KEEP IT GREEN OR MAKE IT BLUE: UNDERSTANDING THE DYNAMICS OF LAND USE CHANGES AND ITS IMPACTS ON ECOSYSTEM SERVICES IN THE CONTEXT OF DEFORESTATION DUE TO BLUEBERRY EXPANSION IN SOUTHERN GEORGIA, USA

by

SURAJ UPADHAYA

(Under the Direction of Puneet Dwivedi)

ABSTRACT

Land use change is central to the overall sustainability debate as it is a primary driver of global environmental change. Forest ecosystems provide a variety of important goods and services for humans. However, forest ecosystems are a victim of deforestation mostly due to ever-expanding commercial agriculture and urbanization. Consequently, deforestation will change the provisions of forest-based ecosystem services in the future. The relationship between deforestation, ecosystem services, and human well-being is complex and influenced by multiple drivers operating across scales. Integrative research is a key in overcoming fundamental problems related to such complex systems.

Several studies have analyzed the social, economic, and environmental impacts of deforestation in the context of developing countries. However, no study, to the best of our knowledge, has focused on the role of expanding demand for agricultural commodities on deforestation in the context of developed countries. An integrative approach was used to understand linkages between deforestation and agricultural expansion in southeastern Georgia where about 15,000 hectares of evergreen forestlands and grasslands have been converted to blueberry farms between 2010 and 2017.

An economic model for understanding the profitability between two competing land use (pine plantation and blueberry) in southeastern Georgia was utilized. A site suitability model using geospatial tools for blueberry production in southeastern Georgia was developed. Using a combination of different tools (InVEST, TerrSet, and ArcGIS), the land use change dynamics in the Alabaha watershed and its effects on the ecosystem services, in general, and habitat quality for Gopher tortoise, in particular, was analyzed. Finally, to understand the motivations of landowners for growing blueberries instead of pine, using Q-method where both qualitative and quantitative research approaches were combined.

This research provides useful information for policymakers and land managers in designing appropriate incentives and extension services for sustaining the forestry sector in Georgia and other neighboring states which are facing similar challenges in the context of deforestation. The study also finds that innovative land use policy and integrated landscape management strategies for the human-dominated landscapes are particularly important for ensuring continuance and enhancement of forest-based ecosystem services.

INDEX WORDS: Georgia; Land Use Change; Deforestation; Blueberry; Agricultural Expansion; Ecosystem Services; Sustainability; Habitat Quality; Biodiversity; Motivations; Economics; Geospatial; Integrative

KEEP IT GREEN OR MAKE IT BLUE: UNDERSTANDING THE DYNAMICS OF LAND USE CHANGES AND ITS IMPACTS ON ECOSYSTEM SERVICES IN THE CONTEXT OF DEFORESTATION DUE TO BLUEBERRY EXPANSION IN SOUTHERN GEORGIA, USA

by

SURAJ UPADHAYA

B.Sc. Forestry, Tribhuvan University, 2012

M.Sc. Forestry, University of Kentucky, 2015

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2019

KEEP IT GREEN OR MAKE IT BLUE: UNDERSTANDING THE DYNAMICS OF LAND USE CHANGES AND ITS IMPACTS ON ECOSYSTEM SERVICES IN THE CONTEXT OF DEFORESTATION DUE TO BLUEBERRY EXPANSION IN SOUTHERN GEORGIA, USA.

by

SURAJ UPADHAYA

Major Professor: Puneet Dwivedi
Committee: Marguerite Madden
Jeff Hepinstall-Cymerman
Esendugue Greg Fonsah
Robert L. Izlar

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
May 2019

ACKNOWLEDGMENTS

This research project could not have been successfully completed without the invaluable support of several people. First of all, I would like to express my deepest gratitude to my major professor, Dr. Puneet Dwivedi, for taking a chance on a stranger, for his expert guidance throughout my graduate studies, for the time he always set aside to discuss any research problems that arose, and for assisting me to keep a clear focus of the job ahead and for encouraging me when times got rough. I enjoyed learning and growing with him. I would also like to thank Dr. Marguerite Madden, Dr. Jeff Hepinstall-Cymerman, Dr. Esendugue Greg Fonsah, and Mr. Robert L. Izlar for their assistance in formulating and completing this study as members of my committee.

My sincere thanks are also for the CICR, ICON UGA and Warnell for granting me the graduate fellowship to conduct my graduate study. I am truly grateful to all the faculties and staff at ICON UGA and the Warnell School especially Talley Vodicka, Dr. Nik Heynen, Dr. Nate Nibbelink, Dr. Sonia Hernandez, and Kate deDufor who were always there to answer my questions and extending help.

I would like to acknowledge the support of the Georgia Blueberry Growers Association for allowing me to conduct a survey during their meetings. I also like to thank all the landowners who participated and responded to my survey.

I am grateful to my friends Chantal Tumpach, Arundhati Jagadish, David Hecht, Dan Read, Asif Alam, Noah Goyke, Sagar GC, Sameen Raut, Steve Padgett-Vasquez, Surendra Shrestha, Karuna Paudel, and all lab members of Dwivedi Forest Sustainability Lab. Sorry to anyone else I have forgotten!

Finally, I would like to thank my parents, dad, mom, and aunty, for making sacrifices to home-school me, providing me with the best education they could. Also, I thank my dear brothers and sisters Akash, Rashmi, Akhanda, Beeju, and Mala, for never letting me settle for “good enough.” Thank you to Sanskar aka Mini Akash for bringing joy into my life every day.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS iv

LIST OF APPENDICES viii

LIST OF TABLES ix

LIST OF FIGURES x

INTRODUCTION & LITERATURE REVIEW 1

1.1 Land Use Change: Deforestation and Agricultural Expansion 2

1.2 Sustainability and Land Use Change 5

1.3 Integrative Framing 7

1.4 Strategic Communication 9

1.5 Study Site 11

THE ROLE AND POTENTIAL OF BLUEBERRY FARMING IN INCREASING DEFORESTATION IN SOUTHERN GEORGIA, UNITED STATES 19

2.1 Introduction 21

2.2 Theoretical Framework 23

2.3 Methods 25

2.4 Results 33

2.5 Discussion 40

2.6 Conclusion 43

FORESTLANDS TO BLUEBERRIES: ASSESSING IMPLICATIONS FOR HABITAT QUALITY IN ALABAHA RIVER WATERSHED IN SOUTHERN GEORGIA, UNITED STATES 50

3.1 Introduction 52

3.2 Literature Review 53

3.3 Material and Methods 57

3.4 Results 68

3.5 Discussion 78

3.6 Conclusion 80

KEEP IT BLUE OR MAKE IT GREEN: CAPTURING MOTIVATIONS OF FAMILY LANDOWNERS FOR GROWING BLUEBERRIES INSTEAD OF PINE IN SOUTHERN GEORGIA, USA USING Q METHODOLOGY 92

4.1 Introduction 94

4.2 Material and Methods 99

4.3 Results 105

4.4 Discussion 112

4.5 Conclusion 115

CONCLUSION 125

APPENDICES

A Yield of blueberry in the study area …………………………………………..…………129

B Input costs for ascertaining Net Present Value of blueberry production……………130

C Description of Landsat Imagery used for land use classification.………………......131

LIST OF TABLES

Table 2.1. Costs related to silvicultural activities for management of selected yellow pine species. 31

Table 2.2. Net Present Value (NPV), Annualized Net Present Value (ANPV), and Benefit Cost Ratio (BCR) for blueberry and selected pine species. Each project is of different time periods. 34

Table 2.3. Sensitivity analysis for selected pine species and blueberry price and discount rate changes. Base scenarios represent Net Present Value (NPV) obtained by farmers from different land use practices (pine plantation and blueberry production) in SE Georgia. 37

Table 3.1. Landscape metrics that explain the configuration and composition of the landscape for the different stages (2006, 2010, 2015, 2022, and 2030). 72

Table 3.2. Landscape habitat quality classes and percentage of landscape under different habitat quality classes for different years. 73

Table 4.1. Factor Q-sort values of each statement and its corresponding theme. Here, -3 represents strongly disagree, and +3 represents strongly agree. Eco LT stands for Economics Long Term, Eco ST stands for Economic Short Term, Env stands for Environmental, Social and Pol stands for Political. 102

Table 4.2. Respective loading of each landowner across four factors. Marked in bold are defining sorts, which are used to create the factor arrays. 107

Table 4.3. Characteristic of the landowners who loaded significantly in different four factors. 109

LIST OF FIGURES

Figure 2.1. Conversion of different land covers to blueberry farms in SE Georgia between 2010 and 2017. (Source: USDA NASS Cropland Data Layer). 23

Figure 2.2. A theoretical framework describing the conversion of forestlands into blueberry farms. 25

Figure 2.3. Map of the SE Georgia. County names are mentioned along with the location of weather stations. The location of blueberry farms is reported based on Cropscape 2015 data. 27

Figure. 2.4. A flowchart illustrating the blueberry site suitability modeling. 33

Figure 2.5. Relative distribution and cumulative frequency of simulated NPV for loblolly, slash, and longleaf pines. 35

Figure 2.6. Relative distribution and cumulative frequency of simulated NPV for blueberry. 36

Figure 2.7. The mean and standard deviation of the simulated (n=1000) annualized net present value (ANPV) of the investment for three different pine species (longleaf, loblolly, and slash) and blueberry. 36

Figure 2.8. Spearman's rank-order correlation coefficient of the critical input variables [pulpwood (PW) price, chip-and-saw (CNS) price, saw timber (ST) price, discount rate, and blueberry price] in relation to the simulated NPVs of selected pine species and blueberry. 37

Figure 2.9. Site suitability map for blueberry production in SE Georgia. 38

Figure 2.10. Percentage of existing NLCD land cover types under the blueberry suitability. 39

Figure 2.11. Blueberry suitable area under existing land covers (evergreen forest, hayland/pasture land, croplands, and mixed forest) in different counties in SE Georgia..... 40

Figure 3.1. Location of the study area with the land use classification map in 2015. 58

Figure 3.2. Spatial distribution of land uses in the study area over time. 69

Figure 3.3. Area under different land uses as a percentage of the total area of the selected watershed. 70

Figure 3.4. Spatial distribution of habitat quality in the study area. 74

Figure 3.5. Landscape habitat quality score (Mean value) along different stages (2006, 2010, 2015, 2022, 2030, 2030A and 2030 B). 76

Figure 3.6. Land use map and habitat quality for the year 2030 with two different scenarios 2030A and 2030B (double and fourfold respectively) of blueberry expansion................... 77

Figure 4.1. Map showing locations of blueberry production in Georgia (Source: USDA, 2018). As evident, the majority of blueberry production in Georgia is located in the southeastern part of the state, which corresponds to the District Five of the Georgia Forestry Commission (GFC). 98

Figure 4.2. Q sort ranking grid. Each cell represents one statement where -3 represents strongly disagree, and +3 represents strongly agree. 104

CHAPTER 1

INTRODUCTION & LITERATURE REVIEW

The expansion of commercial agriculture is a primary driver of global land use changes (LUCs). Economic development along with globalization has led to the transformation of natural ecosystems into agricultural land and the intensification of land use (Zhao et al., 2006). Global and free-market arrangements, international market demands, and local regional and global policies also play a key role in LUCs in most North American countries (FAO, 2016).

In the United States, the agricultural frontier has expanded over the last decades. The expansion of agricultural land on previously forested land has become one of the leading causes of deforestation in the country (FAO, 2016; Morales-Hidalgo, Oswalt, & Somanathan, 2015). Laurance et al. (2014) suggested that the coming era will be, in effect, an "agricultural bomb" with remarkable magnitude and pace of LUCs. The study also argued that rapid transformation would have profound challenges for environmental conservation and potentially, global human welfare. Large scale conversion of forestland into commercial crops will lead to a decrease in several forest-based ecosystem services (Fearnside, 2000; Lawler et al., 2014; Polasky et al., 2011). Perhaps the most obvious challenges and impacts are habitat loss, degradation, fragmentation (Sala et al., 2000), the emergence of invasive species (Corbin & D'Antonio, 2004), changes in hydrological cycles, water quality/water pollution (Fitzpatrick, Knox, & Whitman, 1999; Shaw, Marrs, Bhattarai, & Quackenbush, 2014), change in biogeochemical cycles (Houghton & Goodale, 2004), and modification of climate (Vitousek, 1994; Wear et al., 2014).

Although a number of studies have addressed the issue of LUCs specifically deforestation and agriculture expansion in developing countries (Morton et al., 2006), practically no study has looked into deforestation-related issues in the United States and especially in the southeastern United States, a prime producer of round wood products nationwide. An understanding of LUCs, its impacts on ecosystem services (ESs) in general and biodiversity conservation, in particular, and landowner's motivations of land use change will feed into the development of suitable policies for ensuring sustainable landscape management. This could potentially lead to maintenance and enhancement of landscape-based ESs, which are vital for ensuring the wellbeing of society and natural ecosystems in a mutually assuring manner. LUCs, the core field of global environmental change, influence the function and structure of the ecosystem, and an assessment of the ecosystem services can be used to assess the ecological effects of land use planning and play a guiding role in obtaining sustainable landscape management (Lawler et al., 2014; Zhao, Liu, Sohl, Young, & Werner, 2013).

This dissertation used an integrative approach for characterizing the dynamics of LUCs, its impacts on ESs, particularly, habitat quality, a proxy to biodiversity, and understanding the motivation of landowners for changing land use on land previously forestland in southeastern Georgia, where landowners are replacing their forestlands and pastures with blueberry farms for economic gains (Upadhaya & Dwivedi, 2019).

1.1 Land Use Change: Deforestation and Agricultural Expansion

Humans begin converting from one land use to other uses-using fire, and primitive tools-thousands of years ago to facilitate their livelihoods. Today their actions, such as the clearing of forests, practicing intensive agriculture production, urbanization are changing the World's landscapes (Foley et al., 2005; Meyer and Turner II, 1992; Zhao et al., 2006). Though humans have been altering the land surface for meeting their needs for thousands of years, current rates, extents, and intensities of LUCs are far greater than ever before (Zhao et al., 2006). These LUCs exhibit regional dominance including tropical deforestation, agricultural expansion, temperate reforestation or afforestation, cropland intensification, and urbanization (Song et al., 2018).

The term "land use" is defined by Turner et al. (1994) as the way in which people employ the land and its resources, for example, agriculture, urban development, plantations, logging, mining, or grazing. While the land cover is the biophysical or natural state of the land surface, such as vegetation, developed areas, and water bodies. Therefore, LUC is the alteration of one type of land use into another or the intensification of previous land use.

Globally, the most important LUC has been the expansion of agricultural land at the expense of forest area (Costanza, Abt, McKerrow, & Collazo, 2017; Lawler et al., 2014). Forests cover about four billion hectares (30.6%) of the global land area from which the global human population depends on several ESs for sustaining their livelihoods (FAO, 2016; Morales-Hidalgo et al., 2015). The global community has recognized the importance of forest for its contribution to sustaining locals livelihoods (World Bank, 2016). Despite the global recognition, the forest area is continuously declining worldwide as a result of agricultural expansion. For example, over 55% of new agricultural land across the tropics during 1980 and 2000 was developed at the expense of intact forests, while 28% came from disturbed forests (Gibbs et al., 2010). It is estimated that the area of agricultural land has increased globally from an estimated 300-400 million ha in 1700 to

1500-1800 million ha in 1990 (Lambin, Geist, & Lepers, 2003). A recent study by the Food and Agriculture Organization of the United Nations (FAO) estimated historical changes in land use at global scale during last thirty years and reported a net forest loss of some 129 million ha of forest between 1990 and 2015, representing an annual net loss rate of 0.13% in the 1990s and 0.08% over the last five—year period (FAO, 2016)

Large-scale LUCs in the North American continent began with the arrival of Europeans in the late fifteenth century (Sleeter et al., 2013). The LUCs such as conversion of forestland to agriculture or changing forest management practices on human-dominated landscapes have transformed a large portion of the United States (Sleeter et al., 2013; Sohl et al., 2016). For instances between 1973 and 2000, more than 67.3 million ha (8.6% of the total land area) in the United States experienced a change in land use. Among 67.3 million ha of land that experienced change, more than 9.7 million ha forestland was converted into other land use (Sleeter et al., 2013). The rate of conversion rose sharply as the human population grew. United States has faced a high deforestation rate in the past with the national average rate of 0.38 million ha/year (FAO, 2016), but its primary driver continues to be the expansion of agricultural land, facilitated by greater mechanization.

Within the contiguous United States, the southern region has faced high deforestation rates in particular due to urbanization and demand for commercial agriculture. The dominant land use and land cover types in this region are forest (including forested upland and woody wetlands), agricultural land (including cropland and hay/pasture), and developed areas (Zhao et al., 2013). Land use conversion from forest to agricultural land is increasing in Georgia (Wear & Greis, 2013). For instance, landowners are replacing forestlands with blueberries in southern Georgia (Wear and

Greis., 2013). The initial data analysis shows that about 15,000 ha of forest and pasture/hay land have been converted into blueberries between 2010 and 2017 (USDA, 2018). This is also evident from the fact that Georgia is the largest producer of blueberries in the United States, as it produced about 16% of the total blueberry crop in 2014 nationwide (Georgia Info, 2015).

1.2 Sustainability and Land Use Change

Land use change is central to the sustainability debate: it is a primary driver of global environmental change (Huber, Bugmann, Buttler, & Rigling, 2013; Turner, Lambin, & Reenberg, 2007). The need for managing environmental resources has become a political agenda in the most developed countries of the world since the Stockholm Conference in 1972. The awareness was raised to its peak at the Rio Earth Summit in 1992 by the global action programme on sustainability-Agenda 21 (Nwokoro & Dekolo, 2011). The concept of sustainable development has since moved from the environmental conservationist paradigm to a holistic model which seeks to deliver basic environmental, social and economic services to all residents of the community without threatening the viability of the natural, built, and social systems upon which the delivery of these services depends (Giddings, Hopwood, & O'Brien, 2002). Lange et al. (2015) explained that sustainability considers the following three dimensions that are closely inter-linked and between which trade-offs are inevitable.

Environmental Dimension: The environmental dimension of sustainability generally deals with maintaining the stock of natural resources above certain thresholds. It included biodiversity preservation, monitoring resources depletion, ensuring non-renewable resources are preserved for the future generation and minimizing environmental impact.

Economic Dimension: This dimension of sustainability ensures a steady and continuous stream of income for everyone and at different levels. It also ensures increased food availability, real income, and cash. There is a thrust to increase food production and real income, promote efficient investment through cost/benefit analysis, maintain productivity at all times and derive real benefits from land management.

Social Dimension: This dimension of sustainability aimed at ensuring equitable access to resources, information, and services. It also protects acquired rights to land and promotes active stakeholders' participation in law and policy development. Sustainability also ensures redistribution of wealth derived from land resources, while ensuring accountability and proper management of land resource benefits and integrating environment and development considerations in decision-making.

Moreover, due to the overwhelming importance of land use decisions in achieving sustainable development, Agenda 21 of United Nations Sustainable Development affirmed that land use planning was essential in achieving an integrated approach to planning and management of land resources (United Nations, 2019). Similarly, maintaining and restoring land resources can play a vital role in achieving many of Sustainable Development Goals (SDGs). Developing local strategies for improving the quality of the environment and integrating decisions on land use and land management requires that alternative, and congruent land-use management strategies and policies be identified (Huber et al., 2013). These strategies and policies should support both the provisions of ESs and the economic viability of the regions (de Groot et al., 2010). Thus, management and policy alternatives that support the provisions of ESs in this region should not only be economically and ecologically efficient but also socially acceptable.

Forest ecosystems provide a variety of important goods and services for humans such as food, timber, fresh water (Foley et al., 2005). These ecosystems, however, are highly sensitive to LUCs. Consequently, the provision of ESs is very likely to change in the future due to land use change. The analysis of the LUCs dynamics and its impacts on the provision of ESs requires complex system approaches in which both environmental and social dynamics are studied over a range of spatial and temporal scales. Only integrated, multi-disciplinary research, in combination with dedicated disciplinary research on individual processes and mechanisms, can provide the kind of information needed to understand complex systems and to address interlinked environmental and social problems (Carpenter et al., 2009).

1.3 Integrative Framing

Land use is one of the most closely related links between human beings and nature. Changes in land use will inevitably lead to changes in ecosystem structure and services (de Groot et al., 2010). The relationship between LUCs, ESs, and human well-being is complex and influenced by multiple factors and drivers and operates across multiple spatial and temporal scales. Effective conservation to obtain sustainability in coupled human and natural systems requires the understanding of how actions (here land use change and land management practices) will affect ecological processes, economic output and stakeholder’s views. As a result, exploring this interconnectedness and complexity is not an easy task. Various approaches addressing the complexity of land use systems have been proposed, and the tradition of research on human-nature interactions is emerging (Huber et al., 2013). Integrative research is generally seen as the key to overcoming fundamental problems in the analysis of such complex systems (Carpenter et al., 2009; Millenium Ecosystem Assessment, 2005).

Integrative conservation research is a research approach which is conducted primarily by crossing the boundaries between disciplines and other epistemologies. This approach can add understanding to the environmental, economic, and social context of land use change and its dynamics. This dissertation adopted an integrative approach to obtain the objectives of the research. As being integrative is more than being multidisciplinary, we crossed disciplinary lines and epistemologies to give a more space to understand complex issues related to land use change from multiple perspectives.

This research was complex in nature and contained all three dimensions of sustainability and so approaching it through a single epistemological lenses would not have provided better solutions. Instead, we combined methods from economics, geography, social and natural sciences, which fulfills the core principles of integrative research which is complexity, pluralism, and context was used (McShane et al., 2011). We used economic, and biophysical analysis at the landscape scale. The results of these analyses to narrow down the ecological analysis (LUCs dynamics and its impacts on ESs) at the watershed level was explicitly linked. Later, these ecological and economic analyses were linked to understand the motivation of landowners' decisions of land use change at the regional scale.

This led to three distinct, but interrelated chapters that represent the broader integrative objective of this research: Understanding the distinct spatiotemporal patterns of LUCs and the complexity of, and relationships among environmental, social and economic factors in order to continue the multifunctionality of the landscape for sustaining ESs in the context of deforestation. The chapters address the following questions:

1. How the economics of forests and blueberries differ and how much area is potentially suitable for blueberry production?
2. How evolving land use affects the ecosystem services at the watershed level?
3. What are the typologies of blueberry farmers in the context of changing land use from forests to blueberries?

These three distinct, but interrelated chapters were constructed through collaboration among the different disciplines to address three main dimensions of sustainability, i.e., environmental, economic and social. The methods and analyses used to investigate these questions are reviewed in more detail in the methods and objectives section of each chapter individually.

1.4 Strategic Communication

It is clearly established that knowledge about ESs, values, and landscape management should be clearly communicated, and made readily available to policymakers, stakeholders, and the general public (de Groot et al., 2010). Effective communication is crucial to disseminate research findings. With this in mind, since the start of this project, we have been involved in communicating with different stakeholders as much as possible. de Groot et al. (2010) suggested that the internet is an ideal medium of strategic communication as several interesting application are being developed, and it possesses the ability to reach out to multiple audiences at one. As de Groot et al. (2010) suggested, we used the internet to reach out to landowners and communicate our research and results. We designed a dedicated webpage (http://surajupadhaya.com/projects/) to disseminate the information from my research to a wider audience. It has been already visited more than 700 times.

Similarly, we used social media (Facebook page https://www.facebook.com/standforforest/) to reach out to different stakeholders to disseminate our research results and create awareness on conservation. Also using social media, we are establishing regular communication with blueberry growers and landowners. This allows us to share updates and new results from our research directly with the landowners.

In an effort to further disseminate our work, we presented our results in several conferences and symposiums during my time as a Ph.D. student at the UGA. We presented our results of economic analysis of growing blueberries and pine at 2016 meeting of the International Society of Forest Resources and Economics (ISFRE) held in Raleigh, North Carolina. We also presented our research and its results at Symposium on Integrative Conservation (SIC) organized by the ICON Network & Cooperative (OINC), Warnell Graduate Student Symposium organized by Graduate Student Association of Warnell School of Forestry and Natural Resources, and 3rd Annual UGA Sustainability Science Symposium, Athens. Presenting at these different conferences and symposiums helped us to create awareness within the academic community about ongoing deforestation in Georgia. Also, their feedback and suggestions were helpful in making this dissertation more effective.

To reach out to wider forestry professionals and landowners who are the major stakeholders of sustainable land management, I presented my research at the Society of American Foresters (SAF) Conference held on 2017 at Albuquerque, New Mexico. We additionally submitted an article synthesizing the results of our research to get published in Online Athens.

1.5 Study Site

This dissertation research is multi-scalar, extending from regional to the local. Chapters 2 and 4 focus on the southeastern region of Georgia, particularly District Five of the Georgia Forestry Commission, a state agency responsible for protection and conservation of Georgia's forest resources. Chapter 3, focused on the Alabaha River Watershed (USGS Gauge 02227270, HUC 8-03070201) which is located in southern Georgia's Lower Coastal Plains. This watershed lies within the Satilla River Basin covering about 985 km^2 out of which blueberry, deciduous forests, evergreen forests, pasture/hay, agriculture, woody wetlands, and water bodies occupied 8%, 9%, 23%, 15%, 25%, 12%, and 2% of total land in 2015, respectively. Due to the variation in precipitation and temperature the area is rich in biodiversity and is home to several threatened wildlife species such as the red-cockaded woodpecker (*Picoides borealis*) and the gopher tortoise (*Gopherus Polyphemus*). The area is notable because of its mixture of federal, state, industrial and nonindustrial private forestlands. The selected region is ideal for a land use change study. Southeastern Georgia has changed significantly from a single dominant land use, loblolly/slash/longleaf pine forest to include large blueberry farms. The area is a major producer of blueberries and accounts for 97% of all blueberry plants in the state (Fonsah et al., 2013). Additionally, the area is home to a large number of wood products mills. Certain parts of the area (such as Valdosta of Lowndes County, and Waycross of Ware County) are urbanized. The study area encompasses a wide range of forest ownership, urban growth trends, wood utilization types-typical characteristics of the southeastern United States.

References

Carpenter, S. R., Mooney, H. A, Agard, J., Capistrano, D., Defries, R. S., Diaz, S., and Whyte, A. (2009). Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences of the United States of America, 106(5), 1305–1312. https://doi.org/10.1073/pnas.0808772106,

Corbin, J. D., & D'Antonio, C. M. (2004). Competition between native perennial and exotic annual grasses:implications for an historical invasion. Ecology, 85(5), 1273–1283. https://doi.org/10.1890/02-0744

Costanza, K. J., Abt, R. C., McKerrow, A. J., & Collazo, J. A. (2017). Bioenergy production and forest landscape change in the southeastern United States. GCB Bioenergy, 9(5), 924–939. https://doi.org/10.1111/gcbb.12386

de Groot, R. S., Alkemade, R., Braat, L., Hein, L., & Willemen, L. (2010). Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecological Complexity, 7(3), 260–272. https://doi.org/10.1016/j.ecocom.2009.10.006

FAO. (2016). Global Forest Resources Assessment 2015: how are the world's forest changing? FAO Forestry Paper No. 1 (Second). Rome: FAO. Retrieved from http://www.fao.org/forest-resources-assessment/current-assessment/en/

Fearnside, P. M. (2000). Global warming and tropical land-use change: Greenhouse gas emissions from biomass burning, decomposition and soils in forest conversion, shifting cultivation and secondary vegetation. climatic change, 46(1), 115–158. https://doi.org/10.1023/A:1005569915357

Fitzpatrick, F. a., Knox, J. C., & Whitman, H. E. (1999). Effects of Historical land-cover changes on flooding and sedimentation, North Fish Creek, Wisconsin. USGS Water-Resources Investigations, (June), 1–12.

Foley, J. a, Defries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., … Snyder, P. K. (2005). Global consequences of land use. Science (New York, N.Y.), 309(5734), 570–574. https://doi.org/10.1126/science.1111772

Fonsah, E. G., Massonnat, J., Wiggins, L., Krewer, G., Stanaland, D., & Smith, J. E. (2013). Southern highbush blueberry marketing and economics (No.1413), UGA Cooperative Extension Bulletin, (UGA Cooperative Extension Bulletin No. 1413). Athens, GA.

Georgia Info. (2015). Economy - Blueberries. Retrieved August 16, 2016, from http://georgiainfo.galileo.usg.edu/topics/economy/article/blueberries

Gibbs, H. K., Rueschb, A. S., Achard, F., Clayton, M. K., Holmgren, P., Ramankutty, N., & Foley, J. A. (2010). Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. PNAS, 107(38), 16732–16737. https://doi.org/10.1073/pnas.0910275107

Giddings, B., Hopwood, B., & O'Brien, G. (2002). Energy, environment, economy, and society: Fitting them together into sustainable development. Sustainable Development, 10, 187–196. https://doi.org/10.1002/sd.199

Houghton, R A, Goodale, C. L. (2004). Effects of land-use change on the carbon balance of terrestrial ecosystems. Ecosystems and Land Use Change Geophysical Monograph, 153, 85–98. https://doi.org/10.1029/153GM08 85

Huber, R., Bugmann, H., Buttler, A., & Rigling, A. (2013). Sustainable land-use practices in European mountain regions under global change: An integrated research approach. Ecology and Society, 18(3). https://doi.org/10.5751/ES-05375-180337

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. Annual Review of Environment and Resources, 28, 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459

Lange, A., Siebert, R., & Barkmann, T. (2015). Sustainability in land management: An analysis of stakeholder perceptions in Rural Northern Germany. Sustainability, 7(1), 683–704. https://doi.org/10.3390/su7010683

Laurance, W. F., Sayer, J., & Cassman, K. G. (2014). Agricultural expansion and its impacts on tropical nature. Trends in Ecology and Evolution, 29(2), 107–116. https://doi.org/10.1016/j.tree.2013.12.001

Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C.,and Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. Proceedings of the National Academy of Sciences, 111(20), 7492–7497. https://doi.org/10.1073/pnas.1405557111

McShane, T. O., Hirsch, P. D., Trung, T. C., Songorwa, A. N., Kinzig, A., Monteferri, B., … O'Connor, S. (2011). Hard choices: Making trade-offs between biodiversity conservation and human well-being. Biological Conservation, 144(3), 966–972. https://doi.org/10.1016/j.biocon.2010.04.038

Meyer, B., & Turner II. (1992). Human population growth and global land-use / cover change. Annual Review of Ecology and Systematics, 23(1992), 39–61. https://doi.org/10.2307/2097281

Millenium Ecosystem Assessment. (2005). Ecosystems and human well-being: Synthesis. Ecosystems. Washington D: Island Press. https://doi.org/10.1196/annals.1439.003

Morales-Hidalgo, D., Oswalt, S. N., & Somanathan, E. (2015). Status and trends in global primary forest, protected areas, and areas designated for conservation of biodiversity from the Global Forest Resources Assessment 2015. Forest Ecology and Management, 352, 68–77. https://doi.org/10.1016/j.foreco.2015.06.011

Morton, D. C., DeFries, R. S., Shimabukuro, Y. E., Anderson, L. O., Arai, E., del Bon Espirito-Santo, F., … Morisette, J. (2006). Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. Proceedings of the National Academy of Sciences of the United States of America, 103(39), 14637–14641. https://doi.org/10.1073/pnas.0606377103

Nwokoro, I. I. C., & Dekolo, S. O. (2011). Land use change and environmental sustainability: The case of Lagos Metropolis. WIT Transactions on Ecology and the Environment, 155, 157–167. https://doi.org/10.2495/SC120141

Polasky, S., Nelson, E., Pennington, D., & Johnson, K. A. (2011). The impact of land-use change on ecosystem services, biodiversity and returns to landowners: A case study in the state of Minnesota. Environmental and Resource Economics. https://doi.org/10.1007/s10640-010-9407-0

Sala, O. E., Chapin III, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., … Wall, D. H. (2000). Global biodiversity scenarios for the year 2100. Science, 287, 1770–1774. https://doi.org/10.1126/science.287.5459.1770

Shaw, S. B., Marrs, J., Bhattarai, N., & Quackenbush, L. (2014). Longitudinal study of the impacts of land cover change on hydrologic response in four mesoscale watersheds in New York State, USA. Journal of Hydrology, 519(PA), 12–22. https://doi.org/10.1016/j.jhydrol.2014.06.055

Sleeter, B. M., Sohl, T. L., Loveland, T. R., Auch, R. F., Acevedo, W., Drummond, M. A., … Stehman, S. V. (2013). Land-cover change in the conterminous United States from 1973 to 2000. Global Environmental Change, 23(4), 733–748. https://doi.org/10.1016/j.gloenvcha.2013.03.006

Sohl, T., Reker, R., Bouchard, M., Sayler, K., Dornbierer, J., Wika, S., … Friesz, A. (2016). Modeled historical land use and land cover for the conterminous United States. Journal of Land Use Science, 11(4), 476–499. https://doi.org/10.1080/1747423X.2016.1147619

Song, X. P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. Nature, 560(7720), 639–643. https://doi.org/10.1038/s41586-018-0411-9

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. Proc Natl Acad Sci USA, 104(52), 20666–20671.

Turner, B. L., Meyer, W. B., & Skole, D. L. (1994). Global land-use land-cover change - towards an integrated study. Ambio, 23(1), 91–95. https://doi.org/10.2307/4314168

United Nations. (2019). Sustainable development goals. Retrieved March 7, 2019, from https://sustainabledevelopment.un.org/sdgs

Upadhaya, S., & Dwivedi, P. (2019). The role and potential of blueberry farming in increasing deforestation in southern Georgia, United States. Agricultural Systems, 173(August 2018), 39–48. https://doi.org/10.1016/j.agsy.2019.01.002

USDA National Agricultural Statistics Service Cropland Data Layer. (2018). Published crop-specific data layer. Retrieved August 20, 2018, from https://nassgeodata.gmu.edu/CropScape/

Vitousek, P. M. (1994). Beyond global warming: ecology and global change. Ecology, 75(7), 1861–1876.

Wear, D. N., & Greis, J. G. (2013). The Southern forest futures project: technical report. Gen. Tech. Rep. SRS-GTR-178, 178, 1–152. Asheville, NC https://doi.org/10.1017/CBO9781107415324.004

Wear, D. N., Joyce, L. A., Butler, B. J., Gaither, C. J., Nowak, D. J., & Stewart, S. I. (2014). Climate change and United States forests. In D. L. Peterson, J. M. Vose, & T. Patel-Weynand (Eds.), Climate Change and United States Forests (pp. 93–112). Springer Netherlands. https://doi.org/10.1007/978-94-007-7515-2

World, B. (2016). Why forests are key to climate, water, health, and livelihoods. Retrieved from http://www.worldbank.org/en/news/feature/2016/03/1

Zhao, S., Liu, S., Sohl, T., Young, C., & Werner, J. (2013). Land use and carbon dynamics in the southeastern United States from 1992 to 2050. Environmental Research Letters, 8, 044022. https://doi.org/10.1088/1748-9326/8/4/044022

Zhao, S., Peng, C., Jiang, H., Tian, D., Lei, X., & Zhou, X. (2006). Land use change in Asia and the ecological consequences. Ecological Research, 21(6), 890–896. https://doi.org/10.1007/s11284-006-0048-2

CHAPTER 2

THE ROLE AND POTENTIAL OF BLUEBERRY FARMING IN INCREASING DEFORESTATION IN SOUTHERN GEORGIA, UNITED STATES[1]

[1]Upadhaya S, & Dwivedi, P. Accepted by [Agricultural Systems] Reprinted here with permission of publisher.

Abstract

Several studies have analyzed the social, economic, and environmental impacts of deforestation in the context of developing countries. However, no study, to the best of our knowledge, has focused directly on the role of expanding demand for agricultural commodities on deforestation in the context of developed countries, in general, and the United States, in particular. An integrative approach to understand the linkages between deforestation and agricultural expansion in Southeast (SE) Georgia where about 15,000 hectares of evergreen forestlands and grasslands have been converted to blueberries between 2010 and 2017 was used. An economic model was first developed to understand any differences in profitability between a hectare of pine plantation and blueberry farm. The economic analysis showed that the annualized net present value of blueberry production is higher by $3,848.0/ha than loblolly pine in the region. We developed a site suitability model using geospatial tools for blueberry production in SE Georgia as well and found out that about 85% of the available land is suitable for blueberry production in SE Georgia. Furthermore, about 80% of existing pine forestlands overlap with the land that is suitable for blueberry production. Our results indicated that a further rise in the demand for blueberries could increase deforestation in SE Georgia. An integrated approach based on innovative economic policies for reducing deforestation in SE Georgia is suggested.

Keywords

Economic Modeling; Geospatial Modeling; Site Suitability; Sustainable Development; Yellow Pines

2.1 Introduction

Forests cover about four billion hectares of the global land area and provide critical ecosystem services (ESs) for ensuring human welfare (FAO, 2016; Fearnside, 2000; Morales-Hidalgo et al., 2015). The global community has also recognized the importance of forests for sustaining local livelihoods (World Bank, 2016). However, recent data show that forest cover is continuously declining worldwide averaging 3.3 million ha/year between 2010 and 2015 (FAO, 2016; Keenan et al., 2015).

Agricultural expansion is the leading cause of deforestation (Kissinger et al., 2012; Song et al., 2018). In the near future, current forestlands are expected to face even greater pressures of deforestation as additional agricultural land will be needed for feeding rising human population (Dobrovolski et al., 2011; Tilman et al., 2001). Laurance et al. (2014) suggest that the coming era will be, in effect, an "agricultural bomb" with the remarkable magnitude and pace of land use and land cover change, in general, and deforestation, in particular. It is also argued that the rapid transformation of forestlands into other land cover classes will have profound challenges for environmental conservation and potentially, global human welfare in the coming decades.

The impacts of agricultural expansion on deforestation have been well studied in developing countries (Morton et al., 2006), but only a few studies have focused on deforestation in the context of developed countries. This is especially true in the context of the United States which has faced a high deforestation rate in the past at an average rate of 0.38 million ha/year (FAO, 2016). Within the United States, the southern region has faced the highest deforestation rate mostly due to the conversion of forestlands for agriculture and urban development purposes (Lawler et al., 2014;

Wear, 2013). Alig et al. (2003) reported that the southern region lost about five million hectares of forest cover between 1953 and 1997. Wear (2013) forecasted that forest cover in the southern United States would decline by 4.4 (7%) to 9.3 (13%) million hectares over the next 50 years to urbanization and agricultural expansion.

Higher profitability of crops is responsible for deforestation (Chakravarty et al., 2012). This is particularly true for the SE Georgia where landowners are converting their forestlands to blueberry (*Vaccinium spp.)* farms from past 20 years or so (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008). The analysis of the CropScape data shows that about 15,000 ha of evergreen forestlands and grasslands have been converted into blueberries between 2010 and 2017 in SE Georgia (Figure.2.1). This trend in land use change is further reflected in the fact that Georgia was annually producing only 2.3 to 4.5 thousand metric tons of blueberry in the 1990s while in 2014 alone, Georgia produced 43.5 thousand metric tons of blueberry and became number one blueberry state nationwide (Georgia Info, 2015).

Understanding the relationship between deforestation and agricultural expansion is key for defining actions needed to eliminate deforestation and maintaining the vitality of ESs provided by forestlands. In this regard, this study first evaluates the economics of blueberry production (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008), and compares the same with the economics of three yellow pine (loblolly (*Pinus taeda* L.), slash (*Pinus elliottii*, Engelm.), and longleaf (*Pinus palustris*, Mill.)) species typically planted by landowners in SE Georgia. The objective of the economic analysis was to ascertain differences across profitability between blueberry and yellow pines for developing targeted economic incentives for forest landowners in the region. Second, we developed an advanced geospatial model for understanding the spatial distribution of sites suitable for blueberry production in SE Georgia. The objective of the geospatial modeling was to ascertain the potential of blueberry expansion in the region in case the demand for blueberry increases further. Finally, we combined the results of our study for exploring the potential policy solutions which could help in reducing deforestation in SE Georgia.

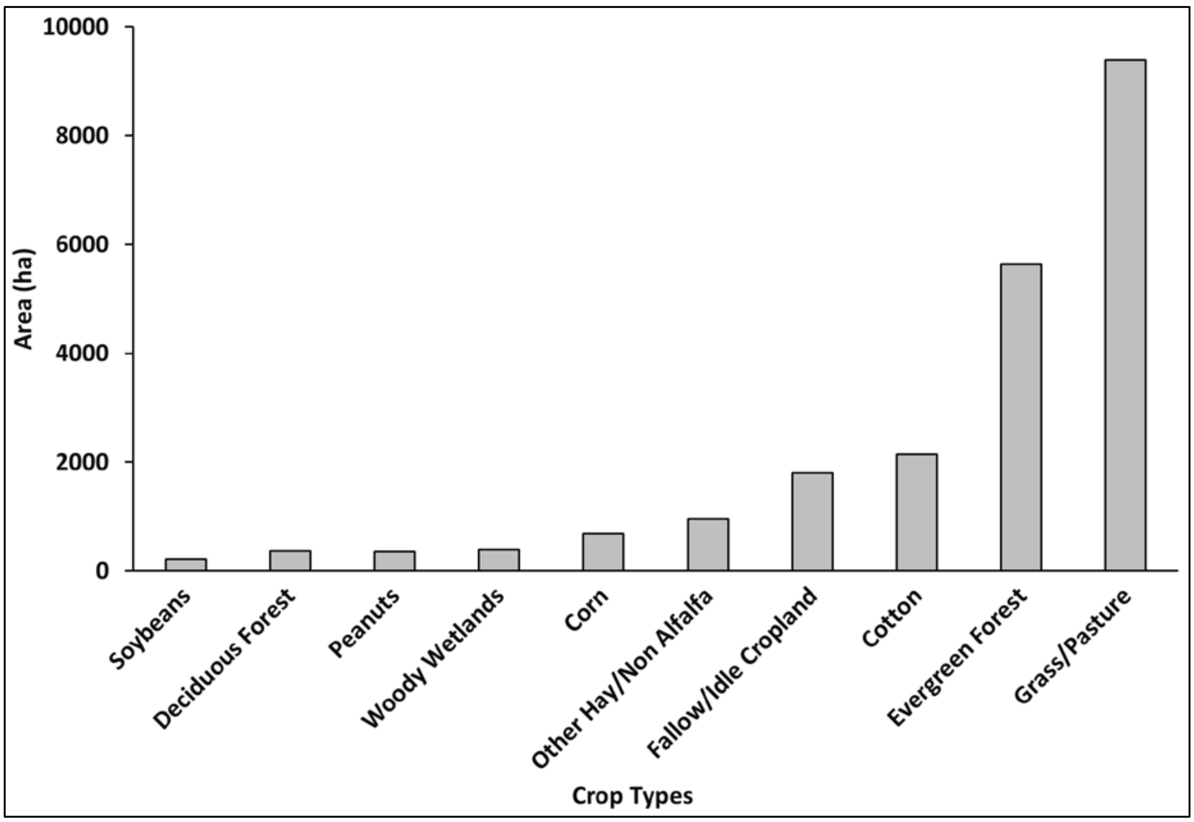


Figure 2.1. Conversion of different land covers to blueberry farms in SE Georgia between 2010 and 2017. (Source: USDA NASS Cropland Data Layer).

2.2 Theoretical Framework

The process of blueberry expansion can be modeled as a competition among land uses for the limited available land. Mendelsohn and Dinar (2009) suggested that one could model the demand for farmland (D_A) and the demand for forestland (D_F) given the supply of arable land (L). The decision variables are Q_A and Q_F:

$$Q_A=D_A\,(P_A,\ P_L,\ Z)$$

$$Q_F=D_F\,(P_F,\ P_L,\ Z)$$

$$Q_A+Q_F=L$$

where P_A is the price of agricultural products, P_F is the price of forest products, and Z represents population and income which is a set of demand shifting variables. When the price of agricultural products increases, the demand for agricultural land increases and the demand curve move outwards which leads to an increase in the amount of agricultural land at the expense of forestland. We modified this model and adapted to suit our research where an increase in the price of blueberries increases the demand for land for blueberry farms which can only be met at the expense of existing forestlands (Figure. 2.2).

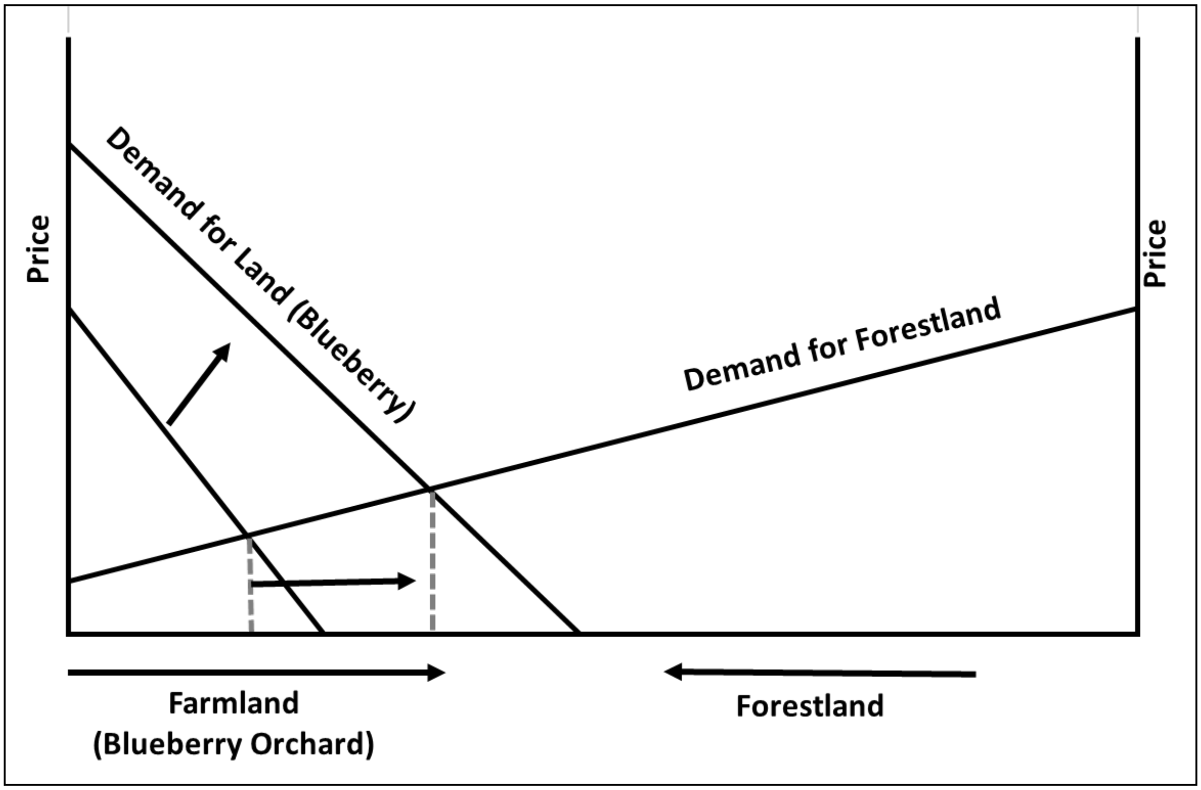


Figure 2.2. A theoretical framework describing the conversion of forestlands into blueberry farms.

2.3 Methods

We divided this section into six sub-sections. The first section gives details of the study area. The second and third section details growth and yield modeling for selected pine species and blueberry respectively. The fourth section discusses the tools used for profitability analysis for growing blueberries and yellow pines in the SE Georgia on per hectare basis. The fifth section describes the financial risk and sensitivity analysis. In the last section, we have provided details of the site suitability modeling for blueberry production.

2.3.1 Study Area

We selected SE Georgia for this study (Figure. 2.3). The selected region is a major producer of blueberries and accounts for 97% of all blueberry plants in Georgia (Fonsah et al., 2013). Additionally, the region is a major producer of roundwood products obtained from softwoods in Georgia. For example, the total inventory of softwood roundwood in Georgia was 616 million metric tons in 2014 out of which about 32% was in the selected region only (Brandeis et al., 2016). Furthermore, the area is rich in biodiversity, and home to several threatened species such as red-cockaded woodpecker (*Picoides borealis*) and gopher tortoise (*Gopherus Polyphemus*). Certain parts of the selected region (Valdosta of Lowndes County and Waycross of Ware County) are urbanizing at a rapid rate.

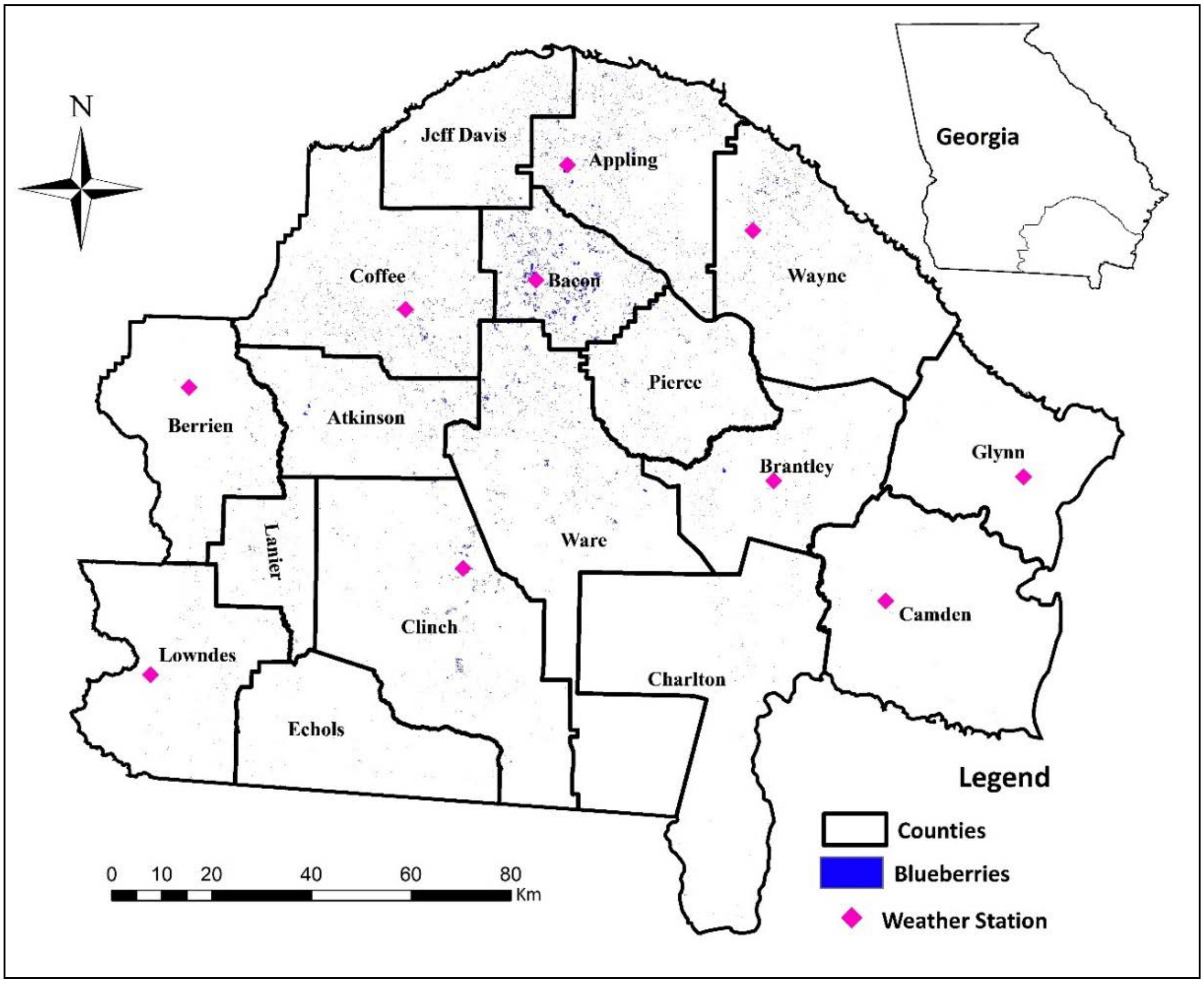


Figure 2.3. Map of the SE Georgia. County names are mentioned along with the location of weather stations. The location of blueberry farms is reported based on Cropscape 2015 data.

2.3.2 Growth and Yield of Yellow Pines

We used Simulator for Managed Stands (SiMS) 2009 for estimating growth and yield of loblolly, slash, and longleaf pines. SiMS is a whole-stand model and allows for projections starting from new or existing stands for a specific physiographical region and soil type (Henderson et al., 2013). We selected loblolly pine and slash pine in this study as these are popular plantation species in the southern United States (Baker and Langdon, 1990; Samuelson et al., 2012). We selected longleaf pine for the analysis as there is an interest in restoring longleaf pine for high-quality lumber, pine straw production, and ESs benefits such as biodiversity and carbon sequestration in the region (South, 2006). We defined three roundwood products (sawtimber, chip-n-saw, and pulpwood) obtained at the time of thinning and harvesting based on diameter at breast height (dbh) and top diameter (td). The portion of the stem between 30.5 cm (dbh) and 20.30 (td) was classified as sawtimber (ST). The portion of the stem between 22-28 cm (dbh) and 10.16 cm (td) was classified as chip-n-saw (CNS). The portion of the stem between 12.7 cm (dbh) and 5.08 cm (td) was classified as pulpwood (PW). We defined thinning (33% removal rate) at the 12th year of the plantation for loblolly and slash pines and the 20th year for longleaf pine. We raked straw between eighth and 12th years of the plantation for loblolly and slash pines between 12th and 20th years for longleaf pine. The major inputs of the growth and yield model were site index (SI) and initial planting densities. The site index was assumed as 21.36 m for loblolly and slash pines, and 12.19 m for longleaf pine at the 25th year of plantation. The planting density was constant for all the selected pine species at 1,495 trees/ha for comparison purposes. The use of fertilizers was presumed for loblolly and slash pines in the first, sixth, and 12th year of plantation. No fertilizer was applied in the case of longleaf pine. Herbicide was applied at year 2 for selected pine species.

2.3.3 Blueberry Yield

We collected blueberry yield data by reviewing the University of Georgia (UGA)’s extension publications (Fonsah et al., 2013), consulting with experts at the UGA’s College of Agricultural and Environmental Sciences, and by interviewing farmers. The trajectory of blueberry yields over a period of 12 years is shown in Appendix A. Based on our consultations with experts, farmers, and extension publications, we assumed that eight percent of the total blueberry yield was lost at the time of collection and the remaining was sold for the fresh market.

2.3.4 Profitability Evaluation

We applied three quantitative methods [Net Present Value (NPV), Annualized Net Present Value (ANPV), and Benefit Cost Ratio (BCR)] for evaluating the profitability of growing selected pine species and blueberry in the selected region.

NPV is used to estimate the net benefit over the lifetime of a project. It is expressed as:

$$NPV = \sum_{t=1}^{n} \frac{C_t}{(1+I)^t}$$

where, C_t = cost in each year, t = a total number of years, and I = discount/interest rate. Projects are considered financially feasible when the NPV is greater than \$ 0.

The ANPV is regarded as an efficient approach as it converts NPVs of mutually exclusive projects with unequal duration into an annualized present value of each specific project. ANPV gives the equivalent net present value at the same discount rate (Godsey, 2010) and is expressed as:

$$ANPV = \frac{\text{NPV}}{\frac{1-(1+I)^{-t}}{I}}$$

where NPV = Net Present Value of Project, I = discount/interest rate, t = a total number of years.

The BCR of the project is the present value of benefits (revenues) divided by the present value of costs expressed as:

$$BCR = \frac{\sum_{t=1}^{n} \frac{Bt}{(1+I)^t}}{\sum_{t=1}^{n} \frac{Ct}{(1+I)^t}}$$

where B_t = benefit in each year, C_t = cost in each year, t = a total number of years, and I = discount/interest rate.

We used 2017 Timber Mart-South average prices of the round wood products (ST: $30.04/metric ton, CNS: $22.90/metric ton, PW: $15.87/metric ton) for the Georgia Region 2 to compute NPV, ANPV, and BCR. Along with the income from the major round wood products, we also considered incomes by selling pine straw ($0.4/bale for loblolly and slash pine and $0.7/bale for longleaf pine) and hunting lease ($29.7/ha/year). Costs related to silvicultural activities are described in Table 2.1. The blueberry valuation criteria are based on traditional costs, yields, and price estimates (Appendix B). We interviewed blueberry growers to obtain the current market and input price of blueberries. The revenue and marketing costs were calculated assuming that farmers will sell in the fresh market as it fetches higher prices than a frozen market. For the valuation, we used the real discount rate of six percent for selected pine species and blueberry.

Table 2.1. Costs related to silvicultural activities for management of selected yellow pine species.

Activity	**Loblolly Pine ($/ha)**	**Slash Pine ($/ha)**	**Longleaf Pine ($/ha)**
Annual Management Fee	24.7	24.7	24.7
Site Preparation and Planting (year 0)	1,019.8	1,019.8	1,271.8
Herbicide	135.9	135.9	135.9
Fertilization	766.0	704.2	0
Total Cost	1,946.4	1,884.6	1,432.4

2.3.5 Financial Risk and Sensitivity Analysis

The profitability of growing pine and blueberry is based on the expected cash flows. However, the main determinants of expected cash flows are inherently uncertain in nature. For example, a change in real discount rate, variation in prices, and uncertain yields could affect expected cash flows. Given the uncertainties in the expected cash flow, the choice to invest in either pine or blueberry is based on the risk related such investments (Simões et al., 2016). Therefore, we performed risk analysis using the stochastic Monte Carlo simulation method with 1,000 iterations, implemented in the MS Excel® with the assistance of the @Risk software (Copyright © 2014 Palisade Corporation, Ithaca, USA). We analyzed the impact of changes in the discount rate, prices ($/kg for blueberry, $/metric ton for round wood products, and $/bale for pine straw) and income from hunting lease on risks and sensitivity associated with NPV. We used the Triangular probability distribution to describe the input variables of the discount rate, prices, and hunting lease for the risk analysis. This distribution has a central peak, which represents the most likely value, and endpoints represent minimum and maximum. This distribution is commonly used in risk analysis when there is no reliable information about the probability distribution of the variables (Simões et al., 2016). We analyzed the sensitivity of NPV with varying prices and discount rates. We used the variant of ±10% for prices, and hunting lease and ±2 % for the discount rate.

2.3.6 Blueberry Production Suitability Mapping

We developed an advanced geospatial model in ArcGIS for determining the suitability of blueberry production. The pertinent factors for suitability mapping were identified using the information from interviews with scientists at UGA's College of Agricultural and Environmental Sciences, interviewing blueberry farmers, and desk research. The factors identified were climate (chilling hours), soil (soil pH, soil permeability, and soil drainage), and land cover. A continuous raster of chilling hours for the entire study area was created using the Inverse Distance Weighted (IDW) techniques. We used the average chilling hour data of each station as the Z-value field to create a chilling hour raster. The 2016 Gridded Soil Survey Geographic Database (gSSURGO) was downloaded from the geospatial data gateway of the Natural Resources Conservation Service (NRCS, 2016). Using the 'Map Soil Properties and Interpretation' tool in ArcMap, three separate maps of soil drainage, permeability, and soil pH were prepared. These soil layer attributes were used as conversion fields to develop individual raster layers of 30 m resolution. The resulting four continuous criteria rasters were rescaled into comparable units (1-3) using the near transformation function available within Rescale by Function tool in ArcGIS. This function is appropriate for situations where the highest preference is near a specific value as is the case with our data - more than 600 chilling hours (area with less than 600 chilling hours were not suitable), pH ranging between 4.4 and 5, and well-drained soil with the permeability of 15-50 cm/hour. Once the criteria were rescaled to the same units, we used the Reclassify tool to reclassify them as low, medium, and high suitability. The reclassified criteria rasters were overlaid using the spatial tool, Weighted overlay in ArcGIS 10.3.1 to prepare the suitability map. For the weighted overlay, we gave equal weights to each criterion. The present land cover map and the suitability map for blueberry were then overlaid to mask developed/urban, public lands, and for identifying pine forestlands that met the suitability criteria. The workflow of the suitability model is shown in Figure. 2.4.

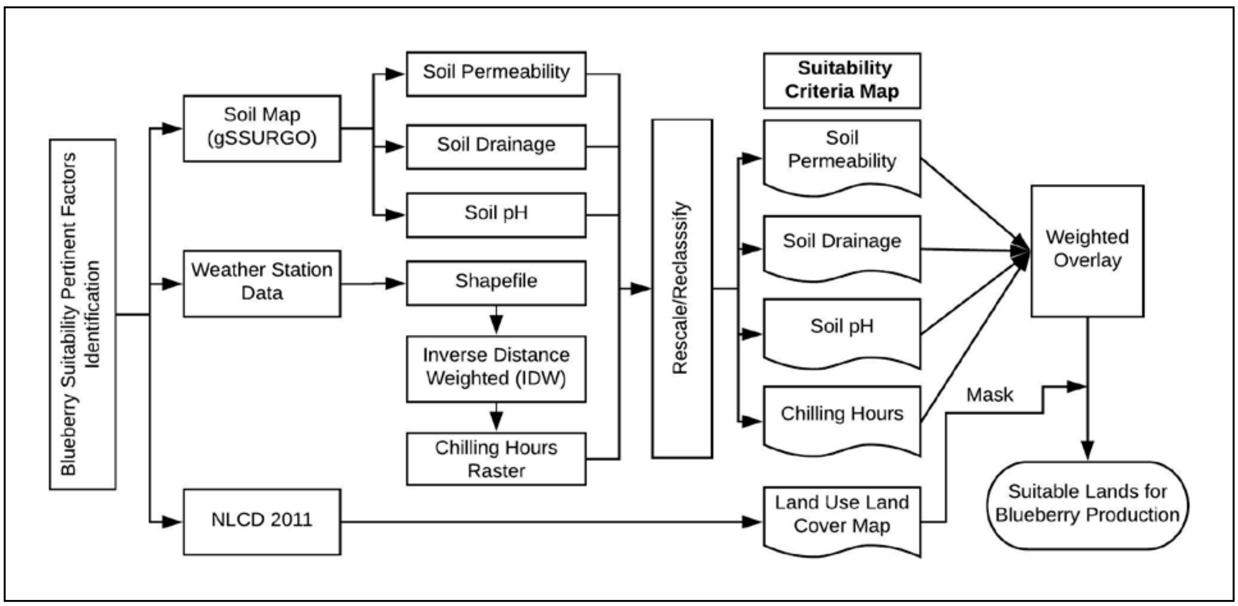


Figure. 2.4. A flowchart illustrating the blueberry site suitability modeling.

2.4 Results

2.4.1 Profitability

Using the six percent discount rate and 12 years of the production cycle, the NPV for a hectare of blueberry was $34,437.8 (Table 2.2). The NPVs of loblolly, longleaf, and slash pines were $3,053.6, $1,1761.4, and $2,072.9, respectively. The ANPV of blueberry was higher than that of three selected pines by a vast margin, although the BCRs for pines were higher than blueberry

(Table 2.2). The NPV, ANPV, and BCR were highest at the plantation age of 21 years for loblolly pine, 22 years for slash pine, and 26 years for longleaf pine (Table 2.2).

Table 2.2. Net Present Value (NPV), Annualized Net Present Value (ANPV), and Benefit Cost Ratio (BCR) for blueberry and selected pine species. Each project is of different time periods.

	Rotation (Years)	**NPV (\$ ha^{-1})**	**ANPV (\$ ha^{-1})**	**BCR**
Loblolly Pine	21	\$3,053.6	\$259.6	1.9
Longleaf Pine	26	\$1,761.4	\$135.4	1.1
Slash Pine	22	\$2,072.9	\$172.1	1.6
Blueberry	12	\$34,437.8	\$4,107.6	1.1

2.4.2 Financial Risk and Sensitivity Analysis

The simulated NPV for loblolly pine was highest among the selected pine species with a minimum of \$1,919.30 and maximum of \$4,800.16 ha^{-1} (Figure. 2.5). The range of simulated NPV for blueberry showed that there exists an 11.8 % probability of getting a negative NPV while with all selected pine species, this probability was zero (Figure. 2.5 and Figure. 2.6). The simulated ANPV showed that the investment on blueberry might return the adverse return while investment on any pine crops will be profitable, but the difference in ANPV between blueberry and other pine crops was high (Figure. 2.6 and Figure. 2.7).

We used Spearman's rank-order correlation to identify the correlation of the input variables on the NPV of a hectare of selected pine species plantations and blueberry farms. Figure 2.8 shows that the price (\$/kg) of the blueberry had a significant positive correlation with the NPV. The discount rate for the loblolly pine had a significant negative correlation with the NPV. The condition was identical with blueberry but with a lower magnitude. The discount rate for all selected pine species had a significant negative correlation with the NPV and price had a positive correlation with the NPV (Figure. 2.8). As expected, the NPV of blueberry increased with an increase in the blueberry price (Table 2.3). The decrease in price with the base discount rate decreased the NPV (Table 2.3). Among three pine species, NPV from longleaf pine was highly sensitive to the price of pine straw while slash pine was more sensitive to the income from hunting lease (Figure. 2.8 and Table 2.3).

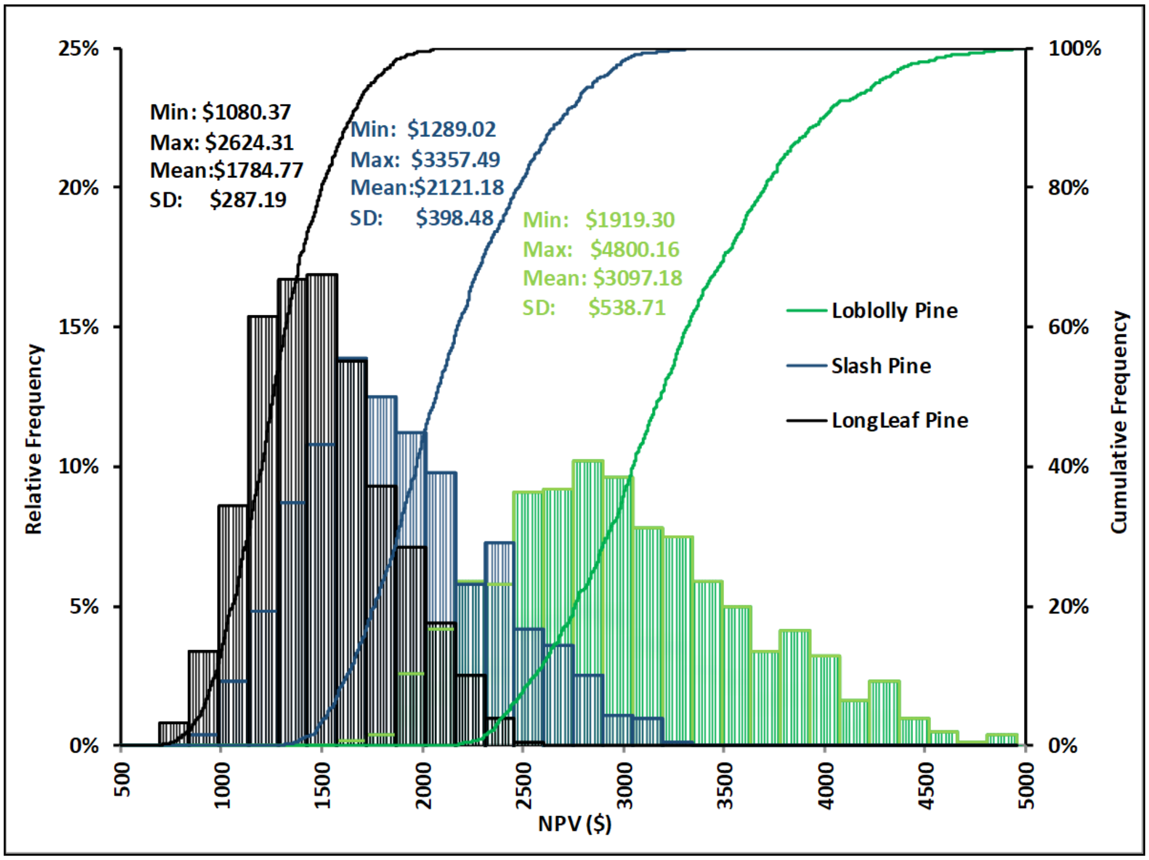


Figure 2.5. Relative distribution and cumulative frequency of simulated NPV for loblolly, slash, and longleaf pines.

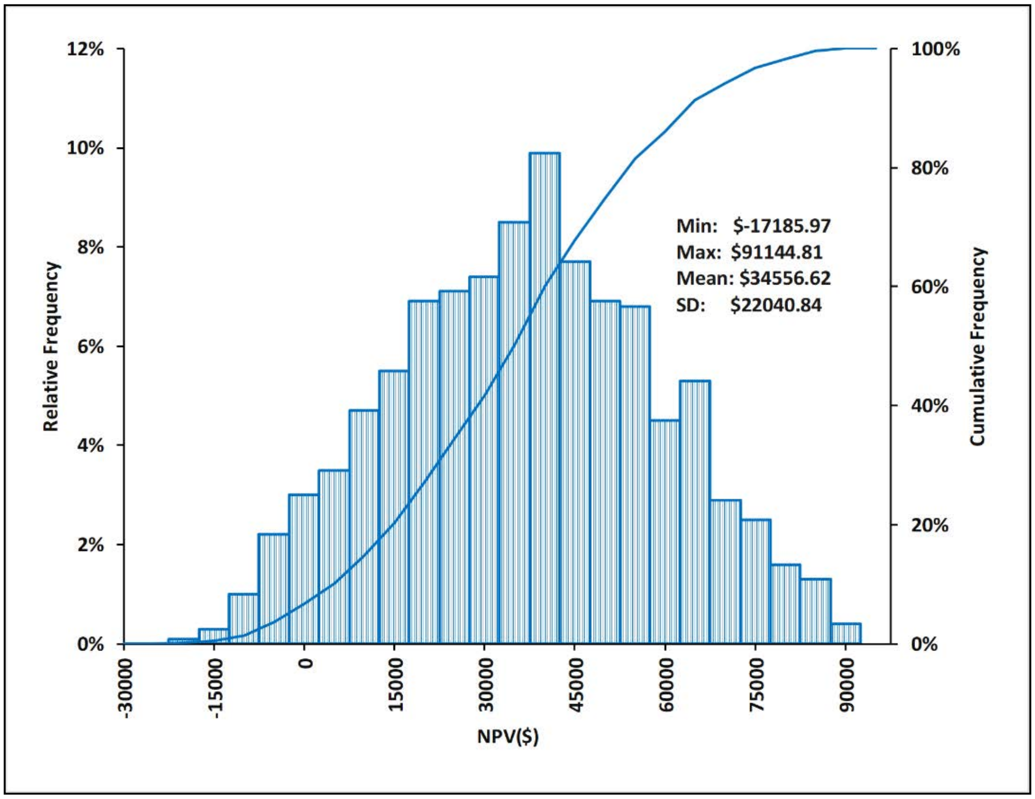


Figure 2.6. Relative distribution and cumulative frequency of simulated NPV for blueberry.

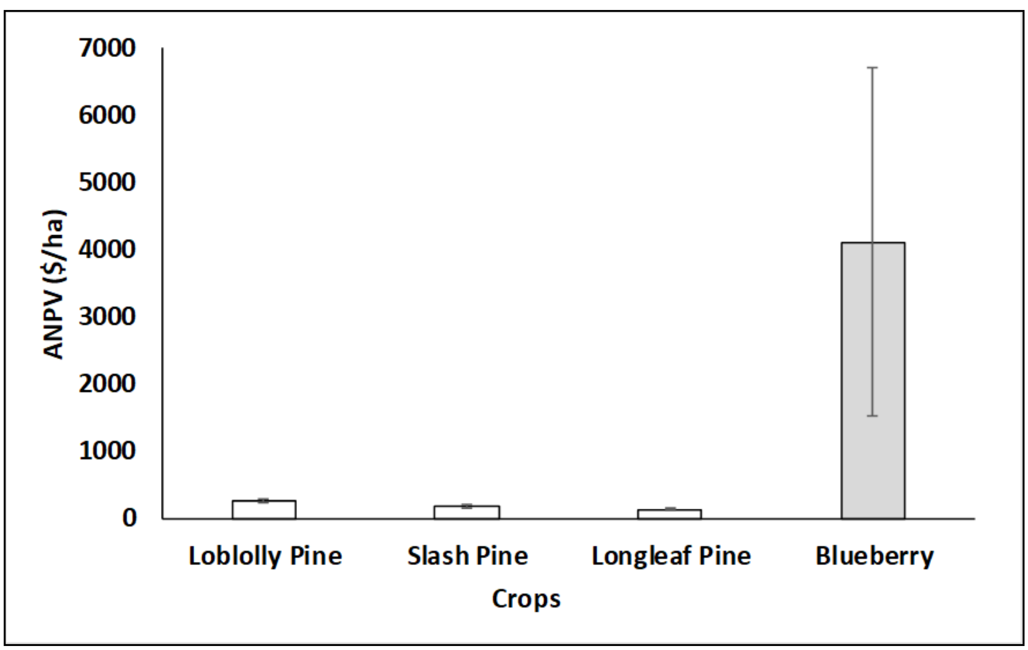


Figure 2.7. The mean and standard deviation of the simulated (n=1000) annualized net present value (ANPV) of the investment for three different pine species (longleaf, loblolly, and slash) and blueberry.

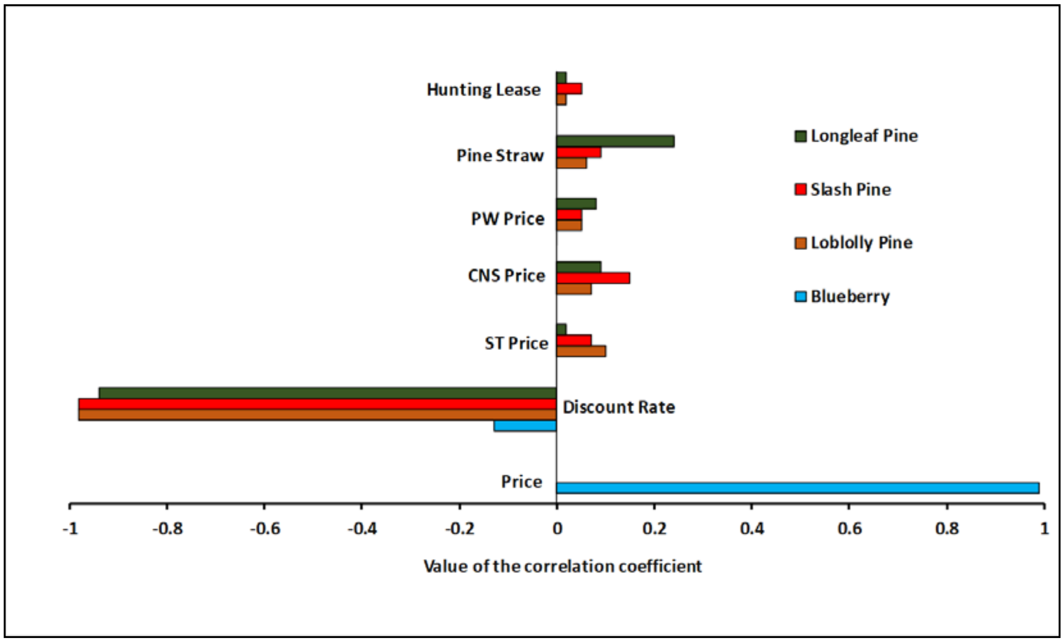


Figure 2.8. Spearman's rank-order correlation coefficient of the critical input variables [pulpwood (PW) price, chip-and-saw (CNS) price, saw timber (ST) price, discount rate, and blueberry price] in relation to the simulated NPVs of selected pine species and blueberry.

Table 2.3. Sensitivity analysis for selected pine species and blueberry price and discount rate changes. Base scenarios represent Net Present Value (NPV) obtained by farmers from different land use practices (pine plantation and blueberry production) in SE Georgia.

Crops	**Base**	**Scenarios**							
		Discount Rate		**Price**		**Pine Straw Price**		**Hunting Lease**	
	Base	**4%**	**8%**	**10%**	**-10%**	**10%**	**-10%**	**10%**	**-10%**
Loblolly Pine	$3,053.6	$4,771.5	$2,046.3	$3,412.9	$2,694.2	$3,157.6	$2,949.5	$3,088.4	$3,018.7
Longleaf Pine	$1,761.4	$2,659.8	$1,231.5	$1,860.3	$1,662.5	$1,971.5	$1,551.3	$1,800.0	$1,722.9
Slash Pine	$2,072.9	$3,349.0	$1,373.6	$2,331.0	$1,814.9	$2,177.0	$1,968.8	$2,109.3	$2,037.2
Blueberry	$34,437.8	$41,503.8	$28,455.4	$66,379.9	$2,495.7	-	-	-	-

2.4.3 Suitability Analysis

The low, medium, and high suitability classes occupied about 5251, 913,763, and 145,536 hectares representing about 1%, 85%, and 14% of the total available land area, respectively (Figure. 2.9).

Overlaying of existing land cover map and site suitability map for blueberries showed that about 80% of the existing pine forest was suitable for blueberry production in the study area (Figure. 2.10). About 69,610 ha of evergreen forest across 17 counties were under the high suitability category. Among these counties, Clinch county possessed the highest suitable area under evergreen forest with 8,171 hectares (Figure. 2.10 and Figure. 2.11). We also found that about 56,251 ha of pastures/hay land was under medium and high blueberry suitability. Similarly, 39,277 ha of cultivated land was highly suitable for blueberry production, and 18,210 ha of mixed forestland was either moderately or highly suitable for blueberry production (Figure. 2.10 and Figure. 2.11).

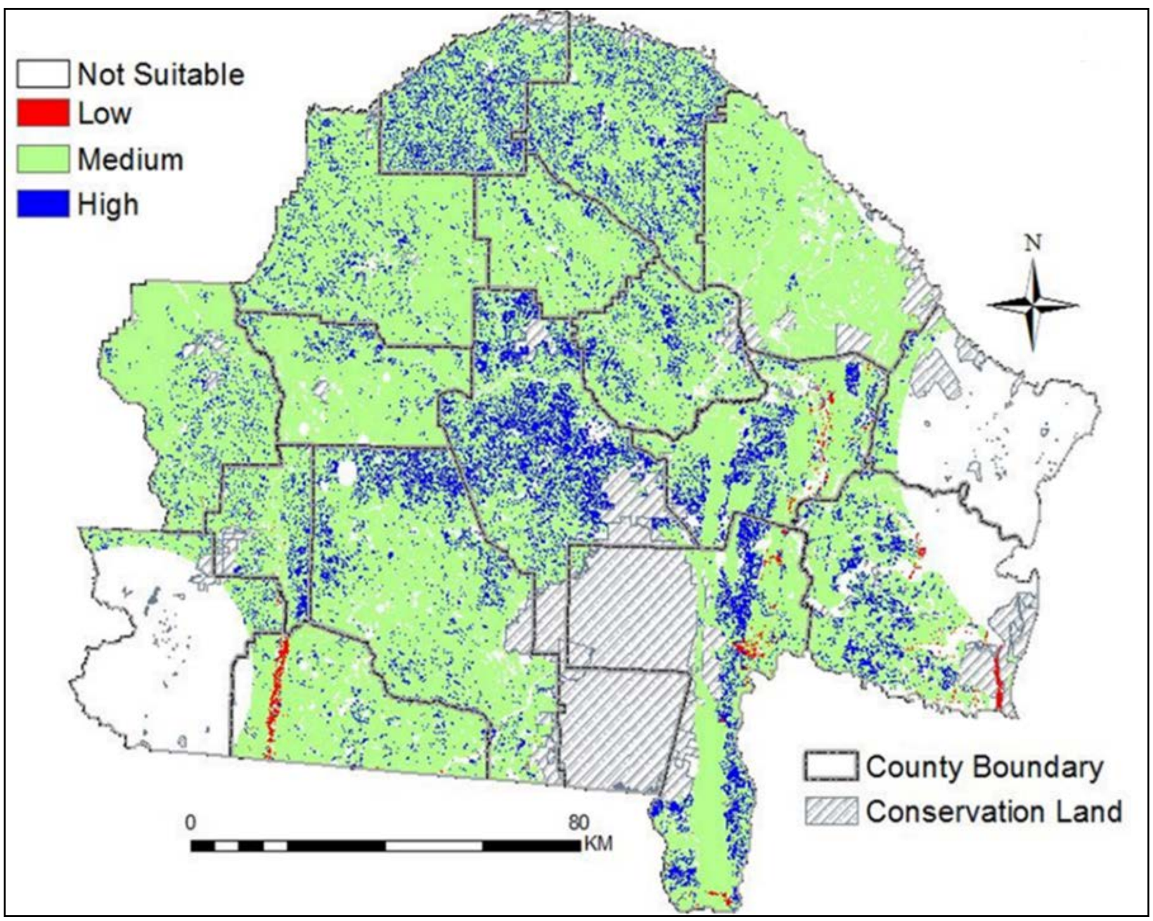


Figure 2.9. Site suitability map for blueberry production in SE Georgia.

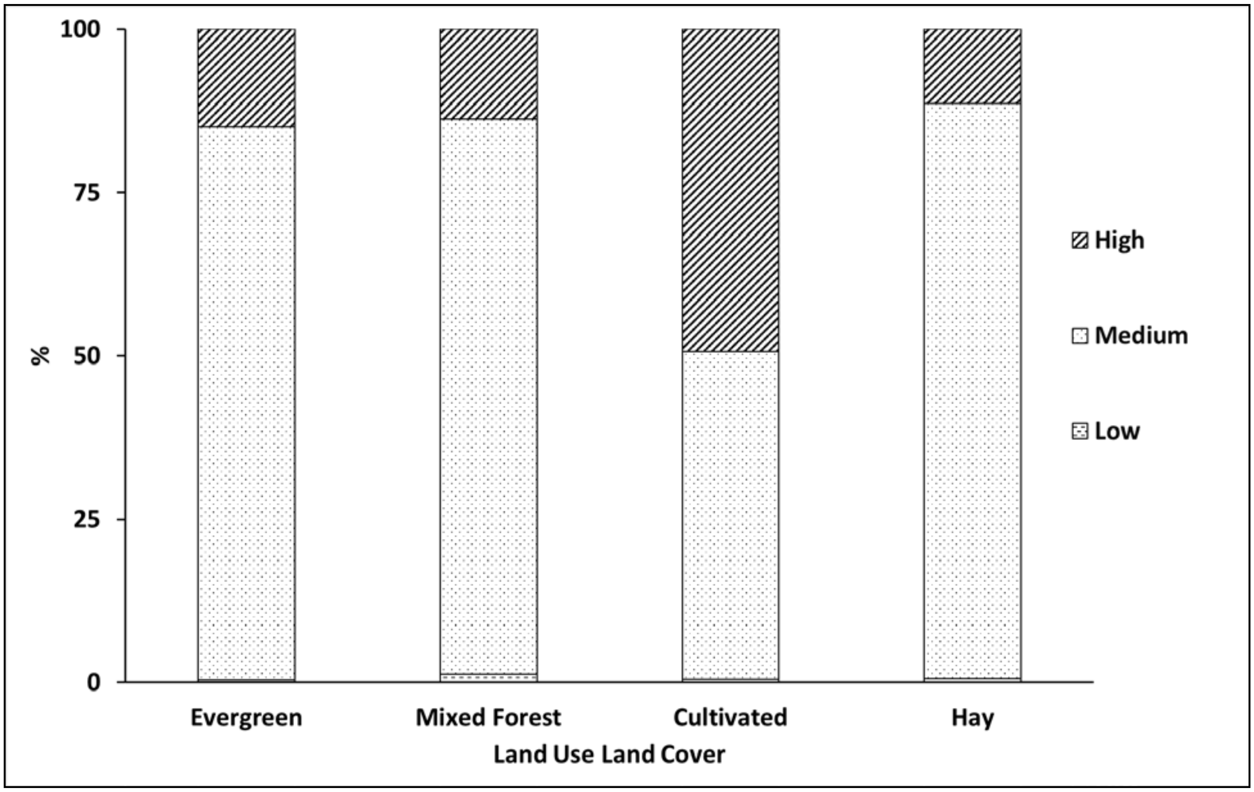


Figure 2.10. Percentage of existing NLCD land cover types under the blueberry suitability.

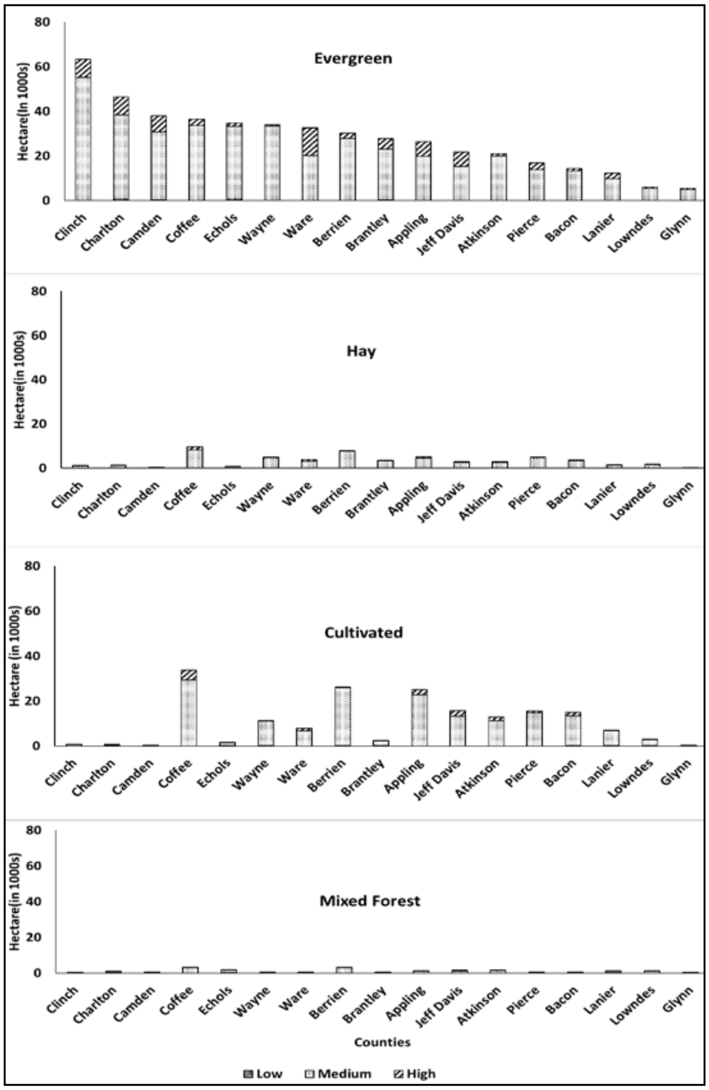


Figure 2.11. Blueberry suitable area under existing land covers (evergreen forest, hayland/pasture land, croplands, and mixed forest) in different counties in SE Georgia.

2.5 Discussion

Several authors have portrayed agriculture as a driver for deforestation in developing countries (Dobrovolski et al., 2011). Based on a review of 140 studies that focused on the causes of deforestation, Angelsen and Kaimowitz (1999) found that agricultural expansion is the major causes of deforestation worldwide. However, very few studies have explored the issue of deforestation in the context of developed countries especially in the United States where deforestation rates have been historically higher relative to other developed countries. In this context, this study explored and analyzed the role and potential of blueberry production towards deforestation in SE Georgia.

The results of our analysis show that investment in blueberry yields more profit than planting yellow pines (loblolly, slash, or longleaf). It was found that loblolly pine is more profitable than slash and longleaf pines in SE Georgia reflecting upon findings of Dickens et al. (2014). Additionally, the geospatial suitability model suggests that adequate land is suitable for blueberry production in the SE Region. This significant difference of NPV, ANPV, and BCR between blueberry and three different pine species and adequate availability of suitable land for blueberry plantation indicates that a high chance exists that landowners could convert their pine plantation to a blueberry farm if the demand for the blueberries increases further. Our argument is supported by other studies (Cuba, 2012; Geist and Lambin, 2002), which also argue that economic factors are one of five major drivers of deforestation globally.

Our economic analysis indicated that the income from pine straw and hunting leases contributed to additional income and affected the overall profitability of yellow pines species. This implies that additional income opportunities from the existing forestlands have a positive impact on NPV, but this additional income is not enough to compete with the profit that landowners can derive from blueberry farms. Therefore, it is crucial to implement programs and policies that focus on reducing the economic burden that forest landowners typically face. For example, the study conducted by Cushing and Newman (2018) found that most of the landowners and foresters in the southern United States are concerned about the impact of taxes on the profitability of growing trees. They suggest that tax burden often encourages the land use change. A deliberation on tax incentives will help in reducing deforestation in SE Georgia especially which G.C. and Mehmood (2010) clearly state that forest landowners in the southern United States typically prefer tax-based policies over direct subsidy support.

In addition to addressing the economic burdens and increasing the profitability, landowners should also be sensitized to the importance of forestland and ESs they are providing. Many of these ESs are traditionally viewed as “public goods” for example wildlife habitat, carbon sequestration, and improved water quality. However, these ESs are not recognized as natural assets with economic and social value. Implementing an awareness program that can encourage landowners to recognize forest-based ESs as natural assets can help promote conservation and more responsible decision-making. The local, state and federal agencies should explore the potential for payments of ESs for providing alternative income to forest landowners. This is especially true as several agencies in the region are already experimenting with the idea of payments for ESs in the region. For example, via the Healthy Watershed through Healthy Forests Program, the U.S. Endowment for Forestry and Communities, Inc. is developing clean water as a potential revenue source for forest landowners (Majanen et al., 2011). Additionally, developing countries have adopted Reducing Emissions from Deforestation and Degradation (REDD) for the protection of forestland and maintenance of local livelihoods (Fischer et al., 2016; Nathan and Pasgaard, 2017; Poudel et al., 2014). REDD programs involve direct payments to countries to prevent deforestation (McDermott et al., 2012). Thus, the feasibility of direct payment to forest landowners for maintaining forest cover should be explored for reducing deforestation in SE Georgia.

2.6 Conclusion

This study evaluated the profitability related to blueberry and three southern yellow pine species (loblolly, slash, and longleaf) in this study to provide an economic justification behind ongoing deforestation in SE Georgia. Our economic analysis indicates that the landowners producing blueberries obtain higher profits compared to the production of loblolly, slash or longleaf pines. The same analysis shows that out of the selected pine species, returns from loblolly pine are greater than the returns obtained from slash or longleaf pines in the study area. The risk analysis showed that there exists probability that the investment in blueberry will yield a negative outcome than pine, but the probability is very low. The additional incomes from pine straw and hunting lease significantly affect the NPV of selected pine species. The suitability model developed in this study suggested that about 85% of the available land is suitable for blueberry in the region. This model also suggests that about 80% of existing pine forestlands overlap with land that is suitable for blueberry production.

Our findings indicate that a high chance exists that an increasing market for blueberries would further promote deforestation in the region. This is especially true when an investment in blueberries provides more return than an investment in yellow pines, and about 80% of existing pineland is suitable for blueberry production in the region. However, we urge using caution against generalizing our findings in a broader context, as we did not consider risk factors such as wildfire, pest infestation, price declines and climate change in our analysis. Future research should focus on assessing the impact of deforestation on ESs in the region. We hope that this study will guide future studies in understanding the impact of blueberry production on deforestation in SE Georgia.

References

Alig, R.J., Plantinga, A.J., Ahn, S., Kline, J.D., 2003. Land use changes involving forestry in the United States: 1952 to 1997, with projections to 2050, General Technical Reports of the US Department of Agriculture, Forest Service

Angelsen, A., Kaimowitz, D., 1999. Rethinking the causes of deforestation: lessons from economic models. World Bank Res. Obs. 14, 73–98. https://doi.org/10.1093/wbro/14.1.73

Baker, J.B., Langdon, O.G., 1990. Loblolly Pine. Silvics North Am. 1383.

Brandeis, T.J., Mccollum, J.M., Hartsell, A.J., Brandeis, C., Rose, A.K., Oswalt, S.N., Vogt, J.T., Vega, H.M., 2016. Georgia's Forests, 2014 (No. SRS-209), Resource Bulletin. Southern Research Station, Knoxville, TN.

Chakravarty, S., Ghosh, S., Suresh, C., Dey, A., Shukla, G., 2012. Deforestation: causes, effects and control strategies, in: Okia, C. (Ed.), Global Perspectives on Sustainable Forest Management. pp. 3–28. https://doi.org/10.5772/33342

Cuba, M., 2012. Deforestation now driven by profit, not poverty [WWW Document]. CIFOR For. News. URL http://blog.cifor.org/10382/deforestation-now-driven-by-profit-not-poverty?fnl=en (accessed 8.2.16).

Cushing, T.L., Newman, D., 2018. Analysis of relative tax burden on nonindustrial private forest landowners in the southeastern United States. J. For. 116, 228–235. https://doi.org/10.1093/jofore/fvx013

Dickens, E.D., Sunday, J., Moorhead, J.D., 2014. Economics of growing loblolly, longleaf, and slash pine to a 33-year rotation with three stumpage price sets, four establishment cost sets, with and without pine straw – net revenue and rate or return (No. 5), 5. Athens.

Dobrovolski, R., Diniz-Filho, J.A.F., Loyola, R.D., De Marco Júnior, P., 2011. Agricultural expansion and the fate of global conservation priorities. Biodivers. Conserv. 20, 2445–2459. https://doi.org/10.1007/s10531-011-9997-z

FAO, 2016. Global Forest Resources Assessment 2015: how are the world's forest changing?, Second. ed, FAO Forestry Paper No. 1. FAO, Rome.

Fearnside, P.M., 2000. Global warming and tropical land-use change: greenhouse gas emissions from biomass burning, decomposition and soils in forest conversion, shifting cultivation and secondary vegetation. Clim. Chang. 46, 115–158.

Fischer, R., Hargita, Y., Günter, S., 2016. Insights from the ground level? A content analysis review of multi-national REDD+ studies since 2010. For. Policy Econ. 66, 47–58. https://doi.org/10.1016/j.forpol.2015.11.003

Fonsah, E.G., Krewer, G., Harrison, K., and Bruorton, M. 2006. Economic Analysis of Producing Southern Highbush Blueberries in Soil in Georgia. *Univ. of Ga Coop. Ext. Ser. Bull: 1303: 31 pages.*

Fonsah, E. G., Krewer, G., Harrison, K., and Bruorton, M. 2007. "Risk Rated Economic Returns Analysis for Southern Highbush Blueberries in Soil in Georgia". *HortTechnology, 17 (4): 571-579 (Oct-Dec).*

Fonsah, E.G., Massonnat, J., Wiggins, L., Krewer, G., Stanaland, D., Smith, J.E., 2013. Southern highbush blueberry marketing and economics. UGA Cooperative Extension Bulletin: No. 1413:1-10.

Fonsah, E. G.**,** Krewer, G., Harrison, K.. and Stanaland, D., 2008. "Economic Returns Using Risk Rated Budget Analysis for Rabbiteye Blueberries in Georgia," *HortTech: 18: 506-515*.

G.C., S., Mehmood, S.R., 2010. Factors influencing nonindustrial private forest landowners' policy preference for promoting bioenergy. For. Policy Econ. 12, 581–588. https://doi.org/10.1016/j.forpol.2010.07.005

Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience 52, 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Georgia Info, 2015. Economy - Blueberries [WWW Document]. URL http://georgiainfo.galileo.usg.edu/topics/economy/article/blueberries (accessed 8.16.16).

Godsey, L.D., 2010. Economic budgeting for agroforestry practices, Agroforestry in Action, AF1006-2008. Columbia,MO.

Henderson, J.E., Roberts, S.D., Grebner, D.L., Munn, I.A., 2013. A graphical comparison of loblolly pine growth-and-yield models. South. J. Appl. For. 37, 169–176. https://doi.org/10.5849/sjaf.10-013

Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J. V., Grainger, A., Lindquist, E., 2015. Dynamics of global forest area: results from the FAO global forest resources assessment 2015. For. Ecol. Manage. 352, 9–20. https://doi.org/10.1016/j.foreco.2015.06.014

Kissinger, G., Herold, M., De Sy, V., 2012. Drivers of deforestation and forest degradation: a synthesis report for REDD+ Policymakers. Vancouver Canada.

Laurance, W.F., Sayer, J., Cassman, K.G., 2014. Agricultural expansion and its impacts on tropical nature. Trends Ecol. Evol. 29, 107–116. https://doi.org/10.1016/j.tree.2013.12.001

Lawler, J.J., Lewis, D.J., Nelson, E., Plantinga, A.J., Polasky, S., Withey, J.C., Helmers, D.P., Martinuzzi, S., Pennington, D., Radeloff, V.C., 2014. Projected land-use change impacts on ecosystem services in the United States. Proc. Natl. Acad. Sci. 111, 7492–7497. https://doi.org/10.1073/pnas.1405557111

Majanen, T., Friedman, R., Milder C, J., 2011. Innovations in market-based watershed conservation in the United States : payments for watershed services for agricultural and forest landowners, Eco Agriculture Partners. Washington D.C.

McDermott, C.L., Coad, L., Helfgott, A., Schroeder, H., 2012. Operationalizing social safeguards in REDD+: Actors, interests and ideas. Environ. Sci. Policy 21, 63–72. https://doi.org/10.1016/j.envsci.2012.02.007

Mendelsohn, R., Dinar, A., 2009. Land use and climate change interactions. Annu. Rev. Resour. Econ. 1, 309–332. https://doi.org/10.1146/annurev.resource.050708.144246

Morales-Hidalgo, D., Oswalt, S.N., Somanathan, E., 2015. Status and trends in global primary forest, protected areas, and areas designated for conservation of biodiversity from the Global Forest Resources Assessment 2015. For. Ecol. Manage. 352, 68–77. https://doi.org/10.1016/j.foreco.2015.06.011

Morton, D.C., DeFries, R.S., Shimabukuro, Y.E., Anderson, L.O., Arai, E., del Bon Espirito-Santo, F., Freitas, R., Morisette, J., 2006. Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. Proc. Natl. Acad. Sci. U. S. A. 103, 14637–14641. https://doi.org/10.1073/pnas.0606377103

Nathan, I., Pasgaard, M., 2017. Is REDD+ effective, efficient, and equitable? Learning from a REDD+ project in Northern Cambodia. Geoforum 83, 26–38. https://doi.org/10.1016/j.geoforum.2017.04.020

NRCS, G.D.G., 2016. NRCS Geospatial data gateway. [WWW Document]. URL https://gdg.sc.egov.usda.gov (accessed 1.28.16).

Poudel, M., Thwaites, R., Race, D., Dahal, R.G., 2014. REDD+ and community forestry: implications for local communities and forest management- a case study from Nepal. Int. For. Rev. 16, 39–54. https://doi.org/10.1505/146554814811031251

Samuelson, L.J., Stokes, T.A., Johnsen, K.H., 2012. Ecophysiological comparison of 50-year-old longleaf pine, slash pine and loblolly pine. For. Ecol. Manag. 274, 108–115. https://doi.org/10.1016/j.foreco.2012.02.017

Simões, D., Daniluk Mosquera, G.A., Batistela, G.C., Souza Passos, J.R. de, Fenner, P.T., 2016. Quantitative analysis of uncertainty in financial risk assessment of road transportation of wood in Uruguay. Forests 7, 1–11. https://doi.org/10.3390/f7070130

Song, X.P., Hansen, M.C., Stehman, S.V., Potapov, P.V., Tyukavina, A., Vermote, E.F., Townshend, J.R., 2018. Global land change from 1982 to 2016. Nature 560, 639–643. https://doi.org/10.1038/s41586-018-0411-9

South, D.B., 2006. Planting longleaf pine at wide spacings. Nativ. Plants J. 7, 79–88. https://doi.org/10.2979/NPJ.2006.7.1.79

Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W.H., Simberloff, D., Swackhamer, D., 2001. Forecasting agriculturally driven global environmental change. Science (80-.). 292, 281–284. https://doi.org/10.1126/science.1057544

Wear, D.N., 2013. Forecasts of land uses. South. For. Futur. Proj. Tech. Rep. 45–69. https://doi.org/10.1017/CBO9781107415324.004

World Bank, 2016. Why forests are key to climate, water, health, and livelihoods [WWW Document]. URL http://www.worldbank.org/en/news/feature/2016/03/1

CHAPTER 3

FORESTLANDS TO BLUEBERRIES: ASSESSING IMPLICATIONS FOR HABITAT QUALITY IN ALABAHA RIVER WATERSHED IN SOUTHERN GEORGIA, UNITED STATES[2]

[2] Upadhaya, S & Dwivedi, P. Submitted to [Land Use Policy] [Feb 12, 2019]

Abstract

This study assesses the dynamics of land use changes (LUCs) and its effects on the habitat quality in the Alabaha River watershed (985 km^2) located in southeastern Georgia, where about 3,940 hectares of evergreen forest and pasture/hay have been converted to blueberry farms between 2010 and 2017. We prepared four (2006, 2010, 2015, and 2017) land use maps with an overall accuracy of 89% using supervised classification methods. Based on these maps, we simulated LUCs for the year 2022 and 2030 by integrating Cellular Automata and Markov Chain analyses. We used FRAGSTATS to assess changes in landscape configuration and composition over time. We also quantified temporal changes in habitat quality using the InVEST model. The evergreen forest decreased by 16% and blueberry increased by 6% between 2006 and 2015. The model predicted that the land under evergreen forest and pasture/hay would decrease by 2% and 1.5%, respectively, whereas the land under blueberries would increase by 3.7% between 2015 and 2030. The Index of Landscape Conservation declined by 19% between 2006 and 2030. The mean habitat quality decreased by 37% in the same period. The areas of high habitat quality were concentrated in regions with less-modified land cover. Our results suggest that a collaborative approach involving various stakeholder groups is needed for the future management of biodiversity and other ESs in the Alabaha River watershed.

Keywords

Biodiversity Conservation; Markov Chain-Cellular Automata; Ecosystem Services; InVEST Tool; Land Use Change; Sustainable Development

3.1 Introduction

Georgia is the largest producer of blueberries in the United States, as the state produced about 16% of the total blueberry production in 2014 nationwide (Georgia Info, 2015). In 2016, about 24,000 hectares of land was under blueberry in Georgia (USDA, National Agricultural Statistics Service Cropland Data Layer, 2018), out of which about 6,800 hectares were harvested. The total harvested area in 2016 was about 3.5 times higher than the total area harvested in 2000 (NASS, 2017; Scherm and Krewer, 2003), clearly indicating a trend where land is continually moving to blueberries from other competing land uses. Furthermore, blueberry production is mostly concentrated in southern Georgia, as this region alone accounts for 97% of all blueberries plants within the state (Fonsah et al., 2013). This land use change (LUC) is severely affecting ecosystem services (ESs) provided by forestlands in southeastern Georgia, as about 24.5% of total land moved into blueberries between 2010 and 2017, originally came from former pine plantations (USDA National Agricultural Statistics Service Cropland Data Layer, 2018).

An understanding of land use dynamics and its impacts on ESs in general and biodiversity conservation, in particular, will feed into the development of suitable policies for ensuring sustainable landscape management. This could potentially lead to maintenance and enhancement of landscape-based ESs which are vital for ensuring the wellbeing of society and natural resources in a mutually assuring manner. In this regard, it is necessary to characterize land use changes at a local spatial level so that its impact on ESs can be specifically identified and accounted as a part of sustainable landscape planning (Chan et al., 2006; Wade et al., 2010).

This study develops an integrative platform using available spatial data and tools for characterizing the dynamics of LUCs and its impact on habitat quality over space and time at Alabaha River watershed located in southeastern Georgia, where landowners are replacing their forestlands and pastures with blueberry farms for economic gains (Upadhaya and Dwivedi, 2019). An analysis of Cropscape data suggests that about 3,940 ha of forest and pasture/hay land have been converted into blueberries between 2010 and 2017 in the selected watershed (USDA National Agricultural Statistics Service Cropland Data Layer, 2018). We initially mapped and modeled historical LUCs at the watershed level and then used the same information for projecting LUCs in the selected watershed. The relationship between expected changes in land use and overall habitat quality was subsequently determined at a finer spatial scale. Our study will help in the development of an integrative modeling platform for expeditious implementation of sustainable landscape initiatives for ensuring continuance and enhancement of ESs and maintenance of societal welfare (Lambin et al., 2003).

3.2 Literature Review

3.2.1 Land Use Change: Agricultural Expansion and Deforestation

Deforestation is the major land use change driven by multiple causes out of which agricultural expansion is the most important one (Angelsen and Kaimowitz, 1999; Lawler et al., 2014). Several studies have estimated the historical LUCs at the global scale from the last three centuries (Agarwal et al., 2002). The area of agricultural land has increased globally from an estimated 300-400 million hectares in 1700 to 1,500-1,800 million hectares in 1990 (Lambin et al., 2003). These increments in agricultural land have led to the clearing of forest and grassland (Lambin et al., 2003). Gibbs et al.(2010) found that over 55% of new agricultural land across the tropics between

1980 and 2000 was developed at the expense of intact forests, while 28% came from disturbed forests. A recent study by the Food and Agriculture Organization of the United Nations (FAO) estimated historical changes in land use at a global scale during the last thirty years and reported a net forest loss of some 129 million hectares of forest between 1990 and 2015, representing an annual net loss rate of 0.13% in the 1990s and 0.08% over the last five-year period (FAO, 2016). A recent study by Song et al. (2018) used remote sensing data and found tree cover had increased by 224 million hectares globally (+7.1% relative to the 1982 level) in contradiction to the prevailing view that forest area has declined globally (FAO, 2016). This overall net gain is the results of a net loss in the tropics being outweighed by a net gain in the extratropics (Song et al., 2018). A closer look into the literature shows that the relationship between deforestation and expansion of agriculture is multilevel in scope operating not only at the global level but at regional and local levels as well (Gibbs et al., 2010; Lambin et al., 2003; Song et al., 2018).

Conversion of forestlands to agriculture or changing forest management practices on human-dominated landscapes has transformed a large portion of the United States (Sleeter et al., 2013; Sohl et al., 2016). Sleeter et al. (2013) reported that during 1973 and 2000 about 67.3 million hectares, including 9.7 million hectares of forestland, experienced changes in the United States. A recent study by FAO (2016) showed that historically the United States had the highest deforestation rates among developed countries with a national average rate of 0.38 million hectares per year. Between 1982 and 1992, approximately 90% of the total 47 million hectares of non-federal LUCs identified involved conversion from forestland to agriculture (Alig et al., 1998). Within the contiguous United States, the southern region has faced the highest deforestation rates due to urbanization and demand for agricultural commodities (Costanza et al., 2017; Lawler et al., 2014), whereby forest area decreased an estimated five million hectares between 1952 and 1997 (Alig et al., 2003) due to expansion of agricultural land and urbanization (Napton et al., 2010; Sohl et al., 2016). Similar dynamics of LUCs is prominent in Georgia as well (Wear et al., 2013) where forest clearances are often carried out on a larger scale with an aim to establish permanent agriculture (Tian et al., 2012; Wear and Greis, 2013; Zhao et al., 2013). These local and regional changes in land use when aggregated globally, significantly affect central aspects of the Earth's ESs (Nelson et al., 2008; Song et al., 2014), thereby raising the need for location-specific assessment using fine-scale information for informed policymaking.

3.2.2 Land Use Change and Ecosystem Services

Forests are home to the majority of the world's terrestrial biodiversity and provide critical ESs such as food, water, shelter, and nutrient cycling (Millenium Ecosystem Assessment, 2005; Morales-Hidalgo et al., 2015). Global forest cover especially in fast-developing regions of the world, however, has been decreasing rapidly due to the increasing intensity of anthropogenic activities, and often resulting in loss of ESs (Nelson et al., 2008; Song et al., 2018). Analysis of deforestation and agricultural expansion plays an important role in determining the spatial and temporal distribution, change and magnitude of impacts on ESs such as biodiversity. Studies have been conducted to understand the impacts of LUCs in general and deforestation and agricultural expansion, in particular, on ESs. For instance, Nelson et al. (2010) spatially assessed the global LUCs and its impacts on ESs using different scenarios and found that 0.0016 square meters of species habitat and 5.2 grams of biomass carbon are released for every additional calorie of crop produced. Similarly, Hasler et al. (2009) evaluated the effects of tropical deforestation on the global hydroclimate and found that between 30% and 75% of the deforested areas will experience a decrease in mean annual precipitation. It was also found that a decrease in forest area and an increase in agricultural intensification lead to higher patch extinction rates eventually resulting in the loss of area-sensitive species and declining species richness and diversity worldwide (Kupfer and Franklin, 2009).

Similar effects of deforestation and agricultural extension on biodiversity have been observed at the local and regional levels. Decaëns et al. (2018) found that Amazonian biodiversity has been highly affected by an increase in agricultural intensification and deforestation. The study conducted by Baral et al. (2014) showed that substantially modified land cover types, especially agriculture land converted from native vegetation, had lower habitat quality than in less modified land over types in Australia. A similar study in Minnesota, United States, found low habitat quality in the area with high agricultural expansion (Polasky et al., 2011). Zhao et al. (2013) used a process-based modeling system to quantify the spatial and temporal patterns of ESs in various terrestrial ecosystems in the southeastern United States between 1992 and 2050. Their results show that the carbon sequestration capacity of the southeastern United States will decrease between the selected periods mostly due to an increase in deforestation rate in the region. These studies show that specific land use such as forestry and agriculture within a landscape largely influences the ecosystem functions. The ecological significance of forest cover changes, however, ultimately rests on the mechanisms by which deforestation affects population dynamics at finer scales through changes in forest area, habitat quality, edge effects and other factors (Kupfer and Franklin, 2009). Therefore, it is necessary to assign location-specific activities to manage the forest ecosystem for maintaining, and hopefully increasing the ESs present in the region (Chan et al., 2006; Wade et al., 2010).

Remote sensing and geographic information systems have become important tools for studying patterns of LUCs at scales ranging from landscapes to the globe (Nagendra et al., 2013; Zaehringer et al., 2017). However, such studies often lack detailed treatment as analysis has been performed at a relatively coarse resolution. For example, Tolessa et al. (2017) used 57m, Zhao et al.(2013) used 250m, Nelson et al. (2010) used 5km resolution for ascertaining interlinkages between deforestation and ESs. To the best of our understanding, no study has used high-resolution data for exploring the consequences of agricultural expansion on potential deforestation first and then on ESs in the context of a developed country. Therefore, this study attempts to fill a critical gap in our understanding of LUCs and its impacts on ESs by adopting an integrative approach to better understand the linkages and consequences of LUCs on ESs of a watershed located in southeastern Georgia. We hope that our results will help in developing a comprehensive understanding of the overall sustainability of the forest ecosystems by providing a fresh perspective on deforestation and ultimately lead to informed policymaking for ensuring conservation of those landscape that can provide multiple functions.

3.3 Material and Methods

3.3.1 Study Area

The Alabaha River Watershed (USGS Gauge 02227270, HUC 8-03070201) is located in southeastern Georgia (Figure. 3.1). This watershed lies within the Satilla River Basin covering about 985 km^2 out of which blueberry, deciduous forests, evergreen forests, pasture/hay, agriculture, woody wetlands, and water bodies occupied 8 %, 9%, 23 %, 15%, 25 %, 12%, and 2% respective total in 2015 (Figure 3. 1). This watershed is spread across six counties (Appling, Bacon, Coffee, Jeff Davis, Pierce, and Ware) that are top blueberry producing counties in Georgia accounting for 65% of the overall production in 2015 (The Center for Agribusiness & Economic Development, 2016). Additionally, the selected watershed is rich in biodiversity as it is home to several threatened wildlife species such as the red-cockaded woodpecker *(Picoides borealis)* and the gopher tortoise *(Gopherus Polyphemus*). Furthermore, the counties present in the watershed are experiencing steady and, in some cases, rapid population growth. For example, the total population of counties present in the watershed jumped 10% over 10 years, from 128,738 in 2000 to 141,826 in 2010 (US Census Bureau, 2018).

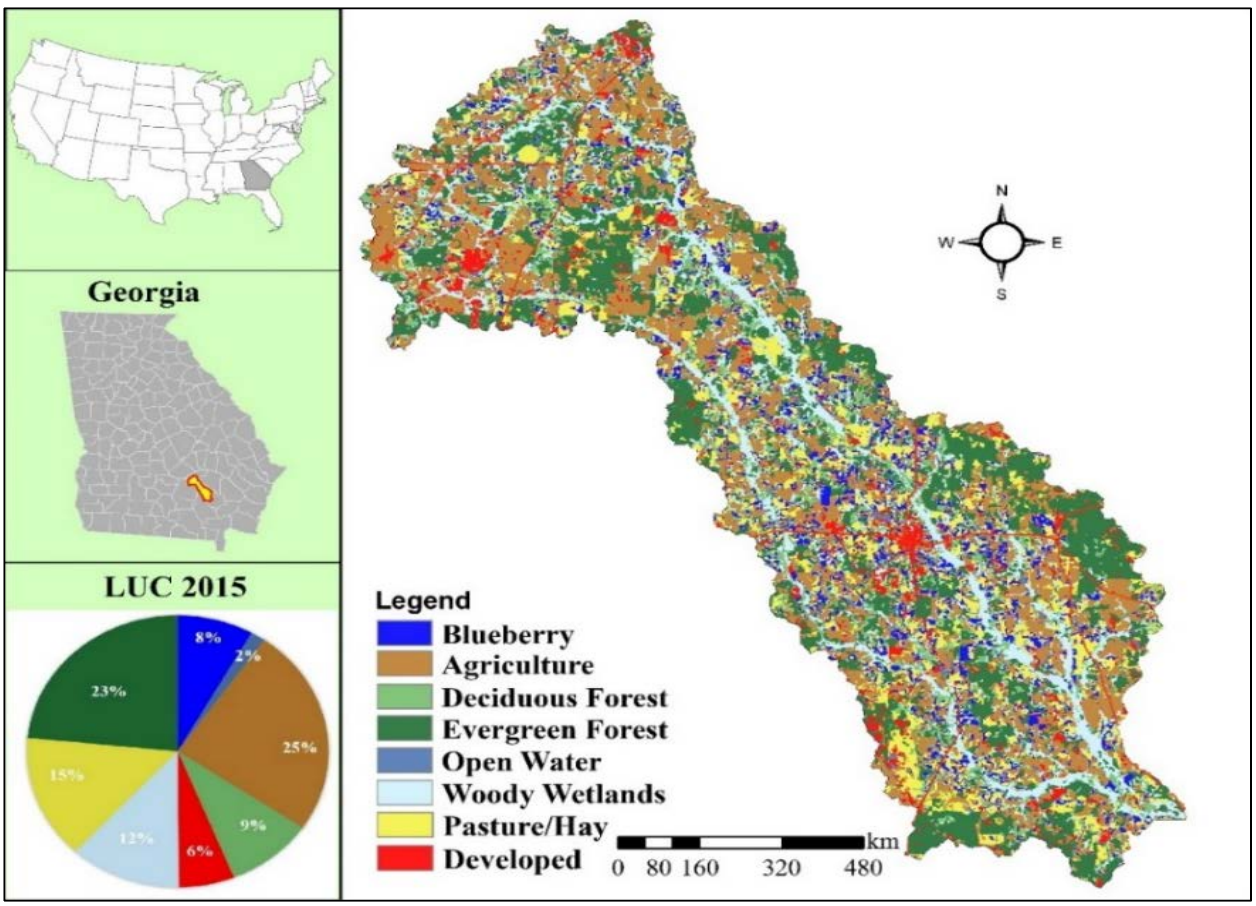


Figure 3.1. Location of the study area with the land use classification map in 2015.

3.3.2 Land Use Classification

3.3.2.1 Satellite Imagery and Data

Landsat TM datasets have been successfully used in LUCs studies due to their high temporal and spectral resolution, capacity to discriminate objects and vegetation typology, and free availability (Bodart et al., 2011; Nagel and Yuan, 2016). Landsat TM images (path/row 17/38) were acquired for four different years (2006, 2010, 2015, and 2017) for studying changes in the landscape over time. The selected images were of the same season (spring) for all the years to minimize classification errors. The selected Landsat images were converted to surface reflectance (Chander et al., 2009), using IDRISI Image Processing tools in TerrSet Software (ClarkLabs, 2017). We compressed Landsat Images using the Principal Component Analysis (PCA) - a mathematical procedure that uses an orthogonal transformation for converting observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (Olmanson and Bauer, 2017). Each band in the output PCA images receives some contribution from all of the input image bands (Panda, 2016). Five to seven independent principal components were derived for each imagery. A yearly composite image using principal components that clearly shows the separability of land use classes were used for further processing (Olmanson and Bauer, 2017).

3.3.2.2 Training Data

Reference data were collected through field surveys (in 2006, 2017 and 2018) and Cropscape data (USDA,2018), NAIP imagery (NRCS, 2018), and Google Earth (https://www.google.com/earth/). We also obtained locations and identification of land use of the property from landowners during the field survey. For the purpose of the field survey, we generated 600 random points within the study area. More than 50% of the points were visited, and each point was assigned to a land use class based on field observation and description. These data were used to create training samples for generating the spectral signatures of various land use classes (i.e., blueberry, open water, agriculture, deciduous forest, developed areas, woody wetlands, pasture/hay, and evergreen forest). The field-collected reference data were divided randomly into two subsets: 50% were used for obtaining a spectral signature, whereas the rest were used for the accuracy assessment.

3.3.2.3 Land Use Classification

The Maximum Likelihood Classification (MLC) method was used for the land use classification. This method was preferred because this classification algorithm is considered to have higher accuracy and is one of the most popular classification methods used with remote sensing data (Yacouba et al., 2009). This method classifies a pixel taking into account the variance and the covariance of the spectral response pattern of each category (Yacouba et al., 2009). MLC method requires a spectral signature to classify the scenes into different land use classes. We used training data for obtaining spectral signatures for eight different land use classes (i.e., blueberry, open water, agriculture, deciduous forest, developed areas, woody wetlands, pasture/hay, and evergreen forest). For training, each land use class was assigned with at least 700 pixels. An exploratory analysis was performed to adjust for overlapping spectral classes. These signatures were analyzed using creating histogram in ArcMap until a satisfactory difference was observed between different land use classes. The Image Classification tool within the ArcMap was used for conducting the land use classification process.

3.3.2.4 Accuracy Assessment

Confusion matrices were used to derive measures of classification accuracy that included the overall accuracy and Cohen's Kappa Statistics (Congalton and Green, 2009). Reference data collected from the field along with NAIP imagery with one-meter resolution were used as a reference for the accuracy assessment of the classified land use map for the years 2006, 2010, and 2015. For the accuracy assessment of classified land use map for the year 2017, we used 50% of the total points collected from the field survey. Random samples of 600 points were generated from classified land use map of each year for this purpose. Additionally, we consulted selected landowners in the selected watershed to validate the produced land use maps.

3.3.3 Land Use Change Prediction

We used Markov-Cellular Automata (CA) approach for predicting future LUCs. This robust approach outperforms other approaches of LUC prediction (Guan et al., 2011; Parker et al., 2003), as it integrates stochastic aspatial Markov techniques with a spatial cellular automata method (Eastman, 2012). Predictions of future LUCs using a Markov-CA model occurs in three steps: i) application of the Markov Chain analysis to 2006, 2010, and 2015 land use maps for calculating transition matrices; ii) calculation of transition potential maps of land use and land cover; and iii) application of the cellular automata model to the transition matrices, and the transition potential maps to predict the spatial distribution of LUCs.

Transition Matrices

We used the Markov Model for projecting the distribution of each land use class based on the transition probability. Transition probabilities represent the potential of the land to experience a particular transition in a specific time frame (Eastman, 2012). The transition probability *Pxy* between two land use classes (*x* and *y*) can be determined over a specific period from time t to time t +1 (Equation 1), where N_x = the total number of pixels of class x transformed over the transition period, and N_{xy} is the number of pixels transformed from class *x* to *y*, and *z* is the number of land use classes.

$$P_{xy} = \frac{N_{xy}}{N_x} \qquad \text{Equation 1}$$

$$\sum_{y=1}^{z} P_{xy} = 1$$

The distribution of each land use class at time t+1 (O_{t+1}) was projected using the land use distribution at the earlier time t(O_t) and the transition probability matrix P (Equation 2).

$$P \times O_t = O_{t+1} \qquad \text{Equation 2}$$

Land use maps for the year 2006, 2010, 2015, and 2017 obtained using MLC method were used to calculate transition probability matrices of land use classes between 2006 and 2010, 2010 and 2015, and 2006 and 2015. These transition matrices were used in the successive steps of LUCs prediction.

Transition Suitability Maps

To define the suitability of each pixel for a transition to any other land use class, we prepared a suitability map in which each pixel has a value that ranges from 0 to 255, 0 representing unsuitable and 255 representing highly suitable for particular land use. The major transitions that have occurred among the land use classes between 2006 and 2015, field surveys, and author's knowledge of the study area were used to define transition rules and identify the variables and constraints for each land use class for generating transition suitability maps. Different explanatory variables (elevation, distance to road, slope, aspect, soil pH, soil permeability, chilling hours) were considered in each model. The selection of explanatory variables was derived from Cramer's V statistics which is based on the degree to which each variable is associated with the distribution of land cover classes (Eastman, 2012). We used a multi-layer perceptron neural network (MLP) to prepare transition suitability maps. These transition suitability maps represent the suitability of a pixel to turn into blueberries in each transition, based on a group of driving factors. We used MLP as it is known to outperform other methods such as logistic regression and weights of evidence (Eastman, 2012; Lin et al., 2011). For proper training of the MLP model, we considered all cells that transitioned from other land use classes to blueberry between 2006 and 2015. The transition potential with MLP accuracy of more than 80% was incorporated in the predictive model. The prepared transition suitability maps were used in the next step for predicting land use distribution in 2017 and simulating the distribution in 2022 and 2030.

Application of the Markov-CA Model

We used Markov-CA approach with the transition probabilities for the period 2006-2015 with the 2015 land use map as a base map to model land use in 2017. The transition probabilities were used to estimate the area of each land use class to be converted to another land use classes. The suitability maps defined the suitability of each pixel to each of the land use classes. The CA model then allocated the transition of one land use type pixel to another depending on the land use within the neighborhood of the pixel. The accuracy of the predicted 2017 land use map was assessed using the Kappa index of agreement with the actual 2017 land use map. Once the prediction model was validated and modified so that its Kappa was above 0.85, we used the probabilities for the period 2006-2015 with the 2015 land use as a base map to model LULC in 2022 and 2030 using the combined Markov-CA approach. This approach was performed within the framework of Land Change Modeler (LCM) which facilitates the process of LUCs analysis and prediction through the following steps: 1) analysis of historical changes; 2) evaluation of the suitability and readiness of the land to experience change; 3) estimation of the demand for land; and 4) prediction of future land cover changes and validation (Sangermano et al., 2012).

3.3.4 Landscape Composition and Configuration

Landscapes analyses are an important part of biodiversity monitoring because the area which provides habitat to different organisms operates at multiple levels where typically a landscape is a unifying theme across different levels. To better understand the distribution of habitat quality, it is important to analyze landscape fragmentation or describe the characteristics of the landscape (McGarigal, 2015). To quantify the landscape structure of the study area, we applied FRAGSTATS to the historical and predicted LUCs maps. We used FRAGSTATS because this spatial statistics program offers a comprehensive choice of landscape metrics for categorical map patterns (McGarigal, 2015). As landscape metrics exists at patch, class, and landscape levels, FRAGSTATS employs various metrics for these different levels of the landscape for describing characteristics of the landscape (Keleş et al., 2008).

Based on the scale of the study area and its characteristics, different class and landscape metrics such as total class area, a percentage of the landscape, number of patches, average size of the patch, Euclidean nearest distance, interspersion and juxtaposition index, and Shannon's diversity index

(Table 1) were obtained. Metrics such as the percentage of area occupied by each land use class, total class area, and the number of patches were used for quantifying the landscape composition. For understanding the central tendency, metrics such as mean area and mean patch size were computed (McGarigal, 2015). Density metrics such as patch density and edge density indicate the configuration of a landscape and can be related to ideas of fragmentation of the different land use classes (i.e., habitats). A detailed description of different metrics can also be found at the user's manual of FRAGSTATS TM (McGarigal, 2015). Finally, we used Equation 3 to calculate the Index of Landscape Conservation (ILC) as a synthetic index to include information for both composition and configuration (Pizzolotto and Brandmayr, 1996), where Xi is the cumulating percentage value of the pixels of different land use classes, and nc is the number of land use classes. The Index of Landscape Conservation (ILC) is:

$$ILC = 1 - \frac{A}{Amax} \qquad \text{Equation 3}$$

$$A = \sum_{i=1}^{nc} Xi - 100$$

$$Amax = 100*(nc-1)$$

This index is the measure of landscape heterogeneity and takes into account the contribution of land use types to the biodiversity of the landscape (De Simone et al., 2017).

3.3.5 Invest Model and Ecosystem Services

We used InVEST to analyze the provision of ESs in the Alabaha River Watershed (Sharp et al., 2016). InVEST was developed by Stanford University, The Nature Conservancy, and the World Wildlife Fund as part of the Natural Capital Project (www.naturalcapitalproject.org). InVEST combines information on biophysical conditions and land use information as inputs into ecological production functions to generate a spatially explicit assessment of the supply of ESs (Sharp et al., 2016). We used the InVEST Habitat Quality model for mapping and analyzing biodiversity using land use and biophysical data from the Alabaha River Watershed.

InVEST assumes that habitat quality of a landscape is associated with the intensity of anthropogenic activities and the land use types of adjacent areas (Baral et al., 2014). Habitat quality model of the InVEST uses habitat quality as a proxy for biodiversity (Baral et al., 2014; Polasky et al., 2011) and simulates the combined effects of land use and anthropogenic activities on ecosystems and provides a visual tool that quantitatively evaluates ESs functions (Sharp et al., 2016). It spatially estimates the extent of habitat quality for a target conservation objective within a landscape. We used a threatened species gopher tortoise *(Gopher Polyphemus*) as an indicator to identify inputs required by the InVEST Habitat model. The model assumes that large areas with high habitat quality would support more flora and fauna species and individuals, and the areas that decrease in habitat extent and quality over time would contain reduced levels of biodiversity (Sharp et al., 2016). As not all habitats are affected by all threats in the same way, we assumed habitat quality as a function of four factors: the relative impact of each threat such as road, highway, street, blueberry, agricultural expansion, the relative sensitivity of each habitat type to each threat, the distance between habitats and sources of threats, and the degree to which the land is legally protected (Sharp et al., 2016).

We transformed the land use maps generated and predicted using the MLC and Markov-CA method into maps of habitat by defining what land use class counts as a habitat for the Gopher tortoise. We assumed that evergreen forest, hay/pastures provide better habitat than agricultural land, blueberry farms or developed areas. These different habitats are sensitive to threats generated by different human activities in the area (Polasky et al., 2011). For our research, we assumed highway, railways, roads, agricultural land, and urban areas as threats to habitat. Additionally, we also considered the distance over which a threat will degrade the natural system. For example, we considered the natural system (habitat) up to one kilometers from the source of threats generated by street will be degraded. The level of sensitivity of different habitats to different threats was derived from a literature review (Baral et al., 2014; Lawler et al., 2014; Liu et al., 2017; Nelson et al., 2010; Polasky et al., 2011; Sharp et al., 2016). Finally, to determine the legal/institutional/social/physical protection against threats and accessibility to sources of degradation, we used the map from Protected Areas Database of the United States (PADUS) (U.S.Geological Survey, 2018). The habitat model was run to obtain the habitat quality maps for the year 2006, 2010, 2015, 2017, 2022, and 2030. Pixels in the output map ranges from 0 to 1, with 0 representing low or no habitat and 1 representing highest habitat quality. Furthermore, we equally divided habitat quality scores into four classes: no habitat (0), low quality (0-0.4), moderate (0.4-0.8) and high (0.8-1).

3.3.6 Sensitivity

To understand how the landscape would evolve in the case of the different rates of expansion in blueberry cultivation, we simulated two different land use maps with two different scenarios (2030A and 2030 B) using validated Markov-CA method explained in section 3.3. The first scenario (2030A) used a doubling of the probability of conversion of other land use classes into blueberry from 2015 to 2030 and the second scenario (2030B) used a quadrupling of the probability of conversion. We also analyzed the landscape configuration, composition, and quality of habitat for these two land use maps.

3.4 Results

3.4.1 Land Use Change

For temporal land use mapping of the study area, Landsat TM and ETM images for the years 2006-2017 were selected to extract land use maps (Appendix C). The use of Supervised Classification using the Maximum Likelihood Classifier (MLC) method to classify the Landsat TM images produced land use maps (Figure. 3.2) with overall accuracies of 90%, 91% 90%, and 89% and kappa indices of 0.87, 0.88, 0.88, and 0.87 for 2006, 2010, 2015, and 2017, respectively.

In the four classified maps, more than 30% of the total area of the landscape was covered by evergreen forest mostly plantation pine stands. Pasture/hay, evergreen forest, and agriculture land dominated the landscape and covered more than 60% of the land each year mapped. Blueberry farms covered 3% to 13% of the landscape and were mostly concentrated in the southern part of the watershed.

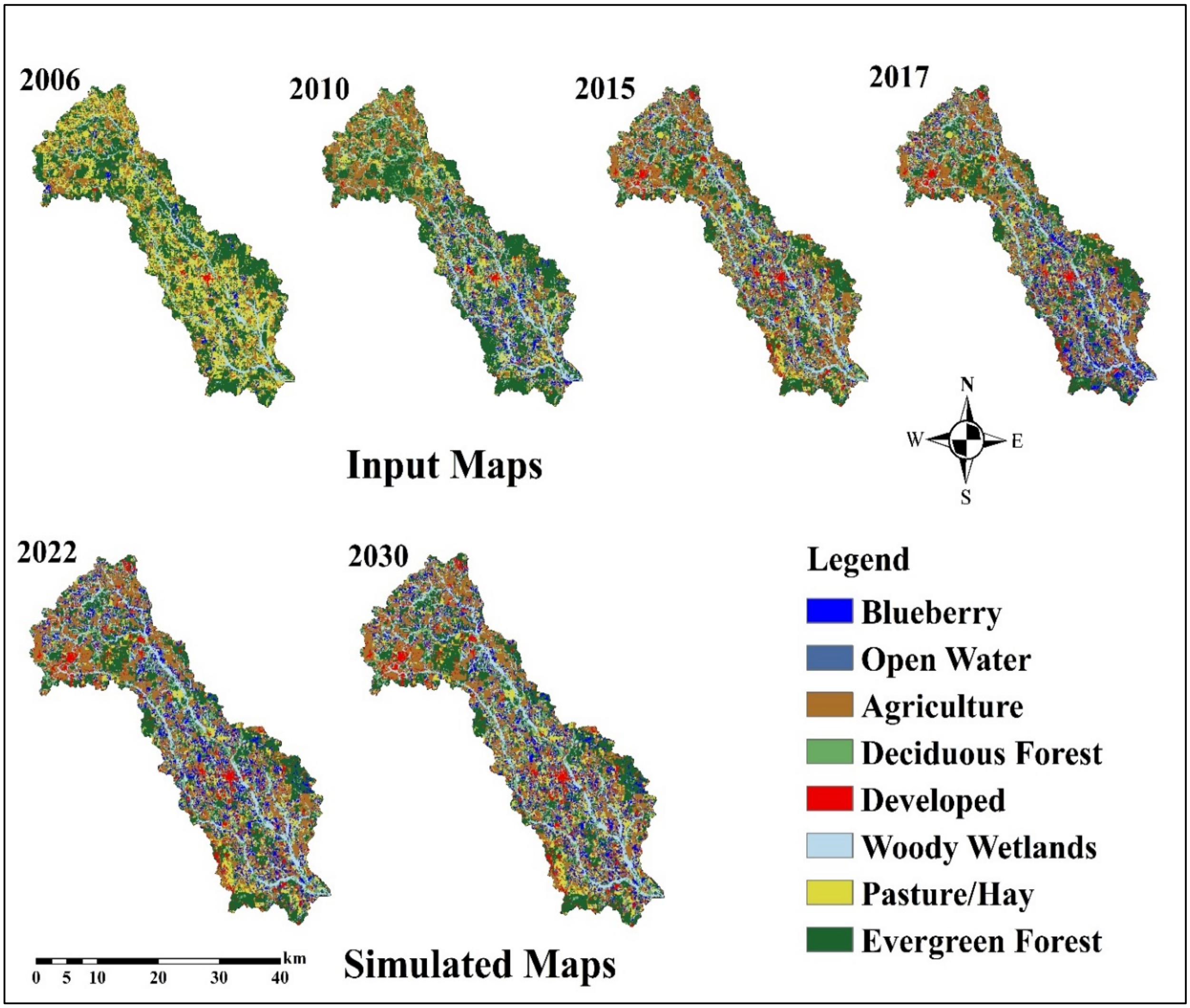


Figure 3.2. Spatial distribution of land uses in the study area over time.

Land use maps provided further insights into LUCs trends and rates. The results of LUCs classification reveal land use history and quantity of change in each land use class. The landscape went through three different stages, with each land use map representing a different stage and each stage dominated by different land use (Figures. 3.2 and Figure. 3.3). The major land use types in the landscape in the initial stage (represented by the 2006 map) was evergreen forest followed by pasture/hay and agriculture. Similar land use activities dominated the second stage (represented by the 2010 map). In this stage, the area covered by blueberries increased significantly in the southern part of the landscape (Figure. 3.2 and Figure. 3.3). In the third stage (represented by the 2015 map), the landscape is dominated by agriculture and blueberry farms. During this stage, the evergreen forest decreased from 35% in 2010 to 23% in 2015 (Figure. 3.3).

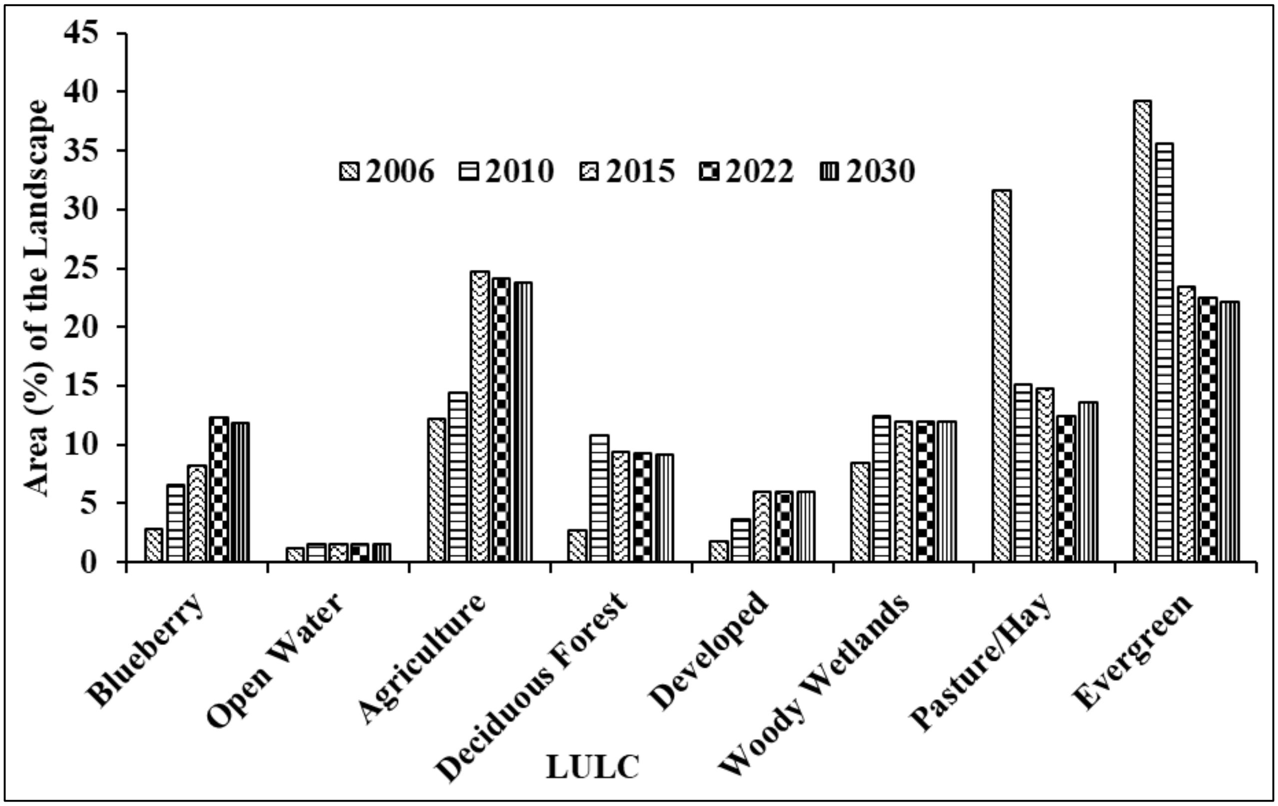


Figure 3.3. Area under different land uses as a percentage of the total area of the selected watershed.

Prediction of LULC Change

We validated the prediction model by estimating the goodness of fit between the 2017 simulation result, actual 2017, and field observation with the kappa index. The validation shows that the calibrated model could simulate and predict the future LUC in a reliable way as the overall accuracy was 88% with a kappa of 0.86. The model was used to predict land use for 2022 and 2030 (Figure. 3.2). The predicted maps show that blueberries likely will increase by 4.11% in the year 2022 and by 3.65% in the year 2030 (Figure. 3.2 and Figure 3.3) relative to 2015. The blueberry expansion affected evergreen forest, and the pasture/hay land uses, with evergreen forest predicted to decrease by half in 2030 compared to that in 2006 (Figure. 3.3). The expansion of blueberries was dominant in the southeastern region of the watershed (Figure. 3.2).

3.4.2 Landscape Composition and Configuration

During the study period, changes occurred in the size, number, distance, and spatial distribution of patches of different land uses and overall patterns in the watershed. Deforestation trajectories was predominant and coincided with increased habitat fragmentation due to a land use decision. Across the landscape, all landscape metrics are significantly different among different year at the significance level of 0.5%.

Across the time period of the study, the density of patches (number per 100 ha) for all land uses increased significantly suggesting increased heterogeneity of the watershed (Table 3.1). More patches over time meant a smaller mean patch size (6.04 ha for the year 2006 and 3.23 ha for 203) and more edges (edge density). The larger number of patches with increased patch density and edge density indicate greater landscape heterogeneity, and likely more fragmentation and isolation of individual land uses. The Shannon's Diversity Index (SHDI) appears to reveal an increase in diversity in the year 2030 relative to the year 2015 (Table 3.1). This can be credited to the increase in patch number in a subsequent year. The Index of Landscape Conservation (ILC) which was calculated as a synthetic index to include information for both composition and configuration declined by 19% from the year 2006 to 2030.

Table 3.1. Landscape metrics that explain the configuration and composition of the landscape for the different stages (2006, 2010, 2015, 2022, and 2030).

Landscape Metrics	**2006**	**2010**	**2015**	**2022**	**2030**
Number of Patch (n)	16,263	24,415	28,564	30,086	30,421
Shannon's Diversity Index	1.52	1.79	1.88	1.90	1.91
Patch Density (n/100ha)	16.55	24.84	29.06	30.61	30.95
Total Edge (m)	8,725.74	10,126.56	10,782.33	11,382.66	11,478.99
Edge Density (m/ha)	88.77	103.03	109.70	115.80	116.78
Mean Patch Size (ha)	6.04	4.03	3.44	3.27	3.23
Contagion	49.92	40.72	37.63	36.34	36.11
Division (LDI)	0.99	0.99	1.00	1.00	1.00
Interspersion and Juxtaposition Index (IJI)	69.71	88.83	89.76	89.89	90.05
Euclidean Nearest Neighbor Distance (m)	180.26	147.12	141.83	138.34	137.57
Total Core Area (ha)	25,559.46	22,302.36	20,236.77	18,188.10	17,760.69
Index of Landscape Conservation	0.70	0.67	0.59	0.57	0.57

3.4.3 Habitat Quality in the Watershed

The results of the InVEST Habitat quality model report a relative habitat quality score in the range from 0 to 1 for each pixel. Large spatial variability in habitat quality in different years across the landscape was observed due to the composition and configuration of the landscape (Figure 3.4). In classified land use maps, a low habitat quality area was mainly associated with the urban/town and the agriculture and blueberry-dominated areas; this demonstrates the negative impacts of urbanization and agricultural expansion on the habitat quality measure (Figure 3.4). The mean habitat quality of the watershed declined as the landscape experienced change. From 2006 to 2015, the mean habitat quality declined by 32%, and similarly, the model shows that the habitat quality decreased by 6% in 2030 compared to 2015 and by 37% compared to 2006 (Figure 3.5).

Furthermore, we found that in 2006, the "high" accounted for the largest proportion (70.85%) while "low" and "moderate" classes only add up to 24% of the total landscape. In 2015, only 38% of the landscape fell under the "high" class. It is projected that in the year 2022 and 2030, the proportion of "high" class will be less than the class "low" (Table 3.2).

Table 3.2. Landscape habitat quality classes and percentage of landscape under different habitat quality classes for different years.

Habitat Quality Classes	2006	2010	2015	2022	2030	2030 A	2030 B
No Habitat	4.54	10.13	14.10	18.21	17.75	21.28	29.37
Low	21.87	28.35	38.33	37.74	37.30	36.44	34.13
Moderate	2.74	10.75	9.43	9.21	9.11	8.74	7.92
High	70.85	50.77	38.14	34.84	35.84	33.54	28.58

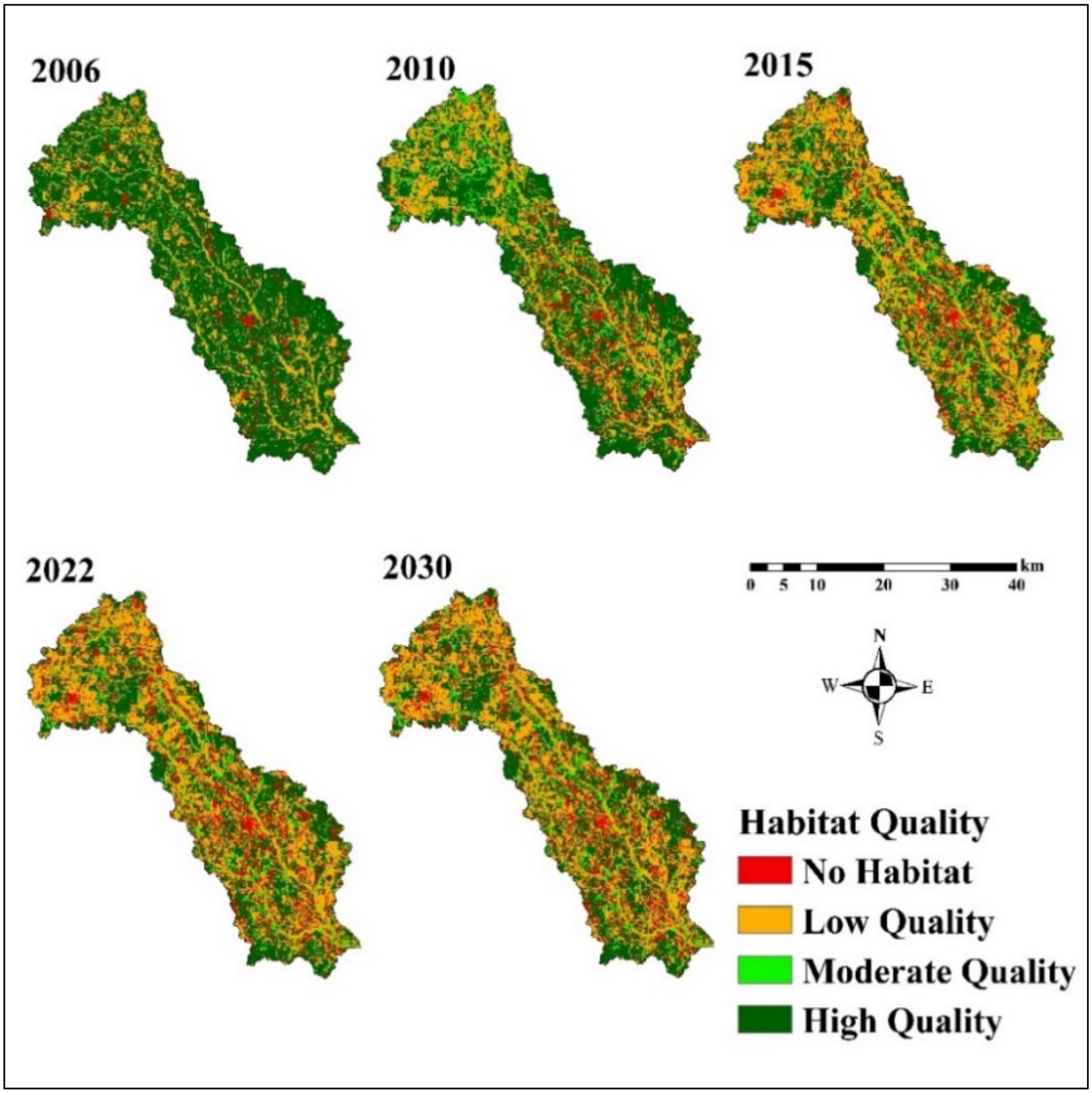


Figure 3.4. Spatial distribution of habitat quality in the study area.

3.4.4 Sensitivity Analysis

The land use map predict blueberry expansion by 7% of the total area in 2030 compared to the year 2015 with the scenarios of the increase in the probability of blueberry expansion twice (Figure. 3.6). In this scenario (2030A), deforestation of evergreen forest and decline in pasture/hay increased with more than 5% for both from the year 2015 to 2030. This change in land use affected the habitat quality of the landscape where the mean value of habitat quality of the landscape declined by 10% to the scenario 2030A (Figure. 3.5). The decline in habitat was confined in the center of the landscape (Figure. 3.6). The second scenario (2030B) where the probability of conversion of land use classes into blueberry increases to four folds from 2015 significantly increased the blueberry area in the landscape where it covered more than 23% of the total area of the study area (Figure. 3.6). This increase in the blueberry area significantly reduced the forest area, and the habitat quality decreased significantly to a mean value by 21% from 0.4994 in 2015 (Figure 6).

The qualitative assessment of LUC dynamics, landscape composition and configuration, and habitat quality indicated that before 2010, the study area was covered with large tracts of pine plantations and pasture/hay area that supported biodiversity and supplied a wide range of ESs except for agricultural commodities. After a rise in the expansion of blueberry farm, the majority of the pasture/hay and evergreen forest were converted into blueberry farm, resulting in increased blueberry production at the cost of other ESs.

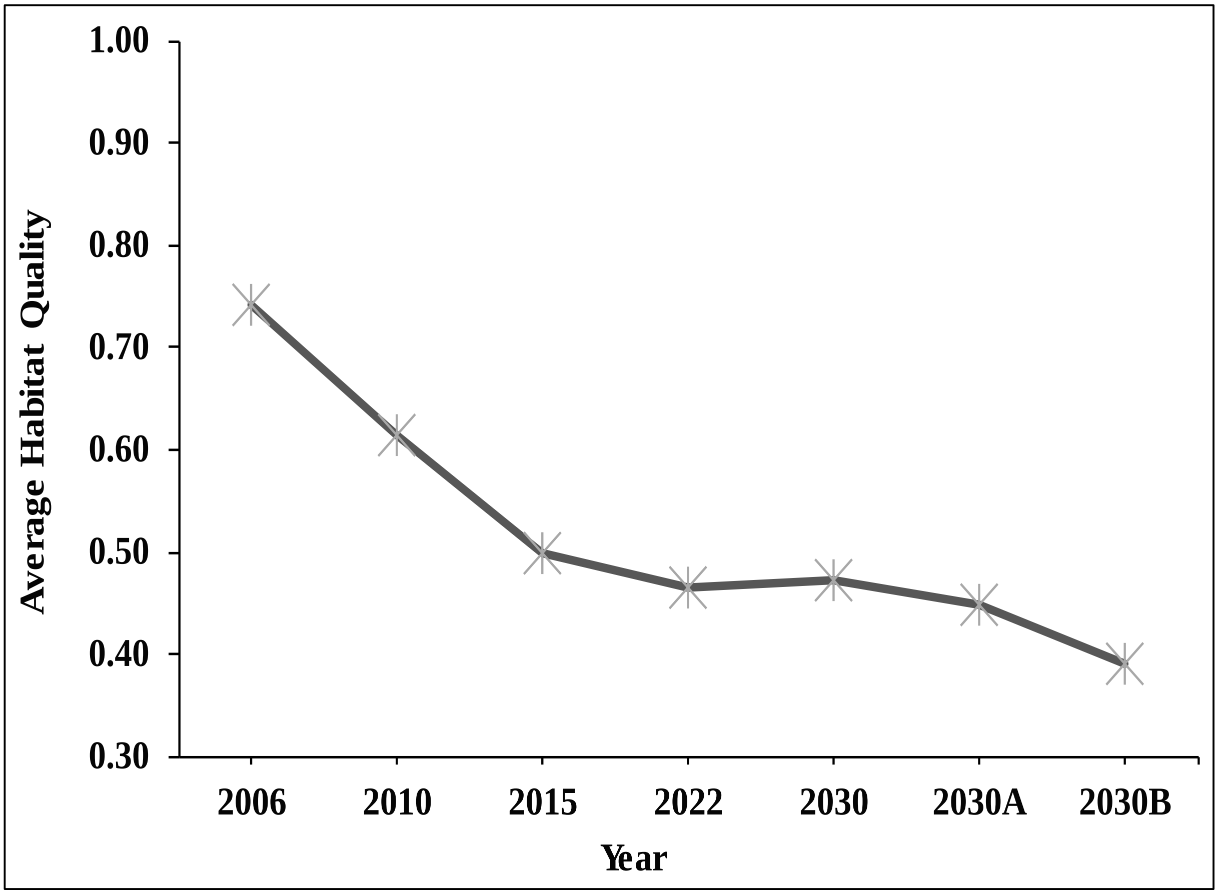


Figure 3.5. Landscape habitat quality score (Mean value) along different stages (2006, 2010, 2015, 2022, 2030, 2030A and 2030 B).

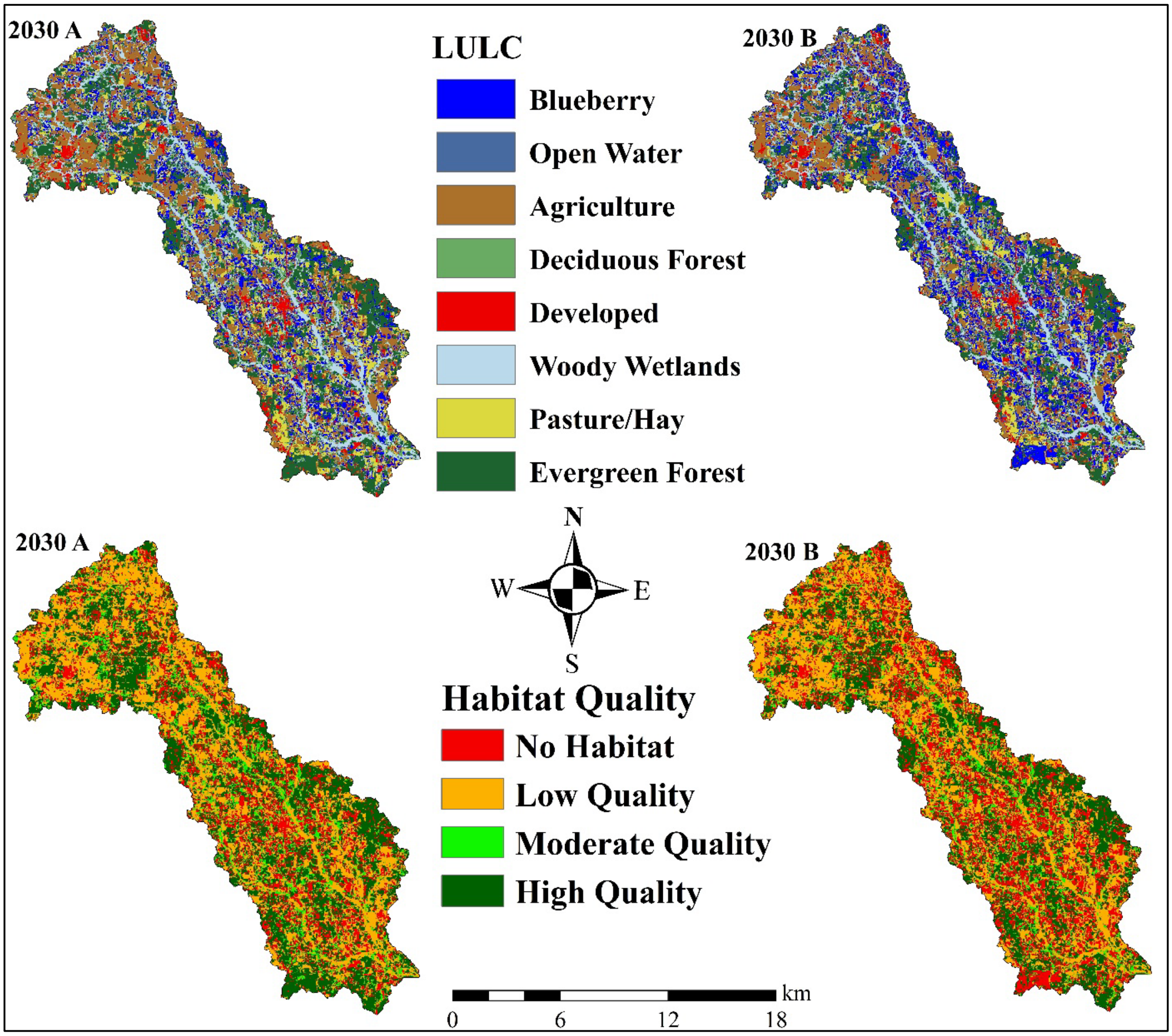


Figure 3.6. Land use map and habitat quality for the year 2030 with two different scenarios 2030A and 2030B (double and fourfold respectively) of blueberry expansion.

3.5 Discussion

Information on the dynamics of LUCs is essential to understand landscape trends and to make necessary land management and conservation interventions, particularly in the mixed landscapes of southern Georgia, United States. In this study, we quantified and modeled historical land use and predicted how land use would change in the future in Alabaha River Watershed in southeastern Georgia. LCM and ArcGIS were used to model LUCs while the InVEST Habitat quality model was used to determine the spatial distribution of habitat quality in the selected landscape. As several studies have demonstrated the benefits of evaluating and visualizing future landscapes before they occur (Naidoo and Ricketts, 2006; Nelson et al., 2008; Polasky et al., 2011), we simulated the future landscapes for the year 2022 and 2030 using a Markov-CA model. This study demonstrated that readily available fine resolution spatial datasets and analysis tools can be used to assess LUCs dynamics, landscapes composition, and configuration, and habitat quality (serving as a proxy for biodiversity) in agriculture-dominated landscapes.

Our findings suggest that deforestation and agriculture expansion are the major land use change in the selected watershed. The subsequent reduction in forestlands and pasture/hay lands was observed from 2006 to 2017 follows similar findings of other studies (Meng and Zhang, 2013; Zhao et al., 2010). The conversion of one land use class to another is dynamic, and it does not follow a linear pattern over a study period in the watershed. This means that certain land use classes such as deciduous forest, agriculture, and pasture/hay showed inconsistent patterns. The rate of forestland conversion and conversion of pasture/hay appeared to slow slightly by 2030, especially for pasture/hay. This pattern of LUCs, particularly large-scale farming of blueberry is the major drivers of deforestation in the selected watershed where local family forest landowners have cleared their forestland to establish blueberry farms. Similar patterns have been reported by other studies in the context of other cash crops like rubber, fruit, hazelnut, coffee, and tea particularly in developing countries (Godone et al., 2014; Graesser et al., 2018; Hylander et al., 2013; Zhang et al., 2014; Ziegler et al., 2009). This further suggests that the pattern of LUC dynamics in our study area is not different than what is observed globally. This further suggests that patterns and processes behind deforestation are similar across developed and developing economies, but magnitude could vary depending upon markets, governance, and land tenures.

The integration of LUCs and landscape metrics in this study allow exploration of the links between landscape composition and configuration and ESs. We found that habitat loss and fragmentation are affecting ESs by reducing the ecosystem functions such as habitat, biodiversity etc provided by important land use classes such as pasture/hay and forestlands (Tolessa et al., 2017), which is consistent with the existing studies (Baral et al., 2014; Costanza et al., 1997; Polasky et al., 2011). Our results also show that habitat quality declined in areas with high agricultural expansion. Similar results have been found by other studies conducted in different part of the world. Baral et al. (2014) assessed land use change and its impacts on habitat quality and found low habitat quality in highly modified areas. Similarly, Polasky et al. (2011) compared different LUC scenarios on the provision of ESs and found that the scenario with agricultural expansion generated declines in habitat quality. In many parts of the world, deforestation and agricultural expansion have altered most of the landscape and resulted in a decline in biodiversity (Millenium Ecosystem Assessment, 2005; Zhao et al., 2006).

The selected watershed has undergone considerable habitat loss and fragmentation in a relatively short time period. We found that the trend of LUCs in the landscape likely will continue, resulting in additional loss of habitat quality for biodiversity in the foreseeable future. The relationship between biodiversity values and the provision of ESs has been discussed extensively (Baral et al., 2014; Kandziora et al., 2013; Turner et al., 2007). Pollination, seed dispersal, climate regulation, carbon sequestration, etc. are ecosystem functions affected by the loss of biodiversity as well (Millenium Ecosystem Assessment, 2005). This can have significant consequences on this landscape where ESs such as soil conservation, water quality, and pollination are important for sustaining rural economies. Therefore, considering conservation activities on forest management practices should be given priority in areas where agricultural expansion is faster, especially in central and southeast regions of the watershed.

3.6 Conclusion

We were able to analyzed and predicted the LUCs in the Alabaha River Watershed by evaluating the impacts of LUCs on habitat quality by integrating Markov-CA analysis with the InVEST modeling. Although this study is not the first to be carried out in this way, it is the first attempt to understand interlinkages between LUCs, landscape metrics, and habitat quality in southern Georgia in the context of deforestation. The integrated framework developed in this study could be useful for advancing the understanding of policymakers and land managers towards integrated land use planning, by balancing the trade-offs between deforestation, agricultural expansion, and habitat quality. It could also be widely applied to other regions at different scales.

Our study suggests that innovative land use policy and integrated landscape management strategies for the watershed are particularly important for ensuring continuance and enhancement of ESs in the Alabaha watershed. We suggest community-led initiatives in partnership with local authorities and non-profits with a focus on environmental education for ensuring a balance between ESs and societal welfare. A framework of such approaches (e.g., Longleaf Alliance) is already in place and could be used as a starting point for potentially seeking a collaborative approach involving various stakeholder groups at the watershed level.

We suggest undertaking a similar study at a larger scale for developing a finer understanding of the impacts of LUCs on ESs at different levels. In this study, we did not include multiple species in our habitat quality assessment. It is expected that future research will account for multiple species habitat modeling for analyzing the impact of deforestation on each species. A future study could also analyze the impacts of LUCs on multiple ESs in a single integrated manner focusing on the economic valuation of ESs. We hope that our research will feed into future research in a constructive manner.

References

Agarwal, C., Green, G.L., Grove, M., Evans, T., Schweik, C., 2002. A review and assessment of land-use change models : dynamics of space , time , and human choice, UFS Technical Report NE-297. Burlington VT. https://doi.org/10.1289/ehp.6514

Alig, R.J., Adams, D.M., McCarl, B.A., 1998. Impacts of incorporating land exchanges between forestry and agriculture in sector models. J. Agric. Appl. Econ. 30, 389–401.

Alig, R.J., Plantinga, A.J., Ahn, S., Kline, J.D., 2003. Land use changes involving forestry in the United States: 1952 to 1997, with projections to 2050, General Technical Reports of the US Department of Agriculture, Forest Service

Angelsen, A., Kaimowitz, D., 1999. Rethinking the causes of deforestation: Lessons from economic models. World Bank Res. Obs. 14, 73–98. https://doi.org/10.1093/wbro/14.1.73.

Baral, H., Keenan, R.J., Sharma, S.K., Stork, N.E., Kasel, S., 2014. Spatial assessment and mapping of biodiversity and conservation priorities in a heavily modified and fragmented production landscape in north-central Victoria, Australia. Ecol. Indic. 36, 552–562. https://doi.org/10.1016/j.ecolind.2013.09.022

Bodart, C., Eva, H., Beuchle, R., Raši, R., Simonetti, D., Stibig, H.J., Brink, A., Lindquist, E., Achard, F., 2011. Pre-processing of a sample of multi-scene and multi-date Landsat imagery used to monitor forest cover changes over the tropics. ISPRS J. Photogramm. Remote Sens. 66, 555–563. https://doi.org/10.1016/j.isprsjprs.2011.03.003

Chan, K.M.A., Shaw, M.R., Cameron, D.R., Underwood, E.C., Daily, G.C., 2006. Conservation planning for ecosystem services. PLoS Biol. 4, 2138–2152. https://doi.org/10.1371/journal.pbio.0040379

Chander, G., Markham, B.L., Helder, D.L., 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens. Environ. 113, 893–903. https://doi.org/10.1016/j.rse.2009.01.007

ClarkLabs, 2017. Clark Labs | Geospatial software for monitoring and modeling the earth system [WWW Document]. URL http://clarklabs.org/wp-content/uploads/2016/03/TerrSet18-2_Brochure_WEB.pdf (accessed 1.15.17).

Congalton, R.G., Green, K., 2009. Assessing the accuracy of remotely sensed Data: Principles and Practices, 2nd ed. Taylor & Francis Group.

Costanza, K.J., Abt, R.C., McKerrow, A.J., Collazo, J.A., 2017. Bioenergy production and forest landscape change in the southeastern United States. GCB Bioenergy 9, 924–939. https://doi.org/10.1111/gcbb.12386

Costanza, R., Arge, R., Groot, R. De, Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V, Paruelo, J., Raskin, R.G., Suttonkk, P., van den Belt, M., 1997. The value of the world ' s ecosystem services and natural capital. Nature 387, 253–260. https://doi.org/10.1038/387253a0

De Simone, S., Sigura, M., Boscutti, F., 2017. Patterns of biodiversity and habitat sensitivity in agricultural landscapes. J. Environ. Plan. Manag. 60, 1173–1192. https://doi.org/10.1080/09640568.2016.1205971

Decaëns, T., Martins, M.B., Feijoo, A., Oszwald, J., Dolédec, S., Mathieu, J., Arnaud de Sartre, X., Bonilla, D., Brown, G.G., Cuellar Criollo, Y.A., Dubs, F., Furtado, I.S., Gond, V., Gordillo, E., Le Clec'h, S., Marichal, R., Mitja, D., de Souza, I.M., Praxedes, C., Rougerie, R., Ruiz, D.H., Otero, J.T., Sanabria, C., Velasquez, A., Zararte, L.E.M., Lavelle, P., 2018. Biodiversity loss along a gradient of deforestation in Amazonian agricultural landscapes. Conserv. Biol. 32, 1380–1391. https://doi.org/10.1111/cobi.13206

Eastman, J.R., 2012. IDRISI Selva Tutorial. Idrisi Prod. Clark Labs-Clark Univ. 45, 51–63.

FAO, 2016. Global Forest Resources Assessment 2015, FAO Forestry Paper No. 1.

Fonsah, E.G., Massonnat, J., Wiggins, L., Krewer, G., Stanaland, D., Smith, J.E., 2013. Southern highbush blueberry marketing and economics (No.1413), UGA Cooperative Extension Bulletin, (No. 1413), UGA Cooperative Extension Bulletin. Athens,GA.

Georgia Info, 2015. Economy - Blueberries [WWW Document]. URL http://georgiainfo.galileo.usg.edu/topics/economy/article/blueberries (accessed 8.16.16).

Gibbs, H.K., Rueschb, A.S., Achard, F., Clayton, M.K., Holmgren, P., Ramankutty, N., Foley, J.A., 2010. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. PNAS 107, 16732–16737. https://doi.org/10.1073/pnas.0910275107

Godone, D., Garbarino, M., Sibona, E., Garnero, G., Godone, F., 2014. Progressive fragmentation of a traditional Mediterranean landscape by hazelnut plantations: The impact of CAP over time in the Langhe region (NW Italy). Land use policy 36, 259–266. https://doi.org/10.1016/j.landusepol.2013.08.018

Graesser, J., Ramankutty, N., Coomes, O.T., 2018. Increasing expansion of large-scale crop production onto deforested land in sub-Andean South America. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aad5bf

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., Hokao, K., 2011. Modeling urban land use change by the integration of cellular automaton and Markov model. Ecol. Modell. 222, 3761–3772. https://doi.org/10.1016/j.ecolmodel.2011.09.009

Hasler, N., Werth, D., Avissar, R., 2009. Effects of tropical deforestation on global hydroclimate: A multimodel ensemble analysis. J. Clim. 22, 1124–1141. https://doi.org/10.1175/2008JCLI2157.1

Hylander, K., Nemomissa, S., Delrue, J., Enkosa, W., 2013. Effects of coffee management on deforestation rates and forest integrity. Conserv. Biol. 27, 1031–1040. https://doi.org/10.1111/cobi.12079

Kandziora, M., Burkhard, B., Müller, F., 2013. Interactions of ecosystem properties, ecosystem integrity and ecosystem service indicators: A theoretical matrix exercise. Ecol. Indic. 28, 54–78. https://doi.org/10.1016/j.ecolind.2012.09.006

Keleş, S., Sivrikaya, F., Çakir, G., Köe, S., 2008. Urbanization and forest cover change in regional directorate of Trabzon forestry from 1975 to 2000 using landsat data. Environ. Monit. Assess. 140, 1–14. https://doi.org/10.1007/s10661-007-9845-5

Kupfer, J.A., Franklin, S.B., 2009. Linking spatial pattern and ecological responses in human-modified landscapes: The effects of deforestation and forest fragmentation on biodiversity. Geogr. Compass 3, 1331–1355. https://doi.org/10.1111/j.1749-8198.2009.00245.x

Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459

Lawler, J.J., Lewis, D.J., Nelson, E., Plantinga, A.J., Polasky, S., Withey, J.C., Helmers, D.P., Martinuzzi, S., Pennington, D., Radeloff, V.C., 2014. Projected land-use change impacts on ecosystem services in the United States. Proc. Natl. Acad. Sci. 111, 7492–7497. https://doi.org/10.1073/pnas.1405557111

Lin, Y.P., Chu, H.J., Wu, C.F., Verburg, P.H., 2011. Predictive ability of logistic regression, auto-logistic regression and neural network models in empirical land-use change modeling - a case study. Int. J. Geogr. Inf. Sci. 25, 65–87. https://doi.org/10.1080/13658811003752332

Liu, J., Li, J., Qin, K., Zhou, Z., Yang, X., Li, T., 2017. Changes in land-uses and ecosystem services under multi-scenarios simulation. Sci. Total Environ. 586, 522–526. https://doi.org/10.1016/j.scitotenv.2017.02.005

McGarigal, K., 2015. Fragstats.Help.4.2 1–182. https://doi.org/10.1016/S0022-3913(12)00047-9

Meng, L., Zhang, D., 2013. Impacts of property tax on land use change decisions in Georgia. Urban Ecosyst. 16, 3–12. https://doi.org/10.1007/s11252-011-0172-9

Millenium Ecosystem Assessment, 2005. Ecosystems and human well-being: Synthesis, Ecosystems. Island Press, Washington D. https://doi.org/10.1196/annals.1439.003

Morales-Hidalgo, D., Oswalt, S.N., Somanathan, E., 2015. Status and trends in global primary forest, protected areas, and areas designated for conservation of biodiversity from the Global Forest Resources Assessment 2015. For. Ecol. Manage. 352, 68–77. https://doi.org/10.1016/j.foreco.2015.06.011

Nagel, P., Yuan, F., 2016. High-resolution land cover and impervious surface classifications in the twin cities metropolitan area with NAIP imagery. Photogramm. Eng. Remote Sens. 82, 63–71. https://doi.org/10.14358/PERS.83.1.63

Nagendra, H., Lucas, R., Honrado, J.P., Jongman, R.H.G., Tarantino, C., Adamo, M., Mairota, P., 2013. Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. Ecol. Indic. 33, 45–59. https://doi.org/10.1016/j.ecolind.2012.09.014

Naidoo, R., Ricketts, T.H., 2006. Mapping the economic costs and benefits of conservation. PLoS Biol. 4, 2153–2164. https://doi.org/10.1371/journal.pbio.0040360

Napton, D.E., Auch, R.F., Headley, R., Taylor, J.L., 2010. Land changes and their driving forces in the Southeastern United States. Reg. Environ. Chang. 10, 37–53. https://doi.org/10.1007/s10113-009-0084-x

NASS, 2017. 2016 blueberry statistics. Trenton,NJ.

Nelson, E., Polasky, S., Lewis, D.J., Plantinga, A.J., Lonsdorf, E., White, D., Bael, D., Lawler, J.J., 2008. Efficiency of incentives to jointly increase carbon sequestration and species conservation on a landscape. Proc. Natl. Acad. Sci. U. S. A. 105, 9471–6. https://doi.org/10.1073/pnas.0706178105

Nelson, E., Sander, H., Hawthorne, P., Conte, M., Ennaanay, D., Wolny, S., Manson, S., Polasky, S., 2010. Projecting global land-use change and its effect on ecosystem service provision and biodiversity with simple models. PLoS One 5. https://doi.org/10.1371/journal.pone.0014327

NRCS, 2018. NRCS Geospatial data gateway. [WWW Document]. URL https://gdg.sc.egov.usda.gov (accessed 1.28.16).

Olmanson, L.G., Bauer, M.E., 2017. Land cover classification of the Lake of the Woods/Rainy River Basin by object-based image analysis of Landsat and lidar data. Lake Reserv. Manag. 33, 1–12. https://doi.org/10.1080/10402381.2017.1373171

Panda, S.S., 2016. Blueberry farm delineation with high-resolution imagery and self-organizing map neural image classification. Agric. Res. Technol. Access J. 3, 1–11. https://doi.org/10.19080/ARTOAJ.2016.03.555602

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: A review. Ann. Assoc. Am. Geogr. 93, 314–337. https://doi.org/10.1111/1467-8306.9302004

Pizzolotto, R., Brandmayr, P., 1996. An index to evaluate landscape conservation state based on land-use pattern analysis and geographic information system techniques. Coenoses 11, 37–44.

Polasky, S., Nelson, E., Pennington, D., Johnson, K.A., 2011. The impact of land-use change on ecosystem services, biodiversity and returns to landowners: A case study in the state of Minnesota. Environ. Resour. Econ. https://doi.org/10.1007/s10640-010-9407-0

Sangermano, F., Toledano, J., Eastman, R., 2012. Land cover change in the Bolivian Amazon and its implications for REDD+ and endemic biodiversity. Landsc. Ecol. 27, 571–584. https://doi.org/10.1007/s10980-012-9710-y

Scherm, H., Krewer, G., 2003. Blueberry production in Georgia : historical overview and recent trends. Small Fruits Rev. 2, 83–91. https://doi.org/10.1300/J301v02n04_09

Sharp, R., Chaplin-kramer, R., Wood, S., Guerry, A., Tallis, H., Ricketts, T., 2016. InVEST User ’ s Guide. Minneapolis, MN, USA,.

Sleeter, B.M., Sohl, T.L., Loveland, T.R., Auch, R.F., Acevedo, W., Drummond, M.A., Sayler, K.L., Stehman, S. V., 2013. Land-cover change in the conterminous United States from 1973 to 2000. Glob. Environ. Chang. 23, 733–748. https://doi.org/10.1016/j.gloenvcha.2013.03.006

Sohl, T., Reker, R., Bouchard, M., Sayler, K., Dornbierer, J., Wika, S., Quenzer, R., Friesz, A., 2016. Modeled historical land use and land cover for the conterminous United States. J. Land Use Sci. 11, 476–499. https://doi.org/10.1080/1747423X.2016.1147619

Song, X.P., Hansen, M.C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E.F., Townshend, J.R., 2018. Global land change from 1982 to 2016. Nature 560, 639–643. https://doi.org/10.1038/s41586-018-0411-9

Song, X.P., Huang, C., Townshend, J., 2014. An integrated framework for evaluating the effects of deforestation on ecosystem services. IOP Conf. Ser. Earth Environ. Sci. 17, 0–6. https://doi.org/10.1088/1755-1315/17/1/012061

The Center for Agribusiness & Economic Development, 2016. 2015 Georgia farm gate value report.

Tian, H., Chen, G., Zhang, C., Liu, M., Sun, G., Chappelka, A., Ren, W., Xu, X., Lu, C., Pan, S., Chen, H., Hui, D., McNulty, S., Lockaby, G., Vance, E., 2012. Century-scale responses of ecosystem carbon storage and flux to multiple environmental changes in the Southern United States. Ecosystems 15, 674–694. https://doi.org/10.1007/s10021-012-9539-x

Tolessa, T., Senbeta, F., Kidane, M., 2017. The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. Ecosyst. Serv. 23, 47–54. https://doi.org/10.1016/j.ecoser.2016.11.010

Turner, W.R., Brandon, K., Brooks, T.M., Costanza, R., da Fonseca, G.A.B., Portela, R., 2007. Global conservation of biodiversity and ecosystem services. Bioscience 57, 868–873. https://doi.org/10.1641/B571009

U.S. Census Bureau (2018). Quick Facts. Retrieved from https://www.census.gov/quickfacts/fact/table/coffeecountygeorgia,ga/PST045218

U.S.Geological Survey, G.A.P. (GAP), 2018. Protected areas database of the United States (PAD-US, version 1.4 combined feature class. [WWW Document]. URL https://gapanalysis.usgs.gov/padus/data/ (accessed 5.15.18).

Upadhaya, S., Dwivedi, P., 2019. The role and potential of blueberry farming in increasing deforestation in southern Georgia, United States. Agric. Syst.

USDA National Agricultural Statistics Service Cropland Data Layer, 2018. Published crop-specific data layer [WWW Document]. URL https://nassgeodata.gmu.edu/CropScape/ (accessed 8.20.18).

Wade, A.S.I., Asase, A., Hadley, P., Mason, J., Ofori-Frimpong, K., Preece, D., Spring, N., Norris, K., 2010. Management strategies for maximizing carbon storage and tree species diversity in cocoa-growing landscapes. Agric. Ecosyst. Environ. 138, 324–334. https://doi.org/10.1016/j.agee.2010.06.007

Wear, D.N., Greis, J.G., 2013. The Southern forest futures project: technical report. Gen. Tech. Rep. SRS-GTR-178 178, 1–152. Asheville, NC. https://doi.org/10.1017/CBO9781107415324.004

Wear, D.N., Huggett, R.N., Li, R., 2013. Forecasts of forest conditions in U.S. regions under future scenarios: a technical document supporting the Forest Service 2010 RPA assessment. Gen. Tech. Rep. SRS-170. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station 101.

Yacouba, D., Guangdao, H., Xingping, W., 2009. Applications of remote sensing in land use/land cover change detection in Puer and Simao counties, Yunnan province. J. Am. Sci. 5, 157–166.

Zaehringer, J.G., Schwilch, G., Andriamihaja, O.R., Ramamonjisoa, B., Messerli, P., 2017. Remote sensing combined with social-ecological data: The importance of diverse land uses for ecosystem service provision in north-eastern Madagascar. Ecosyst. Serv. 25, 140–152. https://doi.org/10.1016/j.ecoser.2017.04.004

Zhang, L., Kono, Y., Kobayashi, S., 2014. The process of expansion in commercial banana cropping in tropical China: A case study at a Dai village, Mengla County. Agric. Syst. 124, 32–38. https://doi.org/10.1016/j.agsy.2013.10.006

Zhao, S., Liu, S., Sohl, T., Young, C., Werner, J., 2013. Land use and carbon dynamics in the southeastern United States from 1992 to 2050. Environ. Res. Lett. 8. https://doi.org/10.1088/1748-9326/8/4/044022

Zhao, S., Peng, C., Jiang, H., Tian, D., Lei, X., Zhou, X., 2006. Land use change in Asia and the ecological consequences. Ecol. Res. 21, 890–896. https://doi.org/10.1007/s11284-006-0048-2

Zhao, S.Q., Liu, S., Li, Z., Sohl, T.L., 2010. A spatial resolution threshold of land cover in estimating terrestrial carbon sequestration in four counties in Georgia and Alabama, USA. Biogeosciences 7, 71–80. https://doi.org/10.5194/bg-7-71-2010

Ziegler, D.A., Fox, M.J., Xu, J., 2009. The Rubber Juggernaut. Science (80-.). 324, 1024–1025. https://doi.org/10.1126/science.1173833

CHAPTER 4

KEEP IT BLUE OR MAKE IT GREEN: CAPTURING MOTIVATIONS OF FAMILY LANDOWNERS FOR GROWING BLUEBERRIES INSTEAD OF PINE IN SOUTHERN GEORGIA, USA USING Q METHODOLOGY[3]

[3] Upadhaya, S & Dwivedi, P. To be submitted to [Human Ecology]

Abstract

Several studies have analyzed forestland conversion to agriculture using the Ricardian rent perspective. However, no study, to the best of our knowledge, focuses directly on the intrinsic motivations of family landowners about their current land use and historical land use change decisions. In this study, we used Q-methodology for characterizing landowners on the basis of motivations of growing blueberries on the former forestlands in southern Georgia where more than 6,000 hectares of forestland has moved into blueberries between 2010 and 2017. Our analysis classified landowners into four groups depending upon their motivations behind growing blueberries. Family-Oriented Owners are growing blueberry as a family legacy. Opportunistic Owners see more opportunities of getting a higher value from their land than forestry, while Profit Motivated Owner converted forestlands into a blueberry farm for higher profit. They also see forestry as a long-term investment. Environmental Cautious Owners converted their forestlands into a blueberry farm for profit, but they see a direct connection between deforestation and blueberry expansion. A majority of the landowners suggest that with proper incentives they could convert back to forestry from blueberries mostly due to intrinsic risks involved with blueberry farming. Our findings provide useful information for policymakers and land managers in designing appropriate incentives and extension services for influencing and sustaining the forestry sector in Georgia and other neighboring states which are facing similar challenges.

Keywords

Family Landowners; Land Use Change; Motivations; Q Method, Pine Forest, Blueberries

4.1 Introduction

Private landowners control a greater proportion of forestlands in the United States than any other single ownership group (Butler et al., 2016). Approximately 179 million ha of forestland (57% of the total forest area) in the United States is owned by private forest landowners (Oswalt et al., 2018). In the southern United States, about 86% of the total forest area (93 million ha) is owned by 9.9 million private landowners (Butler and Wear, 2013). A closer look at the state level statistics in Georgia, the largest round wood-producing state in the United States, reveals that as much as 89% of the total forestland (9.9 million ha) is owned by private forest landowners (Oswalt et al., 2018). In Georgia, family forestland has declined by 0.4 million hectares between 2007 and 2017 (Oswalt et al., 2018), and this trend is expected to continue due to expanding urbanization and commercial agriculture (Wear, 2013).

Georgia is the largest producer of blueberries in the United States, as it produced about 16% of the total blueberries in 2014 nationwide (Georgia Info, 2015). More than 97% of the total blueberry plants in Georgia are located in the southeast region of the state (Fonsah et al., 2013). Between 2010 and 2017, private forest landowners converted more than 6,000 hectares of evergreen forestland into blueberry farms in the state and majority of which were located in southeastern Georgia (USDA 2018). This land use change decision of private forest landowners could have a long-term negative effect on the forestry sector in the state which supports 144,537 jobs, generates $8.5 billion in wages and salaries, and contributes $778 million in the form of tax (Georgia Institute of Technology, 2016). This is especially true as the southeastern region of the state is also a major producer of softwood round wood products. In 2014, the average annual removal of softwood round wood was 31.1 million metric tons in the region while average annual net growth was 41 million metric tons (Brandeis et al., 2016). This land use change could also affect the supply of ESs (carbon sequestration, clean water, soil conservation, etc.) to the citizens of Georgia and other neighboring states. Therefore, an understanding of the drivers of land use change is crucial in developing an appropriate land use plan for ensuring the multifunctionality of a landscape in southern Georgia.

Conversion of forestland into commercial agriculture continues to be a major concern globally. This land use change is the result of various drivers which are governed by the range of environmental, socioeconomic, policy, and institutional factors (Geist and Lambin, 2002). Identifying the drivers of land use change has been one of the main concerns of the literature on land use and land cover change (Angelsen and Kaimowitz, 1999; DeFries et al., 2010; Lubowski et al., 2008; Rueda et al., 2019). Most of the literature on the causes and drivers of land use change had focused on the proximate and distal causes such as socioeconomic (Pielke, 2005), demographic (Hosonuma et al., 2012), environmental (Druga and Falťan, 2014), and policy (Polyakov and Zhang, 2008). Most of these studies have analyzed land use change from an economic perspective by adopting Ricardian rent approach (Angelsen and Kaimowitz 1999; Parker et al. 2003; Alig et al. 2010; Chakravarty et al. 2012) arguing that productivity determines the use of land or the expected return from its alternative uses. Angelsen and Kaimowitz (1999) synthesized more than 140 models analyzing the causes of deforestation and reported that as the price of agricultural products rises, the pressure on forest increases. Lubowski et al. (2008) analyzed drivers of land use change in the United States between 1982 and 1997 and identified the decline in net returns from agricultural crops affects forest area. Lambin et al. (2001) argue that landowners' responses to economic opportunities, mediated by institutional factors, drive land use change. The basic assumption of these studies is that landowners behave like rational agents who respond to the economic incentives, given by the opportunity cost of land use change such as deforestation. However, research exploring the psychological drivers of land use change, i.e., motivations, is still scant despite being crucial to understanding the process of land use change and individual decision making within the social-ecological system (Huiyi, 2013; Rueda et al., 2019).

Few studies have attempted to understand the landowner's motivation behind land use and land use change. Huiyi (2013) revealed people's pursuit of increasing labor productivity as the underlying motivation for land use change in China. Rueda et al. (2019) used a questionnaire-based survey method for exploring the relationship between motivations of landowners and deforestation in Colombia. It was found that motivational factors explain differences in self-reported deforestation regardless of similar socio-economic characteristics or the biophysical conditions of the landowners' farm. Poudyal et al. (2014) found that sociodemographic factors and ownership characteristics significantly influenced the landowners' decisions to convert forestland in Tennessee, United States. Only a few studies have characterized landowners by their motivations of land use change. Sorice et al. (2012) classified landowners from central Texas, USA into three groups (agricultural production, multi-objective, and lifestyle-oriented), on the basis of motivations using cluster analysis. Majumdar et al. (2008) used multivariate cluster analysis to characterize family forest landowners in Alabama, Georgia, and South Carolina, based on their feelings about forest stewardship and their stated reasons for owning forestland. They suggest that it is important to understand landowners motivations for policy implementation to promote better stewardship of family forestlands. They characterized landowners into three clusters, namely, multi-objective, nontimber, and timber. More than 49.1% of the respondents were characterized as the Multi-objective ownership type and 29.4% timber cluster in their study. They confirmed that family forest landowners do tend to be heterogeneous in their land use motivations and objectives (Majumdar et al., 2008). Kurtz and Lewis (1981) used Q methodology and classified nonindustrial private forest landowners into four groups (Timber agriculturalist, Timber Conservationist, Forest environmentalist, and Range pragmatist) in the Missouri Ozarks based on their motivations and objectives of holding land.

To the best of our knowledge, no study has tried to develop typologies of family landowners on the basis of their motivations for practicing commercial agriculture in place of forestry. This is especially true in the context of blueberry growers in Georgia where family landowners dominate the forestland ownership controlling 62% of the total forestland (9.9 million ha) in Georgia (Oswalt et al., 2018). Therefore, understanding the motivations behind decisions of family landowners on land use changes is crucial for sustaining existing forestlands in the region. Therefore, the objectives of this study are to understand what motivates landowners to grow blueberries in place of pine in southern Georgia and develop a typology of such landowners based on their motivations. We used Q methodology to categorized landowners on the basis of their motivations of growing blueberries. A categorizing scheme of this type, based on motivations, would be important in designing suitable policy incentives for reducing the deforestation in Georgia and other surrounding states which face similar issues.

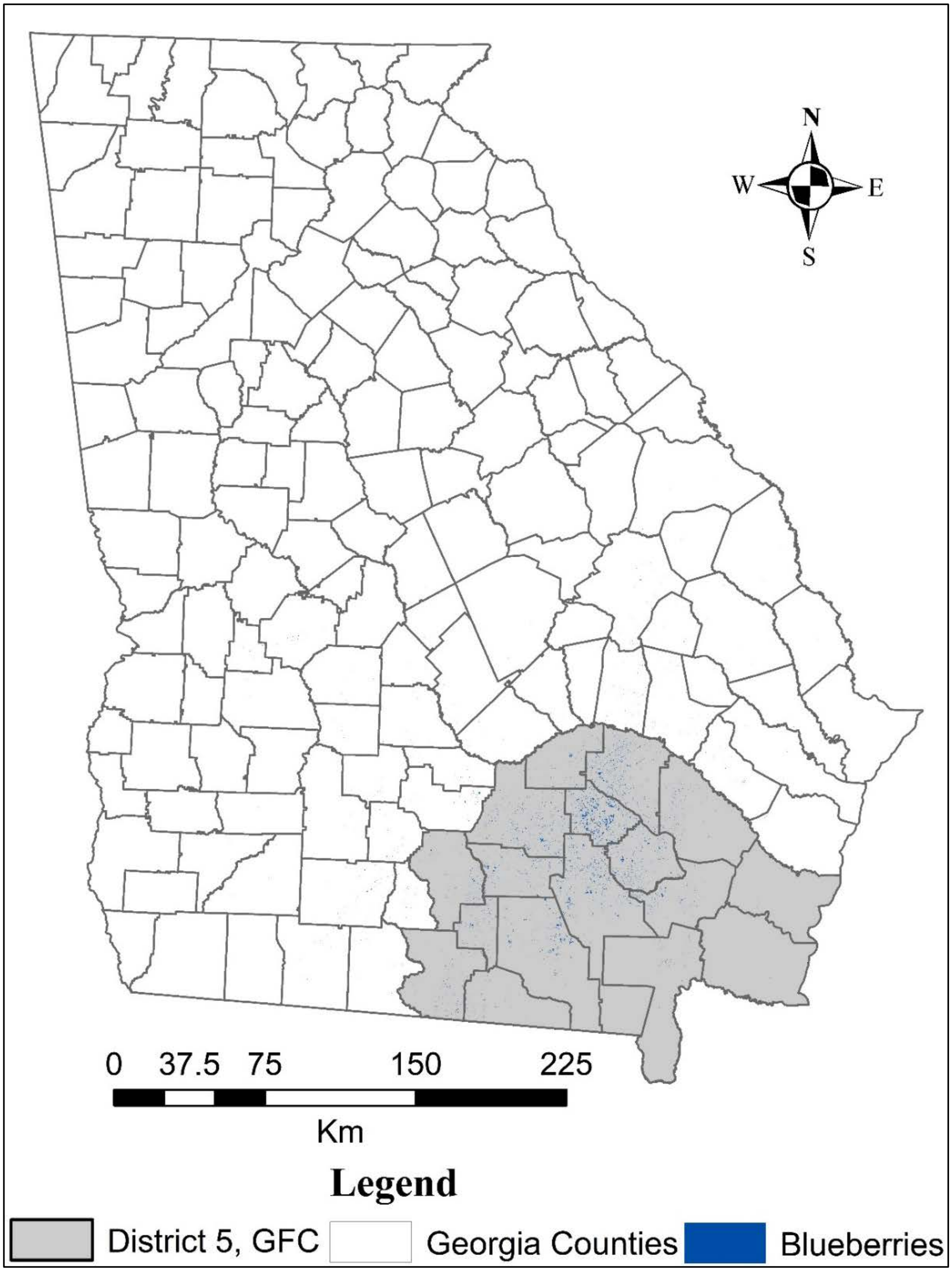


Figure 4.1. Map showing locations of blueberry production in Georgia (Source: USDA, 2018). As evident, the majority of blueberry production in Georgia is located in the southeastern part of the state, which corresponds to the District Five of the Georgia Forestry Commission (GFC).

4.2 Material and Methods

4.2.1 Background to Q Methodology

Q methodology is a pile-sorting method that systematically explores and analyses different perspectives on a particular topic based on similarities and differences in how much people agree or disagree with statements about that topic (Watts and Stenner, 2012). Q methodology combines the strength of both quantitative (factor analysis) and qualitative (ethnographic interviews) research traditions. It uses factor analysis to find idealized models of how participants sort those statements from subjective dimension such as “strongly agree” to “strongly disagree”, and then interprets those models qualitatively based on how the statements are arranged in relation to each other for detecting any shared modes of engagement, orientations or forms of understanding (Brown 1993; Watts and Stenner 2012). This methodology was first developed by psychologist/physicist William Stephenson in 1930s, with the goal of revealing human subjectivity in attitudes in an objective manner (Stephenson 1935; Watts and Stenner 2005). Although it was initially developed as a tool for psychological research, Q methodology has been used in various field of environmental topics, including human geography (Robbins and Krueger, 2000), integrated water resource management (Ward, 2013), global environment change (Dayton, 2000), forest and wildlife conservation (Davies and Hodge, 2012; Kamal and Grodzinska-Jurczak, 2014; Peters and Ward, 2017; Rodríguez-Piñeros and Mayett-Moreno, 2014), and forest management (Kurtz and Lewis 1981; Urquhart et al. 2012).

The value of Q methodology compared to other traditional survey-based methods is that it provides a systematic means of identifying and exploring the different perspectives about a topic that are represented within a selected group of participants (Sumberg et al., 2017; Zabala et al., 2018).

Though it has been critiqued for being subjective and too dependent on the researcher's interpretation, it is now widely accepted as providing valuable insights into participant's views and perspectives (Watts and Stenner, 2012). Traditional survey-based methods often clustered participants' response into pre-defined categories and variables but in contrast, Q methodology avoids the researcher's bias on participants clustering by allowing analytic categories to emerge from the research as shared perspectives on a particular topic (Robbins and Krueger, 2000). Our study creates categories by analyzing similarities and difference in participants responses instead of relying on source-based or procedural categories.

4.2.2 Q sample-The Statement

Q methodology follows a series of pre-defined steps for exploring perspectives of respondents on a given topic of interest. The first and most important step in any Q methodological study is the formulation of a list of statements (Q-sample) that represents as many ideas about the research topic as possible. Brown (1996) suggests that Q-sample should not be theory-driven, but it can be carried out as a sampling task. In practice, different sources, such as extensive literature reference, magazines, films, television programs, formal interviews, informal discussions, and sampling studies can be used to prepare the Q-sample (Brown, 1996; Watts and Stenner, 2005). We sampled statements by initial interview and review of academic and extension articles believing that constructing statement using interview and other source yields more diverse statements and reflect the particular research questions (Sæbjørnsen et al., 2016).

Statements used for our Q methodological study were derived from interviews and literature review. We conducted 12 initial interviews with landowners, representatives of the Georgia

Blueberry Growers Association (GBGA) and Blueberry Growers Listserv of the University of Georgia (UGA). We interviewed only those landowners who have converted their forestlands into blueberry farms for developing an understanding of critical factors considered as important by landowners behind their decision of land use change based on personal experiences. The interviews were face-to-face and structured, but we allowed landowners to take the conversation where they wanted. However, we formulated questions in a way that reflected upon the personal experiences of landowners with respect to their decision on growing blueberry instead of continuing forestry. Through interview and literature review, 33 statements were selected to demonstrate a range of opinion towards land use change decisions. As Brown (1993) state that the statements, however, of any Q sample are not facts but merely views and opinions in the widest sense, the size of the Q sample should be manageable as a longer Q set will require more time and resources for analyzing (Kamal and Grodzinska-Jurczak, 2014; Logo, 2013).

We identified four major thematic categories (economic, environmental, social, and political) for narrowing down the Q-sample. The economic category was further divided into two, long term and short term, categories. In this regard we selected four statements in each category, resulting in a twenty-statement Q-sample (Table 1). The selected statements were pre-tested with UGA blueberry extension staff, volunteer landowners, and academic researchers familiar with Q methodology for clarity improvements.

Table 4.1. Factor Q-sort values of each statement and its corresponding theme. Here, -3 represents strongly disagree, and +3 represents strongly agree. Eco LT stands for Economics Long Term, Eco ST stands for Economic Short Term, Env stands for Environmental, Social and Pol stands for Political.

			Factor			
#	**Statement**	**Theme**	**1**	**2**	**3**	**4**
S1	For me, forestry is a too long-term investment.	Eco LT	-1	1	0	3
S2	It is valuable to brand blueberry “Georgia Grown.”	Pol	2	2	2	0
S3	You always have to choose between conservation and profits.	Env	-2	0	-1	-3
S4	I value the blueberry production advice I get from local extension personnel.	Pol	0	1	-1	2
S5	For me, growing blueberries is a better use of my land than timber.	Eco ST	2	3	0	-2
S6	Labor availability is a major challenge in blueberry production.	Soc	3	3	3	0
S7	There is a direct connection between deforestation and expansion of blueberry farm.	Env	-3	-1	1	-2
S8	I grow blueberries as a retirement plan.	Eco LT	1	-3	-3	-1
S9	Blueberry farm does provide environmental services like wildlife habitat, flood control, and erosion control.	Env	0	0	0	1
S10	Moving forestland into blueberry could potentially affect the local environment.	Env	-2	-1	1	-1
S11	Blueberry farmers benefit more from the reduced tax burdens than forest landowners.	Pol	0	-2	-2	1
S12	Societal acceptance and awareness is the major reason behind the blueberry promotion.	Soc	0	-2	1	1
S13	I feel good about supplying a crop with health benefits to the local market.	Soc	1	-1	3	3
S14	More rules and regulations are important for the development of blueberry production.	Pol	-1	-3	-1	0
S15	Growing blueberries is a family business.	Soc	1	1	2	-1
S16	I grow blueberries as part of the family legacy to leave for future generations.	Eco LT	2	0	0	-2
S17	With the right financial incentives, I would convert my blueberry farms into the forest.	Eco LT	-3	0	-2	-3
S18	Blueberry is good for local economic growth.	Eco ST	3	2	2	2
S19	The timber market is riskier than the blueberry market.	Eco ST	-2	-2	-3	2
S20	Markets for blueberries and blueberry products are easily available.	Eco ST	-1	2	-2	0

4.2.3 P Sample-The Participants

The second step in Q methodological study is to recruit the participants. The recruitment of participants was purposive rather than random to capture different perspectives (Dziopa and Ahern, 2011). For the purpose of this study, we were primarily interested in soliciting views and opinions from landowners who have converted their forestland into blueberry farms in southern Georgia. We approached landowners at GBGA meeting in Clinch County, Georgia, and the Fall Equipment and Technology Day at the UGA Extension's Blueberry Research and Demonstration Farm in Alma, Georgia. At the meetings, we explained our research first to landowners and then obtained their oral consent for participation. Ultimately, we ended up with a P sample of 34 landowners which is acceptable and appropriate for Q study (Watts and Stenner, 2012). These landowners are growing blueberries instead of pine on their lands though the majority of their blueberry farms were located on erstwhile forestlands.

4.2.4 Q Sorting

The interested participants have to rank-order each of the 20 statements in relation to each other using their subjectivity. After oral consent, we instructed each participant to read all 20 statements and make two piles "agree" and "disagree." After sorting the statements into two piles, we instructed participants to sort the statements into a grid-shaped as quasi-normal distribution, with strongly agree, and disagree at each end of the distribution (Figure 2). The use of quasi-normal distribution grid with strongly agree and disagree on two ends makes them sort the rest of the statements into the middle of the distribution and restricts them to strongly agreeing or disagreeing with only a few statements (Brown 1996; Brown et al. 2018). Throughout the Q sorting process, participants were allowed to move statements between columns and reorder within the column.

After the completion of sorting of all statements on the grid, we asked participants to comment on any interesting placement of statements. Along with Q sorting, we conducted a short survey to collect the participant's demographic and landholding characteristics. We also gather information on how much and when they converted forestlands into blueberry farms.

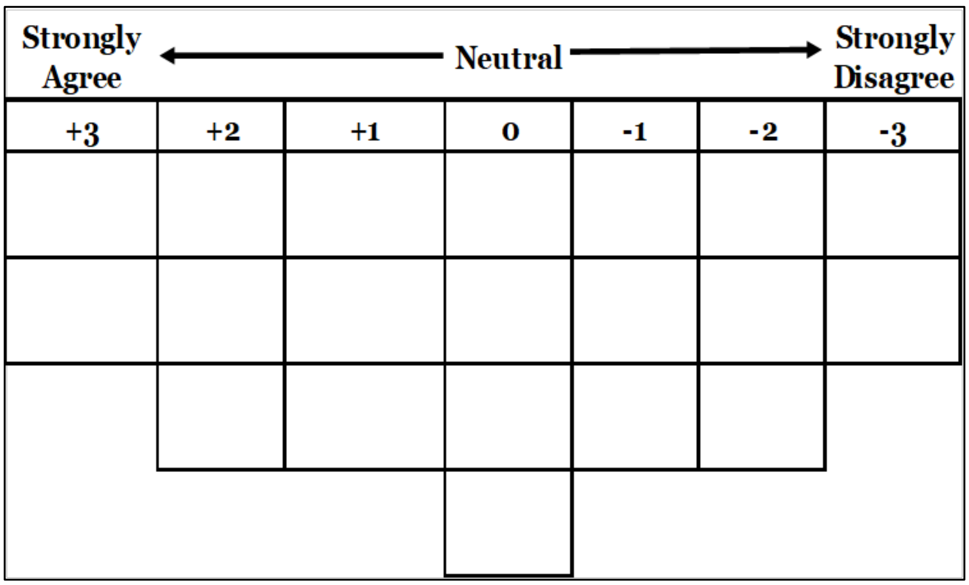


Figure 4.2. Q sort ranking grid. Each cell represents one statement where -3 represents strongly disagree, and +3 represents strongly agree.

4.2.5 Analysis

The last step of Q methodological study is to interpret how participants sorted the statements. We used PQMethod software (Schmolck, 2014) to analyze the collected data. The sort patterns of the participants were then intercorrelated, and the resulting correlation matrix offered the basis for the extraction of factors, i.e., common sort patterns across a number of participants. We performed Principal Component Analysis (PCA) to extract relevant factors. PCA resulted in eight components out of 20 with an eigenvalue of at least 1.00. Following Watts and Stenner (2012), we eliminated 16 factors with eigenvalues below 1.00, which implies that factors with eigenvalue less than one do not capture enough variation to account for even a single participant's perspective.

We selected four factors for interpretation because the rest of the 4 factors had less than two participants significantly loading on them (Lynch et al., 2014; Watts and Stenner, 2012). As a result, four factors were selected for further analysis.

We then rotated remaining factors using the Varimax module (QVARIMAX). We did so to maximize the differences between them to make them as distinct from each other as possible (Watts and Stenner, 2012). The Q sorts of two or more participants who loaded highly on the factor, as determined by the factor (loading) matrix, were used as the "defining sorts" for that particular factor. We then created factor arrays using weighted averaging of these defining sorts. We have weighted averaged so that those participants whose Q sort had higher loading with the factor had more influence on the final factor score. Factor score is assigned to each statement for each factor. The factor score range from +3 (strongly agree) to -3 (strongly disagree) (Watts and Stenner, 2012). The magnitude and sign of the factor scores indicate the relationship of the statements within each factor. Using the "crib sheet" method described by Watts and Stenner (2012), we systematized the interpretation process and built a narrative for each factor.

4.3 Results

In our study, 34 family landowners participated among which 82% were males and rest were females. The reported education level ranged from high school to a university degree. A majority of the participants identified themselves as self-employed while some also included occupations like medical doctor, dentist, banker, and farm manager. The mean age of participants was 56 years with the youngest of 21 years old and the oldest of 80 years old. Some of the landowners reported that they first planted blueberries in 1970 while the newest blueberry growers planted in 2017 indicating that some are experienced blueberry farmers, and some are beginning farmers. More than 47% of the landowners converted their forestland into blueberries between 2000 and 2010. The mean reported land occupancy was 154 hectares while the average blueberry farms holding was 74 hectares.

Based on our understanding as developed while surveying these landowners, we extracted four factors (Table 4.2). Together, these four factors explain 72% of the variance in the data, where first, second, third, and fourth accounted for 33%, 15%, 14%, and 10% of the total variance, respectively. These four factors are described in the following section by discussing the salient statements for each of them. In the idealized Q sort, the statements were assigned +3 (strongly agree with) and -3 (strongly disagree with). Also, statements that distinguish each factor from the others at a significant level at $p<0.01$ are discussed together with evidence from the interviews. Of the 34 Q sorts, 16 loaded heavily on factor 1; five on factor 2; six on factor 3; and two on factor 4 (Table 4.2). Each factor is identified with a name representing its dominant characteristics and the views of groups of similarly minded family forest landowners.

Table 4.2. Respective loading of each landowner across four factors. Marked in bold are defining sorts, which are used to create the factor arrays.

	Factors			
Landowners	Family Oriented (1)	Opportunistic (2)	Environmental Cautious (3)	Profit Motivated (4)
1	**0.754**	0.444	-0.121	0.087
2	0.222	0.292	**0.867**	0.079
3	**0.857**	0.249	0.236	0.070
4	**0.888**	0.114	0.242	0.105
5	**0.769**	0.400	-0.116	-0.059
6	**0.720**	0.022	0.440	-0.071
7	0.035	-0.207	**0.570**	0.170
8	0.142	**0.540**	0.034	0.245
9	**0.612**	-0.163	0.385	0.029
10	**0.692**	0.175	0.328	-0.257
11	-0.083	0.193	0.088	**0.854**
12	0.508	0.603	0.413	0.013
13	0.233	**0.840**	-0.003	-0.053
14	**0.693**	0.326	0.437	0.221
15	0.299	0.242	**0.823**	0.091
16	0.232	0.350	**0.637**	0.293
17	0.279	0.064	**0.555**	0.066
18	**0.805**	0.182	0.284	0.146
19	**0.787**	0.437	-0.073	0.069
20	**0.871**	0.174	0.246	0.075
21	-0.342	**0.607**	0.184	-0.054
22	0.450	**0.710**	0.018	0.389
23	0.334	**0.695**	0.293	0.329
24	0.102	-0.062	0.120	**0.927**
25	0.107	0.188	0.436	0.449
26	0.380	0.530	0.540	-0.219
27	**0.734**	0.273	-0.135	0.265
28	**0.661**	-0.156	0.239	0.395
29	-0.132	-0.097	**0.477**	-0.406
30	**0.666**	0.332	0.121	0.278
31	0.553	0.498	0.079	0.473
32	**0.721**	-0.131	0.277	0.073
33	**0.890**	0.123	0.190	0.076
34	0.541	0.441	0.274	0.612
Explained variance in %	33	15	14	10
Number of defining variable	16	5	6	2
Correlation between factor scores				
Factor 1		0.477	0.500	0.181
Factor 2			0.379	0.174
Factor 3				0.222

4.3.1 Family Oriented Owner (Factor One)

The first group of landowners, Family-Oriented Owner, exemplified by factor one, are continuing family legacy of growing blueberries (S16). This is the largest group of owners with 16 participants loading heavily on it. Some of the landowners have managed their blueberry farms since 1980 as the family legacy. Landowners associated with this group strongly believe that growing blueberries is a family business (S15). Either they are continually growing blueberries on the land that the family owned, or they are extending their blueberry business. The young generations and the older generation both are participating in growing blueberries. The youngest and oldest landowners who associated with this group were of age 21 years and 64 years respectively. They also considered blueberries as a good source of retirement funds as the motivation behind growing blueberries. Landowner #30 mentioned that the return from blueberries is higher which he/she can put towards retirement fund. Apart from family benefits, landowners under this group also think that growing blueberries is good for their community and is well reflected in the form of a strong local economy (S18). Landowner # 33 mentioned that the local businesses in his area have flourished due to an increase in the blueberry industry. He/she also mentioned that most of the county revenue comes from the blueberry industry. Of all the four owner groups, they agree least with the statement “For me, forestry is a too long-term investment (S1)”. They also agree that labor availability is a major challenge in blueberry production (S6). This group is also the one that doesn’t believe that you always have to choose between conservation and profits. Landowners under this group have an average qualification of college and dominated by male (100%). On average they own 35 hectares of blueberry farms (Table 3).

Table 4.3. Characteristic of the landowners who loaded significantly in different four factors.

	Family Oriented (Factor One) n=16	**Opportunistic (Factor Two) n=5**	**Environmental Cautious (Factor Three) n=6**	**Profit motivated (Factor Four) (n=2)**
	Mean (min/max)			
Age	48.18 (21/64)	55 (37/70)	57.3 (38/65)	62 (62/62)
Gender				
Male	100%	60%	50%	100%
Female	-	40%	50%	
Level of Education				
High School	13%	80%	-	100%
College	81%	20%	67%	-
Graduate Degree	6%	-	33%	-
Year Blueberry Planted	2005 (1980/2017)	2004 (1987/2016)	2005(1991/2015)	2014(2013/2016)
Blueberry Farm (ha)	35 (6/121)	109.3 (12/283)	86.2 (2/182)	22 (2/40.5)

4.3.2 Opportunistic Owner (Factor Two)

Landowners belonging to the second factor, Opportunistic Owner, see growing blueberries as a better use of their land than forestry. This is illustrated by the support for the statement S5, i.e., for me, growing blueberries is a better use of my land than timber. The availability of the market for blueberries and blueberry products seems like an opportunity for them to get more benefits from growing blueberries (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008). Though they are encouraged by various opportunities that exist within the blueberry market, they agree that with good financial incentives they might get back to forestry again as they don't think the timber market is riskier than the blueberry market. Of all the owner groups, they agree with the statement S17, "With the right financial incentives, I would convert my blueberry farms into the forest" reflecting their opportunistic stance. They are also encouraged by the option available for branding their blueberry products as "Georgia Grown." Landowner 23 mentioned that selling products using the "Georgia Grown" brand fetches him/her more profit than selling under the generic brand. But this is the only group that least agree with the statement "I feel good about supplying a crop with health benefits to the local market" (S13). It revealed that landowners under this group are motivated by the wide range of opportunities that lie in the blueberry market. Although this group sees growing blueberries as a good use of their land, they see lots of challenges too. Labor availability is the major challenge felt by them which is reflected by their support for the statement S6, i.e., labor availability is the major challenge in blueberry production. But this group doesn't see the advantages of rules and regulations. This is the only group that strongly disagree with the statement S14 (more rules and regulations are important for the development of blueberry production). Landowners in this group believed that blueberry farmers were not benefited more from the reduced tax burdens than forest landowners (S11). A majority of the landowners belonged to this group converted their forestlands to blueberry farms during 2004 when the market for blueberries was booming, further reflecting on opportunistic behavior. On average they have 109 hectares of blueberry farms and have an average qualification of high school and dominated by male (60%) (Table 3).

4.3.3 Environmental Cautious Owner (Factor Three)

This is the only group of landowners who emphasize on the statement S10 (moving forestlands into blueberries could potentially affect the local environment) and see a direct connection between deforestation and expansion of blueberry farms (S7). In addition, landowners under this group did not think that blueberry farms provide environmental services like wildlife habitat, flood control, and erosion control (S9). Landowner 29 mentioned that though he/she doesn't see immediate environmental consequences after he/she converted his/her forestland into blueberries, he/she sees fewer birds and animals around his/her farm. These landowners seem to be happy from supplying a crop with health benefits to the local market. Furthermore, the Environmental Cautious Owner thinks that societal acceptance and awareness is the major reason behind the blueberry promotion (S12). Among all the owner groups, this is the only group where male and female loaded equally, and this group has an average qualification of a college degree. They have an average blueberry farm of 86 hectares, and they first planted blueberries in 1991 (Table 3).

4.3.4 Profit Motivated Owner (Factor Four)

The major motivation for this group for growing blueberries is earning more money in a short time from blueberries than forestry, as they strongly believe in the statement S1, (For me, forestry is a too long-term investment.). Landowner 11 said, "I can get a return from blueberry within three years of plantation." They strongly believe that blueberries are good for local economic growth (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008), Landowners under this group loaded positively on statement S11 (Blueberry farmers benefit more from the reduced tax burdens than forest landowners). This showed that reduced tax burdens drive their land use decisions. They strongly agree that there is less risk in the blueberry market than the timber market. Landowners who loaded strongly on this group do not express a strong opinion that they have to choose between conservation and profits (S3).

Furthermore, this group does not think there is any connection exists between deforestation and expansion of blueberry farms. This is the only group that is not growing blueberries as a family business. Their motivation is to make money now; they do not believe that they are earning for legacy and future generations (S16). Landowner # 10 mentioned that he/she entered into the blueberry market because he/she saw this as a more potential profit-making crop than others. The landowners who loaded significantly on this group are very new to the market, as they converted their forestland into blueberries between 2013 and 2016. This was that time when the blueberry market was at its peak, and Georgia became the number one producers of blueberries in the country. To make more profit and as they are new in the industry, this is the only group that strongly values the blueberry production advice they get from local extension personnel. Landowners under this group started growing blueberries in 2013 with an average blueberry farm of 22 hectares. They have an average qualification of high school and dominated by male (100%) (Table 3).

4.4 Discussion

This study characterized the family landowners based on their motivations for growing blueberries instead of forests in southern Georgia. The four groups identified in this study suggest that family landowners in southern Georgia have diverse motivations towards land use change, specifically, growing blueberries instead of forests on the lands. While some landowners such as Family Oriented Owners are growing blueberries as a family business and legacy, others see blueberries as an excellent opportunity to make more money relative to managing the land for forests. For example, Opportunistic Owner is growing blueberries instead of pine on their land as they realize that growing blueberries is a better use of their land than managing the same land for forestry. Profit Motivated Owners are growing blueberries to earn more money in a short time period (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008), relative to forestry. However, some landowners, such as Environmental Cautious, have converted their forestland into blueberry farms but still they value the conservation benefits of the forest.

Our study developed typologies (family, economy, environmental and opportunity) of blueberry farmers in the context of deforestation in southern Georgia. Poudyal et al. (2014) categorized their variables into different major themes, sociodemographic, forest ownership, and management objective, and land rent and external factors. In our study, the first types of owners are always motivated by family and legacy. They are practicing and expanding blueberry farms as a family legacy where they inherited the land with blueberries from their family members. In addition, these owners do see their blueberry farms as a source of income for future generations. A majority of the landowners loaded significantly to this owners group suggesting that this is the major motivation behind growing blueberries instead of forests on their lands.

Economic returns from different land use options directly affect land use decisions (Angelsen and Kaimowitz, 1999; Rashford et al., 2011) implying that factors which increase profitability motivate landowners to practice different land uses. The Opportunistic and Profit Motivated Owners in this study most closely resemble the *Multifunctional Owner* identified in Urquhart et al. (2012) and *Range pragmatist* in Kurtz and Lewis (1981) and *agricultural production landowners* in Sorice et al. (2012). These landowners are motivated by the economic benefits available in blueberry farming (Fonsah et al., 2006; Fonsah et al., 2007; Fonsah et al., 2008),   Also, similar results have been reported by several other studies which analyzed land use change from a Ricardian rent perspective (Alig and Healy, 2016; Nagubadi and Zhang, 2005). This perspective argues that the use of a piece of land is primarily determined by its productivity or more importantly, the expected return from its alternative uses. Landowners in the Opportunistic Owner group see growing blueberries as a better use of their land than practicing forestry. They are motivated by the factor that the return from blueberries will be sooner relative to forestry. Economic analysis of net present value (NPV) between yellow pines and blueberries in southern Georgia shows that returns from blueberries are higher than yellow pines in a shorter time period (Upadhaya and Dwivedi, 2019). Poudyal et al. (2014) also found that an increase in net return from forestland use decreases the probability of conversion. Similarly, Nagubadi and Zhang (2005) suggest that an increase in return from softwood will increase acreage under softwood forests which further implies that if the returns from forest decrease, landowners will be motivated to convert their forestland to non-forestland. Schroth and Ruf (2014) also suggest that farmers changed their land use to more lucrative crops to increase their income. Our results also show that the availability of a market for blueberries and its products also motivates landowners to prefer growing blueberry farms than growing timber on their lands. It has been evident from other studies that better access to markets is positively correlated with the expansion of agricultural areas, especially for cash crops cultivation (Vance and Geoghegan 2002; Ellis et al. 2010).

Environmental benefits of the forest have also affected the motivations of landowner's decision on land use change in the study area. The majority of the landowners under Environmental Cautious group value environmental benefits of the forest more than blueberry farms. Similar types of landowners groups have been identified in other studies as well (Hugosson and Ingemarson, 2004; Kurtz and Lewis, 1981; Sorice et al., 2012). Hugosson and Ingermarson (2004) explained that economic concerns might motivate these landowners, but they also value environmental values. Similar motivations have been identified by Kurtz and Lewis (1981) in their *forest environmentalist* group where owners under this group regard the forest as a reservoir for a host of different ESs and benefits. Even though these landowners are not primarily profit-oriented; they recognize the investment value of forestland. Similarly, the landowners under Environmental

Cautious owner group think that moving forestland into blueberries could potentially affect the local environment and they do not see any ESs being provided by blueberry farms. Because of environmental awareness, landowners under this group they have not converted the majority of their land into blueberry compared to other landowners. The significant motivations behind growing blueberries instead of forests on their lands for this group of landowners are that they feel happier about supplying a crop with health benefits to the local market. They also got motivated by the societal acceptance and awareness about blueberries.

The findings of our study suggest that specific owner type such as Opportunistic Owners are more likely to convert back to forestry from blueberries if proper financial assistance is provided. Similar types of motivations have been reported by Urquhart et al. (2012) where many woodland owners expressed their desire to manage their woodlands better, especially if there were appropriate incentives and policy. Also, most landowners in our study expressed that they convert forestlands into blueberry farms or preferred growing blueberries over pine due to the reduced tax burdens in growing blueberries. This aligned well with Cushing and Newman (2018) who suggest that tax burden often encourages land use change in the southern United States.

4.5 Conclusion

The land use change decisions of family landowners have become an issue of concern in sustaining the supply of forest products and ESs to society (Poudyal et al., 2014). This is very important specifically in Georgia where forestry is the second largest industry (Georgia Institute of Technology, 2016). To our knowledge, little is known in terms of what influences family landowners' decision to convert their forestland to agricultural land, particularly blueberry farms.

Using a Q methodology, we characterize the landowners on the basis of their motivations of growing blueberries instead of pine in the land that was formerly forestlands. We identified four different owner groups with distinct motivations for growing blueberries. The findings of this study may provide useful tools and information for policy makers and land managers in designing appropriate incentives and extension services for influencing and sustaining the forestry sector in Georgia and beyond. Understanding the typologies of landowners on the basis of their motivations will reduce the duplication of resource utilization in creating extension program.

The findings of this research provide important insights into family landowners' motivations behind owing land and land use change decisions. However, we urge using caution against generalizing our findings in a broader context, as we consider only those landowners who are growing blueberries on the land that was formerly forestlands in southern Georgia in our analysis. Future research should focus on a wider group of landowners in different region and state to obtain a more nuanced understanding of motivations behind land use and land use change decisions. We hope that this study will suitably guide future research.

References

Alig, R., Stewart, S., Wear, D., Stein, S., 2010. Conversions of forest land : Trends , determinants , projections , and policy considerations, in: Pye, John M.; Rauscher, H. Michael; Sands, Yasmeen; Lee, Danny C.; Beatty, J.S. (Ed.), Advances in Threat Assessment and Their Application to Forest and Rangeland Management. U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, Gen. Tech. Rep. PNW-GTR-802. Portland, OR, pp. 1–26.

Alig, R.J., Healy, R.G., 2016. Urban and built-up land area changes in the United States : An empirical investigation of determinants. Land Econ. 63, 215–226.

Angelsen, A., Kaimowitz, D., 1999. Rethinking the causes of deforestation: Lessons from economic models. World Bank Res. Obs. 14, 73–98. https://doi.org/10.1093/wbro/14.1.73

Brandeis, T.J., Mccollum, J.M., Hartsell, A.J., Brandeis, C., Rose, A.K., Oswalt, S.N., Vogt, J.T., Vega, H.M., 2016. Georgia's Forests, 2014 (No. SRS-209), Resource Bulletin. Southern Research Station, Knoxville, TN.

Brown, S.R., 1996. Q methodology and qualitative research. Qual. Health Res. 6, 561-567

Brown, S.R., 1993. A primer on Q methodology. Operant Subj. 16, 91–138. https://doi.org/10.1177/104973239600600408

Brown Walker, B., Lin, Y., Mccline, R.M., Stephenson, W., Walker, B.B., 2018. Q methodology and Q-perspectives® online: Innovative research methodology and instructional technology Q methodology overview) first conceived of Q methodology as means of objectively measuring subjectivity. TechTrends 62, 450–461. https://doi.org/10.1007/s11528-018-0314-5

Butler, B.J., Hewes, J.H., Dickinson, B.J., Andrejczyk, K., Butler, S.M., Markowski-Lindsay, M., 2016. Family forest ownerships of the United States, 2013: Findings from the USDA Forest Service's National Woodland Owner Survey. J. For. 114, 638–647. https://doi.org/10.5849/jof.15-099

Butler, B.J., Wear, D.N., 2013. Forest ownership dynamics of southern forests, in: Wear, D.N., Greis, J.G. (Eds.), The Southern Forest Future Project: Technical Report. pp. 103–121.Raleigh, NC.

Chakravarty, S., Ghosh, S., Suresh, C., Dey, A., Shukla, G., 2012. Deforestation: causes, effects and control strategies, in: Okia, C. (Ed.), Global Perspectives on Sustainable Forest Management. p. 3–28, doi 10.5772/33342. https://doi.org/10.5772/33342

Cushing, T.L., Newman, D., 2018. Analysis of relative tax burden on nonindustrial private forest landowners in the southeastern United States. J. For. 116, 228–235. https://doi.org/10.1093/jofore/fvx013

Davies, B.B., Hodge, I.D., 2012. Shifting environmental perspectives in agriculture: Repeated Q analysis and the stability of preference structures. Ecol. Econ. 83, 51–57. https://doi.org/10.1016/j.ecolecon.2012.08.013

Dayton, W.B., 2000. Policy frames, policy making and the global climate change discourse, in: Social Discourse and Environmental Policy: An Application of Q Methodology. Edward Elgar, Northampton, Massachusetts, USA, pp. 71–99.

DeFries, R.S., Rudel, T., Uriarte, M., Hansen, M., 2010. Deforestation driven by urban population growth and agricultural trade in the twenty-first century. Nat. Geosci 3, 178–181. https://doi.org/10.1038/ngeo756

Druga, M., Falťan, V., 2014. Influences of environmental drivers on land cover structure and its long-term changes: A case study of the villages of Malachov and Podkonice in Slovakia. Morav. Geogr. Reports 22, 29–41. https://doi.org/10.2478/mgr-2014-0016

Dziopa, F., Ahern, K., 2011. A systematic literature review of the applications of Q-technique and its methodology. Methodology 7, 39–55. https://doi.org/10.1027/1614-2241/a000021

Ellis, E.A., Baerenklau, K.A., Marcos-Martínez, R., Chávez, E., 2010. Land use/land cover change dynamics and drivers in a low-grade marginal coffee growing region of Veracruz, Mexico. Agrofor. Syst. 80, 61–84. https://doi.org/10.1007/s10457-010-9339-2

Fonsah, E.G., Massonnat, J., Wiggins, L., Krewer, G., Stanaland, D., Smith, J.E., 2013. Southern highbush blueberry marketing and economics (No.1413), UGA Cooperative Extension Bulletin, (No. 1413), UGA Cooperative Extension Bulletin. Athens,GA.

Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience 52, 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Georgia Info, 2015. Economy - Blueberries [WWW Document]. URL http://georgiainfo.galileo.usg.edu/topics/economy/article/blueberries (accessed 8.16.16).

Georgia Institute of Technology, 2016. Economic benefits of the forest industry in Georgia : 2016 1–2.

Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., Romijn, E., 2012. An assessment of deforestation and forest degradation drivers in developing countries. Environ. Res. Lett. 7, 12pp. https://doi.org/10.1088/1748-9326/7/4/044009

Hugosson, M., Ingemarson, F., 2004. Objectives and motivations of small-scale forest owners; theoretical modelling and qualitative assessment. Silva Fenn. 38, 217–231. https://doi.org/10.14214/sf.430

Huiyi, Z., 2013. Underlying motivation for land use change: A case study on the variation of agricultural factor productivity in Xinjiang, China. J. Geogr. Sci. 23, 1041–1051. https://doi.org/10.1007/s11442-013-1061-3

Kamal, S., Grodzinska-Jurczak, M., 2014. Should conservation of biodiversity involve private land? A Q methodological study in Poland to assess stakeholders' attitude. Biodivers. Conserv. 23, 2689–2704. https://doi.org/10.1007/s10531-014-0744-0

Kurtz, W.B., Lewis, B.J., 1981. Decision-making framework for forest nonindustrial private owners : An application in the Missouri Ozarks. J. For. 79, 285–288.

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Skånes, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T.A., Vogel, C., Xu, J., 2001. The causes of land-use and land-cover change: Moving beyond the myths. Glob. Environ. Chang. 11, 261–269. https://doi.org/10.1016/S0959-3780(01)00007-3

Logo, E., 2013. Q-method based environmental awareness measurement in transportation. Int. J. Traffic Transp. Eng. 3, 45–53. https://doi.org/10.7708/ijtte.2013.3(1).04

Lubowski, R.N., Plantinga, A., Stavins, R.N., 2008. What drives land-use change in the United States? A national analysis of landowner decisions. Land Econ. 84, 529–550. https://doi.org/10.2139/ssrn.1281520

Lynch, A.H., Adler, C.E., Howard, N.C., 2014. Policy diffusion in arid basin water management: A Q method approach in the Murray-Darling Basin, Australia. Reg. Environ. Chang. 14, 1601–1613. https://doi.org/10.1007/s10113-014-0602-3

Majumdar, I., Teeter, L., Butler, B., 2008. Characterizing family forest owners: A cluster analysis approach. For. Sci. 54, 176–184. https://doi.org/10.1007/s00296-011-1931-x

Nagubadi, R. V., Zhang, D., 2005. Determinants of timberland use by ownership and forest type in Alabama and Georgia. J. Agric. 37, 173–186. https://doi.org/10.1017/S1074070800007185

Oswalt, S.N., Miles, P.D., Pugh, S.A., Smith, W.B., 2018. Forest resources of the United States, 2017: A technical document supporting the Forest Service 2020 update of the RPA assessment, U.S. For. Serv., Gen. Tec. Rep. NC-219. Washington D.C. https://doi.org/10.1126/science.3.72.734-a

Parker, D.C., Manson, S.M., Janssen, M. a., Hoffmann, M.J., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: A review. Ann. Assoc. Am. Geogr. 93, 314–337. https://doi.org/10.1111/1467-8306.9302004

Peters, D.T., Ward, L., 2017. Greater sage-grouse in Montana: Mapping archetype viewpoints across stakeholder groups using Q methodology. Wildl. Soc. Bull. 41, 34–41. https://doi.org/10.1002/wsb.727

Pielke, R.A., 2005. Land use and climate change. Science. 310, 1625–1626. https://doi.org/10.1126/science.1120529

Polyakov, M., Zhang, D., 2008. Property tax policy and land-use change. Land Econ. 84, 396–408. https://doi.org/10.3368/le.84.3.396

Poudyal, N.C., Poudyal, N.C., Joshi, O., Hodges, D.G., Hoy, K., 2014. Factors related with nonindustrial private forest landowners' forest conversion decision in Cumberland Plateau, Tennessee. For. Sci. 60, 988–993. https://doi.org/10.5849/forsci.13-622

Rashford, B.S., Walker, J.A., Bastian, C.T., 2011. Economics of grassland conversion to cropland in the Prairie Pothole Region. Conserv. Biol. 25, 276–284. https://doi.org/10.1111/j.1523-1739.2010.01618.x

Robbins, P., Krueger, R., 2000. Beyond bias? The promise and limits of Q method in human geography. Prof. Geogr. 52, 636–648. https://doi.org/10.1111/0033-0124.00252

Rodríguez-Piñeros, S., Mayett-Moreno, Y., 2014. Forest owners' perceptions of ecotourism: Integrating community values and forest conservation. Ambio 44, 99–109. https://doi.org/10.1007/s13280-014-0544-5

Rueda, X., Velez, M.A., Moros, L., Rodriguez, L.A., 2019. Beyond proximate and distal causes of land-use change: Linking individual motivations to deforestation in rural contexts. Ecol. Soc. 24. https://doi.org/10.5751/ES-10617-240104

Sæbjørnsen, S.E.N., Ellingsen, I.T., Good, J.M.M., Ødegård, A., 2016. Combining a naturalistic and theoretical Q sample approach: An empirical research illustration. Operant Subj. Int. J. Q Methodol. 38, 15–32. https://doi.org/10.15133/j.os.2016.005

Schmolck, P., 2014. PQMethod-2.35.

Schroth, G., Ruf, F., 2014. Farmer strategies for tree crop diversification in the humid tropics. A review. Agron. Sustain. Dev. 34, 139–154. https://doi.org/10.1007/s13593-013-0175-4

Sorice, M.G., Kreuter, U.P., Wilcox, B.P., Fox, W.E., 2012. Classifying land-ownership motivations in central, Texas, USA: A first step in understanding drivers of large-scale land cover change. J. Arid Environ. 80, 56–64. https://doi.org/10.1016/j.jaridenv.2012.01.004

Stephenson, W., 1935. Technique of factor analysis. Nature. https://doi.org/10.1038/136297b0

Sumberg, J., Yeboah, T., Flynn, J., Anyidoho, N.A., 2017. Young people's perspectives on farming in Ghana: a Q study. Food Secur. 9, 151–161. https://doi.org/10.1007/s12571-016-0646-y Accessed March 21, 2019.

Upadhaya, S., Dwivedi, P., 2019. The role and potential of blueberry farming in increasing deforestation in southern Georgia, United States. Agric. Syst. 173, 39–48. https://doi.org/10.1016/j.agsy.2019.01.002

Urquhart, J., Courtney, P., Slee, B., 2012. Private woodland owners' perspectives on multifunctionality in English woodlands. J. Rural Stud. 28, 95–106. https://doi.org/10.1016/j.jrurstud.2011.08.006

USDA National Agricultural Statistics Service Cropland Data Layer, 2018. Published crop-specific data layer [WWW Document]. URL https://nassgeodata.gmu.edu/CropScape/ (accessed 8.20.18).

Vance, C., Geoghegan, J., 2002. Temporal and spatial modelling of tropical deforestation: A survival analysis linking satellite and household survey data. Agric. Econ. 27, 317–332. https://doi.org/10.1016/S0169-5150(02)00074-9

Ward, L., 2013. Eco-governmentality revisited: Mapping divergent subjectivities among Integrated Water Resource Management experts in Paraguay. Geoforum 46, 91–102. https://doi.org/10.1016/j.geoforum.2012.12.004

Watts, S., Stenner, P., 2012. Doing Q methodological research, theory, method and interpretation. Sage, London.

Watts, S., Stenner, P., 2005. Doing Q methodology: theory, method and interpretation. Qual. Res. Psychol. 2, 67–91. https://doi.org/10.1191/1478088705qp022oa

Wear, D.N., 2013. Forecasts of land uses. South. For. Futur. Proj. Tech. Rep. 45–69. Asheville, NC. https://doi.org/10.1017/CBO9781107415324.004

Wicker, G., 2002. Motivation for private forest landowners, in: Wear, D.N., Greis, J.G. (Eds.), Southern Forest Resource Assessment. U.S Department of Agriculture, Forest Service, Southern Research Station, Asheville, NC, pp. 225–237.

Zabala, A., Sandbrook, C., Mukherjee, N., 2018. When and how to use Q methodology to understand perspectives in conservation research. Conserv. Biol. 32, 1185–1194. https://doi.org/10.1111/cobi.13123

CHAPTER 5

CONCLUSION

Land use change is a manifestation of interconnectedness between environmental, economic, and social dimensions of sustainability in a human-dominated landscape. Understanding these linkages in a human-dominated system requires conservation researchers, planners, and practitioners to accept and engage pluralistically with knowledge and information acquired through different disciplines. It also entails engaging stakeholder groups beyond academia. In this dissertation, we embraced an integrative approach to navigate multiple questions related to land use changes in the context of deforestation in southern Georgia. As it would be beyond the scope of any dissertation to capture all ways of answering questions and knowing a problem, we chose to examine the issue of land use change by applying mixed methods and multiple epistemologies moving from regional to the local scale as follows: (1) a regional scale economic analysis of profitability of different land uses specifically pine plantation and blueberry farms and (2) a regional scale, geospatial analysis of production suitability of blueberries (Chapter 2); (3) a regional scale, qualitative analysis of motivations of landowners for growing blueberries instead of pine on on their lands (Chapter 4), and (4) a landscape (single watershed) scale, quantitative analysis of spatiotemporal dynamics of land use changes and its impacts on ESs (Chapter 3).

In Chapter 2, we evaluated the profitability related with blueberries and three southern yellow pine species (loblolly, slash, and longleaf) to provide an economic understanding behind ongoing deforestation in SE Georgia. Our economic analysis shows that landowners obtained higher profits from blueberries than pine. To have further insights into economic analysis, we performed risk analysis and found that the probability of getting a negative outcome on the investment in blueberries is very low. To further broaden the scope of understanding about ongoing deforestation in SE Georgia, in addition to the economic analysis, we used geospatial tools to examine the site suitability of blueberry production. The integration of economic and geospatial analysis suggested that a high chance exists that an additional increase in demand for blueberries could further promote deforestation in the region. This is especially true when an investment in blueberries provides more return than an investment in yellow pines, and about 80% of existing pineland in the region is suitable for blueberry production in the region.

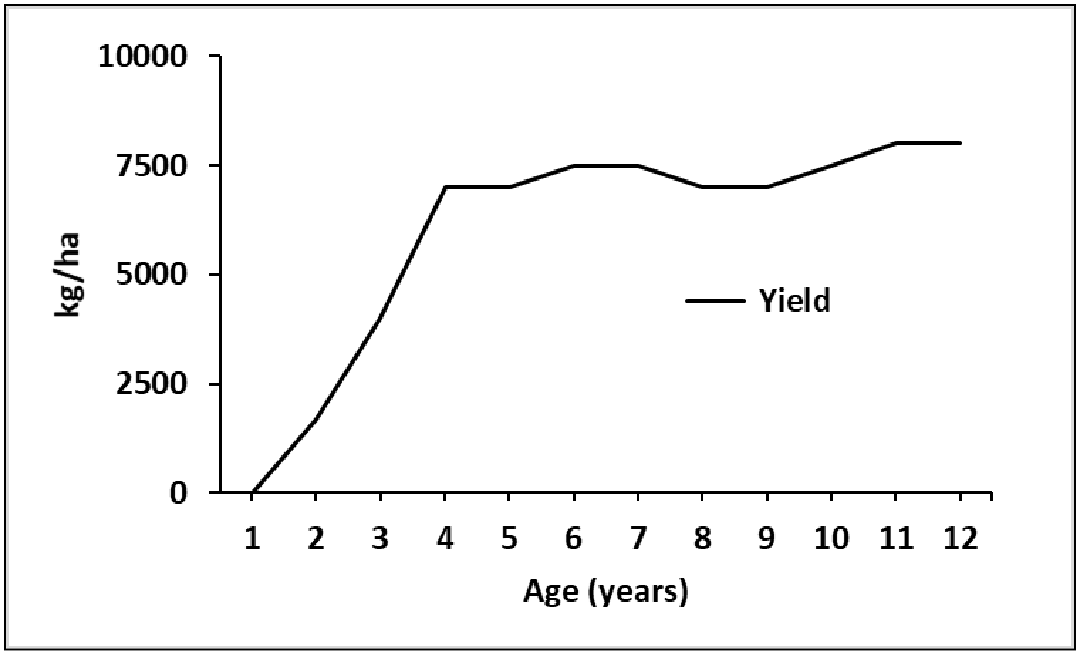
To understand LUCs, specifically deforestation in the context of blueberry expansion, we analyzed and predicted LUCs in the Alabaha River Watershed using multiple tools and approaches. We integrated Markov-Cellular Automata analysis with InVEST modeling to evaluate the impacts of LUCs on habitat quality. We examined the interlinkages between LUCs, landscape metrics, and ESs, particularly, habitat quality, as a proxy to the biodiversity in southern Georgia in the context of deforestation. We believe that the integrated framework developed in this study could be useful for advancing the understanding of policymakers and land managers towards sustainable land use planning by balancing the trade-offs between different land uses and ESs.

Moving forward, understanding the local landowner's motivations of practicing a particular land use such as growing blueberries or pine on their land could provide in-depth insights on sustainable land use planning. In the fourth chapter, we employed a mix of qualitative and quantitative approaches to understand the motivations of a rural landowner for growing blueberries in place of pine. We used Q-methodology which combines the strength of both quantitative (factor analysis) and qualitative (ethnographic interviews) research traditions to characterize the landowners based on their motivations of growing blueberries on the former pine plantations. We identified four different owner groups (Family oriented, Opportunistic, Environmental Cautious and Profit motivated) with distinct motivations for growing blueberries. Landowners preferred growing blueberries over forests on their land because of different motivations towards blueberry production. Motivations of these four landowner groups centered around a family, economy, environment and opportunity. Though these landowners are growing blueberries instead of forests on their lands, with appropriate financial incentives, they are willing to convert back to forestry from growing blueberries on their land.

In this dissertation, we have attempted to understand the relationship between land use changes and its impacts on ESs under the context of deforestation and agricultural expansion which is an important cross-boundary topic in research concerning society and natural resources. As land use is one of the most closely associated links between humans and nature, change in land uses will inevitably affect the structure of natural ecosystems. As this dissertation shows, economic, environmental, and social information is required to understand how local and regional drivers are affecting land use changes. This implies that all three dimensions of sustainability (social, environmental, and economic) need to be considered and assessed with the multiple research lens. The knowledge produced through these assessments should reach policymakers and all stakeholders. To gather and disseminate this information, an integrative approach is the most appropriate way. We used an integrative approach of understanding the multiple aspects of LUCs to continue supporting the multifunctionality of the landscapes for sustaining ESs. We found that understanding the complexity and dynamics of land use changes can only be gained with an integrative approach that uses both qualitative and quantitative methods to answer those critical questions which will ensure sustainability of ESs across landscapes. Our study suggests that innovative land use policy and integrated landscape management strategies for the human-dominated landscapes are particularly important for ensuring continuance and enhancement of ESs in SE Georgia.

APPENDIX A

The yield of blueberry in the study area (Chapter 2)



APPENDIX B

Input costs for ascertaining Net Present Value of blueberry production (Chapter 2).

Items	Application	Unit	Quantity	Price	$Amt
Pre-plant weed Control		Ltr	23.4	9.5	222.3
Stumping, pushing, burning		ha	1.0	2965.1	2965.1
Chopping		ha	3.0	123.5	370.5
Triple Super Phosphate		kg	168.1	0.3	50.4
Copper Sulfate		kg	4.5	4.4	19.8
Harrowing		ha	3.0	123.5	370.5
Bedding		ha	1.0	370.6	370.6
Breaking aisles		ha	1.0	185.3	185.3
Ditching and drainage		ha	1.0	321.2	321.2
Milled Pine Bark		M Ton	44.8	44.1	1975.7
Planting					
Plants (5'*12")		ha	1210.0	5.7	6897.0
Planting labor (5 people)		ha	1210.0	0.5	605.0
Trans-planter rental		ha	1.0	27.8	27.8
Fertilizers					
Fertigation	7/yr	kg	71.7	4.1	294.0
Weed Control					
Pre-emergence	2/yr	ha	2.0	74.1	148.2
Post emergence	2/yr	ha	2.0	49.4	98.8
Tractor & Sprayer	4/yr	Hrs	9.9	12.0	118.8
Labor	4/yr	Hrs	9.9	9.0	89.1
Insect and Disease Control					
Pre-harvest	2/yr	ha	2.0	123.5	247.0
Post-Harvest	2/yr	ha	2.0	123.5	247.0
Tractor and Sprayer	4/yr	Hrs	9.9	12.0	118.8
Labor	4/yr	ha	1.6	22.2	35.5
Pruning (hand)	1/yr	Hrs	7.4	9.0	66.6
Irrigation		ha	1.0	110.3	110.3
Interest on Operating Costs		$	10561.0	0.1	844.9
Tractor & Equipment		ha	1.0	1717.7	1717.7
Overhead & Management		$	11405.9	0.1	1140.6
Drip Irrigation		ha	0.4	533.7	213.5

APPENDIX C

Description of Landsat Imagery used for land use classification.

Image	Path/Row	Date
Landsat TM Sensor	17/38	2006
Landsat ETM Sensor	17/38	2010
Landsat OLI Sensor	17/38	2015
Landsat OLI Sensor	17/38	2017