Timberland Investment under Both Financial and Biophysical Risk

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ABSTRACT *We extend real options analysis of timberland investments to examine a combination of financial and biophysical risk effects on optimal investment strategies in the southeastern United States. Results show that, despite a slight downward drift in price, expected returns for loblolly pine management fall between entry and exit thresholds, indicating an optimal "hold" strategy. This is explained by an offsetting upward trend in biophysical productivity associated with climate changes across a range of modeled futures. Monte Carlo analysis indicates a small positive difference between entry and exit outcomes consistent with observed rates of expansion in timberland investments in the region.* (JEL D81, Q23)

1. Introduction

Since 1980, U.S. timber production has concentrated in the southeast and increasingly in planted loblolly pine *(Pinus taeda)* forests. The region's softwood timber production rose by 49%, from 33% to 60% of total U.S. output between 1976 and 2006, and the area of planted pine forests increased by 11 million ha (Oswalt, Smith, et al. 2014; Wear and Greis 2012). In 2012, planted pine represented 19% of all timberland in the southeastern states, 27% in the southeastern Coastal Plain, and 81% of the expansion in planted forest area in the United States (Oswalt, Smith, et al. 2014; Wear and Greis 2012). With respect to ownership, 95% of the planted loblolly-shortleaf forest type group in the Southeast is held by private owners; 56% is held by corporate land owners, primarily timber investment management organizations and real estate investment trusts with large land holdings (Oswalt, Smith, et al. 2014). Overall, the forest industry plays an important role in the southeastern economy.

While forest sector assessments project long-term expansion in the southeastern timber sector (e.g., Wear et al. 2013), the potential future of expansionary investment in planted pine forestry is unclear, as softwood prices, which rose strongly through the 1990s, have leveled off or declined in the most recent decade. Price trend and volatility have been shown to influence pine timberland investment strategies in the Southeast (Mei and Clutter 2015), and recent price dynamics may dampen new entries to production, though the area of planted pine has continued to expand at low rates. However, price dynamics are not the only sources of change and uncertainty affecting potential returns. Uncertainty related to climate-driven changes in productivity or disturbance events may also affect harvest yields and net returns.

Due to its long production period, timber has a long exposure to damage and mortality risks relative to other agricultural endeavors. Natural hazards such as fire, wind throw related to hurricanes, or insect epidemics are infrequent events that can generate catastrophic outcomes at a specific location. Hedging investments with multiple locations provides a means of mitigating these risks with known occurrence frequencies. Nonetheless, climate change introduces new uncertainties regarding not only risks of disturbance events (Ayres

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et al. 2014) but also the underlying biological productivity of the forest by altering solar insolation, temperature, and precipitation, and increasing atmospheric concentrations of CO_2 and levels of nitrogen deposition (Payn et al. 2015). Depending on location, biological growth may be enhanced or decreased by an altered climate, and biome boundaries between forests and savannahs are likely to shift (Kirilenko and Sedjo 2007). Several authors, including those cited here, have enumerated the potential influence of climate change on timber yields, but these uncertainties have not been explicitly incorporated as a component of the forest investment decision-making environment.

The objective of this study is to examine the joint influence of price and yield uncertainty on potential investments in planted loblolly pine forests in the southeastern United States. We model forest investments in terms of entry and exit conditions within a real options framework. Following Mei and Clutter (2015) we set up the investment analysis as a contingent claims approach influenced by both price and yield uncertainties. Several forest investment studies have applied real options with price uncertainty to address optimal harvest timing (e.g., Clarke and Reed 1989; Morck, Schwartz, and Stangeland 1989; Reed and Clarke 1990; Thomson 1992), and others have extended these models to address timberland investment choices, including entry/exit for a forest portfolio (e.g., Mei and Clutter 2015; Yin 2001; Yin and Newman 1999). While biophysical risks arising from disturbances such as wildfires or insect outbreaks have been incorporated in the optimal rotation net present value calculus (e.g., Ning and Sun 2017; Xu, Amacher, and Sullivan 2016), to our knowledge, no study has effectively integrated price and biophysical uncertainties in a study of timberland investments. Price and Wetzstein (1999) examine a similar question regarding investments in perennial peach crops with annual yields, which serves as a starting point for our analysis.

Our approach is to blend stochastic processes for prices and net yields within a real options framework that accounts for the temporal structure of forest production. Price volatility is described using the ex post stochastic process models frequently deployed in the literature. Yield volatility, especially as it relates to anticipated climate changes, requires ex ante simulation approaches. We use a physiological forest growth model that is sensitive to climate inputs to generate observations of expected changes in forest productivity over time. We also incorporate a model of age-dependent disturbances to account for stand-replacing events in determining anticipated harvest area. Monte Carlo analysis generates estimates of potential net yield changes that are summarized as a stochastic process model. The merger of the price and net yield models allows us to address questions regarding the potential for expansionary investment in loblolly pine production and the potential influence of climate change on forest investment.

2. Methods

Model Specification

This study focuses on the management of planted loblolly pine forests in the Coastal Plain of the southeastern United States, the most actively managed forest species in the nation's most productive timber region (Oswalt, Smith, et al. 2014). Loblolly pine is native to the Southeast, and decades of tree-breeding and management research have greatly enhanced its yields under even-aged management. Future yields are likely to be affected by changes to physiological inputs including temperature, solar insolation, and precipitation, as well as CO_2 fertilization. The species is subject to a variety of catastrophic disturbances including wildfire and wind throw linked to tropical storms. The Southern pine beetle (*Dendroctonus frontalis* Zimmermann), a native insect, can cause widespread mortality during episodic outbreaks. While overall mortality rates are low (less than 0.5%/year aerial measure, according to Forest Inventory and Analysis data), climate change may increase these rates: wildfire is expected to be more frequent (Liu, Stanturf, and Goodrick 2010); southern pine beetle epidemic locations, frequencies, and intensity may be altered due to changes in both host stress and insect population dynamics (Ayres et al.

2014); and frequency of tropical storms may be altered due to uncertain changes in future climates.

We examine an investment in loblolly pine management as a decision to install an irreversible lump sum cost to provide an uncertain value stream from a forest holding dependent on uncertain prices and harvested yields of timber. For analytical tractability, we assume a forest investor starts with a 6 acre forest holding with a uniform age structure: 1 acre in each of six age classes with a starting age vector: age = [0, 5, 10, 15, 20, 25]. In a deterministic model, at the end of the five-year time step, all forest area ages five years, and the 30-year-old forest is harvested and regenerated to reset the initial conditions for the subsequent period and a regular flow of harvest volume. However, the investor anticipates that forest productivity may change over time in response to evolving climate conditions and that the investment is also subject to stochastic nonharvest events that can kill the forest at any age. Furthermore, the investor may anticipate that rates of disturbance could also be influenced by future climate conditions. We address yield uncertainty arising from productivity change and disturbances with separate mechanisms.

To address disturbances, we develop an age transition model that defines their influence on the investor's expectations regarding harvest area and regeneration area at the end of the five-year time step. Define $\mathbf{A}_t$ as the 1 × 6 vector of forest area (set to the unitary vector in the first period). Define $\mathbf{T}$ as a 6 × 6 transition matrix:

$$\mathbf{T} = \begin{bmatrix} d_1 & d_2 & d_3 & d_4 & d_5 & 1 \\ 1-d_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-d_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-d_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-d_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-d_5 & 0 \end{bmatrix}, \quad [1]$$

where the 1 × 6 vector $\mathbf{d}$ defines the rate of stand-replacing disturbance by age class so that disturbed areas return to the first age class while the undisturbed forests transition to the next age class. The distribution of forest area at the end of the period is defined as $\mathbf{A}_{t+1} = \mathbf{A}_t \times \mathbf{T}'$. At each time step, the area harvested (H) is the value of $\mathbf{A}[6]_t$ and the area to be regenerated (R) is defined as $\mathbf{A}[1]_{t+1}$. Because all values of $\mathbf{d}$ are nonnegative, the area harvested will be less than or equal to 1 acre and the area regenerated will be greater than or equal to 1 acre. To implement the age transition matrix, random draws from a binomial distribution centered on an observed average disturbance probability for planted pine forests ($\bar{d} = 0.0044$/year) are used to estimate T and therein produce multiple realizations of expected harvest area (H).

To define our expectations for the future productivity of planted loblolly pine forests, we simulate forest growth using the 3-PG (physiological processes predicting growth) model developed by Landsberg and Waring (1997) and modified by Thomas, Brooks, et al. (2017) and Thomas, Jersild, et al. (2018) for a set of spatially downscaled climate futures. The 3-PG model simulates the accumulation of aboveground biomass for a loblolly pine stand to age 40 for several origin years between 1990 and 2030 for each of the climate futures. From this dataset we draw the expected volume at age 30 (harvest age) for each climate future by state for reference years 2020, 2030, 2040, 2050, and 2060.

We merge the disturbance estimates resulting in harvest area H with the productivity changes resulting in average harvest volume at age 30 ($Q_{30,t}$) to define net harvest volume within a Monte Carlo simulation framework. Multiple realizations of harvest area, generated by taking random draws from the disturbance distribution, applying the resulting transition matrix ($\mathbf{T}$), and calculating H, are merged with the alternative projections of change in forest volume—replicates are generated using independent random selection with replacement for H and $Q_{30,t}$. Expected harvest volume, defined as $\hat{Q} = \hat{H} \times Q_{30,t}$ at time t, is generated for each reference year. We summarize change in net harvest volume as a geometric Brownian motion (GBM) stochastic function with drift:

$$d\hat{Q} = \alpha_Q \hat{Q} dt + \sigma_Q \hat{Q} dz, \quad [2]$$

where α is the drift term and σ is the volatility term. Using the pseudodata described above, we estimate separate GBM parameters for each state for five different reference years. The number of observations for each estimated state model is between 4,000 and 17,400 as defined by the number of climate futures ($m = 20$), the number of counties within the Coastal Plain region of each state (average of 60), and the number of replicates.

Our treatment of price similarly utilizes a GBM stochastic function to describe the expected increment and volatility in price over time:

$$dP = \alpha_P P dt + \sigma_P P dz\,. \quad [3]$$

For both volume and price processes, if dX/X is normally distributed, the parameters can be readily derived from summary statistics for the series: $\alpha = m/\Delta - 0.5 s^2/\Delta$ and $\sigma = s/\sqrt{\Delta}$, where m is the mean and s^2 is the variance of the log difference of X, and Δ is the equally spaced time interval expressed in years (Tsay 2005). For prices we estimate GBMs for each state for time series of product prices. For net yield we estimate GBMs for each state of expected change in average annual yield using a cross-section of pseudodata from the simulation approach described above.

Given the GBM specifications of blended stumpage price (dollars per ton) and yield (tons per acre), proceeds $R = PQ$ from harvesting age 30 class forests (dollars per acre) of the multiaged forest also follows a GBM by Ito's lemma,

$$dR = \alpha_R R dt + \sigma_R R dz\,, \quad [4]$$

where $\alpha_R = \alpha_P + \alpha_Q + \rho\sigma_P\sigma_Q$, $\sigma_R^2 = \sigma_P^2 + \sigma_Q^2, + 2\rho\sigma_P\sigma_Q$, and ρ is the correlation coefficient between stumpage price and yield (Price and Wetzstein 1999).

Solution by Contingent Claims Approach

As described by McDonald and Siegel (1986), an investment decision is analogical to choosing the optimal time to install a lump-sum cost I in return for a project with an uncertain value V, given that the investment is irreversible. As such, investment timing is like a call option. An exercise of the option triggers the investment cost I, and in return the investor holds a project with a stochastic value V. Denoting the value of a timberland investment opportunity by F, the optimal decision rule can be described as

$$F = \max_T E[(V_T - I)e^{-rt}], \quad [5]$$

where $E[\bullet]$ denotes expectation, T indicates time, and r is the discount rate (Dixit and Pindyck 1994). Because V and F are contingent assets whose values depend on timber revenue R, they are expressed as functions of R as $V(R)$ and $F(R)$.

The contingent claims approach assumes an equilibrium in capital markets. It starts with forming a riskless portfolio by going long one unit of the option to invest $F(R)$ and short $F'(R)$ units of the basic asset R.[1] The portfolio's current value is $F - F'(R)R$, and its total return over a time interval dt is $dF - F'(R)dR - \delta RF'(R)dt$, where δ is convenience yield defined as the discount rate (r) minus drift rate of timber revenue (α_R). Using Ito's lemma, the total return can be expressed as $[0.5\sigma_R^2 R^2 F''(R) - \delta RF'(R)dt$. To avoid arbitrage, the total return must be risk-free return:

$$[0.5\sigma_R^2 R^2 F''(R) - \delta RF'(R)]dt = r[F - F'(R)R]dt]. \quad [6]$$

Rearranging terms of equation [6] results in the following differential equation:

$$0.5\sigma_R^2 R^2 F''(R) + (r - \delta)PF'(R) - rF = 0. \quad [7]$$

Entry and Exit Options

Assume that the payoffs of a pine forest depend on timber revenue R, then the value (V) of the pine forest can be expressed as a function of R. Using the contingent claims method, $V(R)$ can be derived. Specifically, Dixit and Pindyck (1994) show that the option value to invest $V_0(R)$ and the value of an active project $V_1(R)$ (profit from operation plus the option value to exit) are

$$V_0(R) = A_1 R^{\beta_1}, R \in [0, R_H], \quad [8]$$

[1] Short selling is feasible on financial assets but not on hard assets such as timberland. However, this does not invalidate the use of the real options approach.

Table 1
Summary Statistics of Blended Real Timber Prices in 2017 Constant Dollars per Ton and Parameter Estimates for Geometric Brownian Motions

	AL	AR	FL	GA	LA	MS	NC	SC	TX	VA
Mean	29.22	24.61	29.02	30.05	25.62	27.01	21.95	26.58	26.22	21.93
SD	9.52	7.18	7.23	9.86	7.04	9.57	3.57	6.25	7.02	4.73
α_P	–0.0090	–0.0091	–0.0043	–0.0027	–0.0094	–0.0078	–0.0015	–0.0057	–0.0063	0.0021
σ_P	0.1442	0.1547	0.1151	0.1567	0.1168	0.1652	0.1045	0.1015	0.1664	0.1202

Note: Using annual Timber Mart–South data (1980–2017) with Q2 price representing the annual one. α_P and σ_P are drift and volatility parameters of timber price. Abbreviations and their corresponding states are AL (Alabama), AR (Arkansas), FL (Florida), GA (Georgia), LA (Louisiana), MS (Mississippi), NC (North Carolina), SC (South Carolina), TX (Texas), and VA (Virginia).

$$V_1(R) = B_2 R^{\beta_2} + R/\delta - C/r, \qquad [9]$$

where A_1 and B_2 are parameters to be determined, β_1 and β_2 are parameters derived from the GBM of timber revenue, and C is the variable cost of operation. Applying the value matching and smooth pasting conditions, entry and exit revenue thresholds (R_H and R_L) can be solved numerically from the following system of four nonlinear equations (Dixit and Pindyck 1994),

$$-A_1 R_H^{\beta_1} + B_2 R_H^{\beta_2} + R_H/\delta - C/r = I,$$
$$-\beta_1 A_1 R_H^{\beta_1 - 1} + \beta_2 B_2 R_H^{\beta_2 - 1} + 1/\delta = 0,$$
$$-A_1 R_L^{\beta_1} + B_2 R_L^{\beta_2} + R_L/\delta - C/r = -E,$$
$$-\beta_1 A_1 R_L^{\beta_1 - 1} + \beta_2 B_2 R_L^{\beta_2 - 1} + 1/\delta = 0, \qquad [10]$$

where E is the lump-sum abandonment cost.

3. Data

Stumpage Price

Pulpwood, chip-n-saw, and sawtimber prices in 10 southern states, Alabama (AL), Arkansas (AK), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Texas (TX), and Virginia (VA),[2] over 1980–2017 were obtained from Timber Mart-South (TMS).[3] TMS is a nonprofit corporation that compiles and publishes prices of major timber products in the U.S. south. Sawtimber, chip-n-saw, and pulpwood are primary products of pine plantations, and their prices are therefore used to generate a blended stumpage price. The weights are harvest volumes in the three products from a multiaged forest. Nominal prices are deflated using the consumer price index (2017 = 100). Descriptive statistics of real blended prices are reported in Table 1. Among the 10 states, GA has the highest mean ($30.05/ton) and standard deviation ($9.85/ton), whereas NC has the lowest mean ($21.95/ton) and standard deviation ($3.57/ton).

Growth and Yield

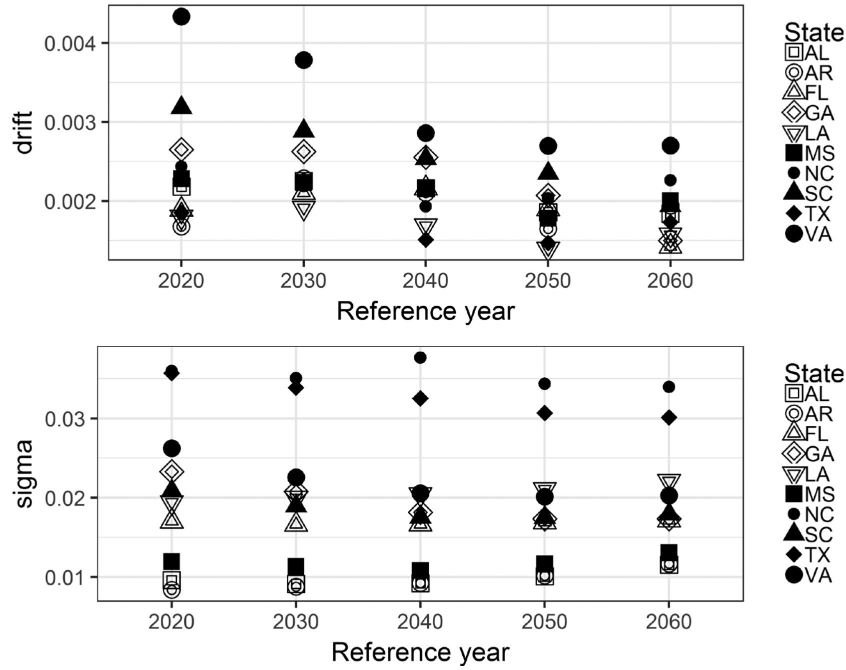
To characterize potential forest productivity for planted loblolly pine, we use simulations of forest growth from the 3-PG model for a set of climate futures. We use outputs from 20 global circulation models (GCMs) based on the emissions future for the 8.5 representation concentration pathway (RCP8.5) from the Intergovernmental Panel on Climate Change 5th Assessment Report (Moss et al. 2010; Riahi et al. 2011) and statistically downscaled based on the MACA framework (Abatzoglou and Brown 2012). These projections are linked to climate normals defined by the PRISM climate history (Gibson et al. 2002). The 3-PG model is used to simulate the development of a planted loblolly pine stand to age 40 for several origin years for each of the climate futures. Simulations are conducted for each county within a 10-state region of the southeastern United States (Figure 1[4]). The pro-

[2] Hereafter, we use the two-letter U.S. Postal Service state abbreviations for these southern states.

[3] Timber Mart–South, Warnell School of Forestry and Natural Resources, University of Georgia, Athens, available at http://www.timbermart-south.com.

[4] Abbreviations and their corresponding states are AL (Alabama), AR (Arkansas), FL (Florida), GA (Georgia), LA (Louisiana), MS (Mississippi), NC (North Carolina), SC (South Carolina), TX (Texas), and VA (Virginia).

Figure 1
Parameter Estimates for Geometric Brownian Motion of Harvestable Volume (Age 30) by State and Reference Year



jected yield at harvest age 30 for each state is reported in Table 2.

The dataset is organized as a multidimensional matrix of total aboveground biomass quantities $Q(a,y,m,l)$, where Q is measured as green tons per hectare, a indexes age from 2 to 40, y indexes origin (planting) year from 1990 to 2030 on a five-year increment, m indexes the GCM, and l indexes location as county FIPS code for the study region.[5] Expected change in harvest yield for reference year y^* is defined as $Q(30,y^*+5,m,l)-Q(30,y^*,m,l)$. Changes in aboveground biomass are converted to growing stock inventory (green tons per acre) using conversion factors, and product distribution at age 30 is defined as the proportional distribution of growing stock across products defined by the SiMS growth and yield model.

Table 2
Projected Harvest Yield (Green Tons per Hectare) at Age 30 by State and Reference Year

	Reference Year				
	2020	2030	2040	2050	2060
AL	205.50	210.18	215.07	219.34	223.58
AR	199.89	204.12	208.34	212.46	216.27
FL	217.13	222.40	226.88	231.90	235.45
GA	191.55	197.40	202.89	207.44	210.90
LA	207.90	212.47	216.84	220.94	224.59
MS	205.32	210.36	214.94	219.15	223.69
NC	204.98	210.21	216.29	221.98	228.24
SC	195.46	201.73	207.53	212.01	216.69
TX	193.38	199.06	202.15	207.57	211.10
VA	196.00	203.76	210.15	215.97	222.88
Average	201.71	207.17	212.11	216.88	221.34

Note: Abbreviations and their corresponding states are AL (Alabama), AR (Arkansas), FL (Florida), GA (Georgia), LA (Louisiana), MS (Mississippi), NC (North Carolina), SC (South Carolina), TX (Texas), and VA (Virginia).

Other Economic Variables

Similar economic assumptions as provided by Mei and Clutter (2015) are used in this study. Investment cost I includes purchase of 6 acres of land ($600/acre), purchase of standing inventory, and regeneration cost ($180/acre) on 1 acre. Variable cost includes administrative

[5] FIPS stands for Federal Information Processing Standard.

Table 3

Values of Key Economic Variables for the Multiaged Pine Forest by State and Reference Year

	AL	AR	FL	GA	LA	MS	NC	SC	TX	VA
Reference 2020										
I	1,979	1,758	2,591	2,010	2,087	1,805	1,953	2,013	1,797	2,063
C	18	17	19	22	18	18	17	18	19	19
E	–660	–586	–864	–670	–696	–602	–651	–671	–599	–688
α_R	–0.0069	–0.0073	–0.0025	0.0000	–0.0076	–0.0055	0.0008	–0.0027	–0.0045	0.0065
σ_R	0.1445	0.1549	0.1163	0.1584	0.1184	0.1656	0.1103	0.1036	0.1702	0.1230
Reference 2030										
I	2,026	1,798	2,651	2,064	2,133	1,845	2,004	2,070	1,836	2,132
C	18	17	19	22	18	18	17	18	19	19
E	–675	–599	–884	–688	–711	–615	–668	–690	–612	–711
α_R	–0.0068	–0.0069	–0.0022	–0.0001	–0.0075	–0.0055	0.0008	–0.0028	–0.0041	0.0058
σ_R	0.1445	0.1549	0.1163	0.1580	0.1184	0.1656	0.1103	0.1032	0.1697	0.1222
Reference 2040										
I	2,070	1,836	2,707	2,118	2,174	1,881	2,053	2,127	1,875	2,197
C	18	17	19	22	18	18	17	18	19	19
E	–690	–612	–902	–706	–725	–627	–684	–709	–625	–732
α_R	–0.0067	–0.0070	–0.0022	–0.0002	–0.0078	–0.0057	0.0005	–0.0033	–0.0047	0.0050
σ_R	0.1445	0.1549	0.1163	0.1577	0.1186	0.1655	0.1105	0.1031	0.1695	0.1219
Reference 2050										
I	2,102	1,858	2,754	2,160	2,201	1,907	2,100	2,173	1,905	2,254
C	18	17	19	22	18	18	17	18	19	19
E	–701	–619	–918	–720	–734	–636	–700	–724	–635	–751
α_R	–0.0072	–0.0075	–0.0024	–0.0006	–0.0080	–0.0061	0.0005	–0.0034	–0.0047	0.0049
σ_R	0.1445	0.1550	0.1163	0.1576	0.1186	0.1656	0.1104	0.1030	0.1692	0.1219
Reference 2060										
I	2,138	1,890	2,787	2,195	2,238	1,941	2,152	2,220	1,936	2,320
C	18	17	19	22	18	18	17	18	19	19
E	–713	–630	–929	–732	–746	–647	–717	–740	–645	–773
α_R	–0.0071	–0.0072	–0.0029	–0.0012	–0.0079	–0.0058	0.0007	–0.0038	–0.0047	0.0049
σ_R	0.1447	0.1551	0.1164	0.1576	0.1188	0.1657	0.1101	0.1031	0.1692	0.1219

Note: Investment cost I, variable cost C, and abandonment cost E are in 2017 constant dollars per acre for the six-age-class, regulated pine forest. α_R and σ_R are drift and volatility parameters of timber revenue. Real discount rate r = *4% across all states.* Abbreviations and their corresponding states are AL (Alabama), AR (Arkansas), FL (Florida), GA (Georgia), LA (Louisiana), MS (Mississippi), NC (North Carolina), SC (South Carolina), TX (Texas), and VA (Virginia).

and management cost ($10/acre) and property tax that varies by state (Izlar and Li 2017). Abandoning cost is assumed to be $-0.33I$, implying a positive salvage value net of other liquidation costs. Real discount rate is 4% across all states. Values of these key variables by state are reported in Table 3.

4. Results

Key Parameter Estimates

Estimates of GBM parameters for prices in the 10 southern states are reported in Table 1. The magnitudes of the drift parameters imply that all states, except for VA, exhibit slightly declining trends of timber prices. In particular, timber prices in AL, AR, and LA decline more rapidly. According to the estimates of volatility parameters, timber prices in AR, GA, and MS exhibit higher variations. Projected average harvest yields (green tons per hectare) at age 30 by state and reference year are reported in Table 2. Regardless of the state, there is a monotonic increasing trend of yield over time. Across states, FL has consistently higher yield than other states.

Estimates of the drift and volatility parameters for net yield (age 30) models by state and by reference year are displayed in Figure 1. The drift parameters, which approximate the average proportional growth increment, are positive across all states and reference years with a slight downward trend over time for most states, indicating an upward drift in anticipated net yields at age 30 through 2060. Drift values range from 0.0015 to 0.0043. While most states cluster around 0.0025, VA, the northern-most state, has substantially higher drift values. TX and LA, the western-most states have the lowest drift values. Sigma values range from 0.010 to 0.035 and follow no clear geographic pattern. Highest values for sigma are found for TX and NC, while the lowest values are found for AL, AR, and MS.

Estimated values of other key economic variables are reported in Table 3. Acquisition cost is rising monotonically with time primarily because of higher growth and yield for all age classes, which implies higher inventory values. Similarly, acquisition cost is highest in FL and lowest in AR because of the difference in growth and yield and timber demand. Variations in variable cost result primarily from differences in property tax, and GA has the highest. Abandonment cost changes the same way as acquisition cost because it is assumed to be one-third of acquisition cost. Drift and volatility parameters of timber revenue are dominated by the impact of those of timber price. NC and VA have positive drift estimates, but all others have negative drift estimates. In terms of volatility, TX has the highest while NC has the lowest.

Entry and Exit Thresholds

From the static net present value (NPV) analysis of a numerical example in GA, the respective revenue thresholds for the multiaged forest with reference year 2020 are \$103/acre and \$49/acre. Considering both financial and biophysical uncertainty in timber revenue, a forest investor requires a premium to trigger a new investment, and an existing forest owner is more reluctant to exit. That is, the entry threshold becomes higher and the exit threshold becomes lower. In the numerical example above, the respective revenue thresholds incorporating uncertainty become \$173/acre and \$30/acre. Using the average stumpage price in the last five years, annual harvest generates a revenue of \$2,799, or \$467/acre, from the multiaged forest with the same reference year. The average annual equivalent value (AEV) of \$86/acre falls between the entry and exit thresholds of both the static NPV and the real options analyses. Coupling the Monte Carlo simulations for yields with the GBM model for timber prices, we generate multiple realizations of AEV in GA for the 2020 reference year (Figure 2[6]). About 97% of AEV realizations for GA are between exit and entry thresholds, indicating an optimal "hold" strategy. About 3% of realizations exceed the entry threshold, while less than 1% fall below the exit threshold, indicating the potential for a very slight upward trend in timberland investments. Our major conclusions remain the same with respect to other states and reference years, with net entry shares ranging from 0% to 2%.

Figure 2
Simulated Annual Equivalent Values (AEVs) of Timber Revenue for Georgia over Five Years with Reference Year 2020

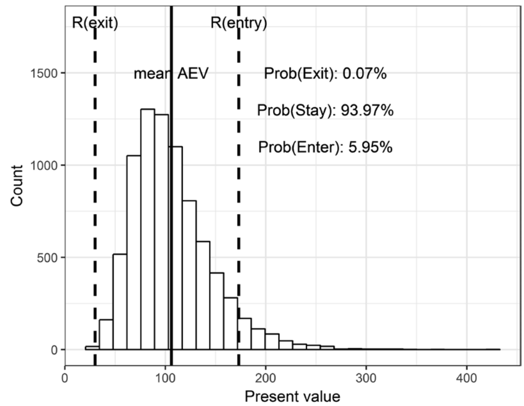


Table 4 summarizes the results by state and by reference year. Similar to GA, AEVs in other regions fall between the two thresholds by both static NPV and real options analyses. Therefore, given current market conditions, it

[6] R(exit) and R(entry) indicate exit and entry thresholds for AEV, and Prob(·) values summarize the displayed distribution.

Table 4
Entry and Exit Revenue Thresholds for a Multiaged Pine Forest Investment by State and Reference Year

	AL	AR	FL	GA	LA	MS	NC	SC	TX	VA
Reference 2020										
AEV	85	75	115	86	91	76	85	87	86	86
Static Entry	97	87	123	103	101	90	95	99	91	101
Static Exit	44	40	54	49	46	42	43	45	43	46
R_H	167	154	187	173	162	163	138	145	164	146
R_L	30	27	37	30	33	27	30	33	26	28
Reference 2030										
AEV	87	76	118	89	93	78	88	89	88	90
Static Entry	99	89	125	105	103	92	97	101	92	104
Static Exit	45	41	54	50	46	43	44	46	43	47
R_H	170	157	190	177	165	166	141	148	166	150
R_L	30	27	38	31	34	27	30	34	27	29
Reference 2040										
AEV	89	78	120	91	95	80	90	92	90	92
Static Entry	101	90	127	107	105	93	99	103	94	106
Static Exit	46	41	55	50	47	43	45	47	44	48
R_H	173	160	193	181	168	169	144	152	169	154
R_L	31	27	38	31	34	27	31	34	27	30
Reference 2050										
AEV	91	79	123	93	97	81	92	94	92	95
Static Entry	102	91	129	109	106	95	101	105	95	109
Static Exit	46	42	56	51	47	44	45	47	44	49
R_H	176	162	197	184	171	171	147	155	172	158
R_L	31	27	39	31	35	28	31	35	27	31
Reference 2060										
AEV	93	81	125	95	98	83	95	96	93	98
Static Entry	104	92	131	110	107	96	103	107	96	111
Static Exit	47	42	56	51	48	44	46	48	44	50
R_H	178	164	200	187	173	173	150	158	174	162
R_L	31	28	39	32	35	28	31	35	28	31

Note: Annual equivalent value (AEV) is value of timber revenue every five years. Static entry and exit revenue thresholds corresponding to the NPV analysis are $C+rI$ and $C-rE$, where C is the variable production cost, r is the real discount rate, I is the investment cost, and E is the abandonment cost. R_H and R_L are entry and exit revenue thresholds from the real options analysis. All values are in 2017 constant dollars per acre. Abbreviations and their corresponding states are AL (Alabama), AR (Arkansas), FL (Florida), GA (Georgia), LA (Louisiana), MS (Mississippi), NC (North Carolina), SC (South Carolina), TX (Texas), and VA (Virginia).

is not rational to make new timberland investments in the South, and existing timberland investors should hold their properties to explore other managerial options such as temporary suspension of active timber management.

Sensitivity Analysis

Our approach provides a compact representation of the biomass dynamics simulated by the 3-PG model in response to variable climate realizations described by the collection of GCM outputs, as well as changes in disturbance frequencies attributable to climate changes (e.g., wildfire and pest outbreaks). It therefore captures a portion of extant uncertainty regarding future biomass realizations. Other components would include emissions levels, and unaddressed model error components (e.g., parameter uncertainty) in both GCM and 3-PG models. That is, if we assume that estimates of drift are unbiased, we should expect the estimates of variance to be downward biased, but to an unknown extent. In addition,

Table 5
Sensitivity Analysis

No.	Variable	Description	Base Value	New Value	P_H	P_L
1	Base case				173	30
2	Price only				176	31
3	Δr	Discount rate	0.04	0.05	198	35
4	$\Delta\alpha_P$	Price drift	–0.0027	0	170	29
5	$\Delta\sigma_P$	Price volatility	0.1567	0.2	196	27
6	$\Delta\alpha_V$	Yield drift	0.0027	0.01	164	28
7	$\Delta\sigma_V$	Yield volatility	0.0232	0.04	175	30
8	$\Delta\rho$	Correlation	0	0.2	175	29
9	I	Investment cost ($/acre)	2,010	1,800	158	30
10	C	Variable cost ($/acre)	22	15	162	25
11	E	Abandonment cost ($/acre)	–670	–500	175	26

Note: All values are in real terms. R_H and R_L are entry and exit thresholds (2017 constant dollars per acre) from the real options analysis. Analysis based on investment in GA (Georgia) with reference year 2020.

it is well known that the stochastic behavior of timber price is time dependent. For decision-making, assumptions should be forward rather than backward looking. Accordingly, we conduct sensitivity analysis to explore the impact of these key assumptions on optimal decisions (Table 5). We use GA as our case study, but similar results can be generalized for other states.

First, we totally separate the impact of yield uncertainty by simply considering price risk. This reduces both drift and volatility of timber revenue, and the net effect is higher entry and exit revenue thresholds. Then, we change values of the key variables one at a time and examine the impact. An increase in real discount rate decreases the present value of the investment cost of the investment timing option and thus discourages an early exercise. So the entry revenue threshold goes up. Similarly, an increase in real discount rate decreases the present value of the guaranteed payoff of the abandonment option and thus encourages an early exercise.[7] So the exit revenue threshold also goes up.

An increase in timber price drift rate leads to an increase in the timber revenue drift rate, which makes investment more likely (lower entry revenue threshold) and abandonment less likely (lower exit revenue threshold). An increase in timber price volatility results in an increase in timber revenue volatility. Therefore, both investment and abandonment become less likely. Increases in yield drift rate and volatility have the same impact as increases in those of timber price. An increase in correlation between timber price and yield increases both drift rate and volatility of timber revenue.[8] The net impact is trivial.

A lower investment cost implies a higher NPV and makes an investment more likely. So the entry revenue threshold goes down. A lower variable cost means a higher profit, and hence, both entry and exit revenue thresholds decrease. An increase in abandonment cost implies a lower salvage value, which makes the investment opportunity less appealing. Thus, the entry revenue threshold rises. Moreover, a lower salvage value makes the exercise of the abandonment option less likely, leading to a lower exit revenue threshold.

5. Discussion and Conclusion

Using TMS timber price data and 3-PG models with Monte Carlo simulations, we incorporate both financial and biophysical risk in GBMs under the real options framework and examine the optimal entry and exit opportunities of timberland investment in 10 southern states in the United States. Our results show that it is generally not economical to make

[7] Abandonment is a put option with the net salvage value being the exercise price.

[8] Trees know nothing about timber prices, but timber prices can send signals to forest landowners on what and how to produce. Thus, a moderate positive correlation between price and yield is reasonable.

new timberland investments in the South and that current forest landowners should hold and explore other managerial options. In the 10 southern states, the majority of current annual timber revenue expectations fall between the entry and exit thresholds. However, "entry" outcomes slightly exceed "exit" outcomes across AEV realizations, indicating a potential for 0% to 2% annual increases in timberland investments despite a downward drift in prices. These findings are consistent with inventory change data for the Southeast (see Appendix), where planted pine area increased by 169,100 ha yr^{-1} (1.1%) between 2007 and 2012, and by 133,500 ha yr^{-1} (0.8%) between 2012 and 2017 (Oswalt, Miles, et al. 2017; Oswalt, Smith, et al. 2014; Smith et al. 2009).

Optimal timberland entry and exit decisions remain invariant with respect to reference years despite the impact of climate change. This is because the impact on growth and yield has been absorbed in both cost and revenues of timberland investments. Within the same reference year, however, there are considerable variations in investment cost, operation cost, and timber revenue across states. For instance, FL has the highest timber revenue potential with relatively low volatility while being the most expensive place to invest. In addition, our analysis does not account for simultaneous changes in returns to other competing land uses that would ultimately influence adoption of timberland investments and switching among land uses. This remains an important area for additional research.

Our analysis indicates that both market risk and climate-driven biophysical risk influence the viability of forest investments in the southeastern United States. Our focus on loblolly pine forests in the Southeast allowed us to utilize extensive price records, forest inventory data, and detailed forest growth for a globally significant production area to develop our methods. Investments in this region benefit from relatively stable forest area combined with stable markets and governance and relatively moderate climate change risks to forests, when compared with other regions (Payn et al. 2015). Projections based on our analysis indicate continued stability to slight growth in planted pine production given current expectations regarding prices and climate change. While the projected increases are small (up to 2% per annum) they are not inconsequential (expansion of up to 10% over a five-year period). In contrast, running these models without climate-driven changes in yields leads to no increase in planted pine area in the Southeast.

Extension of this analysis to other regions of the world could be challenged by data limitations. We anticipate that combinations of market and biophysical risks may be more influential on future investments in regions where climate impacts are more severe. For example, commercially significant planted eucalyptus are expected to experience declines in productivity due to temperature increases, range shifts, and increases in catastrophic disturbances in Oceania, with important consequences for forest viability and investment returns (Binkley et al. 2017; Payn et al. 2015; Shabani, Kumar, and Ahmadi 2017).

Our methods would benefit from linkages between disturbance risk probabilities and the outputs of GCMs that would allow for connecting each yield projection with a disturbance regime, that is, information on the correlation of yields and disturbance frequencies. A next step in the analysis would be to examine investment in a land use choice/switching context that would account for climate change influences on the yields expected from alternative land uses.

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