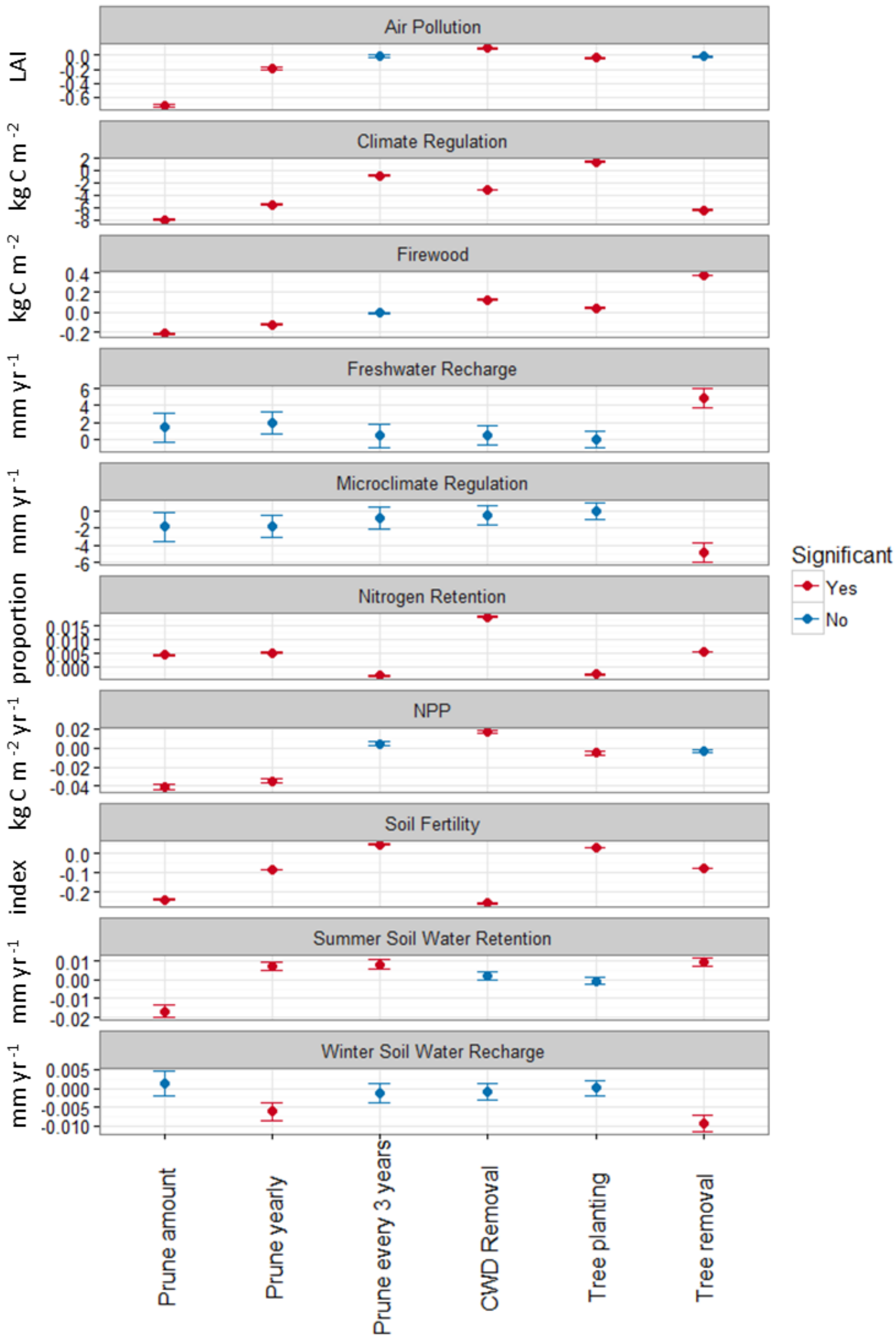
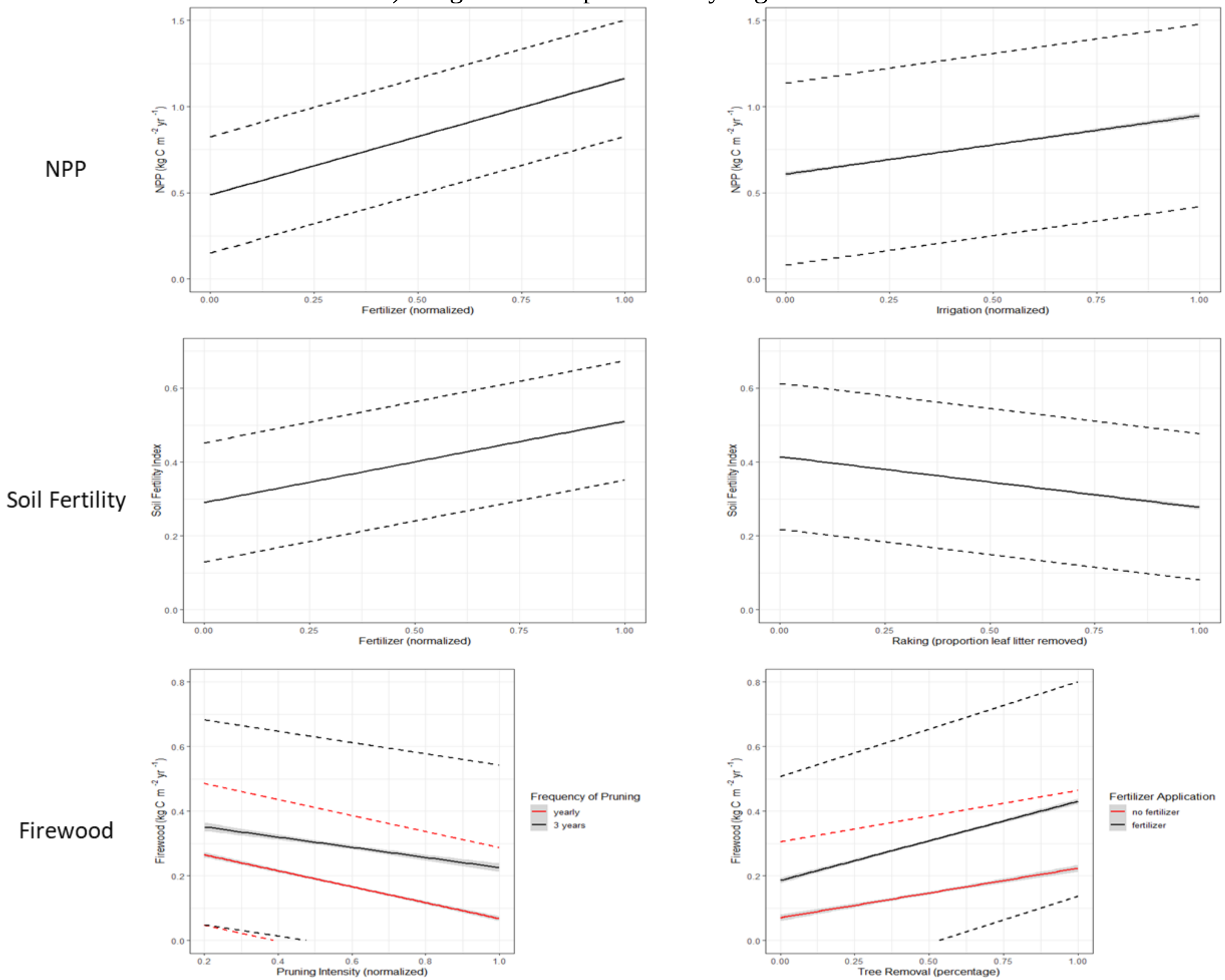
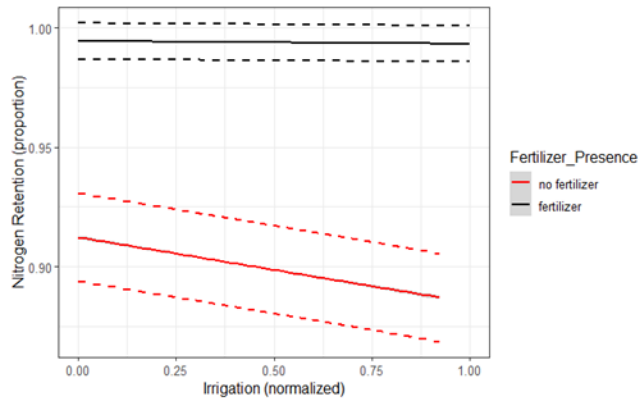


Figure C-1 Regression Coefficient Plots for 1) turfgrass with sparse woody, 2) turfgrass, and 3) dense woody.

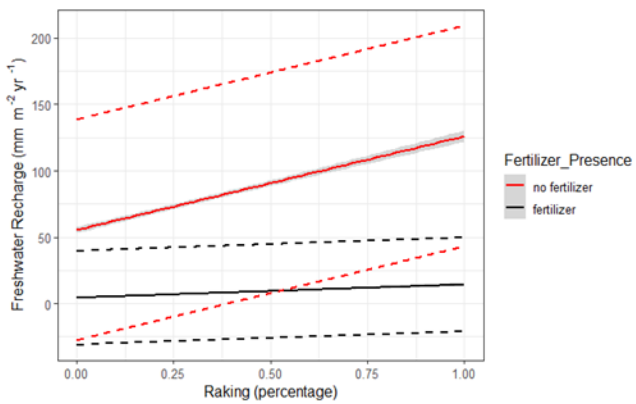
1)Turfgrass with Sparse woody vegetation



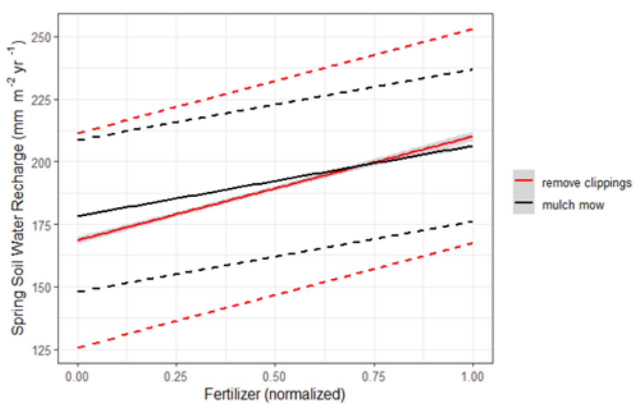
Nitrogen Retention

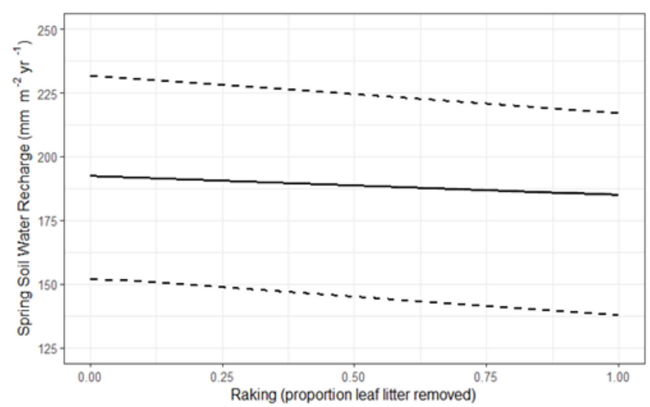


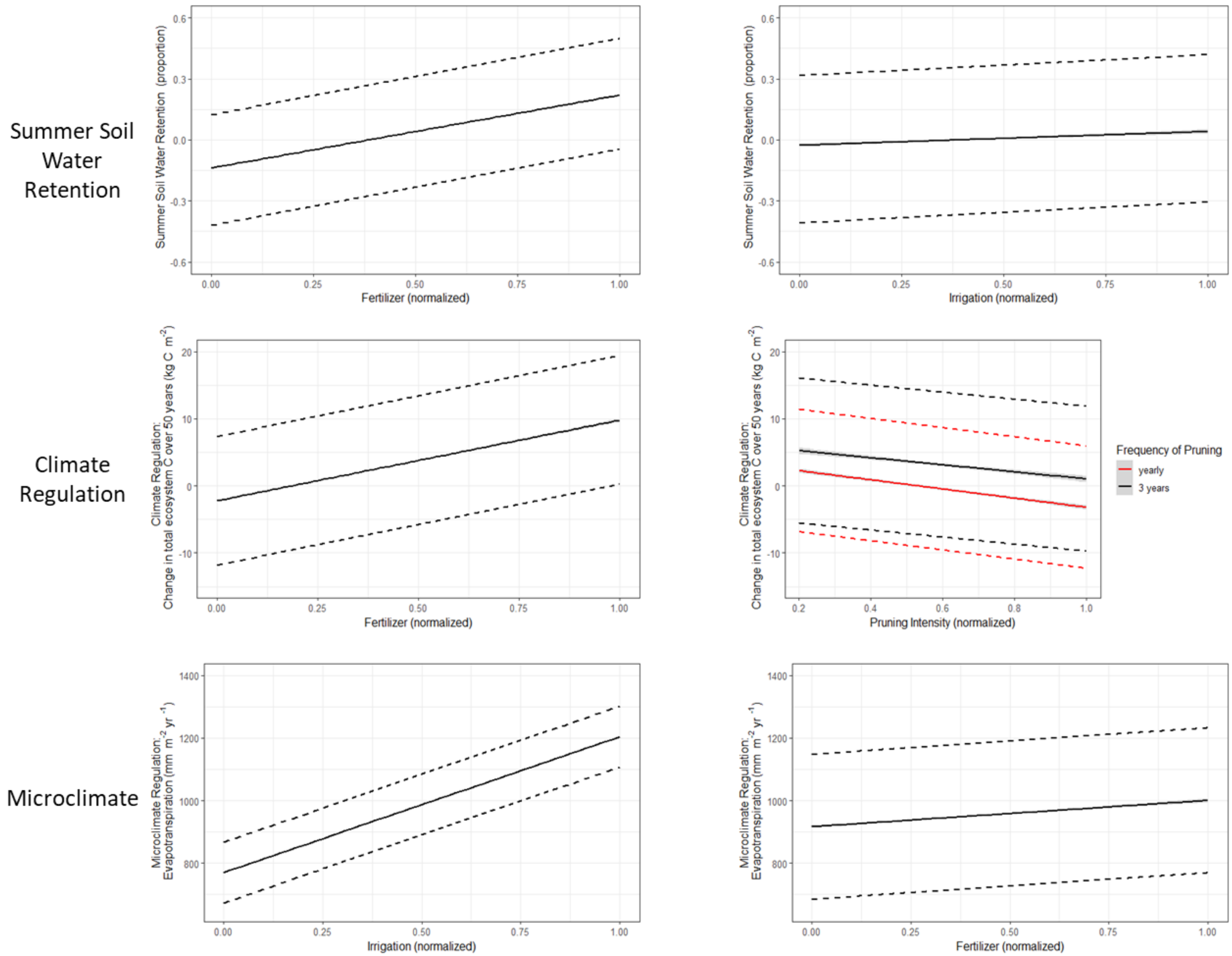
Freshwater Recharge



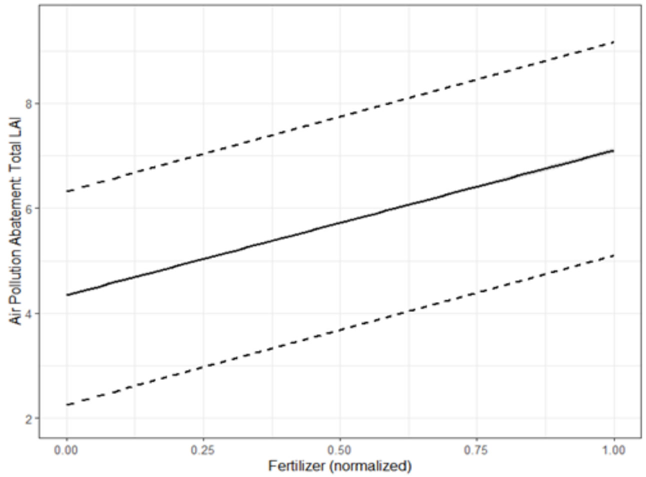
Spring Soil Water Recharge

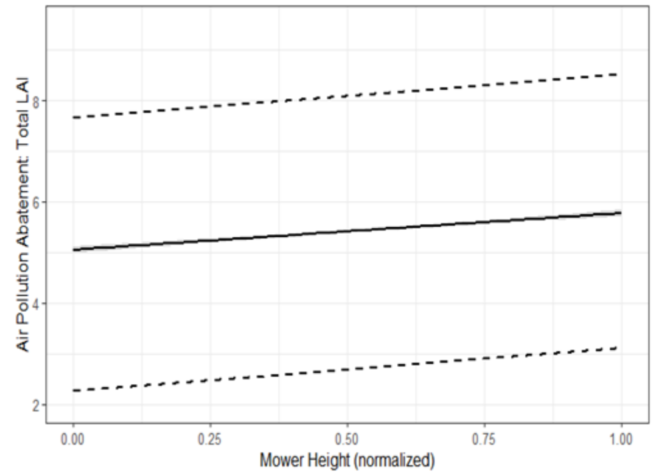




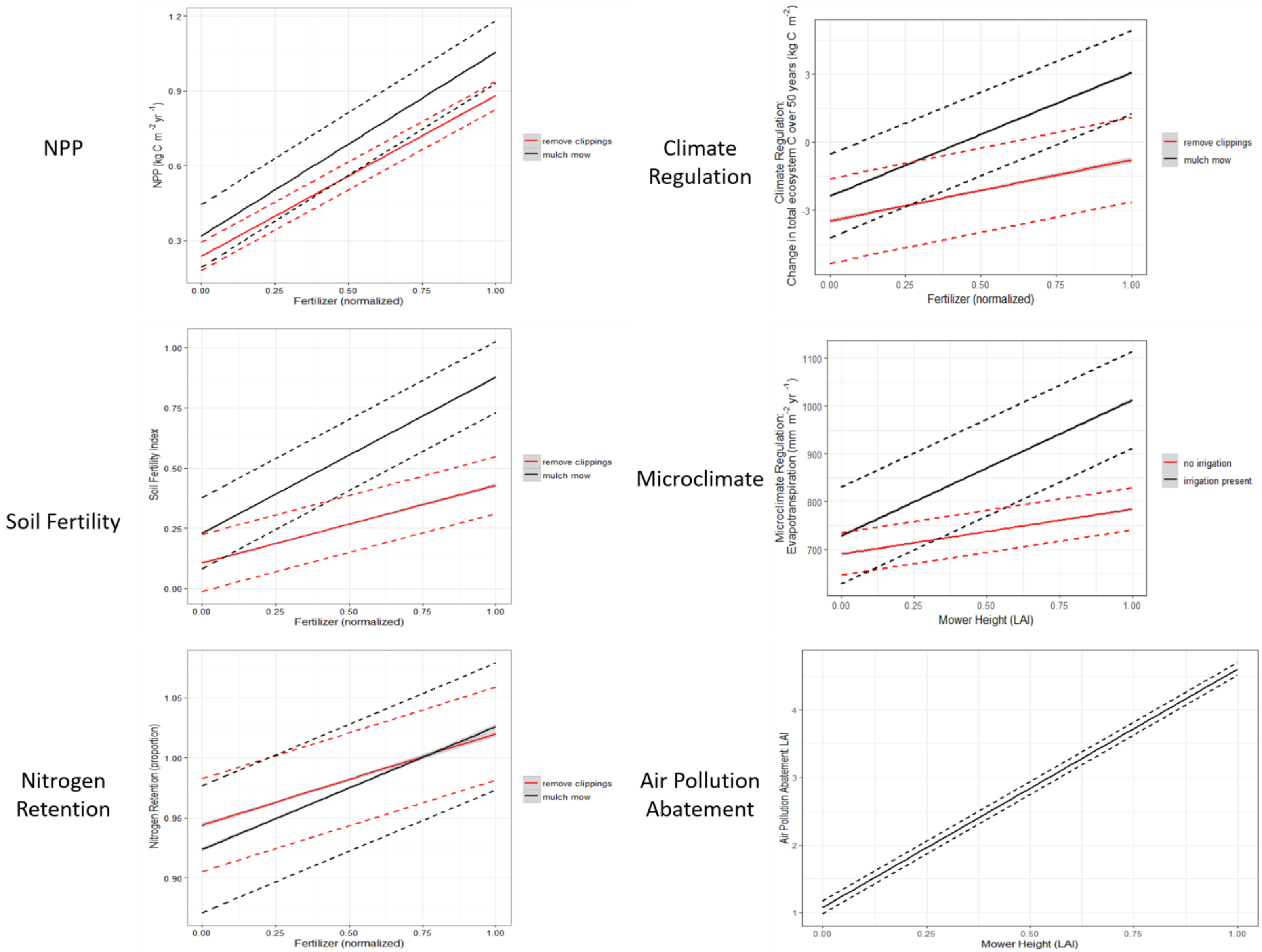

Summer Soil Water Retention
Climate Regulation
Microclimate
Summer Soil Water Retention (proportion)
Fertilizer (normalized)
Irrigation (normalized)
Climate Regulation: Change in total ecosystem C over 50 years (kg C m-2)
Pruning Intensity (normalized)
Frequency of Pruning
yearly
3 years
Microclimate Regulation: Evapotranspiration (mm m-2 yr -1)
Irrigation (normalized)
Fertilizer (normalized)

Air Pollution Abatement

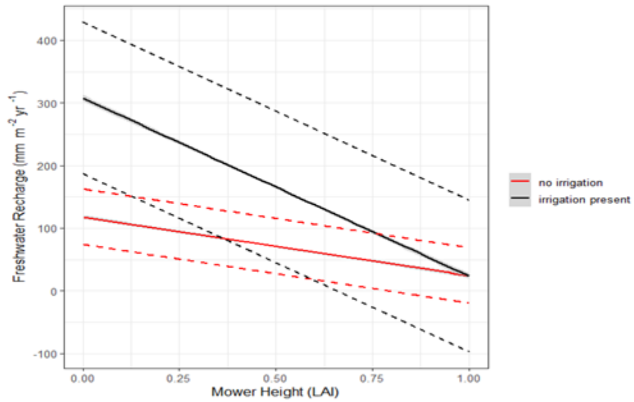




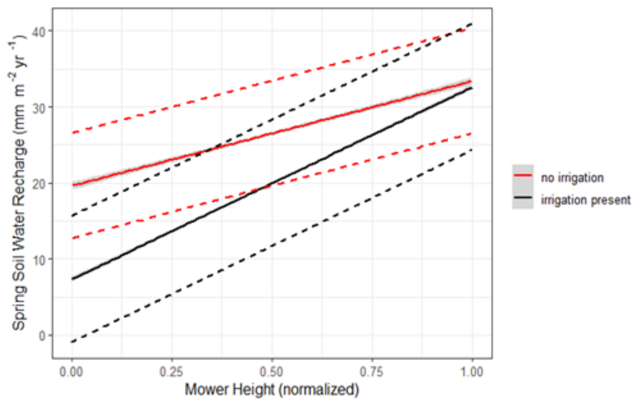
2)Turfgrass


NPP
NPP (kg C m^{-2} yr^{-1})
Fertilizer (normalized)
remove clippings
mulch mow
Climate Regulation
Climate Regulation: Change in total ecosystem C over 50 years (kg C m^{-2})
Fertilizer (normalized)
remove clippings
mulch mow
Soil Fertility
Soil Fertility Index
Fertilizer (normalized)
remove clippings
mulch mow
Microclimate
Microclimate Regulation: Evapotranspiration (mm m^{-2} yr^{-1})
Mower Height (LAI)
no irrigation
irrigation present
Nitrogen Retention
Nitrogen Retention (proportion)
Fertilizer (normalized)
remove clippings
mulch mow
Air Pollution Abatement
Air Pollution Abatement: LAI
Mower Height (LAI)

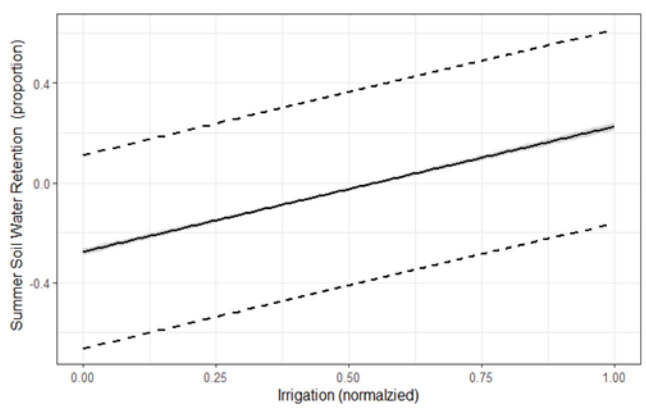
Freshwater Recharge

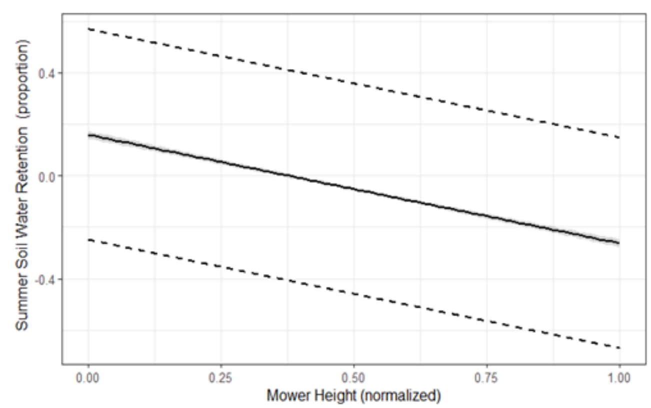


Spring Soil Water Recharge



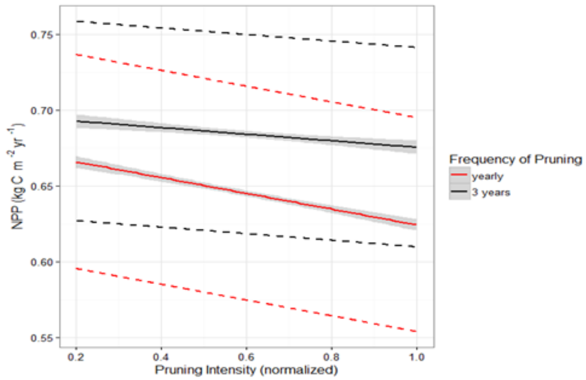
Summer Soil Water Retention



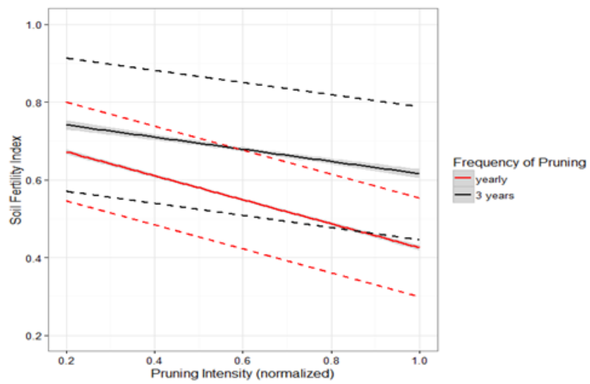


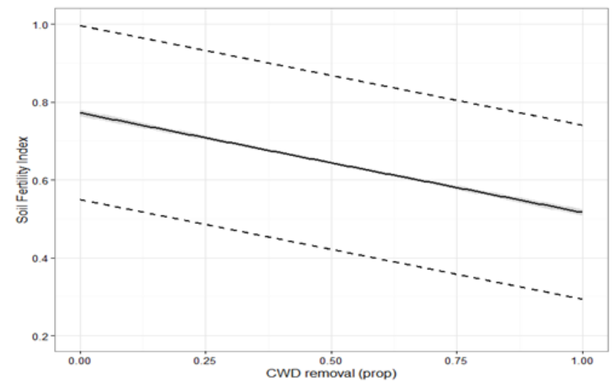
3) Dense Woody

NPP

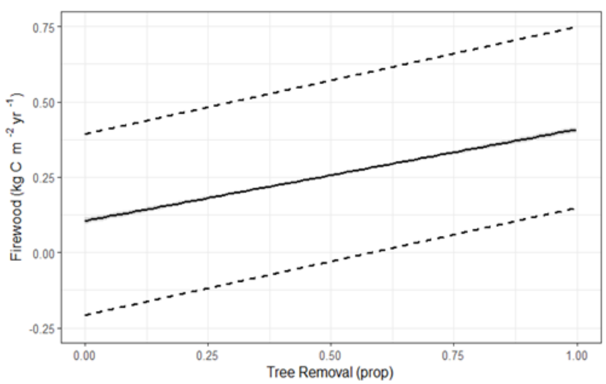


Soil Fertility

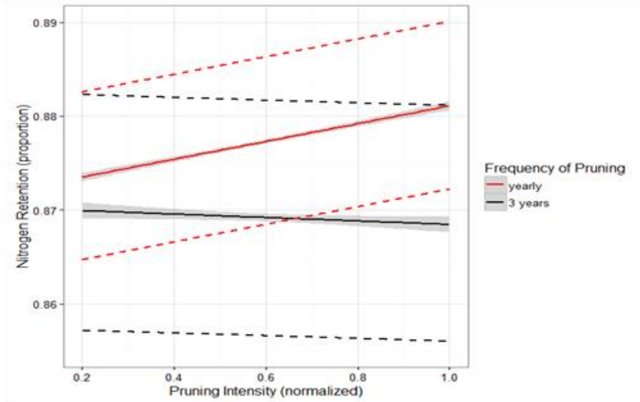




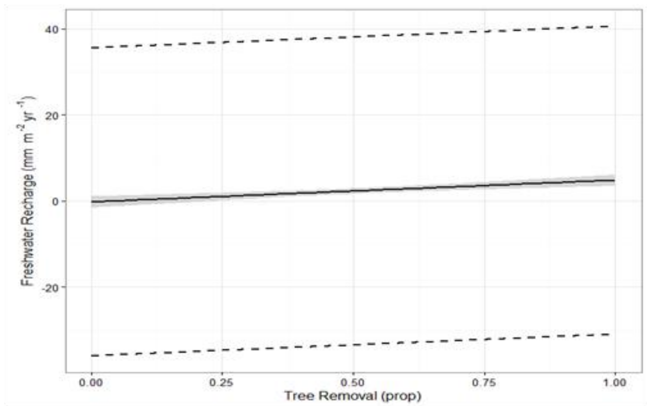
Firewood

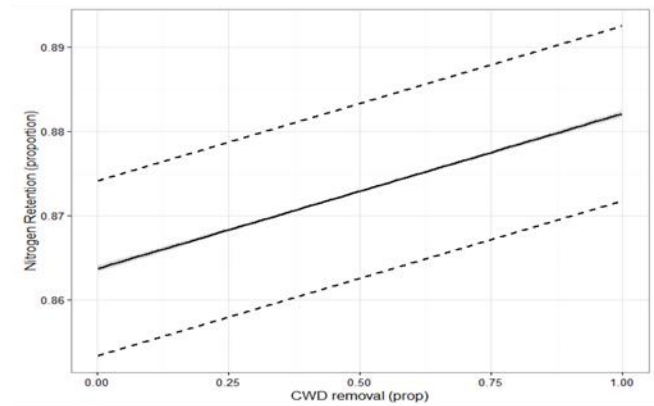


Nitrogen Retention

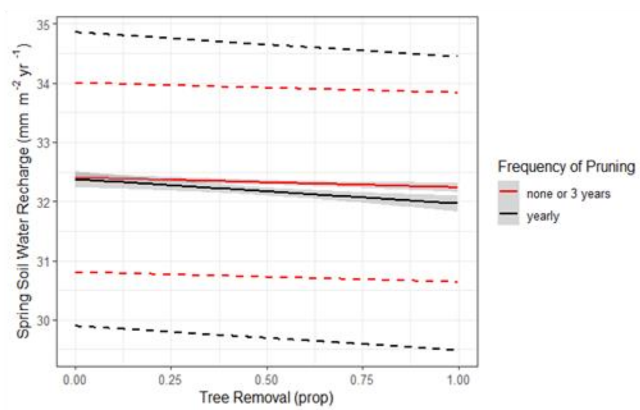


Freshwater Recharge

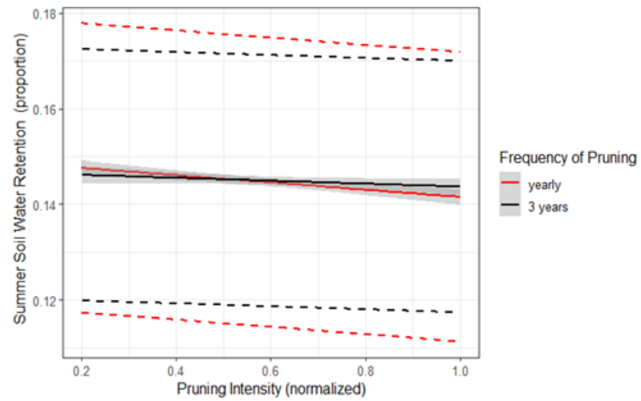




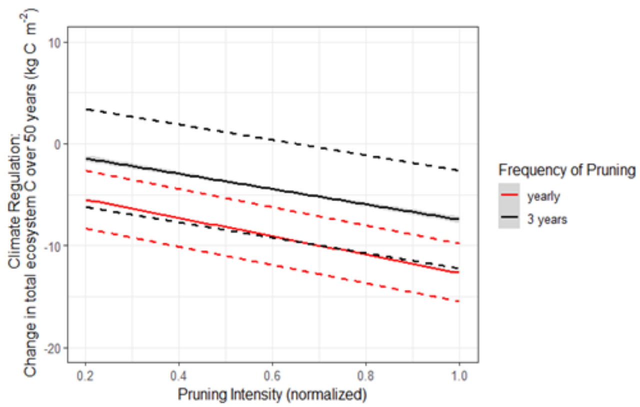
Spring Soil Water Recharge

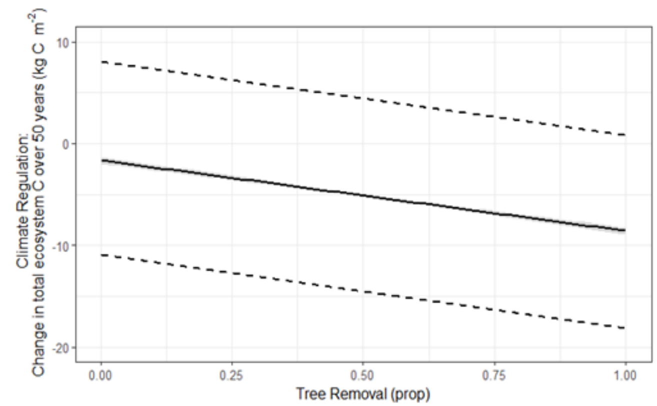


Summer Soil Water Retention

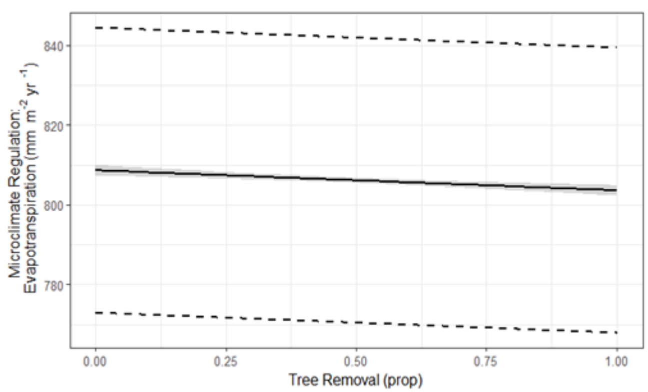


Climate Regulation





Microclimate



Air Pollution
Abatement

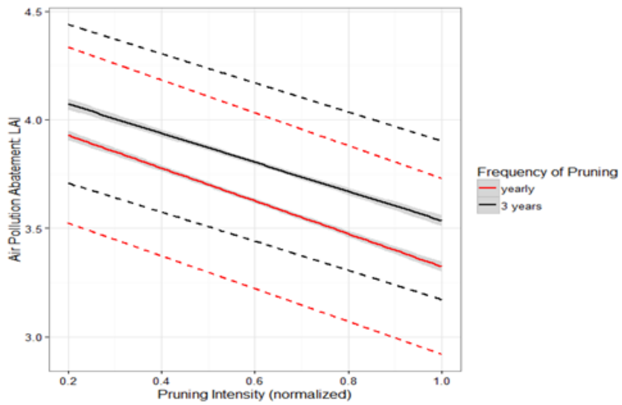


Figure C-2 Partial linear regression plots for each ES and their top management drivers for 1) turfgrass with sparse woody, 2) turfgrass, and 3) dense woody

Appendix D Supplementary Information, Tables, and Figures for Chapter 4

Table D-1 Comparison of ES Assessment Tools

Assessment Tool	Model Description	Strengths	Limitations	Sources
ARIES - Artificial Intelligence for Ecosystem Services Available at: http://aries.integratedmodelling.org/	• Couples probabilistic or deterministic models of ecosystem service supply and demand with network flow propagation models that quantify service flows. Bayesian networks or deterministic models are used, as appropriate, to map the ecological and socioeconomic factors contributing to the provision and use of ecosystem services (Bagstad et al. 2014). • Is built as an online platform that allows the building and integration of various kinds of models. The most appropriate ecosystem services model is assembled automatically from a library of modular components, driven by context-specific data and machine-processed ecosystem	• Spatially assess ES synergies and trade-offs • Can be linked to other models, including ecosystem process models and agent-based models. • Goal of becoming a large-scale meta-modeling framework. • "The artificial intelligence-assisted process pioneered in ARIES emphasizes user simplification without trivializing the application, a paradigm that could also be valuable for broader application in modern environmental and economic decision-making" (Villa et al. 2104). • "When equipped with appropriate decision rules, ARIES can determine which areas of the landscape to apply which data and models toward, better	• Does not necessarily rely on feedbacks between ecological processes • A user workflow that hides complexities under familiar metaphors and can transparently produce sophisticated models can carry subtle but important disadvantages. Early pilot tests with users have highlighted that while even limited user-level complexity is poorly tolerated by users, a lack of it can be perceived as lack of sophistication in the approach and lead to incorrect assumptions that influence decisions (Villa et al. 2014). • "None of these models fully consider the complex interdependencies and feedback flows among ecosystems and socio-	(Bagstad et al. 2013a, 2014, Villa et al. 2014, Zank et al. 2016, Martínez-López et al. 2019)

	services knowledge (Sharps et al. 2017).	accounting for key contextual factors in ecosystem service provision" (Bagstad et al. 2011) • "ARIES represents a good option in data scarce areas and its probabilistic approach can cope with data gaps, providing maps of modelled outputs along with associated uncertainty…can provide information (e.g. flows, mass, concentrations) for every point in the landscape" Sharps et al. 2017.	economic systems at large scale" (Arbault et al. 2014).	
EBI – ecosystem service bundle index	• Goal to map ecosystem services in terms of their supporting systems, namely the biophysical potential for the delivery of services (Van Der Biest et al. 2014). • Causal network combines GIS data-layers of biophysical characteristics and land use as inputs, to calculate the delivery of ecosystem services as an	• Spatially assesses ES. • Bayesian methods can make predictions when information on the state of input variables is partially missing. • Assesses the capacity of ecosystems to deliver services regardless of the actual land use as well as the effect of different land use scenarios (Van Der Biest et al. 2014).	• Uses indicators to calculate probabilities and does not rely on ecosystem processes. • "As feedback mechanisms can be difficult to implement in Bayesian belief networks, another challenge when increasing the number of services lies in implementing spatial and temporal interactions between ecosystem services and	(Van der Biest et al. 2014)

	integrated ecosystem service bundle index (EBI). • Uses Bayesian belief network modeling for when data is limited or uncertain.	• Since multiple services are comprised in the index, optimization scenarios for a whole bundle of services can be developed by managing controlling factors (biophysical and land use) toward a maximum total ecosystem service delivery scenario (Van Der Biest et al. 2014).	conditions" (Van Der Biest et al. 2014). • Does not seem to be a publicly accessible model – more proof of concept at this point.	
ESTIMAP – Ecosystem service mapping tool	• Collection of spatially explicit models that were originally developed to support European policies at a local scale. • Includes different models for different services that consist of either a lookup table or a regression that is filled by GIS data.	• " An effective analytical framework for mapping and assessing ES should exist within a basic conceptual structure and include models and spatially explicit indicators to provide a holistic and consistent view that informs an evaluation of multiple ES." (Zulian et al. 2018)	• Service models are not interconnected and do not depend on ecosystem processes	(Zulian et al. 2013, 2018)
InVEST - Integrated Valuation of Ecosystem Services and Trade-offs Available at: naturalcapitalproject.org	• Combines land use and land cover (LULC) data with information on the supply (biophysical processes) and demand of ecosystem services to provide a spatially explicit service output value in biophysical	• Production functions are based on ecology. • Spatially assess ES synergies and trade-offs. • InVEST has been used widely, has a comprehensive user manual and provides example input data per model (Doug et al. 2020).	• Production functions are not linked to ecosystem processes. • There are no feedbacks between services. • "These approaches fail to explicitly account for the ***dynamic*** character of CHANS despite the fact that	(Tallis and Polasky 2009, Doug et al. 2020)

	or economic terms (Sharps et al. 2017).	• "In addition to biophysical outputs, InVEST also provides estimates of valuation, based on user inputs, highlighting areas with high levels of provision for particular services... straightforward and simple to use for those with basic GIS skills; the gathering of input data is often the most time consuming step" (Sharp et al. 2017). • "InVEST is useful for understanding the consequences of alternative decisions when little information exists about a system (or when it is otherwise necessary to rely on more generalized functional relationships)"(Boumans et al. 2015).	concepts such as sustainability and adaptation (often stated goals of EBM) require a dynamic perspective. These core concepts are based upon the principles that Earth is made up of human and natural elements that ***interact*** and have ***feedbacks***, characteristics unique to time-evolving systems"(Boumans et al. 2015). • "None of these models fully consider the complex interdependencies and feedback flows among ecosystems and socio-economic systems at large scale" (Arbault et al. 2014).	
LUCI - Land Utilization and Capability Indicator Available at: https://www.lucitools.org/	• Uses a digital elevation model (DEM), land cover information, and soil information to determine the spatial distribution, supply, and opportunities of individual ecosystem	• Spatially assess ES synergies and trade-offs. • Can be run at multiple scales. • "LUCI's traffic light maps allow quick and easy interpretation of the model	• Does not rely on ecosystem processes or on feedback between processes and services.	(Jackson et al. 2013, Trodahl et al. 2017)

	services. It generates a series of ecosystem service maps to show where trade-offs or synergies in ecosystem services exist (LUCI website). • The models incorporate biophysical processes, applying topographical routing for hydrological and related services, and uses lookup tables where appropriate (Sharps et al. 2017).	output. LUCI is also the only tool with a trade-off module, providing a useful visual output of the impacts of land-use change on multiple services, and the only tool that respects fine-scale spatial configuration of landscape elements" (Sharps et al. 2017). • "can provide information (e.g. flows, mass, concentrations) for every point in the landscape" (Sharps et al. 2017).		
MIMES - Multi-scale Integrated Model of Ecosystem Services Available at: http://www.afordablefutures.com	• Is analytical framework designed to assess the dynamics associated with ecosystem service function and human activities. It requires that *multiple* ecological and human *dynamics* be specified, and that outputs may be understood through different temporal and spatial lenses to assess the effects of different actions in the short and long term and at different spatial scales (Boumans et al. 2015).	• Potential to link processes with services and to have feedbacks between them. • Spatially assess ES synergies and trade-offs. • Can be run at multiple scales. • Modular, tiered approach to deal with data availability • "The benefits of this complex nature are that an implementation can be used to execute different kinds of scenarios, even those which were not anticipated during the initial development	• Currently has not demonstrated interconnectedness between multiple processes and services. • Requires a lot of data input and data gathering. • Requires training.	(Boumans et al. 2002, 2015, Arbault et al. 2014, Boumans and Costanza 2015)

		stages of the model" Boumans et al. 2015. • "able to take into account the inter-linkages among natural and human-driven systems, their feedback and the resulting connections among multiple environmental mechanisms in a holistic way" (Arbault et al. 2014, in reference to GUMBO a previous iteration of MIMES).		