INVESTIGATING GAPS AND OPPORTUNITIES IN TIMBERLAND INVESTMENTS IN THE US SOUTH: SPATIAL PRICE TRANSMISSION, RETURNS AND RISKS, AND PORTFOLIO OPTIMIZATION

by

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(Under the Direction of Bruno Kanieski da Silva)

ABSTRACT

The US South hosts the world's largest forestry sector, characterized by a complex interplay between private corporate and noncorporate landowners and wood-consuming mills. Despite its importance, research gaps remain in areas like spatial price transmission, returns and risk assessment, and portfolio optimization. In Chapter 2, I used copula-based and smooth transition autoregressive models to explore spatial price transmission of sawtimber stumpage prices across 11 timber markets, including the state of Georgia and its neighbors. In Chapter 3, I used a strategic landscape planning model and a stochastic simulation process for assessing returns and risks on 15-year timberland investments. I complemented the literature by including current market trends, such as small-scale land selling for HBU, formal lease contracts, and call option contracts for solar developments. Finally, I applied modern portfolio theory to optimize timberland investment portfolios in the US South. In Chapter 4, I used returns and risks in a mean-variance model and estimated optimized portfolios across different risk budgets. Results from this study can help financial decision-making and enhance portfolio management strategies for investors and portfolio managers navigating timberland complexities and new market trends.

INDEX WORDS: price transmission, stochastic simulation, risk assessment, portfolio theory.

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CHAPTER 1

GENERAL INTRODUCTION

The US South is home to one of the largest forest sectors in the world. Unlike other regions, timber supply is decentralized across thousands of landowners. For these landowners, land costs and the biological growth are determining factors in the success of their investments. However, after managing their forests for decades, they expect to sell the timber at the best possible price, while buyers are constantly seeking to supply their mills at the lowest price. This fascinating and complex dynamic is known as the law of supply and demand and will determine timber prices.

In this thesis, I sought to better understand how this dynamic can affect the success of timberland investments in the US South. In Chapter 2, I assessed the spatial price transmission of sawtimber stumpage prices in south Georgia, one of the most competitive markets in the US South, and 10 adjacent markets in Alabama, Florida, North Carolina, South Carolina, and Tennessee using two novel approaches, smooth transition autoregressive and copula-based models.

In Chapter 3, I estimated potential returns in 15-year timberland investments. I designed a strategic landscape planning model and simulated returns in four different scenarios. These scenarios included land sales for HBU, leases and option contracts for solar developments on a small scale (up to 5% of the investment area). These new land returns have become popular in the last couple years across the US South. Small landowners and industries are converting their timberland and hosting new solar power plants. On the one hand, they are experiencing higher land returns. On the other hand, this could disrupt timber supply and accelerate the land-use change process.

Finally, in Chapter 4 I estimated timberland portfolios using a mean-variance model. Mean-variance model is a modern portfolio theory tool designed to identify tradeoffs between maximizing expected returns and minimizing risks. This study provides empirical support for landowners and institutional investors in their decision-making process.

CHAPTER 2

UNRAVELING NONLINEAR AND ASYMMETRIC PRICE TRANSMISSION IN US SOUTH TIMBER MARKETS: A COPULA APPROACH[1]

[1]Sanquetta, M. N. I, Kanieski da Silva, B., Kinane, S. M., Bettinger, P., Siry, J. To be submitted to Empirical Economics

Abstract

The US South is arguably home to the largest forest sector in the world, where timber production plays a critical role in supporting the local economy. The timber market in the US South is competitive, driven by the interaction between thousands of landowners and thousands of wood-consuming mills. Many of the landowners are assumed to be either utility or profit maximizers; therefore, price movements could affect their harvest and contractual agreements and, consequently, the dynamics of timber supply and demand across multiple markets. These movements are dictated by multiple external factors, such as microeconomic and macroeconomic conditions, and natural catastrophes. To capture price transmission across different regions in the US South, we applied two novel approaches, smooth transition autoregressive and copula-based models. We used pine sawtimber stumpage prices from the state of Georgia and its adjacent markets in Alabama, Florida, North Carolina, South Carolina, and Tennessee, quarterly from 1976 to 2023. Our findings indicate that logarithmic price ratios in all adjacent markets have a negatively skewed distribution and that all markets are cointegrated with south Georgia. Copula-based models captured nonlinearities in the extreme of joint distributions and tail dependencies. In most of our scenarios, the price transmission occurred when price ratios were between 0.80 and 0.90. Landowners and timberland investors could use this study to strategically plan their financial decisions after-market shocks.

2.1 Introduction

In the United States (US) South, timber prices are established through a complex interaction between wood-consuming mills and landowners (Prestemon and Wear, 2000; Prestemon and Abt, 2002; Wear et al., 2013; Sun, 2016; Klepacka et al., 2017; Regmi et al., 2022). Knowing the behavior and trend of these prices is extremely important for managerial decisions. The expected timber price could lead to a different operational plan, therefore collectively affecting supply curves and procurement costs. When abrupt changes in market conditions occur, the effect on local prices could be transmitted to adjacent markets, changing supply and demand interactions (Bingham et al., 2003). Fluctuations in timber prices and demand can lead to significant variations in profitability for landowners (Amacher et al., 2003). Usually, the profitability of timberland investments is driven by three main drivers: (1) biological growth, (2) land price appreciation, and (3) timber price change (Mei et al., 2010). The contribution of each driver can change depending on market conditions. In the US South, timber price fluctuation can impact profitability from 33% to 40% (Timberland Investment Resources, 2016). Therefore, it is crucial for landowners to understand the spatial relationship between their market and adjacent markets to enhance their decision-making process before, during, and after a market structure shock.

Sources and effects of market shocks can influence timber prices in each market differently. Recent examples of price-increasing shocks include sawmill expansions (Forisk, 2023), and price-decreasing shocks include pulp and paper mill closures (Brandeis and Guo, 2016; Forisk, 2023), as well as public regulations implemented due to COVID-19 (Bruck et al., 2023), the lasting effects of the Great Recession in 2008 (Keegan et al., 2012; Sun and Ning, 2014), and natural catastrophes like hurricanes (Blake et al., 2011; Prestemon and Holmes, 2010). The occurrence of market structure shocks implies an imbalance between timber supply and demand (Prestemon and Holmes, 2000; Kinnucan, 2016; Bruck et al., 2023; Hlaváčková et al., 2024). This imbalance, caused by sudden changes in timber inventory or demand capacity, can result in changes in prices (Prestemon and Holmes, 2010; Bruck et al., 2023), leading wood-consuming mills to react by expanding or reducing their procurement area in adjacent or closely located markets.

Depending on the magnitude of the supply imbalance, the effects on timber prices can last for months or years (Kinnucan, 2016). For example, natural catastrophes such as hurricanes (tropical cyclones) can cause significant impacts on timber markets and prices, especially in the US South (Prestemon and Holmes, 2000; Prestemon and Holmes, 2010; Kinnucan, 2016; Sartorio et al., 2024). The impact of hurricanes on timber prices is evident through varied effects on different timber products. Pulpwood prices often decrease due to elevated costs of salvage logging and temporary oversupply, while sawlog prices may increase because of supply reductions caused by damage within sawlogs (Sun, 2016; Janiskee, 1990; Syme and Saucier, 1992; Prestemon and Holmes, 2000). The tendency is for adjacent markets offering similar products to eventually transact in similar prices for the same product, as stated by the law of one price – LOP (Bingham et al., 2003; Goodwin et al., 2018).

This relationship between prices across multiple locations is known as spatial price transmission or horizontal price transmission (Meyer and von Cramon-Taubadel, 2004). Although the relationship between sawtimber prices has been investigated in the past (*e.g.*, Hood and Dorfmann, 2015; Gan et al., 2022), studies on spatial price transmission were typically limited to linear methods, which assume linear and static relationships (Daníelsson et al., 2013). These linear methods may not adequately capture the dynamics of complex markets, such as those found in the

US South, for several reasons. First, they assume constant relationships over time, ignoring how market conditions can change due to external factors like economic shocks or policy changes (von Cramon-Taubadel and Goodwin, 2021). Second, linear models might miss critical price adjustments that occur during extreme market conditions due to their simplification (Meyer and von Cramon-Taubadel, 2004). Lastly, these approaches often overlook asymmetrical responses to price changes, for which transmission differs according to whether prices are increasing or decreasing (Meyer and von Cramon-Taubadel, 2004), which can lead to inaccurate estimations of how prices transmit across different markets (Vavra and Goodwin, 2005).

With this context, this study aims to assess the spatial price transmission of sawtimber stumpage prices in south Geogia, one of the most competitive markets in the US South. The state of Georgia contains the largest amount of privately-owned timberland (22 million acres of commercial timberland) in the US and produces the highest annual harvest volume (Georgia Forestry Commission, 2023). More specifically, south Georgia contains the largest privately-owned timberland area (16.23%) and market values across 22 regions in the US South, and 30.3% of the available corporate private timberland as of 2019 (Zhang and Mei, 2019). Hence, these events highlight the importance of understanding how prices in one market respond to regional supply shocks. By identifying relationships and how prices are spatially transmitted across adjacent markets, landowners and investors can mitigate risks and make informed decisions when managing their assets. To complement a linear model, we use two nonlinear approaches: smooth transition autoregressive (STAR) and copula-based models. Our models use sawtimber stumpage prices from eleven timber markets, with south Georgia (GA-02, Figure 2.1) as the reference market, and compared our results with the traditional error correction model. The results provide empirical support for the cointegration of these markets but also highlight the importance of nonlinearities in the price adjustment process.

2.2 Literature review

Spatial price transmission refers to the process by which price movements in one market are transmitted to prices in geographically separated markets (McNew, 1996; von Cramon-Taubadel and Goodwin, 2021). This phenomenon can occur due to the efforts of market players to capitalize on arbitrage opportunities with risk-free profits (Ganneval, 2016). The foundational concept underlying spatial price transmission is the LOP, which asserts that in efficient markets, identical goods have identical prices, adjusted only for transaction costs related to spatial trade (Fackler and Goodwin, 2001). If prices deviate beyond these transaction costs, it can lead to inefficiencies and distortions in decision-making by producers and consumers, ultimately impacting overall economic well-being (Cudjoe et al., 2010). Understanding spatial price transmission is particularly crucial in the context of timberland investments, as timber prices can be influenced by market structure shocks and the interrelationships between different regional markets can significantly affect investment strategies and outcomes.

Several methodologies based on cointegration have been used to evaluate market integration and price transmission in agricultural, financial, and timber markets (Frey and Manera, 2007; Ning and Sun, 2014). Early studies addressed price transmission between markets based on simple correlation statistics, ordinary least squares regressions, and linear error correction models (Sun and Ning, 2014; Goodwin et al., 2018). More recently, the literature shifted to nonlinear models capable of empirically representing regime switches (Ihle et al., 2009; Ganneval, 2016; Holt and Teräsvirta, 2020). Often this regime-switching and mean-shifting behavior reflects the influences of unobserved transactions or processing costs, which have been represented through the application of various econometric specifications and techniques such as smooth transition autoregressive (STAR) (Goodwin et al., 2011; Silva et al., 2020), and discrete threshold error correction models (Goodwin and Harper, 2000). Nonlinear models have been applied in different areas of economic research to capture the price relationship between markets, such as agriculture (Balagtas and Holt, 2009; Ubilava, 2022; Emediegwu and Rogna, 2024), finance (Lamont and Thaler, 2003; Chevillon and Hendry, 2005; Teräsvirta et al., 2010), and forest products (Goodwin et al., 2018).

Forest economists have examined the cointegration across different timber products (Ning and Sun, 2014; Parajuli et al., 2016; Gan et al., 2022). Most of these studies found that the prices of the main products, such as pulpwood, chip-n-saw, and sawtimber, are cointegrated (Nagubadi et al., 2001; Tang and Laaksonen-Craig, 2007; Shahi and Kant, 2009; Gan et al., 2022). For example, the cointegration between softwood stumpage and lumber prices in the US South is reported to be weak (Zhou and Buongiorno, 2005), while hardwood sawtimber and lumber are found to be closely correlated (Luppold et al., 1998). However, despite some research on the spatial relationship between timber markets (Buongiorno and Uusivuori, 1992; Bingham et al., 2003; Silva et al., 2019), there is a lack of literature on the use of nonlinear models in the US South. Nonlinear models can capture regime shifting, and asymmetric adjustments that cannot be captured by linear models. Regime shifting is a process in which cointegration changes at some time during the sample period, while asymmetric adjustments reflect different price reactions to upstream or downstream price changes. Silva et al. (2019) investigated the impact of wood pellet mills on the pulpwood price structure in the US South using a STAR model. Similarly, Hood and Dorfman (2015) modified a time-varying smooth transition autoregressive model (TV-STAR) to examine timber market linkages in the US South. The use of nonlinear approaches, such as STAR, allows for more flexibility in determining market linkages. Smooth transition autoregressive models allow for the possibility of gradual adjustments between price linkages and structural changes through the embedded transition function (Hood and Dorfman, 2015), showing how market dynamics change over time (Silva et al., 2019).

Goodwin et al. (2018) first introduced the use of copula-based models to assess the spatial price transmission of forest products. Although copula models have been extensively used in financial economics and risk management studies (Patton, 2012; MacKenzie and Spears, 2014; Smith, 2023), they have not been applied in modeling nonlinear, spatial arbitrage relationships (Goodwin et al., 2018). A copula is a joint cumulative distribution that can describe the dependence structure between two or more variables. The formal definition states that a copula is a multivariate cumulative distribution function (CDF) that captures the dependence between variables while maintaining their individual marginal distributions (Sklar, 1959). Copulas allow for varying degrees of tail dependence and thus can capture patterns of adjustment that may arise when price differentials are extreme (Dewick and Liu, 2022). Tail dependence indicates that markets are linked to each other under extreme market conditions. The dependence on the tails of a distribution is particularly important when studying spatial price linkage, especially how extreme price movements in one market may lead to extreme movements in another (Goodwin et al., 2011).

Outcomes from smooth or discrete regime-switching models, such as the STAR model, often used in spatial arbitrage studies (Hamulczuk, 2020), suggest that large price differentials, which indicate significant deviations from equilibrium, should result in faster adjustment rates to restore market equilibrium (Goodwin et al., 2018; Ubilava, 2022). This dependence on large price differentials reflects unobservable transaction costs. Small differentials, within transaction costs, do not lead to profitable arbitrage, while large differentials, exceeding transaction costs, are quickly eliminated through arbitrage. Copula models are well-suited for analyzing tail behavior as they offer flexible characterizations of tail dependence. Hence, this paper aims to complement the existing literature on the spatial price transmission of sawtimber stumpage prices in the US South using two nonlinear approaches: STAR and copula-based models.

2.3 Microeconomic foundation

The cointegration of prices in different markets means price variations in one market will lead to price variations in another market, indicating price linkage and market dependence (Fackler and Goodwin, 2001). These authors defined cointegration as "a measure of the degree to which demand and supply shocks arising in one region are transmitted to another region." Consider the one good being traded in two markets *A* and *B* with individual prices being represented by p_t^A and p_t^B at some time index *T*. Price transmission between these markets can be mathematically defined as the log price differential $y = [ln(p_t^A) - ln(p_t^B)]$, as in Goodwin et al. (2018) or equivalently by the logarithmic price ratio $y = \left[ln\left(p_t^A / p_t^B\right)\right]$.

Considering a homogeneous commodity traded on two markets (*A* and *B*) at some time index *t* with their respective logarithmic prices represented by $ln(p_t^A)$ and $ln(p_t^B)$ and the transaction cost per unit being $k(0 \leq k \leq 1)$, we have a simple model of the LOP that incorporates the effects of transaction costs as:

$$-\ln(1-k) \geq ln(p_t^A) - ln(p_t^B) \geq ln(1-k) \qquad (2.1)$$

Which is equivalent to*:*

$$-ln(1-k) \geq y = \left[ln\left(p_t^A / p_t^B\right)\right] \geq ln(1-k) \qquad (2.2)$$

In the context of spatial price transmission, Eqs. 2.1 and 2.2 establish a band around zero defined by the transaction costs, within which arbitrage is not profitable (Balke and Fomby, 1997). When price differentials fall outside this band, arbitrage opportunities emerge, prompting market adjustments that bring the price differences back within the band and restore equilibrium.

2.4 Data description

We analyzed the spatial linkage of sawtimber stumpage prices series in ten different markets distributed across six states of the US South (Alabama, Florida, Georgia, North Carolina, South Carolina, and Tennessee) (Table 2.1 and Figure 2.1). Sawtimber is the most valuable among the main forest products in the US South: pulpwood, chip-n-saw, and sawtimber. The spatial linkage of these markets was assessed with respect to the largest regional market (GA-02). All stumpage prices are expressed in US dollars per ton and were observed on a quarterly basis from 1976 (4th quarter) to 2023 (3rd quarter), totaling 187 observations per market (Figure 2.2).

Table 2.1. Summary of 11 TimberMart-South markets that neighbors the state of Georgia.

State	TMS Market	Number of Counties	Area of institutional timberland (hectares)[1]	Relative area (%)
Alabama (AL)	AL-01	41	418,1712	11.65
	AL-02	26	618,981	17.24
Florida (FL)	FL-01	28	345,585	9.63
	FL-02	18	236,498	6.59
Georgia (GA)	GA-01	52	112,117	3.12
	GA-02	107	1,088,565	30.32
North Carolina (NC)	NC-01	40	19,088	0.53
	NC-02	60	624,500	17.40
South Carolina (SC)	SC-01	9	579	0.02
	SC-02	37	41,695	1.16
Tennessee (TN)	TN-01	44	83,882	2.34
		Total	**3,589,662**	**100**

Source: [1]Zhang and Mei (2019).

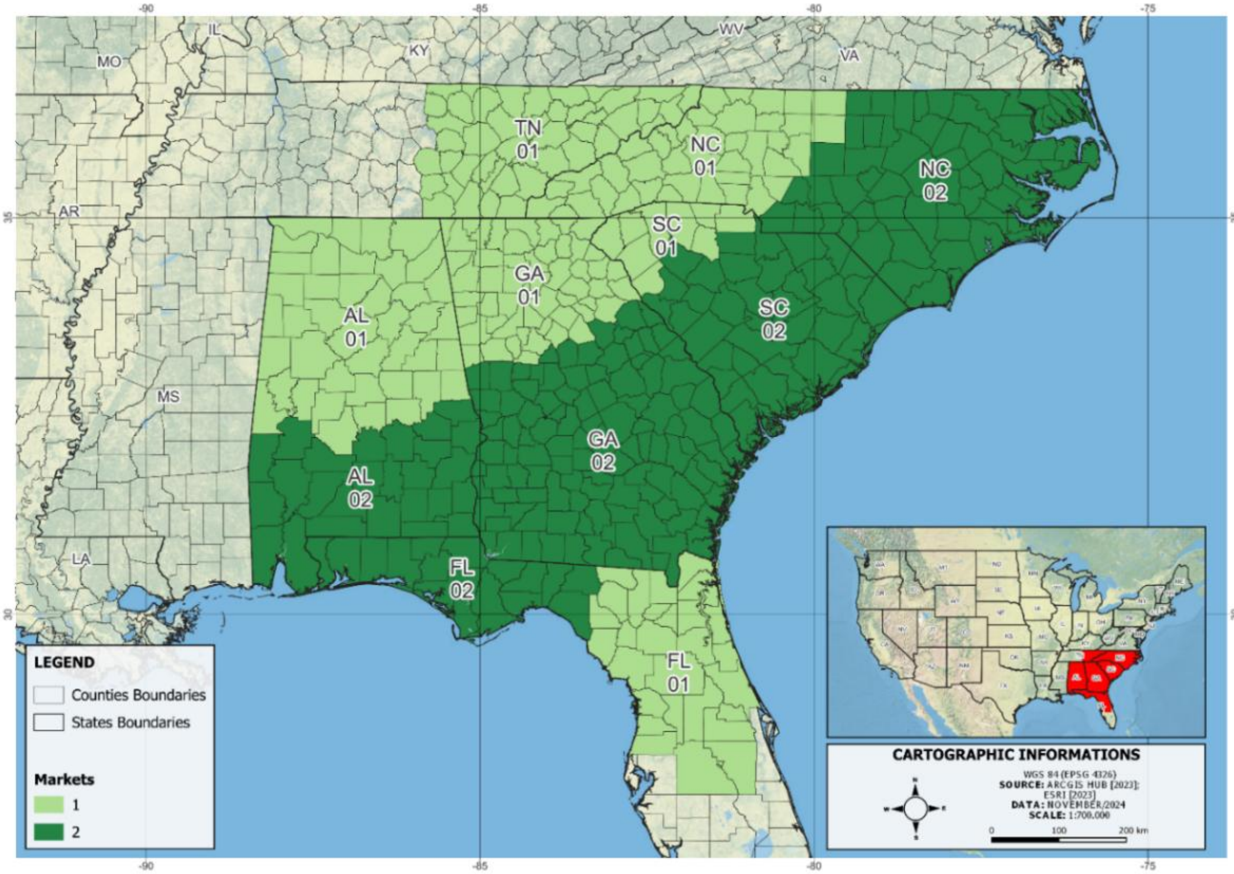

Figure 2.1. Map of TimberMart-South markets that neighbors the state of Georgia.

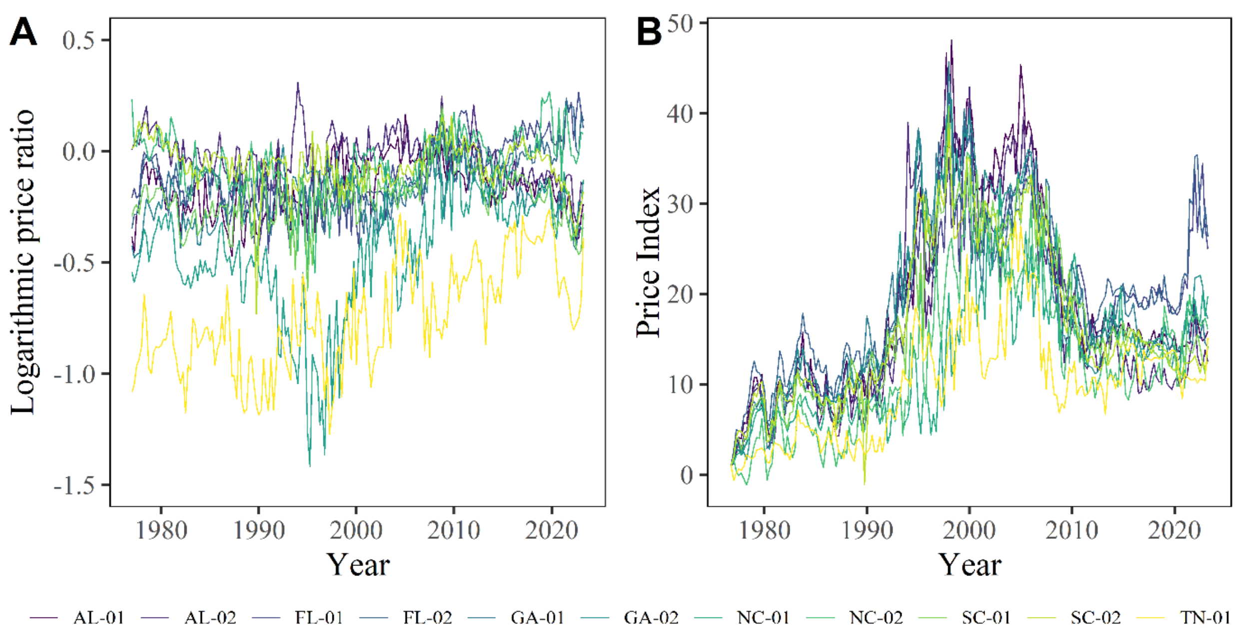

Figure 2.2. Sawtimber stumpage price index in the US South. Source: TimberMart-South.

2.5 Econometrics

Spatial market linkages are based on simultaneous movements that two or more prices can possibly take in the short-term (Silva et al., 2020). In the long-term, however, market and economic forces prevent them from moving too far apart (Fackler and Goodwin, 2001). These cointegration tests are typically based on a linear combination of two or more series. Two individual time series may be non-stationary, but their linear combination may be stationary (Engle and Granger, 1987). In this case, the time series are considered cointegrated. The stationary linear combination is called a cointegrated equation and can be interpreted as a long-run equilibrium relationship between the variables (Yin et al., 2002). To investigate the price linkage between US South timber markets, we used a linear Error Correction Model (ECM) as a benchmark to compare both the Logistic (LSTAR) and Exponential (ESTAR) Smooth Transition Autoregressive models (Teräsvirta, 1994; Silva et al., 2020), and copula-based models (Goodwin et al., 2018).

The basic unit of analysis was the logarithmic price ratio. We used south Georgia (GA-02), following the TimberMart-South classification as the reference market *A*. The logarithmic price ratio between the candidate markets and GA-02 was mathematically described as:

$$y_t^i = ln\left({p_t^i}/{p_t^A}\right) \tag{2.3}$$

where *i* indicates the i^{th} market (*e.g.*, AL-01), *A* indicates GA-02, *t* is a time index (quarterly) such that $t \in \{1,2,\dots,T\}$, where T = 187, and y_t^i is the logarithmic price ratio between the i^{th}-market and *A* (GA-02).

After assessing the stationarity of the logarithmic price ratio, we calculated the first-differenced logarithmic price ratio. The first-differenced logarithmic price ratio (Δy_t) was defined as the difference between the logarithmic price ratio at time *t* and the logarithmic price ratio at time *t*-1:

$$\Delta y_t^i = ln\left({p_t^i}/{p_t^A}\right) - \; ln\left({p_{t-1}^i}/{p_{t-1}^A}\right) \tag{2.4}$$

where i indicates the i^{th} market (*e.g.*, AL-01), A indicates GA-02, t is a time index such that t = 1, … T, where T = 186, Δy_t^i is the first-differenced logarithmic price ratio between the i^{th} market and A (GA-02).

2.5.1 Error Correction Model (ECM)

We used the Augmented Dickey-Fuller (ADF) to test unity root of the logarithmic price ratio.

$$\Delta y_t^i = \alpha_0 + \sum_{p=1}^{P} \delta_p \Delta y_{t-p}^i + \beta y_{t-1}^i + \varepsilon_t \tag{2.5}$$

where δ_p and β are the parameters, p is the optimal lag defined by the lowest Akaike and Bayesian information criteria (AIC and BIC) values, and all other variables are previously defined.

The null hypothesis of the ADF test posits that the logarithmic price ratio possesses a unit root, suggesting non-stationarity and a random walk behavior (Dickey and Fuller, 1979). Formally, if β = 0, y_t^i is non-stationary, indicating that the i^{th}-market and market A are not cointegrated. Conversely, if β < 0, it implies that y_t^i is stationary, suggesting that any deviations from the long-term equilibrium between the i^{th}-market and market A are temporary and the two markets are cointegrated. In other words, the ADF test is equivalent to a test that β = (0, 1) is a cointegrating vector in the log-linear price relationship $ln(p_t^A) - \beta_0 - \beta_1 ln(p_t^i)$, as similarly employed in Goodwin et al. (2011) and Hood and Dorfman (2015).

2.5.2 Smooth Transition Autoregressive Model (STAR)

Eq. 2.5 assumes that transaction costs are constant and proportional to commodity prices, which oversimplifies the reality of discontinuous trade and nonlinear price adjustments (Dumas,1992; Baulch, 1997). In addition, Eq. 2.5 fails to capture the variability in relative price relationships, which might have periods with strong cointegrations and others that there is no linkage between them at all (Silva et al., 2020). To address these limitations, we expanded the ECM specification from Eq. 2.5 to a STAR model, as outlined in Eq. 2.6. The STAR model allows for regime shifts between stationary (regime 1) and non-stationary (regime 2) states, providing a more accurate representation of the complex dynamics in spatial price transmission. Empirical studies on spatial price transmission recognize the presence of transaction costs. Despite being difficult to measure, these costs are fundamental in any spatial price transmission because they can result in nonlinearities. By expanding the ECM to a STAR model, we account for the impact of transaction costs and capture the emergence of arbitrage opportunities that could otherwise be masked.

$$\Delta y_t^i = \underbrace{\left(\alpha'_0 + \sum_{p=1}^{P} \delta'_p \Delta y_{t-p}^i\right)}_{regime\ 1} + \underbrace{\left(\alpha_0 + \sum_{p=1}^{P} \delta_p \Delta y_{t-p}^i\right)}_{regime\ 2} G(s_t, y(\eta), c) + \varepsilon_t \tag{2.6}$$

where $G(s_t, y(\eta), c)$ is the transition function and value ranges from 0 to 1, s_t is the transition variable that determines the threshold for regime shifting, $y(\eta)$ is the speed in which the relative prices switch between regimes, the higher the value the faster is the change between regimes, and all other variables are as previously defined. Because γ must be positive, we opted to transform $y(\eta) = -exp(-\eta)$, thus ensuring positive values without imposing further constraints in the model (Goodwin et al., 2011), c is the threshold value and ε_t is the error term.

The representation of $G(s_t; y(\eta), c)$ is whether a logistic - LSTAR (Eq. 2.7) or exponential - ESTAR (Eq. 2.8) function as defined:

$$G(s_t; y(\eta), c) = \left[1 + exp\left(\frac{-y(\eta)(s_t - c)}{\sigma_{st}^2}\right)\right]^{-1} \tag{2.7}$$

$$G(s_t; y(\eta), c) = 1 - exp\left(-\frac{y(\eta)(s_t - c)^2}{\sigma_{st}^2}\right) \tag{2.8}$$

After defining the transition function $G(s_t; y(\eta), c)$, we specify the transition variable s_t as the four quarter moving average of the first-differenced logarithmic price ratio (Δy_t). The rationale for four quarters is that the movement between regimes should be affected by a shock to change price ratios within a year. Hence, the moving average encompasses 12 months.

$$s_t = \frac{1}{4}\sum_{n}^{N=4} \Delta y_t \tag{2.9}$$

In the following sections, however, s_t is represented in its exponential value (e^{s_t}), reflecting the non-logarithmic price ratio. The selection between the logistic (LSTAR) and exponential (ESTAR) functions was based on the lowest Akaike and Bayesian information criteria (AIC and BIC).

5.3 Copula-based Models

Copulas are functions that can describe the dependence between two or more random variables (Patton, 2012). In other words, copulas are joint cumulative density functions that connect the marginal distributions of the individual random variables. Copula-based models considered the joint distribution functions of $F\left(y_t^i, y_{t-1}^i\right)$ and, alternatively, $F\left(\Delta y_t^i, y_{t-1}^i\right)$. According to Sklar's Theorem (1959), any continuous p-variate cumulative probability function F can be represented using the marginals and a unique copula function $C(.)$, for which:

$$F(y_1, y_2 \dots y_n) = C\{[F(y_1), F(y_2) \dots F(y_n)]; \phi\} \tag{2.10}$$

where F_i (.) are the marginal distributions uniformly distributed on the interval (0,1), y_n are the dependent variables, and ϕ are the set of parameters that characterize dependence. Copula models are capable of tying together marginal probability functions that may be related.

There are several copulas and copulas families that have been described in the literature. In this study, we evaluated the two most used copula families, Elliptical forms and Archimedean (Schepsmeier, 2015). We tested five different copulas, including two Elliptical forms (Gaussian and *t*-Student) and three Archimedean (Gumbel, Clayton, and Frank). Elliptical form copulas have the property of symmetry and have identical tail dependencies in extremes of the distribution. The Gaussian copula is the most similar to linear models (Goodwin et al., 2018). It is symmetric and allows for no dependence on both tails. The *t*-Student copula allows for positive and symmetric tail dependencies. In contrast, Archimedean copulas are asymmetric and single parameter (Rodrigues et al., 2023). The Gumbel copula allows for upper tail dependence, while the Clayton copula allows for lower tail dependence. The Frank copula allows no tail dependence. The coefficients of upper tail dependence (λ_U) and lower tail dependence (λ_L) of each copula studied here are defined and expressed in Table 2.2. We selected the copula formulation that presented the lowest BIC among the five candidate copula models.

Table 2.2. Copula models description and mathematical formulation.

Copula	Form	Lower tail	Upper tail	Mathematical formulation
Gaussian	Ellip.	0	0	$C(y_t, y_{t-1}) = \phi_\rho[\phi^{-1}(y_t), \phi^{-1}(y_{t-1})]$ or $C(\Delta y_t, y_{t-1}) = \phi_\rho[\phi^{-1}(\Delta y_t), \phi^{-1}(y_{t-1})]$
T		$\lambda_L = 2t_{v+1}(-\sqrt{\frac{v+1}{1-p}}$	$\lambda_U = 2t_{v+1}(-\sqrt{\frac{v+1}{1-p}}$	$C(y_t, y_{t-1}) = t_{v,\rho}[t_v^{-1}(y_t), t_v^{-1}(y_{t-1})]$ or $C(\Delta y_t, y_{t-1}) = t_{v,\rho}[t_v^{-1}(\Delta y_t), t_v^{-1}(y_{t-1})]$
Gumbel	Arch.	0	$\lambda_U = 2 - 2^{\frac{1}{\theta}}$	$C(y_t, y_{t-1}) = \{[-\ln (y_t)]^\theta + [-\ln (y_{t-1})]^\theta\}^{\frac{1}{\theta}}$ or $C(\Delta y_t, y_{t-1}) = \{[-\ln (\Delta y_t)]^\theta + [-\ln (y_{t-1})]^\theta\}^{\frac{1}{\theta}}$
Clayton		$\lambda_L = 2^{\frac{-1}{\theta}}$	0	$C(y_t, y_{t-1}) = \left(y_t{}^{-\theta} + y_{t-1}^{-\theta}\right)^{\frac{-1}{\theta}}$ or $C(\Delta y_t, y_{t-1}) = \left(y_t{}^{-\theta} + y_{t-1}^{-\theta}\right)^{\frac{-1}{\theta}}$
Frank		0	0	$C(y_t, y_{t-1}) = -\frac{1}{\theta}\ln\left\{1 + \frac{[(e^{(-\theta y_t)-1})][e^{(-\theta y_{t-1})-1}]}{e^{(-\theta)-1}}\right\}$ or $C(\Delta y_t, y_{t-1}) = -\frac{1}{\theta}\ln\left\{1 + \frac{[(e^{(-\theta \Delta y_t)-1})][e^{(-\theta y_{t-1})-1}]}{e^{(-\theta)-1}}\right\}$

Where Ellip. means Elliptical copulas, Arch. means Archimedean copulas, ϕ_p is the cumulative distribution function (CDF) of the bivariate normal distribution with correlation coefficient ρ, ϕ^{-1} is the inverse of the CDF of the standard normal distribution, $t_{v\rho}$ is the bivariate cumulative distribution function of the *t*-Student with v degrees of freedom and correlation coefficient ρ, t^{-1} is the inverse of the CDF of the *t*-Student with v degrees of freedom. Sources: Bouyé et al. (2000) and Roncalli (2020).

2.6 Empirical results

We assessed the spatial price transmission of sawtimber stumpage prices of ten markets relative to the largest regional market (GA-02) in the US South. We used logarithmic price ratios of these ten market trades to investigate their linkage with the reference market using smooth transition autoregressive and copula-based models. In the next topics, we present the results from (2.6.1) nonparametric densities, (2.6.2) error correction model, (2.6.3) smooth transition autoregressive (2.6.3), and (2.6.4) copula-based models.

2.6.1 Nonparametric densities

Figures 2.3 and 2.4 illustrate nonparametric densities for price ratios $\left({p_t^i}/{p_t^A}\right)$ and first-differenced logarithmic price ratios (Δy_t) for all ten market trades. The average price ratio was always smaller than 1, regardless of the market trade. We observed a negative definite pattern of basis for price ratios (y_t) of the smallest regional markets (FL-02, GA-01, NC-01, SC-01, and TN-01). This pattern suggests that the prices on these markets are consistently lower compared to those on the reference market. The average price ratio was closer to 1 on regional markets with a relative acreage close to or higher than 10% (AL-01, AL-02, FL-01, and NC-02).

The average Δy_t values ranged from -0.0010 (AL-02) to 0.0033 (FL-02), as observed in Figure 2.4. These values represent the relative differences between the two consecutive periods. Small values imply limited frictions in price adjustments, supporting the notion of cointegration in market trades with low transaction costs and with free movement of goods between them (Meyer and von Cramon-Taubadel, 2004). A random distribution around 0 suggests random price fluctuations. The negative skewness, however, indicates that the largest price differences are generally negative and more common in one direction (Goodwin et al., 2021).

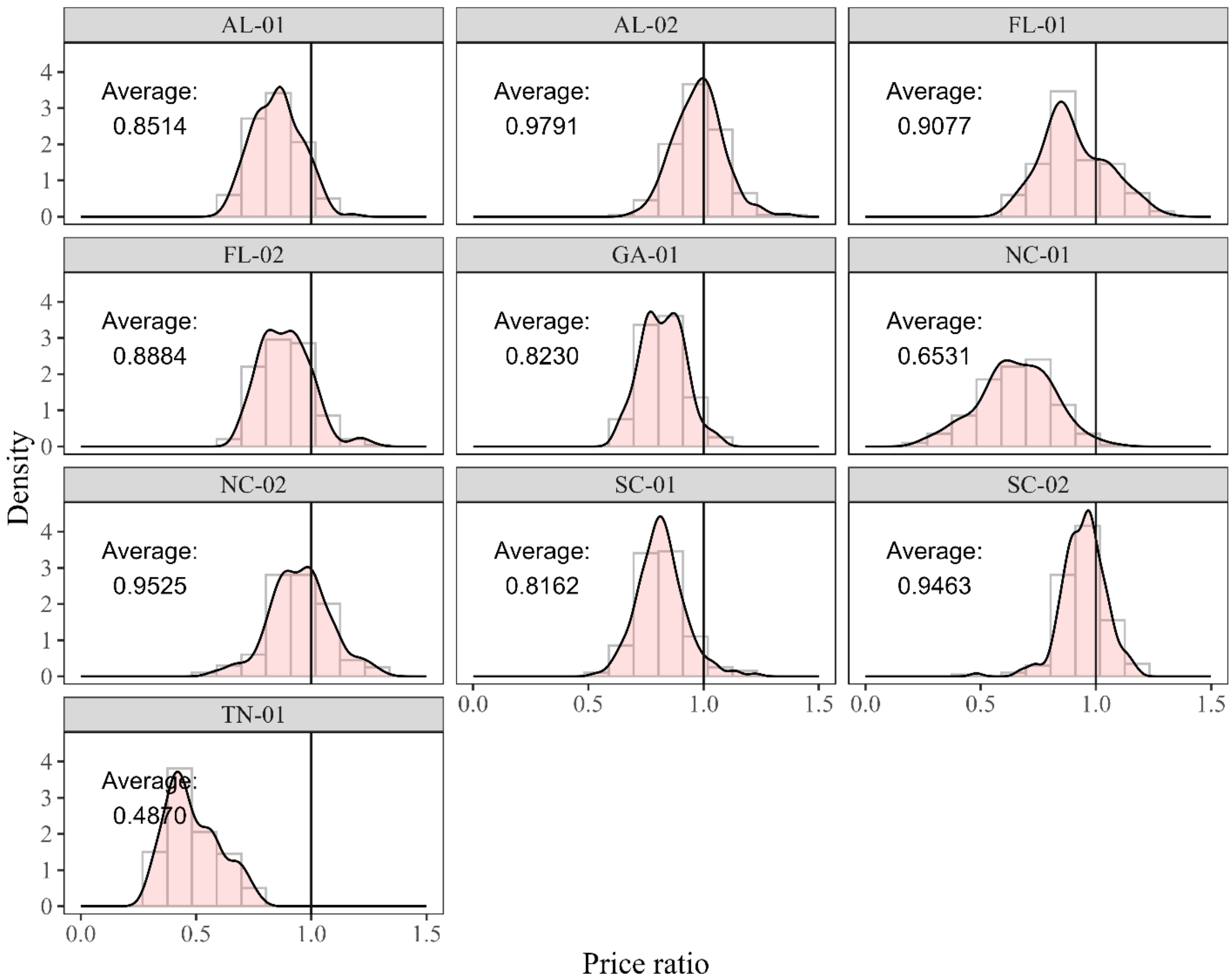

Figure 2.3. Histograms of quarterly price ratios $\left(p_t^i / p_t^A\right)$ of pine sawtimber stumpage for different market trades with respect to GA-02.

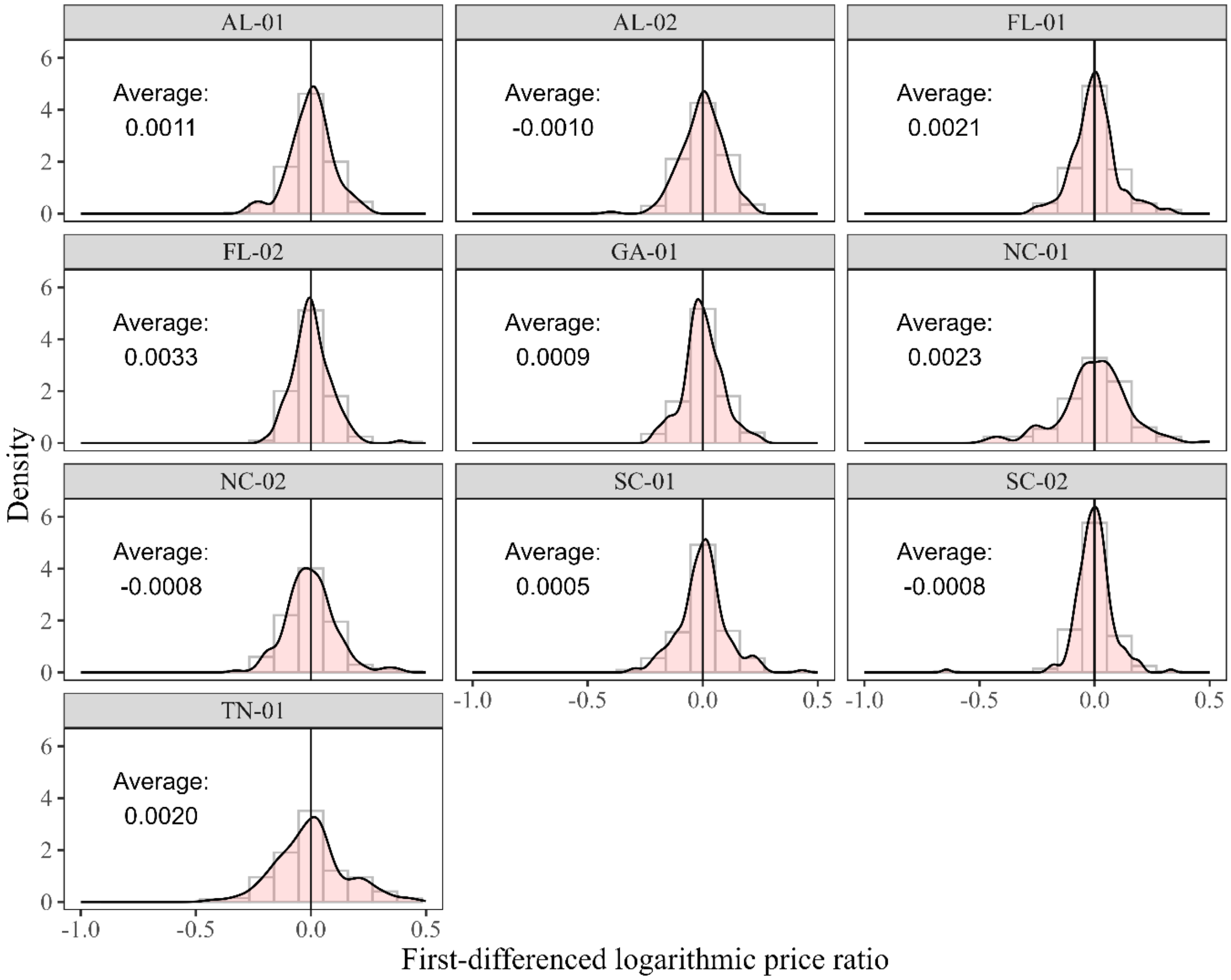

Figure 2.4. Histograms of quarterly first-differenced logarithmic price ratios (Δy_t^i) of pine sawtimber stumpage for different market trades with respect to GA-02.

2.6.2 Error Correction Model (ECM)

We first assessed the relationship between the first-differenced logarithmic price ratio (Δy_t) and its lagged values (Δy_{t-p}) using a linear Error Correction Model (Eq. 2.5). The time series properties were also evaluated using the Augmented Dickey-Fuller (ADF) test. In every case, the ECM presented negative $\hat{\beta}$ values (Table 2.3), rejecting the null hypothesis with 95% confidence and suggesting that the price ratios are stationary and deviations from the mean are temporary.

This suggests that if the price ratio between the two markets diverges from its equilibrium value, market forces act to correct this divergence, restoring the equilibrium relationship. The ADF test statistics were lower than the critical values at 1% (rejecting the non-stationary hypothesis) and the selected lag was one across all market pairs.

Table 2.3. ECM model statistics for quarterly first-differenced logarithmic price ratios.

Market	$\hat{\alpha}$	$\hat{\beta}$	Statistic
AL-01	-0.0431 (0.0115)	-0.2607 (0.0583)	-4.4717
AL-02	-0.0093 (0.0064)	-0.3045 (0.0626)	-4.8606
FL-01	-0.0117 (0.0084)	-0.1312 (0.0459)	-2.8591
FL-02	-0.0213 (0.0087)	-0.1881 (0.0516)	-3.6427
GA-01	-0.0508 (0.0126)	-0.2637 (0.0570)	-4.6227
NC-01	-0.0532 (0.0218)	-0.1191 (0.0410)	-2.9077
NC-02	-0.0130 (0.0079)	-0.2062 (0.0547)	-3.7715
SC-01	-0.0540 (0.0145)	-0.2532 (0.0612)	-4.1400
SC-02	-0.0197 (0.0069)	-0.2857 (0.0604)	-4.7335
TN-01	-0.1175 (0.0362)	-0.1600 (0.0465)	-3.4399

Note: values in parentheses are standard deviations. Lag 1 was consistently selected for all markets based on AIC and BIC. The null hypothesis (H_0) was always rejected at 5% significance.

2.6.3 Smooth Transition Autoregressive Model (STAR)

The logistic specification (LSTAR) presented better-fitting statistics for all market trades, especially when comparing the goodness-of-fit statistics (AIC and BIC). The final model estimation and their respective coefficients are presented in Table 2.4. Figure 2.5 illustrates the transition function $G(.)$ over time and against the exponential of the transition variable s_t. $G(.)$ describes how the transition between regimes (*e.g.*, from non-stationarity to stationarity) evolves over time and it depends on the transition variable s_t. The rationale of presenting e^{s_t} instead of s_t is the practical considerations in model interpretation; the exponential representation of s_t provides a direct view of actual price ratios between markets.

Our results indicated that the transition between regimes was fast for most market trades, as indicated by the steep line between *G*(.) = 0 and *G*(.) = 1. The change from one regime to another was indicated by the smoothness coefficient (γ) that ranged from -1.40 (NC-01) to -5.40 (AL-02, FL-01, and SC-02). In general, the threshold parameter (*c*) ranged from -0.33 (NC-01) to -0.11 (NC-02), except for AL-02 (-0.98) and TN-01 (-0.85). All market trades presented similar behavior as their transition variable (s_t) changes (Figure 2.5). Most regime shifting from *G*(.) = 0 to *G*(.) = 1 happened when e^{s_t} was around 0.8 to 0.9 (AL-01 – 0.84, AL-02 – 0.91, FL-02 – 0.85, GA-01 – 0.91, NC-01 – 0.90, NC-02 – 0.76, SC-01 – 0.87, SC-02 – 0.82), except for FL-01 (1.08) and TN-01 (0.43), indicating that when the prices in the candidate markets are around 10 to 20% lower than the reference market, market prices are nearing a critical threshold where regime shifting is likely, triggering a transition from a non-stationary to stationary regimes. In other words, this indicates that upon reaching this critical threshold, market forces like supply-demand adjustments quickly act to restore price equilibrium.

Slower transitions were observed in GA-01 and NC-01, as reinforced by lower γ values (Table 2.4). The threshold coefficient (*c*) ranged from -0.98 to 0.21, with higher values for FL-01 (0.21), NC-02 (-0.11), AL-01 (-0.17), FL-02 (-0.17), and GA-01 (-0.17). The lowest values were observed for AL-02 (-0.98) and TN-01 (-0.85). Negative *c* values indicate that regime changes are triggered by relatively smaller deviations in the price ratio. Alternatively, positive *c* values indicate that a larger deviation in the price ratio is required to trigger a regime shift. Nevertheless, all candidate markets were cointegrated with the reference market, as indicated by the statistically significant coefficients.

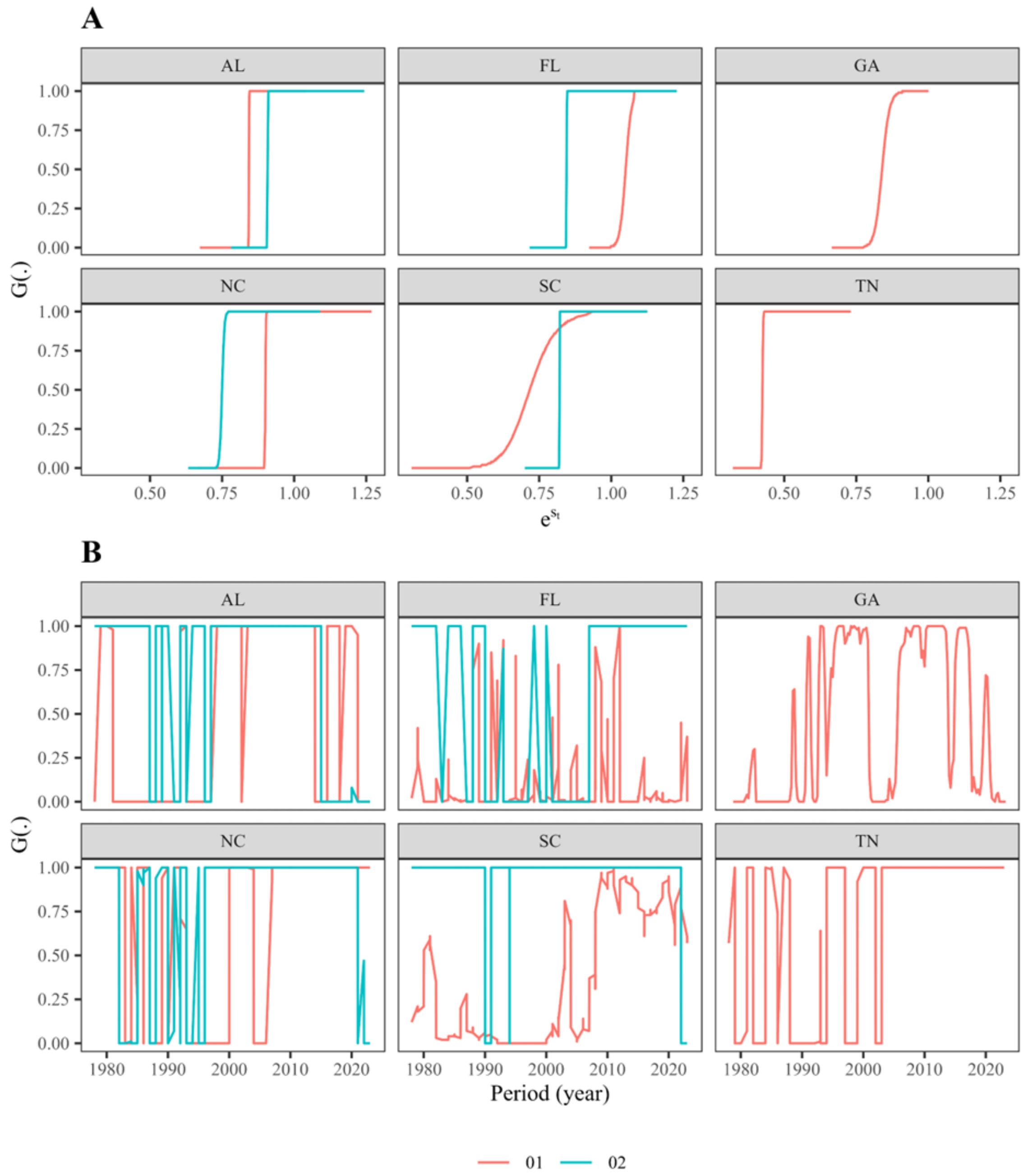

Figure 2.5. Spatial price transmission between pine sawtimber stumpage prices for different market trades with respect to GA-02. (A) show the transition function *G*(.) versus the respective transition variable (s_t), while (B) have the transition function *G*(.) over time (1977 to 2023).

Table 2.4. STAR model estimates for the first-differenced logarithmic price ratio of pine sawtimber stumpage prices for different market trades in the US South.

Trade	AL-01/ GA-02	AL-02/ GA-02	FL-01/ GA-02	FL-02/ GA-02	GA-01/ GA-02	NC-01/ GA-02	NC-02/ GA-02	SC-01/ GA-02	SC-02/ GA-02	TN-01/ GA-02
Regime 1										
y_{t-1}	-0.38 (0.08)	-0.36 (0.99)	-0.21 (0.00)	-0.39 (0.11)	-0.23 (0.08)	-0.41 (0.07)	-0.54 (0.09)	-0.34 (0.25)	-0.32 (0.27)	-0.17 (0.10)
y_{t-2}	-0.42 (0.07)	-	-0.133 (0.06)	-0.37 (0.10)	-	-0.47 (0.07)	-0.49 (0.08)	-0.15 (0.15)	-	-
y_{t-3}	-	-	-	-0.23 (0.08)	-	-0.09 (0.06)	-	-0.64 (0.22)	-	-
Transition										
Γ	-5.30 (0.00)	-5.40 (0.00)	-5.40 (0.00)	-5.30 (0.00)	-1.80 (0.00)	-1.40 (0.00)	-4.90 (0.00)	-3.00 (0.00)	-5.40 (0.00)	-4.40 (0.00)
C	-0.17 (0.00)	-0.98 (0.00)	0.21 (0.00)	-0.17 (0.00)	-0.17 (0.01)	-0.33 (0.04)	-0.11 (0.00)	-0.29 (0.03)	-0.20 (0.00)	-0.85 (0.00)
Regime 2										
Intercept	-0.04 (0.00)	0.02 (0.01)	0.24 (0.03)	-0.01 (0.01)	-0.09 (0.01)	-0.19 (0.05)	0.01 (0.01)	-0.05 (0.01)	-0.01 (0.01)	-0.18 (0.03)
y_{t-1}	-0.16 (0.08)	-0.04 (0.07)	-0.24 (0.03)	-0.22 (0.07)	-0.05 (0.08)	0.07 (0.20)	-0.31 (0.07)	-0.30 (0.07)	-0.17 (0.06)	-0.25 (0.06)
y_{t-2}	-0.23 (0.07)	-	-0.23 (0.08)	-0.15 (0.07)	-	0.24 (0.19)	-0.07 (0.07)	-0.09 (0.09)	-	-
y_{t-3}	-	-	-	-0.05 (0.07)	-	-0.14 (0.12)	-	-0.03 (0.07)	-	-
x_{t-1}	-0.54 (0.08)	-0.53 (0.06)	-0.84 (0.12)	-0.32 (0.06)	-0.89 (0.01)	-0.90 (0.26)	-0.41 (0.07)	-0.36 (0.06)	-0.36 (0.05)	-0.30 (0.05)
BIC	-356.004	-361.701	-358.229	-387.856	-399.934	-169.172	-315.248	-318.166	-368.183	-173.774
AIC	-383.625	-383.358	-385.851	-421.336	-421.591	-202.653	-342.869	-351.647	-389.840	-195.431
RSS	1.105	1.134	1.091	0.873	0.916	2.961	1.388	1.288	1.094	3.241
SD	0.083	0.079	0.078	0.075	0.082	0.128	0.088	0.085	0.078	0.145

Note: values in parentheses are standard deviations for each parameter.

2.6.4 Copula-based models

Table 2.5 presents the parameters, tail dependences, and BIC for the optimal copula specification fitted to $C(y_t^i, y_{t-1}^i)$ and $C(\Delta y_t^i, y_{t-1}^i)$. Marginal distributions of each variable are represented using nonparametric, empirical cumulative density functions (CDFs).

In all cases, the Clayton copula was preferred when comparing BIC values with other copulas. The negative skewness observed in Figures 2.3 and 2.4 reinforces the advantage of the Clayton copula when compared to the other copulas because it was designed to capture asymmetric tail dependencies, particularly strong dependencies in the lower tails. In other words, the Clayton copula can model joint distributions where extremely low values on both y_1 and y_2 are highly correlated. This dependency highlights the importance of tail-specific adjustments. Interpretation of tail dependence in cases where such dependence is only allowed in one tail can be aided by a consideration of the typical basis relationships among markets.

The parameters for $C(y_t^i, y_{t-1}^i)$ in Table 2.5, all positive, ranged from 1.7913 (AL-02) to 3.8901 (NC-01), indicating a moderate to strong dependence on lower tails. In the context of the Clayton copula, these $\hat{\theta}$ values represent the strength of the asymmetric dependence, particularly under extreme low values of y_t^i and y_{t-1}^i. Higher $\hat{\theta}$ values, such as 3.8901 (NC-01), suggest stronger dependence on the lower tails of the joint distributions, implying that when one market experiences significantly low prices, the other is likely to mirror this behavior more closely. Lower $\hat{\theta}$ values, such as 1.7913 (AL-02) still indicate weaker, lower-tail dependence under extreme conditions.

In contrast, $\hat{\theta}$ parameters were all negative for the joint distribution of Δy_t^i and y_{t-1}^i, the negative parameters suggest that extreme deviations tend to occur in opposite directions. For instance, $\hat{\theta}$ = -0.2257 (AL-02) implies a stronger inverse relationship compared to -0.0715 (NC-

01), where the inverse dependence is weaker. These results reflect how markets adjust differently when considering changes versus levels, providing nuanced insights into price dynamics and inter-market linkages. Figures 2.6 and 2.7 present the nonparametric densities for $C\left(y_t^i, y_{t-1}^i\right)$ and $C\left(\Delta y_t^i, y_{t-1}^i\right)$ of all 10 market trade pairs. These densities are represented by the standard normal marginals on both axes to illustrate the dependencies in the joint distributions. The empirical marginals were used to evaluate the price adjustment process (Table 2.5).

Table 2.5. Copula-based model estimates for $C\left(y_t^i, y_{t-1}^i\right)$ of pine sawtimber stumpage prices for different markets (using empirical marginals).

Trade	**Parameter**	**Lower**	**BIC**
AL-01/GA-02	2.2169 (0.216)	0.7315	33.9322
AL-02/GA-02	1.7913 (0.190)	0.6791	31.9886
FL-01/GA-02	3.5274 (0.308)	0.8216	-0.0507
FL-02/GA-02	2.8533 (0.252)	0.7843	22.7542
GA-01/GA-02	2.3283 (0.220)	0.7425	55.0694
NC-01/GA-02	3.8901 (0.320)	0.8368	80.2046
NC-02/GA-02	2.3066 (0.219)	0.7404	44.5999
SC-01/GA-02	1.9470 (0.206)	0.7005	23.8383
SC-02/GA-02	2.3989 (0.223)	0.7490	42.3392
TN-01/GA-02	2.9213 (0.264)	0.7888	26.8825

Note: Clayton copula was selected for all trades based on the lowest BIC.

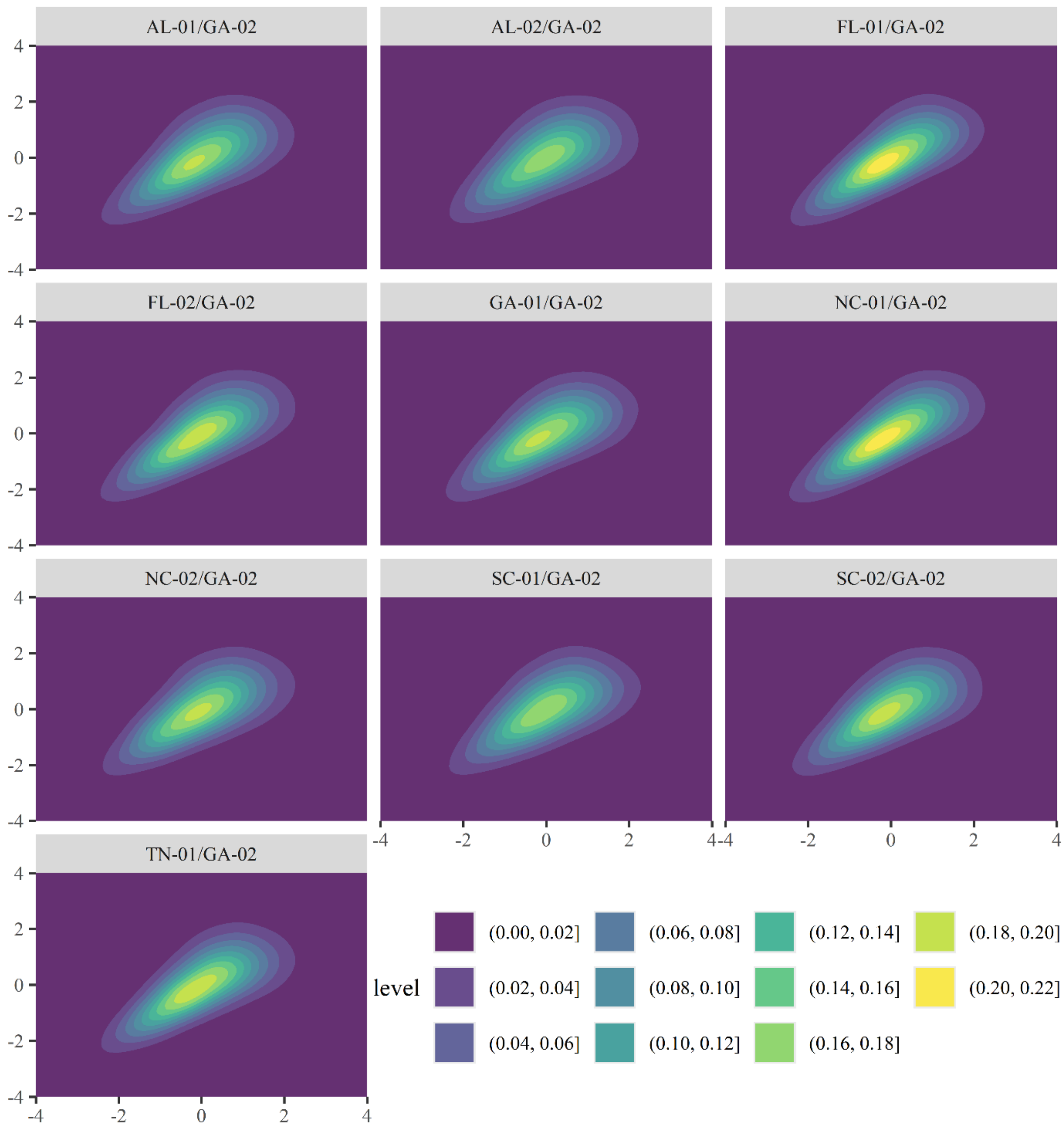

Figure 2.6. Joint probability density function from the estimated optimal copula, simulated using standard normal marginals): $C(y_t^i, y_{t-1}^i)$.

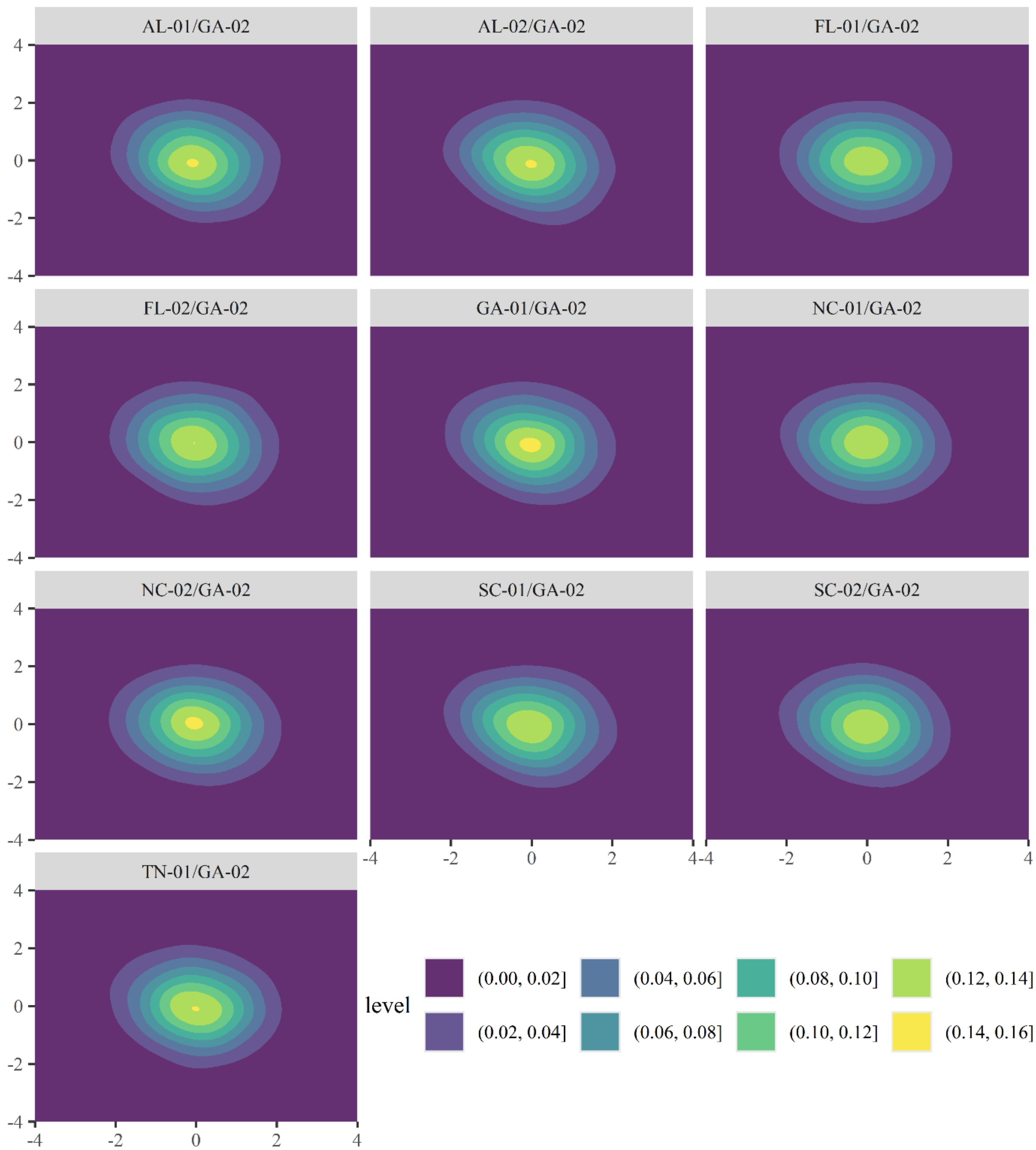

Figure 2.7. Joint probability density function from the estimated optimal copula, simulated using standard normal marginals): $C\left(\Delta y_t^i, y_{t-1}^i\right)$. The tail dependences were reversed by rotating the copulas 180°.

To illustrate how the price adjustment process varies over the quantiles of the marginal distributions, we employed nonparametric density estimates for the marginal distributions and parameters from the estimated copula function. We simulated the joint distribution using nonparametric densities drawn from the univariate values and then estimated a nonparametric inverse CDF. Figure 2.8 displays the relationship between the y_t^i and its lagged values (y_{t-1}^i). In contrast, Figure 2.9 highlights the relationship between the first-differenced logarithmic price ratio (Δy_t^i) and the lagged value of the logarithmic price ratio (y_{t-1}^i). The mean relationship implied is highlighted in blue using splines. The nonlinearities in the error correction price adjustment processes indicate market linkages (Figure 2.8), characterized by nonlinearities. In general, large deviations typically tend to result in stronger adjustment among prices. However, the degree of nonlinearity was more explicit when observing the relationship between the first-differenced logarithmic price ratio (Δy_t^i) and the lagged value of the logarithmic price ratio (y_{t-1}^i), as observed in Figure 2.9.

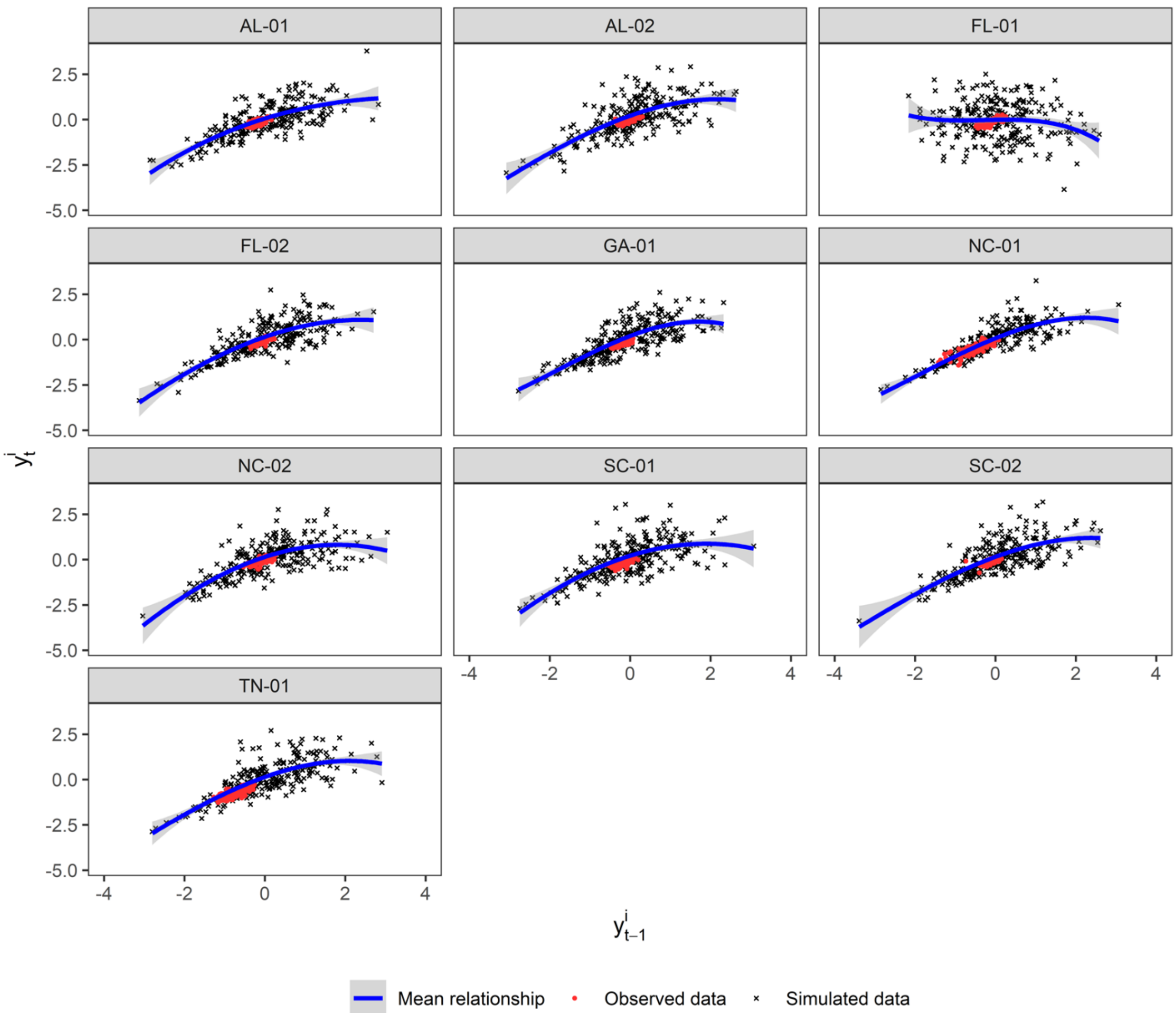

Figure 2.8. Estimated mean relationship (nonparametric marginals) using Clayton copula for $C(y^i_t, y^i_{t-1})$.

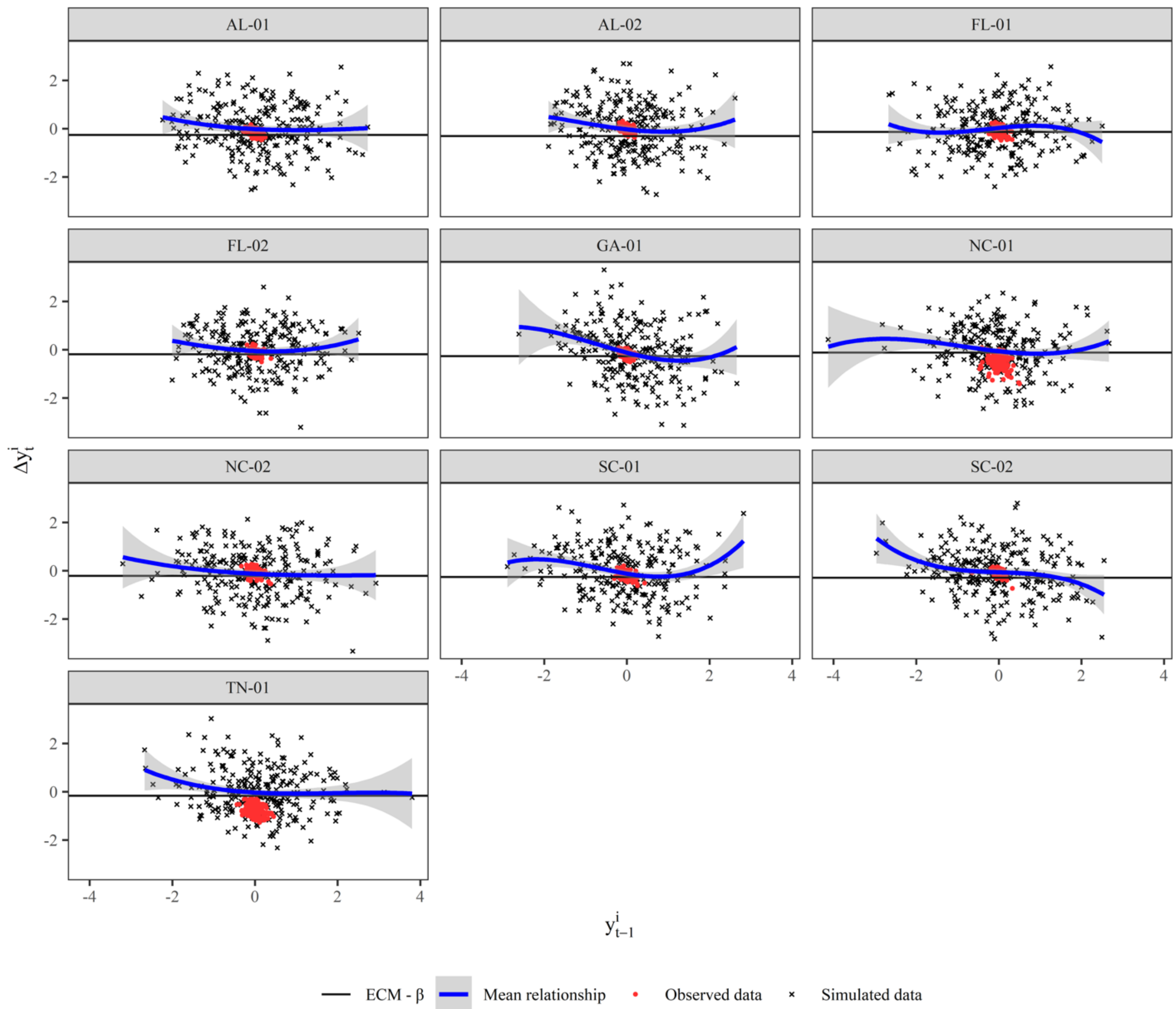

Figure 2.9. Estimated mean relationship (nonparametric marginals) using Clayton copula for $C(\Delta y_t^i, y_{t-1}^i)$.

2.7 Discussion and conclusions

In this paper, we investigated the spatial price transmission of pine sawtimber stumpage prices across the US South with respect to the largest regional market (GA-02). We used two approaches to understand the relationship between sawtimber prices in one of the most competitive markets in the world. Our results indicate that, regardless of the modeling approach, the sawtimber market in south Georgia is cointegrated with all markets analyzed in this study.

The ECM results indicated that the price ratios are stationary and deviations from the means are temporary. In this case, if the price ratio between two markets diverges from its equilibrium value, market forces act to correct this divergence, restoring the equilibrium relationship. The STAR model reinforced the idea of cointegration, showing that when prices in adjacent markets are around 10 to 20% lower than the reference market, prices are nearing a critical threshold where regime shifting is likely, triggering a transition from non-stationary to stationary regimes and restoring equilibrium. Ultimately, the Clayton copula highlighted a moderate to strong dependence on lower tails for of Δy_t^i and y_{t-1}^i. For, Δy_t^i and y_{t-1}^i, the Clayton copula suggested that markets adjust differently, providing nuanced insights into price dynamics and inter-market linkages.

Studies on price transmission have been an important topic in both theoretical and empirical research (Jung and Doroodian, 1994; Goodwin and Holt, 1999; Hänninen et al., 2007; Koutroumanidis et al., 2009; Listorti and Esposti, 2012; Sun and Ning, 2014; Fousekis et al., 2016; Silva et al., 2020; Kinnucan, 2022). In the US South, forest economists have examined price linkage across different products (Yin et al., 2002; Parajuli et al., 2016; Silva et al. 2019) and regions (Mei et al., 2010; Hood and Dorfman, 2015). Bingham et al. (2003) showed that 33-42% of the US South timber markets are cointegrated when using sawlog prices, while 18% to 28% were cointegrated with respect to pulpwood prices. Hood and Dorfman (2015) found that the entire Southeastern US was linked during the 2000's housing bubble. Similarly, Yin et al. (2002) found cointegration between 13 pine sawtimber and 11 pulpwood regional markets. Mei et al. (2010) observed that North Carolina (NC-02) and Georgia coastal plains (GA-02) can drive the prices in other regional and adjacent markets. These authors also noticed that 12 different markets, accounting for 90% of the annual harvested volume, distributed across the states of Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina and Texas should not be considered separate in terms of short-term forecasting.

In this study, we complement the current literature on spatial price transmission in several aspects. First, we found that all 11 price pairs were cointegrated, differing from Yin et al. (2002) who suggested that southern US timber markets are not strongly cointegrated. We also observed that timber prices in all adjacent markets to the state of Georgia, regardless of their size and distance, will respond to movements in the largest regional market (GA-02). When prices in these markets are around 10 to 20% lower than the largest regional market, they reach a critical threshold, and market forces like supply-demand adjustments quickly act to restore price equilibrium. Second, our work reinforces the limitations of Error Correction Models. ECMs assume linear and static relationships (Daníelsson et al., 2013), which may not adequately capture the dynamics of complex markets that include nonlinear behaviors or asymmetric dependencies. Moreover, ECMs are unable to show changing market interactions over time (Hood and Dorfman, 2015), as highlighted by the STAR model in Figure 2.5. Relative prices can have time periods in which there is a strong cointegration and others time periods with no linkage between them at all (Silva et al., 2020). Hence, STAR models were designed to recognize and capture nonlinear relationships and different market dynamics and behaviors that vary over time. These dynamics can depend upon the state of the economy, or they may simply be due to the presence of transaction costs in spatial and temporal arbitrage (Hood and Dorfman, 2015). Models such as the STAR model have gained popularity due to their capacity to capture essential features of complex dynamics and their ability to provide considerable flexibility when assessing horizontal and vertical price transmission (Goodwin et al., 2018; Ubilava, 2022). Several studies have employed STAR models on the prices of forest products (Fan and Wei, 2006; Goodwin et al., 2011, Hood and Dorfman, 2015; Goodwin et al., 2018; Silva et al., 2019). Hood and Dorfman (2015) investigated the cointegration dynamics of sawtimber prices across different markets in the US South using an ECON-STAR model, and found that market regimes vary over time, which is consistent with our results (Figure 2.5). The flexibility of STAR models in adjusting parameters according to the transition variable allowed us to conduct a more detailed analysis of market trade dynamics, providing a better understanding of how timber prices adjust under different market conditions and shocks.

We employed copula-based models when modeling nonlinear, spatial price transmission, as they are extensively applied in financial economics and risk management (Goodwin et al., 2018). These models are particularly effective in modeling tail dependencies, which are crucial for understanding cointegrations in extreme price scenarios and market volatility (Joe et al., 2010). The separation between the modeling of marginal distributions and the dependence structure facilitates a flexible and detailed analysis of price relationships, which is essential for validating the LOP. Our application of copula-based models was tailored to capture differences in patterns of adjustment that may arise when logarithmic price ratios and their first difference are large enough to exceed transaction costs. Copulas models can also capture patterns of adjustment that may arise when price differentials are extreme (Qiu and Goodwin, 2012), expanding previous studies that were limited to threshold effects and regime switching (Rogers, 2014). Our empirical approach involved the use of conventional goodness-of-fit statistics, such as the Bayesian information criterion (BIC) to determine the optimal copula specification for each of the ten market trades. The Clayton copula specification was preferred according to the BIC in all market trades, which agrees with the logarithmic price ratios and its first-difference distributions.

Our study brings together two nonlinear approaches that help explain the cointegration over time and asymmetric dependencies under extreme low values across different markets in the US South. This paper is another contribution of the movement toward increasingly flexible, nonlinear models of price linkages, as stated by Goodwin et al. (2018) that first introduced copula-based models on spatial price transmission analysis for timber products. We found that imbalances in sawtimber prices in the largest regional market can affect prices in all adjacent markets. This information can help landowners and corporate investors to understand the impact of possible market shocks and disturbances (*e.g.*, hurricanes) on timber supply and prices and, ultimately, help forest practitioners to predict price trends.

Despite the findings in this study, further research can overcome the following limitations: 1) while the work focused on two aggregated regional (state) markets, this analysis could be used in large scale models, such as global timber models or across different local markets; and 2) this work was limited to 11 timber markets adjacent to south Georgia (GA-02) yet could be expanded further. While the data employed are representative regional markets, future studies can provide insights into the spatial price transmission over a broader range of markets across the US South. Further, 3) although copula-based models provided a flexible and detailed analysis of price relationships, this study was limited to five single parameter copulas. It is possible that other copula-based models may result in better fitness and thus stronger capabilities to indicate price relationships.

REFERENCES

AMACHER, G.S., CONWAY, M.C., SULLIVAN, J. 2003. Econometric analyses of nonindustrial forests landowners: Is there anything left to study? J. For. Econ. 9(2): 137-164. https://doi.org/10.1078/1104-6899-00028

BALAGTAS, J.V., HOLT, M.T. 2009. The commodity terms of trade, unit roots, and nonlinear alternatives: a smooth transition approach. Am. J. Agric. Econ. 91(1): 87-105. https://doi.org/10.1111/j.1467-8276.2008.01179.x

BALKE, N.S., FOMBY, T.B. 1997. Threshold cointegration. Int. Econ. Rev. 38 (3): 627-645. https://doi.org/10.2307/2527284

BAULCH, B. 1997. Transfer cost, spatial arbitrage, and testing for food market integration. Am. J. Agric. Econ. 79(2): 477-487. https://doi.org/10.2307/1244145

BINGHAM, M.F., PRESTEMON, J.P., MCNAIR, D.J., ABT, R.C. 2003. Market structure in U.S. southern pine roundwood. J. For. Econ. 9(2): 97-117. https://www.sciencedirect.com/science/article/pii/S1104689904700239

BLAKE, E.S., LANDSEA, C.W., GIBNEY, E.J. 2011. The deadliest, costliest, and most intense United States tropical cyclones from 1851 to 2010 (and other frequently requested hurricane facts). National Weather Service, National Hurricane Center, Miami, FL. National Oceanic and Atmospheric Administration Technical Memorandum NWS NHC-6. https://repository.library.noaa.gov/view/noaa/6929

BOUYE, E., DURRLEMAN, V., NIKEGHBALI, A., RIBOULET, G., RONCALLI, T. 2000. Copulas for finance - A reading guide and some applications. https://ssrn.com/abstract=1032533

BRANDEIS, C., GUO, Z. 2016. Decline in the pulp and paper industry: Effects on backward-linked forest industries and local economies. For. Prod. J. 66: 113-118. https://doi.org/10.13073/FPJ-D-14-00106

BRUCK, S.R., PARAJULI, R., CHIZMAR, S., SILLS, E.O. 2023. Impacts of COVID-19 pandemic policies on timber markets in the Southern United States. J. For. Bus. 21(1): 130-167.

BUONGIORNO, J., UUSIVUORI, J. 1992. The Law of One Price in trade of forest products: co-integration tests for US exports of pulp and paper. For. Sci. 38(3): 539-553. https://doi.org/10.1093/forestscience/38.3.539

CHEVILLON, G., HENDRY, D. 2005. Non-parametric direct multi-step estimation for forecasting economic processes. Int. J. Forecast. 21(2): 201-218. https://doi.org/10.1016/j.ijforecast.2004.08.004

CUDJOE, G., BREISINGER, C., DIAO, X. 2010. Local impacts of a global crisis: food price transmission, consumer welfare and poverty in Ghana. Food Policy 35(4): 294-302. https://doi.org/10.1016/j.foodpol.2010.01.004

DANÍELSSON, J., JORGENSEN, B., SAMORODNITSKY, G., SARMA, M., DE VRIES, C. 2013. Fat tails, VaR and subadditivity. J. Econom. 172(2): 283-291. https://doi.org/10.1016/j.jeconom.2012.08.011

DEWICK, P.R., LIU, S. 2022. Copula modelling to analyse financial data. J. Risk Financial Manag. 15(3): 104. https://doi.org/10.3390/jrfm15030104

DICKEY, D.A., FULLER, W.A. 1979. Distribution of estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74(366): 427-431. https://doi.org/10.2307/2286348

DUMAS, B. 1992. Dynamics equilibrium and the real exchange rate in a spatially separated world. Rev. Financ. Stud. 5(2): 153-180. https://doi.org/10.1093/rfs/5.2.153

EMEDIEGWU, L.E., ROGNA, M. 2024. Agricultural commodities' price transmission from international to local markets in developing countries. Food Policy 126: 102652. https://doi.org/10.1016/j.foodpol.2024.102652

ENGLE, R.F., GRANGER, C.W.J. 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 55(2): 251-276. https://doi.org/10.2307/1913236

FACKLER, P.L., GOODWIN, B.K. 2001. Spatial market integration. In Rausser, G., Gardner, B. (eds). Handbook of Agricultural Economics. Amsterdam, NL: Elsevier Publishing, 2001, pp. 971-1024.

FAN, C.S., WEI, X. 2006. The Law of One Price: Evidence from the transitional economy of China. Rev. Econ. Stat. 88(4): 682-697. https://doi.org/10.1162/rest.88.4.682

FORISK. 2023. Mill investments and closures in the US South. https://forisk.com/blog/2023/08/25/mill-investments-and-closures-in-the-u-s-south/

FOUSEKIS, P., EMMANOUILIDES, C., GRIGORIADIS, V. 2016. Price linkages in the international skim milk powder market: empirical evidence from nonparametric and time-varying copulas. Aust. J. Agric. Econ. 61(1): 135-153. https://doi.org/10.1111/1467-8489.12147

FREY, G., MANERA, M. 2007. Econometric models of asymmetric price transmission. J. Econ. Surv. 21(2): 349-415. https://doi.org/10.1111/j.1467-6419.2007.00507

GAN, J., TIAN, N., CHOI, J., PELKKI, M. 2022. Synchronized movement between US lumber futures and southern pine sawtimber prices and COVID-19 impacts. Can. J. For. Res. 52(4): 614-621. https://doi.org/10.1139/cjfr-2021-0326

GANNEVAL, S. 2016. Spatial price transmission on agricultural commodity markets under different volatility regimes. Econ. Model. 52: 173-185. https://doi.org/10.1016/j.econmod.2014.11.027

GEORGIA FORESTRY COMMISSION. 2023. Georgia: The #1 Forestry State in the Nation. https://gfagrow.org/wp-content/uploads/2023/10/2023-Report_1-Forestry-State-in-the-Nation.pdf

GOODWIN, B.K., HARPER, D.C. 2000. Price transmission, threshold behavior, and asymmetric adjustment in the U.S. pork sector. J. Agric. Appl. Econ. 32(3): 543-553. https://doi.org/10.1017/S1074070800020630

GOODWIN, B.K., HOLT, M.T. 1999. Price transmission and asymmetric adjustment in the U.S. beef sector. Am. J. Agric. Econ. 81(3): 630-637. https://doi.org/10.2307/1244026

GOODWIN, B.K., HOLT, M.T., ÖNEL, G., PRESTEMON, J.P. 2018. Copula-based nonlinear modeling of the law of one price for lumber products. Empir. Econ. 54: 1237-1265. https://doi.org/10.1007/s00181-017-1235-4

GOODWIN B.K., HOLT, M.T., PRESTEMON, J.P. 2011. North American oriented strand board markets, arbitrage activity, and market price dynamics: a smooth transition approach. Am. J. Agric. Econ. 93(4) 993-1014. https://doi.org/10.1093/ajae/aar024

GOODWIN, B.K., HOLT, M.T., PRESTEMON, J.P. 2021. Semi-parametric models of spatial market integration. Empir. Econ. 61: 2335-2361. https://doi.org/10.1007/s00181-020-01985-2

HAMULCZUK, M. 2020. Spatial integration of agricultural commodity markets – methodological problems. Probl. Agric. Econ. 2(363): 32-52. https://doi.org/10.30858/zer/120038

HÄNNINEN, R., TOPPINEN, A., TOIVONEN, R. 2007. Transmission of price changes in sawnwood and sawlog markets of the new and old EU member countries. Eur. J. For. Res. 126: 111–120. https://doi.org/10.1007/s10342-006-0135-5

HLAVÁČKOVÁ, P., BANAŚ, J., UTNIK-BANAŚ, K. 2024. Intervention analysis of COVID-19 pandemic impact on timber price in selected markets. For. Policy Econ. 159: 103123. https://doi.org/10.1016/j.forpol.2023.103123

HOLT, M.T., TERÄSVIRTA, T. 2020. Global hemispheric temperatures and co-shifting: A vector shifting-mean autoregressive analysis. J. Econom. 214(1): 198-215. https://doi.org/10.1016/j.jeconom.2019.05.011

HOOD, H.B., DORFMAN, J.H. 2015. Examining dynamically changing timber market linkages. Am. J. Agric. Econ. 97(5): 1451-1463. https://doi.org/10.1093/ajae/aau151

IHLE, R., VON CRAMON-TAUBADEL, S., ZORYA, S. 2009. Markov-switching estimation of spatial maize price transmission processes between Tanzania and Kenya. Am. J. Agric. Econ 91(5): 1432-1439. https://doi.org/10.1111/j.1467-8276.2009.01360.x

JANISKEE, R.L. 1990. "Storm of the Century": Hurricane Hugo and its impact on South Carolina. Southeast. Geogr. 30(1): 63-67. https://doi.org/10.1353/sgo.1990.0000

JOE, H., LI, H., NIKOLOULOPOULOS, A.K. 2010. Tail dependence functions and vine copulas. J. Multivar. Anal. 101(1): 252-270. https://doi.org/10.1016/j.jmva.2009.08.002

JUNG, C., DOROODIAN, K. 1994. The Law of One Price for U.S. softwood lumber: A multivariate cointegration test. For. Sci. 40(4): 595-600. https://doi.org/10.1093/forestscience/40.4.595

KEEGAN, C.E., SORENSON, C.B., MORGAN, T.A., DANIELS, J.M., HAYES, S.W. 2012. Impact of the great recession on the forest products industry in the western United States.

In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 5-9.

KINNUCAN, H.W. 2016. Timber price dynamics after a natural disaster: Hurricane Hugo revisited. J. For. Econ. 25: 115-129. https://doi.org/10.1016/j.jfe.2016.09.002

KLEPACKA, A.M., SIRY, J.P., BETTINGER, P. 2017. Stumpage prices: a review of influential factors. Int. For. Rev. 19(2): 158-169. https://doi.org/10.1505/146554817821255114

KOUTROUMANIDIS, T., ZAFEIRIOU, E., ARABATZIS, G. 2009. Asymmetry in price transmission between the producer and the consumer prices in the wood sector and the role of imports: The case of Greece. For. Policy Econ. 11(1): 56-64. https://doi.org/10.1016/j.forpol.2008.09.002

LAMONT, O.A., THALER, R.H. 2003. Anomalies: The law of one price in financial markets. J. Econ. Perspect. 17(4): 191-202. https://doi.org/10.1257/089533003772034952

LISTORTI, G., ESPOSTI, R. 2012. Horizontal price transmission in agricultural markets: Fundamental concepts and open empirical issues. Bio-based Appl. Econ. 1(1): 81-102. https://doi.org/10.13128/BAE-10769

LUPPOLD, W.G., PRESTEMON, J.P., BAUMGRAS, J.E. 1998. An examination of the relationship between hardwood lumber and stumpage prices in Ohio. Wood Fiber Sci. 30(3): 281-292.

MACKENZIE, D., SPEARS, T. The formula that killed Wall Street: The Gaussian copula and modelling practices in investment banking. Soc. Stud. Sci. 44(3): 393-417. https://doi.org/10.1177/0306312713517157

MCNEW, K. 1996. Spatial market integration: Definition, theory, and evidence. Agric. Econ. Res. Rev. 25(1): 1-11. https://doi.org/10.1017/S1068280500000010

MEI, B., CLUTTER, M., HARRIS, T. 2010. Modeling and forecasting pine sawtimber stumpage prices in the US South by various time series models. Can. J. For. Res. 40: 1506–1516. https://doi.org/10.1139/X10-087

MEYER, J., VON CRAMON-TAUBADEL, S. 2005. Asymmetric price transmission: A survey. J. Agric. Econ. 55(3): 581-611. https://doi.org/10.1111/j.1477-9552.2004.tb00116.x

NAGUBADI, V., MUNN, I.A., AHAI, A.T. 2001. Integration of hardwood stumpage markets in the Southcentral United States. J. For. Econ. 7(1): 60-98.

NING, Z., CHANGYOU, S. 2014. Vertical price transmission in timber and lumber markets. J. For. Econ. 20(1): 17-32. https://doi.org/10.1016/j.jfe.2013.07.002

PARAJULI, R., TANGER, S., JOSHI, O., HENDERSON, J. 2016. Modeling prices for sawtimber stumpage in the South-Central United States. Forests 7(7): 148. https://doi.org/10.3390/f7070148

PATTON, A.J. 2012. A review of copula models for economic time series. J. Multivar. Anal. 110: 4-18. https://doi.org/10.1016/j.jmva.2012.02.021

PRESTEMON, J.P., ABT, R.C. 2002. Timber products supply and demand. In: Wear, D.N.; Greis, J.G., eds. The Southern Forest Resource Assessment. General Technical Report GTR-SRS-53. Asheville, North Carolina: U.S. Department of Agriculture, Forest Service, Southern Research Station. 299-325. https://research.fs.usda.gov/treesearch/42386

PRESTEMON, J.P., HOLMES, T.P. 2000. Timber price dynamics following a natural catastrophe. Am. J. Agric. Econ. 82(1): 145-160. https://doi.org/10.1111/0002-9092.00012

PRESTEMON, J.P., HOLMES, T.P. 2010. Economic impacts of hurricanes on forest owners. In: Pye, John M.; Rauscher, H. Michael; Sands, Yasmeen; Lee, Danny C.; Beatty, Jerome S., tech. eds. 2010. Advances in threat assessment and their application to forest and rangeland management. Gen. Tech. Rep. PNW-GTR-802. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations: 207-221. https://research.fs.usda.gov/treesearch/37043

PRESTEMON, J.P., WEAR, D.N. 2000. Linking harvest choices to timber supply. For. Sci. 46(3): 377-389. https://doi.org/10.1093/forestscience/46.3.377

QIU, F., GOODWIN, B.K. 2012. "Asymmetric Price Transmission: A Copula Approach," 2012 Annual Meeting, August 12-14, 2012, Seattle, Washington 124906, Agricultural and Applied Economics Association. https://ageconsearch.umn.edu/record/124906/

REGMI, A., GREBNER, D.L., WILLIS, J.L., GRALA, R.K. 2022. Sawmill willingness to pay price premiums for higher quality pine sawtimber in the Southeastern United States. Forests 13: 662. https://doi.org/10.3390/f13050662

RODRIGUES, G.M., ORTEGA, E.M.M., VILA, R., CORDEIRO, G.M. 2023. A new bivariate family based on Archimedean copulas: Simulation, regression model and application. Symmetry 15(9): 1778. https://doi.org/10.3390/sym15091778

ROGERS, E. 2014. "Spatial Price Transmission and Market Linkages in US Framing Lumber Markets," 2014 Annual Meeting, July 27-29, 2014, Minneapolis, Minnesota 174436, Agricultural and Applied Economics Association.

RONCALLI, T. 2020. Handbook of Financial Risk Management. CRC Press: Boca Raton, FL, USA. 1146 p.

SARTORIO, I.P., SILVA, B.K., HENDERSON, J.D., MARUFUZZAMAN, M., CROSBY, M.K., TANGER, S.M. 2024. Understanding hurricane effects on forestlands: Land cover changes and salvage logging. For. Ecol. Manag. 569: 122132. https://doi.org/10.1016/j.foreco.2024.122132

SCHEPSMEIER, U. 2015. Efficient information based goodness-of-fit tests for vine copula models with fixed margins: A comprehensive review. J. Multivar. Anal. 138: 34-52. https://doi.org/10.1016/j.jmva.2015.01.001

SHAHI, C.K., KANT, S. 2009. Cointegration relationship and the degree of market integration among the North American softwood lumber product markets. Can. J. For. Res. 39(11) 2129-2137. https://doi.org/10.1139/X09-110

SILVA, B.K., CUBBAGE, F.W., ABT, R.C. 2019. Structural changes on pulpwood market in the US South: wood pellets investments and price dynamics. For. Sci. 65(6): 675-687. https://doi.org/10.1093/forsci/fxz043

SILVA, B.K., SHONS, S.Z., CUBBAGE, F.W., PARAJULI, R. 2020. Spatial and cross-product price linkages in the Brazilian pine timber markets. For. Policy Econ. 117: 102186. https://doi.org/10.1016/j.forpol.2020.102186

SKLAR, M. 1959. Fonctions de répartition à N dimensions et leurs marges. Publications de l'Institut Statistique de l'Université de Paris 8(3): 229-231.

SMITH, M.C. 2023. Implicit copulas: an overview. Econom. Stat. 28: 81-104. https://doi.org/10.1016/j.ecosta.2021.12.002

SUN, C. 2016. Timber market recovery after a hurricane. For. Sci. 62(6): 600-612. https://doi.org/10.5849/forsci.15-123

SUN, C., NING, Z. 2014. Timber restrictions, financial crisis, and price transmission in North American softwood lumber markets. Land Econ. 90(2): 306-323. https://doi.org/10.3368/le.90.2.306

SYME, J.H., SAUCIER, J.R. 1992. Impacts of Hugo Timber Damage on Primary Wood Manufacturers in South Carolina. Gen. Tech. Rep. SE-80. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station. 28 p. https://research.fs.usda.gov/treesearch/1766

TANG, X., LAAKSONEN-CRAIG, S. 2007. The law of one price in the United States and Canadian newsprint market. Can. J. For. Res. 37(8): 1495-1504. https://doi.org/10.1139/X06-322

TERÄSVIRTA, T. 1994. Specification, estimation, and evaluation of Smooth Transition Autoregressive Models. J. Am. Stat. Assoc. 89(425): 208-218. https://doi.org/10.1080/01621459.1994.10476462

TERÄSVIRTA, T., TJØSTHEIM, D., GRANGER, C.W.J. 2010. Modelling nonlinear economic time series. Oxford University Press, Oxford, UK. https://doi.org/10.1093/acprof:oso/9780199587148.001.0001

TIMBERLAND INVESTMENT RESOURCES. 2016. Timberland return drivers: a fresh look using empirical data. https://tirllc.com/wp-content/uploads/2017/05/Timberland-Return-Drivers-2016-10-24.pdf

UBILAVA, D. 2022. A comparison of multistep commodity price forecasts using direct and iterated smooth transition autoregressive methods. Agric. Econ. 53(5): 687-701. https://doi.org/10.1111/agec.12707

VAVRA, P. GOODWIN, B.K. 2005. Analysis of price transmission along the food chain. OECD Food, Agriculture and Fisheries Papers, No. 3, OECD Publishing, Paris. https://doi.org/10.1787/752335872456

VON CRAMON-TAUBADEL, S., GOODWIN, B.K. 2021. Price transmission in agricultural markets. Annu. Rev. Resour. Econ. 13: 65-84. https://doi.org/10.1146/annurev-resource-100518-093938

WEAR, D.N., GREIS, J.G. 2013. The Southern Forest Futures Project: Technical Report. Gen. Tech. Rep. SRS-GTR-178. Asheville, NC: USDA-Forest Service, Southern Research Station. 542 p. https://research.fs.usda.gov/treesearch/44183

YIN, R., NEWMAN, D.H., SIRY, J. 2002. Testing for market integration among southern pine regions. J. For. Econ. 8: 151-166. https://doi.org/10.1078/1104-6899-00009

ZHANG, W., MEI, B. 2019. Assessing the risk and return of optimal portfolios of US timberland and farmland. J. Real Estate Portf. Manag. 25(1): 99-113. https://doi.org/10.1080/10835547.2019.12090026

ZHOU, M., BUONGIORNO, J. 2005. Price transmission between products at different stages of manufacturing in forest industries. J. For. Econ. 11(1): 5-19. https://doi.org/10.1016/j.jfe.2005.02.002

CHAPTER 3

SETTING TIMBER ASIDE? THE IMPACT OF LAND RETURNS AND SOLAR DEVELOPMENTS ON TIMBERLAND INVESTMENT RETURNS[2]

[2]Sanquetta, M. N. I, Kanieski da Silva, B., Kinane, S. M., Bettinger, P., Siry, J. To be submitted to Forest Policy and Economics

Abstract

Landowners and corporate investors are changing the way they manage timberland in the US South due to land returns driven by land sales, leases, and lease-sale call option contracts for solar developments. The impact of these new revenue layers on returns and risks of timberland investments is unknown. In this paper, we developed a strategic landscape planning model to optimize the forest value over 15 years across 22 timber markets in the US South. Also, we estimated potential internal rates of return (IRR) and risks (IRR standard deviation) using a stochastic simulation process from four different scenarios: S1 - business as usual (only timber revenues and land appreciation), S2 – up to 5% land sale, S3 – up to 5% land lease, and S4 - 5-year call option contract for the total area with up to 5% selling at the strike period. Our results indicated a South-wide average return of 8.02% ±3.14% for S1. S2 increased the South-wide return by 4.32%, with no significant impact on risk (12.34% ± 3.26%). S3 increased the South-wide return by 5.90%. Again, with no significant impact on risk (13.92% ± 3.55). In S3, the average increase was higher than the lowest returns in S1. The call option contract increased average returns significantly, adding 11.40% to the South-wide average return over 15 years. In this scenario, however, the risk increased by 5.51%. Our results indicated increased potential returns in all alternative scenarios. Even in the worst case, S2, S3 and S4 are 80% likely to provide higher returns when compared to the business as usual (S1). Landowners and corporate investors could benefit from these results to better plan their investments.

3.1 Introduction

During the past few decades, timber prices have declined substantially, especially after the Great Recession (Keegan et al., 2011; Sun and Ning, 2014) and the COVID-19 pandemic (Bruck et al., 2023). Also, timber prices decreased due to mill closures and capacity reductions across the US South (Forisk, 2024). All those movements increased concerns about the economic health of the forest sector (Riddle, 2021). Although timber prices are one of the most important return drivers on timberland investments (Mei et al., 2010), land appreciation could provide substantial returns to timberland investments (Caulfield, 1998). Therefore, investors began looking for new alternatives to make their land more profitable and offset losses from declining timber prices by converting timberland to other land uses such as agriculture or urbanization. For instance, urbanization, population growth and other factors reduced forestlands by more than 12 million acres in the US South from 1950 until 2020, and it is projected that forestland area will keep reducing in the next decades (Alig et al., 2004).

A recent opportunity for landowners is the conversion of timberlands to new solar power plants. Federal policies, such as the Inflation Reduction Act, have boosted the investment in solar and wind energy across the United States. Currently, energy generated from renewable sources is setting new records and is expected to increase in the next years. In 2024, 37 gigawatts from new solar power were added to the national grid last year and almost doubled 2023 solar capacity additions (Wall Street Journal, 2024; EIA, 2025). The Energy Information Administration (EIA) expects that another 26 gigawatts will be added by 2026.

Due to the lack of large areas to install solar power plants close to urban areas, investors started looking for self-storage buildings, outlet malls, and southern timberlands (Wall Street Journal, 2023). In terms of profitability, new solar plants in the US South provide extensive margins to timberland investors (Cooper and Dwivedi, 2024) and there is an increasing interest in transitioning from timberlands towards renewable energy (Woodson, 2019; Cooper and Dwivedi, 2024; Landgate, 2024). Roughly 3 to 7.5 million acres would be needed within the next 20 years for new solar power plants (Wall Street Journal 2024; Wear et al., 2025).

There are several social and environmental benefits of solar energy, such as greenhouse gas emission reduction compared to fossil fuel sources (such as coal), reduced local air pollutants, decreasing dependence on imported fuels, and low operational costs (Cooper and Dwivedi, 2024; Rivera et al., 2024). However, a large-scale timberland conversion into solar power plants can significantly impact deforestation rates. New solar developments can increase land conversion rates by 39 to 71% every year (Wear et al., 2025). According to these projects, most developments are likely to involve switching between agricultural and timberland to solar energy in the US South. This process can also generate a shortage of timber inventory in the long term and at regional scales, in addition to reduced carbon sinks and ecosystem services.

The decision process to convert timberland into a new solar plant depends on several factors and can vary depending on the landowner’s preference. One of them is the ability of these facilities to increase land profitability and the associated risk. This conversion process can start with lease-purchase call option contracts (Landgate, 2025). Call option contracts provide the holder the right to either get into a formal lease contract or buy the asset at the “strike” or “exercise” price. For solar developments, option contracts have a maturity time of 1 to 5 years (Landgate, 2024; 2025). Maturity time indicates the period in which the holder can exercise the option and is used to assess the feasibility of installing a new facility. By exercising the option, both the landowner and the solar developer can enter into a formal land lease (usually 25 to years) or sale agreement.

Given the low returns of traditional timberland investments, and the surge of alternative uses, such as agriculture, urbanization, and solar facilities, the management of timberland is now divided into multiple use assets, that combine multiple land use, leasing and options to other uses. For instance, Zhang and Mei (2019) assessed returns and risks of timberland investments in the US South and compared with other crops; according to the authors, agricultural production could substantially increase profits in an investment portfolio. This mix between assets challenge land managers to wisely allocate investors resources to increase profitability and reduce risks. In this research, we aim to investigate the alternative strategy of land conversion or leasing on timberland returns. We extend the studies proposed by Caulfield (1998), Zhang and Mei (2019) and Cooper and Dwivedi (2024), by investigating the financial contribution of different land return strategies on timberland investments across the US South. In addition, we estimate potential returns and risks involved in these strategies employing a strategic landscape planning model and a stochastic simulation process. Our results encompassed 22 different regions in the US South and can be used in portfolio optimization models, such as Zhang and Mei (2019) and Busby et al. (2020) and support the decision-making process of investors and landowners on allocating or converting their investments.

3.2 Background

Several studies have assessed timberland investment returns in the US South (Cubbage et al., 2007; Callaghan et al., 2019; Mei, 2015; Chudy et al., 2020; Cubbage et al., 2020; Cubbage et al., 2022). However, most of these studies presented at least one of two limitations which we intend to address in this study. First, most studies on returns for timberland investments in the US South have been conducted at the stand level to determine the contribution of each return driver (biological growth, timber prices, and land appreciation) for a hypothetical stand (*e.g.*, Caulfield, 1998; Mei et al., 2013). Other studies have compared returns and risks for different species and regions and have considered the entire US South as one unique region (*e.g.*, Sedjo, 1984; Thomas, 2012; Chudy et al., 2020). However, returns can differ significantly depending on regional characteristics, especially in large markets such as the US South.

Second, although the extensive use of the land expectation value as the financial criteria to evaluate timberland investments and management (*e.g.*, Chang, 2001; Straka 2007; Cubbage et al., 2014; Callaghan et al., 2019; Chudy et al., 2020; Cubbage et al., 2020), some studies did not include land prices in their discounted cash flow analysis (*e.g.*, Chudy et al., 2020) or assessed the impact of land prices on timberland investments (*e.g.*, Cubbage et al., 2014), it implies a management over infinite rotations, without any possibility of land conversion. On the other hand, institutional timberland investments are commonly closed-end funds with a limited investment period of 5 to 20 years (Zhang et al., 2012; Mei and Clutter, 2023), which is shorter than the usual loblolly pine rotation age of 20-40 years (Trim et al. 2020, Trlica et al. 2021). In addition, these investments are usually a group of different assets (stands) acquired at different ages, not bare land, especially in competitive markets such as the US South.

Caulfield (1998) and Restrepo et al. (2020) simulated a 15-year investment in which a hypothetical loblolly pine stand in south Georgia was purchased at age 10 years and sold at age 25 years. However, the average age of a typical timberland investment is 22 years, according to the USDA Forest Inventory Analysis (FIA) (Stanke et al., 2020). Most institutional timberland investments are composed of asset with different ages, in which managers can proceed with thinning and/or harvests in the first years if there are stands with ages defined by the chosen management regimes. Consequently, returns from these investments can differ depending on several factors. The initial forest structure, in terms of spacing and age, will influence the thinning and harvest scheduling (Silva et al., 2024). The productive potential will determine the biological growth, tree growth pattern and form (Li et al., 2020; Sanquetta et al., 2020; Yue et al., 2024), and consequently merchantable product distribution (*e.g.*, pulpwood, chip-and-saw, and sawtimber). The inflow of revenues and costs starts in the initial years as it is not necessary to wait the entire rotation period to harvest a stand.

Furthermore, the conversion of timberlands into solar plants has become more common in recent years (Wall Street Journal, 2023). Cooper and Dwivedi (2024) mentioned that these conversions were focused on small landowners. Nonetheless, expressive timber companies were among the biggest hosts of new solar developments (Wall Street Journal, 2023). This conversion process is typically done through land sales, leases, or option contracts (Landgate, 2025). Although not new on the financial market (Black and Scholes 1972), option contracts are yet to be explored in forestry. To the best of our knowledge, the first studies employing option contracts on timberland investments were conducted by Chang and Zhang (2023, 2024). These authors employed American put options to outsource timber price uncertainty. Option contracts can either provide the holder either the right to buy (call option) or sell (put option) an asset at a specific price moment in time (Brennan and Schwartz, 1977; Hull, 2011). Regardless of how the contracts are set, the impact of this process on timberland investment returns is still unknown. Similar studies conducted previously used indexes such as the National Council of Real Estate Investment Fiduciaries (NCREIF) Timberland Index (NTI) and timber firm index (*e.g.*, Sun and Zhang, 2001; Mei et al., 2013; Wan et al., 2015). For instance, NCREIF does not capture all land use change possibilities explicitly.

To provide more detailed information to landowners, institutional investors and other stakeholders in the forest sector, we propose an approach that uses a strategic landscape planning model and stochastic simulation to enlighten the impact multiple strategies of land use on the profitability and risks of timberland investments in the US South. Our contributions to the current literature are: (1) we use timberland assets from 22 timber markets that are representative in the US South and simulated as if they were a 15-year closed end fund; (2) we assess not only timberland returns, but the possibilities of leasing and selling part of the asset for solar energy developers; and last, (3) we calculate the expected return and risk of these assets within multiple scenarios.

3.3 Methods

In this section, we present our (3.3.1) strategic landscape planning model developed to maximize the forest value. We started our analysis by estimating the bare land, forest and terminal values at the stand level. A similar framework developed by Clutter et al. (1983) and replicated by González-González et al. (2020) and Silva et al. (2024) was used (see Appendix A). The first step was estimating the land expectation value (LEV) to determine the optimal silvicultural treatment and rotation age. From them, we estimated the forest and terminal values using a discounted cash flow analysis (DCF). The planning horizon was T = 15 years to mimic typical institutional timberland investments in the US South (Mei and Clutter, 2023).

3.3.1 Strategic landscape planning model

A strategic landscape planning model was designed to optimize the forest value by scheduling thinning and harvesting operations among each age strata under different silvicultural regimes (Table 3.2). The forest value was the summation of present values ($/acre) of each age strata. The mathematical formulation is described as follows:

$$\max_{A_{i,t},H_{i,t},R_i} \underbrace{\sum_{k}^{K}\sum_{i}^{I}\sum_{t}^{T}\frac{\left(p_k q_{i,k} H_{i,t}\right)}{(1+r)^t}}_{(A)} + \underbrace{\sum_{i}^{I}\frac{A_{i,t}(TV_i R_i)}{(1+r)^{t=T}}}_{(B)} - \underbrace{\sum_{i}^{I}\frac{(FV_i)A_{i,t=0}}{(1+r)^{t=0}}}_{(C)} - \underbrace{\sum_{i}^{I}\sum_{t}^{T}\frac{A_{i,t}(C_i+ac_t)}{(1+r)^t}}_{(D)} \tag{3.1}$$

Subject to:

$$A_{i,t} \geq H_{i,t} \ \forall\ i \ \in [0, I] \text{ and } t \ \in [0, T] \tag{3.2}$$

$$A_{i,t=0} = a_i \ \forall\ i \ \in [0, I] \tag{3.3}$$

$$A_{i,t=T} - H_{i,t=T} = R_i \ \forall\ i \ \in [0, I] \tag{3.4}$$

$$H_{i,t} = 0 \ \forall\ i \ \in [0, \Gamma] \text{ and } t \ \in [0, T] \tag{3.5}$$

$$H_{i,t} \leq A_{i,t} \tag{3.6}$$

where p_k is the price if the *k* product, $q_{i,k}$ is the volume available of the *k* product at *i* age per acre, *r* is the discount rate of 4% (Cubbage et al., 2020), $H_{i,t}$ is the area harvested of age *i* at period *t*, $A_{i,t}$ is the area available at age *i* at period *t*, a_i is the area available at age *i*, TV_i is the terminal value at $t = T$, *T* is the terminal period (15 years), R_i is the residual area at terminal period $t = T$, FV_i is the forest value per acre at age *i*, C_i is the establishment cost per acre when $i = 0$, and ac_t is the annual cost per acre from $t = 0$ to *T*.

Eq. 3.1 is the objective function, in which section (A) represents the present value of revenues in $/acre. Section (B) is the terminal value at $t = T$ in $/acre. Section (C) represents the initial investment cost at $t = 0$ in $/acre. Section (D) is the present value of costs in $/acre. Eq. 3.2 ensures that the harvested area (*H*) is less than or equal to the area available (*A*). Eq. 3.3 sets the initial forest structure at $t = 0$. Eq. 3.4 calculates the residual area after harvesting at period *T*. Eq.

3.5 ensures that any stand is at least Γ years before harvest. In our study, we set Γ = 20 years as the minimum merchantable age to account for short rotation stands focused on small-end diameter logs.

3.3.2 Scenarios and stochastic simulation

We proposed four scenarios to estimate the impact of different stages of a small-scale lease-purchase call option contract for solar developments (Table 3.1). The first scenario was (S1) business as usual – BAU, in which input variables representing the three main return drivers (i. biological growth, ii. timber prices fluctuation, and iii. land price appreciation) were simulated 1,000 times to generate a stochastic process. The same stochastic process was used to build scenarios S2 to S4.

Table 3.1. Description of different scenarios of land returns and call option.

Scenario	Description	Additional section on Eq. 3.1
S1	15-year timberland investment	-
S2	BAU + up to 5% land sale (Land selling price - Table 3.3).	$Eq. 3.1 + \sum_{t}^{T} \frac{(s_t S_t)}{(1+r)^t}$
S3	BAU + up to 5% land lease ($500/acre per year).	$Eq. 3.1 + \sum_{t}^{T} \left(\frac{(l L_t)}{(1+r)^t}\right) + \frac{\left(\frac{l}{r} L_t\right)}{(1+r)^T}$
S4	BAU + 5-years call option + up to 5% land sale. Strike price is equal to S2.	$Eq. 3.1 + \sum_{t}^{4} \left(\frac{(o O_t)}{(1+r)^t}\right) + \frac{o S_{t=4}}{(1+r)^{t=4}}$

Where s_t is the selling value from Table 3.3; l is the leasing value fixed at $500 per acre per year (Landgate, 2024); o is the option value fixed at $25 per acre per year (Landgate, 2024); S_t is the selling area; L_t is the leasing area; O_t is the area under option contract.

First, growth and yield curves were simulated 1,000 times for each market. To build the growth and yield curves, we simulated site indexes (SI) using average and standard deviations since they were normally distributed (see Appendix B). Timber prices were randomly selected for each product (pulpwood - p_{pw}, chip-n-saw - p_{cns}, sawtimber - p_{st}) and market over 1980-2024 period. In order to mimic the historical difference between their prices, we imposed constraints to ensure that $P_{cns} \geq \alpha_1 + P_{pw}$, (ii) $P_{st} \geq \alpha_2 + P_{pw}$, (iii) $P_{st} \geq \alpha_3 + P_{cns}$, where α_1, α_2 and α_3 are the minimum historical difference between their respective prices. The rationale is that the prices of a lower-value product would never be closer or far to the price of a higher-value product than historically observed. Finally, land prices were randomly selected from a uniform distribution drawn from the minimum and maximum values found for the US South ($1,440.66 to $2,618.79, as in Table 3.3).

Scenarios S2 to S4 considered different stages of a small-scale call option contract. S2 considered selling up to 5% of the land (for solar development or another higher and better use). S3 considered leasing up to 5% of the land for solar development. The annual lease payment was set equal to $500 per acre per year (Landgate, 2024). S4 considered the 5-year maturity stage period (Landgate, 2025) with up to 5% selling only in the strike period (S4). During the option maturity stage period (t = 0 to 4), also known as the development period, an annual payment of $25 per acre was added. During the strike period, up to 5% of the land was sold for the same price as in S2. These new scenarios imply changes in Section (A) of Eq. 3.1 build for S1 (Table 3.1). Similarly, new constraints were imposed. First, the area available ($A_{i,t}$) for harvesting was reduced in S2 and S3 to the same extent that an area was sold ($S_{i,t=T}$) or rented ($L_{i,t=T}$). We also ensured that the timber volume was harvested before selling or leasing the land. Considering that solar farm leases are usually 25-30 years long (Landgate, 2024), we recognize that this piece of land is unlikely to be converted back into timberland after this period. Hence, we added a perpetuity present value of $\left(PV = \frac{l_i}{r} = \$12{,}500 \text{ per acre}\right)$ to reflect the higher market value at the end of the planning horizon or liquidation.

3.3.3 Return and risk assessment

Potential returns and risks were assessed by capital budgeting criteria. We estimated the forest value for each 1,000 simulations generated for each market within every scenario. From these values, we calculated the internal rates of return (IRR) by setting the discount rate at which NPV was equal to zero. The return of each market and scenario combination was equal to its average, while the risk was measured by the IRR standard deviation, similar to Cubbage et al. (2010), Chudy et al. (2020), and Busby et al. (2020).

3.4 Data

3.4.1 Study area

We assessed average potential returns of brownfield investments in 22 different markets within 11 states of the US South (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia), as shown in Figure 3.1. These 22 markets encompassed all TimberMart-South (TMS) regions and more than 35 million acres (14.4 million hectares) of privately-owned corporate timberland. Each one of the 11 states has two markets, named as: Alabama (AL-01 and AL-02), Arkansas (AR-01 and AR-02), Florida (FL-01 and FL-02), Georgia (GA-01 and GA-02), Louisiana (LA-01 and LA-02), Mississippi (MS-01 and MS-02), North Carolina (NC-01 and NC-02), South Carolina (SC-01 and SC-02), Tennessee (TN-01 and TN-02), Texas (TX-01 and TX-02), and Virginia (VA-01 and VA-02).

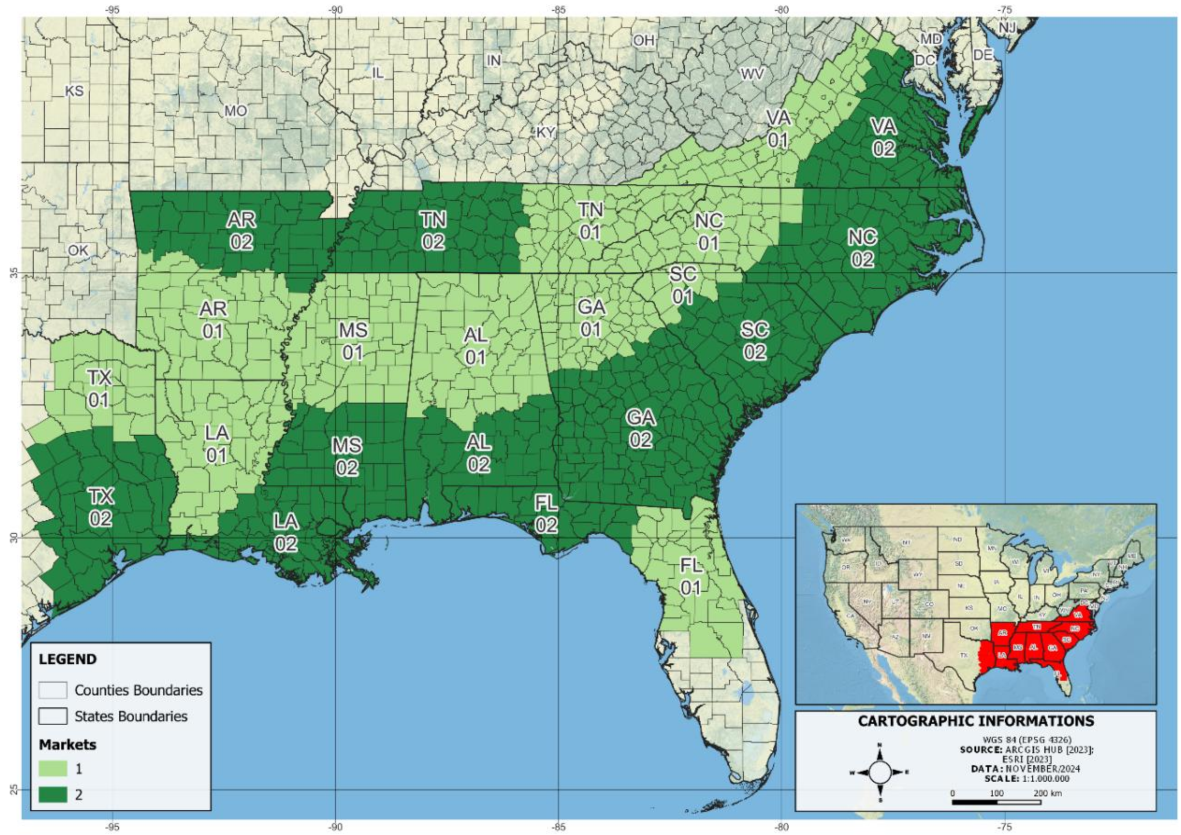

Figure 3.1. Map of TimberMart-South regions. Source: TimberMart-South.

3.3.2 Forest structure

The initial forest structure of each market was assumed to be the current age class distribution, according to the USDA Forest Inventory Analysis (FIA). Loblolly pine (*Pinus taeda* L.) stands managed and owned by private entities, both non-corporate and corporate landowners, were selected and related at the county level with their respective TMS regions. Age class distribution assumed the strata of 5 years from 0 to over 50 years (Figure 3.2).

Figure 3.2. Current age class distribution of each timber market. Source: USDA Forest Inventory Analysis (FIA).

3.4.3 Yield curves

All yield curves were produced using the 1996 Plantation Research Management Cooperative - PMRC model (Harrison and Borders, 1996). Four different silvicultural treatments were simulated when building the growth and yield curves. The first treatment considered a low initial density of 300 trees per acre (TPA), while the other three treatments considered an initial density of 600 trees per acre (TPA). Treatments 1 and 2 were simulated with no thinning, while treatment 3 was simulated with one thinning at age 15 years, and treatment 4 with two thinnings occurring at ages 15 and 24 years (Table 3.2). The main variables to build the growth and yield curves are the initial spacing (TPA), thinning ages (none, 15 and 25 years), residual basal area, and site index. Site indexes were sourced from Soil Survey Geographic Database – SSURGO. This dataset has site indexes at base age 50 years, which were converted to the base age of 25 years using a base-age invariant SI model proposed by Diéguez-Aranda et al. (2006) (See Appendix A). Every thinning reduced the basal area to 80 square feet per acre. Three different products were considered: pulpwood (6-8”), chip-n-saw (8-11”), and sawtimber (≥12”).

Table 3.2. Silvicultural treatments.

Treatment	**TPA**	**1st thinning**	**2nd thinning**
1	300	-	-
2	600	-	-
3	600	15 years	-
4	600	15 years	24 years

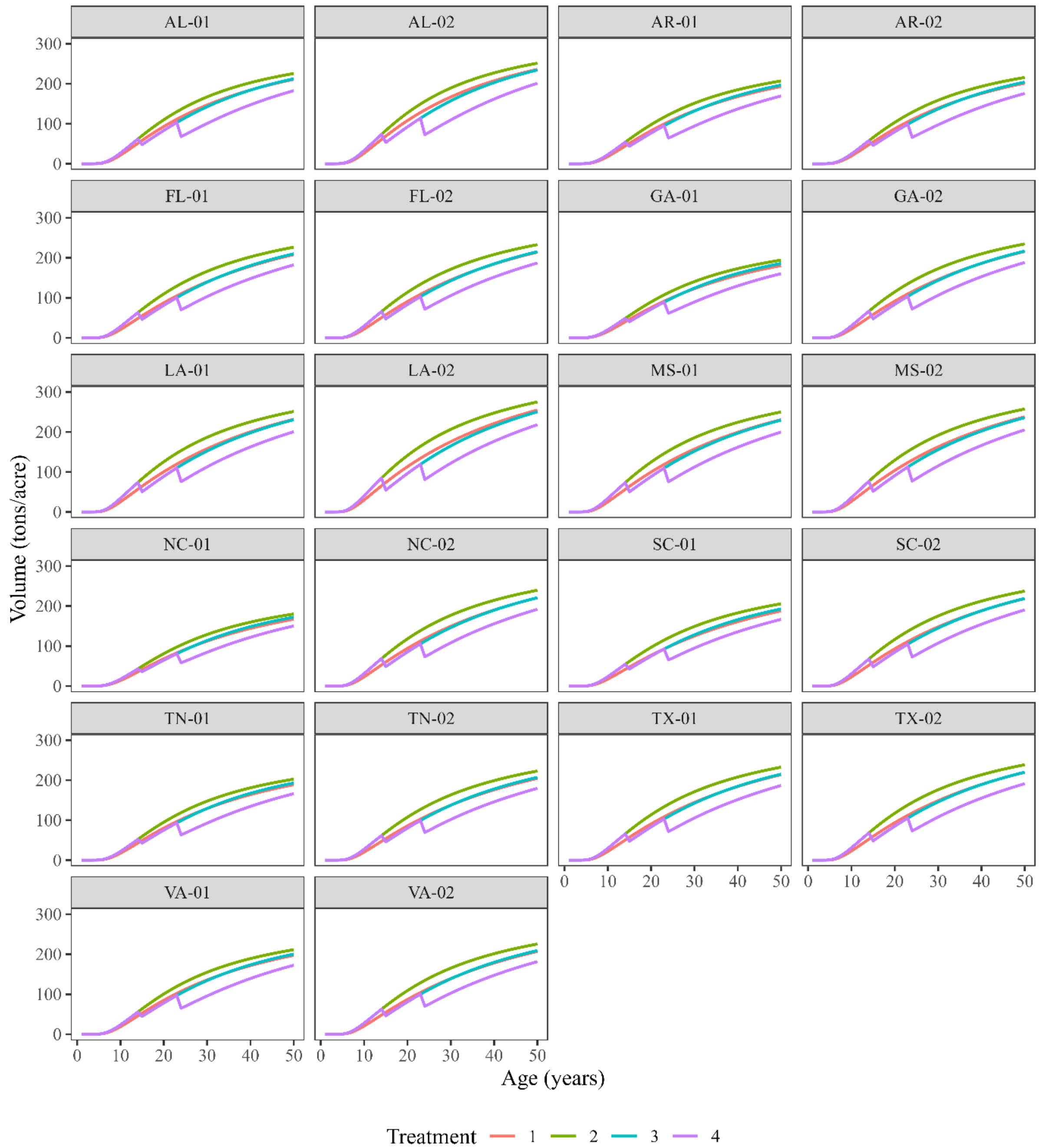

Figure 3.3. Yield curves based for each treatment and timber market.

3.3.4 Prices and costs

Stumpage timber prices for each product were sourced quarterly from 1980 to 2024 from TimberMart-South (2024), see Appendix C. Operational costs were sourced from Costs and Trends of Southern Forestry Practices for 2022 (Maggard and Natzke, 2023) and adjusted to 2024 with the consumer price index - CPI (see Appendix D). The Costs and Trends of Southern Forestry Practices dashboard provides operational costs by ecoregion (*e.g.*, Coastal Plains and Piedmont) and/or state for different landownerships. We considered data provided only by private institutions and weighted the prices according to the area of each ecoregion (Level II from US EPA) within the 22 timber markets (See Appendix E). Initial costs included mechanical site preparation, planting costs, seedlings, and herbicide application. Annual costs include taxes, maintenance, and other costs.

Timberland prices were used as initial costs for acquiring an asset (land and the existing forest), regardless of its age. Due to the lack of available data, we used the TMS South-wide value from 2022 and adjusted to 2024 with the CPI (See Appendix D). The South-wide timberland price was then weighted according to the last sawtimber price of each state, resulting in timberland values ranging from $1,440.66 to $2,618.79 (Table 3.3).

In our strategic landscape planning model (section 3.3.1), we acknowledged that a small portion of the timberland could be converted to another land use, such as annual crops or a new solar facility. Despite the trend toward converting timberland into solar arrays, these areas could also be converted to agriculture, for example. Therefore, we used farm real estate values from the Land Values 2024 Summary (USDA, 2024) as the selling price. These values were adjusted annually over the planning period (T = 15 years) according to the average appreciation rate observed for the past 15 years (2.2% per year). These values were used to approximate the values mentioned in Wall Street Journal (2024) for a deal between a solar developer and a forest-product company.

Table 3.3. Average timber prices, land prices and operational costs for each timber market.

Market	Timber prices ($/ton)[1]			Costs ($/acre)[2]			Timberland cost ($/acre)[3]	Land selling price ($/acre)[4]	
	PW	CNS	ST	Initial		Annual			
	(6-8”)	(8-11”)	(>=12”)	300 TPA	600 TPA			Year 0	Year 15
AL-01	7.37	19.34	28.23	435.24	512.99	12.15	1,778.20	4,000.00	5,440.00
AL-02	9.22	21.78	31.90	475.70	528.92	9.94	2,039.10	4,000.00	5,440.00
AR-01	6.86	17.28	29.07	397.91	499.88	11.14	1,918.44	4,110.00	5,696.46
AR-02	5.76	16.43	24.23	358.83	478.55	12.94	1,832.83	4,110.00	5,696.46
FL-01	12.10	21.85	29.43	320.16	462.39	8.26	1,991.81	8,300.00	11,503.81
FL-02	10.78	20.63	28.87	386.91	497.90	9.15	2,263.31	8,300.00	11,503.81
GA-01	7.77	19.25	27.21	440.03	514.99	11.92	2,004.86	4,500.00	6,137.00
GA-02	11.51	23.14	32.68	426.33	513.41	9.55	2,168.74	4,500.00	6,137.00
LA-01	8.25	17.62	28.92	413.17	508.59	9.43	1,922.51	3,720.00	5,155.92
LA-02	7.29	18.15	27.84	333.32	470.55	8.46	1,817.34	3,720.00	5,155.92
MS-01	6.47	18.39	27.80	419.64	511.00	9.49	1,752.93	3,490.00	4,837.14
MS-02	7.45	19.66	30.66	463.36	525.38	9.85	1,950.23	3,490.00	4,837.14
NC-01	5.38	15.83	20.95	427.58	509.69	12.54	2,061.93	5,190.00	7,193.34
NC-02	7.07	17.95	30.51	396.48	501.97	9.26	2,618.79	5,190.00	7,193.34
SC-01	7.23	17.55	26.66	473.15	527.51	10.45	1,705.64	4,500.00	6,237.00
SC-02	8.88	19.85	30.27	393.64	500.79	9.23	2,048.89	4,500.00	6,237.00
TN-01	5.41	12.92	16.20	389.10	490.88	14.75	1,440.66	6,710.00	9,300.06
TN-02	6.10	13.46	18.61	473.62	528.25	9.99	1,629.00	6,710.00	9,300.06
TX-01	7.76	16.72	28.65	458.37	522.18	11.07	1,778.20	2,800.00	3,880.80
TX-02	7.38	15.95	29.63	412.35	507.83	9.73	2,039.10	2,800.00	3,880.80
VA-01	7.11	16.69	19.64	398.20	495.70	14.18	1,918.44	5,850.00	8,108.10
VA-02	7.84	17.16	24.16	446.23	520.11	9.72	1,832.83	5,850.00	8,108.10

Source: [1] TimberMart-South (2024); [2] Maggard and Natzke (2023), [3] TimberMart-South (2023); [4] USDA (2024).

3.5 Results

In this section, we present the results from the stochastic simulation process. Section 3.5.1 assesses the average potential returns for each market, while section 3.5.2 presents the risk assessment, highlighted by the standard deviation of IRR distributions. Section 3.5.3 highlights the impact on revenue shares in each scenario.

3.5.1 Average returns

The South-wide average potential return for S1 - BAU was 8.02% (± 3.14%), considering all 22 timber markets (Table 3.4). Regionally, IRR ranged from 5.14% (MS-01) to 13.18% (FL-01). Eight markets presented above average returns (VA-01, GA-01, NC-01, GA-02, VA-02, NC-02, FL-02, and FL-01). The highest returns were found for the state of Florida (FL-01 – 13.18% and FL-02 – 12.14%), followed by NC-02 (10.11%), VA-02 (9.95%) and GA-02 (9.78%). South Georgia (GA-02) and east North Carolina (NC-02) are some of the largest timber markets, encompassing together more than 25% of the private corporate timberland in the US South (see Zhang and Mei, 2019). Although representing around 10-11% of the private timberland, the state of Florida presented the two highest returns. Although there is no evident correlation between IRR and sawtimber prices, FL-01 and FL-02 also presented higher sawtimber prices. From 1996 to 2007 and 2021 to 2023, the state of Florida experienced sawtimber prices always greater than $35, reaching the maximum value of $49.89 per ton. These historical high timber prices are likely to help increase IRR. Despite covering more than 13% of the private timberland, Mississippi (MS-01 and MS-02) presented the two lowest returns among all 22 markets. These two markets were followed by TX-01 (6.02%), AR-02 (6.08%), and TX-02 (6.21%). TX-02 also has an extensive timberland area.

The IRR consistently increased when adding up to 5% land-sale (S2) during the 15-year period. The South-wide return for S2 was 12.34%, meaning a 4.32% increase when compared to S1. Average potential returns ranged from 9.35% (MS-01) to 17.71% (FL-01). The strategic landscape planning model decided to sell 5% of the land for every simulation. Land selling prices (Table 3.3) were always higher than the reported timberland market values reported in the literature - $2,000 to $3,000 (Wall Street Journal, 2024). From that, we noticed that IRR increased similarly among all markets, shifting the IRR distribution to the right when compared to S1 distributions (Figure 3.4). When ranking the IRR in ascending order, we noticed that there was no change between S1 and S2. This means that it was possible to increase returns by 4.32%, on average, by adding small-scale land sale, but the most profitable markets remained the same compared to S1, as did the worst ones. In other words, one market did not become more profitable than the other.

Similarly, potential returns increased for S3 when compared to S1. The South-wide return was 13.92%, increasing 5.90% when compared to S1. This 5.90% increase was higher than the average return from MS-01 (5.14%) and almost as high as the average return from MS-02 (5.99%) in S1. Annual lease payments helped keep the cashflow positive over the planning horizon, differently from land sale (S2). In addition, the perpetuity present value increased the selling price at the end of the planning horizon. Some markets became more profitable than others in this scenario. For example, TN-02 presented the lowest return instead of MS-01 from S1, while MS-02 became more profitable than AR-02, TX-01, and TN-01. However, the same five most and less profitable markets remained the same as in S1 and S2 (not necessarily on the same order).

The call option contract scenario (S4) presented the highest returns among all scenarios. The South-wide return was 19.42%, being 11.40%, 7.08%, and 5.50% higher when compared to S1, S2, and S3, respectively. Returns increased for all markets, except for both in Tennessee (TN-

01 – 8.88% and TN-02 – 9.20%) when compared to S2 and S3. The highest returns were greater than 30% (30.96% in GA-02 and 30.95% in FL-01), and 6 other markets presented returns greater than 20% (FL-01 – 22.22%, SC-02 – 23.18%, NC-02 – 24.17%, VA-02 – 25.00%, NC-01 – 25.33%, and SC-01 – 25.57%. All other returns ranged from 14.35% (AL-01) to 19.20% (AL-02).

Table 3.4. Internal rate of return (%) across 22 timber markets in the US South.

Market	S1 - BAU				S2 – Land sale				S3 – Land lease				S4 – Call option			
	Average	**SD**	**Q1**	**Q3**	**Average**	**SD**	**Q1**	**Q3**	**Average**	**SD**	**Q1**	**Q3**	**Average**	**SD**	**Q1**	**Q3**
AL-01	6.61	2.11	5.01	8.05	10.87	2.19	9.21	12.37	12.62	2.50	10.80	14.23	14.35	5.10	10.64	17.26
AL-02	7.80	2.15	6.18	9.32	12.11	2.24	10.43	13.69	13.88	2.78	11.72	15.68	19.20	7.08	13.48	23.42
AR-01	7.01	2.54	5.19	8.50	11.29	2.64	9.40	12.84	13.16	2.86	11.01	14.95	17.98	8.67	11.62	22.30
AR-02	6.08	2.18	4.37	7.48	10.32	2.27	8.54	11.78	11.98	2.75	10.01	13.80	16.21	8.86	10.08	20.42
FL-01	13.18	2.94	10.98	15.06	17.71	3.05	15.41	19.66	17.01	4.15	14.01	19.20	22.22	8.23	16.04	26.76
FL-02	12.14	2.30	10.36	13.63	16.62	2.39	14.77	18.17	15.52	3.07	13.15	17.58	30.95	12.16	20.97	39.43
GA-01	9.06	3.01	6.85	10.75	13.42	3.13	11.12	15.18	15.46	3.99	12.68	17.55	16.69	11.56	8.07	21.52
GA-02	9.78	2.71	7.87	11.50	14.17	2.82	12.18	15.96	16.11	3.32	13.68	18.29	30.96	12.74	20.82	38.99
LA-01	7.05	2.44	5.22	8.57	11.33	2.54	9.43	12.91	13.01	2.85	10.93	14.86	16.52	6.37	12.18	19.68
LA-02	6.47	1.87	4.98	7.90	10.73	1.94	9.18	12.22	12.54	2.27	10.74	14.24	15.23	4.58	11.55	18.35
MS-01	5.14	1.74	3.76	6.45	9.35	1.81	7.91	10.71	10.69	1.94	9.19	12.07	14.40	5.33	10.17	17.65
MS-02	5.99	1.99	4.49	7.31	10.23	2.07	8.67	11.61	12.45	2.35	10.62	13.99	17.05	6.43	12.35	20.65
NC-01	9.57	2.78	7.54	11.21	13.96	2.89	11.85	15.66	16.11	3.59	13.45	18.01	25.33	11.13	17.26	30.69
NC-02	10.11	2.73	8.28	11.72	14.51	2.84	12.61	16.19	16.95	3.86	14.20	19.22	24.17	10.76	16.22	29.69
SC-01	7.65	2.31	5.91	9.08	11.96	2.40	10.15	13.44	13.95	2.91	11.86	15.66	25.57	12.92	16.04	32.37
SC-02	7.68	2.31	5.96	9.19	11.99	2.40	10.20	13.56	13.96	2.93	11.76	15.61	23.18	13.45	13.18	31.15
TN-01	7.04	1.39	5.91	8.11	11.32	1.44	10.15	12.43	12.38	1.57	11.09	13.58	8.88	2.77	7.06	10.82
TN-02	7.13	1.56	5.88	8.26	11.42	1.62	10.12	12.59	10.60	1.72	9.26	11.88	9.20	2.90	7.25	11.33
TX-01	6.02	2.57	4.23	7.67	10.26	2.68	8.39	11.97	12.34	3.04	10.11	14.23	18.12	7.86	12.85	21.18
TX-02	6.21	3.61	3.95	7.66	10.46	3.75	8.11	11.96	13.20	3.31	10.96	15.05	19.06	10.13	12.29	24.25
VA-01	8.34	2.28	6.69	9.77	12.67	2.37	10.96	14.16	14.07	2.68	12.04	15.84	17.02	9.93	10.67	20.67
VA-02	9.95	2.68	7.91	11.64	14.35	2.79	12.23	16.10	16.48	3.50	13.81	18.58	25.00	11.29	16.96	31.11
South-wide	**8.02**	**3.14**	**5.78**	**9.79**	**12.34**	**3.26**	**10.01**	**14.18**	**13.92**	**3.55**	**11.39**	**15.82**	**19.42**	**8.65**	**11.92**	**24.30**

Note: SD is the standard deviation, Q1 is the 1st quartile, and Q3 is the 3rd quartile.

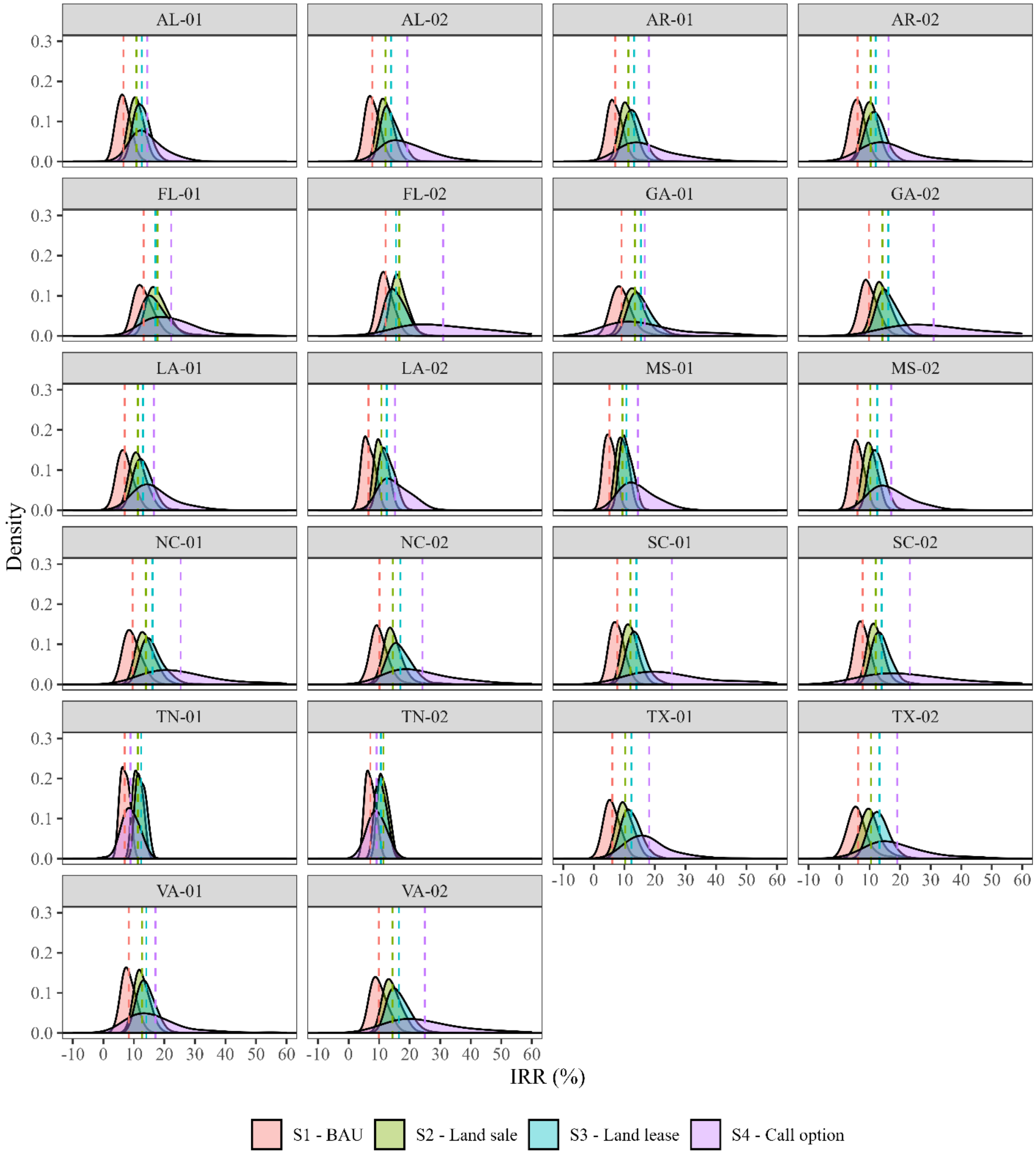

Figure 3.4. Potential return distributions for each timber market and land return scenario.

To reinforce the increase in IRR in scenarios S2 through S4, we calculated the probability that both the lower (Q1 or 0.25 quantile) and upper (Q3 or 0.75 quantile) quartiles of the IRR distributions from these scenarios are greater or equal to those in S1 (Table 3.5). To calculate Q1 and Q3, we split sorted all IRR values for each market and scenario into four equal parts (25% each). First, we calculated the Q1 value for each market and then calculated the probability of these values being greater or equal than those in S1.

In every case, it was very likely (from 79 to 100% chance) that average returns from S2 would be higher than S1 - BAU. For Q1, there was a 99-100% certainty that returns from S2 would be higher than S1 - BAU. This value ranged from 79 to 100% for Q3. There was a 97-100% certainty that returns from S3 would exceed those found for Q1 in S1 – BAU, while a 63-100% likely to exceed those found for Q3, indicating that a 5% land lease can significantly increase the returns. S4 increases were not as consistent as in S2 and S3. Although presenting an 81-100% chance of exceeding Q1 from S1, the probability of exceeding Q3 ranged from 58 to 99%. This means that in the worst case, S2 and S3 are 97-100% likely to provide higher returns than the lowest returns from S1. For S4, this probability ranged from 81 to 100%. Probabilities for S2 to S4 present higher returns than 75% of all returns from S1 ranged from 79-100%, 63-100%, and 58-99%, respectively. It is very likely, then, that the returns from these scenarios are higher than the business as usual (S1).

Table 3.5. Average potential returns change (Δ%) and probabilities (%) of estimated returns of each scenario being equal or greater than Q1 and Q3 from S1 – BAU.

Market	**S2 – Land sale**			**S3 – Land lease**			**S4 – Call option**		
	Δ $\overline{IRR}$	**Q1**	**Q3**	**Δ $\overline{IRR}$**	**Q1**	**Q3**	**Δ $\overline{IRR}$**	**Q1**	**Q3**
AL-01	4.26	100	91	6.08	100	99	7.74	99	94
AL-02	4.31	100	91	6.15	100	99	11.40	100	99
AR-01	4.28	100	89	5.90	100	98	10.97	99	91
AR-02	4.24	100	91	3.83	100	97	10.13	96	88
FL-01	4.53	100	79	3.38	97	63	9.04	97	81
FL-02	4.48	100	92	6.40	99	69	18.81	99	96
GA-01	4.36	100	81	6.33	100	94	7.63	81	62
GA-02	4.39	100	83	5.96	100	95	21.18	100	97
LA-01	4.28	100	87	6.07	100	96	9.47	99	94
LA-02	4.26	100	95	5.55	100	100	8.76	100	99
MS-01	4.21	100	97	6.46	100	100	9.26	100	98
MS-02	4.24	100	94	6.54	100	100	11.06	100	99
NC-01	4.39	100	83	6.84	100	97	15.76	100	95
NC-02	4.40	100	86	6.30	100	95	14.06	99	94
SC-01	4.31	100	90	6.28	100	98	17.92	100	95
SC-02	4.31	100	90	5.34	100	98	15.50	93	87
TN-01	4.28	100	100	3.47	100	100	1.84	87	58
TN-02	4.29	100	100	6.32	100	93	2.07	88	61
TX-01	4.24	99	84	6.99	100	96	12.10	100	97
TX-02	4.25	100	81	5.73	100	98	12.85	98	93
VA-01	4.33	100	92	6.53	100	98	8.68	93	79
VA-02	4.40	100	84	6.08	100	97	15.05	100	94

3.5.2 Risk assessment

The IRR standard deviation was used to assess the investment's risk. The South-wide standard deviation ranged from 3.14% (S1) to 8.65% (S4), showing a risk increase. South-wide risks increased by 0.12% (IRR = 3.26%) and 0.41% (3.55%) in S2 and S3 when compared to S1, respectively. Meanwhile, S4 experienced a 5.51% risk increase.

In S1, risks ranged from 1.39% (TN-01) to 3.61% (TX-02). TX-02 (3.6%) and GA-01 (3.0%) presented the higher risks among all 22 markets. Meanwhile, TN-01 and TN-02 presented the lower risks. This is reinforced by the peaked curves in Figure 3.4. The same behavior persisted for both markets in all four scenarios. When comparing S2 and S3 with respect to S1, we noticed that, on average, risks slightly increased. In S2, some markets presented lower risks when compared to S1. Differently, all 22 markets presented higher risks in S3 when compared to S1. Nonetheless, the shape of the IRR distributions remained virtually the same, the main difference was that IRR distributions were shifted to the right.

S4 provided the highest risk among all scenarios. This is reinforced by the flatter distributions in Figure 3.4. Surprisingly, FL-02 (30.95% ±12.16%), GA-01 (16.69% ±11.56%), GA-02 (30.96% ±12.74%), NC-01 (25.33% ±11.13%), NC-02 (24.16% ±10.76%), SC-01 (25.57% ±12.92%), and SC-02 (23.18% ±13.45%) presented high returns at a cost of above average risks. Consequently, these markets presented flatter distributions compared to when compared to other markets. Despite the significant overall increase in risk for most markets in S4, an investment decision based solely on the risk (standard deviation) may be misleading. For most markets, IRR distributions for S4 started to the right of S1 tails. This means that S4 investments are very likely to generate higher returns than S1. This is reinforced by Q1 probabilities from Table 3.5. On average, S4 investments are 97% likely to present higher returns when compared to S1. The less likely markets are GA-01 (81%), TN-01 (87%) and TN-02 (88%), while all other markets are at least 93% or more likely to present higher returns than S1. Two main factors could explain this. First, the call value added during the maturity stage (first 5 years of the investment) led to positive cashflows, and consequently, different harvest schedules and revenue shares (see section 3.5.3). Second, higher selling prices in the strike period also resulted in another year with positive cash flow, but with significant revenue.

We noted that in some prices and costs combinations, the strategic landscape planning model preferred to harvest forests in the first years in S1. After that, the thinning and harvest volume reduced and remained close to zero until the end of the planning horizon. This resulted in negative cash flows from year 1 to 14. In contrast, the strategic landscape planning model sought to keep positive cashflows throughout the planning horizon, generating high IRR values.

One analysis that may be of interest to investors is the relationship between returns and risks. Figure 3.5A shows this relationship within each market and scenario. The limits for defining the quadrants followed the logic of dividing the maximum value on each axis by 2, therefore being 7.5% for the x-axis (risk) and 17.5% for the y-axis (return). All markets in S1, S2, and S3 were located in the II quadrant (low risk - low return), except for FL-01 in S2 (17.71%) which is right above the edge of the I quadrant (low risk - high return). S4 investments were spread across all four quadrants, reflecting the higher risk of this scenario. The only S4 investment in I quadrant was AL-02. When we removed S4 (Figure 3.5B) and adjusted the quadrants' thresholds, we noticed more investments in the I quadrant (mainly S2 and S3), meaning that it is possible to achieve returns over 10% with lower risk (>2.5%) in these scenarios. Only one market from S1 in I quadrant was FL-02 (12.14% ±2.30%). This information is useful for landowners and investors to assist with their portfolio management depending on their risk aversion and return target. It is worth noting that this classification was based on the strategic landscape planning model and the stochastic simulation process, as well as the historical prices. Hence, this analysis does not consider prices that are outside the ranges observed during the period 1980-2024.

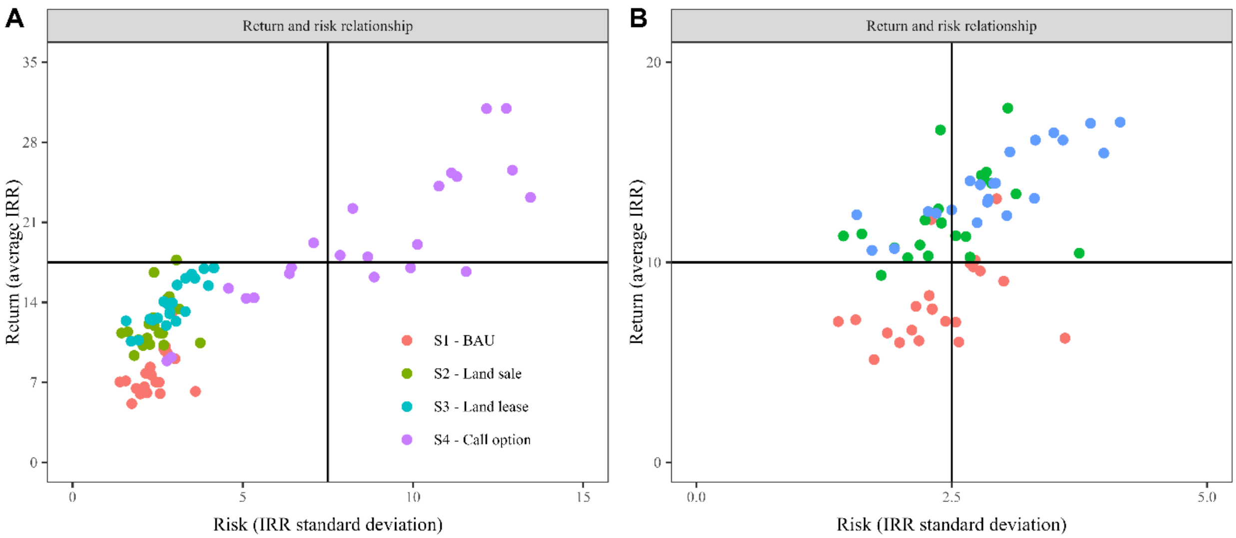

Figure 3.5. Return and risk relationship for timberland investments in the US South.

3.5.3 Revenue share

Figure 3.6 illustrates the share of each revenue layer across all four scenarios. In S1 – BAU, land appreciation accounted for 63% of the asset value, while timber revenues comprised 37%. This value, however, ranged significantly from 97-3% (TN-02) to 33-67% in FL-02. As expected, timber revenues were most significant in FL-01, FL-02, GA-02, and NC-02. These markets presented a positive combination of historical timber prices, site indexes, and initial timber stock, causing the model to choose to harvest the largest available area over 15 years. In contrast, timber share was lower in markets with a negative combination of the three variables. For example, we noticed that the area harvested over the 15 years was only, on average, 6% in TN-02. The model chose to leave the forest standing and benefit from the constant rate of land appreciation (2.2% per year).

Land appreciation share reduced from 63% for S1 to 29% for S2 and S3. Timber revenues increased significantly from S2 (59%) and S3 (53%) when compared to S1 – BAU. This happened to all markets, especially for those with small timber shares in S1 – BAU. Since only 5% of the land was sold in S2, the land sale share was consistently around the average (11%), ranging from 9 to 14%. Similarly, the land formal lease ranged from 13% to 27%, with an average share of 19%. The land lease share was higher than the land sale because the cash flow benefited not only from annual lease payments but also from the perpetuity present value added in the last year of the planning horizon. This also reduced the timber share in S2.

Although representing only 10% (from 5 to 16%) of the total share, the call option contract caused a significant change in the harvest schedule. The annual payment during the option period, combined with the 5% selling in the strike period, helped the cash flow to have positive values. Depending on the combination of biological growth, timber prices, and asset costs, the harvested area changed considerably, resulting in a great IRR variation.

Figure 3.6. Revenue share from each land return scenario.

3.6 Discussion and conclusions

In this paper, we assessed maximum potential returns and risks across 22 timber markets using four different scenarios of land returns in addition to timber revenues in a 15-year investment period. We designed a stochastic simulation process using a strategic landscape planning model to account for different growth rates, timber and land prices. We extended the prior literature in three different ways. First, we complemented the studies conducted by Caulfield (1998), Mei et al. (2013), Restrepo et al. (2020), and Cooper and Dwivedi (2024), estimating potential returns for a post-pandemic period with multiple initial age strata, instead of starting at age 0 or 10 years using a planning model. Also, estimated returns were generated by a planning model instead of indexes.

In general, our results from the business as usual scenario (S1 – BAU) are aligned with previous research. The south-wide return was 8.02% (± 3.14%), with MS-01 presenting the lowest return (5.14% ±1.74%) and FL-01 with the highest return (13.18% ± 2.94%). Some studies estimated returns over the entire rotation period (*e.g.*, Chudy et al. 2020), others for a specific investment period (*e.g.*, Mei et al., 2013). Nonetheless, returns were similar. For example, Chudy et al. (2020) found south-wide returns of 5.97% (± 0.61%) and 7.33% (± 0.63%) for medium and high productive sites, respectively. These authors estimated returns over the entire rotation period, excluding land costs and compared its effect on timberland returns. The authors also mentioned that excluding land could decrease overall returns from 3%. Mei et al. (2013) simulated expected returns for 2010-2025 and found average returns ranging from 7.25% (± 3.71%) to 8.35% (± 1.51%) when using random and mean-reverting timber prices. Callaghan et al. (2019) estimated returns for loblolly pine investments in the US South under different cost scenarios. Although they did not publish return values, they found positive NPVs using a 7% discount rate, indicating IRRs higher than 7%. Cubbage et al. (2020) found average IRRs of 3.2% and 5.9% with and without land costs, respectively.

The returns varied significantly across the 22 markets. Five markets always presented above-average returns in all four scenarios: FL-01, FL-02, GA-02, NC-01, and NC-02. Although no regional demand or the actual size of each forest sector was considered in this study, FL-01, FL-02, GA-02, and NC-02 are among the biggest regional markets in the US South. We acknowledge that NC-01 is a small market compared to other regions. High returns for this market can be attributed to input's combination (timber prices, land appreciation, land selling value). Despite the large area of timberland in AL-01, AL-02, MS-01, MS-02 and TX-02, these markets always presented one of the lowest returns in this study. This could be attributed to the low timber and land selling prices (Table 3.3).

Regional returns are not commonly published in related literature. As mentioned before, most studies reported IRR for the entire US South as a unique region. One exception was the study published by Zhang and Mei (2019), in which the authors compared returns across the 22 markets with other crops (almonds, apples, corn and others). Similarly, FL-01, FL-02, GA-02, NC-01, and NC-02 figured in above-average returns, while AL-01, AL-02, MS-01 and MS-02 presented lower returns. However, this study was focused on comparing timberland investments against other crops, while our study focused on assessing the impact of land revenues from call option contracts for solar developments. Another difference is that these authors used NCREIF and timber prices to estimate returns, while our returns were estimated from a landscape planning model. NCREIF does not capture the effects of these call option contracts or other land use change possibilities on timberland investments.

The inclusion of land returns increased timberland investment potential returns and risks. This new market trend could increase returns from 4.32 to 11.40%, while risks increased from 0.14% to 5.51%. Scenario S2 with 5% land sale for another higher and better use could increase timberland returns by 4.32%. We acknowledge that not every timberland could be converted to solar plants, whether due to the slope or proximity to any facility. However, selling a small piece of land that could be used for farm crops would increase returns significantly. Similarly, small-scale formal lease agreements for solar could also increase a timberland investment significantly (by 5.90%, on average). This is true, especially because annual payments benefit the cashflow and increase the land selling price. Reported annual payments range from $500 to $2,000 per acre per year for 25-30 years.

Our study presents some limitations. First, we estimated maximum potential returns, meaning that no other constraint was added to the strategic planning model. We recognize that returns within a context with operational constraints should be lower than those reported. Any unforeseen shift in timber prices outside the historical range can result in returns outside the distributions. Timber prices in local transactions could differ from the regional average, due to the distance to mills or transportation costs. The same applies to yield gaps caused by natural catastrophes or diseases. We acknowledge that land prices can also vary significantly depending on size, site quality and many other factors. Hence, portfolio managers should take those variables into account when performing such financial analysis (Chudy et al., 2020). Our goal was to complement the literature by assessing potential returns across different regions in the US South and highlight the impact of new revenue layers from land management over timber management. It is in the interest of landowners and investors to understand the benefits and losses before deciding whether to accept selling or leasing their land. The strategic landscape planning model and the stochastic process we presented here could be expanded to other areas globally or even when simulating other local or regional market trends. Finally, we recognize that future maintenance and land conversion after the lease period could also decrease returns.

REFERENCES

ALIG, R.J., KLINE, J.D., LICHTENSTEIN, M. 2004. Urbanization on the US landscape: looking ahead in the 21st century. Landsc. Urban Plan. 69(1-2): 219-234. https://doi.org/10.1016/j.landurbplan.2003.07.004

BLACK, F., SCHOLES, M. 1972. The valuation of option contracts and a test of market efficiency. J. Financ. https://doi.org/10.2307/2978484

BRENNAN, M., SCHWARTZ, E. 1977. The valuation of American put options. J. Financ. 32: 449-462. https://doi.org/10.2307/2326779

BRUCK, S.R., PARAJULI, R., CHIZMAR, S., SILLS, E.O. 2023. Impacts of COVID-19 pandemic policies on timber markets in the Southern United States. J. For. Buss. Res. 2(1): 130-167.

BUSBY, G.M., BINKLEY, C.S., CHUDY, R.P. 2020. Constructing optimal global timberland investment portfolios. For. Policy Econ. 111: 102083. https://doi.org/10.1016/j.forpol.2019.102083

CALLAGHAN, D.W., KHANAL, P.N., STRAKA, T.J. 2019. An analysis of costs and cost trends for southern forestry practices. J. For. 117 (1): 21–29. https://doi.org/10.1093/jofore/fvy060

CAULFIELD, J.P. 1998. Timberland return drivers and investing styles for an asset that has come of age. Real Estate Finance 14(4): 65-78.

CHANG, S.J. 2001. One formula, myriad conclusions, 150 years of practicing the Faustmann formula in Central Europe and the USA. For. Policy Econ. 2(2): 97–99. https://doi.org/10.1016/s1389-9341(01)00053-3

CHANG, S.J., ZHANG, F. 2023. Active timber management by outsourcing stumpage price uncertainty with the American put option. For. Policy Econ. 154: 103024. https://doi.org/10.1016/j.forpol.2023.103024

CHANG, S.J., ZHANG, F. 2024. Outsourcing stumpage price uncertainty with American put option for active timber management. For. Policy Econ. 169: 103355. https://doi.org/10.1016/j.forpol.2024.103355

CHUDY, R.P., CHUDY, K.A., KANIESKI DA SILVA, B., CUBBAGE, F.W., RUBILAR, R., LORD, R. 2020b. Profitability and risk sources in global timberland investments. For. Policy Econ. 111: 102037. https://doi.org/10.1016/j.forpol.2019.102037

CHUDY, R.P., CUBBAGE, F.W. 2020a. Research trends: Forest investment as a financial asset class. For. Policy Econ. 119: 102273. https://doi.org/10.1016/j.forpol.2020.102273

CLUTTER, J.L., FORSTON, J.C., PIENNAR, L.V., BRISTER, G.H., BAILEY, R.L. 1983. Forest-level management and planning: Current techniques. In: Timber Management: A quantitative approach. 1st ed. John Wiley & Sons. Inc. (1983), pp. 272-304.

COOPER, C., DWIVEDI, P. 2024. Economic comparison of loblolly pine and solar power in South Georgia, United States. Trees, Forests and People 16: 100528. https://doi.org/10.1016/j.tfp.2024.100528

CUBBAGE, F., KOESBANDANA, S., MAC DONAGH, P., RUBILAR, R., BALMELLI, G., OLMOS, V.M., DE LA TORRE, R., MURARA, M., HOEFLICH, V.A., KOTZE, H., GONZALEZ, R., CARRERO, O., FREY, G., ADAMS, T., TURNER, J., LORD, R., HUANG, J., MACINTYRE, C., MCGINLEY, K., ABT, R., PHILLIPS, R. 2010. Global timber investments, wood costs, regulation, and risk. Biomass Bioenergy 34: 1667-1678. https://doi.org/10.1016/j.biombioe.2010.05.008

CUBBAGE, F.W., KANIESKI, B., RUBILAR, R., BUSSONI, A., OLMOS, V.M, BALMELLI, G., MAC DONAGH, P., LORD, R., HERNÁNDEZ, C., ZHANG, P., HUANG, J., KORHONEN, J., YAO, R., HALL, P., DE LA TORRE, R., DIAZ-BALTEIRO, L., CARRERO, O., MONGES, E., THU, H.T.T., FREY, G., HOWARD, M., CHAVET, M., MOCHAN, S., HOEFLICH, V.A., CHUDY, R., MAAS, D., CHIZMAR, S., ABT, R. 2020. Global timber investments, 2005-2017. For. Policy Econ. 112: 102802. https://doi.org/10.1016/j.forpol.2019.102082

CUBBAGE, F.W., MAC DONAGH, P., BALMELLI, G., OLMOS, V.M., BUSSONI, A., RUBILAR, R., DE LA TORRE, R., HUANG, J., HOEFLICH, V.A., MURARA, M., KANIESKI, B., HALL, P., YAO, R., ADAMS, P., KOTZE, H., MONGES, E., PÉREZ, C.H.P., WIKLE, J., ABT, R., GONZALEZ, R., CARRERO, R. 2014. Global timber investments and trends, 2005-2011. N. Z. J. For. Sci. 44 (Suppl 1): S7. https://doi.org/10.1186/1179-5395-44-S1-S7

CUBBAGE, F.W., MAC DONAGH, P., SAWINSKI JÚNIOR, J., RUBILAR, R., DONOSO, P., FERREIRA, A., HOEFLICH, V., MORALES OLMOS, V., FERREIRA, G., BALMELLI, G., SIRY, J., NOEMI BÁEZ, M., ALVAREZ, J. 2007. Timber investment returns for selected plantation and native forests in South America and the Southern United States. New Forests 33(3): 237-255. https://doi.org/10.1007/s11056-006-9025-4

CUBBAGE, F.W., RUBILAR, R., MAC DONAGH, P., KANIESKI DA SILVA, B., BUSSONI, A., MORALES, V., BALMELLI, G., HOEFLICH, V.A., LORD, R., HERNÁNDEZ, C., ZHANG, P., THU, H.T.T., YAO, R., HALL, P., KORHONEN, J., DÍAZ-BALTEIRO, L., RODRÍGUEZ-SOALLEIRO, R., DAVIS, R., CHUDY, R., DE LA TORRE, R., LOPERA, G., PHIMMAVONG, S., GARZÓN, S., CUBAS-BAEZ, A. 2022. Comparative global timber investment costs, returns, and applications, 2020. J. For. Bus. 1(1): 90-121. https://doi.org/10.62320/jfbr.v1i1.16

DIÉGUEZ-ARANDA, U., BURKHART, H.E., AMATEIS, R.L. 2006. Dynamic site model for Loblolly Pine (*Pinus taeda* L.) plantations in the United States. For. Sci. 52(3): 262-272. https://doi.org/10.1093/forestscience/52.3.262

ENERGY INFORMATION ADMINISTRATION (EIA US). 2025. New solar plants expected to support most U.S. electric generation growth. https://www.eia.gov/todayinenergy/detail.php?id=64364

FAUSTMANN, M. 1849. Berechnung des Wertes welchen Waldboden sowie noch nicht haubare Holzbestände für die Waldwirtschaft besitzen. Allgemeine Forst- und Jagdzeitung 12: 441-455.

FORISK. 2024. Concentration of demand is a key metric for timberland investors and wood-using mills. https://forisk.com/wp-content/uploads/20241205-Press-Release-Forisk-Custom-Market-Forecast.pdf

GONZÁLEZ-GONZÁLEZ, J.M., VÁZQUEZ-MÉNDEZ, M.E., DIÉGUEZ-ARANDA, U. 2022. Multi-objective models for the forest harvest scheduling problem in a continuous-time framework. For. Policy Econ. 136: 102687. https://doi.org/10.1016/j.forpol.2021.102687

HARRISON, W.M., BORDERS, B.E. 1996 Yield prediction and growth projection for site-prepared loblolly pine plantations in the Carolinas, Georgia, Alabama and Florida. PMRC Tech. Rep. 1996, 66p.

HULL, J.C. 2011. Options, futures, and other derivatives, 8th ed. Pearson, Upper Saddle River

KEEGAN C.E., SORENSON C.B., MORGAN T.A., HAYES S.W., DANIELS J.M. 2011. Impact of the Great Recession and housing collapse on the forest products industry in the western United States. For. Prod. J. 61(8): 625–634.

LANDGATE. 2024. Solar farm leasing in South Carolina. https://www.landgate.com/news/solar-farm-leasing-in-south-carolina

LANDGATE. 2025. Getting paid for solar lease on your land. https://www.landgate.com/news/getting-paid-for-solar-lease-on-your-land

LI, C., BARCLAY, H., ROITBERG, B., LALONDE, R. 2020. Forest productivity enhancement and compensatory growth: A review and synthesis. Front. Plant Sci. 11: 575211. https://doi.org/10.3389/fpls.2020.575211

MAGGARD, A., NATZKE, J. 2023. Costs and trends for southern forestry practices. https://forestlandowners.com/cost-and-trends-of-southern-forestry-practices/

MEI, B. 2015. Illiquidity and risk of commercial timberland assets in the United States. J. For. Econ. 21(2): 67-78. https://doi.org/10.1016/j.jfe.2015.01.003

MEI, B., CLUTTER, M.L. 2023. Forestland Investment: Valuation and Analysis (1st ed.). Routledge. https://doi.org/10.4324/9781003366737

MEI, B., CLUTTER, M.L., HARRIS, T. 2010. Modeling and forecasting pine sawtimber stumpage prices in the US South by various time series models. Can. J. For. Res. 40(8): 1506-1516. https://doi.org/10.1139/X10-087

MEI, B., CLUTTER, M.L., HARRIS, T.G. 2013. Timberland return drivers and timberland returns and risks: A simulation approach. South. J. Appl. For. 37(1): 18–25. https://doi.org/10.5849/sjaf.11-022

RESTREPO, H., ZHANG, W., MEI, B. 2020. Time time-varying role of timberland in long-term, mixed-asset portfolios under the mean conditional value-at-risk framework. For. Policy Econ. 113: 102136. https://doi.org/10.1016/j.forpol.2020.102136

RIDDLE, A. 2021. COVID-19 and the US timber industry (updated 29 July 2021). Congressional Research Service, Washington, D.C.

RIVERA, N.M., RUIZ-TAGLE, J.C., SPILLER, E. 2024. The health benefits of solar power generation: Evidence from Chile. J. Environ. Econ. Manag. 126: 102999. https://doi.org/10.1016/j.jeem.2024.102999

SANQUETTA, M.N.I., MCTAGUE J.P., SCOLFORO, H.F., BEHLING, A., SANQUETTA, C.R., SCHMIDT, L.N. 2020. What factors should be accounted for when developing a generalized taper function for black wattle trees? Can. J. For. Res. 50(11): 1113-1123. https://doi.org/10.1139/cjfr-2020-0163

SEDJO, R.A. 1984. An economic assessment of industrial forest plantations. For. Policy Econ. 9(4): 245-257. https://doi.org/10.1016/0378-1127(84)90011-2

SILVA, B.K., REZAEI, F., TANGER, S., HENDERSON, J., MCCONNELL, E., SUN, C. 2024. Terminal value: A crucial and yet forgotten element in timber harvest scheduling and timberland valuation. For. Policy Econ. 162: 103188. https://doi.org/10.1016/j.forpol.2024.103188

STANKE, H., FINLEY, A.O., WEED, A.S., WALTERS, B.F., DOMKE, G.M. 2020. rFIA: An R package for estimation of forest attributes with the US Forest Inventory and Analysis database. Environ. Model. Softw. 127: 104664. https://doi.org/10.1016/j.envsoft.2020.104664

STRAKA, T. 2007. Valuation of bare forestland and pre-merchantable timber stands in forest appraisal. J. Am. Soc. Farm Manage. Rural Appraisers 70: 142-146. https://doi.org/10.22004/ag.econ.189899

SUN, C., NING, Z. 2014. Timber restrictions, financial crisis, and price transmission in North American softwood lumber markets. Land Econ. 90(2): 306-323. https://doi.org/10.3368/le.90.2.306

SUN, C., ZHANG, D. 2001. Assessing the financial performance of forestry-related investment vehicles: Capital asset pricing model vs Arbitrage pricing theory. Am. J. Agric. Econ. 83(3): 617-628. https://doi.org/10.1111/0002-9092.00182

THOMAS, M. 2012. Maybe it's time to look at timber growing through contrarian eyes. F&W For. Rep. Spring, 112 (2012), pp. 1-2.

TIMBERMART-SOUTH. 2024. Quarterly market news. https://timbermart-south.com/industry-reports/quarterly-market-news/

TRIM, K.R., COBLE, D.W., WENG, Y., STOVALL, J.P., HUNG, I-K. 2020. A new site index model for intensively managed loblolly pine (*Pinus taeda*) plantations in the West Gulf Coastal Plain. For. Sci. 66(1): 2-13. https://doi.org/10.1093/forsci/fxz050

TRLICA, A., COOK, R.L., ALBAUGH, T.J., PARAJULI, R., CARTER, D.R., RUBILAR, R.A. 2021. Financial returns for biomass on short-rotation Loblolly pine plantations in the Southeastern United States. For. Sci. 67(6): 670-681. https://doi.org/10.1093/forsci/fxab033

UNITED STATES DEPARTMENT OF AGRICULTURE (USDA). 2024. Land values 2024 summary. https://www.nass.usda.gov/Publications/Todays_Reports/reports/land0824.pdf.

WALL STREET JOURNAL. 2023. Solar boom spreads to timberlands and self-storage rooftops. https://www.wsj.com/business/energy-oil/solar-boom-spreads-to-timberlands-and-self-storage-rooftops-e6cd7b23.

WALL STREET JOURNAL. 2024. U.S. renewable power growth is setting new records on the back of federal support. https://www.wsj.com/articles/u-s-renewable-power-growth-is-setting-new-records-on-the-back-of-federal-support-2f844b66.

WAN, Y., CLUTTER, M.L., MEI, B., SIRY, J.P. 2015. Assessing the role of U.S. timberland assets in a mixed portfolio under the mean-conditional value at risk framework. For. Policy Econ. 50: 118-126. https://doi.org/10.1016/j.forpol.2014.06.002

WEAR, D.V., WINGENROTH, J., BARTUSKA, A. 2025. Converting forests to solar facilities: Causes, potential, and implications. Resources for the Future. Washington, DC. https://www.rff.org/publications/reports/converting-forests-to-solar-facilities-causes-potential-and-implications/

WOODSON, J. S. 2019. Benefits of using southern buffer forest lands for timber production versus solar energy. [Master’s Thesis, Mississippi State University].

YUE, C., HAHLE, H.P., KLÄDTKE, J., KOHNLE, U. 2024. A growth-effective age-based periodic site-index for the estimation of dynamic forest site productivity under environmental changes. Ann. For. Sci. 81: 33. https://doi.org/10.1186/s13595-024-01253-8

ZHANG, D., BUTLER, B.J., NAGUBADI, R.V. 2012. Institutional timberland ownership in the US South: Magnitude, location, dynamics, and management. J. For. 110(7): 355–361. https://doi.org/10.5849/jof.12-015

ZHANG, W., MEI, B. 2019. Assessing the risk and return of optimal portfolios of U.S. timberland and farmland. J. Real Estate Portf. Manag. 25(1): 99-113. https://doi.org/10.1080/10835547.2019.12090026

CHAPTER 4

BUILDING AN OPTIMAL TIMBERLAND PORTFOLIO FOR BROWNFIELD INVESTMENTS IN THE US SOUTH[3]

[3]Sanquetta, M. N. I, Kanieski da Silva, B., Kinane, S. M., Bettinger, P., Siry, J. To be submitted to Journal of Forestry

Abstract

Modern portfolio theory is a crucial tool to support budget allocation and risk-efficient management of corporate and institutional investments. Timberland portfolios reflected the current investment environment at their time. In this study, we used updated returns and risks for 22 timber markets across the US South. Using a mean-variance (M-V) model, we estimated three portfolios for 22 timber markets in the US South. A total of two portfolios were estimated. The first portfolio – P1 considered 15-year timberland investments with timber revenues and land appreciation, while the second portfolio **-** P2 accounted for small-scale land returns from sales, leases and call option contracts for solar development and reflected the current market trend. The business as usual portfolio presented returns ranging from 5.16% and 11.31% for the risk minimizing and return maximizing portfolios. We noticed a 6.23% increase on both risk minimizing and return maximizing portfolios for P2 when compared to P1. In the minimum risk case, P2 presented a return higher return when compared to P1, highlighting the impact of land returns on timberland investments. The Sharpe ratio ranged from 0.54 to 0.99 for P1, and from 1.31 to 1.69 for P2. Allocation in FL-01, FL-02, and NC-01 increased as the risk budget increased.

4.1 Introduction

Commercial timberland has received increasing attention from institutional investors in the US South during the last decades (Cascio and Clutter, 2008; Waggle and Johnson, 2009; Timberland Investment Resources, 2024). Timberland investments have been recognized as a mean of portfolio diversification among institutional investors due to low risk, low correlation with traditional stocks, bonds, and equities (Liao et al., 2009; Wan et al., 2013; Busby et al., 2020). Hence, investment portfolios could benefit from diversification and protection against inflation (Binkley et al., 2001).

According to the financial theory, a portfolio is a collection of different assets/investments (Gunjan and Bhattacharyya, 2023). Combining these different assets, investors tend to maximize returns and minimize risks. However, high returns often come at the cost of high risks. Depending on the degree of risk and return, portfolios can be further characterized as (i) aggressive portfolios, (ii) defensive portfolios, (iii) income portfolios, (iv) speculative portfolios, and (v) hybrid portfolios. Usually, aggressive portfolios aim for higher returns and undertake high risks, while defensive portfolios aim for minimum risks and give minimum returns (Gunjan and Bhattacharyya, 2023). Income and speculative portfolios are focused on dividends and other types of benefits or are somehow similar to gambling. In contrast, hybrid portfolios aim to provide optimum returns with optimum degrees of risk.

To optimize the tradeoffs between maximizing expected returns and minimizing risks, Markowitz (1952) proposed the mean-variance (M-V) model. M-V is one of the most common approaches for identifying the tradeoffs between maximizing expected returns and minimizing risks (Chen et al. 2021). Different studies employed the M-V model to optimize timberland portfolios (*e.g.*, Reeves and Haight, 2000; Knoke, 2008; Zhang and Mei, 2019; Busby et al. 2020).

Reeves and Haight (2000) ran a harvest schedule model for loblolly pine stands in Georgia, USA, and derived returns and risks to employ in an M-V model. Differently, Zhang and Mei (2019) used timber prices and NCREIF to calculate returns and risks for 22 markets across the US South and compared them with other crops.

Timberland investments can present very different returns, depending on the region, species, timber products, and other factors. One recent study conducted by Busby et al. (2020) estimated an optimal portfolio of global timberland portfolio, including different species (*e.g.*, pine plantations, Douglas-fir, eucalypt, teak, poplar, and other mixed hardwood and conifers). These authors found returns (nominal) ranging from 5.3% to 12.4%. However, even in the same region, local variability can result in different returns (see Cubbage et al. 2007; Callaghan et al. 2019; Mei et al. 2019; Chudy et al. 2020; Cubbage 2020; Cubbage et al. 2022). This is reinforced by the results presented by Zhang and Mei (2019), in which authors found returns ranging from 2.08 to 8.12%.

However, since this study, timber prices declined significantly due to the COVID-19 pandemic and mill closures (Bruck et al. 2023; Forisk Consulting, 2024). Additionally, landowners are being exposed to new opportunities to make their land more profitable than focusing solely on timber production. The Inflation Reduction Act boosted investments in solar and wind energy across the United States. Usually, both solar and wind require big areas to be profitable (Cooper and Dwivedi, 2024). It shifted attention to US South timberlands. So far, different states in the US South are experiencing a significant transition from timberlands towards new solar plants (Woodson, 2019; Cooper and Dwivedi, 2024; Landgate, 2024) and 3 to 7.5 million acres of timberland are expected to be converted to solar plants in the next 20 years (Wall Street Journal, 2024; Wear et al. 2025).

Under this context, we complement the literature by: i. calculating returns from different regions other than the state of Georgia (Reeves and Haight, 2000) or the average South-wide (Busby et al. 2020; Chudy et al. 2020; Restrepo et al. 2020), ii. updating returns and risks from Zhang and Mei (2019) after the COVID-19 pandemic. Although these authors used a different approach to estimate returns, we encompassed the same markets and considered a larger timber prices window (1980-2024). Finally, we extend the literature by building an optimized timberland investment portfolio including returns from land returns from solar developments.

4.2 Portfolio optimization model

The portfolio optimization model used in this study is based on mean-variance (M-V). The M-V model was proposed by Markowitz (1952) and can be used for effective portfolio selection when the objective is to (i) minimize variance for a given expected return and (ii) maximize expected return for a given variance. According to Gunjan and Bhattacharrya (2023), the M-V model is fast, useful and easy to implement. It maximizes expected returns at several different levels of risk and the objective is to find the weight of the assets that will minimize the variance at a given rate of return.

M-V model was recently applied in Busby et al. (2020) for a global timberland investment portfolio. In this study, we replicate the model in the same fashion, in which the model is subject to three main constraints. First, the portfolio risk budget must be smaller or equal to the maximum level of risk (portfolio variance). Second, the portfolio must be fully invested (*i.e.*, the sum of weights has to be equal 1). Finally, weights assigned to each asset have to be non-negative. The model is mathematically defined as follows:

$$E(r) = max \sum_{i=1}^{n} r_i w_i \tag{4.1}$$

Subject to:

$$\sum_{i=1}^{n} w_i^2 s_i^2 + 2 \sum w_i w_j cov(w_i w_j) \leq s_m^2 \tag{4.2}$$

$$\sum_{i=1}^{n} w_i = 1.0 \tag{4.3}$$

$$w_1, w_2, \ldots, w_n \geq 0 \tag{4.4}$$

where $E(r)$ is the expected portfolio return. i and $j = 1, 2, \ldots, n$ is the number of assets, r_i is the expected return from the i^{th} asset, w_i is the weight assigned to the i^{th} asset, s_i^2 is the variance of the i^{th} asset and s_m^2 is the maximum level of risk (or the portfolio variance)

After estimating several portfolios along a range of risk budgets, we generated the risk-efficient frontier. The risk-efficient frontier is defined as the set of portfolios that maximize $E(r)$ across the range of risk budgets. This process was used to generate the highest possible return for a specific risk budget and, equivalently, the lowest possible risk at the risk budget range. For each combination of maximized return and risk budgets, we estimated the Sharpe ratio (S). The Sharpe ratio is a measure of risk-adjusted return, which compares the portfolio return (minus the risk free ratio), divided by its risk.

$$S = \frac{E(r) - r_f}{s} \tag{4.5}$$

where S is the Sharpe ratio, r is the portfolio return, r_f is the risk-free return rate (2.63%[1]), and s is the portfolio risk.

[1] We assumed the risk-free rate to be the average between the 10- and 20-year Treasury Rate from the last 10 years to approximate a 15 year Treasury Rate (U.S. Department of the Treasury).

To better understand different investment possibilities and account for new land returns, we estimated two portfolios. The first portfolio (P1) encompassed all 22 markets in the business as usual scenario – S1 BAU (see Section 4.4), in which only timber revenues and land appreciation were considered. This was also considered as our business as usual portfolio. In order to have some diversification, we constrained the model so no single asset could comprise more than 20% of the total portfolio. However, every single market (investment opportunity) had to be investment at least 0.1%. Meanwhile, the second portfolio (P2) considered returns and risks from all four scenarios.

After trying to run the model with all 88 investment possibilities, we noticed that the model did not converge due to the large number of assets, and when it did converge, the portfolio variance was inflated. Also, since this is a matrix-based optimization problem, increasing the number of investment options raised computational time. Considering that our objective was to assess the impact of different land returns, we decided to create 22 portfolios with the four investment options in each of the 22 markets. These portfolios had no diversification constraints. The 22 best investment opportunities, one for each market, were chosen to compose the set of possible investments in P2.

Table 4.1. Set of constraints imposed on the portfolio optimization model.

Constraint	**Description**
(P1) and $w_1, w_2, \dots, w_n \leq 0.2$	The portfolio must include all 22 markets from S1.
(P2) $w_1, w_2, \dots, w_n \leq 0.2$	No single asset can comprise more than 20% of the total portfolio. This portfolio considered the 22 selected assets from S1 to S4.

where *i* and *j* = 1, 2, …, *n* is the number of assets and w_i is the weight assigned to the *ith* asset.

4.3 Methods

In this section, we present the strategic landscape planning model developed to maximize the forest value. We started our analysis by estimating the bare land, forest and terminal values at the stand level. A similar framework developed by Clutter et al. (1983) and replicated by González-González et al. (2020) and Silva et al. (2024) was used (see Appendix A). The first step was estimating the land expectation value (LEV) to determine the optimal silvicultural treatment and rotation age. From them, we estimated the forest and terminal values using a discounted cash flow analysis (DCF). The planning horizon was T = 15 years to mimic typical institutional timberland investments in the US South (Mei and Clutter, 2023).

4.3.1 Strategic landscape planning model

A strategic landscape planning model was designed to optimize the forest value by scheduling thinning and harvesting operations among each age strata under different silvicultural regimes (Table 4.2). The forest value was the summation of present values ($/acre) of each age strata. The mathematical formulation is described as follows:

$$\max_{A_{i,t},H_{i,t},R_i} \underbrace{\sum_k^K \sum_i^I \sum_t^T \frac{\left(p_k q_{i,k} H_{i,t}\right)}{(1+r)^t}}_{(A)} + \underbrace{\sum_i^I \frac{A_{i,t}(TV_i R_i)}{(1+r)^{t=T}}}_{(B)} - \underbrace{\sum_i^I \frac{(FV_i)A_{i,t=0}}{(1+r)^{t=0}}}_{(C)} - \underbrace{\sum_i^I \sum_t^T \frac{A_{i,t}(C_i + ac_t)}{(1+r)^t}}_{(D)}$$

(4.6)

Subject to:

$A_{i,t} \geq H_{i,t} \; \forall \, i \; \in [0, I]$ and $t \; \in [0, T]$ (4.7)

$A_{i,t=0} = a_i \; \forall \, i \; \in [0, I]$ (4.8)

$A_{i,t=T} - H_{i,t=T} = R_i \; \forall \, i \; \in [0, I]$ (4.9)

$H_{i,t} = 0 \; \forall \, i \; \in [0, \Gamma]$ and $t \; \in [0, T]$ (4.10)

$H_{i,t} \leq A_{i,t}$ (4.11)

where p_k is the price if the k product, $q_{i,k}$ is the volume available of the k product at i age per acre, r is the discount rate of 4% (Cubbage et al. 2020), $H_{i,t}$ is the area harvested of age i at period t, $A_{i,t}$ is the area available at age i at period t, a_i is the area available at age i, TV_i is the terminal value at $t = T$, T is the terminal period (15 years), R_i is the residual area at terminal period $t = T$, FV_i is the forest value per acre at age i, C_i is the establishment cost per acre when $i = 0$, and ac_t is the annual cost per acre from $t = 0$ to T.

Eq. 4.6 is the objective function, in which section (A) represents the present value of revenues in \$/acre. Section (B) is the terminal value at $t = T$ in \$/acre. Section (C) represents the initial investment cost at $t = 0$ in \$/acre. Section (D) is the present value of costs in \$/acre. Eq. 4.7 ensures that the harvested area (H) is less than or equal to the area available (A). Eq. 4.8 sets the initial forest structure at $t = 0$. Eq. 4.9 calculates the residual area after harvesting at period T. Eq. 4.10 ensures that any stand is at least Γ years before harvest. In our study, we set $\Gamma = 20$ years as the minimum merchantable age to account for short rotation stands focused on small-end diameter logs.

4.3.2 Scenarios and stochastic simulation

We proposed four scenarios to estimate the impact of different stages of a small-scale lease-purchase call option contract for solar developments (Table 4.2). The first scenario was (S1) business as usual – BAU, in which input variables representing the three main return drivers (i. biological growth, ii. timber prices fluctuation, and iii. land price appreciation) were simulated 1,000 times to generate a stochastic process. The same stochastic process was used to build scenarios S2 to S4.

Table 4.2. Description of different scenarios of land returns and American call options.

Scenario	Description	Change in section (A) - Eq. 4.6
S1	15-year timberland investment	-
S2	BAU + up to 5% land sale (Land selling price - Table 4.4).	$Eq. 4.6 + \sum_{t}^{T} \frac{(s_t S_t)}{(1+r)^t}$
S3	BAU + up to 5% land lease ($500/acre per year).	$Eq. 4.6 + \sum_{t}^{T} \left(\frac{(lL_t)}{(1+r)^t}\right) + \frac{\left(\frac{l}{r} L_t\right)}{(1+r)^T}$
S4	BAU + 5-years call option + up to 5% land sale. Strike price is equal to S2.	$Eq. 4.6 + \sum_{t}^{4} \left(\frac{(oO_t)}{(1+r)^t}\right) + \frac{oS_{t=4}}{(1+r)^{t=4}}$

Where s_t is the selling value from Table 4.4; l is the leasing value fixed at $500 per acre per year (Landgate, 2024); o is the option value fixed at $25 per acre per year (Landgate, 2024); S_t is the selling area; L_t is the leasing area; O_t is the area under option contract.

First, growth and yield curves were simulated 1,000 times for each market. To build the growth and yield curves, we simulated site indexes (SI) using average and standard deviations since they were normally distributed (see Appendix B). Timber prices were randomly selected for each product (pulpwood - p_{pw}, chip-n-saw - p_{cns}, sawtimber - p_{st}) and market over 1980-2024 period. In order to mimic the historical difference between their prices, we imposed constraints to ensure that $P_{cns} \geq \alpha_1 + P_{pw}$, (ii) $P_{st} \geq \alpha_2 + P_{pw}$, (iii) $P_{st} \geq \alpha_3 + P_{cns}$, where α_1, α_2 and α_3 are the minimum historical difference between their respective prices. The rationale is that the prices of a lower-value product would never be closer or far to the price of a higher-value product than historically observed. Finally, land prices were randomly selected from a uniform distribution drawn from the minimum and maximum values found for the US South ($1,440.66 to $2,618.79, as in Table 4.4).

Scenarios S2 to S4 considered different stages of a small-scale call option contract. S2 considered selling up to 5% of the land (for solar development or another higher and better use). S3 considered leasing up to 5% of the land for solar development. The annual lease payment was set equal to $500 per acre per year (Landgate, 2024). S4 considered the 5-year maturity stage period (Landgate, 2025) with up to 5% selling only in the strike period (S4). During the option maturity stage period (t = 0 to 4), also known as the development period, an annual payment of $25 per acre was added. During the strike period, up to 5% of the land was sold for the same price as in S2. These new scenarios imply changes in Section (A) of Eq. 4.6 build for S1 (Table 4.2). Similarly, new constraints were imposed. First, the area available ($A_{i,t}$) for harvesting was reduced in S2 and S3 to the same extent that an area was sold ($S_{i,t=T}$) or rented ($L_{i,t=T}$). We also ensured that the timber volume was harvested before selling or leasing the land. Considering that solar farm leases are usually 25-30 years long (Landgate, 2024), we recognize that this piece of land is unlikely to be converted back into timberland after this period. Hence, we added a perpetuity present value of $\left(PV = \frac{l_i}{r} = \$12{,}500 \text{ per acre}\right)$ to reflect the higher market value at the end of the planning horizon or liquidation.

4.3.3 Return and risk assessment

Potential returns and risks were assessed by capital budgeting criteria. As beforementioned, we estimated the forest value for each 1,000 simulations generated for each market within every scenario. From these values, we calculated the internal rates of return (IRR) by setting the discount rate at which NPV was equal to zero. The return of each market and scenario combination was equal to its average, while the risk was measured by the IRR standard deviation, similar to Cubbage et al. (2010), Chudy et al. (2020), and Busby et al. (2020).

4.4 Data

4.4.1 Study area

We assessed average potential returns of brownfield investments in 22 different markets within 11 states of the US South (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia), as shown in Figure 4.1. These 22 markets encompassed all TimberMart-South (TMS) regions and more than 35 million acres (14.4 million hectares) of privately-owned corporate timberland. Each one of the 11 states has two markets, named as: Alabama (AL-01 and AL-02), Arkansas (AR-01 and AR-02), Florida (FL-01 and FL-02), Georgia (GA-01 and GA-02), Louisiana (LA-01 and LA-02), Mississippi (MS-01 and MS-02), North Carolina (NC-01 and NC-02), South Carolina (SC-01 and SC-02), Tennessee (TN-01 and TN-02), Texas (TX-01 and TX-02), and Virginia (VA-01 and VA-02).

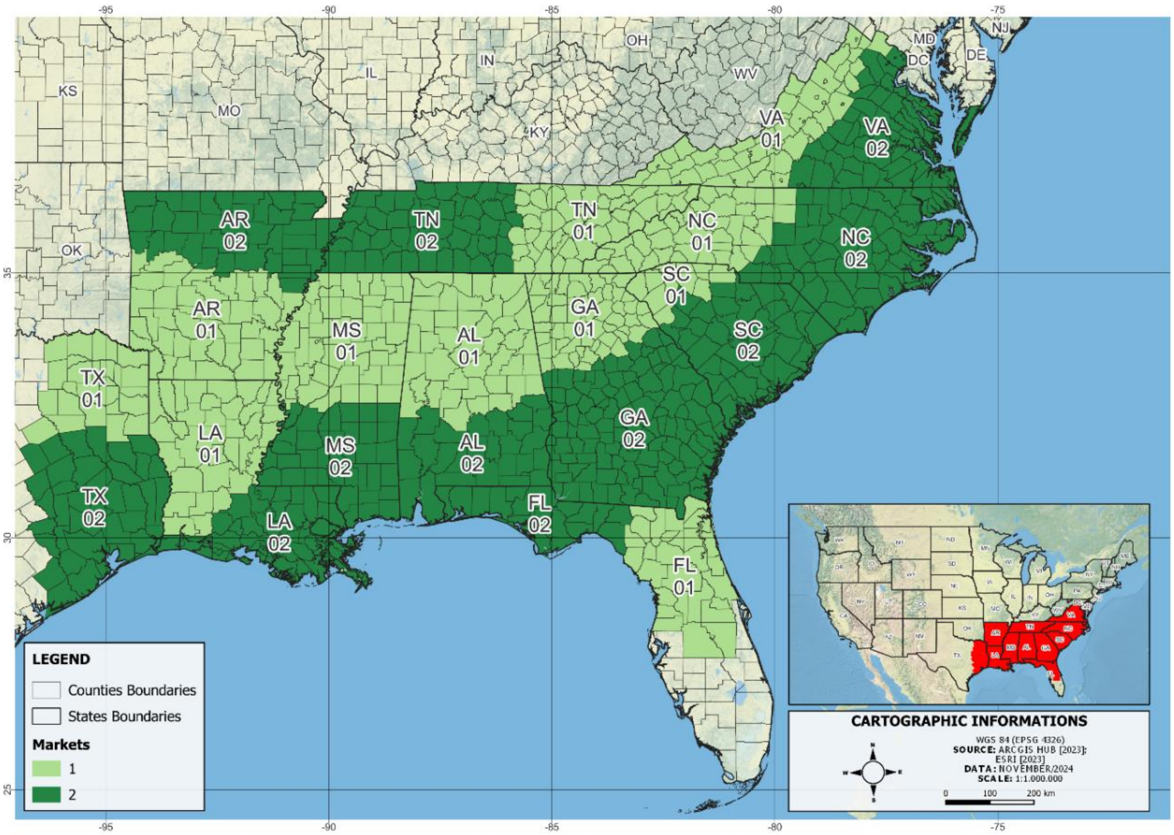

Figure 4.1. Map of TimberMart-South regions. Source: TimberMart-South.

4.4.2 Forest structure

The initial forest structure of each market was assumed to be the current age class distribution, according to the USDA Forest Inventory Analysis (FIA). Loblolly pine (*Pinus taeda* L.) stands managed and owned by private entities, both non-corporate and corporate landowners, were selected and related at the county level with their respective TMS regions. Age class distribution assumed the strata of 5 years from 0 to over 50 years (Figure 4.2).

Figure 4.2. Current age class distribution of each timber market. Source: USDA Forest Inventory Analysis (FIA).

4.4.3 Yield curves

All yield curves were produced using the 1996 Plantation Research Management Cooperative - PMRC model (Harrison and Borders, 1996). Four different silvicultural treatments were simulated when building the growth and yield curves. The first treatment considered a low initial density of 300 trees per acre (TPA), while the other three treatments considered an initial density of 600 trees per acre (TPA). Treatments 1 and 2 were simulated with no thinning, while treatment 3 was simulated with one thinning at age 15 years, and treatment 4 with two thinnings occurring at ages 15 and 24 years (Table 4.3). The main variables to build the growth and yield curves are the initial spacing (TPA), thinning ages (none, 15 and 25 years), residual basal area, and site index. Site indexes were sourced from Soil Survey Geographic Database – SSURGO. This dataset has site indexes at base age 50 years, which were converted to the base age of 25 years using a base-age invariant SI model proposed by Diéguez-Aranda et al. (2006) (See Appendix A). Every thinning reduced the basal area to 80 square feet per acre. Three different products were considered: pulpwood (6-8”), chip-n-saw (8-11”), and sawtimber (≥12”).

Table 4.3. Silvicultural treatments.

Treatment	**TPA**	**1st thinning**	**2nd thinning**
1	300	-	-
2	600	-	-
3	600	15 years	-
4	600	15 years	24 years

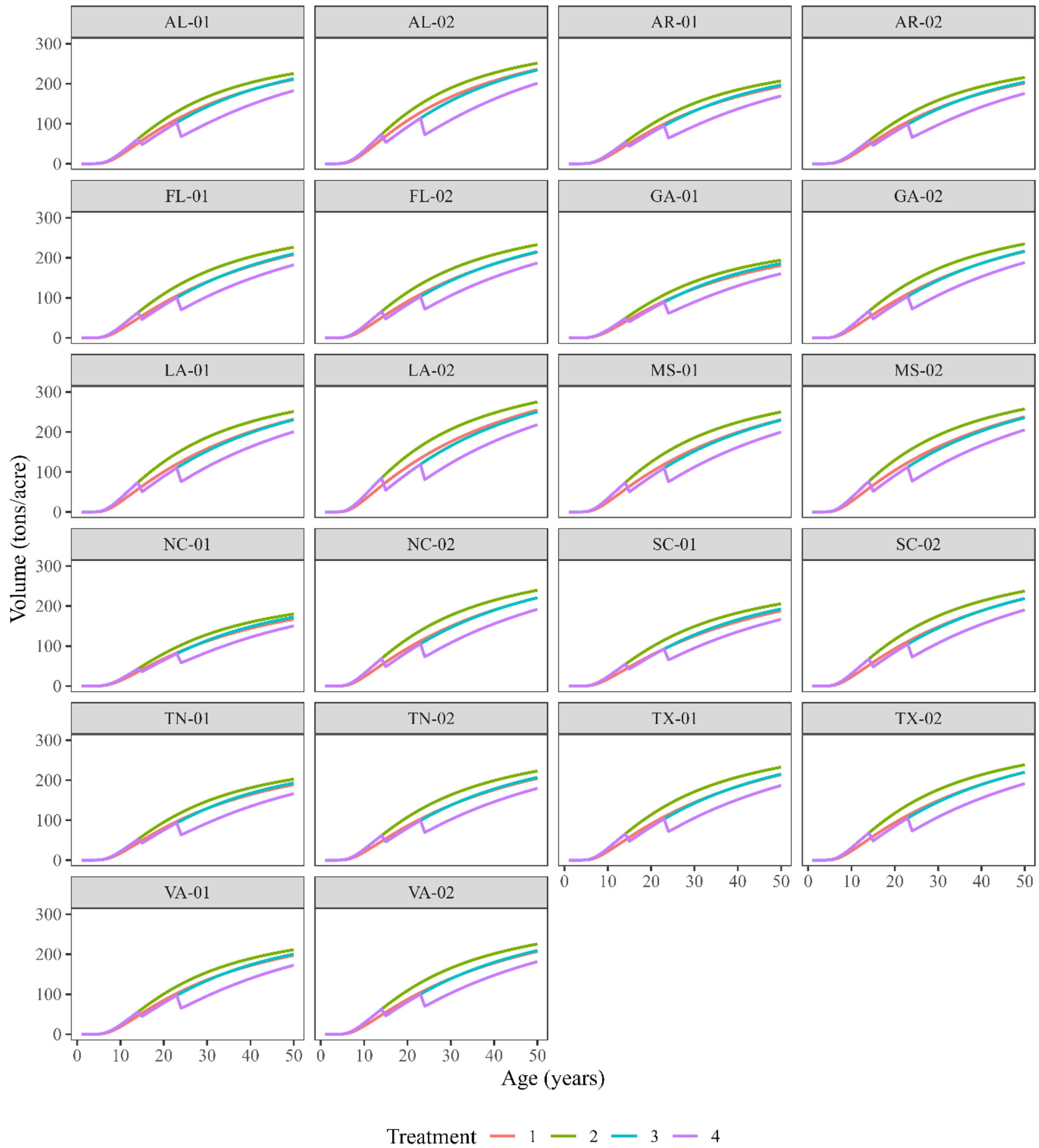

Figure 4.3. Yield curves based for each treatment and timber market.

4.4.4 Prices and costs

Stumpage timber prices for each product were sourced quarterly from 1980 to 2024 from TimberMart-South (2024), see Appendix C. Operational costs were sourced from Costs and Trends of Southern Forestry Practices for 2022 (Maggard and Natzke, 2023) and adjusted to 2024 with the consumer price index - CPI (see Appendix D). The Costs and Trends of Southern Forestry Practices dashboard provides operational costs by ecoregion (*e.g.*, Coastal Plains and Piedmont) and/or state for different landownerships. We considered data provided only by private institutions and weighted the prices according to the area of each ecoregion (Level II from US EPA) within the 22 timber markets (See Appendix E). Initial costs included mechanical site preparation, planting costs, seedlings, and herbicide application. Annual costs include taxes, maintenance, and other costs.

Timberland prices were used as initial costs for acquiring an asset (land and the existing forest), regardless of its age. Due to the lack of available data, we used the TMS South-wide value from 2022 and adjusted to 2024 with the CPI (See Appendix D). The South-wide timberland price was then weighted according to the last sawtimber price of each state, resulting in timberland values ranging from $1,440.66 to $2,618.79 (Table 4.4).

In our strategic landscape planning model (section 4.3.1), we acknowledged that a small portion of the timberland could be converted to another land use, such as annual crops or a new solar facility. Despite the trend toward converting timberland into solar arrays, these areas could also be converted to agriculture, for example. Therefore, we used farm real estate values from the Land Values 2024 Summary (USDA, 2024) as the selling price. These values were adjusted annually over the planning period (T = 15 years) according to the average appreciation rate observed for the past 15 years (2.2% per year). These values were used to approximate the values mentioned in Wall Street Journal (2024) for a deal between a solar developer and a forest-product company.

Table 4.4. Average timber prices, land prices and operational costs for each timber market.

Market	Timber prices ($/ton)[1]			Costs ($/acre)[2]			Timberland cost ($/acre)[3]	Land selling price ($/acre)[4]	
	PW	CNS	ST	Initial		Annual			
	(6-8”)	(8-11”)	(≥12”)	300 TPA	600 TPA			Year 0	Year 15
AL-01	7.37	19.34	28.23	435.24	512.99	12.15	1,778.20	4,000.00	5,440.00
AL-02	9.22	21.78	31.90	475.70	528.92	9.94	2,039.10	4,000.00	5,440.00
AR-01	6.86	17.28	29.07	397.91	499.88	11.14	1,918.44	4,110.00	5,696.46
AR-02	5.76	16.43	24.23	358.83	478.55	12.94	1,832.83	4,110.00	5,696.46
FL-01	12.10	21.85	29.43	320.16	462.39	8.26	1,991.81	8,300.00	11,503.81
FL-02	10.78	20.63	28.87	386.91	497.90	9.15	2,263.31	8,300.00	11,503.81
GA-01	7.77	19.25	27.21	440.03	514.99	11.92	2,004.86	4,500.00	6,137.00
GA-02	11.51	23.14	32.68	426.33	513.41	9.55	2,168.74	4,500.00	6,137.00
LA-01	8.25	17.62	28.92	413.17	508.59	9.43	1,922.51	3,720.00	5,155.92
LA-02	7.29	18.15	27.84	333.32	470.55	8.46	1,817.34	3,720.00	5,155.92
MS-01	6.47	18.39	27.80	419.64	511.00	9.49	1,752.93	3,490.00	4,837.14
MS-02	7.45	19.66	30.66	463.36	525.38	9.85	1,950.23	3,490.00	4,837.14
NC-01	5.38	15.83	20.95	427.58	509.69	12.54	2,061.93	5,190.00	7,193.34
NC-02	7.07	17.95	30.51	396.48	501.97	9.26	2,618.79	5,190.00	7,193.34
SC-01	7.23	17.55	26.66	473.15	527.51	10.45	1,705.64	4,500.00	6,237.00
SC-02	8.88	19.85	30.27	393.64	500.79	9.23	2,048.89	4,500.00	6,237.00
TN-01	5.41	12.92	16.20	389.10	490.88	14.75	1,440.66	6,710.00	9,300.06
TN-02	6.10	13.46	18.61	473.62	528.25	9.99	1,629.00	6,710.00	9,300.06
TX-01	7.76	16.72	28.65	458.37	522.18	11.07	1,778.20	2,800.00	3,880.80
TX-02	7.38	15.95	29.63	412.35	507.83	9.73	2,039.10	2,800.00	3,880.80
VA-01	7.11	16.69	19.64	398.20	495.70	14.18	1,918.44	5,850.00	8,108.10
VA-02	7.84	17.16	24.16	446.23	520.11	9.72	1,832.83	5,850.00	8,108.10

Source: [1] TimberMart-South (2024); [2] Maggard and Natzke (2023), [3] TimberMart-South (2023); [4] USDA (2024).

4.5 Estimated returns and risks

Table 4.5 presents returns and risks estimated for every market within each scenario using the strategic landscape model described in the previous sections. The South-wide average potential return for S1 - BAU was 8.02% (± 3.14%), considering all 22 timber markets (Table 4.5). Regionally, IRR ranged from 5.14% (MS-01) to 13.18% (FL-01). Eight markets presented above average returns (VA-01, GA-01, NC-01, GA-02, VA-02, NC-02, FL-02, and FL-01

The IRR consistently increased when adding up to 5% land-sale (S2) during the 15-year period. The South-wide return for S2 was 12.34%, meaning a 4.32% increase when compared to S1. Average potential returns ranged from 9.35% (MS-01) to 17.71% (FL-01). The strategic landscape planning model decided to sell 5% of the land for every simulation. Similarly, potential returns increased for S3 when compared to S1. The South-wide return was 13.92%, increasing 5.90% when compared to S1. This 5.90% increase was higher than the average return from MS-01 (5.14%) and almost as high as the average return from MS-02 (5.99%) in S1. Annual lease payments helped keep the cashflow positive over the planning horizon, differently from land sale (S2). In addition, the perpetuity present value increased the selling price at the end of the planning horizon.

The call option contract scenario (S4) presented the highest returns among all scenarios. The South-wide return was 19.42%, being 11.40%, 7.08%, and 5.50% higher when compared to S1, S2, and S3, respectively. Returns increased for all markets, except for both in Tennessee (TN-01 – 8.88% and TN-02 – 9.20%) when compared to S2 and S3. The highest returns were greater than 30% (30.96% in GA-02 and 30.95% in FL-01), and 6 other markets presented returns greater than 20% (FL-01 – 22.22%, SC-02 – 23.18%, NC-02 – 24.17%, VA-02 – 25.00%, NC-01 – 25.33%, and SC-01 – 25.57%. All other returns ranged from 14.35% (AL-01) to 19.20% (AL-02).

The IRR standard deviation was used to assess the investment's risk. The South-wide standard deviation ranged from 3.14% (S1) to 8.65% (S4), showing a risk increase. South-wide risks increased by 0.12% (IRR = 3.26%) and 0.41% (3.55%) in S2 and S3 when compared to S1, respectively. Meanwhile, S4 experienced a 5.51% risk increase.

In S1, risks ranged from 1.39% (TN-01) to 3.61% (TX-02). TX-02 (3.6%) and GA-01 (3.0%) presented the higher risks among all 22 markets. Meanwhile, TN-01 and TN-02 presented the lower risks. When comparing S2 and S3 with respect to S1, we noticed that, on average, risks slightly increased. In S2, some markets presented lower risks when compared to S1. Differently, all 22 markets presented higher risks in S3 when compared to S1. S4 provided the highest risk among all scenarios. Surprisingly, FL-02 (30.95% ±12.16%), GA-01 (16.69% ±11.56%), GA-02 (30.96% ±12.74%), NC-01 (25.33% ±11.13%), NC-02 (24.16% ±10.76%), SC-01 (25.57% ±12.92%), and SC-02 (23.18% ±13.45%) presented high returns at a cost of above average risks.

We noticed that in some prices and costs combinations, the strategic landscape planning model preferred to harvest forests in the first years in S1. After that, the thinning and harvest volume reduced and remained close to zero until the end of the planning horizon. This resulted in negative cash flows from year 1 to 14. In contrast, the strategic landscape planning model sought to keep positive cashflows throughout the planning horizon, generating high IRR values.

Table 4.5. Returns and risks for four different investment scenarios across 22 timber markets in the US South.

State	Market	S1 – BAU		S2 – Land sale		S3 – Land lease		S4 – Call option	
		IRR	SD	IRR	SD	IRR	SD	IRR	SD
Alabama	AL-01	6.61	2.11	10.87	2.19	12.62	2.50	14.35	5.10
	AL-02	7.80	2.15	12.11	2.24	13.88	2.78	19.20	7.08
Arkansas	AR-01	7.01	2.54	11.29	2.64	13.16	2.86	17.98	8.67
	AR-02	6.08	2.18	10.32	2.27	11.98	2.75	16.21	8.86
Florida	FL-01	13.18	2.94	17.71	3.05	17.01	4.15	22.22	8.23
	FL-02	12.14	2.30	16.62	2.39	15.52	3.07	30.95	12.16
Georgia	GA-01	9.06	3.01	13.42	3.13	15.46	3.99	16.69	11.56
	GA-02	9.78	2.71	14.17	2.82	16.11	3.32	30.96	12.74
Louisiana	LA-01	7.05	2.44	11.33	2.54	13.01	2.85	16.52	6.37
	LA-02	6.47	1.87	10.73	1.94	12.54	2.27	15.23	4.58
Mississippi	MS-01	5.14	1.74	9.35	1.81	10.69	1.94	14.40	5.33
	MS-02	5.99	1.99	10.23	2.07	12.45	2.35	17.05	6.43
North Carolina	NC-01	9.57	2.78	13.96	2.89	16.11	3.59	25.33	11.13
	NC-02	10.11	2.73	14.51	2.84	16.95	3.86	24.17	10.76
South Carolina	SC-01	7.65	2.31	11.96	2.40	13.95	2.91	25.57	12.92
	SC-02	7.68	2.31	11.99	2.40	13.96	2.93	23.18	13.45
Tennessee	TN-01	7.04	1.39	11.32	1.44	12.38	1.57	8.88	2.77
	TN-02	7.13	1.56	11.42	1.62	10.60	1.72	9.20	2.90
Texas	TX-01	6.02	2.57	10.26	2.68	12.34	3.04	18.12	7.86
	TX-02	6.21	3.61	10.46	3.75	13.20	3.31	19.06	10.13
Virginia	VA-01	8.34	2.28	12.67	2.37	14.07	2.68	17.02	9.93
	VA-02	9.95	2.68	14.35	2.79	16.48	3.50	25.00	11.29
	South-wide	**8.02**	**3.14**	**12.34**	**3.26**	**13.92**	**3.55**	**19.42**	**8.65**

Where IRR is the average internal rate of return and SD is the IRR standard deviation (risk).

4.6 Results

The efficient frontier for business as usual timberland investments in the US South is presented on Fig. 4.4. The efficient frontier represents a set of optimal portfolios that offer the highest expected return for different levels of risk, reflecting the tradeoff between risk and return. It is also bound by the risk-minimizing and return-maximizing limits (Table 4.6).

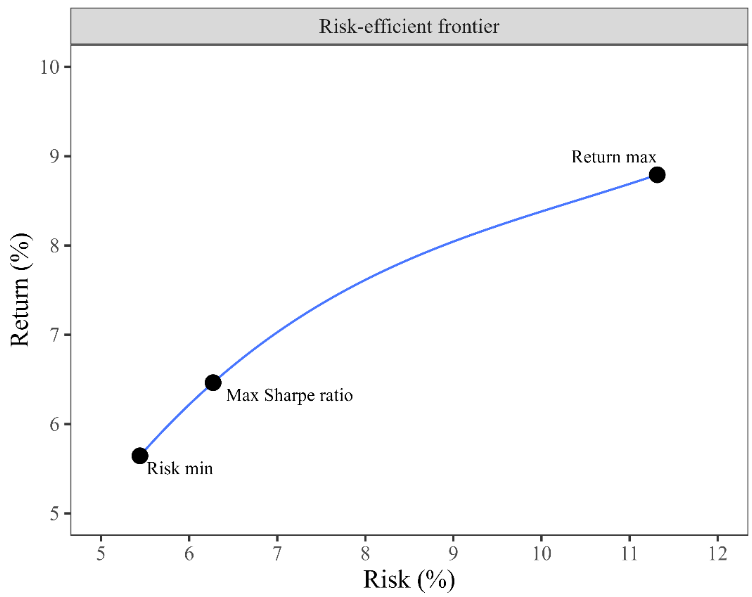

Figure 4.4. Risk-efficient frontier based S1 – BAU investment possibilities.

Table 4.6. Efficient frontier for portfolios 1 and 2.

	P1			P2		
	Risk min	**Return max**	**Sharpe ratio max**	**Risk min**	**Return max**	**Sharpe ratio max**
E(*r*)	5.16%	11.31%	6.25%	11.39%	17.54%	12.26%
Risk (*s*)	5.64%	8.81%	6.46%	6.70%	8.82%	7.10%
Sharpe ratio	0.76	0.54	0.99	1.36	1.31	1.69

The P1 return ranged from 5.16% (risk minimizing) to 11.31% (return maximizing), while risk ranged from 5.64% to 8.81%, respectively (Table 4.7). We noticed that markets with above-average returns (Table 4.1), such as FL-01, FL-02, GA-02, and NC-01 represented over 35% of the return maximizing portfolio. Meanwhile, most selected markets on the risk minimizing portfolio (AR-01, FL-01, MS-01, TX-01, and VA-02) presented below-average returns and low risks. LA-02 and FL-01 were the two markets that approximated the 20% upper bound on both the risk minimizing and return maximizing portfolios from S1. All 22 markets were invested, with minimum values of 0.2% (GA-02) and 0.5% (AL-01). In contrast, the two most invested markets in each portfolio accounted for 12.36% (TX-01) and 15.42% (FL-01). We also optimize a third portfolio for both P1 and P2 to maximize the Sharpe ratio. As beforementioned, this portfolio assumed a risk-free rate of 2.63%. The maximum Sharpe ratio portfolio presented an average return of 6.25% (±6.46%), with a Sharpe ratio of 0.99.

Table 4.7. Portfolios' allocation for risk minimization, return maximization, and Sharpe ratio maximization.

Portfolio	**P1**			**P2**		
Market	**Risk Min**	**Return Max**	**Sharpe ratio**	**Risk Min**	**Return Max**	**Sharpe ratio**
AL-01	2.64	0.45	6.64	0.88	2.25	5.20
AL-02	1.35	2.40	1.09	3.10	6.87	2.41
AR-01	9.09	2.48	9.84	5.12	1.28	1.85
AR-02	0.18	1.84	7.29	19.95	0.54	6.59
FL-01	7.43	15.42	9.22	13.24	14.78	1.87
FL-02	11.00	10.85	0.75	2.37	10.94	1.54
GA-01	3.27	1.89	6.80	4.46	4.08	4.34
GA-02	0.03	5.70	4.28	2.31	4.90	7.23
LA-01	0.74	5.85	8.05	7.06	0.04	5.32
LA-02	2.43	2.95	3.31	4.87	9.12	8.16
MS-01	7.76	1.84	2.51	6.78	1.08	5.23
MS-02	3.38	0.78	2.28	0.63	5.10	3.96
NC-01	3.19	13.69	4.12	0.31	11.80	8.17

NC-02	0.91	2.06	1.56	1.95	0.68	3.25
SC-01	1.16	5.37	6.09	9.05	3.22	2.19
SC-02	2.68	0.84	3.28	0.84	0.64	1.94
TN-01	4.05	8.07	6.44	13.06	9.87	11.07
TN-02	4.18	3.09	3.57	0.63	1.46	0.74
TX-01	12.36	0.85	1.42	0.53	1.83	5.15
TX-02	6.88	7.38	1.33	1.85	2.64	0.63
VA-01	7.27	2.40	2.56	0.44	2.05	7.91
VA-02	8.03	3.80	7.57	0.55	4.81	5.24

When optimizing single market portfolios, we noticed that S1 and S4 were not selected as the best investment possibilities for any market. S2 and S3 were the best investment possibilities in 10 and 12 markets, respectively. Markets in which the best investment possibility was S2: AL-02, FL-01, FL-02, GA-01, GA-02, NC-01, NC-02, SC-02, TN-02, and VA-02. Meanwhile, the best investment possibilities from S3 were AL-01, AR-01, AR-02, LA-01, LA-02, MS-01, MS-02, SC-01, TN-01, TX-01, TX-02, and VA-01 (refer to returns and risks from Table 4.5). We optimized portfolios - P2 using the best investment possibilities from each market. P2 return ranged from 11.39% to 17.54% for risk minimizing and return maximizing, respectively. Returns increased from 5.16% to 11.39% on the risk minimizing portfolio and from 11.31% to 17.54% for the maximizing portfolio. We noticed that, for both risk minimization and return maximization portfolios, returns increased around 6.0% when compared to P1. This reinforces the impact of land returns (from land sales and leases) on timberland investments, even at a small scale of (up to) 5%. Portfolio risk did not increase significantly, especially for the return maximizing portfolio when compared to P1 (8.81 and 8.82%). A 1.06% increase in risk was observed for the risk minimizing portfolios, when comparing P1 and P2, while a 0.01% and 0.64% for return and Sharpe ratio maximizing. The Sharpe ratio decreased as the return increased. The maximum Sharpe ratio was found around the 15th percentile of the efficient frontier. It ranged from 0.54 to 0.99 in P1, and from 1.31 to 1.69 for P2

4.7 Discussion and conclusions

Our results indicated that land returns for solar developments, such as small-scale land sale and lease (up to 5%), can increase timberland investment returns by 6.23%. This increase was observed for both risk minimizing and return maximizing portfolios. Both S2 and S3 increased returns significantly, adding 4.32% and 5.90% to the South-wide return. On the other land, risks did not increase on the dimension. Risks increased by 0.14% and 0.41% when compared to S1. From that, we could expect that P2 would present higher returns.

The risk minimizing portfolio (P1) allocated more than 40% in four markets (AR-01, FL-02, TX-01, and VA-02). AR-01, TX-01, and VA-02 presented below-average returns and average risks. Similarly, over 48% of return maximizing - P1 was allocated in four markets (FL-01, FL-02, NC-01, and TN-01). Using a different set of possible investments, Chudy et al. (2020) noticed that their portfolio allocated over 40% of the portfolio in three different regions. This high concentration is expected when possible investments present high returns and considerably low risks. This study also used average returns to optimize a global timberland investment portfolio. The authors considered an average return of 5.0% (real) and 7.3% (nominal) for the US South, with a standard deviation of 0.0863 (8.63%). Despite considering the US South as one region, our risk minimizing portfolio – P1 presented a similar return (5.16%-11.31%), especially after optimizing the allocation across 22 timber markets.

In 2019, Zhang and Mei published two optimized portfolios for the same 22 markets we used in this study. These authors used timber prices and NCREIF to estimate quarterly returns and compared timberland investments with other crops. Two portfolios were optimized with US$2 and US$10 billion, respectively. Our return maximizing P2 presented some similarities with the unconstrained portfolio from Zhang and Mei (2019). Two markets (FL-01 and NC-01) presented a high proportion of the invested universe. Their portfolios, however, did not account for the same period for timber prices (1980-2024 in this study). In their study, Zhang and Mei (2019) considered prices from 2000-2016. We acknowledge that after that, the COVID-19 pandemic affected the prices (Bruck et al. 2023). In addition, the US South forest sector also experienced declined timber prices due to mill closures. Hence, in this study we assessed how different scenarios of land returns influenced portfolio allocation and returns across the US South. Unlike previous studies that compared timberland with other crops (*e.g.*, Zhang and Mei, 2019), our scenarios considered up to 5% land sale, lease, and call option contracts for solar developments. In the recent years, there has been a recent increase of land use conversion to solar developments in the US South (Landgate, 2024; Wall Street Journal, 2024).

When analyzing the results from P1 and P2, we noticed that even the risk minimizing portfolio from P2 presented higher returns (risk minimizing return of 11.39%) when compared to the return maximizing portfolio from P1 (11.31%). These results reinforce the findings from Cooper and Dwivedi (2024). These authors found that new solar plants can provide extensive margins to timberland investors, by providing higher returns and when compared to loblolly pine plantations. Consequently, any small piece of land sold or leased for solar development can increase significantly a timberland investment return. Especially when considering the land sale at higher prices, and the selling of the lease area, timberland portfolios can benefit from a high land market value at the liquidation.

Despite presenting new findings to assist corporate investors and market analysis, this study presents some limitations that could be addressed by future studies. First, although we have used historical timber prices in a stochastic process, returns only cover a limited period of time. Consequently, our M-V model provided returns from portfolios invested during that period.

Furthermore, constraints imposed on the minimum and maximum weights to be invested can also influence the portfolio outcomes. Future studies are needed to address this issue through imposing different lower and upper bounds for weights.

REFERENCES

BINKLEY, C., COURTLAND, W., ARONOW, M.E. 2001. Timberland as a portfolio diversifier. Hancock Timber Resource Group: Research Notes 2001.

BRUCK, S.R., PARAJULI, R., CHIZMAR, S., SILLS, E.O. 2023. Impacts of COVID-19 pandemic policies on timber markets in the Southern United States. J. For. Buss. Res. 2(1): 130-167.

BUSBY, G.M., BINKLEY, C.S., 2015. Sources of Risk in Timberland Returns. In: Meeting of the Western Forest Economists and International Society of Forest Resource Economists. Vancouver, BC, Canada. June 1.

BUSBY, G.M., BINKLEY, C.S., CHUDY, R.P. 2020. Constructing optimal global timberland investment portfolios. For. Policy Econ. 111: 102083. https://doi.org/10.1016/j.forpol.2019.102083

CALLAGHAN, D.W., KHANAL, P.N., STRAKA, T.J. 2019. An analysis of costs and cost trends for southern forestry practices. J. For. 117 (1): 21–29. https://doi.org/10.1093/jofore/fvy060

CASCIO, A.J., CLUTTER, M.L. 2008. Risk and required return assessments of equity timberland investments in the United States. J. For. Prod. 58(10): 61-70.

CHEIN, W., ZHANG, H., MEHLAWAT, M.K., JIA, L. 2021. Mean-variance portfolio optimization using machine learning-based stock price prediction. Appl. Soft. Comput. 100: 106943. https://doi.org/10.1016/j.asoc.2020.106943

CHUDY, R.P., CHUDY, K.A., KANIESKI DA SILVA, B., CUBBAGE, F.W., RUBILAR, R., LORD, R. 2020. Profitability and risk sources in global timberland investments. For. Policy Econ. 111: 102037. https://doi.org/10.1016/j.forpol.2019.102037

COOPER, C., DWIVEDI, P. 2024. Economic comparison of loblolly pine and solar power in South Georgia, United States. Trees, Forests and People 16: 100528. https://doi.org/10.1016/j.tfp.2024.100528

CUBBAGE, F.W., KANIESKI, B., RUBILAR, R., BUSSONI, A., OLMOS, V.M, BALMELLI, G., MAC DONAGH, P., LORD, R., HERNÁNDEZ, C., ZHANG, P., HUANG, J., KORHONEN, J., YAO, R., HALL, P., DE LA TORRE, R., DIAZ-BALTEIRO, L., CARRERO, O., MONGES, E., THU, H.T.T., FREY, G., HOWARD, M., CHAVET, M., MOCHAN, S., HOEFLICH, V.A., CHUDY, R., MAAS, D., CHIZMAR, S., ABT, R. 2020. Global timber investments, 2005-2017. For. Policy Econ. 112: 102802. https://doi.org/10.1016/j.forpol.2019.102082

CUBBAGE, F.W., MAC DONAGH, P., SAWINSKI JÚNIOR, J., RUBILAR, R., DONOSO, P., FERREIRA, A., HOEFLICH, V., MORALES OLMOS, V., FERREIRA, G., BALMELLI, G., SIRY, J., NOEMI BÁEZ, M., ALVAREZ, J. 2007. Timber investment returns for selected plantation and native forests in South America and the Southern United States. New Forests 33(3): 237-255. https://doi.org/10.1007/s11056-006-9025-4

CUBBAGE, F.W., RUBILAR, R., MAC DONAGH, P., KANIESKI DA SILVA, B., BUSSONI, A., MORALES, V., BALMELLI, G., HOEFLICH, V.A., LORD, R., HERNÁNDEZ, C., ZHANG, P., THU, H.T.T., YAO, R., HALL, P., KORHONEN, J., DÍAZ-BALTEIRO, L., RODRÍGUEZ-SOALLEIRO, R., DAVIS, R., CHUDY, R., DE LA TORRE, R., LOPERA, G., PHIMMAVONG, S., GARZÓN, S., CUBAS-BAEZ, A. 2022. Comparative global timber investment costs, returns, and applications, 2020. J. For. Bus. 1(1): 90-121. https://doi.org/10.62320/jfbr.v1i1.16

FAUSTMANN, M. 1849. Berechnung des Wertes welchen Waldboden sowie noch nicht haubare Holzbestände für die Waldwirtschaft besitzen. Allgemeine Forst- und Jagdzeitung 12: 441-455.

FORISK CONSULTING. 2024. Concentration of demand is a key metric for timberland investors and wood-using mills. Available at: https://forisk.com/wp-content/uploads/20241205-Press-Release-Forisk-Custom-Market-Forecast.pdf. Accessed March 3, 2025.

FU, C.H. 2012. Reducing timberland portfolio risk through strategic diversification. SOFAC Annual Meeting, 8–9 August 2012. Marriott Hotel, Durham, NC.

GUNJAN, A., BHATTACHARYYA, S. 2023. A brief review of portfolio optimization techniques. Artif. Intell. Rev. 56: 3847-3886. https://doi.org/10.1007/s10462-022-10273-7

KNOKE, T. Mixed forests and finance – Methodological approaches. Ecol. Econ. 65(3): 590-601. https://doi.org/10.1016/j.ecolecon.2007.08.009

LANDGATE. 2024. Solar farm leasing in South Carolina. Available at: https://www.landgate.com/news/solar-farm-leasing-in-south-carolina. Accessed 18, December 2024.

LIAO, X., ZHANG, Y., SUN, C. 2009. Investment in timberland and softwood timber as parts of portfolio selection in the United States: A cointegration analysis and Capital Asset Pricing model. For. Sci. 55(6): 471-479. https://doi.org/10.1093/forestscience/55.6.471

MAGGARD, A., NATZKE, J. 2023. Costs and trends for southern forestry practices. https://forestlandowners.com/cost-and-trends-of-southern-forestry-practices/

MARKOWITZ, H., 1952. Portfolio selection. J. Financ. 7, 77–91. https://doi.org/10.2307/2975974

MEI, B. 2019. Timberland investments in the United States: A review and prospects. For. Policy Econ. 109: 101998. https://doi.org/10.1016/j.forpol.2019.101998

MEI, B., CLUTTER, M.L. 2023. Forestland Investment: Valuation and Analysis (1st ed.). Routledge. https://doi.org/10.4324/9781003366737

REEVES, L.H., HAIGHT, R.G. 2000. Timber harvest scheduling with price uncertainty using Markowitz portfolio optimization. Ann. Oper. Res. 95: 229-250. http://dx.doi.org/10.1023/A:1018974712925

RESTREPO, H., ZHANG, W., MEI, B. 2020. Time time-varying role of timberland in long-term, mixed-asset portfolios under the mean conditional value-at-risk framework. For. Policy Econ. 113: 102136. https://doi.org/10.1016/j.forpol.2020.102136

TIMBERLAND INVESTMENT RESOURCES. 2021. Natural capital: Timberland's evolving value proposition. Available at: https://www.tireurope.com/wp-content/uploads/2021/04/Timberlands-Evolving-Value-Proposition-041321.pdf

TIMBERMART-SOUTH. 2024. Quarterly market news. https://timbermart-south.com/industry-reports/quarterly-market-news/

UNITED STATES DEPARTMENT OF AGRICULTURE (USDA). 2024. Land values 2024 summary. https://www.nass.usda.gov/Publications/Todays_Reports/reports/land0824.pdf

WAGGLE, D., JOHNSON, D.T. 2009. An analysis of the impact of timberland, farmland and commercial real estate in the asset allocation decisions of institutional investors. Rev. Financ. Econ. 18(2): 90-06. https://doi.org/10.1016/j.rfe.2008.03.003

WALL STREET JOURNAL. 2024. U.S. renewable power growth is setting new records on the back of federal support. Available at: https://www.wsj.com/articles/u-s-renewable-power-growth-is-setting-new-records-on-the-back-of-federal-support-2f844b66

WAN, Y., CLUTTER, M.L., MEI, B., SIRY, J.P. 2015. Assessing the role of U.S. timberland assets in a mixed portfolio under the mean-conditional value at risk framework. For. Pol. Econ. 50: 118-126. https://doi.org/10.1016/j.forpol.2014.06.002

WEAR, D.N., WINGENROTH, J., BARTUSKA, A. 2025. Converting forests to solar facilities: Causes, potential, and implications. Resources for the Future. Washington, DC https://www.rff.org/publications/reports/converting-forests-to-solar-facilities-causes-potential-and-implications/

WOODSON, J. S. 2019. Benefits of using southern buffer forest lands for timber production versus solar energy. [Master's Thesis, Mississippi State University].

ZHANG, W., MEI, B. 2019. Assessing the risk and return of optimal portfolios of U.S. timberland and farmland. J. Real Estate Portf. Manag. 25(1): 99-113. https://doi.org/10.1080/10835547.2019.12090026

CHAPTER 5

CONCLUSIONS

This thesis aimed to investigate the gaps and opportunities in timberland investments by analyzing key factors affecting investment returns, market trends and structure shocks, and spatial price transmission in the US South. Through comprehensive economic approaches, this research contributes to a deeper understanding of how these elements interact, shaping strategic decisions for investors and policymakers.

Results from Chapter 3 indicated a South-wide average return of 8.02%, similar to previous studies. The alternative scenarios increased the average return by 4.32% (S2), 5.90% (S3), and 11.40% (S4). Risk increased slightly for S2 (0.14%) and S3 (0.41%), while S4 saw a more significant rise of 5.51%. The revenue share from land appreciation declined as additional land revenues were introduced, even on a small scale of 5%. Based on the portfolio optimization model from Chapter 4, a timberland investment portfolio in the US South can achieve returns ranging from 5.16% to 17.54%, while risks ranged from 5.64% to 8.82%. Risk minimizing and return maximizing portfolios presented different allocation. On both portfolios, however, the state of Florida presented a high allocation, as well as NC-01, LA-02, and TN-01.

In conclusion, this research underscores the potential of timberland investments as a strategic asset class. However, several limitations must be acknowledged, including data constraints, methodological assumptions, and market-specific factors that could influence investment outcomes. Future studies could expand the geographic scope to include international markets or even look at the multiple markets in each state in the US South, bringing more details to transaction prices and reflect the reality faced by different timberland investors. Additionally, further research is needed to better understand the effects of land use change process in the US South from the timber supply perspective and how timberland investors can protect their portfolio under the uncertainty of high returns from solar developments or lease contracts that could not succeed in the long term. By addressing these aspects, future research can enhance decision-making in timberland investments and help both institutional and individual landowners.

APPENDIX A. Forest value estimation framework

The forest value followed a rule depending on the current forest age. The bare land value (land expectation value – LEV), optimal silvicultural prescription and rotation was estimated using Eq. A1 (Faustmann, 1849). Eqs. A2 and A3 were used to estimate the forest value when the forest was younger or (equal or) older than the optimal age, respectively. The terminal value was estimated using Eq. A4.

A.1 Land expectation value (LEV)

$$LEV_{i^*} = \frac{\sum_k^K p_k q_{i^*,k} - \sum_{i=0}^{i^*} C_i (1+r)^{i^*-1}}{(1+r)^{i^*} - 1} \qquad \text{(A1)}$$

where i^* is the age when the rotation is optimal, r p_k is the price if the k product, $q_{i^*,k}$ is the volume available of the k product at i^* age per acre, r is the discount rate of 4% (Cubbage et al. 2020), LEV_{i^*} is the LEV for rotation age i^*, and C_i are the operational costs from age zero to i^*.

A.2 Young forest ($i < i^*$)

The forest value of a stand younger than the optimal rotation age (i^*) is based on the potential income in future years and the LEV_{i^*}:

$$FV_i = \frac{\sum_k^K p_k q_{i^*,k} - \sum_{i=0}^{i^*} C_i (1+r)^{i^*-1} + LEV_{i^*}}{(1+r)^{(i^*-i)}} \qquad \text{(A2)}$$

where FV_i is the forest value per acre at age i, $\sum_k^K p_k q_{i^*,k} - \sum_{i=0}^{i^*} C_i (1+r)^{i^*-1}$ represents timber revenues.

A.3 Mature forest ($i \geq i*$)

The value of a stand that is equal to or older than the optimal rotation age ($i*$) is estimated by calculating the current revenues and costs and the LEV_{i*}:

$$FV_i = \sum_k^K p_k q_{i^*,k} - C_i + LEV_{i^*} \qquad \text{(A3)}$$

where all variables were previously defined.

A.4 Terminal value

The terminal value is defined as the timberland value upon liquidation and is estimated as the present value of the forest value:

$$TV_i = \frac{FV_i}{(1+r)^{t=T}} \qquad \text{(A4)}$$

where TV_i is the terminal value per acre at $t = T$, T is the terminal period, and FV_i is the forest value estimated using the previous equations.

APPENDIX B. Site index estimation

In order to mimic the potential productivity on each market, we used loblolly pine site index (SI) data from Soil Survey Geographic Database - SSURGO. This dataset has site index at base age 50 years, which was converted to the base age of 25 years using a base-age invariant SI model from Diéguez-Aranda et al. (2006):

$$Y = {}^{85.75 + X_0}\Big/_{1 + \frac{4474}{X_0 t^{-1.107}}} \tag{B1}$$

where Y_0 and to represent the predictor height (feet) and age (years), Y is the predicted height at age t, and

$$X_0 = 0.5\left(Y_0 - 85.75 + \sqrt{(Y_0 - 85.75)^2 + 4\,.\,4474 Y_0 {t_0}^{-1.107}}\right) \tag{B2}$$

Hence, to estimate the site index at the desired age of 25 years, we substituted Y_0 and t_s for t_0 in Equation B2. Average SI was weighted by acreage for every market (Table B1 for SI distribution). Figure B1 highlights the average yield curves for each treatment and timber market.

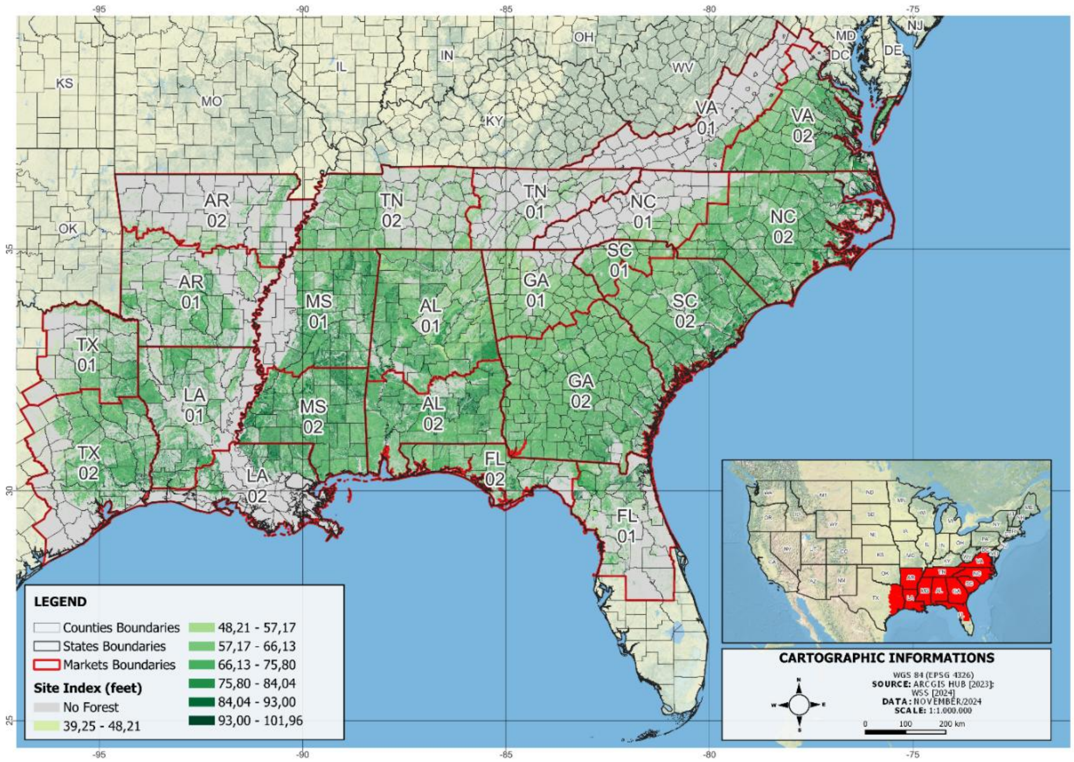

Figure B1. Site index distribution of TimberMart-South markets. Source: adapted from Soil Survey Geographic Database (SSURGO).

Table B1. Average site index (feet) at base age 25 years weighted by acreage for each market.

Market	Site index (feet)			
	25 years²	SD	Min	Max
AL-01	69.66	13.27	41.84	93.51
AL-02	73.79	11.06	52.35	93.51
AR-01	66.54	15.48	47.94	88.84
AR-02	68.02	20.39	39.25	88.84
FL-01	69.23	12.86	51.47	89.77
FL-02	70.36	11.33	51.37	89.77
GA-01	64.35	12.61	39.25	85.11
GA-02	70.68	13.79	39.25	89.77
LA-01	73.53	16.42	52.35	101.96
LA-02	77.54	9.71	54.13	92.57
MS-01	73.33	12.40	47.94	89.77
MS-02	74.60	11.71	52.35	92.57
NC-01	61.80	10.87	39.25	85.11
NC-02	71.52	13.90	39.25	93.51
SC-01	65.41	14.51	39.25	93.51
SC-02	71.14	14.72	39.25	93.51
TN-01	65.78	12.73	47.94	84.19
TN-02	68.56	14.64	52.35	88.84
TX-01	70.28	15.12	47.94	93.51
TX-02	71.34	19.51	44.44	101.96
VA-01	67.30	11.81	47.94	88.84
VA-02	69.05	12.71	39.25	90.70

Sources: SSURGO Data (USDA) and Diéguez-Aranda et al. (2006).

APPENDIX C. Historical timber prices

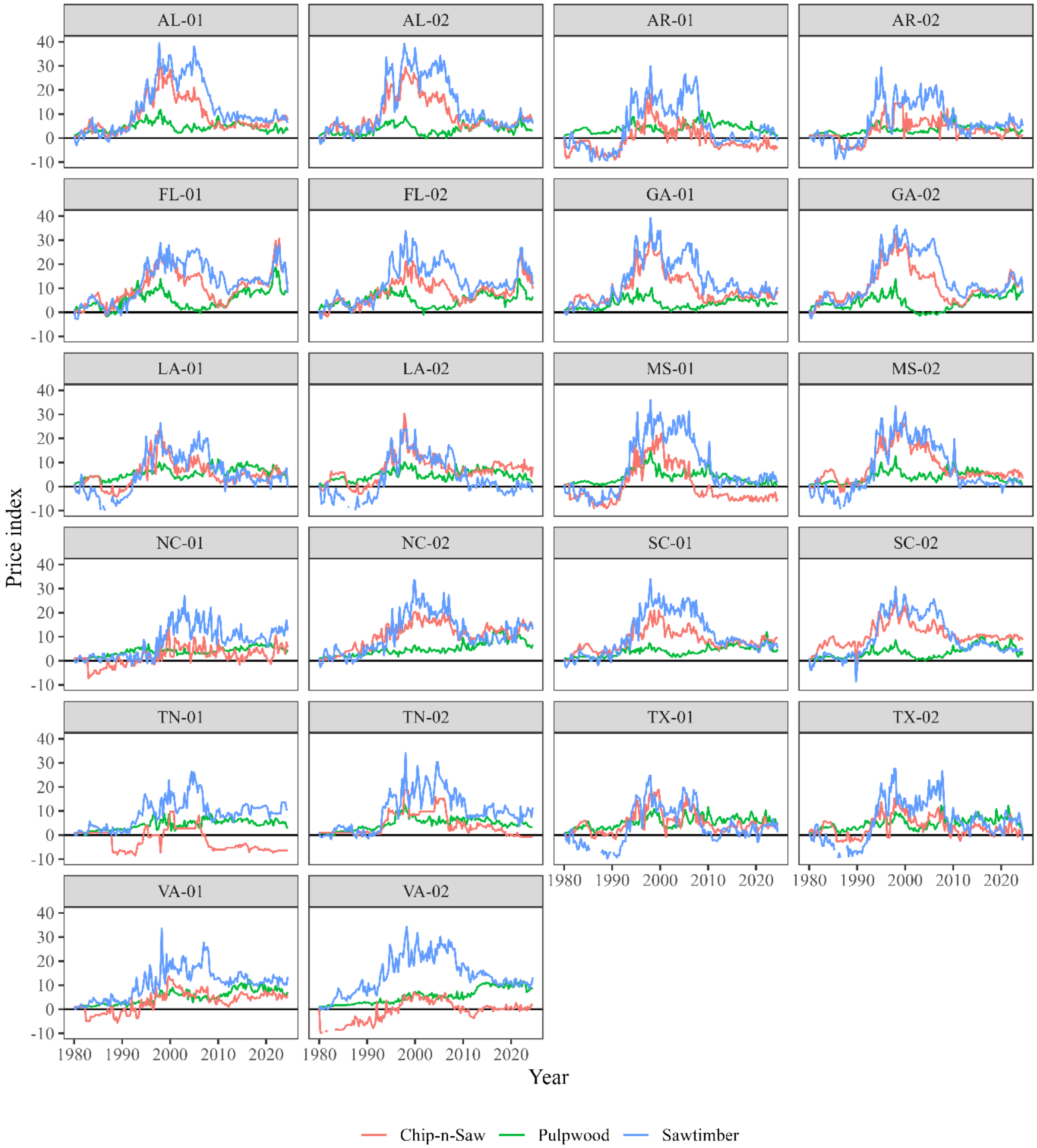

Figure C1. Historical stumpage sawtimber prices indexes. Source: TimberMart-South (TMS). Timber prices were indexed by setting the first value (I_t when t = 0) to 1. Subsequent values were calculated as the cumulative sum of differences between prices at time t and t-1 ($I_t = I_{t-1} + [P_t - P_{t-1}]$).

APPENDIX D. Historical consumer price index (CPI).

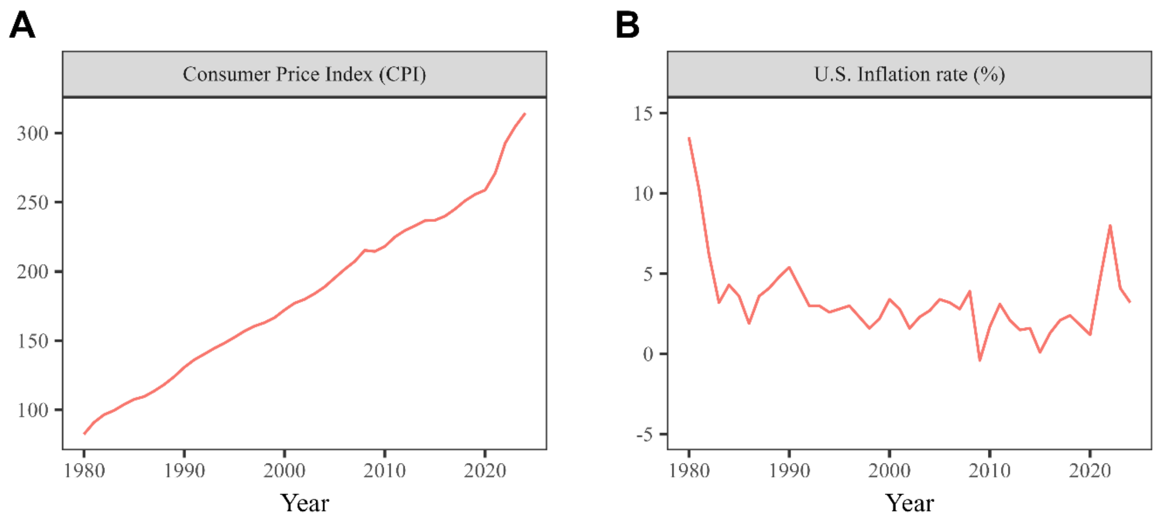

Figure D1. (A) Historical Consumer Price Index (CPI) from 1980 to 2024 and (B) U.S Inflation rate. Source: U.S. Bureau of Labor Statistics

APPENDIX E. Ecoregion estimation.

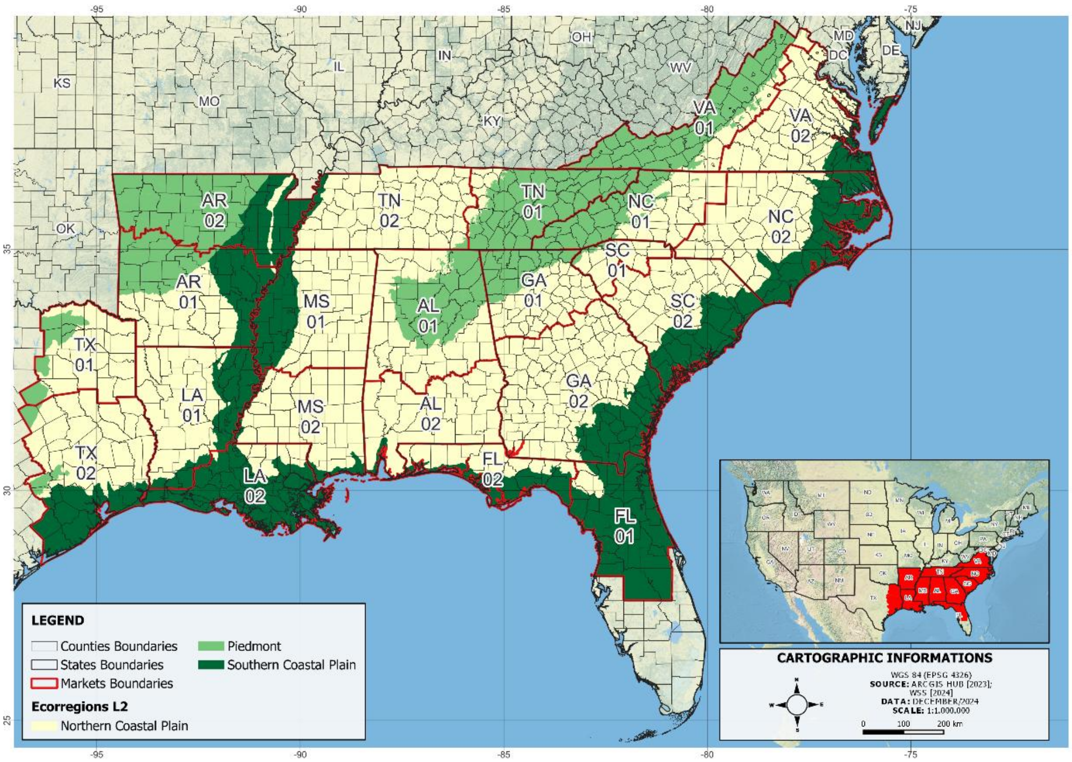

Figure E1. Ecoregions of TimberMart-South markets. Source: United States Environmental Protection Agency.

Table E1. Ecoregions of TimberMart-South markets.

Ecoregion	South. C. Plain	North. C. Plain	Piedmont and others	Total
AL-01	-	59.6%	40.4%	100%
AL-02	3.2%	96.8%	-	100%
AR-01	24.2%	45.9%	29.8%	100%
AR-02	30.8%	3.0%	66.1%	100%
FL-01	93.2%	6.8%	-	100%
FL-02	45.2%	54.8%	-	100%
GA-01	-	64.0%	36.0%	100%
GA-02	24.2%	75.8%	-	100%
LA-01	30.7%	69.3%	-	100%
LA-02	82.2%	17.8%	-	100%
MS-01	27.5%	72.5%	-	100%
MS-02	8.0%	92.0%	-	100%
NC-01	-	52.3%	47.7%	100%
NC-02	39.7%	60.3%	-	100%
SC-01	-	91.6%	8.4%	100%
SC-02	41.3%	58.7%	-	100%
TN-01	-	10.8%	89.2%	100%
TN-02	3.5%	95.5%	1.1%	100%
TX-01	-	79.9%	20.1%	100%
TX-02	28.7%	66.3%	4.9%	100%
VA-01	-	21.4%	78.6%	100%
VA-02	15.1%	84.8%	0.1%	100%

Where Southern Coastal Plain accounts for Mississippi Alluvial and Southeast USA Coastal Plains and Texas-Louisiana Coastal Plain, Northern Coastal Plain accounts for Southeastern USA Plains, Piedmont and others accounts for Ozark Ozark/Ouachita-Appalachian Forests and South Central Semi-Arid Prairies, adapted from Ecoregions of North America Level II. Source: United States Environmental Protection Agency.