AN ABSTRACT OF THE DISSERTATION OF

Matthew R. Sloggy for the degree of Doctor of Philosophy in Applied Economics presented on May 21, 2018.

Title: Advances in Modeling Natural Resource Management Under Uncertainty: Forest Mortality, Policy Design, and the Value of Information

Abstract approved:

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Andrew J. Plantinga

Advancing the understanding of natural resource management is an important step in mitigating the effects of human activity on the environment, and ensuring efficient outcomes for many sectors of the economy. As humanity's role in the natural world becomes better understood, the importance of interdisciplinary modeling has grown in leaps and bounds. This is evidenced by the rise of fields such as bioeconomics, the economics of climate change, and the increasing influence of "societal dimensions" departments in universities around the country. It is becoming evident that a holistic understanding of feedbacks between the natural and economic realms is crucial for developing the research agenda of tomorrow. In addition, advances in computing resources have made research questions previously restricted by their computational complexity viable for analysis. Both of these developments bode well for interdisciplinary modeling; however, much of these developments remain unrealized in the literature. For instance, the continued utilization of large scale earth system models such as the Community Earth System Model (CESM) for impact studies (e.g. Law et al., 2018) has highlighted the importance of representing the social systems accurately within the model. Despite this, the use of natural resource models that are consistent with economic theory are nowhere to be found amongst the many modules of CESM, or other similar models. Instead, economic

models are used to inform the input datasets of these models, which is rigorous but unsatisfying once one realizes that this approach completely fails to capture the feedback between the natural and social systems that intuition tells us is there. The lack of such modeling also precludes running sophisticated policy experiments within CESM and her sister models.

These policy experiments, with their robust representations of physical processes, can be better positioned to examine the effect of these policies on a variety of outcomes, both environmental and economic than what currently exists. This is in addition to the fact that there are still many aspects of policy design that are unexplored in natural resource management. The details about the design of environmental policies, especially those targeting the private provision of ecosystem benefits, must be fine tuned to achieve an optimal outcome. One particular aspect of policy design that is understudied in the literature is that of the duration of contracts for ecosystem service programs. Many policies currently in practice base the duration of the contract on environmental goals of the policy. However, economic incentives could change the impacts of the policy should the duration be changed.

The efficient design of policies depends on the feedbacks between social and natural systems. Though models such as CESM can address uncertainties about future effects of climate change and disturbance, it is a deterministic model of natural resources. In reality, natural resources effectively behave in a stochastic manner. This results in management strategies that require substantial investments in monitoring and learning, as good information is crucial for optimal management. This has led to many studies examining adaptive management of natural resources, and learning in systems such as fisheries (Kling et al. 2017), livestock management (MacLachlan et al., 2017), and regulatory enforcement (White, 2005). There is a substantial gap in what the literature addresses. Previous studies ignore the role of price stochasticity, as well as stochasticity in other observable variables, in determining the optimal learning strategy of natural resource owners. This is a more generalized description of natural resource management that has implications far outside of private natural resource management.

This dissertation advances the the design and application of modeling techniques in natural resource management, as well as theory behind these models. In what follows, we analyze the feedback between natural and social systems in forestry. We show that the forest sector adapts to disturbance events such as wildfire or pine beetle outbreaks through shifting harvests to different areas. This model has the potential to improve the representation of social systems within large scale earth system models, and to allow for economic policy experiments on a larger scale than what has been previously observed in the literature. We explore the economics of contract duration within a forest-based carbon offset program, which is the first time such a question has been addressed through modeling. It also contributes to current discussions of implementing forest-based carbon offsets in Oregon’s carbon abatement plan. This dissertation achieves an advancement of the economics of information in partially observable resource systems by solving a model of forest management where the volume of timber is observed imperfectly, and observations are costly and noisy.

In Chapter 1, I introduce the common themes of the dissertation, and provide an overview of what is to follow. The natural resource system this work addresses is primarily forestry. In particular, it focuses on the issues surrounding ecosystem service provision and management within private forestry.

In Chapter 2, I construct a partial equilibrium (PE) model of the forest sector in the western United States. The model is spatially explicit, and overcomes issues involving its solve time by utilizing a novel algorithm that simulates an auction between agents in the model. Furthermore, the model can be coupled to CESM in order to obtain a more realistic representation of biological processes and climate change relative to what is available to forest sector models currently. The realism of the model is aided by the incorporation of numerous datasets such as land ownership and transportation costs. The model is unique in its scale, and is solvable over a larger range and with a higher resolution than other forest sector models. It also has a realistic depiction of the ecology of forestry through its ability to couple to CESM.

This model is particularly useful for modeling the feedback between the natural system of the forest and economic system of the forest sector. Specifically, it's beneficial for understanding the impact of forest disturbances on the economy, and how that shapes future disturbance patterns. The results suggest that in the short run, the spatial distribution of harvests changes substantially, with the difference in overall harvests growing over time due to the effects the disturbances have on mill capacity and profitability. We also utilize our model for understanding the impacts of policies specifically addressing disturbance vulnerability, as well as the impacts of state-level policies and how those may affect the surrounding region.

In Chapter 3, I utilize a regional forest sector model of western Oregon in order to analyze the effects of changing the duration of forest-based carbon offset contracts. The model is a spatially explicit model that tracks both sawtimber and pulp production, as well as price levels and mill capacities. It keeps track of the amount of timber being exported as well, and average management decisions such as rotation lengths. The model is applied to scenarios that vary in the duration of the contract as well as the price of the carbon, which is fixed during the model run.

Whereas previous studies have examined the effects of these contracts on the Oregon forest sector (Latta et al., 2011), no study has yet addressed the role of contract duration on enrollment and program performance. We find that market forces stabilize the amount of carbon being removed from the landscape every time step. This analysis is useful in serving as a critique of current approaching to contracting for forest-based carbon offset programs such as the one in California by showing that alternative contract lengths are capable of higher levels of sequestration over given time periods.

In Chapter 4, I construct a model of forest management under state uncertainty that optimizes both the timing of harvest as well as measurement of the forest resource, known as "inventory". Forest resources, along with practically every other natural resource, exhibit state uncertainty – uncertainty about the present state of the resource. Oftentimes natural resources are only observed when investments are made in measurement of the resource. Furthermore, a perfect measurement of the resource is oftentimes infeasible, either for reasons having to do with the biology of the resource or because it is cost prohibitive. In this chapter I solve the forest manager's problem under state uncertainty as a continuous-state Mixed Observability

Markov Decision Process (MOMDP). I find that the optimal timing of learning is influenced not just by price level, but surprisingly by price stochasticity as well.

Chapter 4's innovation is that it presents the first continuous state model of natural resource management under state uncertainty that includes price stochasticity. For a majority of natural resource management problems, price stochasticity plays an important role, and the results from this project allow us to understand how it influences not just harvest timing, but the optimal investments in measurement and learning. We find that learning is valuable. Using an empirical model of forest growth that captures its natural stochasticity, we are able to calculate the costs associated with state uncertainty when inventory is not an option. We find that conducting costly yet accurate inventories in an optimal way greatly reduces the burden of state uncertainty, and increases the value of the stand through improved management. This chapter also presents the first model of forest inventory that is grounded in microeconomic theory.

The expansion of interdisciplinary research as well as the availability of new computational techniques in the field of economics have resulted in opportunities for researchers looking to address difficult problems in natural resource economics. My dissertation is a combination of methodological advances, as well as inquiries into potential policy applications. I hope that what follows from here will aid both future researchers interested in similar topics, as well as policymakers with questions about the design of schemes targeting private forest landowners. The extensions and limitations of all of these studies will be discussed as they are presented. Because of the methodological nature of much of this dissertation's content, the possibility exists to greatly expand on what has been done here in future studies.

Advances in Modeling Natural Resource Management under Uncertainty: Forest Mortality, Policy Design, and the Value of Information

by

Matthew R. Sloggy

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Matthew R. Sloggy, Author

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CONTRIBUTION OF AUTHORS

Andrew Plantinga and Greg Latta provided advice and mentorship for the model design in Chapter 2, as well as mentorship in designing the policy experiments featured in the manuscript. Greg Latta contributed to Chapter 3 by providing modeling. Andrew Plantinga and David Kling contributed to the writing and preparation of Chapter 4, and David Kling contributed to the coding.

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1. Introduction

Understanding the interactions between society and the environment is a crucial step in crafting policies that manage natural resources efficiently and effectively. There are countless examples of natural resource systems that are characterized by heavy societal influence, where understanding of just one of these systems alone is inadequate. More and more, what is needed is an interdisciplinary approach in which models can effectively represent the feedback between the ecological and economic aspects of the system. Furthermore, as the computational resources that scientists have access to grows, we are able to incorporate more nuance into models of resource management. For instance, computational advances have made studying aspects such as state uncertainty achievable only recently for models of natural resource management (LaRivierre et al., 2017). This dissertation advances the theory and application of modeling natural resource management under uncertainty. This provides new models and theoretical advances that will allow future researchers to conduct nuanced policy experiments within large scale climate simulations, study the effect of localized policies on an entire region, and to optimally model information investments for privately managed natural resources. For policy makers, this dissertation advances topics of policy design, namely contract duration, for forest-based carbon offsets, and reports on the expected effects of subsidies aimed at reducing forest disturbance in the western United States.

The studies presented in this collection focus on private forest management, though many of the theoretical advances and research questions can be generalized to other systems as well. Private forest management is an important aspect of environmental policy in the United States and around the world, especially from the perspective of conservation. In the context of carbon, forests represent a massive carbon stock. According to Pan et al. (2011), the world's forests sequester an estimated 2 petagrams of carbon annually. Furthermore, forests provide benefits such as biodiversity (Drechsler et al., 2017), and recreation (Bestard and Font, 2010), and countless forest products (e.g. White et al., 2013). Modeling forest management has a long and detailed history within the natural resource management literature, and features famous theoretical contributions (Faustmann, 1849) as well as many modeling applications (e.g. Latta et al., 2013). However, there are still aspects of modeling this resource (and natural resources in general) that require advancement if we are to effectively tackle the problems of the future.

In the first essay (Chapter 2), I examine methods of modeling the feedback between the forest sector, and forest ecology. I present a spatially explicit, partial equilibrium model of the forest sector that can be coupled to large-scale land process models, and used to estimate the economic effects of ecological disturbance. In particular, the model is built to conduct analysis within the Community Land Model (CLM), and future work will involve the full coupling of the two models. Presently, the model I construct resolves limitations of previous modeling in that it allows me to address the effects of forest disturbance on forest landscapes. The model presented in essay 1 extends over a large spatial range: the western United States. It is solved at a high resolution, allowing for localized policy experiments to be conducted within the model. The model overcomes the significant computational burden associated with solving a problem of its size through a novel price-search algorithm.

We use the model presented in Essay 1 in order to investigate two different scenarios. The first is the region-level effects of localized forest disturbance. We examine how timber harvest patterns change based on the presence of forest disturbance. We test whether the change in harvest is localized around the disturbance event, or whether, through market forces, the harvest patterns change throughout the region, and if so to what degree. Our modeling results suggest that the market does indeed spread the effects of disturbance around the landscape by affecting timber removals in other parts of the region by a substantial degree. The second question we focus on concerns the effects of a policy geared at reducing the risk of disturbance on vulnerable landscapes. We implement subsidies of various size and scope within our model, and observe what the overall effects are of a regional level subsidy, as well as whether localized subsidies have effects outside of the region. We find that the presence of subsidies results in fewer harvests that are larger in size. Furthermore, we observe that the effects of subsidizing harvests in Oregon have substantial impacts in other regions as well.

In essay 2 (Chapter 3) I address the design of forest-based carbon offset contracts, specifically focusing on the role that the duration of the contract plays in program performance. As more states continue to adopt market approaches for limiting CO_2 emissions, the optimal design of offset provisions within those approaches is growing in importance. Notably, the California carbon market allows for forest-based carbon offset contracts that allow power producers to pay for sequestration on forestland instead of abating the pollution themselves. On the forest manager's side, enrollment in such a program is required to last for one hundred years in order to ensure that the carbon is sequestered permanently. However, very little is known about the effect of changing the duration of the enrollment period. Very few studies (e.g. Juutinen et al., 2014) address contract duration for ecosystem service programs such as forest-based carbon offsets even with a theoretical approach, let alone with a modeling approach. The study presented here uses a partial equilibrium model of the forest sector of western Oregon to examine the effects of forest-based carbon offset contracts of different lengths. We additionally test whether the price of carbon influences the effects of contract duration. We find that carbon prices influence the role of contract duration in program performance to a large extent. Though we find limited differences between shorter contracts and enrollment, we find large differences between carbon sequestration levels and contract length, with some shorter contracts resulting in less carbon on the landscape after 100 years than a scenario in which there was no policy at all. Interestingly, we find that for shorter contracts and lower carbon prices, the presence of a maintenance period in which the manager is not paid for the carbon they sequester but is charged for the carbon that leaves their landscape, works to smooth out price volatility seen in other contract specifications and in some cases can outperform other contracts over a limited time range.

In the third and final essay (Chapter 4), I examine the role of state uncertainty in private forest management, as well as the role of price volatility on the decision of a private forest manager to invest in information about their resource. We model forest management as a Mixed Observability Markov Decision Process (MOMDP), in which the timber volume is only partially observable for the forest manager. In fact, the forest manager cannot observe the resource unless she invests in conducting an inventory, which provides a costly and imperfect observation of the timber volume in the stand. Furthermore, timber prices are volatile, and though they are perfectly observable in the present period, uncertainty about future values affects the optimal timing of forest inventory, as well as timber harvesting. This study expands on previous work in this field (e.g. Kling et al., 2017; MacLachlan et al., 2016), by examining how price stochasticity influences optimal investment in monitoring behavior. Among other findings, we uncover that price stochasticity plays a substantial role in the optimal timing of inventories. We also expand on previous papers (e.g. Plantinga 1998) by demonstrating that state uncertainty influences the timing of harvest. Through calculating the differences in value between stands that invest in inventory and those that cannot, we find that inventory improves the value of the forest stand in the presence of state uncertainty.

Taken together, the three essays presented in this work advance our ability to understand the interactions between ecological and economic systems. It allows us to conduct policy experiments, as well as understand the impacts of forest disturbance to a much greater extent. Furthermore, this work explores previously untouched areas of forest resources research, such as modeling the effects of contract duration on carbon sequestration, or the role of price stochasticity in inventory investments for private landowners. The results from this study will be used in the future to inform additional modeling efforts, as well as conduct experiments to inform policy on ecosystem service provision in forest landscapes.

2. A Spatially Explicit Model of Timber Harvest for the Western United States with Applications

2.1. Introduction

Forests in the western United States play a large role in the environmental and economic health of the region. In addition to providing considerable economic benefits, including the supply of wood products, forests also sequester significant amounts of carbon from the atmosphere, and are sources of recreation and critical habitat for many species. These ecosystems are subject to various disturbances, including harvests, wildfire, and pest outbreaks. In the western United States, forest disturbances such as wildfire can cause substantial damages to property and human health (Westerling & Bryant, 2008). Forest disturbances also impact the economic well being of industries and communities that rely on forest resources. Due to the inherent feedback between the forest ecosystem and forest sector, a disturbance in one area can translate to disturbances in other areas through market forces. For instance, if supply is reduced in one area, timber will be supplied by the next most profitable area. However, our understanding of the role of this adaptive behavior is unaccounted for in many ecological modeling exercises.

Past modeling efforts that focus on the ecological representation of forest growth (e.g. Hudiburg et al., 2013) often lack detailed representations of the forest sector, including a representation of forest product markets. Forest product pools are important because they differentiate the rate at which CO_2 is released into the atmosphere. Furthermore, economic variations can cause disproportionate impacts to some products, while leaving others relatively unaffected. Shifting demand for wood products is also a crucial determinant of where harvest occurs as well as the intensity of that harvest. However, this feedback is unaccounted for in many models, especially the large-scale climate simulations used regularly to evaluate the impacts of climate change on various natural systems.

A forest sector model with the ability to link to large scale climate simulations can improve the representation of forest management within those models. The biological and social systems involved in the forest sector are naturally coupled. Current approaches to modeling forest management within climate simulations and land system models generally consist of calculating estimates and projections of country-level timber harvests, and then downscaling that to the grid cell level. Datasets such as those found in Hurtt et al. (2006) can limit the resolution of the modeling results. This work provides a way to calculate better resolution datasets, which will improve the resolution of the modeling effort as a whole.

A modeler using these datasets performing analysis at a much higher resolution will still find their results limited by the poorer resolution of the harvest data. A contribution of this work is the development of a model that calculates timber harvests for conceivably any model resolution, which alleviates the limitations of previous datasets.

Furthermore, our forest sector model is capable of running in conjunction with the Community Land Model (CLM), allowing it to respond to disturbances and other biological phenomena in CLM in a way that prescribed harvests cannot. Climate change and its effects on forest ecosystems incentivize resource managers to change their management strategies as conditions shift. A changing climate will change the productivity of forestland in the US (Pastor and Post, 1988ß). This will then affect the location and intensity of harvests. Because our forest sector model is capable of coupling to CLM, it can more accurately capture the effects of climate change on the forest sector. Additionally, the harvest pattern that CLM has access to will now be adaptive to changes in climate and forest productivity.

Another benefit of our forest sector model is that provides the ability to conduct experiments within CLM. Previous policy experiments in CLM often come in the form of differentiated input datasets (e.g. Law et al., 2018) on land management. Our forest sector model, because of its partial equilibrium set up, allows for more sophisticated policies to be implemented within the model, for instance taxes or subsidies on timber removal. This improves the economic sophistication of the experiments that CLM is capable of. Establishing a coherent economic framework within the model itself opens CLM up to a broader range of academics who may now find it useful.

The development of this model is motivated by a number of research questions that are relevant to the economics of forest mortality in the western United States. We first want to know what the economic impacts of disturbance events are to the forest sector. Previous studies have examined economic impacts of wildfires (e.g. Kochi et al., 2010), and pine beetle outbreaks (e.g. Price et al., 2010), however there is little focus on impacts to the forest products sector itself. Extended exposure to these sorts of disturbances will have economic impacts that our model will be able to capture.

We are also interested in understanding the effect of forest disturbance and climate change on the pattern of timber harvests. The economics of forest management play a significant role in determining the ecological impacts of harvest (Van Kooten et al., 1995). The forest sector model presented in this paper allows for the investigation of this relationship. Understanding the roles and effects of natural processes is important, but a major aspect of our model is the ability to conduct detailed and theoretically consistent policy experiments. We want to know about the impacts of policies targeting vulnerable areas. What is a sufficient policy to reduce the risk, and what are the impacts of enacting the policy in the first place? We can utilize the novel aspects of our model to address these questions.

The impact of climate change on forests and the wood products industry has been a subject of intense research (e.g. Sohngen et al., 2001). Land use change out of forestry has been linked to large environmental impacts (Lubowski et al., 2006). Furthermore, it is known that forest management can be influenced by a changing climate (Spittlehouse & Stewart 2004). This feedback loop is a difficult thing to endogenize within a model, as modeling both systems simultaneously incurs a massive computational cost. Despite the obstacles, there is a significant benefit to performing such an analysis. For instance, it becomes possible to investigate the impacts of future climate change on forestry at a regional scale, as well as adaptive economic behavior. It can also clarify ways in which human activities can manipulate environmental phenomena, such as wildfire frequency and pest outbreaks.

As part of a project investigating forest mortality in the western United States, we have developed an economically motivated, spatially explicit model of timber harvesting for the western United States within CLM (Oleson et al. 2013). The community land model is a large-scale environmental model of land processes used as part of Community Earth System Model (CESM) (Hurrell et al. 2013). The Timber Harvest Model (THM) presented here solves for the market equilibrium harvest pattern, and is grounded in economic theory. This project is novel in that it represents a major advance in coupling a theoretically consistent social science model to a large-scale environmental model, which allows for a more detailed study of the feedback between the two systems that was not possible before. Furthermore, the model can facilitate detailed policy experiments within CLM.

This chapter will largely address the methodology behind the THM, as well as the theory that motivates that methodology. Two case studies are used to demonstrate the model. The first is an investigation into the effects of pine beetle outbreaks, and the second is the implementation of a localized policy aimed at alleviating the risk of natural forest disturbance. The biology of forest growth is modeled using a deterministic model found in many other bioeconomic applications (e.g. Clark et al., 1973) instead of CLM. In the next section, I discuss the details behind the methodology of the THM. Afterwards, I explore the input datasets required for the model, and discuss how they help improve the quality of the model solution. Afterwards, I briefly discuss the parameterization process, and then discuss the policy apparatus in the model, and what kinds of policies can be implemented in the THM. I then proceed to set up and explain the policy experiment I perform in the THM, demonstrate the results, and conclude with what we learned about the policy, the harvest model, and potential extensions of the project.

2.2. Methodology

The goal of the THM is to solve for the equilibrium harvest pattern, which includes the location and quantity of harvests on the landscape. This is consistent with other forest sector models (Latta et al., 2013) and represents the level of harvest one would expect to see on the landscape from private forest managers. This approach is also useful for establishing harvest on public lands, as much of that timber is processed by mills and used by agents in the forest sector. We acknowledge that there may be factors that prevent the forest sector from reaching a state of market equilibrium. Markets are often in a state of adjustment. The market equilibrium is an indication of where the future of the market will trend towards given no other factors change.

We assume that the influences of these factors cancel one another out, or are negligible on the scale we consider. One potential method of calculating the equilibrium harvest level is to search over the quantity space. This method includes testing different locations and harvest levels until one such combination balances supply and demand better than all the others. Given the scale of the model, this would require an extensive search or computationally expensive solution procedure. Such a procedure may be feasible for smaller models, but for a model that covers a wide region at a high resolution, it is infeasible with currently available computational resources and solution methods. Instead, we search over price space, which greatly reduces the number of variables that require optimization. Thus, the goal of our algorithm is to calculate the set of mill-level timber prices and market-level output prices that result in the amount of timber and output demanded matching the amount supplied. The model solves on an annual time step.

In order to achieve an equilibrium level of harvest, supply and demand must be matched in all markets associated with timber harvest. We therefore need to represent the forest sector itself in the model in a way that allows us to infer the amount of product demanded. We construct a model of the forest sector that consists of three different types of transactions. The first transactions are between timber plot owners and mills, wherein the mills purchase timber from the plots. The second is between mills and other mills, who trade intermediate goods with one another. Wood chips are a byproduct of production for many wood products (e.g. lumber), and can also be used as an input for other products (e.g. paper products). Thus, mills will trade chips instead of harvesting timber if it is cheaper. Finally, we represent transactions between mills and output markets. The output market is assumed to be a regional level market, having no specific location or set of locations (unlike the plots and mills). The way these three markets are represented in the THM are as a set of nested markets, each with their own mathematical representations. The algorithm we implement (which will be discussed later in the section) solves each market iteratively. The algorithm relies on finding the equilibrium price level, which in turn depends on each level of the market's response to price levels and timber supply.

The supply of timber is determined by either the Community Land Model (CLM), or if the THM is being run independently from CLM, a set of biomass growth equations that are derived empirically. More details about CLM can be found in the appendix. The study region – which spans across the western United States – is split into grid cells that are 4km x 4km ($16km^2$). The volume of timber is tracked at the grid cell level. However, the representation of timber in the model is limited in that it does not have any age structure. This is a substantial difference from many other forest sector models. There are 14 different species represented in the model, called Plant Function Types (PFTs) that are tracked by CLM. In cases where we run the model uncoupled from CLM, our empirical growth models still follow CLM's lead, and track the same 14 PFTs. The list of these can be found in Table 2.1. The empirical growth functions are derived from tables in Smith et al. (2006) that report the volume of timber at regular intervals for a representative stand, as well as an additional growth table for Larch (Stage et al., 1988). For the PFTs for which no reliable data could be found, an average of other PFT growth functions were used. The growth functions used follow a Beverton-Holt form (Beverton and Holt, 1957), the functional form of which is reported in Equation 2.1.

$$X_{t+1} = X_t \left(\frac{r}{1 + \left[\frac{r-1}{K}\right] X_t} \right) \tag{2.1}$$

In Equation 2.1, X_{t+1} and X_t are the next period's and current period's timber volume, respectively. The parameters r and K are the intrinsic growth rate of the grid cell and intrinsic capacity of the grid cell, respectively. The parameters r and K require parameterization for each grid cell. After we attain a growth function for each PFT, we calculate growth functions that are specific to each grid cell. We combine each PFT specific growth function with data on PFT prevalence at the grid cell level to compute an averaged growth function for each grid cell in our study region. An example growth function from a grid cell in northern Oregon is shown in Figure 2.1.

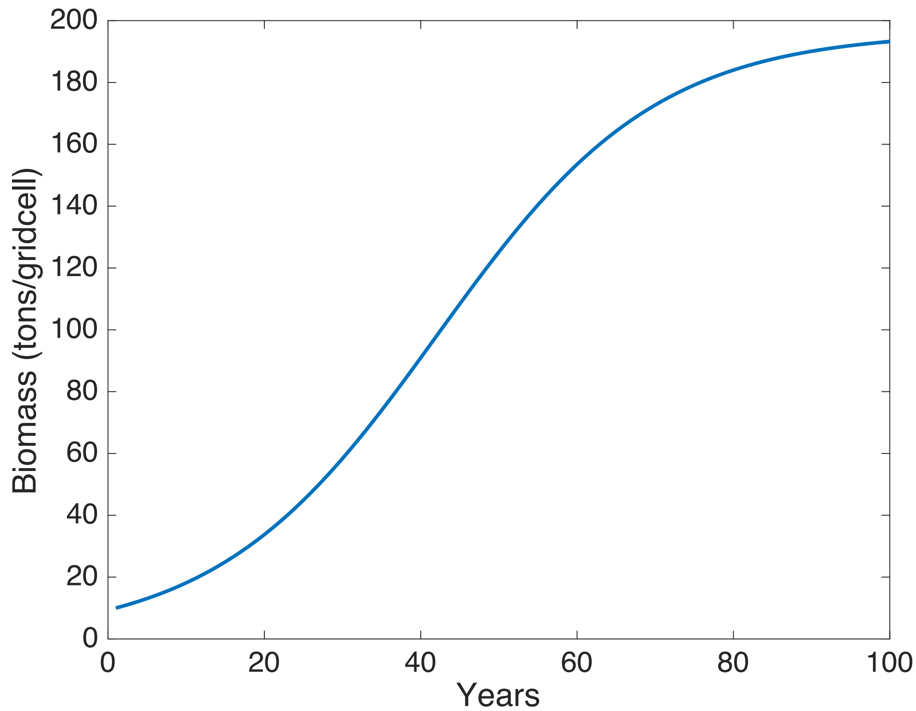


Figure 2.1: Example of a Beverton-Holt growth function for a grid cell in Oregon

Each grid cell has a potential timber supply that is at least as large as the amount of volume on the grid cell, multiplied by the proportion of that grid cell that is privately owned. Additionally, some of the timber on public land can be made available. The actual amount that the grid cell supplies depends on the prices that mills offer for the timber, along with the distance of the grid cell from any mill, and the profit function of the grid cell (including harvest costs).

We assume that each grid cell that is designated as private land is managed by a profit maximizing agent. The agent obtains revenue from selling timber to mills, and costs through harvest. This representation is slightly different from other models of forest management, where oftentimes the mills themselves pay for the rights to harvest timber (Leffler and Rucker, 1991). It is important to note that the net price of timber remains unchanged between these approaches, meaning that the solution to our problem is robust to this assumption. It is well documented that harvesting costs decline with the intensity of the harvest (Kluender et al., 1998). However, this latter concern is addressed by the fact that within a 16km^2 grid cell, there are a variety of different parcels from which the agent can harvest. Though within each parcel, the costs of harvest decline with intensity, the agent will naturally harvest the most accessible and cheapest parcels first. In this way, the cheapest parcels will be harvested before the most expensive, resulting in an upward sloping timber supply curve. We model the forest managing agent's profit maximization problem in Equation 2.2

$$\max_{t} \; P_t t - \gamma t^{\beta} \tag{2.2}$$

Where P_t is the per unit price of timber that the mill is paying, and t is the volume of timber sold by the plot. The parameter γ is scaling parameter for harvest cost, and β is an exponential parameter. The solution to the profit maximization problem in Equation 2.2 yields the supply curve reported below in Equation 2.3

$$t^* = \left(\frac{P_t}{\gamma\beta}\right)^{\frac{1}{\beta-1}} \tag{2.3}$$

The functional form we obtain in Equation (3) is important because it is increasing in P_t, contingent on $\beta > 1$ and $\gamma > 0$. Equation (3) is monotonically increasing in prices, convex, and continuous. Because of the specification we have selected for the profit maximization problem (and thus supply curve), we are required to solve for two parameters of our supply function. These include the two parameters of the cost function shown in Equations 2.2 and 2.3. We simplify our representation by assuming that forest managers all have access to the same harvesting technology, which results in the same cost function. Heterogeneity in the timber supply enters through the plot's distance from any given mill. We parameterized the supply curve such that it recreates historically observed levels of harvest in the region. Using the Timber Products Output (TPO) (USDA Forest Service, 2012), we parameterized

Equation 2.3 such that the study region would produce the highest and lowest harvest levels seen in the TPO reports given a range of prices observed in test runs of the harvest module. We utilized a non-linear fit routine to optimize these parameters. A more detailed description can be found in Section 2.4. The prices that are plugged into Equation 2.3 are those that are offered by the mills, adjusted for the cost of transportation between the plot and the mill.

Each mill iterates through different prices in a guided fashion until they receive the amount of timber that they demand. This requires a representation of mill-level timber demand. One option that was explored previously was to derive the timber demand function from the mill's profit maximization problem. Mill production is represented in a variety of different ways throughout the forest sector modeling literature. Oftentimes, production is represented as a fixed ratio that converts timber into product, and the rest into byproduct residue (such as chips). However, this method prevents us from deriving a downward sloping demand curve for timber demand, as the cost function in representations found elsewhere in the literature generally do not have the proper qualities to result in downward sloping timber demand. In order to simultaneously keep consistent with the literature and utilize downward sloping timber demand, we adopt the ratio approach for determining output, but utilize empirically derived timber demand functions estimated in the literature from Guerrero Ochoa (2012) that represent relationships between price and mill level timber demand.

Each mill is constrained in the quantity they can produce by their capacity. These capacities are obtained through data on capacities from 2009 (Spelter et al., 2009) as well as 2014 (Latta et al., 2017). It is very common for mills to change capacities year after year in response to economic forces the mill faces. Our model incorporates capacity changes as a function of the mill's profitability. At every time step, we assume there a certain percentage of the mill's capacity that decays, which is consistent with the way other forest sector models treat capacity (e.g. Latta et al., 2017). Mills with negative profitability cannot pay to recover this loss; however, mills with positive profitability can pay a proportion of their profits to recover it. The cost of recovery is a fixed per-unit capacity cost. An intuitive way to consider these costs is as that of maintenance. This representation is rooted in the realistic assumption that larger mills must pay more for maintenance costs than smaller mills.

After all maintenance costs are paid by the mills, the new capacity is then distributed amongst the profitable mills. The level of new capacity is first calculated on a per-product basis across the whole region based on the increase in GDP from the Shared Socioeconomic Pathway (SSP) data, as well as income elasticities derived from previously estimated market demand curves. This gives us an estimate for how the demand for a given product will change, which we are able to use to calculate the magnitude of capacity change in our region. This calculated magnitude is then distributed across the profitable mills in proportion to the profit level, such that more profitable mills receive a higher proportion of the capacity than less profitable mills for a single product.

The output market in the model is represented by a set of national level product demand curves for each product that is represented in the model. The demand curves are parameterized with both price and income elasticities. The price elasticities for the output markets are used in the price search algorithm, discussed later in this section, to estimate changes in price levels with respect to changes in the quantity of a product supplied. The income elasticities are used to shift the demand curves according to the growth in GDP per capita that are obtained from the SSP. The national level demand curves are disaggregated to the study region using a ratio of national product capacity levels and product capacity levels specific to the region (Latta et al., 2017).

We utilize our model of the forest sector in the Western United States to solve for the equilibrium level of harvest (and production) using a price search algorithm. The choice of searching over price space versus quantity space is chosen because the number of price variables are limited by the number of mills, whereas the number of quantities are only limited by the number of grid cells, which are much larger in number. Furthermore, for any given set of prices, we can use our models of harvest costs, mill production, and output markets, to derive the quantity of timber supplied, and where it is supplied to.

The functional forms of the demand and supply curves have been selected for several reasons. Importantly, supply curves that slope upward and downward sloping demand are in keeping with commonly observed and well understood principles of economics. Furthermore, the supply and demand curves have mathematical properties that result in an equilibrium being possible. This is necessary for our solution approach, which is a price search algorithm across mill-level prices for timber and chips, as well as output prices. A description of the proof for the existence of equilibrium given the set of assumptions we have utilized in our model can be found in Arrow and Debreu (1957).

The price search algorithm begins with an arbitrary guess of mill-level prices for both timber and chips, and output prices. We evaluate the quantity of timber supplied to the mills at that price level, and then check it against the amount demanded by the mills. If these do not match, we update the prices by taking a convex combination of the current price level, and the price that is implied by the amount of timber supplied. Because of the functional forms of the supply and demand curves in the model are well behaved, namely that supply is monotonically increasing in price and demand is monotonically declining in price, enough iterations of this convex combination will eventually yield an equilibrium price at which quantity supplied will be sufficiently close to quantity demanded. One iteration of the price search algorithm is visualized in Figure 2.2 Because of the functional forms, each iteration will be closer and closer to the true equilibrium price.

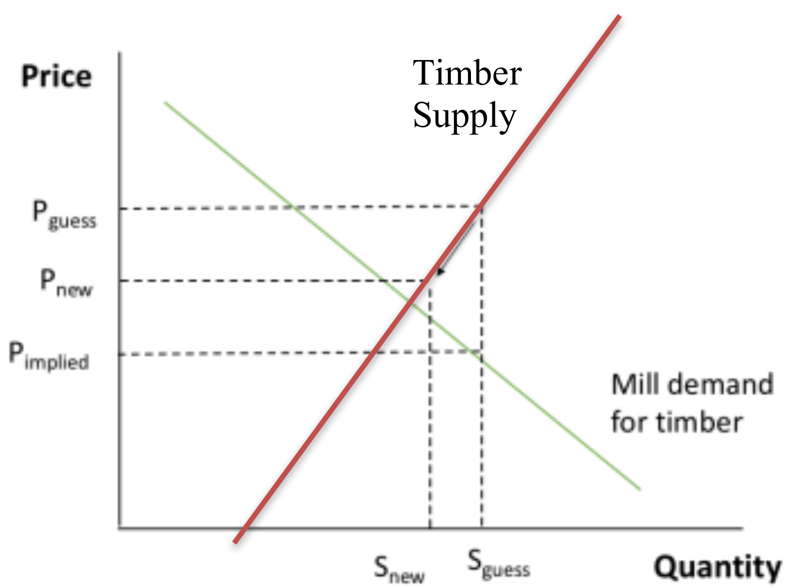


Figure 2.2: A single iteration of the price search algorithm for a single mill.

This process is repeated until the amount of timber supplied by plots matches the level demanded by mills for each mill. Having a specific level of timber at each mill also implies a specific level of chip supply. Thus, the same type of calculation is performed for the intermediate goods market immediately following the timber market.

Our model of the forest sector is naturally a nested model. Though we have the quantity of forest product demanded at a given price level, we do not know the quantity of product supplied until we have solved for the equilibrium in the input (timber) and intermediate goods (chips) markets. Because the demand for timber and chips is a function of output prices, the equilibrium price in the input and intermediate goods market depend on output prices, meaning every time the output price is updated, the equilibrium price levels for timber and chips must be recalculated. In the model, we first solve for the timber and input price equilibrium simultaneously. Using the level of output produced at that price level, we use the output market demand curves to check whether the supply of a given product matches the amount demanded at the current price level. Should it not, the output price is updated using a convex combination of current and implied price – similar to the mill price update – wherein the functional form of the market demand curve guarantees that the new price is closer to the equilibrium price. Because the timber demand is a function of the output price, once the output price is updated we repeat our iterations of the timber price loop. This whole process iterates until the output market, and thus the timber and intermediate goods market, are in equilibrium. Figure 2.3 visualizes this process.

The result of solving the price search algorithm is a spatially explicit map of timber harvest, which contains both the locations of harvests as well as their intensities. Additionally, we obtain mill output, mill profitability, as well as the profitability of the forest land itself. If we have a map of initial biomass, we can solve the model for a year.

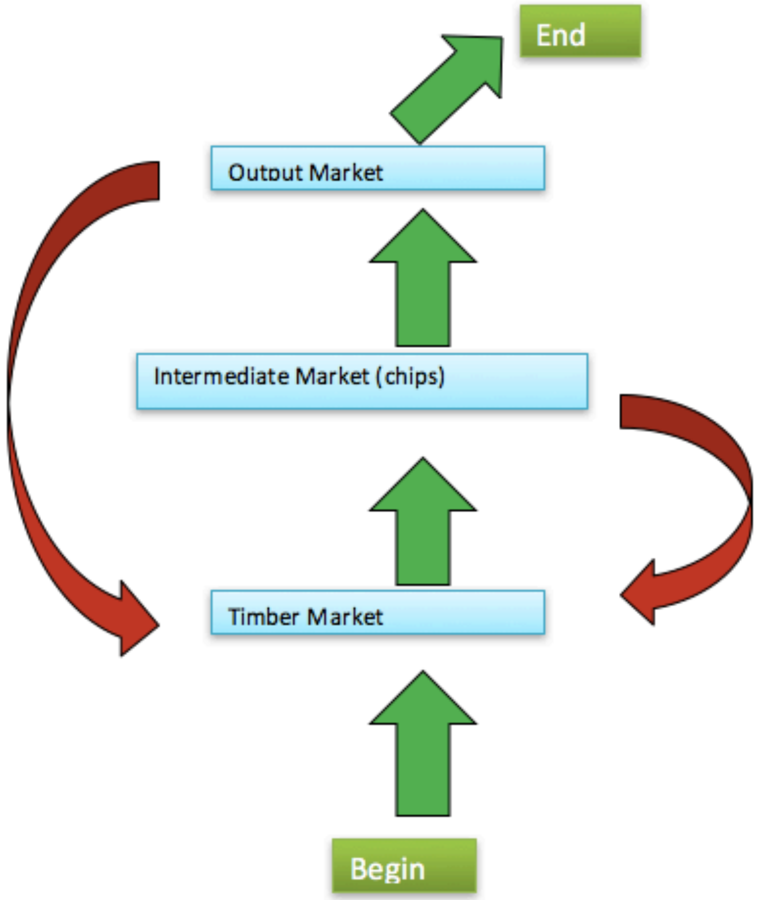


Figure 2.3: Schematic of the price search algorithm. Each market must clear in order for the algorithm to terminate. If a market clears, the algorithm moves on to the next market (green arrows). Should a market not clear, the price guesses for that market are adjusted and the algorithm starts back at the input market (red arrows).

However, solving it for additional time steps requires a model of forest growth. That forest growth is modeled by CLM, but only during coupled runs. CLM is cumbersome for running multiple policy experiments, and so a simpler model of forest growth must be utilized when it becomes necessary to do many iterations of the THM across the same timespan. This simpler model is shown in Equation 1, and is a deterministic Markov model of forest growth. One drawback of this approach is that it does not include climate change, wildfires, beetles, or other disturbances in the same way that CLM does. Additional work on the uncoupled version of the model could potentially incorporate these factors through letting either the intrinsic growth rate or the intrinsic capacity (or both) change with respect to climate variables, or disturbance-related variables.

As time progresses in the model, we need a way of representing changes in the economic context of the model. These include variables such as population and GDP. These two factors have been demonstrated to be important drivers of forest product demand (Buongiorno et al., 2003), and ignoring their influence would significantly bias the model results. Our model incorporates national level GDP and population projections into the model by utilizing the Shared Socioeconomic Pathways (SSPs) developed by various research groups for use in climate change research. In particular, we utilize SSP5 (Kriegler et al., 2017) which corresponds to a scenario in which there is rampant CO2 emissions tied with steady economic growth.

We combine these methods discussed above with data discussed in the following sector to simulate and project future harvest levels, and how they may be affected by climate change, forest disturbance, or targeted government policies.

2.3. Data

The THM incorporates data from a variety of sources to improve its representation of the forest sector. Some of these data are optional, while others are required to run the model. These include data on land ownership, mill location and capacity, and biological data on forest type and initial volumes. The section that follows will discuss and explore each dataset, as well as those that are needed for running experiments in the model. One of the most valuable outputs of the model is the grid cell level harvests, which in turn at least require data on biomass.

The THM has two ways of modeling biomass growth through time, depending on whether the model is coupled to CLM or not. If the model is coupled to CLM, it will receive a new biomass level every time step that has been calculated within CLM. Taking the harvest of the previous year provided by the THM, CLM will grow the biomass in each grid cell conditional on harvests as well as other disturbances and natural factors that influence growth. More about the coupling procedure can be found in a subsequent section. If coupling to CLM is not available, the THM requires an initial condition and a set of growth functions, which are discussed earlier in the methods section. The data used to parameterize the growth function mostly come from growth tables (Smith et al., 2006; Stage et al., 1988). When growth tables are unavailable, model output from CLM is used. If not enough observations are available from CLM, then a growth function is inferred by combining those that are available. The initial condition from biomass is provided by a CLM dataset based on estimated biomass levels from Berner at al. (2017).

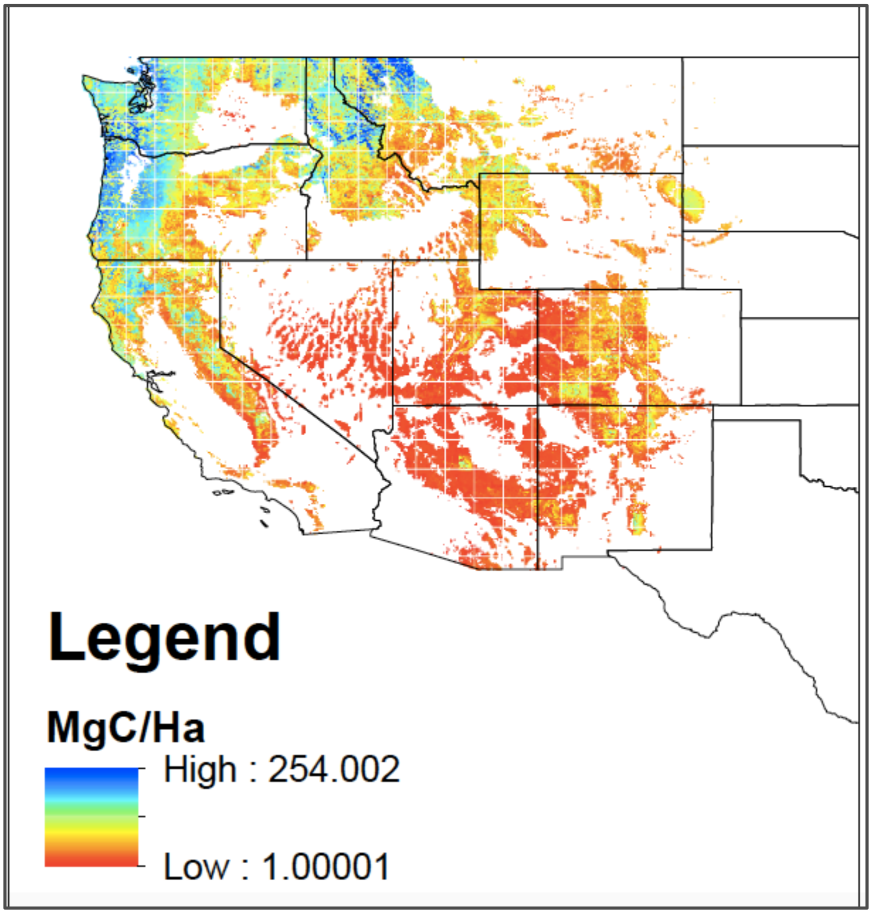


Figure 2.4: Input data on biomass used for the initial level of timber volume.

Along with data on the initial state of the biomass and its associated growth functions, we also utilize data on the distribution of tree species. Within the model, the species group that a given tree belongs to is referred to as a Plant Functional Type (PFT). The set of PFTs in the model were selected due to their economic and ecological significance in the western United States. Synchronizing the PFTs in the

THM with CLM increases the value of the model output for researchers looking to utilize the THM with CLM.

Table 2.1: List of Plant Functional Types in THM

PFT
Doug Fir
Lodgepole Pine
Ponderosa Pine
Pinyin/Juniper
Eng Spruce/Subalpine fir
5-needle Pine
Aspen/Hardwood
Oak
Hemlock/Cedar/Sitka
Western Doug Fir
Mixed Fir
CA mixed con
Redwood
Larch

The THM utilizes the PFT map by assigning a softwood ratio to each PFT. This then allows for the softwood ratio to be calculated for each grid cell. Knowing the softwood and hardwood prevalence in each grid cell is important for the economics of the model, as it constrains which mills the wood on a given grid cell can go to, and how much of it can be used by any given mill.

Another important determinant of harvest level is ownership of the land. Harvest on private land occurs in a very different manner than harvest on public land, and ignoring that distinction would be problematic. In order to classify grid cells into either public or private categories, we make use of the protected areas database (US Geological Survey, 2016). On top of providing a means of sorting the private and public land, it also allows us to differentiate the public land by government agency, as well as at the National Forest level. This is important, as management differs greatly amongst public owners as well, with harvest allowed in some public forest whereas in others it is not. This allows us to allow harvests on specific public lands, while preventing harvests on others.

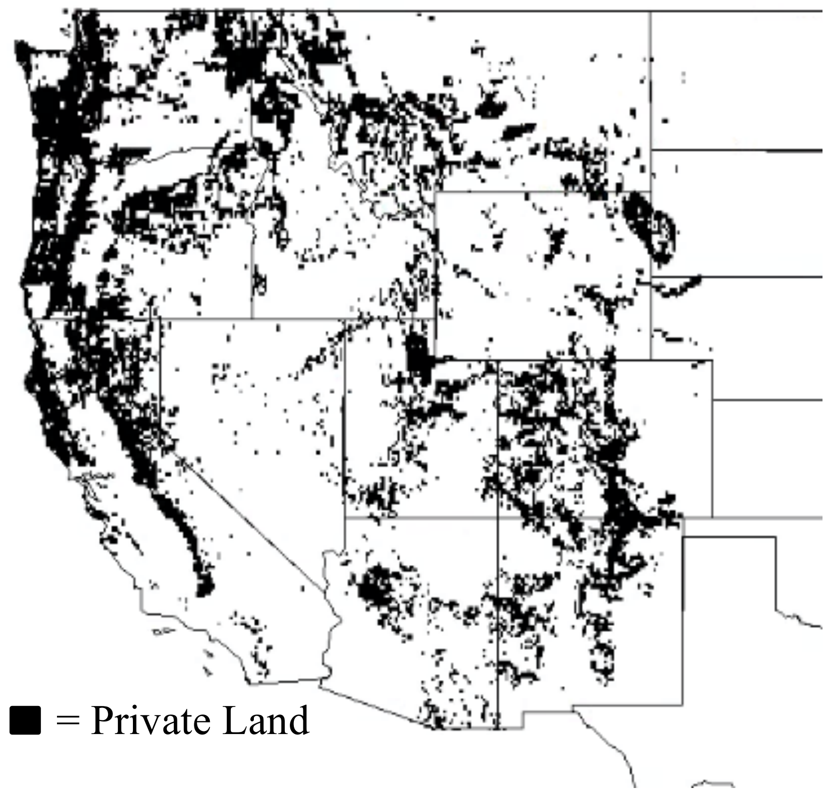


Figure 2.5: Private forested land in the western United States. This map is a combination of the ownership data from the Protected Areas Database and the initial biomass map in Figure 2.4

Data on mill locations and capacities are collected from two datasets. These include data collected from Spelter (2009) as well as data from another forest sector model, LURA (Latta et al., 2018). Both of these datasets provide snapshots of mill locations and capacity levels at different periods of time. For use in the model, the data from Latta et al. (2018) is used as it is the most current dataset we have on the mills in the western US. However, the data from Spelter (2009) is useful for checking our model of capacity growth, discussed in the previous section. The data from Latta et al. (2018) allow us to utilize the location, capacity, and product type, of 421 mills across the western United States.

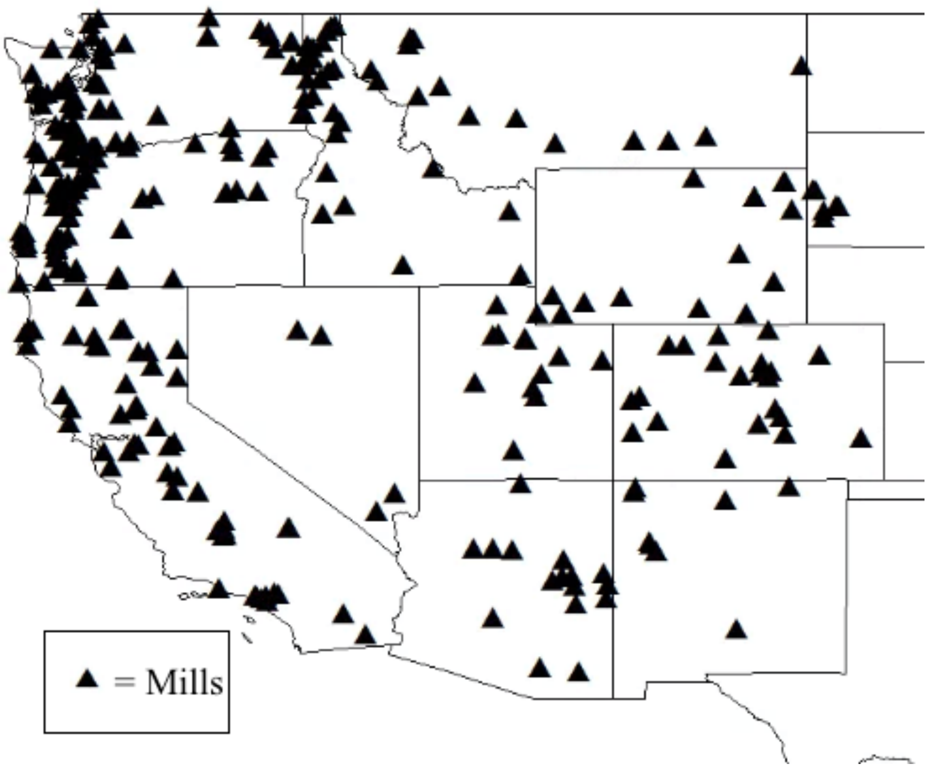


Figure 2.6:Locations of mills used in the THM

The spatially explicit nature of the model, both the input data on mill locations as well as the spatial representation of grid cells on the landscape, allows for us to determine the transportation cost between the different agents in the model. It is well established that the costs of transportation are major determinants for where and how much timber is supplied to mills. In order to calculate the cost of transport, we utilize a proprietary software package called PC Miler (ALK Technologies, 2016) that converts the locations of mills and grid cells into transportation distances and driving times. We calculate distances and times between every mill and every grid cell, as well as every mill and every other mill. We assumed a constant per-gallon cost of gasoline and per-hour labor costs.

There is also a considerable amount of data we utilize that pertains to the economic conditions of the forest sector in the western United States. This includes information on national-market level demand elasticities for forest products, such as lumber, plywood, newsprint, and other goods. Furthermore, we incorporate projections of population and GDP using SSP5 (Kriegler et al., 2017). This projection assumes a rapid release of greenhouse gasses (GHGs) into the atmosphere due to economic expansion and limited mitigation of GHGs. These data are used to estimate the region-wide expansion of capacity. Price points for the market level demand curves are calculated from FAO data on production and production value (United Nations FAOSTAT, 2017).

2.4. Parameterization Procedure

For many components of the THM, data provided in previous studies is sufficient to capture the relationships among agents in the model. These include data on market demand curves, grid cell level ownership, and transportation costs. For several parameters in the model, the data are insufficient to accurately capture the relationships in the model in a way that is consistent with our representation. This includes the timber harvest cost function, growth functions, and mill production functions. In this section, we will detail the parameterization procedures required for setting up the model.

Our approach includes a generalized representation of timber harvests. The production of timber is dictated by the biological dynamics of the problem. The costs, on the other hand, are a generalized representation of harvests across a grid cell. It is common to characterize within-plot harvest costs as declining in the intensity of the harvest (Kluender et al., 1998). Though we accept that this is certainly true at smaller scales, as it is cheaper per unit to fell large swaths of timber as opposed to selectively harvesting, on the scale of a whole grid cell, this is likely not be the case. A single grid cell contains many different plots of timber land that are more or less accessible, sloped, or otherwise difficult to reach. We assume that the forest manager chooses to harvest the cheapest and easiest-to-get-to timber first, followed by the next cheapest, and so on. Using this assumption, we can generalize a cost function over the harvest of timber on the grid cell that has an increasing per-unit cost. Furthermore, this results in a timber supply curve that slopes upwards. Because our cost function is a generalization, we must parameterize it ourselves.

In order to parameterize the harvest cost function, we first must select an objective with which to optimize the parameter. Through the course of the project, two methods with two different objectives were utilized. The first set the objective as recreating historic harvest levels in the state of Oregon. The second was recreating a realistic range of harvests for a range of prices that the grid cells would observe during the simulation.

The development of the first method was part of another project examining the application of different heuristic algorithms in fitting model parameters. Because models such as the one developed in this project are large and difficult to run many times, heuristic approaches can be used to speed up the parameterization process. The application utilizes simulated annealing (Kirkpatrick et al., 1983) and particle swarm (Kennedy, 2011) in order to create an optimal set of parameters for both harvest costs and mill production. This analysis encountered numerous obstacles, including the fact that the harvest model itself took a very long time to run (this is before many time-saving changes were made to the code). Furthermore, these two algorithms did not generate usable results when optimization of one set of parameters influenced the objective function on a different scale than another set. That is, the algorithm would optimize either the production costs or the harvest costs, but not both. Revisiting this analysis, and including additional meta-modeling are potential areas of expansion.

The second method involves recreating historically observed harvest ranges using a range of prices. This methodology is the one currently employed in the harvest module. Applying the method in the above paragraph would often result in parameters that would recreate realistic harvest levels for a limited set of prices. Any prices beyond that would result in unrealistically high or low harvests. Fitting the parameters to a range of prices alleviates this issue. This method consists of taking state level harvests from the TPO (USDA Forest Service, 2012). This is then used to generate region-wide estimates of harvest for both high and low harvest levels. Next, the harvest model is run and the set of mill level prices is extracted from the model run. This provides the needed information on the price ranges being observed in the model. Using information on average rotation length as well as the number of harvestable grid cells in the region, the average range of per-grid cell harvest is obtained. Finally, Microsoft Excel's non-linear fit algorithm (Fylstra et al., 1998) is used to minimize deviations between the observed range of grid cell harvests and module-generated grid cell harvests across the range of prices observed. Parameters obtained from this procedure are included in the appendix.

The mill level production function is another aspect of the model that required parameterization. Many previous forest sector models represent mill production as an input-output model, with labor, timber, and capital combining to create a unit of product. Initially, we traded this approach for a Cobb-Douglas production function. This allowed us to derive the mill-level demand for timber from solving the mill's profit maximization problem. However, parameterizing these functions became very difficult, and it became clear that accurately representing mill product and timber demand with this approach would require more sophistication. We turned to a representation that matches previous forest sector models (e.g. Latta et al., 2017), wherein every mill has a fixed factor that converts timber into product. This approach is made more attractive by the fact that we have an empirically based representation of timber demand from a previous study (Guerrero Ochoa, 2012).

The growth functions are needed for model runs in which CLM is not coupled to the THM. Initially, our method of fitting the growth function parameters was to utilize CLM data for each grid cell in order to fit specific grid cell level growth functions. This proved problematic, as many grid cells do not exhibit sufficient growth to successfully identify the intrinsic growth rate for grid cells. The second approach was to use the CLM data in order to fit PFT-level growth functions, and then use the PFT proportions on each grid cell to generate grid cell level growth functions. For many of the more productive PFTs, there was a substantial number of cells that were already at capacity. This resulted in identification issues. We instead employed growth tables from Smith et al. (2006) and interpolated the other PFT-level growth functions using a combination of data from CLM and similar growth functions.

2.5. Policy Module

A goal of this project is to be able to implement policy experiments within the THM, both while it is coupled to CLM and when it is not. In particular, there are two aspects of our model that we leverage to explore novel policies. The first is the superior representation of biological processes in our model. The incorporation of CLM into the THM allows us to model the effects of climate change in a way that is not found elsewhere in the literature. Furthermore, the improved biological representation allows the forest sector to respond to disturbance events, and for that response to affect the disturbance itself. Taking advantage of this in the context of a policy experiment, we can incorporate data on vulnerability or risk in order to implement subsidies or taxes on timber harvest or mill production. This is made more appealing by the fact that our model is spatially explicit at a high resolution, allowing for targeting specific plots or mills. Another aspect of our model is the large spatial scale at which the model is solved. Other models of similar size are lower in resolution, and high resolution models have a much more limited range. This allows us to be selective about where we implement policies. This means that our model provides a means of testing state-level policies, and observing the potential spillovers of those policies.

Implementing targeted subsidies or taxes at the grid cell level requires the reading in of additional data. Future research may focus on incorporating endogenous means of calculating grid cell level taxes and subsidies. For now, we can utilize data from CLM (as well as data produced from previous CLM runs). An example of such data includes data on timber vulnerability to drought, fire, and other disturbances, calculated using multiple CLM runs. Implementing such subsidies requires the addition of a per-unit subsidy or tax. In the case of the subsidy, this is a payment the forest manager receives per-unit of timber harvested per-unit of vulnerability. The more vulnerable the timber is, the higher the payment is. This subsidy is applied to the gate-price that the forest manager observes, but not to the cost that the mill pays. In this way, it resembles a payment from the government for social benefit of removing risky timber.

Once the above policy apparatus has been incorporated into the code, we can utilize a state-level map to run policy experiments that are state-specific. This requires a dataset mapping each grid cell to a state. We can then utilize code that limits the application of a policy to a single state.

2.6. Policy and Disturbance Experiments

The THM specializes in addressing two phenomena in particular – the economic response and adaptation to climate change and forest disturbance, and policies that are spatially targeted. This is due in part to the scale at which the model is solved at, being both high resolution and spatially vast compared to similar models. In what follows, we demonstrate both of these specializations through simulating disturbance events, and by enacting policies that target harvests on forested grid cells that are vulnerable to disturbances. In the rest of this section we will set up both experiments, and then in subsequent sections we will describe and discuss the results of the experiment.

The first experiment we conduct in the THM is an induced natural disturbance. When the THM is linked to CLM, this process will occur endogenously within the model; however, for this experiment linkage to CLM is not required. Natural forest disturbances induce a large economic cost, with fire resulting in an average of $261 million annually (Dale et al., 2001) and insect outbreaks and other pathogens (the costliest natural disturbance) result in over $2 billion of annual damages on average (USDA, 1997). These economic damages are substantial enough that the industry must adapt to them in some fashion. The value of the destroyed timber is easy to calculate; however, there are many unknowns regarding additional effects of disturbance. The forest sector adapts by shifting harvests around the landscape, such that if a timber plot is destroyed, a mill will purchase timber from the next cheapest plot available. The increase in scarcity with respect to timber may marginally increase the value of the timberland not affected by the disturbance. Furthermore, there is a lasting effect of disturbance that occurs through its effects on mill profitability. If it is the case that previously harvestable timber is destroyed, and the mill must now purchase more expensive timber, it means that the mill's profit will be reduced. This leads to long run changes in capacity, as the mill will no longer be able to maintain their current capacity, or easily purchase new capacity. Additionally, the forest sector spreads the disturbance around the landscape. On top of the natural disturbance occurring in the forest, through the market the mills access and remove additional timber from the landscape. This results in an overall larger magnitude of disturbance than the natural disturbance alone.

In order to examine the effects of forest disturbance, we conduct an experiment within the THM in which we induce pine beetle outbreaks on the landscape, and compare those results to THM runs in which no natural disturbance occurs. The data we use on pine beetle mortality comes from Burner et al. (2017). We run the model for 30 years, effectively modeling the years 2014-2044 for the whole region. We track the evolution of harvests on the landscape, as well as the profits of the landowners. Furthermore, we track the changes in capacity that occur at the mill level. The initial biomass is taken from a CLM run in which the data are based on Berner et al. (2017).

In the second experiment we conduct a policy that subsidizes harvests on forest land deemed vulnerable to harvest. This experiment covers two aspects of natural resource regulation, including the reduction of risk for disturbance, as well as the effects of state-level policy versus national or region-wide policies. The risk of disturbance is an externality whose full extent may not be internalized by the landowner. Though the risk to their own property is internalized and has effects on management (Reed, 1984), the additional cost of increasing risk to other nearby forest landowners is not internalized. A subsidy would be a corrective measure in order to achieve harvest levels that reflect the greater risk to the region. Additionally, the differences amongst the state-level policies and between the state-level policies and a national level policy are important for determining the scale of the approach. It is also one of the first modeling exercises in natural resources explicitly addressing the difference between state and national level policies, and the spillovers that could potentially occur though state-level policies alone.

In order to implement this policy within the THM, we utilize the policy apparatus described in Section 2.5 in order to test the effects of targeted subsidies.

The subsidies themselves will increase the per-unit price of harvest that the forest landowner receives, while not imparting any cost on the mill. In this way, it can be seen as a government intervention, assuming that the policy is paid for via taxation of some other sector or borrowing. The distortionary effect of the tax or subsidy is not taken into account for this analysis. The vulnerability data comes from Buotte et al. (forthcoming), and ranks parcels within CLM on a scale of 1-3, with 1 being the least vulnerable and 3 being the most vulnerable. A single subsidy payment is applied to grid cells with a vulnerability ranking of “2”, whereas two subsidy payments are applied to grid cells with a vulnerability ranking of “3”. In practice, the magnitude that this subsidy should take has not been calculated in the literature, and so the values given here are applied conservatively. The magnitudes of the subsidy payments that are selected for this experiment are “$10/unit” and “$20/unit”. We conduct 10-year runs, effectively making the time frame of the experiment from 2014-2024. We run a no-policy benchmark, and then run experiments for both policy levels for the states of California, Oregon, Washington, and additionally the whole region. This comprises a total of 9 model runs.

This paper does not address the impacts of climate change; an important caveat to the results. The representation of climate change is something that CLM captures very well; however, at the time, coupling capabilities of the THM are not fully developed. Another option is to develop growth functions whose parameters can shift with changes in climate variables such as temperature and precipitation. Such work is a possibility for future work on the THM.

2.7. Results and Discussion from Disturbance Experiment

For this experiment, we implemented two model runs: one with no disturbance from pine beetles, and one with disturbances taken into account. The pine beetle disturbances remove carbon from the landscape in a similar fashion as the harvest: in percentage terms. The shock we modeled involved a persistent pine beetle invasion, rather than a one-time shock. We find that this persistent shock has major implications for the harvest pattern in the model.

The amount of harvest in the simulation changes in two ways. First, the magnitude of harvests across the two simulations changes. In the early part of the simulation, very little change occurs across either scenario in terms of total harvest. However, the discrepancy grows larger as the simulation progresses. The lack of difference in the initial few years of the simulation highlights the important role that the market plays in adapting to the impacts of forest disturbance. However, the adaptation involves achieving a state that is less profitable than the one in which no disturbance occurs. This results in the capacity levels of given mills diverging from one another during the course of simulation. This divergence eventually becomes great enough to cause substantial differences in the total harvest level at the end of the simulation.

The harvest pattern itself is different in every year the simulation takes place. However, the pattern becomes dramatically more different in the later years of the simulation. We plot the absolute difference in harvest level from the no-beetle baseline as a function of time in Figure 2.7. The sum of absolute differences between the two simulations is a way to quantify the difference in harvest pattern between the two scenarios. From Figure 2.7, we observe that although the sum of absolute differences behaves almost cyclically, it trends upwards over time.

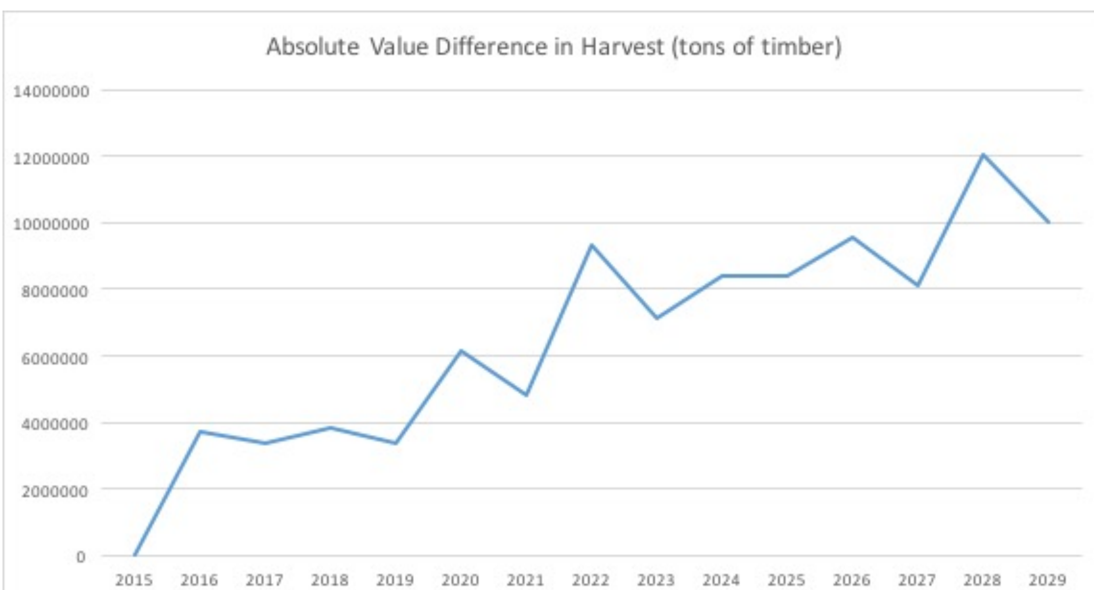
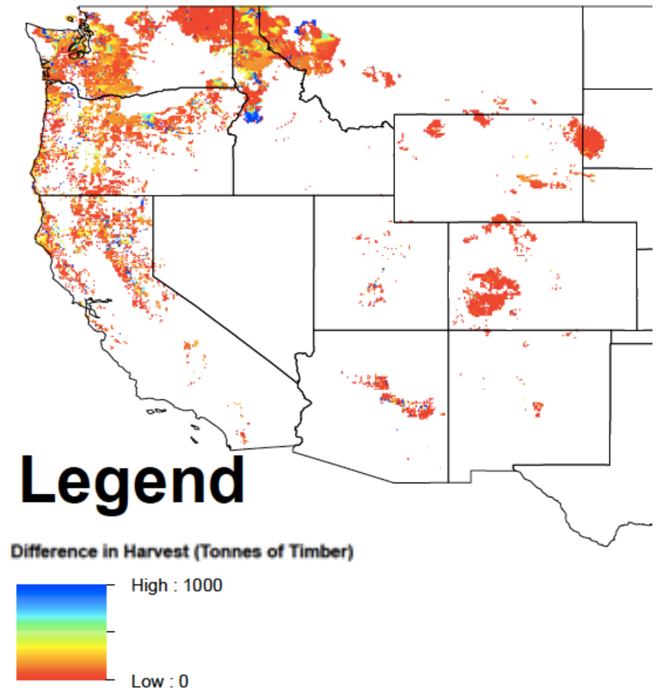


Figure 2.7: Absolute value of harvest differences over time

As with the total changes in harvest, this growing discrepancy in harvest pattern is mostly due to changes in the capacity level that are result of a less profitable equilibrium from beetle infestations. As mill capacities change over time, the effects of these changes begin to interact with one another, eventually leading to a substantially different map of harvest than in the scenario with no beetle outbreaks.

One of the questions we are interested in addressing with this study is whether localized beetle outbreaks have effects that are spread out across the region by the market. In Figure 2.8, we present two different maps of differences in timber harvest. In Figure 2.8, Panel (A), we present the difference in timber harvests between the beetle scenario and no-beetle scenario after 5 years. We see that there are a few areas of substantial difference in areas affected by beetles, with small or no differences elsewhere. For instance, western Oregon is total unchanged, for the most part. However, we can still see that small changes are occurring throughout the landscape. Panel (B) shows the difference in harvests at the end of ten years, and we can see from the map that the region experiencing differences in harvest is now much more expansive. There are many changes at plots near mills, even mills that are not necessarily close to areas affected by beetle outbreaks. This indicates that the influences of the market are playing a substantial role in spreading the disturbance.

(A) Harvest map at five years



(B) Harvest map at ten years

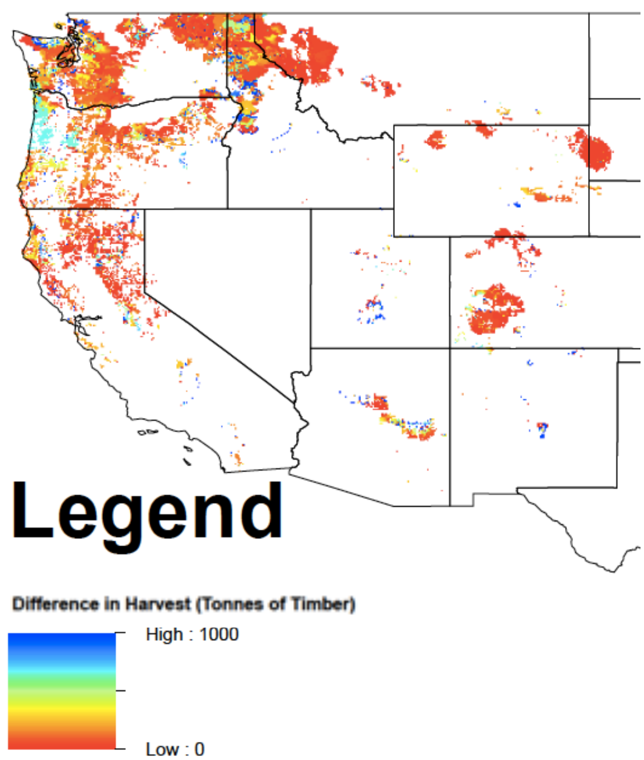


Figure 2.8: The differences in harvest levels after year 5 (A) and year 10(B) between the no-beetles and with-beetles scenarios.

The beetle infestations lower the supply of timber, but also affect the profitability of the mills surrounding the outbreak region. As an additional consequence, regions not affected by the beetle outbreaks are also impacted because the price of timber increases, which lowers the profitability of each mill. We present a map of capacity differences in Figure 2.9. The difference reported in Figure 2.9 is calculated as the difference between the no-beetles scenario and the with-beetles scenario, such that a positive value indicates lower capacity in the no-beetles scenario. There are some regions that experience increases in capacity. This is due to the fact that the demand for forest products is still shifting out, resulting in higher output prices for some products. This results in the profitable mills obtaining more capacity in the scenario with pine beetles than the scenario without pine beetles.

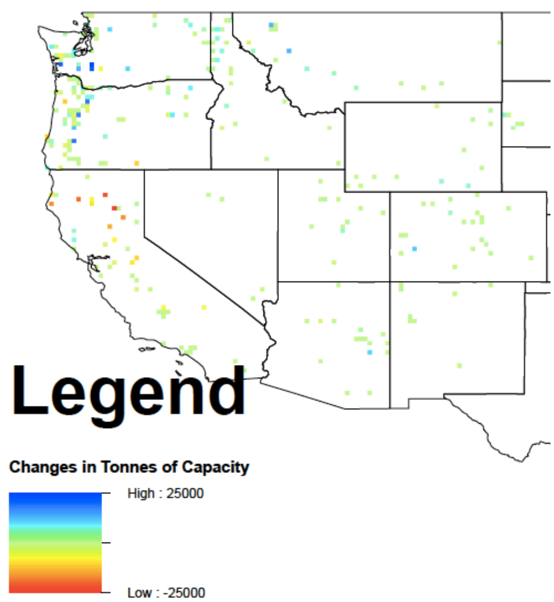


Figure 2.9: Capacity differences between the no-beetles and with-beetles scenarios at the end of the simulation ($K_{NB} - K_{WB}$) where K_{NB} is the capacity in the no-beetles scenario and K_{WB} is the capacity in the with-beetles scenario .

Surprisingly, at the end of the simulation many regions have approximately the same capacity as the no-beetles scenario. However, there are some major regional differences. For instance, northern California emerges from the with-beetles scenario with more capacity than in the no-beetles scenario. This is due to that region absorbing capacity from other regions more affected by beetle outbreaks, such as northern Idaho and eastern Washington.

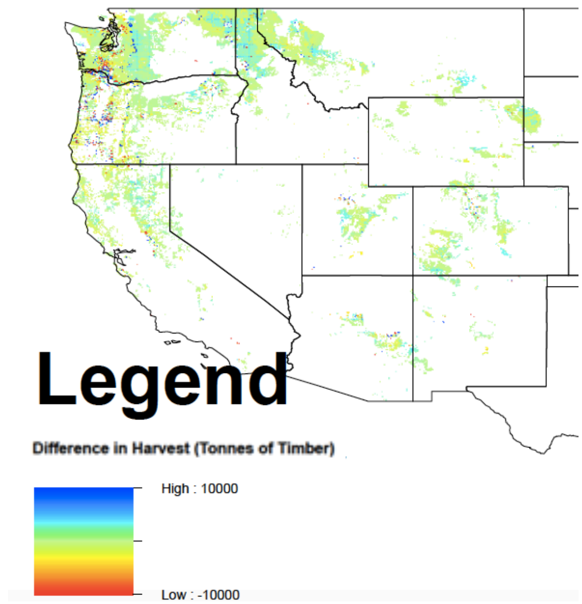
The results presented here indicate that not only are the effects of localized disturbances not localized, but that their impact is increased as time progresses. We show that substantial changes occur in the forest sector as a result of localized disturbance, including increases in capacity in regions not affected by the disturbance event. This finding indicates that policies that aim to reduce forest disturbances may be impacting the forest sector in a different region altogether through effects on market forces. In the next experiment, we set up such a policy, implementing it first on the regional level, and then on the state level.

2.8. Results and Discussion from Policy Experiment

We also conducted a series of policy experiments in the THM in which we applied subsidies to timber harvests on forestland that were vulnerable to disturbance. This application is an experiment in potential policies that could reduce the severity of disturbance events. However, without the model being coupled to CLM, we cannot test the effectiveness of counteracting disturbance. However, this policy experiment also provides an important contribution in that it tests the effects of a localized environmental policy on the greater region. In the rest of this section I will present the results of model runs in which the subsidy is applied across our study region, as well as a subsidy that is only applied in Oregon.

In the first part of this experiment, we implemented region-level subsidies at a low level ($10 per tonne of timber per vulnerability unit) and a high level ($20 per tonne of timber per vulnerability unit). We then examined the difference between either scenario and a no-policy counterfactual. Figure 2.10 visualizes these differences for the low level (Panel A) and the high level (Panel B). Both of these policies result in less harvest around the Willamette Valley, with substantially more harvest in eastern Oregon, eastern Washington, and northern Idaho. Figure 2.10 clearly demonstrates that harvests in the Willamette region are being substituted for harvests in different regions. Additionally, the larger the subsidy, the more substantial the increase in harvest is in northern California, as well as in the Rockies.

(A) Harvest differences at the end of a simulation between the no-policy scenario and the low-subsidy scenario



(B) Harvest differences at the end of a simulation between the no-policy scenario and the high-subsidy scenario

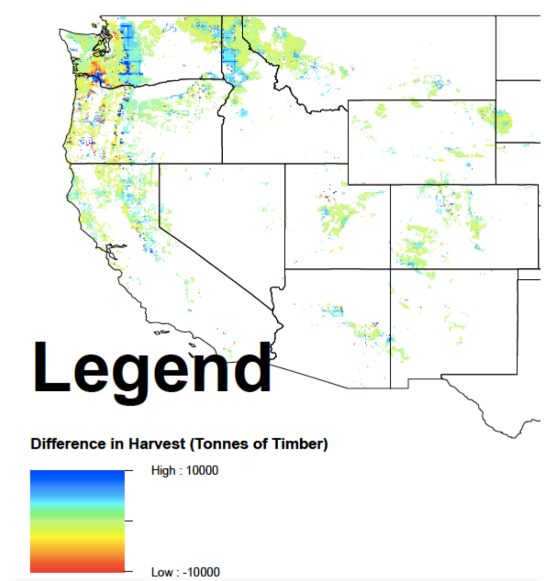


Figure 2.10: Harvest differences between the no-policy scenario and the low value policy (A) and high value policy (B)

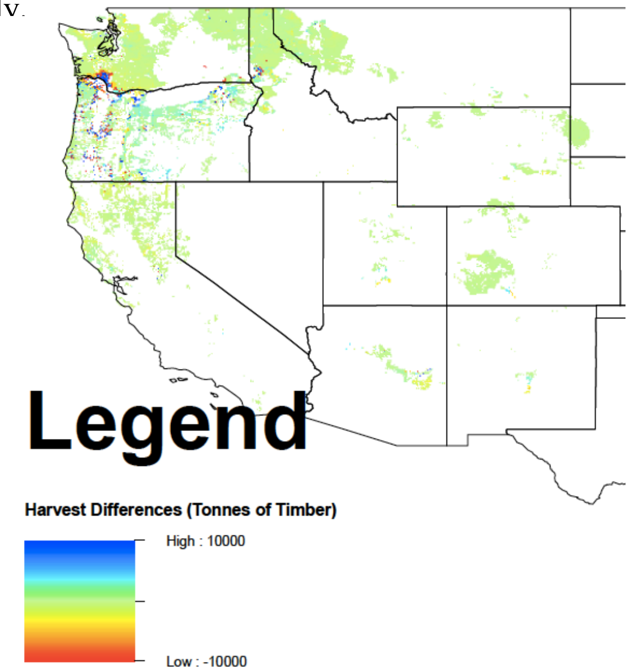
Additionally, larger region-wide subsidies result in greater amounts of overall harvest. However, the frequency of harvest is reduced as the subsidy level rises, leading to less area that experiences removal, though the removals that do occur are more intense. Though harvests increase dramatically on land vulnerable to disturbance, harvests are reduced on lands that are not vulnerable. For marginal timber land, this could mean a steep reduction in the value of timber land, as the subsidy allows vulnerable timber to be shipped further.

In addition to conducting an experiment on region-wide subsidies, we also implemented state-level subsidies. Figure 2.11 displays the difference in harvests between the no-policy scenario and the scenarios in which the subsidies are restricted to Oregon alone for a low level (Panel A) and a high level (Panel B). It is clear from the figure that the most substantial changes occur within Oregon itself. As the level of subsidy increases, more harvest occurs in the eastern part of the state, while Cascade Range sees reductions in harvest levels.

The spillovers that occur are limited from the Oregon-only subsidy scenario. The entire region experiences minor changes in harvest, though these changes are not very substantial. There are two areas in which the subsidy appears to have a large spillover effect: northwest Idaho and southern Washington. The effects that the Oregon subsidy have in southern Washington are more substantial than the region level subsidies displayed in Figure 10. Whereas in Figure 10 the harvest levels in eastern Washington are higher, this is not the case in the Oregon level subsidy seen in Figure 2.11. Therefore, it appears that mills in Washington are substituting Washington timber for cheaper Oregon timber being removed from vulnerable lands. A table that includes statistics on harvest levels for each version of this experiment can be found in the appendix.

In general, the subsidies impact a limited number of forest products. Region-wide subsidies result in large increases in lumber production, as well as biomass production. However, other products see only meager increases in production as a result of these subsidies.

(A) Harvest differences at the end of the simulation between the no-policy scenario and the low-subsidy scenario for Oregon only.



(B) Harvest differences at the end of the simulation between the no-policy scenario and the high-subsidy scenario for Oregon only.

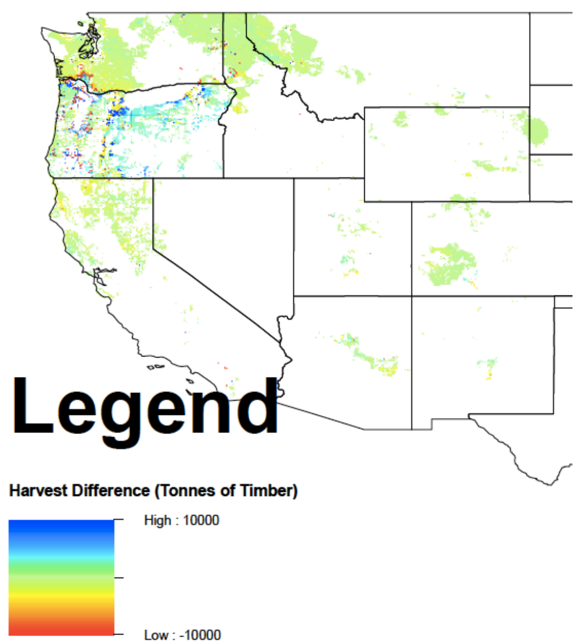


Figure 2.11: Harvest differences between the no-policy scenario and the Oregon-only subsidy for a low subsidy (A) and a high subsidy (B

2.9. Conclusion

Advancing the modeling of coupled systems, including forestry, is an important step towards more accurately capturing the effects society has on the environment, and how society responds to environmental disturbances such as beetle outbreaks. Furthermore, the added nuance of these models will improve our measurement of policy impacts on the environment. This essay addresses this need through modeling interactions between the forest sector and forest ecosystem.

In this essay, I have constructed and demonstrated a spatially explicit partial equilibrium model of forest sector. It can run at a high resolution over a vast spatial scale using a novel price-search algorithm that approximates the market equilibrium level of timber harvest in the western United States. Furthermore, it incorporates data from numerous sources such as land ownership and transportation costs in order to construct an accurate model of forest management for the region. This model allows us to conduct spatially explicit policy experiments as well as measure the effects of forest disturbances on the forest sector of the western United States.

We conduct an experiment in the model in which we simulate a pine beetle outbreak across the western United States. In general, we are interested in whether localized disturbance events are distributed across the region through market forces. We find that in the case of our experiment, localized disturbances not only have non-local effects, but that these effects grow through time.

Our second policy experiment involved the implementation of a harvest subsidy on land that was vulnerable to natural forest disturbances. We were interested in what the region-wide effects of such a subsidy would be, as well as whether there are spillovers from localized policies such as a state-wide subsidy. We find that region-wide subsidies result in larger amounts of total harvest, though these harvests occur across a smaller range. This results in less-vulnerable land possibly losing value as mills will ship in the cheaper resource. We also find evidence for potential spillovers from state-level policies. We observe an Oregon-specific subsidy influencing harvest levels in southern Washington and Northern Idaho.

There are numerous extensions to this current work. This model has the capability of linking to large scale climate simulations and models of land processes such as CLM. An extension of this project involves coupling this model to CLM and running simulations that involve not just forest disturbance but also different climate change regimes. Additionally, the modeling advances made in this paper can be applied to other contexts as well, such as agriculture. Another interesting area to continue studying is the effect of a collection of localized policies on region-wide outcomes.

3. The Effects of Contract Duration on the Performance of a Forest-Based Carbon Offset Program in Western Oregon

3.1. Introduction

Forests are responsible for significant levels of carbon sequestration, both worldwide and in the United States. Globally, forests absorb an estimated 2 petagrams of carbon annually (Pan et al., 2011). In the United States alone, earlier estimates placed the amount of carbon sequestered by forests at approximately 162 teragrams per year (Ryan et al., 2010). The ecosystem service of carbon sequestration continues to grow in value as the expected costs of climate change continue to rise (Hsiang et al., 2017). From previous studies, the potential value of a program targeting afforestation and changes in management could result in a benefit of at least $649 billion (Bluffstone et al., 2017). In order to fully utilize that potential value, forest managers must be incentivized properly, which means that policies must designed as efficiently as possible (Kline & Mazzotta, 2009). Current policies aimed at incentivizing forest-based carbon sequestration, though based on rigorous scientific analysis, often lack consideration of the economics of the policy, and whether a better outcome could be achieved through changes in the policy design.

Forest-based carbon offsets are utilized in a number of different contemporary policies aimed at limiting carbon emissions. Many of these offsets are tied to carbon trading schemes, such as the European GHG trading scheme, the oldest such scheme (Ellerman & Buchner, 2007). Furthermore, the state of Oregon is considering the design of a carbon trading program (Sickinger, 2018), which plans to allow for forest-based carbon offsets to account for a fixed percent of offsets. Though the design and requirements of forest-based carbon offsets differs across programs, the California program, represents an important standard. This is in part because the ambitions of the California program are to link itself with other contemporary carbon markets. This will likely have the effect of standardizing the features of the forest-based carbon offsets used elsewhere.

However, the contracts that govern forest-based carbon offsets are difficult to design, and many questions regarding the optimality of their structure exist. For instance, there are rigorous monitoring requirements for the resource (e.g. California Air Resource Board, 2017) that have been identified as potential barriers for adoption, along with the complexity of such programs (Kelly & Schmitz, 2016). Additionally, the duration of the contract itself varies across programs. The California program in particular requires the duration of these contracts last for 100 years, a standard adopted in order to ensure the permanence of the carbon sequestered. However, this does not necessarily optimize the performance of the program over shorter time horizons that may be relevant for carbon sequestration programs.

This chapter addresses questions regarding the role that contract duration plays in the performance of forest-based carbon offset programs. We are interested in how the duration of the contract first and foremost influences enrollment in the program. Previous research looking into landowner preferences over contract length indicate that a shorter contract may incentivize more land to be enrolled. Does a shorter contract duration result in more sequestration over a given time frame? We are interested not just in sequestration on lands enrolled in the program, but also on land that does not enter into the program. We also want to explore the interaction between the price of carbon and the contract duration on program performance. Relatively higher carbon prices may result in larger discrepancies in program performance between contract lengths. One argument against forest-based carbon offsets is that the reduction in timber will increase the price, resulting in leakage as unenrolled lands harvest more. This chapter will explore the extent of this effect, and whether the price of carbon and length of the contract influence this effect. Furthermore, we are also interested in exploring differences in other management variables, such as average rotation length of enrolled versus unenrolled lands, and economic outcomes such as prices, capacity shifts, and effects on land prices.

We choose to explore these problems using a regional partial equilibrium model of western Oregon. Timber plots as well as mills are represented in an explicitly spatial way, allowing for us to observe the origin and destination of the timber harvested in the model. The model solves over a 100-year time horizon at a 5-yearly time step, allowing us to observe the evolution of the western Oregon forest sector through time. To the best of our knowledge, this represents the first study that explores the effects of contract duration in a partial equilibrium modeling framework. We set up a number of scenarios with varying values for the price of carbon, as well as varying contract specifications. We are able to track numerous economically relevant variables that range from management details such as average rotation, to mill-level data on capacity, and include economic variables such as land prices.

We find evidence that contract duration influences the performance of forest-based carbon offset programs. Though we do observe a relationship between enrollment and duration, the relationship is relatively weak. However, we do see a non-linear relationship between the duration of the contract and amount of carbon sequestered. Surprisingly, we find that very short contracts result in worse outcomes with respect to carbon sequestration over long time frames than not having any program at all. Also surprisingly, we find that the 100-year contract – the standard for the California program – is outperformed by numerous shorter contracts over long (though not indefinite) time horizons. Further evidence suggests that by expanding our time horizon beyond 100 years, the shorter contracts may outperform the 100-year contract. This raises the possibility that future applications of forest-based carbon offsets should consider shorter contracts.

In what follows, we will present the background, results, and discussion from our analysis. In the next section, we will discuss the background of these programs in order to provide the proper context of the problem. The next section will provide a literature review to demonstrate how this current work fits into the studies that have come before it. We will then discuss the set up of the model and the methodology. The following section will present the results, which will then be followed by a section discussing the implications of the results. Afterwards, this chapter will conclude with a brief summary and discussion about future work.

3.2. Background

Forest management has long been a target of efforts looking to biologically sequester carbon. Programs looking to pay forest landowners for the ecosystem service of carbon sequestration are relatively recent. Because forestry has substantial potential to sequester carbon, it has become a popular option for offsetting pollution elsewhere. The environmental benefits these programs generate are due to the changes they make to forest management. Rather than force a forest landowner to manage in a particular way, these programs will incentivize the landowner through different payment structures. We know through the Hartman model (Hartman, 1976) that once an environmental benefit is internalized by the forest landowner, either through payments or some other method, that management will change such that rotation lengths are extended. This is also demonstrated through various extension documents detailing best practices for alternative management (e.g. Collins et al., 2008). A policy that explicitly adds the value of the ecosystem service into the forest managers profit equation will, in theory, achieve the desired effect. Typically, policies attempt to ensure that the carbon sequestered is both additional and permanent.

Forest-based carbon offsets are a means by which regulated power producers whose carbon emissions are limited or capped through regulation can purchase pollution offsets through paying forest managers to sequester carbon (California Air Resource Board, 2017). Within the California carbon market, offsets are generated from a number of different sources, including agriculture, methane capture, and ozone depletion (California Air Resource Board, 2017). Forestry represents the largest source of offsets, accounting for approximately 81.7% of offsets in the program (California Air Resource Board, 2017). For the forest manager, this means that they would receive payments for the carbon sequestered on their landscape, as determined by annual measurements they are required to take (California Air Resource Board, 2015). To prove that the carbon sequestration is additional, the forest manager must submit a harvest plan that serves as a counterfactual basis for determining the extra amount of carbon sequestered. This plan represents what the landowner would have done absent the forest-based carbon offset, and gets paid for the carbon sequestered in the forest above this counterfactual harvest plan, conditional on it being above a pre-determined baseline. Anecdotal evidence suggests that forest landowners will never submit a plan in which the timber volume is above the pre-set standard, which indicates that strategic behavior is involved in the design of these future harvest plans. Some have criticized this approach as not accurately ensuring that the carbon sequestered by forest landowners is additional. The modeling approach we adopt will be able to capture the expected differences between counterfactuals, and so although the criticism may be valid, it is not important for the analysis that follows.

In many programs, facets of the program aim to ensure that the carbon sequestered is done so permanently. The forest-based carbon offset accomplishes this by having the forest manager legally commit to a contract in which the manager will be paid for all the carbon sequestered and charged for the carbon removed from their forest. The duration of these contracts is a subject of importance for regulators looking to design forest-based carbon offset programs. The California carbon market requires that these contracts last for one-hundred years (California Air Resource Board, 2015). From the perspective of a regulator, a longer contract may be preferable because it better ensures that the carbon is sequestered permanently. A shorter contract may result in the landowner harvesting earlier, and the carbon stored in the forest flowing back into the atmosphere. However, it may be the case that such programs could benefit from contracts of shorter duration by incentivizing more land to enter the program. Little work has been done with respect to the optimal duration of conservation contracts in general, let alone the duration of forest-based carbon offset contracts. This is despite the fact that this is a critical aspect of contract design. The duration of these contracts is important not just to the forest manager who has enrolled, but also to those that have not enrolled. Previous studies (e.g. Schwarze et al., 2002) have shown that enrollment in such programs can result in leakage as unenrolled forests increase harvest levels.

Following Latta et al., 2016, we simulate a program based on the Climate Action Reserve protocol, or CAR (Climate Action Reserve, 2012). This protocol is used in the California cap-and-trade program (California Air Resource Board, 2015), which was put in place after the passage of AB-32. Passed in August of 2006, AB-32 required that California's emissions be reduced by approximately 25% (estimated 1990 levels) by the year 2020 (Hanemann, 2007).

Many other emissions trading schemes exist, not only in the United States but also internationally. Another well-known example is the Regional Greenhouse Gas

Initiative (RGGI), which encompasses Connecticut, Maine, Delaware, New Hampshire, New York, New Jersey, and Vermont. The RGGI focuses on Green House Gases (GHGs) produced by power generators (Hanemann, 2007). A number of noteworthy carbon markets exist outside the United States as well. These include the New Zealand Emissions Trading Scheme (NZ ETS), the Australian Carbon Pollution Reduction Scheme (CPRS), and recently a cap-and-trade program in Quebec (Grüll and Taschini, 2011). Though the study presented here focuses on just a single program, it may be possible to draw parallels between the others. This is made even more true by the fact that programs can and will be linked together to create a larger market for offsets, such as the case with the California and Quebec markets (Newell et al., 2013).

	CA	*Acres*	**WA**	*Acres*	**OR**	*Acres*	**Other**	*Acres*	**Total**	*Acres*
ACR	10	129382	2	506077	3	659092	38	1586167	53	2880718
CAR	51	783905	1	521	0	0	58	1694213	110	2478638
VCS	0	0	0	0	1	987	2	22497	3	23478

Table 3.1: Acres enrolled by registry and by state.

An important aspect of the offsets under the California cap-and-trade program is that they can be generated out of state. Though the legislation only regulates GHG emissions within the state of California, offsets can be provided by entities outside the state, as is the case for offsets from the forest sector. These offsets are of particular interest to landowners in Oregon, where forestry is a significant sector of the economy. Private forests make up 34 percent of the land area, where 14 percent of the total is considered small private (Oregon Forest Resource Institute, 2016). Carbon offsets have the potential to provide an alternative revenue stream for smaller forest landowners. There are many registries that the verifying agencies can go through to obtain their offsets. In the case of the California market, there are three: The American Carbon Registry (ACR), the Climate Action Reserve (CAR), and the Verified Carbon Standard (VCS). The distribution of improved forest management projects across these registries and by state and by registry is presented in Table 3.1. It is interesting to note that, despite the forest sectors of Washington and Oregon being as large as they are, there is still very little activity in those states with respect to offset production. This could indicate substantial potential for carbon sequestration in those states. The standards applied to forest managers enrolled in the program is still consistent across registries due to the requirements imposed by the California carbon market. Because the payments that the enrolled forest landowners receive originate from power producers paying the state for the right to pollute, the California program has leverage over the standards the registries adopt, including the duration of the contract.

Another aspect of these offset programs is that a proportion of the enrolled forestland does not receive payments for the carbon sequestered. Ever present in forest management is the risk of a major disturbance, such as a wildfire, that will release the sequestered carbon into the atmosphere (Galik & Jackson, 2009). In the jargon of the policy maker, this is referred to as a reversal risk. In order to buffer against reversal risk, every forest landowner enrolled in the program is required to contribute to an insurance bank. The forestland in this bank must be managed in the same way as the other enrolled land, however payments are not received for the carbon sequestered by that land.

3.3 Literature Review

The topic of carbon offsets and carbon trading in general have been a significant focus of the carbon policy literature. The literature review that follows is limited to those studies that are most pertinent to the work in this chapter. The review is split into two major sections based on the subject matter. The first group of papers reflect the work that has been done to date concerning the issues of contract length and permanence. The second section analyzes the impacts of carbon markets and offsets in general.

Permanence is an important feature in pollution offset projects. With respect to carbon offsets, it refers to the duration of time the carbon is kept out of the atmosphere. Most programs target a completely permanent offset, meaning the carbon is sequestered indefinitely. This is despite the fact that carbon stored in biological systems, such as a forest, may not exhibit complete permanence (Sedjo & Marland, 2003).

A number of studies discuss the issue of impermanent sequestration, and some studies introduce potential methods to address it. One approach involves incorporating the temporary nature of land-based carbon sequestration into the contract. Herzog et al. (2003) analyzes the value of temporary carbon storage, while Marland et al. (2001) considers methods of carbon accounting that address the potential lack of permanence. These studies take issue with the ton-year approach described in Boyd et al. (2001), which relies on converting impermanent sequestration into permanent sequestration using an equivalence factor. Marland et al. (2001) favors an approach where offsets are rented, instead of purchased. Other studies that relate to Boyd et al. (2001) attempt to develop methods for calculating this equivalence factor (e.g. Costa and Wilson 2000; Fearnside et al., 2000).

Following in a similar fashion, Kim et al. (2008) develops an analytical discount factor for impermanent carbon sequestration. They find that impermanent carbon storage can result in large discount factors, even as large as 50% of the carbon's price (Kim et al., 2008). Cacho et al. (2003) assess different accounting methods, including the year-ton approach, through simulation. It is shown that transaction costs vary depending on what accounting method is chosen (Cacho et al., 2003). Feng et al. (2002) addresses the efficiency of three carbon payment mechanisms that include a pay-as-you-go system, a variable contract length approach, and a carbon annuity account approach, all of which are shown to be efficient.
It has been suggested that, with respect to carbon offset markets, contract duration plays an important role in establishing the permanence of the offsets (Layton & Siikamäki, 2012). Contract duration has also been suggested to be a factor in program enrollment (Latta et al., 2016). It has been noted that a shorter contract may encourage additional landowners to enroll (Dickinson et al. 2012). However, this relationship is not as straightforward as it may seem, as Miller et al. (2012) estimates that for some programs, a longer contract length could improve enrollment.

There have been studies that focus on the impacts and effects of forest carbon markets on land use decisions, landowner costs, and land-based carbon sequestration

(Latta et al. 2016). These can be grouped into econometric studies that focus on land-use change, market simulations, and engineering focused approaches, as in Richard and Stokes, (2004). Other reviews of the literature include Sedjo et al. (1995), van Kooten (2004), and Stavins & Richards (2005). Engineering studies have historically focused on afforestation (e.g. Moulton & Richards 1999). The methodology in these studies hinges on comparisons of cost evaluations for different sets of projects.

Econometric studies focusing on land-use utilize statistical approaches to model land-use decisions and their impacts on carbon sequestration (Plantinga et al., 1999). Many of these center around approaches that describe an agent's preference between different classes of land (e.g. forestry, agricultural, urban, etc.) and what motivates that preference (Lubowski et al., 2006). Expanding on that, Plantinga and Wu (2003) model the additional benefits of forest based carbon sequestration from land-use change, and find that they reduce agricultural externalities, such as fertilizer runoff. These models rely on land-use change being a voluntary decision based on an agent maximizing their profits or utility (e.g. Stavins 1999; Newell & Stavins 2001). These approaches can be expanded to analyze carbon leakage due to land-use change as well (e.g. Murray et al. 2004).

Forest sector modeling, such as Adams et al. (1999) and Sohngen and Mendelsohn (2003) utilize surplus maximization to simulate land-use decisions. Agents are assumed to select land-uses, typically between agriculture and forestry (e.g. Adams et al., 1993), such that their land rents are maximized given a set of prices, costs, and a discount rate. In the papers that look at carbon sequestration, enrollment in a program that values carbon is usually mandatory (e.g. Adams et al., 1999; Sohngen and Mendelsohn, 2003). However, both Latta et al. (2004) and Latta et al. (2016) deviate from this trend by modeling voluntary markets. Still other studies, such as Parks and Hardie (1995) focus on choosing the most efficient land to purchase, turning the simulation into a land selection problem.

Literature on contract duration and design for conservation programs such as forest-based carbon offsets is limited. One study by Juutinen et al., (2014) solves for the optimal duration of contracts incentivizing biodiversity-based ecosystem service provision on forestland. Juutinen et al., (2014) constructs a theoretical model in which a government agency is contracting to conserve private forestland, and then uses the results from the model in a numerical analysis. The government agency is shown to use a mixture of long and short contracts. As the budget the government agency increases, the agency tends to use longer contracts more frequently (Juutinen et al., 2014). Expanding this analysis, Drechsler et al. (2017) examines how different economic and ecological parameters influence the optimal length of conservation contracts. They find that the optimality of longer contracts increases with the extinction rate of the conserved species, decreasing rate of species colonization, and with variability in conservation costs, amongst other things. Leaving the context of biodiversity, Juutinen et al., 2018 explores the role of short-term payments for carbon sequestration on forestland, and its feasibility as an alternative to longer term contracts. They find that though annual carbon payments influence the management of private forestland, the effect is somewhat small, indicating that such a scheme might only be optimal for either very dense forests or high carbon prices.

The work presented in this study expands the previous work on contract duration in a number of ways. To our knowledge, we are the first study to address this topic on a sector-wide scale. Previous studies look at how contract duration may affect a government agency as well as private forest managers; however, our model considers the entire forest sector of our study region including mills and output markets. We study the effect that carbon prices have on the optimality of different contract specifications. Another extension of previous work is that our model allows for us to study how management changes on land that is not enrolled in the offset program, and thus gives us an estimate of potential leakage from other lands. This is because, unlike other models here, timber price is endogenized in our model. Yet another extension of our model allows for us to examine changes in the value of land by county.

3.4 Model

The forest manager's decision of whether to enroll in an offset program is based on whether that enrollment will be more profitable than management-as-usual. In general, a forest manager will enroll in such a program if the payments they receive for the carbon sequestration exceed the costs of enrollment as well as the expected profit they would have received had they not enrolled in the program. Furthermore, the enrollment of forest land into an offset program influences the surrounding forestland that has not enrolled through limiting supply and increasing the price of timber. That is, enrollment creates a pecuniary externality on the surrounding private forest managers who are not enrolled.

In order to capture the full range of effects of the forest-based carbon offset program, we utilize a regional forest sector model of western Oregon. The model, called the Pacific Northwest Regional Log Model (Montgomery et al., 2006; Adams & Latta, 2007; Latta et al., 2016), is a spatial-temporal partial equilibrium model. Incorporated into the model is the option of whether to enroll in a forest-based carbon offset program. The model simulates management on forest lands that are enrolled in the offset program, as well as land that is not. Furthermore, the model captures decisions made at the mill level, specifically what the levels of production are, as well as decisions about expanding and contracting levels of capacity. The price levels are endogenous in the model as well.

The model is an intertemporal, forward-looking optimization model that provides results at 5-year intervals over a 100-year time horizon. The model consists of a set of objective functions, the area under the mill-level log demands, and various constraints. There are two kinds of agents represented in the model: timber plots and mills. Timber plots are discrete points on the landscape that have a given acreage, species mix, and biomass level. The biomass is grown using vegetation simulator provided by the forest service. These timber plots are called log supply points. The mills, on the other hand, act as log demand points. Each plot can exchange demand points with other plots to maximize net returns from their timber sale. Similarly, mills can swap suppliers with other mills to minimize their costs. By finding the optimal matching of plots and mills, the model solves for the market solution and net benefits are maximized. The model breaks the entire time line of the simulation (in this case 100 years) into five year increments. Each increment has its own set of equations relating to the net returns of the timber plots and costs of the timber mills. Instead of solving for the optimum in each time step independently, the model is solved for all time steps simultaneously. For example, if there are 20 time steps as in the example above, with two plots and two mills, that would make 4 equations per time step, and so the model would solve a system of 80 equations for supply and demand. The mills are broken into two different categories: lumber and plywood. Mill capacity changes at each time step relative to prescribed projections of output demand. If the demand for lumber increases at a given time step, then the capital will be distributed to make up for the change in demand relative to which mills are most profitable. This is solved simultaneously along with the rest of the model. The model also captures the relationship between timber volume and carbon on the landscape. The relationship between carbon sequestration and management is based on the model developed in Im et al. (2007). The model is written in GAMS and solved with the CPLEX solver (Brooke et al., 1988).

3.4.1. Scenario Construction

We begin by assuming that carbon dioxide prices are exogenous. In the program that we are simulating, the price is mostly set by the California Energy sector, since they are primary agents in the California carbon market. However, we fully acknowledge that program performance is a function of carbon price, and so we select four price levels that represent a range that is both conservative and realistic for the time period we are examining. The four prices we select are: $5 per ton CO2(e), $10 per ton CO2(e), $25 per ton CO2(e), and $50 per ton CO2(e). At the time of this writing, the California carbon market values carbon at $15.10 per ton CO2(e) (California Carbon Dashboard, 2018), which is comfortably within the range of the price set for our simulations.

Similarly, we assumed that the contract duration is not endogenous. Instead, the regulator is assumed to set the duration of the contract. This is consistent with the actual policy. Since the focus of this paper is to assess the effects of contract duration, we select several scenarios that represent a reasonable range of potential contracts. The first five contract scenarios have assigned lengths of 20 years, 40 years, 60 years, 80 years, and 100 years. The static length of the contract reflects the design of the policy in the real world. Though it is tempting to optimize the length for each landowner, that would require information not available to the government agency. Instead, the agency issues a blanket standard. An alternative approach is possible, such as that described in Mason and Plantinga (2013), in which landowners sort into contracts of different lengths. Modeling a regional program with this scheme represents a potential extension of this current work. Furthermore, we assume that the duration of the contract is also the duration of the program in general. This means that a forest manager cannot re-enroll their land in the program after their contract expires. Addressing the problem of consecutive enrollment represents an interesting extension to this current work.

. We also model two additional versions of the contracts that have a maintenance period requirement. Such a requirement requires that the forest manager gets paid for the carbon they sequester for the first half of the length of the contract, but then are required to continue to manage their forest for sequestration for the following half. These two contracts have payment lengths of 20 years and 40 years, with additional maintenance periods of 20 years. and 40 years respectively. These contracts allow for the cost of the program to be minimized while the carbon is stored on the landscape longer. However, maintenance periods affect the landowner's incentives, and make it less profitable to enroll in the program. An examination of these contracts is reported in the sensitivity analysis.

We run a scenario for each price and each contract type. This means that we have a results for twenty-eight different scenarios. We also run a scenario with no carbon market at all, bringing the total up to twenty-nine.

3.5. Results

Solving the forest sector model for each of the scenarios outlined above, we now present the results of our analysis below. One aspect of the analysis that is particularly tricky is selecting a time frame over which to assess each contract. Latta et al. (2016) selected a time frame of 50 years. The time frame selected for this analysis includes the entire duration of the model run, or 100 years.

A controversial question that we necessarily encounter in a study such as this is whether or not to discount the carbon being sequestered. For the results presented here, the carbon is not discounted; however, in some of the calculations of benefits of sequestration, the price of carbon has. This is both to reflect reality, and so that these calculations are consistent with the forest sector model used.

3.5.1 Enrollment

The first aspect of program performance we address is enrollment of land into the program. Our results in Figure 3.1 confirm those in Latta et al. (2016) that show rising enrollment with the price of carbon. This makes intuitive sense, as a higher carbon price better compensates landowners for missed harvest opportunities.

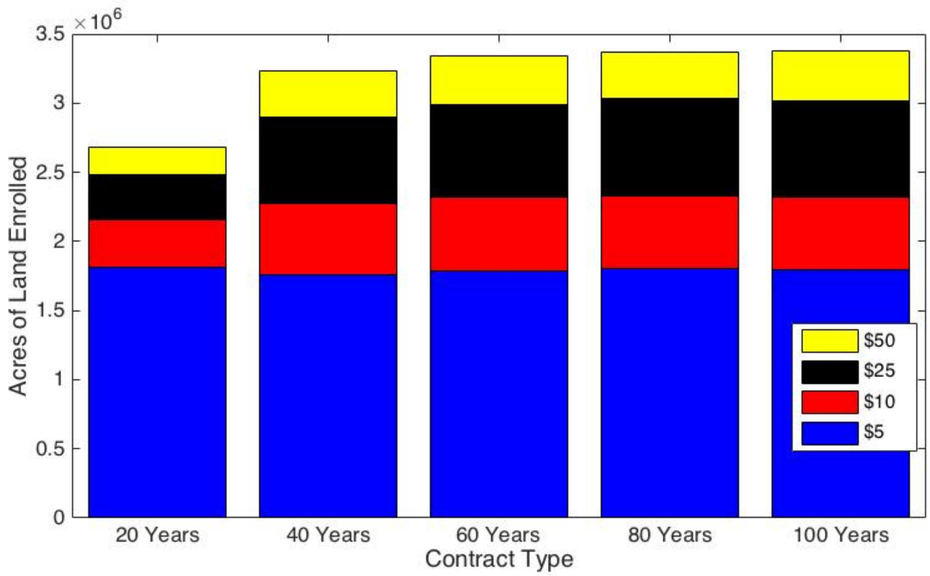


Figure 3.1: Land enrolled in carbon offset program by contract and by price

The effects that price and contract duration have on enrollment interact with one another. At low carbon prices, there is little difference in enrollment between contracts of differing length. In fact, the shortest contract has slightly more acres enrolled than any of the longer contracts. However, as prices increase more acres are enrolled as the contract gets longer. This finding expands on the results of Juutinen et al. (2014) by showing that longer contracts are used not only because the government can afford such contracts with larger budgets, but because it is also more beneficial for landowners to enroll at higher carbon prices.

Figure 3.1 also demonstrates that as contract length and carbon price both increase, their respective effects on the amount of land enrolled diminish. At prices of \$25 and \$50, there are substantial differences in enrollment between contracts of 20 and 40 years, and those that are 60 years or longer. But even at these higher prices, the three contracts with the longest lengths have more or less the same number of acres enrolled. In this regard, these shorter contracts perform as well as the 100-year contract that serves as a benchmark when comparing our results to the performance of the offsets based on the California carbon trading scheme. Given that the price of carbon in the California market as of this writing is \$15.10, it seems that should the price stay at that level, there is very little difference in enrollment between the 40-year contract and the longer contracts as well.

3.5.2. Carbon Sequestration

We have demonstrated that the duration of the contract plays a role in determining program enrollment. Furthermore, we have shown that, compared to the 100-year contract, some of the shorter contracts perform just as well in terms of program enrollment. Another important metric of program performance is the amount of carbon sequestered by the program. Indeed, the whole point of this forest-based carbon offsets is to offset carbon, and so from the government agency's standpoint, this is a metric that matters the most. The time series of carbon on the landscape in excess of the no-policy counterfactual is presented in Figure 3.2. The black horizontal line in each panel is a reference line at zero. From the figure, we can see that the magnitude of sequestration for almost all contracts changes substantially with the price of carbon. This is consistent with observations from Latta et al. (2016), which observed the same relationship. What is remarkable is the extent to which the price of carbon acts to differentiate the effects of different contracts from one another. As the price of carbon increases, forest managers face a stronger incentive to sequester more carbon in their forest. Furthermore, the build up of carbon that occurs due to the increased incentive creates a large stock from which the forest manager can draw on once the contract has expired. This results in a more rapid drawdown of timber stocks following the contracts end than in scenarios with lower carbon prices. This therefore results in substantial differences in the level of carbon in the region between contracts of differing lengths at high carbon prices.

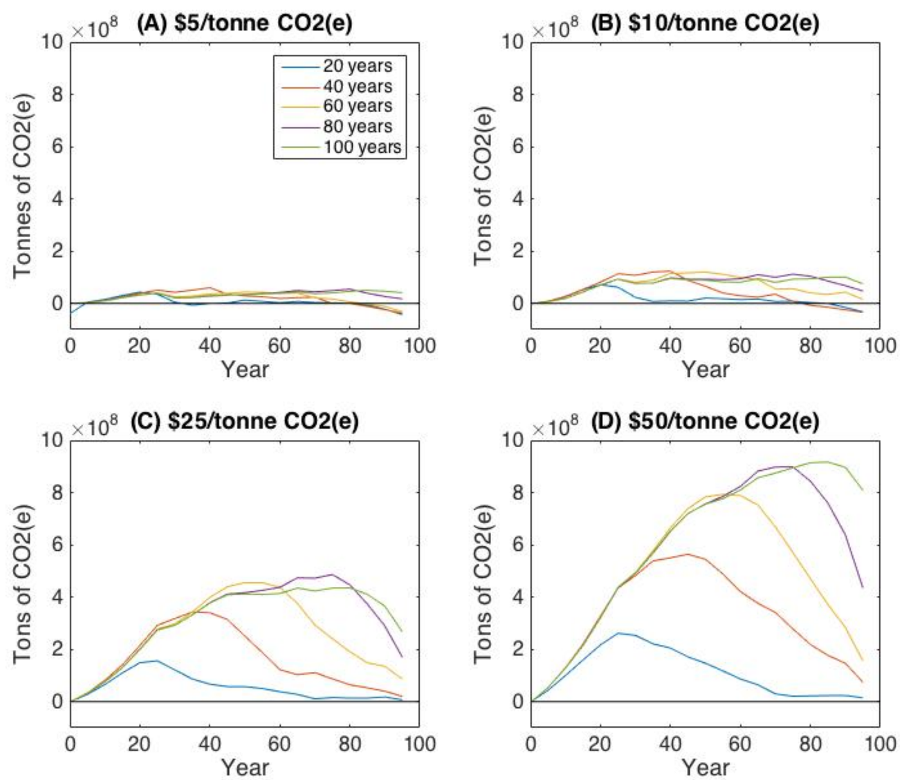


Figure 3.2: Carbon sequestration time series by contract and carbon price

For scenarios in which carbon is priced at either $25/tonne or $50/tonne, each contract performs at least as well as the no carbon-offset case over the entire time horizon. This is not the case for scenarios in which the price of carbon is either $5/tonne or $10/tonne. In order to observe this more clearly, Figure 3.3. presents those cases but magnified for the reader to see more clearly.

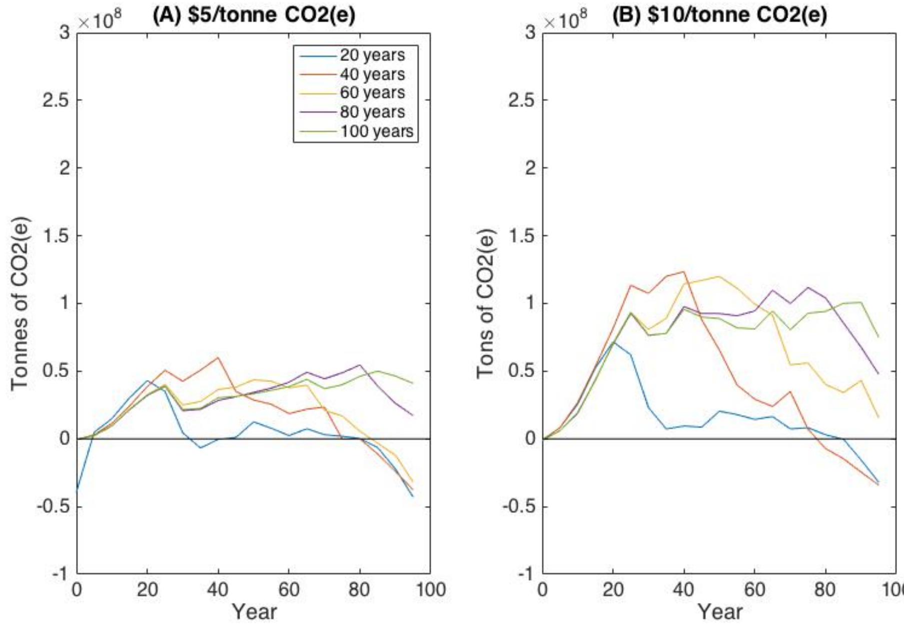


Figure 3.3: Differences in carbon on the landscape for lower carbon prices

At a carbon price of $5/tonne, we see that three contracts result in lower levels of carbon on the landscape than the no-contract scenario: the 20-year, 40-year, and 60-year contracts. At a carbon price of $10/tonne, still two of the contracts perform worse than the no-policy scenario: the 20-year and 40-year contracts. Interestingly, we see that the 40-year contracts do worse than the no-policy scenario for longer, indicating that part of the reason driving this is because of the magnitude of the build-up of forest resources that occur over the duration of the contract.

There is a flip side to this observation, namely that each contract outperforms all the others over different time frames. Generally, over the course of the contract's lifetime, more carbon is sequestered by that contract than the others. This is the reason for the dramatic decline of the 40-year contract in Figures 3.2 and 3.3 Panel (B). Not only does the 40-year contract build up more carbon than any other contract at a carbon price of $10/tonne, but it does so over a briefer time horizon than many of the other contracts. This eventually results in a more dramatic drawdown, which pushes the total carbon down below the level observed in the no-policy counterfactual.

Another interesting observation is that as the price changes, which contract sequestered the most carbon at any given point changes as well. When prices are $5 and $10 per tonne, the 40-year contract has the largest amount of additional carbon at any given time. At a price of $25 per tonne, the 80-year contract has the largest amount while at $50 per tonne, the 100-year contract has the largest amount of carbon. Thus, at lower carbon prices, shorter contracts will sequester more carbon over the course of their lifetime, though not necessarily over a longer time horizon. This is an important concept when considering carbon discounting, or discounting the value of temporarily sequestered carbon. This concept in particular will be discussed in the sensitivity analysis.

3.5.3. Economic Outcomes: Mill Capacities and Log Prices

It is not immediately intuitive what processes are contributing to the 20-year and 40-year contracts resulting in less carbon on the landscape than a scenario with no policy at all. The answer may lie in the sector-level response to the policy. A scenario in which there is a substantial amount of build-up of timber volume will benefit mills during the drawdown period. The increase in supply will boost their capacity, as well as allow for prices to drop. This could have long term effects on the regions harvests, as mills will process more for a time following the termination of these contracts. The results from our simulation show this effect clearly. In Table 3.2, we report the capacity levels for both lumber and plywood for each price and contract scenario at three different points in time: 2055, 2075, and at the very end of the simulation at 2095. We use Table 3.2 to compare each of these scenarios to a no-policy counterfactual. When the capacity level is below that of the no-policy counterfactual, we indicate it by shading, bolding, and italicizing that entry. We report these three points in time because they provide a comprehensive description of what happens to capacity as the price of carbon and length of the contract change.

Looking at the results from the year 2055 tell us something interesting about the relationship between the duration of the contract and price. Though the 20-year contract has long been expired by this time, the lower carbon price scenarios report lower capacity at carbon prices of $5 and $10 per tonne. However, at higher carbon prices, the build up of carbon is so great, and the drawdown so swift, that the mill capacity is dramatically larger for shorter contracts and high carbon prices. This is also evident from the changes in capacity that occur for the 40-year contract.

An important result shown in Table 3.2 is that for the duration of the contract, supply of timber is restricted, which restricts the capacity in the region. This reduction gets larger as the price of carbon climbs. However, this reduction does not last, and the build up of timber that occurs during the contract appears to have lasting results on the region's capacity. This explains the persistent dip below the no-policy counterfactual observed in Figure 3.2. Though this results in more carbon being removed from the landscape in later time periods, it could also mean that this sort of policy has a late breaking benefit to the mills and the industry in the region. The only scenario which has lower capacity at the end of the model run is the highest and longest contract.

The changes in capacity reflect patterns in the price of logs as well. Figure 3.4 shows the price series for lumber and plywood for three different contracts: 20-year, 60-year, and 100-year contracts. Each panel shows four curves that correspond to different carbon prices. In Figure 3.4, the price series that is reported starts in year 5 (second time step), due to the fact that the price variable in the initial period is either unrealistically high or unrealistically low. The difference in initial conditions with respect to both the lumber and plywood log prices are due to the initial level of build up on timber lands that correspond with each successive carbon price. It is important to note that both plywood and lumber prices behave in a similar manner. This indicates that the supply shock that results from the carbon offsets affects the supply of logs for both plywood and lumber equally, or that due to the trade of chips as an intermediate good between lumber and plywood mills, the market spreads the effect

Table 3.2: Capacity by contract type and price, reported at three different time points during the simulation

Year:	2055	0		5		10		25		50	
Contract Length		Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood
20		42595969	8821786	***42015938***	***8726598***	***42141744***	***8746759***	72622383	17663237	45131742	9002436
40				42604127	***8753448***	43859574	***8699154***	46003183	8943433	43409203	***8351996***
60				***41951989***	***8709113***	***42051943***	***8635796***	***39455593***	***8084457***	***34306824***	***7263015***
80				***41854738***	***8748543***	***41944761***	***8670485***	***39938631***	***8161612***	***34946089***	***7324284***
100				***41882470***	***8749751***	***42068910***	***8680868***	***40311407***	***8209404***	***35392777***	***7350288***

Year:	2075	0		5		10		25		50	
Contract Length		Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood
20		41171318	8297267	***41060540***	8363443	41402773	8387590	70656473	17913167	43370337	8666986
40				41536023	8378445	42018356	8471179	43887112	8840383	47253855	9156274
60				41563086	8459712	42051943	8593956	46363890	9205784	47743026	8986265
80				***40798385***	8321587	***40847247***	8348075	***39948451***	***8166125***	***35410941***	***7536108***
100				***40846487***	8331250	***41118424***	8408031	***40433630***	***8242305***	***36202998***	***7484229***

Year:	2095	0		5		10		25		50	
Contract Length		Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood	Lumber	Plywood
20		39025684	7997608	39651474	8131719	39618093	8127228	67951376	16266718	39788717	8136782
40				39455940	8096149	39731087	8123851	40391574	8267360	43575227	8797308
60				39742831	8149301	39686661	8130758	42114955	8613782	48570422	9614868
80				39584266	8127840	40382774	8229738	43726107	9161304	49073430	9468618
100				39047131	8040027	39146675	8149912	40525534	8205734	***36557499***	***7596028***

across both products. An interesting result that emerges from Figure 3.4 is that the initial conditions for lumber and plywood log prices are substantially different depending on the carbon price level. In the initial five years from the time the carbon offsets are distributed, a substantial amount of timber is held out of the market, while the unenrolled land is unable to respond with higher supply. The

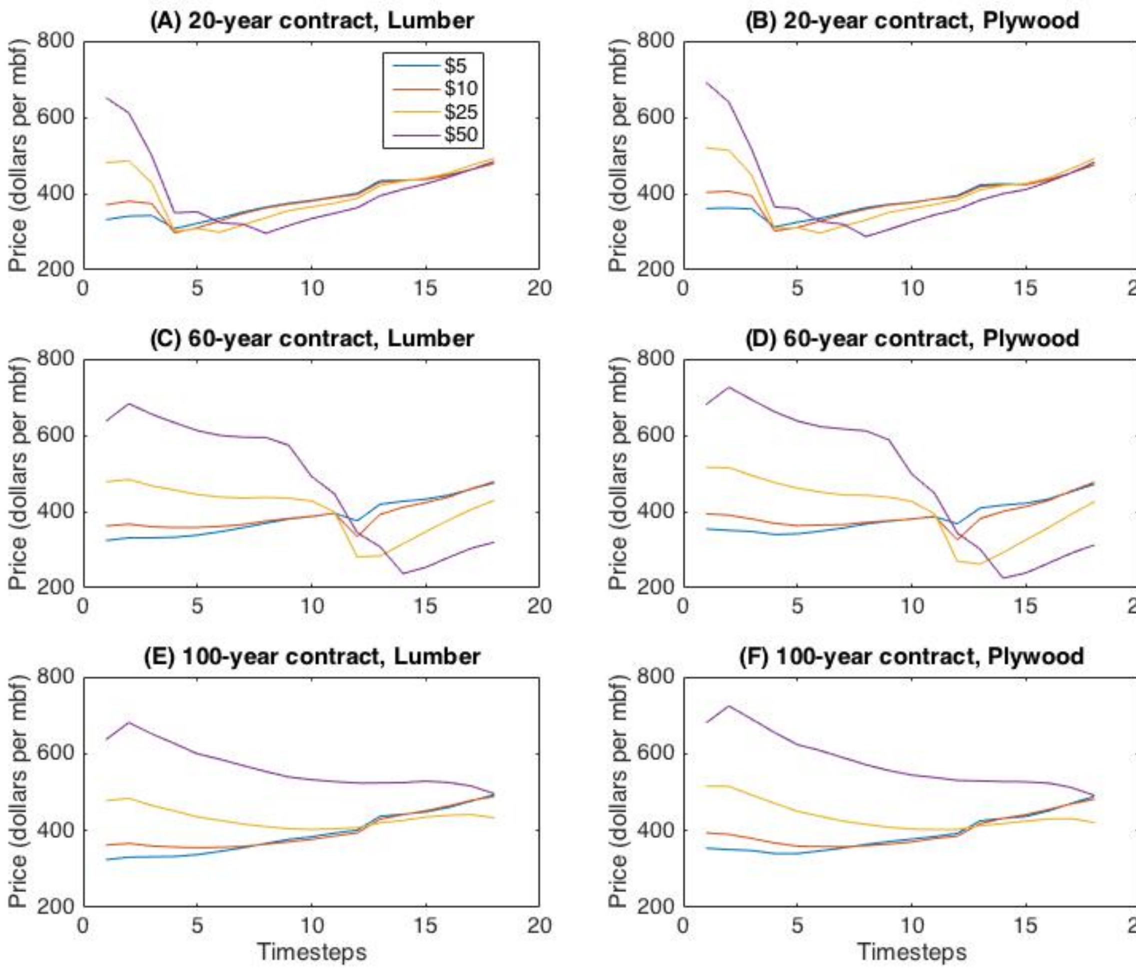


Figure 3.4: Price series for Lumber and Plywood for different carbon prices and different contract types

higher the price of carbon, the more timber is held off the market, which pushes the price up, which explain the price discrepancies between price series of different carbon prices.

The price dynamics behave differently depending on the level of timber build up on private land. Even with the longer contracts featured in Figure 3.4 Panels (C) – (F), scenarios that feature higher carbon prices result in higher log prices that begin declining rapidly, even before the contracts expire. This is due to response of unenrolled land to the higher price and harvesting more timber. For prices of carbon that are lower, the price still continues its upward march despite enrolled lands restricting supply.

There is a large decrease in log prices when the carbon offset contracts expire. Though it is not apparent in Panels (E) and (F) because of the long duration of those contracts, these decreases are immediately evident in the remaining panels of Figure 3.4. Because unenrolled forest land has already adjusted to the massive dip in supply that corresponds to a high carbon price, the rate of price decrease following the expiration of 20-year contracts is much slower for the $50 per tonne scenario. Another interesting observation from the 20-year contract scenarios are that despite the build up that occurs at high carbon prices, the dip in log prices is not sustained like the longer 60-year contract. In the case of the 60-year contract, the higher the carbon price, the more the log prices decline for both lumber and plywood logs. In the 60-year contract scenario, this decline is such that it results is a much larger price swing. It is true that for each of the different contract scenarios, the higher the price of carbon, the higher the price of logs before the contracts expire, and then the lower the price of logs after the contracts expire. The length of the contract appears to interact with the effect of carbon prices on log prices, where longer contracts result in a more differentiated set of log prices, with the exception of the 100-year contract.

3.5.4. Maintenance Periods

There are a number of assumptions that have been used in the course of this analysis. This was done in order to provide the most conservative estimates possible for the effects of contract duration on the performance of forest-based carbon offset programs. One such assumption is that the forest landowner is paid for the carbon they sequester for the entire duration of the contract. However, there are potential configurations of these forest-based carbon offset contracts in which this is not true.

Instead, it is possible to construct contracts that have what are called maintenance periods. A maintenance period requires that, despite not being paid, the forest manager must continue to manage their land for carbon sequestration.

In order to test what the effects of this alternative contract specification were, we ran two different scenarios with maintenance. One such contract includes a 20-year payment period, with a 20-year maintenance period, which lasts a total of 40-years. The second such contract includes a 40-year payment period, and a 40-year maintenance period, and lasts a total of 80 years. We will limit ourselves to comparing these maintenance policies to the 20-year and 40-year policies in order to simplify the presentation of results.

Assessing the enrollment patterns of the contracts that have maintenance provide important insights into how these policies are affecting forest managers within the model in general. From Table 3.3 we see two very interesting things about enrollment in the program. The first observation is that the 20-year contract with a 20-year maintenance period has more acres enrolled in each period than the 20-year contract alone. At first this is counter-intuitive. However, the benefit of everyone else withholding supply increases the price of timber in this scenario more than the 20-year contract alone, and so provides a benefit to enrolled forest managers. Another observation is that for the 40-year contract with a 40-year maintenance period, enrollment goes down at very high carbon prices, but remains higher for prices ranging from $5/tonne through $25/tonne. This is due to the fact that in the 40-year maintenance period, the forest manager is required to pay for the carbon removed from the forest, even if they do not get paid for the carbon they sequester.

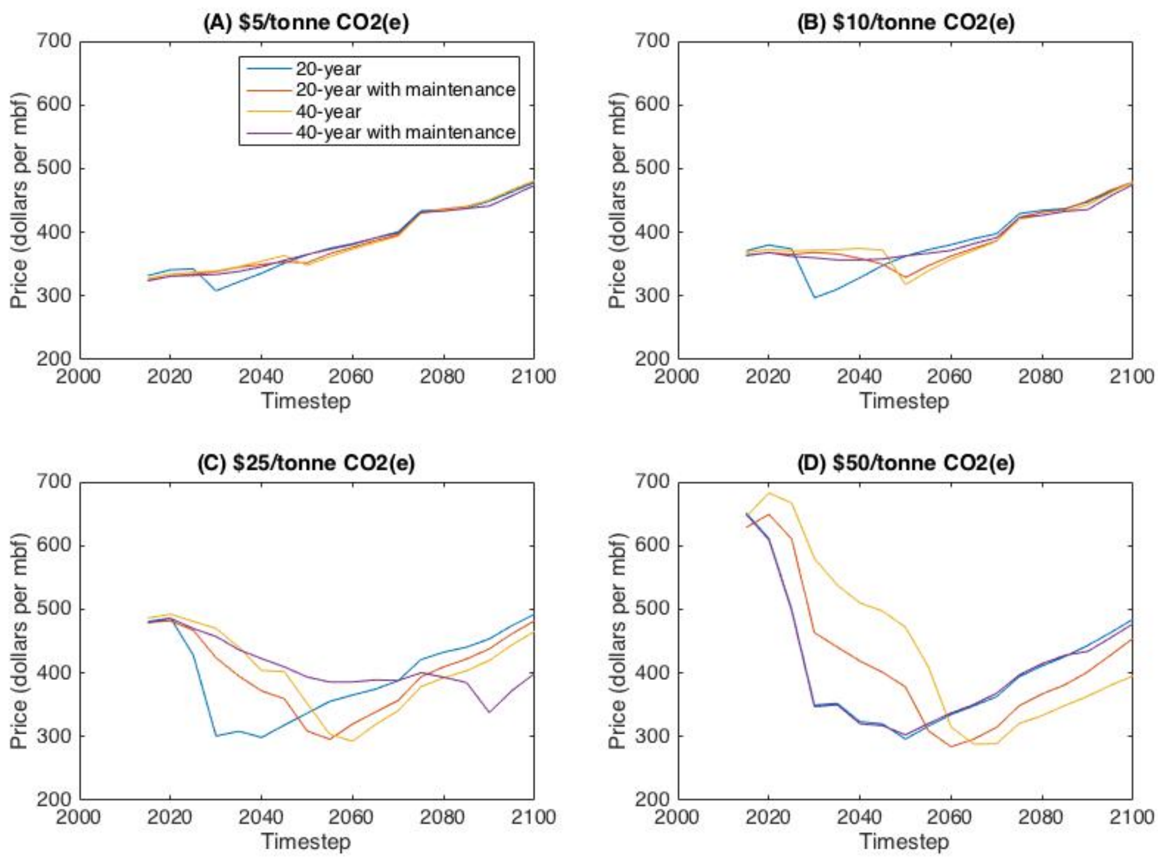


Figure 3.5: Log prices for lumber mills by contract type and by carbon price

One effect of the maintenance period is that it keeps the price of logs higher than with contracts that do not require it. This makes intuitive sense, as the maintenance period results in less timber supply making it onto the market. At low carbon prices the differences between contracts is not very substantial. Although, at a price of $10 per tonne, the maintenance period following the 20-year contract seems to smooth its respective price series out, indicating that at lower carbon prices, these maintenance periods could reduce price volatility. This is further evidenced in Figure 3.5 Panel (C) in which the 40-year contract with a 40-year maintenance period results in less price volatility. The higher prices work as an incentive to join into the program. This indicates that the market-based benefits of forest-based carbon offsets could help the performance of these programs. However, the generalization of this result should be done with caution, as the solution method does not perfectly account for strategic behavior or heterogeneous preferences amongst forest managers. An extended explanation of this result can be found in Section B.2 of the appendix. An interesting observation is that at very high carbon prices, the 40-year contract with a 40-year maintenance has approximately the same price path as the 20-year contract with no maintenance. This is likely due to the fact that both programs have very similar enrollment, indicating that the expected benefits of joining such a program are similar for forest managers.

Table 3.3: Acres enrolled for contracts that include maintenance and their corresponding no-maintenance contracts.

	20 Year 0 Maintenance	**20 Year 20 Maintenance**	**40 Year 0 Maintenance**	**40 Year 40 Maintenance**
$5 / tonne	1813163.58	1736190.75	1756725.23	1763935.17
$10 / tonne	2160276.88	2231630.18	2270635.95	2294237.28
$25 / tonne	2485502.77	2816145.41	2895881.38	3003529.4
$50 / tonne	2681952.55	2986649.29	3228909.06	2680888.78

The maintenance periods consequently impact carbon sequestration in an intuitive way. With one exception, the 20-year contract with a 20-year maintenance period will sequester more carbon for longer than the 20-year contract alone, however it will not sequester as much as the 40-year contract with no maintenance. Similarly, the 40-year contract with a 40-year maintenance period will sequester more carbon for longer than the 40-year or 60-year contract exclusively, but not more than the 80-year contract. This is due to the fact that the 80-year contract has the added incentive or receiving payments for an additional 40 years, and so intuitively it should outperform a contract in which payments are only received for half of its payment period. The exception is the 40-year contract with a 40-year maintenance period, which performs similarly to the 20-year contract with no maintenance. This is due to the same enrollment dynamics. Being charged 50 dollars per tonne of removal in the maintenance period is a substantial cost that, given 40 years of timber build up, many landowners are not willing to pay. Unlike in other scenarios, the discount rate does not diminish the cost as much either.

Maintenance periods appear to have a number of effects on the performance of forest-based carbon offsets. Maintenance periods that are too long supress enrollment at higher carbon prices, resulting in substantially worse outcomes. At lower carbon prices, they result in more carbon sequestration over their duration, and reduce price volatility in the log market. At lower carbon prices, they also incentivize enrollment by pushing later-period log prices up through restricting supply.

3.6. Conclusion

In this paper, we address the effects of contract duration on the performance of forest-based carbon offset programs. These programs are an important tool for the cost-effective abatement of greenhouse gas emissions, and their design is a critical aspect in their performance. We are the first paper to examine the role that contract duration plays in a voluntary forest-based carbon offset program. We are also the first to study contract duration for ecosystem service contracts in a partial equilibrium context, in which we can infer region-wide economic consequences of each type of contract. We further investigated how the price of carbon influences the effect of contract duration on program performance. We assessed program performance in terms of enrollment, carbon sequestration, and economic impacts.

Our methodology involved employing a partial equilibrium model of the forest sector in western Oregon in which log prices are endogenized. Furthermore, our model allows for changes in capacity at the mill level that respond to the supply in the region. Within our partial equilibrium model, we utilize the carbon dynamics described by Im et al. (2007) in order to track the amount of carbon on the landscape. We track prices by product as well as capacity by product. All of this provides a detailed examination of how contract duration influences the program performance as well as the regional forest sector.

We find that enrollment in forest-based carbon offsets is affected by both the price of carbon, as well as the duration of the contract. In general, there is not a substantial difference in enrollment in terms of acres between contracts of differing length at low prices of carbon. However, as prices increase, differentiation begins to occur, especially with respect to the 20-year contract. That being said, at just about every price of carbon, there is little difference in terms of enrolled acres between contracts of 60-years, 80-years, and 100-years.

Though there are not substantial differences observed in terms of acres enrolled, each price and contract specification combination yields substantially different results in terms of carbon sequestration. At a carbon price of $5 per tonne, little difference is seen between the different contracts. However, we also see that at the end of the time horizon, the 20-year, 40-year, and 60-year contracts end up with less carbon on the landscape than a policy in which no carbon offsets are sold at all. The inclusion of a maintenance provision in the contract alleviates the feature. At carbon prices of $25 and $50 dollars, we observe substantially different levels of carbon sequestration on the landscape. With the exception of the contracts with maintenance provision, each contract outperforms the others over the course of it's own lifetime in terms of carbon sequestered. The higher the price and longer the contract, the larger the build up of carbon on the landscape, leading to a more rapid decline once the contract expires. This drawdown is not as substantial for low carbon prices, but for very high carbon prices, it is very rapid.

We find that the rate of the drawdown after the contract expires is related to the price level, and the economics of the forest sector in general. The build up of timber in the region drives the prices of logs for both plywood and lumber up. The higher the price of carbon, the higher the price gets in the beginning, before unenrolled land begins to respond, growing more timber and drawing the price down. When the contract expires, the price of logs plummets as supply floods the market, reducing the amount of harvest on unenrolled lands. The increase in supply after the contract expiration results in mill capacities increasing as well. So much so, that for some of the shorter contracts at lower carbon prices the amount of carbon on the landscape ends up being lower than in the scenario in which no policy occurs.

This paper also investigates the possibility of adding maintenance provisions into the contract. We find that in general they help shorter contracts more than longer contracts. In the case where the maintenance period is longer, and the carbon price is very high, we find that the inclusion of a maintenance provision can have negative effects on program performance through cutting enrollment. However, for lower prices of carbon, maintenance provisions are shown to reduce the price volatility associated with typical offset contracts. Surprisingly, maintenance provisions are shown to attract more acres into enrollment through keeping log prices higher for longer. The generalization of that last result may not hold in situations of price uncertainty, as well as when there is heterogeneous preferences amongst forest managers.

There are a number of limitations with this study that should be taken into account when generalizing results. The model we employ maximizes the net benefit in the regional forest sector across all time-steps simultaneously, and does not incorporate uncertainty about prices. These have been shown in the past to play a large role in forest management (see Chapter 4). Another limitation is that our model is limited to considering a single period of enrollment. That is, the only year that the contracts are available are the initial year. Forest managers cannot re-enroll once the program is over, and unenrolled lands cannot enroll in other time steps. Though log prices are endogenized within our model, the carbon price is exogenous and static.

The limitations discussed above also provide the foundation for future studies in this area. Similar projects which have multiple enrollment periods would shed more insight into the role of contract duration. Also, uncertainty about future values of carbon price, coupled with price dynamics, would be an interesting extension to this work. Furthermore, incorporating forms of permanence discounting, such as (e.g. Kim et al., 2008), would allow for the construction of marginal abatement cost curves that take into consideration impermanent sequestration.

Our study provides evidence of the impacts of contract duration on program performance. As more states, such as Oregon, adopt schemes to reduce their carbon footprint, the design and implementation of offset programs will play an important role in the success of these schemes. Our study contributes to this dialogue in a way that previous work on contract duration has not to this point.

4. Measure Twice, Cut Once: Optimal Inventory and Harvest under Volume Uncertainty and Price Volatility

4.1. Introduction

One reason information is valuable in decision making is that it tends to reduce the expected cost of uncertainty (Stiglitz, 2002). In natural resource management, multiple forms of uncertainty may be encountered that cannot be treated equivalently (LaRiviere et al., 2017). For instance, uncertainty about future realizations of a stochastic state variable must be handled differently from uncertainty about parameters of that variables transition equation in a formal model of optimal decision making. Stochasticity is treated as irreducible, while uncertainty about a parameter may often be reduced over time through learning. A third type of uncertainty that characterizes many natural resources is state uncertainty. State uncertainty involves uncertainty about the current value of a stochastic dynamic state variable, and arises because it is either not possible or cost prohibitive to perfectly observe the variable in every period through precise measurement.

State uncertainty is a challenge that is commonly encountered in decision making for natural resource problems (Kling et al., 2017) as well as many other areas of economics, including regulatory enforcement (White, 2005), quality testing (Matthews & Postlewaite, 1985), and stock pollution regulation (Hoel & Karp, 2002). Since at least the early contribution by Dixon & Howitt (1980), economists have recognized the routine nature of state uncertainty, and noted how natural resource managers (a common label for decision makers in this context) often respond by investing to observe the current state of their resource through measurement. Because these activities are costly and typically yield observations that contain error, it is in the best interest of the manager to plan them efficiently and carefully utilize the information. A challenge is that, while it is typically easy for a resource manager to gauge the upfront cost of investment in information, it is more difficult to measure the benefits of the investment.

Nearly all economic models of optimal natural resource management ignore state uncertainty and effectively assume resource managers have access to costless and arbitrarily accurate observations of state variables. Due in part to recent advances in optimization methods, a growing literature addresses the disconnect between standard theory and the information available to resource managers in the real world (Fackler & Haight 2014; MacLachlan et al., 2016; Kling, Sanchirico, & Fackler 2017). While they vary structurally and in their application, these studies limit their attention to problems where all dynamic state variables important for decision making are subject to uncertainty. However, most problems involve a complicated mix of variables that are imperfectly observable, and variables that can be observed with perfect certainty. A problem such as this is instead one of mixed observability. The challenge in heterogeneous information environments of this type is to understand the joint influence of variables with differing degrees of observability on optimal decision making.

Our aim in this paper is to address the problem of mixed observability in a model of optimal renewable resource harvest timing when the resource is not perfectly observable while the resource price is stochastic but perfectly observable. The framework we employ to construct our model is known as a continuous-state Mixed Observability Markov Decision Process (MOMDP). Examples of MOMDPs addressing natural resource management have so far been limited to highly stylized applications where the resource state variable is discretized into a small number of categories (e.g. Chadés et al. 2012). A continuous-state MOMDP approach allows for a more realistic description of resource dynamics. The apparent lack of continuous-state MOMDPs in economics is partly due to their technical difficulty; continuous-state MOMDPs are in general analytically intractable and cannot be solved exactly on a computer. In order to preserve the realistic continuous-state dynamics of the resource, we extend a solution technique from Zhou et al., (2010) that numerically approximates the solution to our problem. To the best of our knowledge our model represents the first analysis of a continuous-state MOMDP involving state uncertainty in the natural resources literature.

We apply our model to the problem of forest resource management. We believe this is a good choice for several reasons. Forest management involves a combination of perfectly observable variables such as forest product prices, and imperfectly observable variables such as timber volume. Timber volume exhibits state uncertainty because growth is stochastic and observations are obtained through costly surveys, called inventories (Scott & Gove 2002; Pukkala & Kellomäki 2012). Current timber prices in well-functioning markets like those found in industrialized timber producing countries, on the other hand, can be reasonably assumed to be perfectly observable within the time frame of a year at negligible cost. Forest biology and other determinants of productivity with some exceptions (e.g., novel invasive pests or pathogens) are well-studied, making the simplifying assumption of no parameter uncertainty more plausible for this case than other biological resources. Lastly, to our knowledge, no rigorous microeconomic theory of forest inventory exists. Despite inventory being a common activity within forestry (Scott & Gove, 2002), this is the first study to our knowledge that generates optimal timing for inventories.

We find a relationship between price stochasticity and measurement behavior. We show that price stochasticity influences the optimal timing of measurements, for example by making it less likely that the manager measures at high prices. This supports the argument that perfectly observable variables must be considered when optimizing inventory strategy. We also find that state uncertainty influences optimal harvest timing, and that for low levels of certainty and low levels of price, harvest occurs at lower volume levels than without state uncertainty. This indicates that state uncertainty is an important consideration for models of natural resource management. Both results support the argument that inventory and harvest must be optimized together, rather than separately. This contends with other approaches at scheduling measurement that rely on rule-of-thumb scheduling (e.g. Northwest Natural Resource Group and Stewardship Forestry, 2014).

Additionally, we find that inventory adds value to the forest when compared against a counterfactual in which no inventory occurs. We find that the Net Present Value (NPV) of a forest that optimally invests in inventories nearly matches the NPV of a stand that can perfectly observe timber volume. This result contributes to previous studies (e.g. Eid et al. 2000) that show drops in NPV due to misinformation about the timber volume to be substantial for some forests. We demonstrate that inventory has the ability of minimizing this loss, and on average will come very close to eliminating it entirely.

In what follows, section two will present a background on the relevant literature on uncertainty in natural resource management. Section three will discuss the background on forest management under uncertainty as well as details about forest inventory. Section four will present the model and the solution method. Section five will present and discuss the results of our model. This paper will conclude in section six. Further detail on model parameterization and solution methods can be found in the appendix.

4.2 State Uncertainty in Models of Natural Resource Management

While state uncertainty is a common challenge in natural resource management, most research in economics and related quantitative disciplines emphasizes other types of uncertainty encountered by decision makers (LaRiviere et al., 2017). Models of optimal decision making in resource management that consider types of uncertainty that are more general than stochasticity usually focus on parameter uncertainty. Parameter uncertainty describes a situation where a resource manager does not know the true value of a parameter of the problem, such as the carrying capacity of a wild population or coefficients of a resource commodity demand function. For example, Springborn & Sanchirico (2013) model optimal harvest of a fish stock when a key parameter governing survivorship of juvenile fish is unknown, but may be learned about from observing stock dynamics. While this literature provides a wide range of valuable insights into the role of learning and experimentation in resource management, nearly all studies assume that the current values of all state variables relevant for decision making are always known with certainty. This orientation of the literature has left the problem of making choices when key states are either unobserved or partially observed relatively under examined[1].

State uncertainty differs from parameter uncertainty both conceptually and in terms of how it is operationalized in optimal resource management models. While parameters of a decision problem may often be approximated as static (if unknown) quantities, most state variables are inherently stochastic and dynamic. Crucially, because state variables evolve stochastically over time, in the absence of new information (either through direct measurement or indirect signals) a resource manager's uncertainty about the current value of a state variable will typically grow from one decision period to the next (MacLachlan et al., 2016).

The significance of state uncertainty in natural resource management has long been recognized, and there are a few path-breaking economic models that address it in an ad-hoc manner or by using highly simplified models (Dixon & Howitt 1980; Clark & Kirkwood 1986). Due to the computational challenge that state uncertainty presents in optimization models, more studies have appeared recently that owe their progress in part to greater computing power. The common thread among these contributions is their formalization of the management problem as Partially Observable Markov Decision Processes (POMDP) (Papadimitriou & Tsitsiklis, 1987). Due to their greater numerical tractability, most POMDP applications in natural resource economics have assumed unobserved or partially-observable state variables take on only a small number of discrete values. This approach has been fruitful for problems when the state of a resource can be meaningfully categorized into a handful of pre-determined values (e.g., Fackler & Haight 2014). For example,

[1] The multi-disciplinary literature on learning in optimal resource management is often grouped under the banner of "adaptive management" (Walters, 1986). The majority of papers in this literature restrict their attention to stochasticity and parameter uncertainty, and so this adaptive management is sometimes understood to be synonymous with parameter uncertainty. This has changed recently as state uncertainty has begun to receive more attention, and so a current understanding of adaptive management should be inclusive of models that account for state uncertainty (e.g., Chadés et al. 2017). However, because of this informal understanding and in order to emphasize our contribution to the economics of state uncertainty, we do not identify our model with the adaptive management literature.

White (2005) models regulatory compliance for natural vegetation conservation programs as a discrete-state POMDP, and find that the costs of measurement and prior beliefs about vegetation levels influence optimal monitoring strategies.

Part of the reason discrete-state POMDPs are attractive is because the alternative – allowing state variables to vary continuously – results in a dimensionality problem that requires computationally demanding approximation techniques (Kling et al., 2017). On the other hand, most state dynamics in natural resource management are naturally modeled as continuous, or are at least difficult to break into the most relevant categories without advance knowledge of the optimal dynamics of the continuous system. In our application, for example, an implication of the most basic models of timber harvesting is that it will usually be difficult to construct a useful model of optimal harvest by pre-specifying a small number of timber volume categories, unless one knows from the solution to a more accurate continuous-state model how to choose a narrow discrete category that captures the right volume threshold where harvest is optimal.

While they are substantially more challenging to solve, continuous-state POMDPs provide a more realistic depiction of natural resource management problems and align better with standard economic theory, in which resource stocks and most other state variables are modeled as continuous and possibly stochastic. Applications of continuous POMDPs are limited to a few recent studies. MacLachlan et al. (2016) examine disease spread amongst livestock, while Kling et al., (2017) focus on an invasive species management problem. Among several contributions, these recent papers illustrate how benchmark natural resource management models can be generalized to account for state uncertainty. However, neither study accounts for how observable stochastic-dynamic variables may influence optimal decision making, in particular how a resource manager responds to state uncertainty.

In explicitly modeling stochastic price dynamics, we offer a novel economic application of continuous-state MOMDP methodology. As with POMDP applications, MOMDPs in the natural resource literature have so far apparently been confined to discrete-state problems because of the challenging curse of dimensionality. Chadés et al. (2012) outline a methodology for solving MOMDPs as discrete hidden model MDPs (hmMDPs). One contribution of our model is illustrating how recent advances in addressing state uncertainty in continuous-state natural resource models can now be leveraged to analyze more general problems where some important stochastic-dynamic state variables are perfectly observed (or very accurately observed at negligible cost), while others are not.

4.3 Inventory in Forest Science and Management

Our model is applied to a case of forest resource management. Forest management is an important and long-standing area of research within natural resource economics. Forests provide both consumptive benefits through the provision of timber as well as non-consumptive benefits (Hartman, 1976). Previous research on forest management under uncertainty focuses on the influence of stochasticity from sources including price volatility (e.g. Thomson 1992; Plantinga 1998), wildfire risk (Reed, 1984), climate change (Guo & Costello, 2013), and stochastic biomass growth (Reed & Clarke, 1990). Morck et al., (1989) evaluate scenarios where both prices and quantity of the resource, measured as timber volume, behave stochastically. Studies in this field do not address state uncertainty, with the notable early exception of Dixon & Howitt (1980) who investigate timber removals in the Stanislaus national forest using a limited stochastic optimal control technique.

The neglect of state uncertainty in forest economics, although not far out of step with other areas of natural resource economics, has meant that economists have been largely silent on the widespread practice and well-developed science of forest inventory. There are a wide variety of inventory options available to a decision maker, which we label for this context the forest manager. These methods range from collecting data on every tree in a forest (marking) or sampling the forest instead. Because marking is very costly, forest managers tend to survey their land instead to obtain an accurate yet imperfect signal of how much timber is available. These surveys are frequently carried out on the ground in what is called a “timber cruise” (Scott & Gove, 2002), but information can also be obtained from aerial observation (Naesset, 1997), as well as satellite imagery (Haapanen et al., 2000). Each of these techniques has an associated cost and expected level of error.

There is a significant amount of investment in inventory from both public and private sources. For example, total funding for the U.S. Forest Service's Forest Inventory and Analysis (FIA) program in 2015 was $80 million (USDA, 2017). There are also many documents from university extension services with information and suggestions on how and when to inventory forests. Furthermore, surveys like Barlow & Levendis (2015) indicate that inventories are frequently performed on private forest land.

Alongside anecdotal evidence from forest management practice, there exists a large forest science literature that explores methods of conducting forest inventories (Zobrist et al. 2012; Scott & Gove 2002). The focus of this literature is often on the development of more sophisticated statistical methods for better inventory design (e.g. Korhonen & Kangas 1997). Several studies in this area attempt to quantify the implications of poor information on timber volume. Eid et al. (2000) finds that suboptimal management decisions stemming from inaccurate measurements could potentially result in losses in the NPV of the forest. Holopainen et al. (2010b) found that inventory error was the largest contributor to errors in predicted levels of timber. Holopainen et al. (2010a) then calculated the loss in a forest's NPV resulting from inventory error. Results by Kangas et al., (2015) further demonstrate the role of information quality in meeting specific forest management objectives. Waggoner et al. (2009) also provides a valuable discussion on discrepancies in forest inventory, and how those discrepancies influence estimates of important forest attributes, such as carbon stock. Given the large financial impact inaccurate forestry data can have on private management, our case study is economically relevant. These studies typically rely on standard forest sector simulations that do not consider state uncertainty explicitly in determining optimal management. Thus, they quantify the potential impacts of inaccurate forest data, but do not provide insights into how state uncertainty affects management, or optimal inventory timing. Taken together, these papers suggest–but do not rigorously demonstrate–that the optimal planning of inventory is maximizing the returns of managed forests.

4.4. Methods

We develop a model of optimal resource extraction that includes both uncertainty about timber volumes and stochastic prices. The forest manager's objective is to maximize the present discounted value from an infinite series of timber rotations, which includes profits from harvest as well as the cost of replanting the stand. We also introduce a control variable, which we label inventory, that provides an estimate, with error, of the current forest stand volume[2]. Each period, the forest manager chooses whether to harvest and replant the timber stand, to invest in inventory, or to do neither[3]. The decision to conduct an inventory is costly. The manager is assumed to observe the current timber price (but not future values) and to form a belief about the timber volume, which is represented by a probability distribution described by its mean and standard deviation.

There are a number of simplifying assumptions we make in order to focus the analysis on state uncertainty, price dynamics, and the decision to invest in inventory. We assume that the forest is even-aged, comprised of a single species, and provides only consumptive values. Harvests are assumed to be in the form of clear-cuts.

4.4.1 Forest Stand Growth Model

The equation of motion for timber volume is given by:

$$X_{t+1} = f(X_t)Z_t(X_t) \tag{4.1}$$

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[2] In the literature on state uncertainty, a control variable that generates an observation of a state variable is often called "monitoring." We use the label inventory instead because it is more common in the forest science literature. We do so at the risk of some confusion because inventory is sometimes also used as a synonym for the current level of the state variable (e.g., inventory of a durable good). In what follows, inventory is a control variable, not the timber volume state variable.

[3] In practice, forest management involves other activities such as thinning, the removal of biomass to promote the growth of remaining trees (Schultz et al., 1997). An area for future research is to include thinning as a control variable in the model, a possibility considered in the concluding section.

where X_t is the timber volume in period t, $f(X_t)$ is a deterministic component of growth, and $Z_t(X_t)$is a stochastic component. The deterministic component, $f(X_t)$, has the Beverton & Holt (1957) form:

$$f(X_t) = X_t\left(\frac{r}{1+\left[\frac{r-1}{K}\right]X_t}\right) \tag{4.2}$$

where r is the intrinsic growth rate and K is the carrying capacity of the forest. Absent growth shocks, Equation 4.2 implies that volume increases monotonically over time and asymptotes to K.

The stochastic component $Z_t(X_t)$ is specified log-normal with volume-dependent mean and variance:

$$Z_t(X_t) = \exp\left(\frac{1}{(X_t+1)}\left[\sigma_{g1}u_t - \frac{\sigma_{g2}^2}{2(X_t+1)}\right]\right) \tag{4.3}$$

where u_t is a random draw from a standard normal distribution and $\sigma_{g1}$and σ_{g2} are positive parameters. $Z_t(X_t)$ is strictly positive, but can be less than 1. This allows the timber volume to increase or decrease over time, and ensures that it remains positive. Conditional on X_t, the mean and variance of $Z_t(X_t)$ are given by:

$$E(Z_t|X_t) = \exp\left(\frac{[\sigma_{g1}^2 - \sigma_{g2}^2]}{2(X_t+1)^2}\right) \tag{4.4}$$

$$Var(Z_t|X_t) = \exp\left(\frac{2\sigma_{g1}^2 + \sigma_{g2}^2}{(X_t+1)^2}\right) - \exp\left(\frac{\sigma_{g1}^2 + \sigma_{g2}^2}{(X_t+1)^2}\right) \tag{4.5}$$

According to Equations 4.4 and 4.5, the mean and variance of the growth shock is decreasing in X_t. However, since the shock has a proportional effect on the existing stock, a shock of a given magnitude has a greater effect when the volume is larger.

There are many stochastic factors that can affect tree growth, such as weather, pest outbreaks, disease, and fire. Our choice for the form of $Z_t(X_t)$ is based on patterns observed in timber growth data (which we describe in detail in the Appendix). Models of stochastic resource stocks are found in previous studies (e.g., Reed 1984; Morck, Schwartz, & Stangeland 1989), however, it is most common to specify a proportional growth shock with mean and variance that are independent of stock volume. In our application, this specification can lead to implausibly large changes in timber volume at higher volume levels. We adopt the general modeling approach for biological stocks proposed by Sims et al. (2017), which generates more realistic growth dynamics for timber stands

4.4.2. The Forest Manager's Problem

The forest manager is a price-taker who decides, at the start of each period, whether the harvest and replant the stand. The net revenue from harvesting is given by:

$$\pi_H(X_t, P_t) = P_t X_t - C_H \tag{4.6}$$

where C_H is the cost of replanting the stand and P_t is the per-unit timber price, which we model as a first-order autoregressive process[4]:

$$\ln(P_{t+1}) = \beta_0 + \beta_1 \ln(P_t) + \epsilon_t \tag{4.7}$$

where ϵ_t is a mean-zero normally-distributed error term. At the time the harvest decision is made, the manager is assumed to observe P_t, but not future values of the price. The manager never knows X_t with certainty except immediately following a

[4] In our model the per-unit price of the resource is the "stumpage" price, the price a harvester pays for the right to harvest a unit of timber on a parcel of land. The stumpage price is implicitly adjusted for any costs of harvesting.

harvest. The volume of a replanted stand is assumed to be fixed at $\overline{X}$ and known to the manager.

Timber volume is imperfectly observed, but the forest manager can obtain information about the volume with an inventory. For simplicity, an inventory is treated as a binary decision and, thus, managers do not also choose the sampling intensity. An inventory is conducted at the end of a period and yields an estimate of the volume, Y_t, at the start of the next period. Y_t is related to the true volume X_t by:

$$Y_t = \omega_t X_t \tag{4.8}$$

where ω_t is an iid random shock with nonnegative support. The constant variance of ω_t implies that the sampling error of an inventory is constant, which accords with our treatment of inventories as a binary decision. Forest managers incur a cost of C_I for each inventory.

At the start of a period, the forest manager forms a belief about the timber volume, $B_t(X_t)$, using her knowledge of the deterministic growth function $f(X_t)$ the distributions of the random variables $Z(X_t)$ and ω_t , and the relationship in Equation 4.8. If an inventory was conducted at the end of period $t-1$, then the manager updates her belief about $X_t$using the estimate Y_t and Bayes' rule:

$$\begin{aligned} B_{t+1}(X_{t+1}) &= \frac{p(Y_{t+1}\,|X_{t+1}) \int p(X_{t+1}\,|X_t) B_t(X_t) dX_t}{p(Y_{t+1}\,|B_t(X_t))} \\ &= \psi_I(X_{t+1}, B_t, Y_{t+1}) \end{aligned} \tag{4.9}$$

where $p(.\,|.)$ is a conditional probability. As in Zhou, Fu, & Marcus (2010), we specify $\psi_I(.)$ as the Bayesian update function where the subscript I indicates the availability of a new inventory. The denominator of Equation 4.9 is the probability of obtaining the estimate Y_t given current beliefs about timber volume, $B_{t-1}(X_{t-1})$. It is expanded below as:

$$p(Y_t \,|B_{t-1}(X_{t-1})) = \int\int p(Y_t \,|X_{t-1})\; p(X_t|X_{t-1})B(X_{t-1})dX_t dX_{t-1} \tag{4.10}$$

If the forest manager does not conduct an inventory or harvest the stand, the belief state propagates through the stochastic timber volume transition function:

$$\psi_N(X_t, B_{t-1}(X_{t-1})) = \int p(X_t \,|X_{t-1},)B_{t-1}(X_{t-1})dX_{t-1} \tag{4.11}$$

where the N on the update function indicates that no inventory or harvest was done.

Our MOMDP can be represented as a dynamic optimization problem over the Cartesian product of the belief state space and the price state space (Chadés et al. 2012). The "belief × price" Bellman equation is presented below. To simplify the notation, we drop time subscripts and adopt the convention of denoting next period variables with a superscript "+":

$$V(B(X),P) = \max_{H,I} \int \left\{ \begin{array}{c} H \times [\pi_H(X,P) + \delta \int V(\overline{X}\,, P^+)p(P^+|P)\; dP^+] + \\ I\; \times [-C_I + \delta \int \iint V\,(\psi_I(X^+, B(X), Y^+), P^+) \times \\ p(Y^{\,+}|X^+)\;\; p(X^+|X)p(P^+|P)\; dY^+ dX^+ dP^+] \\ (1-H)(1-I) \times [\delta \iint V\big(\psi_N\big(X^+, B(X)\big), P^+\big) \\ p(X^+|X)p(P^+|P)\; dX^+ dP^+\,] \end{array} \right\} B(X)dX$$

$$s.t.\;\; H \in \{0,1\},\;\;\; I \in \{0, 1-H\} \tag{4.12}$$

In Equation 4.12, H and I are indicators for the forest manager's choice of <u>H</u>arvest and <u>I</u>nventory, respectively, and δ is a discount factor. If the forest manager chooses harvest at the start of a period, she receives net revenues from the harvest plus a continuation value that depends on $\overline{X}$, the volume of a replanted stand, and expectations of future prices according to Equation 4.7. In this case, the value function is given by the first term in brackets. If no harvest is done, then the manager has the option of conducting an inventory, which costs C_I but yields a continuation value that accounts for the volume estimate Y^+ that will become available in the next period. The value function in this case is the second term in brackets. Finally, if neither harvest nor inventory is chosen, the value function equals the last term in brackets, which is the continuation value updated for the stochastic volume dynamics in Equation 4.1.

If a solution exists, Equation 4.12 can in principle be solved for the optimal value function $V(B(X), P)$ and a stationary policy function that provides the optimal control choice given the current period belief state and price. Like many dynamic optimization problems in economics involving state uncertainty, this Bellman equation does not have a closed-form solution. The following section summarizes our numerical solution method.

4.4.3. Solution Method

A technical description of the solution method is provided in the Appendix. We focus here on providing intuition and explaining key modeling choices. The high-dimensionality of MOMDPs and POMDPs make them computationally difficult to solve in general (Papadimitriou & Tsitsiklis, 1987). Outside of special cases, exact numerical solutions are not possible due to the curse of dimensionality[5]. We apply a technique developed by Zhou et al., (2010), which uses a parameterized distribution to approximate the belief state. We select a log-normal distribution, which has the desirable property of a non-negative support, thus assigning positive probability only to strictly positive values for timber volume. A second advantage of the log-normal specification is that we can define the approximate belief state using only the mean and the coefficient of variation (CV), which are sufficient statistics for the log-normal[6]. As discussed in Zhou et al., (2010), fitting the (simulated) posterior belief in Equations 4.9) and 4.11 involves finding the log-normal distribution parameters that

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[5] In our application, if timber volume were modeled as discrete with N possible categories, there would be N state variables: N − 1 probabilities defining the manager's beliefs over timber volume and the current price.

[6] The coefficient of variation is the ratio of a random variable's standard deviation to its mean.

minimize the Kullback-Leibler (KL) divergence from the posterior. Because the log-normal is a member of the exponential family, the solution to this minimization problem has a convenient closed-form solution.

The next step in the solution technique is to form a three-dimensional grid over the possible values of the mean and CV of the volume belief state and the price, where each node on the grid is mean, CV, and price triplet. We then employ value function iteration to solve for the policy function and value function, which relate the optimal action and expected value at each node. We adopt several procedures from Kling, Sanchirico, & Fackler (2017), including bilinear interpolation of the value function and the use of Halton draws for posterior belief state simulation. We also apply a numerical technique outlined in Fackler (2017) to reduce computational costs. In previous studies, storing the required state space transition model required a large amount of memory, and following a similar approach for this application would have been costly. To circumvent this problem, we exploit the independence of the price and belief state variables and store the associated state transition models separately.

4.4.4. Numerical Application

We find a numerical solution to the Bellman equation in Equation 4.12 using data on loblolly pine stands in Louisiana (more details on data sources and estimation procedures are found in Appendix C). Loblolly pine is the most commercially important tree species in the southern U.S. and tends to occur in pure stands (Gaby, 1985). We use data from the Forest Inventory and Analysis database USDA (Accessed 2017) to parameterize the deterministic and stochastic components of the timber growth functions in Equations 4.2 and 4.3. Data on real stumpage prices are taken from Howard & Jones (2016) for the period 1965-2013 and used to estimate the autoregressive price function in Equation 4.7. The parameter estimates indicate a stationary price process. Inventory, harvest preparation, and replanting costs are taken from Dooley & Barlow (2013) and data from Reynolds (2013) is used to characterize a typical timber inventory in the region and to derive the sampling error of an inventory. We use a discount factor equal to 0.972, which is an estimate derived by

Provencher (1995) for Southern Pine timber management. All parameters used in the numerical application are reported in the Appendix.

4.5. Results

In addition to the original policy described in previous sections, referred to hereafter as the ’with inventory” (WI) policy, we generate several counterfactual policies. These counterfactual policies are used to explore the implications of the model results. We solve for a policy in which there is state uncertainty, but the forest manager is restricted from investing in inventory (referred to as the “no inventory” (NI) policy). In another counterfactual policy, state uncertainty is removed altogether such that the forest manager can perfectly observe the volume of timber in the forest (referred to as the “perfect observability” (PO) policy). The PO policy is used as a benchmark by comparing its performance in simulations to those of the WI policy and NI policy. In both the NI and PO policies, prices remain stochastic and perfectly observable in the present period, just like in the WI policy. We also generate variants of the WI policy in which prices are held constant at specific values, in order to assess to effect of price stochasticity more explicitly. Wherever relevant, the same functional form choices, parameter values, and solution procedures are used to obtain solutions. An exception to this is in a set of counterfactuals we generate where the forest manager is misinformed as to the proper parameter values of the timber growth function. We include the analysis of this counterfactual as part of the sensitivity analysis.

4.5.1. Optimal Harvest and Inventory with Price Volatility

Approximating a solution to the forest manager’s problem described in Section 4.4 generates a policy function that relates each combination of price level and belief state (summarized by the mean and CV of a log-normal distribution) to an optimal action. The mean of the belief state represents the forest manager’s current point estimate of timber volume, which is also the volume of timber the forest manager would expect to receive should she chose to harvest in the current period. The CV can be intuitively thought of as a measure of the confidence the forest manager has about the expected timber volume. In order to aid in the interpretation of the results, the mean and CV of the belief state will be referred to as the expected timber volume and confidence, respectively.

The policy functions for the WI, NO, and PO policies are three dimensional objects, except when prices are held constant. As these objects are difficult to represent visually, we instead show cross sections of policy functions in which confidence is being held constant Figure 4.1. The levels of confidence are drawn from different ends of the distribution of realized values obtained from simulations of

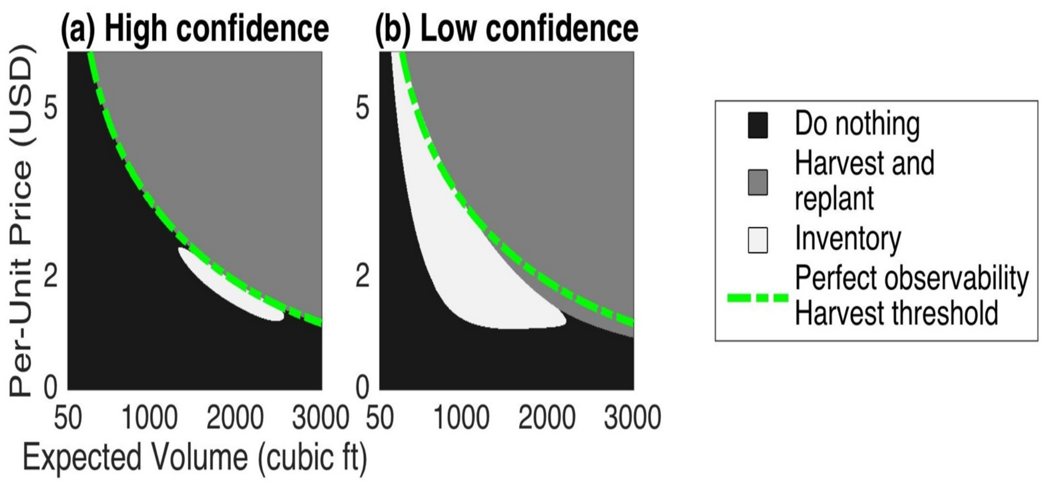

Figure 4.1: Cross sections of the WI policy function holding confidence constant at the 30th percentile (a) and 50th percentile (b) of levels recorded in simulations of stand management. The cv values associated with the 30th and 50th percentile are 0.11 and 0.52, respectively. The perfect observability threshold is overlaid for comparison.

forest management under the WI policy. Each cross section is divided into expected volume-current price regions where it is optimal to conduct an inventory, harvest and replant, or do nothing. For reference, we also show the volume-price harvest threshold from the PO policy. For a given (perfectly-observed) volume, the PO threshold divides price space into harvest and delay regions[7]. When volume is low, a

[7] Similar results are found in Brazee and Mendelsohn (1988) and Plantinga (1998).

high current price is needed for harvesting to be optimal because the manager must be compensated for foregoing future volume growth and the option value associated with harvesting later at higher prices (Plantinga 1998).

The cross sections in Figure 4.1 illustrate that higher per-unit prices result in it being optimal for the forest manager to harvest at lower expected timber volumes compared with lower per-unit prices. This is not solely due to the fact that higher per unit prices generate more revenue from harvest for the forest manager. Estimating the parameters of Equation 4.7 (described in the appendix) reveals that the price process is mean-reverting. Because the price process is mean-reverting, the forest manager expects per-unit prices to fall when they are above the mean, which creates an incentive for the forest manager to take advantage of the high per-unit price while they can. This result is consistent with standard models of timber harvest timing that address price volatility but ignore state uncertainty (e.g. Plantinga 1998).

Per-unit prices also influence optimal investment in inventory. While higher prices result in inventories at lower expected timber volumes (Figure 4.1, Panel (b)), this relationship is not preserved at high confidence (Panel (a)). When the forest manager's confidence is high, inventories are only optimal at prices near the mean price level under our chosen parameter values, an area where the future price is expected to be close to the current price. For expected timber volumes near the level where harvest is optimal, inventory is optimal due to the forest manager expecting to harvest soon. Since action is expected to be imminent, inventory is done to ensure that the true volume is not in reality well within either the "do nothing" or "harvest" zones.

Panel (b) of Figure 4.1 also demonstrates that lower levels of confidence result in inventory being optimal at a greater number of per-unit price levels and expected timber volumes. As confidence decreases, the "inventory" region expands around the mean per-unit price and hugs the border of the "harvest" zone. In Panel (a), which shows a cross section at a lower level of confidence, inventory is optimal for high per-unit price and low expected timber volume combinations. This is similarly due to both high expected timber revenues from harvesting, as well as the expectation that prices will fall. Given the lower level of confidence (and thus higher uncertainty about the true volume of timber), the forest manager has a stronger incentive to have a more accurate volume estimate. At lower per-unit prices, inventory can be optimal when the price is sufficiently close to the mean per-unit price and expected volume is high. This is because the forest manager expects prices to remain at that level, and so they are more cautious about harvesting at low levels of confidence, since there is no perceived risk of missing out on a high price.

So far, the level of state uncertainty – as measured by confidence – appears to have only a modest effect on the expected volume and per-unit price combinations that trigger the forest manager to harvest and replant. The boundary of the region in which harvest is optimal for the WI policy nearly matches the PO harvest threshold in Figure 4.1, Panel (a). However, at low levels of confidence, this is not the case. The policy function cross section in shown in Panel (b) demonstrates that the harvest and inventory zones in the WI policy begin to deviate from the PO harvest threshold when the per-unit price is low and expected volume is high. When confidence is very low, the forest manager internalizes the chance that there may be substantially more timber volume in the forest than she expects. This is due to the fact that the forest manager's beliefs are described by a nonnegative probability distribution. In our application, fixing the CV of the lognormal that approximates the belief state at a low level assigns more probability to higher expected volume levels. As a result, lower confidence levels create an incentive to "gamble" on volume being higher, through either harvesting or investing in inventory, at per-unit price and expected volume combinations at which it would otherwise be suboptimal in the absence of state uncertainty.

4.5.2. Valuing Forest Inventory

We compare the realized performance of the WI, NI, and PO policies as a means of measuring the value of forest inventory. We simulate management of 5,000 different timber stands, managed under each of the three different policies (WI, NI, PO). Each of the 5,000 timber stands we refer to as a simulation. For each simulation, all three policies share the same set of i.i.d. random shocks, allowing each policy to act as a true dynamic counterfactual to the other.

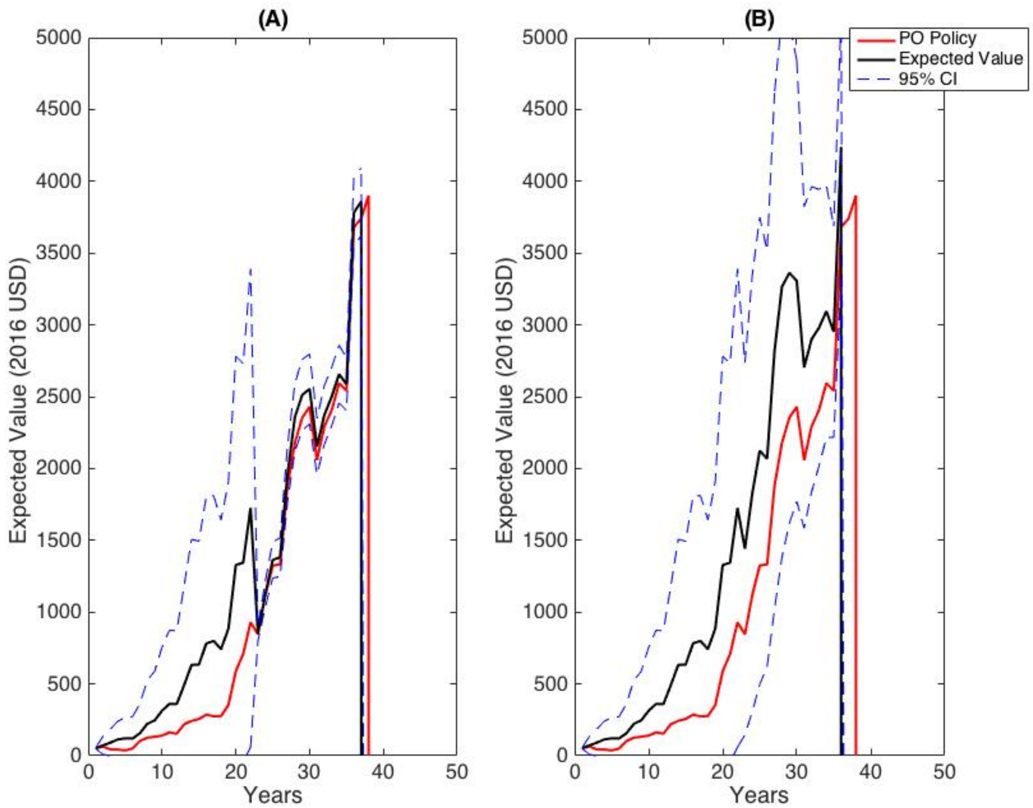

Figure 4.2: The Dynamics of Expected Value for the WI with stochastic prices (A) and the NI policy with stochastic prices (B).

In addition to simulating the three policies mentioned above, we also simulate a myopic version of the WI policy. The myopic WI policy is like the WI policy in that the forest manager faces state uncertainty, but unlike the WI policy, the forest manager must invest in inventory every seven years. This version of the WI policy is meant to mimic rule-of-thumb strategies to investing in inventories. Examples of such strategies can be found throughout the extension literature (e.g. Northwest Natural Resource Group and Stewardship Forestry, 2014).

Figure 4.2 shows expected value over time from one of the 5,000 simulations chosen as an example for the WI policy (Panel (a)), and for the NI policy (Panel (b)). For the PO policy which appears in both panels, the expected volume is simply the actual volume, given that there is no observational uncertainty in that counterfactual. Inventories allow the forest manager to more closely follow the PO policy. In Figure 4.2, Panel (b), beliefs about timber volume are overestimated in the NI policy, which leads the forest manager to harvest earlier than either the PO or WI policies. This example is a stark illustration of how inventory affects harvest timing. This in turn influences the realized NPV of forest management. We also see that the NI policy becomes more responsive to price fluctuations, as it exhibits a greater difference in harvest timing between it and the PO policy. Figure 4.2 also demonstrates that the level of confidence in the expected value of the stand plays a substantial role in management. In both panels of Figure 4.2, the 95% confidence interval is shown along with the PO policy and each panel's respective policy.

We report the average percent differences in NPV relative to the PO policy for both the WI and NI problems in Table 4.1. Within each simulation, we calculate the percent difference in NPV between the PO and WI policies, and between the PO and NI policies. We also calculate the standard deviations of both distributions of realized percent differences[8].

Not being able to invest in inventories reduces the value of the forest stand by 2.31% compared to the PO policy. The standard deviation of the percent difference is substantial at 15.05%, indicating that the returns from the NI policy are less predictable than that of the WI policy. The high standard deviation for the NI policy also provides evidence that without inventory, the forest manager runs the risk of performing far worse than either the NI or PO policies.

[8] The standard deviations reported in Table 1 should not be interpreted as standard errors of a point estimate. In this exercise, the full data generating process of the forest manager's problem is known precisely and these results can be made exact with progressively more simulations at the cost of more computing time; the simulations reported here took 2.5 days to complete done in parallel on a dedicated processing machine with 41 cores utilized

Table 4.1: Mean and standard deviation of WI, NI and myopic WI policy performance relative to the PO policy

Policy	Average NPV relative to PO policy	NPV Standard Deviation
With inventory (WI Policy)	-0.50%	7.25%
Without inventory (NI Policy)	-2.31%	15.05%
Myopic With Inventory (WMI)	-3.26%	6.92%

The WI policy tends to perform better than the NI policy. On average the WI policy comes remarkably close to matching the NPV of forest management in the absence of state uncertainty. This means that the benefit provided by inventory tends to more than cover the cost, adding additional value to the stand relative to the NI counterfactual. This is surprising given the sophisticated Bayesian structure of the NI policy, which makes it tough competition for the WI policy. Furthermore, the returns from the WI policy are far more predictable; the standard deviation of the gap between the WI and PO policies is less than half of its level when the forest manager cannot invest in inventory.

The myopic WI policy tends to perform worse than either the WI policy or the NI policy. The reason for this is because of an over-investment in inventory. Though inventory can improve the value of the stand, it only improves the value if done optimally. On average, the myopic WI policy invests in inventory four times as often as the WI policy, the costs of which reduce the NPV to a level below a forest managed under the NI policy. However, the returns from forest management become more predictable under the myopic WI policy. The frequent investments in inventory result in a lower standard deviation than either the WI policy or the NI policy.

4.6. Sensitivity Analysis

Many aspects of the results are sensitive to the assumptions we make in the model. We selected the assumptions on the basis that they would provide the most conservative estimates of the value from conducting inventory. In this section, we relax and change a set of these assumptions in order to highlight results in the model, such as the effects of price stochasticity, as well as provide additional information using assumptions that may be less conservative but realistic.

4.6.1 Fixed Prices

The role of price stochasticity can be investigated by constructing an additional counterfactual in which prices are constant. We solve for three separate policies in which prices are held constant at a low, medium, and high level. These price levels are based on what is observed in the simulations. The policy functions of these constant price counterfactuals are two-dimensional, unlike the policy function from Figure 1. Instead of showing the combinations of price and expected volume at a specific confidence level at which harvest or inventory is optimal as in Figure 1, Figure 4 shows the combinations of confidence and expected volume at which a given action is optimal for specific levels of price. It is a differently oriented cross-section than Figure 1. This is done in order to provide a proper comparison of the WI policy with its corresponding constant-price policies.

Figure 4.3 demonstrates that although price level alone plays a role, although it is slight. Panels (b), (d), and (f) of Figure 4 all look similar save for the fact that as the per-unit price increases, both the “inventory” and “harvest” regions occur at lower levels of expected volume. This is consistent with classic models that do not consider either price stochasticity or state uncertainty (e.g. Faustmann 1849). The relationship that state uncertainty has on optimal harvest and inventory timing is also apparent from Panels (b), (d), and (f), in that lower levels of confidence (measured by the CV) results in inventories and harvests at lower levels of expected volume.

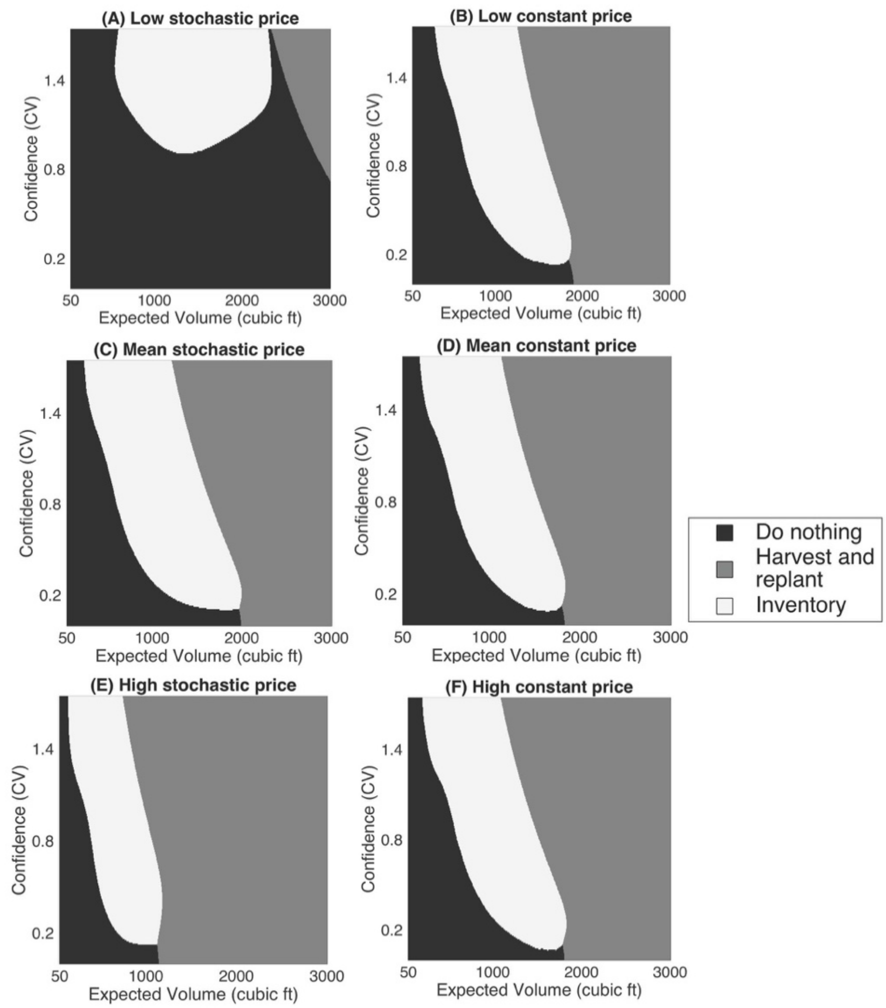

Figure 4.3: Policy cross sections holding price constant at low, medium, and high levels for WI policy with both stochastic prices (Panels A,C,E) and constant prices (Panels B,D,F).

The slight changes in harvest and inventory timing shown in Figure 4.3, Panels (b), (d), and (f) are in contrast to Panels (a), (c), and (e), which show large differences in optimal harvest and inventory timing at differing price levels when prices are stochastic. At low prices, the forest manager is incentivized to only harvest at high levels of biomass as well as low levels of confidence – a result consistent with the "gambling" behavior observed in Figure 4.1 Panel (b). Though the differences between the policies with constant prices are due to the level of the per-unit price, the differences between the policies with and without stochastic prices are attributable to price stochasticity.

Viewing the WI policy from this perspective also reveals important results. Figure 4.4 Panel (a) shows a non-convexity in the policy function that occurs at low levels of confidence (high CV), and high expected volume levels. Similar non-convexities appear elsewhere in the literature (e.g. Marten & Moore, 2011) and have been attributed to fixed costs of treatment. Similarly, the wedge between the "inventory" and "harvest" regions in Panel (a) of Figure 4.2 is a direct result of the fixed cost of inventory. At low prices and high levels of expected volume, there is a very high probability that the state of the system in the next period will lie within the "harvest" region of the WI policy function. The value of an inventory is therefore diminished at very high expected volume levels. At a certain point, the value of the inventory is less than the cost of obtaining one. Therefore, a wedge is created between the "inventory" and "harvest" regions. This wedge can be seen in Figure 4.1 as well.

4.6.2. Alternate Growth Model

The assumption that the forest manager has the correct model with respect to volume growth is a very conservative assumption. In reality, resource managers very rarely have a precise model of their specific resource. We construct two additional counterfactuals that capture the possibility of the forest manager having the wrong growth model. We construct one in which all of the growth parameters are misspecified [9](Figure 4.5, Panel (b)) and one in which only the stochasticity is misspecified (Figure 4.5, Panel (c)). For the sake of comparison, we also include in Figure 4.5 an additional panel which is the WI policy cross section (Figure 4.5, Panel (a)). The parameters for the alternative growth functions can be found in the Appendix.

The effect of a larger proportional shock that is not scaled by timber volume can be seen while comparing Panels (a) and (c) of Figure 4.4. A more substantial shock results in a larger inventory region, holding confidence constant. Furthermore,

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[9] The growth parameters used for this exercise are estimated from the same dataset as the main parameters. The difference is that the stochastic parameters are set to both equal .1, then the intrinsic growth rate, intrinsic capacity, and initial volume are fit as before.

the harvest region is slightly smaller in Panel (c) than in Panel (a). The differences observed between Panels (a) and (b) of Figure 4.4 that are not already observed between Panels (a) and (c) are a result of differences in the deterministic portion of the model. The model used to generate the policy function in Figure 4.4, Panel (b) has a larger capacity, but slower growth rate. Both of those features mean that the forest manager has the option of waiting longer to improve their expected value, as the stand will grow for a longer period of time. This effectively increases the window over which it may or may not be optimal to harvest. Due to this increase, the potential to mistime a harvest also increases, leading to a higher value of inventory, and thus a larger inventory region. The differences seen in Figure 4.4 demonstrate the interaction between the model parameters of the deterministic portion and the stochasticity of growth.

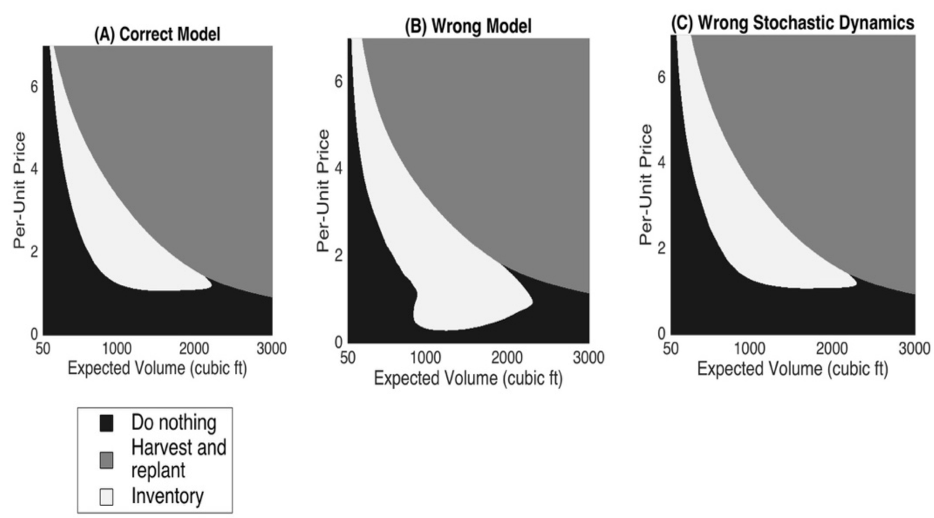

Figure 4.4: Policy Cross Sections at a relatively high CV value for the WI policy (a), WI policy with an incorrect model specification (b), and the WI policy with a correct deterministic specification, but misspecified stochastic dynamics (c).

Additionally, Figure 4.4 reveals another non-convexity in the policy function in Panel (b). A similar shaped non-convexity exists in the WI policy function, but at levels of confidence that are sufficiently low as to not appear in the simulations. Unlike the previous non-convexity on the right-side of the inventory region which is due to fixed cost, the non-convexity on the left side is attributable to price dynamics. The wedge of the left-side non-convexity begins at the mean price level, and then fans out to the left. At that price level, the forest manager does not expect prices to increase or decrease. Thus, the only way the forest manager expects to enter the harvest region is through the timber volume increasing. At higher prices, although the forest manager expects the price to go down, there is still an incentive to harvest earlier, which pushes the inventory to the left. At lower prices, the forest manager expects both the timber volume to increase, and for the price to go up, meaning that there is a higher likelihood of ending up in the harvest region in the next time step. Because of this, it becomes optimal to invest in inventory at lower prices and expected volume levels than if the price were at it's mean value.

4.6.3. Initial Conditions

We test whether the results described in Section 4.5.2 are sensitive to the initial condition of the forest, as well as the initial beliefs about the forest. In our previous simulations, the initial condition for biomass is set to be the replanting biomass, which assumes that we are working with a regenerating stand. Forest management involves payoffs that are separated by long periods of time, which means that discounting will influence the magnitude of the difference in NPV between different policies. Additionally, because the stochastic component of Equation 4.1 is scaled by the timber volume, the initial conditions will affect the belief dynamics of the problem as well. In order to evaluate the effects of the initial conditions on the NPV differences between each policy, we run four additional simulations[10] at a different initial condition under four different belief state specifications.

We begin by setting the initial condition of timber volume in the stand to 911.29 cubic feet of timber. The first counterfactual we analyze is one in which the forest manager has an accurate and certain belief about the true value of the timber volume. This simulates the case following an inventory in which the forest manager

[10] The simulations presented in this section are over a shorter time horizon (50 years) with fewer realizations (50).

receives an accurate measurement from a forest inventory. This will be referred to as the accurate and certain counterfactual. The next counterfactual is one in which the confidence of the forest manager is low, but the expected volume is still accurate, referred to as the accurate and uncertain counterfactual. The third counterfactual has an inaccurate expected volume level, but a forest manager who is confidence about the estimate. This counterfactual refers to a situation in which the forest manager invested in an inventory and received an inaccurate measurement. The third counterfactual is referred to as the inaccurate and certain counterfactual. The fourth and final counterfactual is referred to as the accurate and uncertain counterfactual, and features an inaccurate initial expected volume and a low level of confidence. The table detailing the results of this simulation are shown in Table 4.2.

Table 4.2: The performance of each policy contingent on different initial conditions

Counterfactual	**Policy**	**Average NPV relative to PO**	**NPV Standard Deviation**
Accurate and certain	With Inventory (WI)	1.08%	8.09%
	Without Inventory (NI)	-0.79%	11.96%
	Myopic with Inventory (WMI)	-0.016%	7.48%
Accurate and uncertain	With Inventory (WI)	-1.46%	12.18%
	Without Inventory (NI)	-3.48%	14.32%
	Myopic with Inventory (WMI)	-4.64%	9.13%
Inaccurate and certain	With Inventory (WI)	-2.85%	14.62%
	Without Inventory (NI)	-4.85%	16.62%
	Myopic with Inventory (WMI)	-4.64%	9.13%
Inaccurate and uncertain	With Inventory (WI)	-3.07%	15.56%
	Without Inventory (NI)	-4.85%	16.62%
	Myopic with Inventory (WMI)	-4.64%	9.13%

From the results shown in Table 4.2, we can see that though the relationship between the PO policy and every other policy changes, the rankings of many of the other policies and each other are preserved. An exception is the ranking of the NI policy relative to the MWI policy, which is opposite of that in Table 4.1 in every counterfactual except for the accurate and uncertain counterfactual. From the evidence we have, the initial condition does not change the result that investing in inventory will, on average, improve the NPV of the timber stand, and make the returns more predictable than the NI policy. The magnitude of the WI policy returns the most value in the accurate and uncertain counterfactual. In fact, the WI policy adds more value to the stand in the first three counterfactuals in Table 4.2 than in the baseline scenario with our initial condition set to the replanting volume in Table 4.1. However, in each counterfactual, the returns are more difficult to predict, though this may be due to the low number of simulations used for this sensitivity analysis.

Counterintuitively, the WI policy actually outperforms the PO policy in the accurate and certain counterfactual, though the standard deviation of NPVs is higher than in the baseline simulation results. This result is driven by price stochasticity: the WI policy will occasionally harvest at a higher price than the PO policy because it has a higher expected value of timber, or less confidence than the PO policy. If this occurs enough times, the WI policy will outperform the PO policy. The same phenomenon is seen in comparisons between the WI and the NI policy. However, this result may not be robust to increasing the number of simulation runs. However, this result highlights something that is seen in the comparisons between the NI and MWI policy as well, which is that the NPV from following these respective policies is much closer to the PO policy NPV than in the results from Table 4.

The closeness of the NPV from each policy to the PO policy highlights the role of discounting in this exercise. By starting at an initial condition that is 1) a larger volume than the baseline, and 2) more certain, each policy has a much higher likelihood of harvesting at the same time that the PO policy does for the first harvest. That fact together with that initial harvest occurs much earlier, means that a large share of the stands value over the time horizon nearly matches the PO policy. This results in NPVs that are very close to one another.

However, this result vanishes when the initial condition becomes uncertain, as in the accurate and uncertain counterfactual. Compared to the results in Table 4.1, all policies perform worse. For the WI policy, this is due to the requirement to invest in inventory early on, whereas for the NI policy, this result stems from differences in harvest timing between the NI and PO policies. Interestingly, for the myopic policy, there is no difference between it's NPV in the accurate and uncertain counterfactual and the inaccurate and certain counterfactual. This is due to the MWI policy having an inflexible inventory rule, which allows it to overcome the uncertainty or inaccuracies in the initial condition early, but then proceeds to overinvest in inventory. Intuitively, the level of certainty for inaccurate counterfactuals makes no difference for the NI policy, since it cannot invest in inventory anyway. However, the WI policy's performance reduces dramatically as the initial condition becomes less accurate and less certain.

4.7. Conclusion

Our paper investigates the relationship between stochastic price dynamics and the decision to measure imperfectly observable variables in natural resource management. We advance a continuous-state MOMDP as a model of private forest management under state uncertainty with perfectly observable stochastic prices. To our knowledge, this study presents the first continuous-state MOMDP addressing state uncertainty in the natural resource literature. On top of demonstrating methodological contributions, our case study investigates the extent to which measurement improves the returns on resource management.

Results from our study show that price dynamics influence the optimality of inventory for forest management. The price level itself is shown to influence the timing of inventory through affecting the timing of harvest. Additionally, price stochasticity plays a large role in the timing of inventory. When prices are mean-reverting and stochastic, the resource manager wants to take advantage of the higher price, incentivizing harvests at lower expected volume levels and lower levels of certainty. Though this results in inventories at lower expected volume levels, the frequency with which these inventories occur is reduced.

Though the level of certainty and inventory timing have an intuitive relationship, with lower levels of certainty leading to earlier inventories, our study provides insight into how price stochasticity affects this relationship. Our results show that at the mean timber price, inventory is optimal for expected timber volumes that are very close to the region in which harvest is optimal, while not optimal at other price or expected volume levels. This results in inventories being optimal at higher levels of confidence around the mean price. In previous studies, the relationship between measurement behavior and confidence are results of the dynamics of the resource system. We extend these findings by showing that the relationship between certainty and the optimality of inventory interacts with price stochasticity.

We also find a relationship between state uncertainty and harvest. At very low levels of confidence, harvest occurs at lower expected timber volumes than when confidence is high, or at perfect certainty. This result is especially stark at lower prices. The implication is that the timing of harvest in a natural resource with state uncertainty may not perfectly follow traditional models when certainty is low. Future work on this topic may include further scrutinizing how beliefs are formed by resource managers as well as examining any role these beliefs might play in observed deviations from standard models of resource extraction and harvest.

A problem with investing in information – including inventory in forest management – is that the costs of the measurement are easy for the manager to see but the benefits are often difficult to detect. Our results suggest that in the case of forest management, optimally investing in inventory adds value to the stand above and beyond the cost of the activity. In fact, we find that inventory allows for the forest manager to come very close to matching the returns that would be obtained by a manager operating with perfect observable timber volume. However, this result only holds if inventories are optimally timed. Our results suggest that costs from mistiming inventories could potentially outweigh the benefits, despite alleviating risk of catastrophically bad outcomes.

Our study contributes to the field of forest economics by developing the first bioeconomic model of forest inventory that we are aware of. Although both harvest and inventory are addressed by previous studies in forest management, they are addressed separately. Our model optimizes harvest and inventory timing jointly. The joint optimization provides a microeconomic basis for modeling optimal inventory investments. There are also many areas in forestry where inventory and measurement play important roles, including in detecting disturbance risk (e.g. fire risk, bark beetle prevalence, etc.). Forestry offers a great platform from which to study the spatial aspects of information investments, for instance to prevent the spread of arboreal diseases.

There are also extensions of this work in assessing policies that require information standards. An example of one of these is forest-based carbon offsets, where the forest manager must regularly invest in costly inventories. Furthermore, the relationship between prices and information investments could be useful for agricultural studies as well. Our study is useful for future analyses of these types of programs due to the fact that we address inventory investments in a profit-oriented context with a realistic description of price dynamics.

5. Summary and Conclusion

In three essays, this essay advances the modeling of natural resource management under uncertainty. As environmental problems continue to grow in importance, modeling that incorporates both the ecological and economic aspects of the system are important tools for policy. Furthermore, incorporating and studying inherent sources of uncertainty within natural resource systems is important for optimal management. In this context, my dissertation addresses the following research questions.

In the first essay, I ask whether there are substantial feedbacks between natural and human systems. There is uncertainty within economic models as to what the ecological impacts of private forest management are. In order to address this broader question, I explore two specific research questions that include how the forest sector responds to pine beetle related tree mortality, and how policies targeting harvest on vulnerable lands spill over into other regions, and how they impact the ecological footprint of the forest sector in general. These two policy experiments exploit the benefits of the forest sector model I develop by utilizing its high resolution and large spatial scale, as well as its comprehensive representation of the forest sector. The contribution of this model is that it will now be possible for researchers to incorporate more detailed models of land processes including those that incorporate climate change explicitly into the model, in order to conduct detailed economic policy experiments within their respective ecology models. Furthermore, it provides a means to study the regional effects of localized policies. We show that there are spillover effects from state-level policies. This indicates the need to take market forces into consideration when crafting state-level policies, or when neighboring states are crafting environmental policies.

In the second essay, we ask whether the duration of forest-based carbon offset contracts influences the performance of the program. I conduct this analysis using a partial equilibrium model of the forest sector of western Oregon. Very few studies address the duration of ecosystem service contracts such as the ones studied in Essay 2, and when they have been studied it has been from a theoretical perspective. This study contributes a modeling analysis of an ecosystem service based management contract that is modeled after a real-world application: the California climate market. As more states, such as Oregon, adopt market based approaches to mitigating CO_2 emissions, addressing aspects of the program that can be improved are crucial. In our study, we explore the effects of offering carbon sequestration contracts of differing lengths on program performance including participation, carbon sequestration, and economic consequences. We find that shorter contracts enroll roughly just as many acres into the program as the longer contracts at high prices of carbon. However, we discovered substantial differences in the amount of carbon sequestered between each contract. Each contract outperformed the others across their respective time lifetimes. We did not discount the carbon sequestration in the paper, and doing so may be an important extension in a follow up study. Furthermore, we found that longer contracts under higher carbon prices resulted in a substantial build up of timber, and so when the contract expired, the price of logs would drop. We found that the addition of a maintenance period alleviated the price volatility for the shorter contracts. However, long maintenance periods at high carbon prices resulted in poor program performance, both in terms of participation and carbon sequestered. The results of this study will be useful for policy makers interested in crafting more efficient forest-based carbon offset provisions as part of a state level or regional carbon market. Furthermore, it may motivate future research into the role of contract duration, or the optimality of that duration for programs focusing on carbon sequestration as well as other ecosystem services.

The third essay addresses forest management under state uncertainty and price volatility. We ask whether price volatility influences optimal investment strategies in information for natural resource management. Furthermore, we also ask whether state uncertainty influences the timing of harvest. State uncertainty is an issue integral to natural resource management, including forestry, and yet it is only recently that the problem has been addressed substantially in the literature. We construct a continuous-state Mixed Observability Markov Decision Process model of forest management, a first in the forest resources literature. The model is motivated with empirical estimates matching private loblolly pine management in Louisiana. We find that price volatility plays an important role in determining the optimal timing of investments in forest inventory.

Though this dissertation represents a number of advances in the field, it also points to many additional studies in the future as follow ups and extensions. The methodology utilized in the first essay can be employed in domains other than forestry. For instance, one could conduct additional policy experiments in which taxes or subsidies affect mill level decisions such as how many chips to consume versus timber. Additionally, implementing a coupled version of the model is a follow up study that is currently in process of being done. For the second essay, there are a number of theoretical papers that the study motivates. For instance, constructing a model that solves for the optimal contract length under price volatility, which has not yet been evaluated. Furthermore, conducting a study in which re-enrollment is possible would be an interesting follow up study as well. Finally, conducting similar analyses of other ecosystem service contracts, or even easements, could be an interesting study. The third essay has a variety of interesting applications, including the incorporation of non-market benefits into the forest management problem. Additionally, the MOMDP framework could be utilized for addressing questions of contract and policy design for ecosystem service payments in both forestry and agricultural settings.

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Appendices

Appendix A: Supplementary Material for Essay 1

A.1. The Community Land Model

The community land model is a large-scale model of land processes with the ability of coupling to other models within the Community Earth System Model (CESM). When the models are fully coupled to one another, CESM provides a model of the environment in which many of the natural feedbacks of these systems are well represented. CESM and CLM is used in numerous applications in the earth sciences.

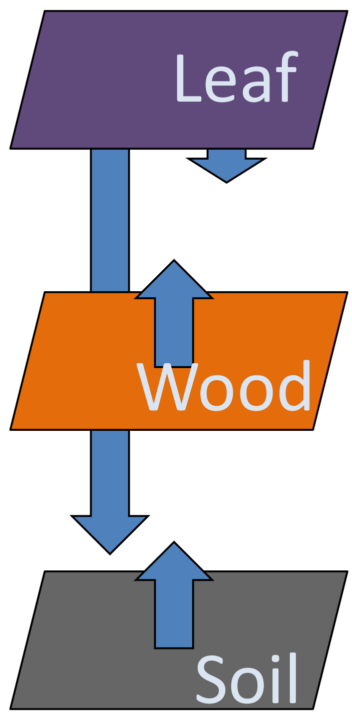

Figure A.1: Simplified representation of carbon flows within a column in CLM

CLM is unique from other models in CESM in that the way it organizes the landscape, the model can be scaled up very easily for parallel processing. The landscapes are split into discrete grid cells, generally of uniform resolution. For large planet-level runs, this resolution is quite coarse, though for region-level runs such as those presented in this paper, the resolution is much finer. Each grid cell is then split into different columns representing different categories of land cover, such as forested, urban, or crop. Each time-step, CLM uses a vast array of equations to calculate the flow of matter (e.g. carbon, nitrogen, etc.) up and down each column. This is visualized in figure A.1. These flows are generally functions of climatic variables, such as precipitation or temperature. However, these are also factors that are determined by social systems, notably timber harvest, that affect the flow of matter within each grid cell.

Timber harvest in CLM is typically accounted for with input datasets that prescribe removals for each grid cell. In the version of CLM employed in this paper (CLM 4.5), these removals are prescribed in terms of a proportion of the biomass on the grid cell removed. This prevents the biomass from going negative, which would betray the laws of physics. However, it makes it more difficult for modelers looking to conduct alternative harvest scenarios that match specific volume targets. Perhaps for that reason, later versions of CLM have switched to represented harvest in terms of the level of removal. Another drawback of the way harvests are represented is that they are not responsive to disturbance events or changes in productivity occurring in the model. That is, the experimenter prescribes the harvest, and those do not change, even if the area they targeted for harvesting burns down. With the THM, harvest levels are determined endogenously. Figure A.2 visualizes the coupling process.

The major difficulty with coupling the THM to CLM is that the THM requires grid cell to grid cell communication, which is not allowed in CLM. Other models in CESM do feature grid cell to grid cell communication, and communicate using a module named the “flux coupler”. However, using the flux coupler along with CLM represents a substantial computational hurdle that was determined to be to expensive, both in terms of time and money, to pursue. Instead, we resort to stopping CLM at every year, and then running the THM to determine the following year’s harvests. Once that is calculated, the new harvest map is passed to CLM, which is then started again to run for another year.

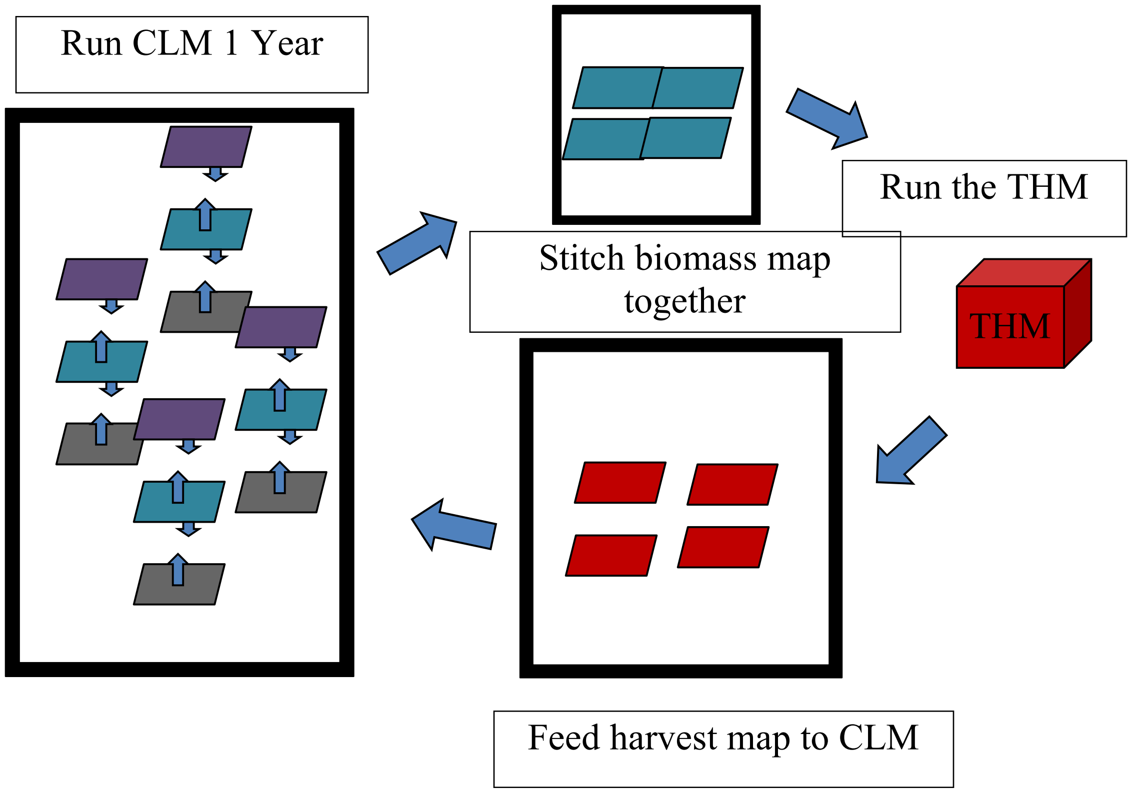

Figure A.2: Visualization of the coupling procedure between the THM and CLM

A.2. Timber Plot Parameterization Results

Previous parameterization procedures (discussed in the following section) focused on fitting the timber plot owner's supply function to data on historical harvest and production level. This was done simultaneously with the fit procedure for the mill production function. However, the fitting procedure would generally fit either harvest level or production level, resulting in modeling outputs that would be realistic for one or the other. Instead, we fit the range of historic harvests given a range of historic prices and an assumed rotation length. We employed Microsoft Excel's non-linear fit algorithm (Fylstra et al., 1998). The estimated coefficients are reported in Table A.1.

Table A.1: Parameters for plot owner's cost function (and supply function).

Parameter	Description	Value
α	Scale Parameter	0.0245
β	Exponential Parameter	1.8378

A.3. Additional Results from the Policy Experiment

The manuscript presents the results from both a region-level subsidy experiment, and from an experiment in which the same subsidy is enacted in Oregon alone. However, the same experiment was run for both Washington and California. In table A.2, we present the results of the state level runs, as well as the no-policy run for the sake of comparison. We report it at two different points in the simulation: year 5 and year 10. We report the number of plots harvested, the overall harvest level, and the average harvest. Future work could involve incorporating these results into a single unified manuscript centered on the effects of vulnerability subsidies.

Table A.2: Harvest statistics from the modeling results of the subsidy policy experiment for each version of the experiment.

		Year 5			Year 10		
		Total Harvest	**Number of Plots Harvested**	**Average Harvest**	**Total Harvest**	**Number of Plots Harvested**	**Average Harvest**
Region	No Subsidy	52132319	19433	2683	50947844	20880	2440
	Low Subsidy	54274906	13966	3886	52886475	15124	3497
	High Subsidy	59118607	10827	5460	58673085	11484	5109
WA	Low Subsidy	52375998	18809	2785	50773350	20948	2424
	High Subsidy	52735838	16974	3107	51227069	18387	2786
OR	Low Subsidy	52261379	18831	2775	50780435	20366	2493.
	High Subsidy	52292685	18531	2822	50910098	20100	2533
CA	Low Subsidy	52160199	19599	2661	50871103	21242	2395
	High Subsidy	52388204	19092	2744	50820039	20629	2464

Appendix B: Supplementary Material for Essay 2

B.1. Mathematical Summary of Forest Sector Model

We employ a partial equilibrium model of the forest sector in western Oregon that solves for the market equilibrium level of timber harvest, mill production, mill capacity level, and enrollment in the carbon offset program. The model maximizes the area under the inverse demand for logs at a given time step, $P_t(q, K_t)$, where K_t is the capacity level and q is the quantity of logs. The acres of forestland under a given management, denoted by the variable X_{nj}, where the subscript n denotes the condition of the stand, including things such as slope, soil type, age, and other factors. For both the enrolled and unenrolled land, the model assigns a management prescription, j, which consists of a series of actions to be taken at each time step over the time horizon. These actions include whether a removal occurs, and how intense that removal is. The model also optimizes the terminal conditions of the stand, which includes $\overline{A}$ the average timber harvest age in the post-modeling period.

The model takes into account a set of costs associated with various activities and states of the forest sector. K_t is the current level of capacity, and has an associated maintenance cost of c_k. Furthermore, K_t depreciates each year at a rate δ. More capacity can be purchased, with I_t is the amount of capacity purchased in time t at a cost of c_I. There are also costs associated with each action in j, c_{jt}. The costs and benefits of the model are discounted at a rate r. The objective function is shown in Equation B.1.

$$\max_{X_{nj}\, I_r\, \overline{A}} \quad \sum_{t=0}^{T} \left(\frac{\int_{q=0}^{Q_t} P_t(q, K_t)\, dq - c_k K_t - c_I I_t - \sum_{n=0}^{N} \sum_{j=0}^{J} c_{njt} X_{nj}}{(1+r)^t} \right) \qquad \text{(B.1)}$$

Where Q_t is the total amount of logs delivered to mills in time period t, and T is the terminal time period. This optimization is constrained by a number of different relationships represented in the model. Q_t must be equal to the amount of net log imports M_t plus the per-acre average log volume produced from a stand of a given management style f_{njt}. This constraint is shown in Equation B.2.

$$Q_t = \sum_{n=0}^{N} \sum_{j=0}^{J} f_{njt} X_{nj} + M_t \tag{B.2}$$

The next constraint (Equation B.3) requires that the capacity level, K_{t+1}, must equal the depreciated current capital plus the capital purchased.

$$K_{t+1} = K_t(1 - \delta) + I_t \tag{B.3}$$

The next constraint (Equation B.4) limits the amount produced such that it cannot exceed capacity.

$$K_t \geq \frac{Q_t}{\gamma} \tag{B.4}$$

Where γ is the capital stock utilization rate.

At this point, we have mathematically described how acres are assigned in and out of the carbon management program, as well as how the capacity level is selected. What follows is the method by which the model selects a management prescription for stand type n. As in Montgomery et al., 2006, we use a random search algorithm similar to the one in Bullard et al., 1985 in order to maximize either the Soil Expectation Value (SEV) for regenerated stands, or the Land Expected Value (LEV) for existing stands. Regenerated stands are stands that have just been harvested and replanted. This is a function of the log price p_i where the subscript i indicates destination type of the log (export, lumber, sawtimber). The model maximizes either SEV or LEV depending on a, the current age of the stand, as well as A_j which is the age at which a clear-cut occurs. Furthermore, each stand has an associated amount of harvest, f_{nja} at a given age and management prescription. Furthermore, that harvest has an associated cost of c_{nja}. The maximization problem for the regenerating stand is presented in Equation B.5.

$$\max_j SEV_n = \frac{\sum_{a=0}^{A_j}(p_i f_{nja} - c_{nja})(1+r)^{A_j-a}}{(1+r)^{A_j}-1} \tag{B.5}$$

The maximization problem for the existing stand is given in Equation B.6. The variable a^0 indicates the age of the stand at the beginning of the simulation

$$\max_j LEV_n = \frac{\sum_{a=a^0}^{A_j}(p_i f_{nja} - c_{nja})(1+r)^{A_j-a} + SEV_n}{(1+r)^{A_j-a^0}} \tag{B.6}$$

The model is parameterized using a number of different sources. The inverse demand functions are linear, and fit to data on log demands from 1970 to 1988 (Adams et al., 2002; Schillinger et al., 2003), with other exogenous variables coming from the Oregon RPA assessment (Haynes 2003). Additional variables on management costs come from a variety of sources such as treatment costs from Rose and Rose and Jacobs (1999), and harvest costs from Fight et al., (1984). Following Adams et al., 2002 we use a discount rate of 6%. The model as well as discussion of the model presented here follows that of Montgomery et al. (2006) closely, and we would refer the reader to that paper, as well as the other papers mentioned, for a more detailed description of the forest sector model.

B.2. Expanded Explanation for Maintenance Period Enrollment

Table 3.3 presents a counterintuitive result regarding the number of acres enrolled in forest based carbon offset programs when the contracts require maintenance periods. In the table, it is shown that 20-year contracts that have an additional 20-year maintenance period have more acres enrolled than the 20-year contract with no maintenance period. Similarly, the 40-year contract with an additional 40-year maintenance period has more acres enrolled than the 40-year contract with no maintenance period. This is unexpected, as the maintenance periods burden enrolled forest land with additional costs should they chose to harvest. However, these contracts also restrict the supply of timber, increasing the price of logs and also the economic returns to forest land. This section will explore this explanation, and expand on discussions in the manuscript as well as provide additional results that suggest this is the case.

Whether or not prices respond to the maintenance period can be seen by examining Figure 3.5. From Figure 3.5, we see that the drop in prices associated with the expiration of a contract are postponed for the duration of the maintenance period as well. As a result, the higher prices creates a more profitable economic environment for the unenrolled land. Also, Figure 3.5 shows that the magnitude of the price decrease is diminished by the maintenance period, as enrolled land will still draw their timber stocks down even with an additional cost over the maintenance period. These market effects should and do appear in the returns the forest land receives for both enrolled and unenrolled lands. It should also reduce the returns from carbon payments in the enrolled lands. To address the aforementioned point, I present a table that shows the net per-acre returns to forestland for enrolled, unenrolled, and the overall average forest land (Table B.1), as well as a table that presents the average per-acre net returns from carbon sequestration on enrolled land (Table B.2).

Table B.1 shows an intuitive result that the per-acre returns on enrolled land increases with the price of carbon. Interestingly, the per-acre returns on unenrolled land decreases as the price of carbon rises. At first this seems to contradict the argument of this section, since higher carbon prices result in larger amounts of timber being withheld from the market. The contradiction is resolved due to the fact that as carbon prices increase, relatively productive land gets enrolled in the program, meaning the average productivity of the unenrolled land decreases. Furthermore, at higher carbon prices, the larger amount of withheld timber results in a steeper decline in the price of logs. This too can reduce the returns for unenrolled land. An additional observation is that for the average acre of forestland, the returns increase with the price of carbon. This is because the gains that unenrolled lands receive from higher carbon prices offsets the reduction in returns for unenrolled lands. The longer the contract, the larger the discrepancy between the average returns at lower carbon prices and higher carbon prices.

Table B.1: Net per-acre returns (real US dollars) for four different contract specifications at each price for enrolled and unenrolled forestland

Contract	Carbon Price	Enrolled	Unenrolled	Average
20-year	$5	9825.167139	5299.975135	6568.21061
	$10	10281.14111	4788.131317	6622.327105
	$25	11882.471	4397.957207	7273.393474
	$50	13712.85889	4040.735771	8050.315017
20-year, 20-maintenance	$5	12198.91705	5322.003506	7167.515628
	$10	12173.22609	4771.928458	7324.958891
	$25	14237.65335	4141.470336	8536.260876
	$50	16468.83022	3853.372015	9677.262034
40-year	$5	15284.46635	6893.662582	9172.080046
	$10	15483.71384	6255.902862	9494.613157
	$25	18492.67455	5370.067602	11243.97084
	$50	21465.3903	4896.185704	13165.76412
40-year, 40-maintenance	$5	19979.44069	8852.497869	11886.2799
	$10	19401.99207	7769.866668	11894.86055
	$25	23444.0011	6816.199531	14535.76086
	$50	25213.23794	7280.872926	14711.78751

The results in Table B.1 also show that as the length of the contract increases, so too do the returns on both enrolled and unenrolled land. Though the 20-year contract with no maintenance period does not produce the same per-acre returns as the contract with a 20-year maintenance period, the 40-year contract outperforms both of them in terms of both enrolled land and unenrolled land. However, it is generally the case that a longer contract results in larger per-acre returns. The fact that this holds true for unenrolled lands as well as enrolled lands demonstrates that these increases are likely due to changes in market conditions. If this were the case, we would expect lower per-acre returns from carbon payments alone on enrolled lands. This is due to the fact that during the maintenance period, enrolled land must pay a penalty for removals on their land, however they would receive no benefit for the additional carbon sequestered.

Table B.2: Net per-acre returns from carbon sequestration for enrolled lands by contract type and carbon price level.

Contract	Carbon Price (per tonne)			
	$5	*$10*	*$25*	*$50*
20-year	64.01063403	120.5373344	305.5140285	615.7804796
20-year, 20-maintence	35.43041413	80.34655957	247.0201775	571.8399582
40-year	40.4442473	91.6113392	289.0864897	680.4918725
40-year, 40 maintenance	38.23438148	84.48383135	283.7915665	503.1929215

At each price level, Table B.2 demonstrates that the contracts that have maintenance periods provide lower returns than the corresponding contracts with no maintenance periods. This result is consistent with our explanation that the higher log prices that come as a result of longer contract durations is what is driving the higher enrollment. Interestingly, we also see that the per-acre carbon benefits decrease between the 20-year contract with no maintenance period and the 40-year contract with no maintenance period for all carbon prices except for $50/tonne.

The results shown here provide evidence that what is driving the higher-than-expected enrollment in contracts with maintenance periods are the price effects those contracts induce. We see that even unenrolled land experiences increases in per-acre returns as contracts become longer. This is backed by the result that although returns are increasing overall, returns from specifically carbon payments are not. Overall, we find evidence that price effects could potentially boost returns on all forestlands for longer contracts. However, our results do indicate that longer maintenance periods may have negative impacts on program performance for higher carbon prices, as we see the number of enrolled acres plummet, and per-acre returns from carbon sequestration decrease as well.

The result explained in this section may be due to the assumptions used to solve the forest sector model. In particular, the forest sector model optimizes the net benefit of the system, under perfect foresight and perfect information. It does not account for the imperfect information that forest land managers have to contend with, specifically about their own future actions, and the future actions of their neighbors.

Appendix C: Supplementary Material for Essay 3

C.1. Empirical Timber Volume Transition Function

Our model is grounded in data on volume growth, prices, and management costs for loblolly pine in Louisiana. The data on volume growth was taken from the Forest inventory and Analysis database (FIAdb) (USDA, accessed 2017), and was fitted to a stochastic Beverton-Holt model (Beverton & Holt, 1957). The subset of the database used in our study contains volumes of private timber in the state of Louisiana, along with the age of the timber stand. We formulate the stochastic version of the Beverton-Holt model by applying a proportional shock $Z(X_t)$to the standard Beverton-Holt model. The functional form is presented below.

$$X_{t+1} = X_t \left(\frac{r}{1 + \left[\frac{r-1}{K} \right] X_t} \right) Z(X_t) \tag{C.1}$$

Where X_t and X_{t+1} are the current and next period timber volume, respectively. The parameters r and K are the intrinsic growth rate and intrinsic capacity of the forest stand, respectively. $Z(X_t)$ is the volume dependent proportional shock, shown in Equation 4.2. We estimate values for the intrinsic growth rate and intrinsic capacity per acre by fitting the model to the FIAdb using a combination of non-linear least squares and simulated stand dynamics. In the first step of our simulation, we simulate many realizations of stand growth using a candidate growth function and a set of random shocks. Next, we average the values of each realization from our candidate growth function, which provides an averaged candidate growth function. We calculate the sum of squared errors between the averaged candidate growth function and the observations from the FIAdb. The optimization is performed with the non-linear Marquardt algorithm (Marquardt, 1963). The parameters for the empirical growth function are reported in Table C.1.

Table C.1: Parameters for the timber volume transition function.

Biological model parameters			
Parameter	Name	Description	Value
r	Growth rate	Stand-level intrinsic growth rate	1.1838
K	Capacity	Long-run average maximum biomass	2,519.40
σ_{g1}	Growth shock	Primary growth shock parameter	17.8538
σ_{g2}	Growth Shock	Secondary growth shock parameter	3.2006
x_0	Biomass initial condition and replanting level	Initial condition for the biomass state variable (for use in dynamic simulations)	26.9174

The data provided by the FIAdb is in units of growing-stock volume; however, the price data we use is reported in units of sawtimber. Sawtimber volume is commonly defined as the volume of growing-stock large enough to be processed by a sawmill into product. Smith et al. (2006) provides tables for converting growing stock to sawtimber (Table 4.4). Table 4 in Smith et al. (2006) reports a sawtimber proportion of 0.658 for a pure loblolly stand. The rest of the volume in the stand we assume can be sold as pulpwood. Instead of splitting Equation A.1 into two equations – one for sawtimber and another for pulpwood – we keep Equation C.1 in units of growing stock. We apply the conversion factors to the prices instead. This process is discussed in the Section C.4 below with the rest of the details of the price model.

The stochastic component of Equation C.1 is scaled by the timber volume such that higher volumes result in less variable random shocks. Though this appeals to intuition, it also appeals to reality, as this scaling bears out in the FIA data. Figure C.1 demonstrates that as the volume increases, the growth in terms of percent change becomes less variable. This is consistent with the set-up of our growth model, as higher volumes will result in less variable shocks.

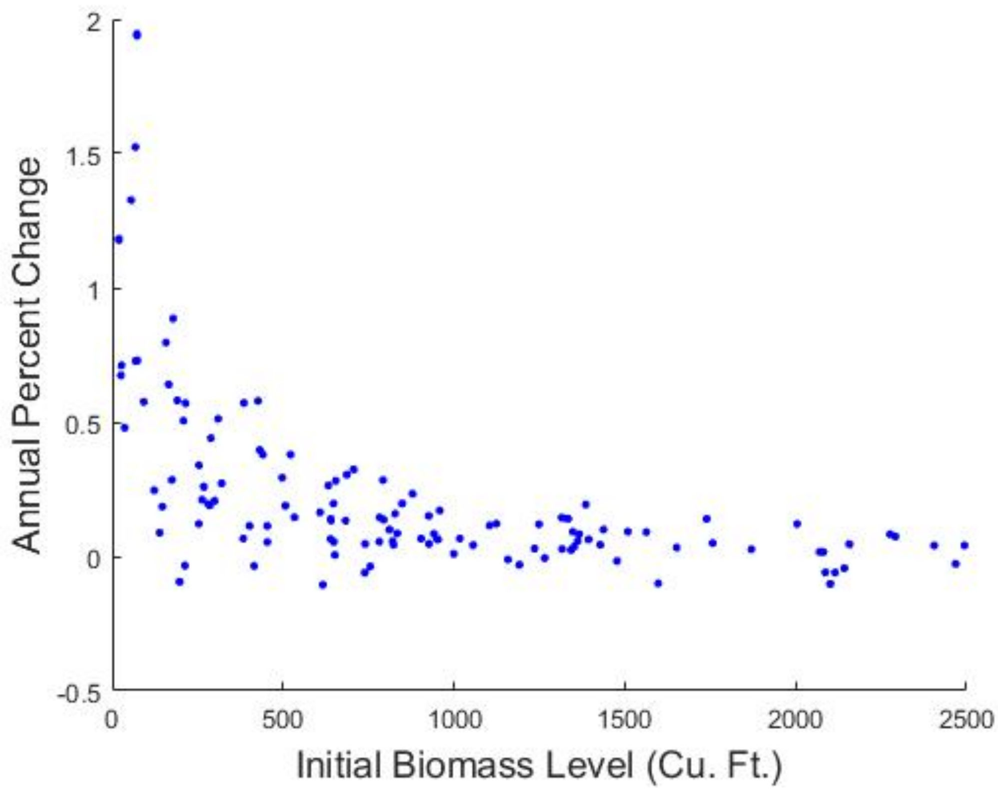

Figure C.1: The annual percent change in biomass as a function of initial biomass level for observations in the FIADB for private forestland in Louisiana. At smaller biomass levels, the variation in percent change is much higher than at higher biomass levels. This indicates that a stochastic growth model which has a constant proportional shock will not be able to accurately model the growth function.

Our sensitivity analysis includes analysis of two alternative versions of the growth model. Both specifications are derived from an alternative fitting routine, but are fit to the same data as the model used in the rest of the paper. In the alternative fit, we manually set the stochastic component of the model such that it is not scaled by the timber volume, and that both parameters σ_{g1} and σ_{g2} are set to a value of .1. From there, the Beverton-Holt equation is fit to the FIADB data to derive an alternate set of deterministic parameters. Policy functions are then calculated for both this growth model, as well as a hybrid growth model in which the stochastic component is from this alternate fit and the deterministic growth parameters are from the fit used in the rest of the paper. We then employ these policy functions in simulations where the true model of volume growth is the baseline model.

C.2. Cost Data

Costs of managing forestland greatly vary between regions and species. The information on management costs utilized in our study comes from a survey collected by researchers at the Alabama Cooperative extension (Dooley & Barlow 2013; Barlow & Levendis 2015) and reports the average costs of specific management activities in the southern United States. Within these surveys, inventory costs are split up by purpose of the inventory. Dooley & Barlow (2013) break inventory into three categories: reconnaissance, sale, and appraisal. Our inventory cost figure comes from pre-sale category of inventory costs. Per-acre inventory costs were reported from the survey, and cross-referenced with reported values from other regions and extension documents in order to ensure that the numbers were realistic (e.g. USDA Forest Service, Accessed January 2018). We also utilized survey results on costs associated with preparation and replanting that the forest manager incurs in the event of a harvest. These costs are adjusted to reflect 2016 US dollars, and are reported in Table C.2.

Table C.2: Parameters of the economic model of forest management

Economic Parameters					
Parameter	**Name**	**Description**	**Value**	**Unit**	**Source**
δ	Discount factor	Discount factor used by forest manager	0.9742	unitless	Provencher (1995)
C_I	Cost of monitoring	Fixed cost of more expensive, more informative monitoring	\$19.61/ acre	2016 US dollars	Dooley and Barlow (2013)
C_H	Fixed cost of harvest	Fixed cost of harvest and replanting	\$251.90	2016 US dollars	Dooley and Barlow (2013)
σ_w	Variance of inventory shock	Variance of wt	0.99965		Reynolds and Daruska (2003)
B_0	Price transition equation intercept	Log-log AR(1) regression intercept coefficient	0.0764		Howard and Jones (2016)
B_1	Slope of price transition equation	Log-log AR(1) regression slope coefficient	0.8773		Howard and Jones (2016)
σ_p	Standard Deviation of Price Transition Equation	Log-log AR(1) regression standard deviation of the residuals	0.1204		Howard and Jones (2016)
P_0	Price initial condition	Initial condition for the price state variable (for use in dynamic simulations)	1.9245	2016 US Dollars per cubic foot	Howard and Jones(2016)

C.3. Observation Model

Forest inventory is typically planned in order to achieve a specific level of accuracy. The number of plots is selected based on previous data on the forest, a selected confidence level, and an acceptable level of error. We model inventory as a binary decision for the forest manager, simplifying the model yet making it necessary to specify a single level of accuracy for the inventory decision. Modeling the accuracy of inventory as a continuous variable is a potentially interesting extension to this current work.

We parameterize the cost of inventory with survey data from Dooley & Barlow (2013), selecting the the per acre cost for pre-sale inventory (as mentioned above). This type of cruise is chosen because it is both common and more expensive than other forms in inventory. It is therefore a more conservative choice for our model. We then reference a separate document, Reynolds (2013), to get values for the confidence level, and expected error level of pre-sale inventories. We choose a 90% confidence level, and an error level of 5%. The costs are adjusted to 2016 US dollars, and the confidence and error levels are used to compute the distribution of the observation shocks from Equation 4.4. These values are reported in Table C.2.

C.4. Price Model

Price data was obtained from Howard & Jones (2016) and is reported as 2016 US dollars per 1000 board feet (MBF). The data describes stumpage prices for sawtimber and pulpwood from private timberland in the state of Louisiana for the years 1965 to 2013. The rule-of-thumb conversion factor from MBF to cubic feet is $83\,\frac{1}{3}$. Therefore, we divide all the prices reported in Howard & Jones (2016) by $83\,\frac{1}{3}$ to find the per cubic foot price of the timber. As mentioned in a previous section, only a portion of the biomass on the stand can be sold as sawtimber. The rest of the growing stock is assumed to be sold as pulpwood. Under this assumption, we construct a price variable from the weighted average of the sawtimber and pulpwood prices reported in Howard & Jones (2016)), where the weights are the sawtimber conversation factor, and one minus the sawtimber conversion factor. We estimate a regression with a log-log specification (Equation 3) where current price is a function solely of the previous year's price. The coefficients for our price model can be found in Table C.2. We characterize the stochasticity of the price process using the distribution of errors from the regression process.

C.5. Calculating the Expected Reward and State Transition Functions

What we present here is the standard method for calculating the reward and transition function. Though we employ Fackler (2017) in this step, we report the standard methodology in this section in order to aid intuition. Please refer to Fackler

(2017) for a detailed explanation of additional methodology. We convert the intractable forest manger MOMDP model (Equation 4.9) into a discrete Markov decision process (MDP) over the product of the approximate belief price state space. Let $g_i = (mean, cv, price)$ be a node in the three dimensional mesh. Next, let $R(g_i, H, I, DN)$ be the expected reward function, which maps the forest manager's decision to an expected instantaneous reward for a given node. Finally, let $P(g_i, H, I, DN)(g_j)$ be the probability of transitioning from node g_i to g_j contingent on the agent's action. Equation 4.9 can be re-written as the following discrete MDP.

$$\hat{V}(g_i) = \max_{H,I,DN} \left\{ \hat{R}(g_i, H, I, DN) \ + \delta \sum_{j=1}^{L} P(g_i, H, I, DN)(g_j)\, \hat{V}(g_j) \right\} \tag{C.2}$$

In order to calculate the policy function, which is the solution to our problem, we first need to calculate the reward function, and probability function. Both the reward function and transition function are calculated using techniques described in Zhou et al., (2010). In our application, we use a Monte-Carlo technique wherein a set of N Halton draws are used to derive a set of random draws from the log-normal density that characterizes the projected belief state (Arulampalam et al. 2002). Applying these N draws from the belief state and averaging by the number of draws integrates the reward function over the belief state, which yields the expected reward function. Let x_j be a random draw from the belief state.

$$\hat{R}(g_i, H, I, DN) = \frac{\sum_{j=1}^{N} \hat{R}(x_j, H, I, DN)}{N} \tag{C.3}$$

Calculating the transition function similarly utilizes particle filter, however because we are transitioning from belief state to belief state, the process is less straightforward. Our solution approach differs from Kling et al. (2017) because of the nature of observability with respect to our state variables.

The transition probabilities matrix requires a more substantial computational cost. We apply methods developed in Zhou et al. (2010) and then extended by Kling et al. (2017). In general, the algorithm operates by beginning with a single node, $g(H, I)$ and four sets of Halton draws of identical length N: $\{\varepsilon_1 \varepsilon_2 \varepsilon_3 \varepsilon_4\}$. The details of this process are further described in Table C.3.

Table C.3: Calculating transition probabilities in a standard MDP framework

Step Number	Price	Monitor	Harvest	Do Nothing
Inputs	$g(H, I, DN)$ $\{\varepsilon_1 \varepsilon_2 \varepsilon_3 \varepsilon_4\}$			
Output	$P(g_i, H, I, DN)(g_j)$			
1	Compute shocks: $x_{1:N} = f_x(\varepsilon_1, \theta_1)$ $P_{1:N} = f_P(\varepsilon_1, \theta_1)$			
2	Predict next-step prices $P_{1:N}^{t+1}$ using eq. 2 and ε_2	Predict next step biomass $x_{1:N}^{t+1}$ using Halton draw sequence ε_3 and eq. 1.		
3	N/A	Compute observations $y_{1:N}$ according to eq. 3	N/A	N/A
4	N/A	For each observation 1…N, updates beliefs according to eq. 5	N/A	N/A
5	N/A	Project beliefs $b_{1:N}$ onto the log-normal density	N/A	N/A
6	Calculate bilinear interpolation weights for all $g_{1:N}$. Sum interpolation weights for each g_i and calculate: $P(g_i, H, I, DN)(g_j) = \frac{Sum\ of\ interpolation\ weights}{N}$		Revert belief mean and CV back to re-planting levels (see appendix)	Calculate new mean and CV from the distribution of propagated biomass values, $x_{1:N}^{t+1}$

C.6. Value Iteration

Once the transition probabilities and reward matrix are estimated, we can begin to solve for the policy function. We do this by solving first for the value function, which maps each node in our mesh ($g_i \in G$)to an expected value, for each action. We accomplish this using standard value iteration. Described simply, value iteration involves iterating equation nine, where the value function, $\hat{V}(g_i)$ is not known. Initially, we set $\hat{V}(g_i)$ to zero, and then calculate Equation 4.9, which gives us an updated set of values for $\hat{V}(g_i)$This operation is repeated until $\hat{V}(g_i)$converges. Once this happens, we can select the action that, for each node g_i, maximizes the expected value. This then yields the policy function, which is the solution to our problem.