Wavelet Analysis and Forecasting using Open-Access Lumber Market Indices for Assessing the Impact of Hurricanes on Southern US Stumpage Prices

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Abstract

In the aftermath of events such as hurricanes, the economic impact of downed timber can reach billions of dollars. Accurate forecasting of stumpage prices after such events is crucial for maximizing recovery value while minimizing salvage costs. However, this poses challenges because of the inherent nature of the data. This study addresses these challenges by exploring the application of wavelet analysis, a novel approach in the field of forestry economic analysis. Wavelet analysis offers a unique framework for studying periodic phenomena in time series data, particularly when frequency changes over time are present. By leveraging wavelet analysis, this study uncovers relationships between timber market indices and hurricane seasons. The combination of traditional correlation analysis and wavelet coherence analysis enhances the statistical analysis in this study, offering a comprehensive examination of the relationship between the Timber Market Survey data and market indices. This innovative analytical approach enables a deeper understanding of the dynamics of the timber market and the potential effects of hurricanes on timber prices. Furthermore, this research highlights the recent advancements in wavelet methodology and the availability of open-source packages in the programming language R, such as WaveletComp and WaveletArima, that facilitate wavelet analysis and time series forecasting. The Wavelet-ARIMA model used in this study demonstrates its effectiveness in reducing noise and improving prediction accuracy. The study incorporates an extensive data set consisting of 10 Consumer Price Indices, 7 Producer Price Indices, 30 state-wide Timber Market Survey indices, 54 TMS subregions, and 6 open market series.

The impact of hurricanes on timber revenue can be significant, with billions of dollars at stake (Henderson et al. 2022). Past hurricane events, such as Hurricane Hugo in 1989 and Hurricanes Katrina and Rita in 2005, have resulted in substantial timber losses (Prestemon and Holmes 1998, Beven et al. 2008). After hurricanes make landfall, forest landowners face numerous challenges that affect local economies, including quality degradation, price declines, salvage difficulties, and decay-related issues such as pests infestation or higher fire risk (Peralta et al. 1993, Taylor and Foster 2005). The timber market experiences price depression during salvage sales, followed by a gradual recovery (Sun 2016). To preserve timber value, landowners are advised to prioritize high-value products and initiate prompt recovery efforts (Van Hensbergen and Cedergren 2021).

Despite salvage efforts, a significant untapped value remains in the downed timber (DT; Brandeis et al. 2022). For example, in the case of Hurricane Hugo, following an extensive timber

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salvage operation by the forest industry, approximately 383 million cubic feet (mostly softwood) were recovered, but this amounted to only a fraction of the estimated volume of timber destroyed, which exceeded 2,000 million cubic feet (Peralta et al. 1993). Biorefinery operations and the extraction of natural polymers from biomass offer potential economic opportunities for utilizing DT (Yamakawa et al. 2018). Biorefineries convert biomass into energy, chemicals, and polymers, contributing to a circular economy (Cherubini 2010). The degradation of DT can facilitate biological and chemical reactions in the polymer recovery process, supporting the development of high-end applications for natural polymers in various industries (Vermaas et al. 2015, Martelli-Tosi et al. 2018, Dutta and Saha 2019). In the context of establishing biorefineries in regions affected by hurricanes, careful planning, investment, and coordination are required (Yue et al. 2014). A key principle is to ensure that the utilization of downed timber does not compete with established forestry industries in the region, especially after they have completed their recovery efforts. The availability and sustainability of biomass feedstocks in the aftermath of a hurricane provide a significant advantage in terms of volume and price discounts, making it a strategically viable option (Dale et al. 2013). As it becomes evident, accurate forecasting is an essential component of conducting feasibility studies and business plans for the establishment of biorefineries (Makepa et al. 2023).

This research aims to address the challenges of forecasting stumpage prices in high detail by analyzing local market-price variations resulting from recent high-cost hurricane seasons. The primary data source for this analysis will be the Timber Mart-South (TMS) database. Additionally, the study will explore the availability and frequent updates of open-access market data. By examining the price correlation between TMS and open-access market indices, this research seeks to provide organizations and individuals with additional data sources and techniques to enhance their ability to forecast stumpage prices reliably and more dynamically. Ultimately, the study supports the idea of bridging the market gap through the biorefinery business, maximizing the utilization of biomass that would otherwise remain unexploited and that is widely available at discounted prices after a hurricane lands.

Literature Review

The impact of natural disasters on economic variables has long been a subject of interest among researchers. In that regard, Hurricane Hugo (1989) has been subject to great study interest in US forest history. One of the first studies by Prestemon and Holmes found Hurricane Hugo caused a 35 percent drop in pine (*Pinus* spp.) sawtimber prices, which recovered within seven quarters. Pine pulpwood prices crashed by 60 percent initially and remained 35 percent lower than pre-Hugo levels for a longer period (Prestemon and Holmes 1998). The researchers employed a method to identify Hugo's price effect by comparing South Carolina's price series with the price series of other southern regions, based on the concept of market cointegration. However, other authors have pointed out that caution should be exercised regarding the potential contamination of the results due to the employed methodology (Yin and Newman 1999). Runsheng Yin and David H. Newman in their study employing intervention analysis and utilizing data from TMS, sought to investigate the hypotheses regarding the effects of Hurricane Hugo on stumpage prices in the region (Yin and Newman 1999). The researchers focused on the coastal plain region of South Carolina, using quarterly data from TMS spanning from the first quarter 1977 to the fourth quarter 1996. This data set encompassed both hardwood and softwood stumpage prices for sawtimber and pulpwood. In their research, intervention analysis is a statistical technique that assumes that the time series, in the absence of the intervention, follows a pure autoregressive integrated moving average (ARIMA) process. The findings were that there was no significant immediate impact on hardwood pulpwood prices in South Carolina's market due to Hurricane Hugo. However, a gradual die-down price effect was observed in the hardwood sawtimber market, indicating a slow decrease in prices over time. There was no persistent price increase observed in the hardwood sawtimber market. Unfortunately, specific findings regarding the pine pulpwood market were not mentioned.

Moreover, in a following publication Prestemon and Holmes (2000) found that Hurricane Hugo had both short-run (there was a 30% price decline due to salvage of damaged timber) and long-run (timber prices were estimated to be 10% to 30% higher than if the hurricane had not occurred) effects on the prices of timber stocks in the South Carolina Coastal Plain (Prestemon and Holmes 2000). Their methodology included intervention analysis, impulse-response functions, and cointegration testing. In a subsequent study, Prestemon and Holmes (2004) utilized three valid replications for sawtimber and four valid replications for pulpwood to estimate the hurricane price effect equations. These replications compared South Carolina prices with submarkets from other states. The parameter estimates and standard errors were derived from these replications, and the bootstrap method was employed to account for variation and uncertainty (Prestemon and Holmes 2004).

Furthermore, in another paper, Prestemon and Holmes (2004) examined the challenges of determining the appropriate assumption of price behavior in the timber industry. They used Monte Carlo simulations to demonstrate how aggregating observations and temporal averaging can influence unit root tests on timber prices. The authors find that recognizing temporal aggregation errors can lead to unit root tests favoring stationarity, particularly for pulpwood stumpage. The study highlights the significance of considering data problems and temporal aggregation complexities when analyzing timber prices. The authors sourced data from the United States Department of Commerce for the Producer Price Index (PPI) and Consumer Price Index (CPI). Nevertheless, they do not specify whether they used the general US index or a particular index. Stock market returns were obtained from the average value of investments, including reinvested dividends, based on the Standard and Poor's 500 index for deflating timber prices (Prestemon et al. 2004).

Finally, Prestemon and Holmes (2010) utilized a welfare approach to measure the implications of Hugo and more recent Hurricanes. Initially, consumer welfare increased as a result of lower prices and increased quantity consumed. Undamaged producers experienced a brief negative impact from salvage activities, while damaged producers were able to capture some value for a few quarters. However, in the long term, consumers were harmed, undamaged producers benefited, and damaged producers faced losses. Their conclusions point to prices in the sawtimber market returning to prestorm levels around 2012, approximately 90 quarters

(23 yr) after the hurricane (Prestemon and Holmes 2010). In more recent times, Ivan and Frances in 2004, and Katrina and Rita in 2005, had significant impacts on the timber market and landowners in their landfall areas (Franklin et al. 2006, Beven et al. 2008). The combined damage from Katrina and Rita was at least double the damage caused by Hurricane Hugo in 1989 (Blake et al. 2011). Hurricane Michael in 2018 affected an estimated 2.8 million acres of forest land (Florida Forest Service 2018).

The timber market in the southeastern United States holds significant importance within the forest products industry. This region is renowned for its vast pine and hardwood forests, making it one of the country's largest timber-producing areas (Prestemon and Abt 2002). A diverse array of stakeholders contributes to the industry, including timberland owners, sawmills, pulp and paper mills, and various wood products manufacturers (Zhang et al. 2011). Public interest in timber assets to hedge against inflation has grown (Chudy and Cubbage 2020). Timberland can hedge inflation based on three advantages: biological growth, timber price change, and land appreciation (Lappalainen 2023). Ownership of timberland has shifted from vertically integrated forest products companies to institutional investors like pension funds, mutual funds, university endowments, foundations, private owners, and publicly traded timber real estate investment trusts (Zhang et al. 2011). In recent decades, organizations such as Timber Investment Management Organizations (TIMOs) and Real Estate Investment Trusts (REITs) control nearly 5 percent of the total forestland in the United States and about 7 percent of the timberland (Fernholz et al. 2007). Some of these organizations are listed as stocks themselves (for example, Weyerhaeuser or Rayonier) or as part of an exchange-traded fund (ETF; D. Zhang et al. 2012). These trusts provide a transparent and accessible platform for investors to access the timber market while offering valuable data and insights into market trends, performance, and financial indicators (Mendell et al. 2007). Through data mining techniques, investors and researchers can analyze historical patterns and identify market trends (Angadi and Kulkarni 2015).

Accurate forecasts of stumpage prices after adverse weather events are crucial for investment decisions and salvage operations (Stanturf et al. 2007). The TMS quarterly reports provide a primary database of stumpage prices, but more detailed and up-to-date market insights are needed (Martin et al. 2007). However, in today's rapidly evolving information technology landscape, quarterly or even monthly data might not suffice for organizations seeking detailed market insights (Modugno 2013).

In addition to the economic challenges posed by hurricanes on timber revenue, analyzing the impact and understanding the patterns of hurricane events is crucial for effective planning and mitigation strategies (Clarke et al. 2023). Wavelet analysis offers a powerful tool for examining and reconstructing time series data, including the study of hurricane events (Cazelles et al. 2008). Wavelet analysis provides a comprehensive approach to analyzing the temporal and frequency characteristics of time series data (Rhif et al. 2019). It allows for the decomposition of a signal into different frequency components, enabling the identification of localized variations and patterns at different scales (Martínez and Gilabert 2009). This analysis technique has been widely used in various fields, including signal processing, image analysis, and geophysics (Kumar and Foufoula-Georgiou 1997, Liu and Chen 2019; Rhif et al. 2019). More recently this procedure has been used in analyzing the synchronized movement between US lumber futures and southern pine sawtimber (PST) prices during COVID-19 events (Gan et al. 2022).

Methodology

Wavelet analysis

Wavelet analysis is a time-frequency domain analysis method that allows for measuring the co-movement and phase difference between two time series (Vacha and Barunik 2012). It utilizes a continuous wavelet transform to represent a time series and calculate cross-wavelet spectra and wavelet coherence (Goodell and Goutte 2021). The wavelet coherence provides a measure of co-movement between two time series, revealing any phase differences between them (Gan et al. 2022). This approach offers several advantages, including the ability to capture both transient and stationary features of a signal with high precision and a multiscale representation of signals, allowing for the examination of different frequency components at various levels of detail (Ganesan et al. 2004). The ability to zoom in and out of the signal is particularly useful for detecting patterns and analyzing signal characteristics across different scales. Additionally, by decomposing a signal into wavelet coefficients, it is possible to remove noise or unnecessary details while retaining important features, resulting in efficient data compression and noise reduction (Rösch and Schmidbauer 2016).

For the processing and wavelet analysis, two R packages were utilized: WaveletComp 1.1 and WaveletArima (Rösch and Schmidbauer 2016, Paul et al. 2017). The frequency structure of time series is analyzed by WaveletComp through the utilization of the Morlet wavelet (Merry 2005). The continuous, complex-valued wavelet transform is a valuable tool for analyzing time series data because it preserves information and allows for careful selection of time and frequency resolution parameters (Percival and Walden 2000). The complex-valued wavelet transform provides a crucial prerequisite for investigating coherency between two time series (Aguiar-Conraria and Soares 2014). By analyzing coherency, it becomes possible to uncover the degree of synchronization or association between the two series (Soares 2011). The transform's ability to capture both amplitude and phase information facilitates the assessment of coherence between the time series, revealing patterns of similarity, periodicity, or relationships that might not be apparent in other types of analysis (Dima et al. 2015). This information is particularly relevant when studying the effects of hurricanes on stumpage prices, because it allows for a comprehensive examination of the relationship between these variables, considering both their magnitudes and their phase relationships.

Meanwhile, the 'WaveletArima' package combines the benefits of wavelet analysis and autoregressive integrated moving average (ARIMA) modeling (Paul et al. 2017). It enables users to perform wavelet decomposition and forecasting on time series data, facilitating the examination of localized frequency components and their variations over time (Kriechbaumer et al. 2014). The package incorporates ARIMA modeling, which is a widely used technique for modeling and forecasting time series data. ARIMA models are composed of three primary components, namely the AutoRegressive (AR) component, the Integrated (I) component, and the Moving Average (MA) component (Luceño and Peña 2008). By combining these components, an ARIMA model can effectively capture a

Table 1.—Available Consumer Price Indices (CPIs).

Series ID	Series title	Base period	Periodicity
CUUR0000SA0	CPI – All items in US city average, all urban consumers, NSA[a]	1982–1984 = 100	Monthly
CUSR0000SA0	CPI – All items in US city average, all urban consumers, SA[b]	1982–1984 = 100	Monthly
SUUR0000SA0	Chained – CPI – All items in US city average, all urban consumers, NSA[a]	December 1999 = 100	Monthly
CUUR0300SA0	CPI – All items in South urban, all urban consumers, NSA[a]	1982–1984 = 100	Monthly
CUUR0350SA0	CPI – All items in South Atlantic, all urban consumers, NSA[a]	December 2017 = 100	Monthly
CUUR0360SA0	CPI – All items in East South Central, all urban consumers, NSA[a]	December 2017 = 100	Monthly
CUUR0370SA0	CPI – All items in West South Central, all urban consumers, NSA[a]	December 2017 = 100	Monthly
CUURS35CSA0	CPI – All items in Atlanta–Sandy Springs–Roswell, GA, NSA[a]	1982–1984 = 100	Bimonthly
CUURS35BSA0	CPI – All items in Miami–Fort Lauderdale–West Palm Beach, FL, NSA[a]	1982–1984 = 100	Bimonthly
CUURS35DSA0	CPI – All items in Tampa–St. Petersburg–Clearwater, FL, NSA[a]	1987 = 100	Bimonthly[c]

[a] NSA = not seasonally adjusted.
[b] SA = seasonally adjusted.
[c] This CPI Index month's publication dates are not the same as the rest.

wide range of time series patterns, including trends, seasonality, and cyclic behavior (Wang et al. 2013). The AR component captures the linear relationship between the current observation and a certain number of lagged observations, modeling the dependence of the current value on its past values. The integration component involves differencing the time series to make it stationary, removing trends or seasonality present in the data. The moving average component models the dependency between the current observation and a series of lagged forecast errors, capturing the influence of past errors on the current value (Salazar et al. 2019).

Price data sources

The data for this study were obtained from the College of Forestry, Wildlife, and Environment and the library of Auburn University, specifically the TMS quarterly reports. TMS compiles and publishes timber prices for 22 US Southern market areas, reporting on PST, chip-n-saw (CNS), and pulpwood (PPW; Misztal 2018). It is important to note that there have been two major revisions in TMS reports: a shift from monthly to quarterly frequency since 1988 and a change in the reporting areas in coastal states from three to two in 1992 (Prestemon and Pye 2000). Previous research has examined temporal and spatial aggregation issues and the efficacy of different statistical tests on TMS timber prices (Prestemon and Pye 2000). The data obtained from TMS cover the time range from the fourth quarter of 1976 to the fourth quarter of 2020 for statewide averages. Additionally, quarterly data for subregions one and two of the states were transcribed for the years 2017, 2018, and 2019.

CPIs provided by the US Department of Labor, Bureau of Labor Statistics (2022), were used to evaluate the effect of inflation correction on the TMS price series. Table 1 provides an overview of the different CPI indices available and their characteristics such as geographical coverage, publication frequency, and base period. Table 2 supplies the Producer Price Indices (PPIs) considered, which measure the average change over time in the prices received by domestic producers for their goods and services (US Bureau of Labor Statistics 2022). Apart from one, the rest of the PPIs lack a geographical coverage component, which could be crucial to understand the price shifts experienced in the Southeast after a hurricane landfall. The comparison between CPIs and PPIs concurrently allows for a more comprehensive understanding of the overall price dynamics within an economy. It provides a broader perspective on the inflationary pressures experienced by both consumers and producers. It can help identify potential supply chain disruptions or shifts in pricing power between consumers and producers (Shah et al. 2021).

Six open market indices specializing in lumber futures or forestry-related data were used for high-frequency data: iShares Global Timber & Forestry ETF (WOOD), PotlatchDeltic Corporation (PCH), Rayonier Inc. (RYN), Weyerhaeuser Company (WY), Acadian Timber Corp (ADN), and Random length lumber futures (LBS1; National Association of Securities Dealers c1996–c1998, CME Group Inc. 2009, TradingView 2021). Pearson's correlation coefficients and coherence were evaluated to select the most suitable public data source for wood prices.

Statistical analysis

Statistical analysis was conducted to examine the relationship between the TMS data and the selected market indices.

Table 2.—Coherence Producer Price Indices' (PPI's) monthly percent change. Table cells have been formatted conditionally to easily represent the higher and lowest coefficients using color code.

		MONTHLY						
		PCU1133-1133	PCU11331-11331	PCU113310113310	PCU113310113310P	WPU08	WPU081	WPU0811
MONTHLY	PCU1133-1133	1	1	0.9997	0.9969	0.884	0.88	0.882
	PCU11331-11331	–	1	0.9997	0.9969	0.884	0.88	0.882
	PCU113310113310	–	–	1	0.9967	0.884	0.881	0.882
	PCU113310113310P	–	–	–	1	0.886	0.882	0.884
	WPU08	–	–	–	–	1	0.965	0.96
	WPU081	–	–	–	–	–	1	0.984
	WPU0811	–	–	–	–	–	–	1

Pearson's correlation coefficients were calculated to assess the degree of correlation between the TMS data and the market indices (Puth et al. 2015). Pearson's correlation coefficient measures the linear association between two variables, providing insights into the strength and direction of the relationship. A positive correlation coefficient indicates a positive linear relationship, while a negative coefficient indicates a negative linear relationship (Udovičić et al. 2007).

The calculation of Pearson's correlation coefficients allowed for a comprehensive analysis of the association between the TMS data and the market indices. This statistical measure provided insights into the direction and strength of the relationships, enabling a better understanding of the market dynamics and potential impacts of external factors such as hurricanes. However, to gain a deeper understanding of the co-movement and phase difference between the TMS data and the market indices, wavelet coherence analysis was also employed. Wavelet coherence analysis is a powerful tool that measures the level of synchronization or association between two time series across different frequencies and time intervals.

Forecasting

To forecast the wood prices, the last quarter's price before the event point by TMS was taken as the base. This approach provides a reference point for comparing and predicting future price movements. In the selection process of the six open market indices, the correlation and coherence tables generated were examined. The correlation table was used to assess the linear association between the TMS data and each market index. The coherence table, derived from wavelet analysis, provided insights into the co-movement and phase difference between the TMS data and each market index. From these tables, the highest value was identified as the most suitable open market index for wood price analysis. This selection criterion prioritizes indices that exhibit a stronger correlation and coherence with the TMS data, indicating a closer relationship and potential predictive power. By selecting the open market index with the highest value, it is expected to capture the most relevant information and provide more accurate forecasts of wood prices. This approach enhances the reliability and validity of the analysis by focusing on the index that demonstrates the strongest statistical relationship with the TMS data.

In Program R, the "wavelets" package provides various wavelet families for analysis (Aldrich 2013). Here are some commonly used wavelet families available in the package: Daubechies ("haar," "db1," "db2," …, "db10"), Symlets ("sym2," "sym3," …, "sym10"), (Coiflets: "coif1," "coif2," …, "coif5"), Biorthogonal ("bior1.1," "bior1.3," "bior2.2," …, "bior6.8"), Reverse Biorthogonal ("rbio1.1," "rbio1.3," "rbio2.2," …, "rbio6.8"), Haar-like ("haar0," "haar1," "haar2," …, "haar15"). These are just a few examples of the wavelet families available in the "wavelets" package. Each family has different properties and characteristics, making them suitable for different types of data and analysis.

The parameters for the waveletArima package include the wavelet filter; for this work we used the "la8" wavelet filter, with five levels of wavelets decomposition, forecast horizon = 360, AR = 3, and MA = 0. The "la8" wavelet is a member of the Daubechies wavelet family. It is also known as the Daubechies 8-tap wavelet, with the following characteristics: orthogonal, 8 coefficients, compact support, symmetry, and frequency response (Paul and Garai 2021). It is characterized by having eight coefficients, making it a compactly supported wavelet. Compact support means that the wavelet function is nonzero only within a finite interval and vanishes outside that interval (Vonesch et al. 2007). The high-pass and low-pass filters associated with the "la8" wavelet allow for analysis of both high-frequency and low-frequency components of a signal. The wavelet exhibits both time and frequency localization properties. It provides a good balance between time and frequency resolution, allowing it to capture both rapid changes in the time domain and localized frequency information (Tzabazis et al. 2018).

Case of study

In addition to the selected indices, the analysis focused on examining the behavior of wood prices in the aftermath of Hurricane Michael in 2018. Hurricane Michael made landfall in the Florida Panhandle as a Category 5 storm and caused extensive damage to forests and timber resources in the affected regions (Blake 2018; Florida Forest Service 2018; NOAA 2021a, 2021b; Brandeis et al. 2022; Henderson et al. 2022).

Sensitivity analysis

In our sensitivity analysis, we explored two critical assumptions within our forecasting model. First, we examined the potential impact of variations in the last quarter's reported price from TMS. To test the model's resilience, we introduced changes of ± 5 percent, ± 10 percent, and ± 15 percent in the last quarter's price. This scenario allowed us to assess the model's sensitivity to fluctuations in input data.

In the second case, we considered a dynamic approach to PST price forecasting. We assumed that an analyst would refresh the forecast daily after the hurricane's landfall until a reasonable return to the original price forecast occurred. This dynamic approach captures the real-world scenario where market conditions can rapidly change postdisaster, and frequent updates to forecasts are necessary.

Discussion

Timber Mart-South data

Timber Mart-South (TMS) is a crucial timber and wood products price-reporting service that covers the southeastern United States. TMS relies on voluntary input from a diverse range of stakeholders, including timber buyers, sellers, brokers, state and federal agencies, private timberland owners, and wood product manufacturers. This collaborative approach enhances the reliability and accuracy of TMS quarterly reports (TimberMart-South | Home 2022).

The University of Georgia's Warnell School of Forestry & Natural Resources compiles and publishes these quarterly reports. Available through paid subscriptions, these reports offer valuable insights into timber market trends and support informed decision-making for government agencies, academics, and researchers involved in forestry and natural resource management (Timber-Mart-South | Resources 2023).

Figure 1 displays TMS quarterly reports, featuring stumpage prices for major timber products across 11 southern US states. Data collection transitioned from monthly to quarterly

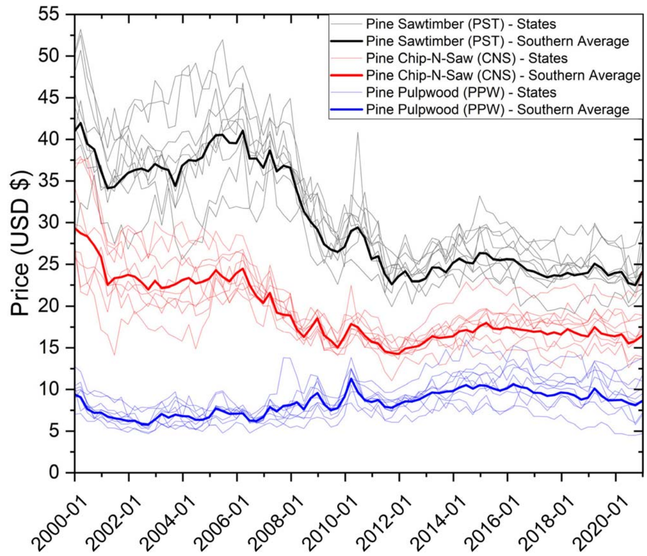

Figure 1.—Southern average and individual state stumpage price indices. Nominal prices. This figure shows individual states' price series for each of the pine products in the Timber Mart-South (TMS) quarterly reports and product average for the southeastern market.

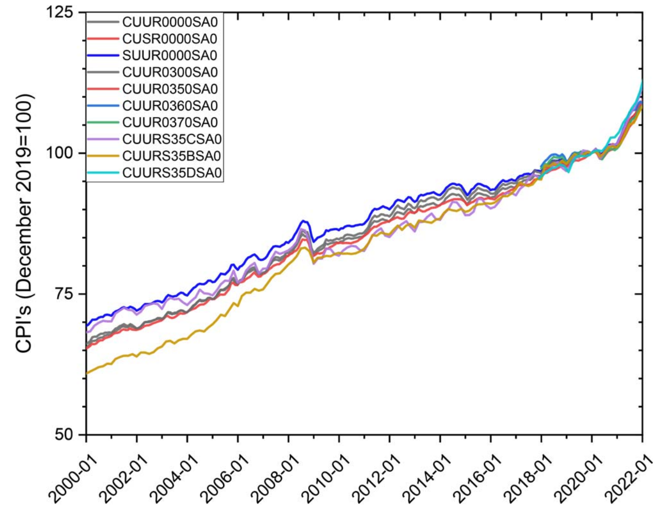

Figure 2.—Consumer Price Indices (CPI) rebased to December 2019 = 100.

reporting in 1988, with previous monthly data averaged to match the new format (Prestemon and Pye 2000). The prices are categorized into three main groups: PPW, CNS, and PST, based on the diameter at breast height thresholds of 6inches and up, 8 to 11 inches, and 12 inches and up, respectively. The reported prices are in (US)$/ton. Each price is independently determined and is not mathematically related to other items. The reported prices represent averages of lows and highs, not absolute lows or highs. Variations in fieldwork and the time element may lead to slight price variations and posterior revisions occur. Additionally, it is vital to recognize that timber prices vary based on several factors, and a reported price represents just one of the prices at which an item has been sold. Salvage sales or special products are typically not included in TMS reports (TimberMart-South | Resources 2023).

Consumer Price Indices

Table 1 provides an overview of various CPI indices, with a focus on the South region. The Consumer Price Index (CPI) is a comprehensive measure of price changes for goods and services in the United States (Bryan and Cecchetti 1993). It is calculated through a two-stage process, which takes both geographical and item structures into account. In the first stage, basic indices are generated to represent specific item–area combinations, capturing price changes for goods and services within particular regions (Consumer Price Index Summary - 2023 M06 Results 2023). In the second stage, the basic indices are aggregated to form broader indices encompassing a wider range of items and geographic areas (US Bureau of Labor Statistics 2023). This process continues until an overall index for all goods and services across the entire United States is achieved (US Bureau of Labor Statistics 2022).

Rebasing CPI indices, using a different period as the reference point (e.g., December 2019 = 100), facilitates clear comparisons of price changes over time. The rebasing process provides a benchmark for assessing the magnitude and direction of price changes (Perrins and Nilsen 2010).

$$IV_{Dec-2019} = \sqrt{IV_{Nov-2019} \times IV_{Jan-2020}} \tag{1}$$

After December 2020, calculate Index Relative Rate of Change (IRRC) and the new Rebased Index Values (RIV) using the following formulas:

$$IRRC_{month} = \frac{CPI_{month}}{CPI_{previous\,month}} \tag{2}$$

$$RIV_{month} = IRRC_{month} \times RIV_{previous\,month} \tag{3}$$

Before December 2019:

$$IRRC_{month} = \frac{CPI_{month}}{CPI_{following\,month}} \tag{4}$$

$$RIV_{month} = IRRC_{month} \times RIV_{following\,month} \tag{5}$$

Figure 2 presents the results of rebasing the indices to December 2019, while Figure 3 shows representative outcomes from the wavelet analysis of monthly CPI data. The wavelet power spectrum highlights significant periods (frequency) and their corresponding time intervals, represented by red areas, demonstrating when CPI indices exhibit notable coherence and synchronized behavior. The horizontal arrows in the plot are indicative of the phase relationship between the two series at the respective periods. When arrows point toward the right, it signifies that the two series are in phase. On the other hand, arrows pointing to the left indicate that the two series are in antiphase.

Contrary to common intuition, extending the length of a time series does not enhance the discriminatory power of the wavelet transform (Rösch and Schmidbauer 2016). The wavelet transform focuses on transforming fixed-length segments of the time series for a given period, enabling the analysis of

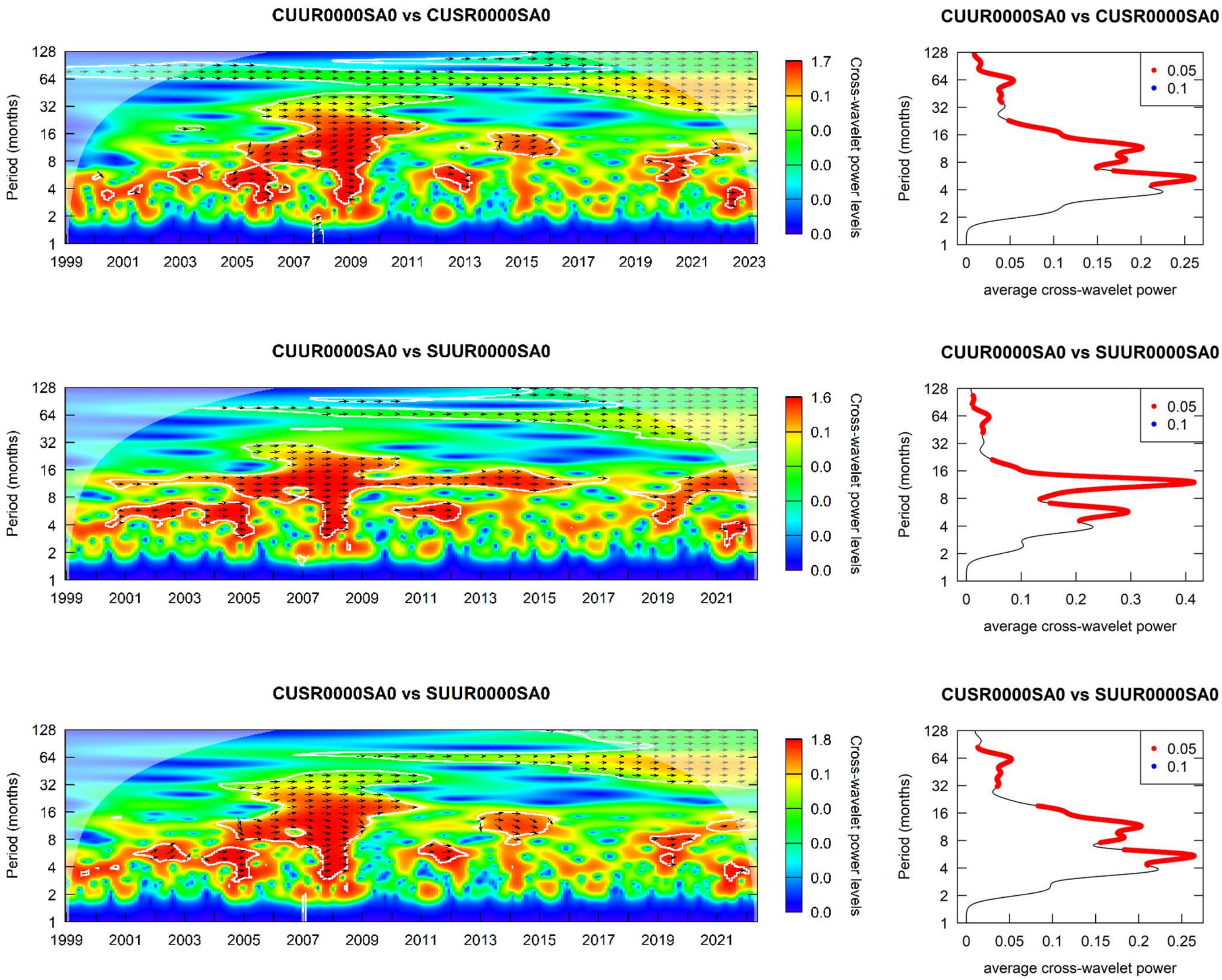

Figure 3.—Consumer Price Indices (CPIs) general indices cross-wavelet coherency analysis (monthly percent change). Power spectrum (left) and corresponding time-averaged wavelet power (right). Red dots in the averaged wavelet power represent significance level ≤0.05.

localized frequency components and variations rather than the series' length (Rösch and Schmidbauer 2016).

Table 3 presents the coherence coefficients of CPI's indexes. The general indices exhibit higher linear correlation coefficients with decreasing values in the specific delimited regional indices and cities. This reflects that overall price movements are closely aligned among general indices, while regional and city-specific indices show more significant variability. The coherence analysis, which captures subtle differences, is more sensitive to small changes between the indices. By considering both correlation and coherence coefficients, we gain a comprehensive understanding of the relationships between the indices. Additional figures are available in the Supplementary Information 1 and 2.

Table 3.—Coherence tests of U.S. Consumer Price Indices' monthly percentage change. Table cells have been formatted conditionally to easily represent the higher and lowest coefficients using color code.

		MONTHLY						
		CUUR0000	CUSR0000	SUUR0000	CUUR0300	CUUR0350	CUURS35C	CUURS35D
MONTHLY	CUUR0000	1	0.9322	0.9725	0.9603	0.9612	0.9164	0.9218
	CUSR0000	–	1	0.9242	0.9314	0.9185	0.9018	0.9072
	SUUR0000	–	–	1	0.9535	0.9555	0.9089	0.9152
	CUUR0300	–	–	–	1	0.9701	0.9171	0.9193
	CUUR0350	–	–	–	–	1	0.9288	0.9153
	CUURS35C	–	–	–	–	–	1	0.9236
	CUURS35D	–	–	–	–	–	–	1

Table 4.—All relevant indices for Producer Price Indices. Hardwood lumber indices not used in this paper.

Series ID	Series title[a]	Base period	Periodicity
WPU08	PPI – Commodity data for Lumber and Wood Products, NSA	1982–84 = 100	Monthly
WPU081	PPI – Commodity data for Lumber and Wood Products – Lumber, NSA	1982–84 = 100	Monthly
WPU0811	PPI – Commodity data for Lumber and Wood Products – Softwood Lumber, NSA	1982–84 = 100	Monthly
WPS0811	PPI – Commodity data for Lumber and Wood Products – Softwood Lumber, SA	1982–84 = 100	Monthly[b]
WPU0812	PPI – Commodity data for Lumber and Wood Products – Hardwood Lumber, NSA	1982–84 = 100	Monthly
WPS0812	PPI – Commodity data for Lumber and Wood Products – Hardwood Lumber, SA	1982–84 = 100	Monthly[c]
PCU1133-1133	PPI – Industry group data for Logging and Sawmills, NSA	Dec 1981 = 100	Monthly
PCU11331-11331	PPI – Industry group data for Logging, NSA	Dec 1981 = 100	Monthly
PCU113310113310	PPI – Industry group data for Logging – Tree-length Southern Pine, NSA	Dec 1981 = 100	Monthly
PCU113310113310P	PPI – Industry group data for Logging – Primary products, NSA	Dec 1981 = 100	Monthly

[a] NSA = not seasonally adjusted; SA = seasonally adjusted.
[b] No data for 1991–1997, 2004–2005, 2011–2013. Not able to rebase.
[c] Only available from 1982 to 2003. No data for 1990–1993. Not able to rebase.

Producer Price Indices

The PPI quantifies price fluctuations experienced by domestic producers for their goods and services over time. Compiled by the Bureau of Labor Statistics in the United States, it focuses on the perspective of sellers rather than buyers, in contrast to the CPI. The PPI encompasses prices at all production stages, from raw materials to finished goods, and can be categorized by industry and commodity. Like the CPI, it utilizes a base period with a value of 100 to compare prices in subsequent periods, revealing changes reflected in the PPI. This index is a valuable tool for businesses and policymakers to monitor inflation trends and adjust pricing strategies. Additionally, it measures price changes at the wholesale level, so it can provide early indicators of inflationary pressures in the economy before such pressures reach consumers.

Table 4 offers an overview of PPI data, outlining key limitations and exclusions. Specific periods, such as 1991 to 1997, 2004 to 2005, and 2011 to 2013, lack data for certain indices. Some indices are only available from 1982 to 2003, with a data gap for the years 1990 to 1993. Recognizing these constraints is essential for understanding data scope and constraints, influencing the interpretation of findings. This paper does not address WPS0811, WPU0812, or WPS0812 because they concern hardwood lumber, which is not within the paper's scope. However, these may warrant discussion in future studies. In Figure 4, we present the rebased PPI values, using December 2019 as the reference period with a base index of 100. Table 2 shows the coherence coefficient calculated for PPI's monthly percent change.

Supplementary file 3 offers comprehensive figures and additional information supporting findings on the differential sensitivity of lumber and wood products (WPU) and logging and sawmills (PCU) PPI indices. These supplementary materials enhance our understanding of wavelet analysis results. The wavelet analysis results indicate that WPU indices exhibited more pronounced fluctuations during the COVID-19 period when compared with PCU indices, likely as a result of factors such as supply chain disruptions, production cost changes, and shifts in market demand. Conversely, the wavelet analysis showed that PCU indices were more sensitive to the 2008 global economic crisis.

Open market indices

Table 5 provides an overview of different investment vehicles: ETFs, REITs, stocks, and futures. Each of these options offers unique features and benefits for investors seeking exposure to various asset classes and markets. ETFs are investment funds that trade on exchanges and track the performance of an underlying index, commodity, or asset (Lettau and Madhavan 2018). They provide diversification by holding a basket of securities, making them attractive to individual investors looking for broad market exposure or specific sector investments. REITs, on the other hand, are investment vehicles that own and operate income-generating real estate properties (Haslam et al. 2015). Investors can purchase shares in a REIT, which grants them a portion of the income and profits generated by the real estate holdings, making them a popular choice for those seeking real estate investments without property ownership. Stocks, also known as shares or equities, represent ownership in a company (Hall 1997). When investors buy stocks, they become shareholders and have a stake in the company's assets and earnings. Stock prices fluctuate based on various factors, including financial performance, market conditions, and investor sentiment. Futures contracts are predetermined agreements standardizing the buying or selling of an underlying asset at a specific future price and date (Telser 1986). These contracts can cover commodities, financial instruments, or indices. Futures serve purposes like speculation on price movements, hedging against

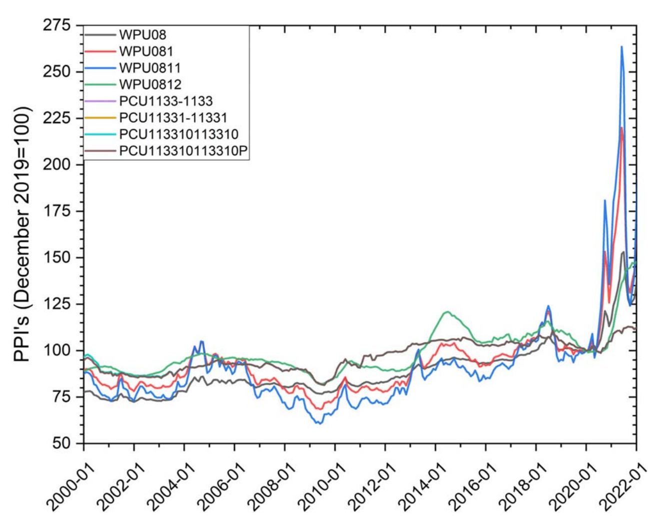

Figure 4.—Producer Price Indices (PPIs) rebased to December 2019 = 100.

Table 5.—Financial instruments.

Type[a]	Series ID	Series title	Data since	Periodicity[b]
ETF	WOOD	iShares Global Timber & Forestry ETF	June 25, 2008	Quarterly, Monthly, Weekly, Daily
REIT	PCH	PotlatchDeltic Corporation	Jan 01, 1969	Quarterly, Monthly, Weekly, Daily
REIT	RYN	Rayonier Inc.	Feb 17, 1994	Quarterly, Monthly, Weekly, Daily
Stock	WY	Weyerhaeuser Company	Jan 02, 1968	Quarterly, Monthly, Weekly, Daily
Stock	ADN[c]	Acadian Timber Corp	Jan 31, 2006	Quarterly, Monthly, Weekly, Daily
Futures	LBS1	Random length lumber futures	Nov 16, 1972	Quarterly, Monthly, Weekly, Daily

[a] ETF is exchange-traded fund; REIT is Real Estate Investment Trusts.
[b] Some instruments are available for up to 1-h frequencies.
[c] In CAD ($).

potential losses, and locking in prices for future transactions (Islam and Chakraborti 2015).

Figure 5 presents the daily percent change wavelet analysis of openly traded market indices, revealing significant periods in the range of 2 to 4 and 32 to 64 days, particularly during 2018, coinciding with Hurricane Michael. Figure 6 presents price data for various financial instruments relevant to the timber and forestry industry used in the study and post-Hurricane Michael price series forecasting.

Results

Case of study: Hurricane Michael 2018

Hurricane Michael underwent rapid intensification and became a hurricane around midday on October 8, 2018. Continuing to strengthen, the storm reached the Gulf of Mexico a few hours later and developed into a major hurricane late on October 9. At 17:30 hours UTC on October 10, Michael made landfall near Panama City, Florida, as a Category 5 hurricane with maximum sustained winds of 160 miles per hour (260 km/h). Michael became the most intense storm of the season and the third-strongest hurricane to make landfall in the United States. After landfall, Michael quickly weakened over land, transitioning to a tropical storm over Georgia on October 11. By October 12, it became an extratropical cyclone over Virginia (Avila 2019).

Figure 7 provides a visual representation of US Southeast timber market areas and hurricane tracks. The Florida Panhandle, including Mexico Beach, Panama City, and Panama City Beach, suffered catastrophic damage from Hurricane Michael, with property damage estimated at least (US)$25 billion. More than 83 million short tons of DT resulted from Michael (Florida Forest Service 2018, North Carolina Forest Service 2018, Brandeis et al. 2022).

Consumer Price Indices

In 2017, the Atlantic Hurricane season extended from April 19 to November 9. In 2018, it started on May 25 and ended on October 31. In 2019, the season began on May 20

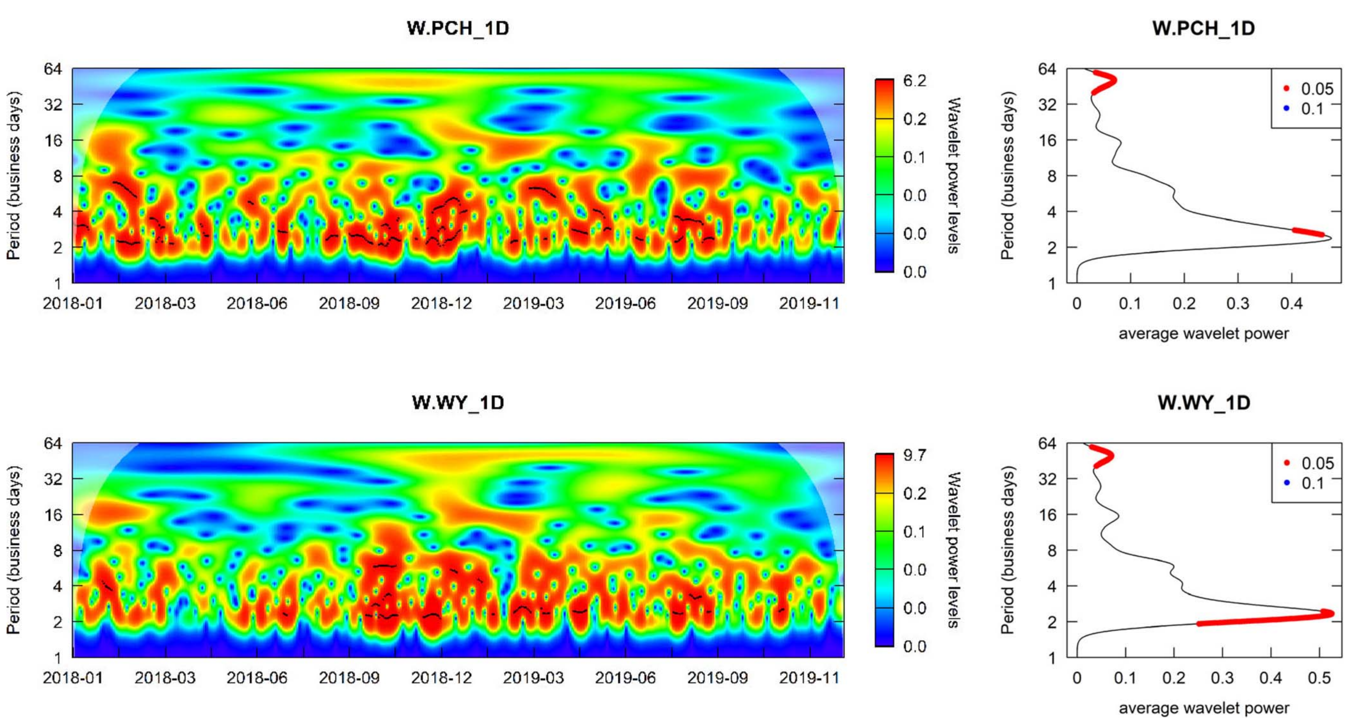

Figure 5.—Wavelet analysis from open market indices (daily). PotlatchDeltic Corporation (PCH) and Weyerhaeuser Company (WY). Power spectrum (left) and corresponding time-averaged wavelet power (right). Red dots in the averaged wavelet power represent significance level $\leq$0.05.

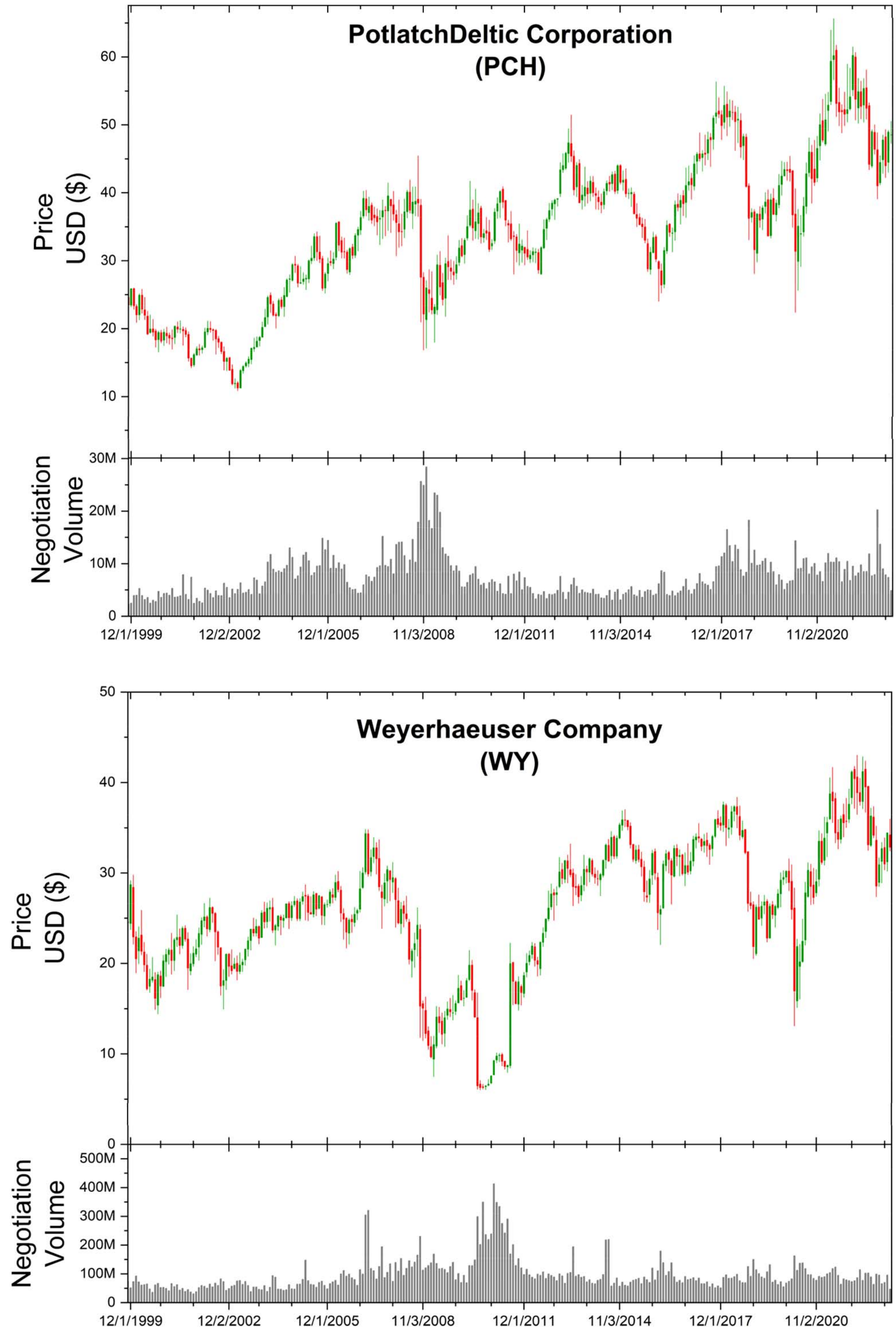

Figure 6.—Open market indices in Monthly basis. The representation of price series is in Heikin-Ashi candles and the corresponding negotiation volume below as columns.

and concluded on November 24, marking the time of heightened tropical cyclone activity. These dates have been used to delimit the hurricane seasons in the following figures.

Figure 8 provides an insightful view of the effect of the CPI adjustment on the TMS Florida general average and regional indices for PPW, as well as the southeastern average. The variation result in the indices during 2018 is relatively small, with a gradual increase observed as we move further back in time. Specifically, adjusting Florida's second region by using CPIs during 2018, the average variation of the indices from the nominal price is 0.4 percent $\pm$ 1.0 percent, with a minimum of -1.6 percent and a maximum of 3.0 percent. The CPI adjustment allows for a more accurate representation of the price movements by accounting for inflationary factors and providing a consistent reference point.

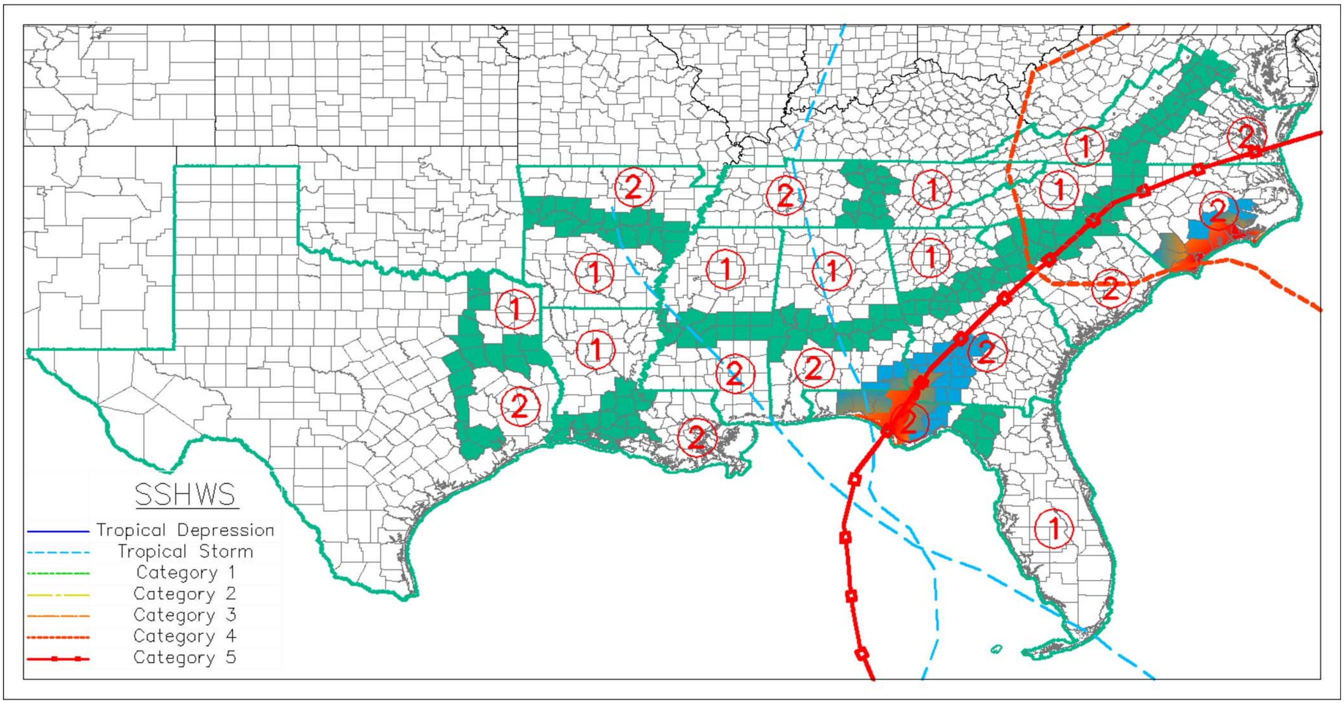

Figure 7.—2018 Atlantic hurricane season. Hurricane tracks and counties damaged.

Producer Price Indices

Figure 9 presents the analysis of PPIs. The results of the analysis reveal a higher level of variation compared with CPIs. This indicates that the PPIs exhibit greater volatility in price movements within the selected period. It is important to note that the higher variation in the PPIs may come at the cost of potentially losing some level of detail in identifying specific price movement patterns. Examples of that are the second and third quarters for 2018 in the figure, in which some adjusted series appear more horizontal than others. The figure uses dashed lines specifically to highlight the adjustment made with the PCU113310113310 index, for logging tree-length southern pine. Specifically, adjusting Florida's second region by using PPIs during 2018, the average variation of the indices from the nominal price is -1.3 percent $\pm$ 4.1 percent, with a minimum of -11.4 percent and a maximum of 5.6 percent.

Wavelet analysis and forecasting

In the context of analyzing the effects of hurricanes on stumpage prices in hurricane-affected states, the results of your time series analysis using TMS quarterly data have indicated areas of significance at 2 to 4 periods (quarters). However, this limited resolution may not capture the full dynamics and nuances of the relationship between hurricanes and stumpage prices. The daily percent change wavelet analysis of two

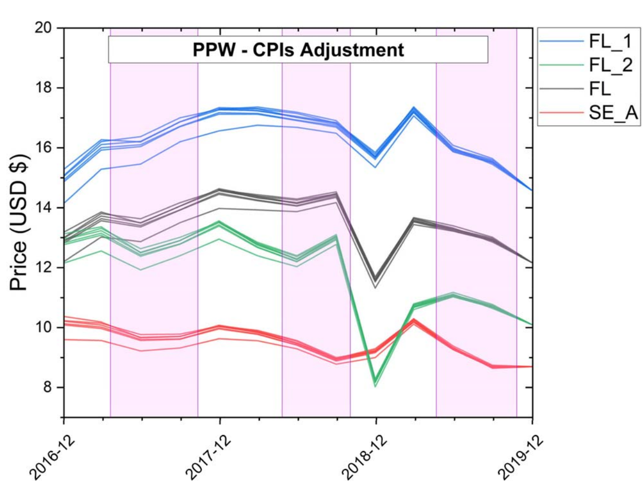

Figure 8.—Effect of Consumer Price Indices' (CPI's) adjustment in Florida's PPW indices. FL_1 was not affected by storms. FL_2 is the region affected by Hurricane Michael. FL is the average for the state and SE_A is the average for all the states. Areas in magenta represent the hurricane seasons.

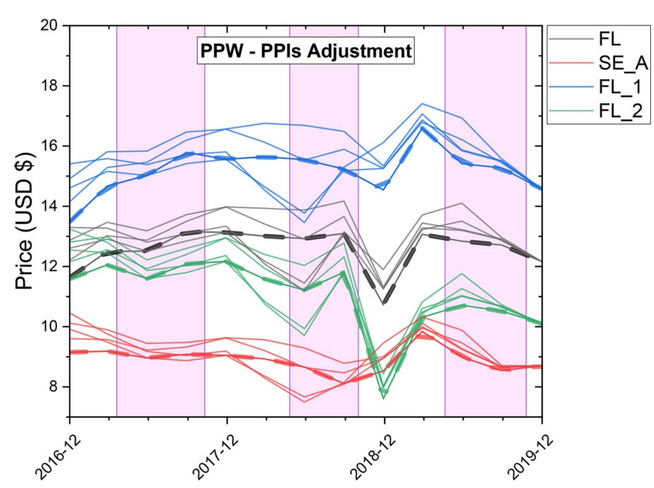

Figure 9.—Effects of Producer Price Indices (PPI's) adjustment on Florida PPW indices. FL_1 was not affected by storms. FL_2 is the region affected by Hurricane Michael. FL is the average for the state and SE_A is the average for all the states. Areas in magenta represent the hurricane seasons.

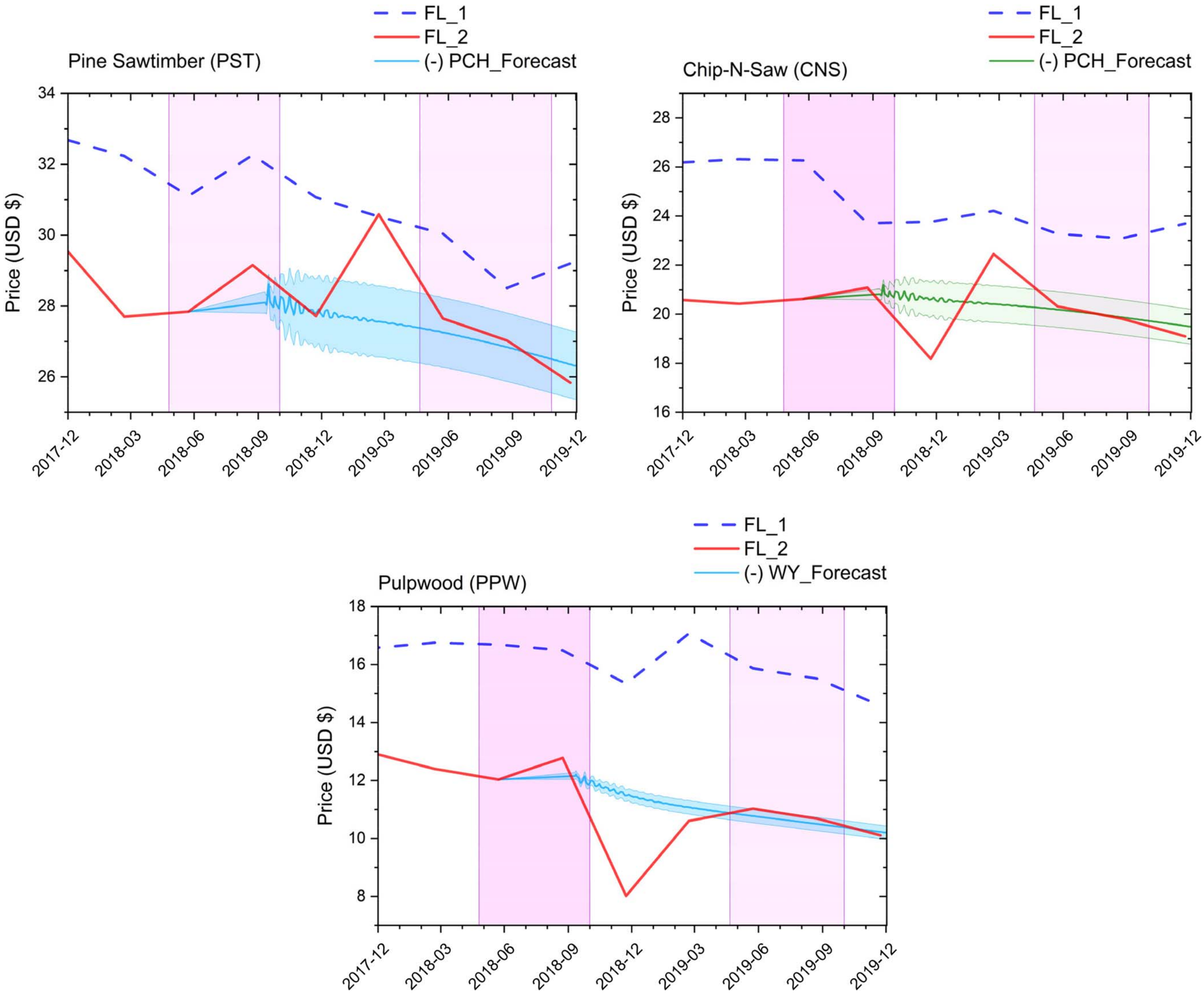

Figure 10.—Florida pine sawtimber (PST), chip-n-saw (CNS), and pulpwood (PPW) forecasting with market indices. The forecast center line corresponds to the average of the four-price series used (open, high, low, close). The probability cone is shown as the standard deviation resulting from the average process of the four series. FL_1 region was not affected by hurricane Michael, and it is plotted as reference to denote the price behavior that occurred in FL_2 as a result of the hurricane downed timber.

openly traded market indices (PCH and WY) reveals significant periods of 2 to 4 days and 32 to 64 days, particularly during the year 2018. These significant periods are of particular interest because they align with the occurrence of Hurricane Michael. Moreover, the coherence coefficient for Florida calculated by wavelet analysis between TMS data and PCH resulted in 0.908 $\pm$ 0.003 and 0.91 $\pm$ 0.007 (for PST and CNS, respectively). Meanwhile, for TMS and WY the coherence coefficient was 0.881 $\pm$ 0.006 for PPW.

Figure 10 depicts the price indices for the products PPW, CNS, and PST in the TMS Florida region. These indices are accompanied by the forecasted results using the two open market indices. The selection of the open market data was performed in conjunction with the correlation coefficients and coherency tables. Once the appropriate data set was chosen, the forecast was recalculated based on the latest quarterly price available from TMS prior to the occurrence of Hurricane Michael, assuming that this was the last price available for analysis at the time of landing. These forecasts corresponded to the daily data of open, high, low, and close, which is one of the advantages of high-frequency open market data. The negative correlation coefficient sign was employed to account for the inverse relationship observed between the forecasted values and the TMS basepoint for PST. By multiplying the forecasted values by -1, the direction of the relationship is reversed, allowing for a more accurate alignment with the TMS historical patterns.

The use of openly traded market indices for high-frequency forecasting, as supported by the results presented, offers several advantages in the context of now-casting or high-frequency forecasting. Timeliness: Openly traded market indices provide up-to-date and real-time information about market conditions. This enables analysts to capture and respond to market dynamics quickly, facilitating timely decision-making and forecasting. Granularity: High-frequency data, such as daily or intraday data, provides a more detailed and granular view of market movements. This allows for a more nuanced analysis of short-term fluctuations and patterns, which may not be captured by

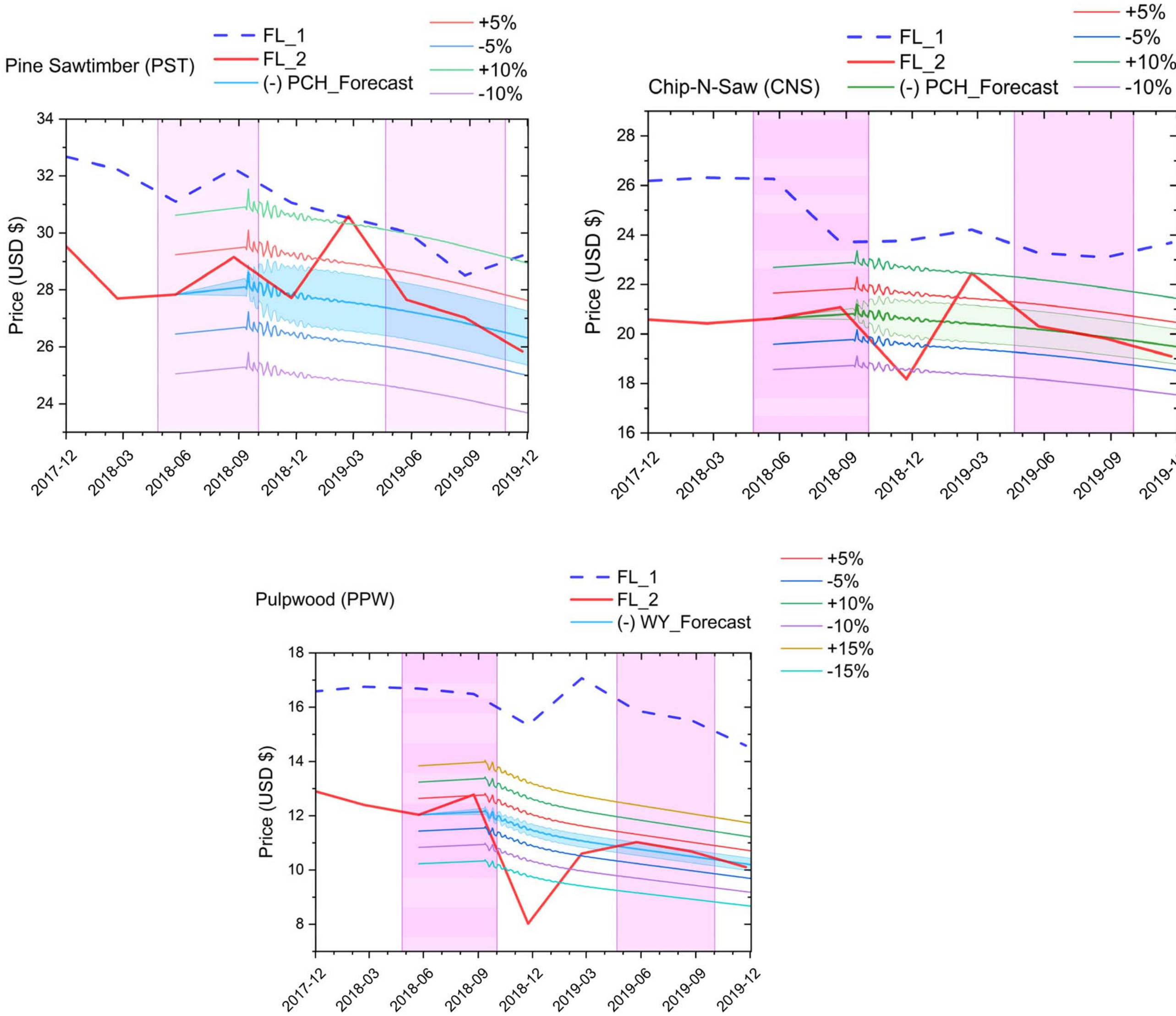

Figure 11.—Florida pine sawtimber (PST), chip-n-saw (CNS), and pulpwood (PPW) forecasting sensitivity analysis. The forecast center line corresponds to the average of the four series used (open, high, low, close). Sensitivity analysis has been conducted with the assumption of a variation of the last price reported quarter Timber Mart-South (TMS) data with values of ±5 percent, ±10 percent, and ±15 percent (in the case of PPW).

lower frequency data. Sensitivity to shocks and events: High-frequency data is more responsive to shocks, events, and news releases that can impact markets. By incorporating these data into forecasting models, analysts can better capture and assess the immediate effects of such events on the market. Improved accuracy: High-frequency forecasting can lead to more accurate predictions by capturing the most recent information and market dynamics. This can be especially beneficial in volatile and rapidly changing markets where traditional lower frequency data may not adequately reflect the current market conditions. Enhanced risk management: The ability to generate high-frequency forecasts allows for more effective risk management strategies. Traders, investors, and policymakers can make timely adjustments to their positions or policies based on the most recent market information, reducing potential losses, or maximizing returns. The results obtained from comparing the forecasts with the remaining data from TMS after the impact of the hurricane demonstrated a good fit. These results indicated a recovery in prices within a period of 2 to 4 quarters. This finding is consistent to a certain degree with the previously reported literature.

However, it is worth noting that the return to the moving average price occurred more rapidly than what has been reported by other authors. The results obtained in this study suggest that there may be structural differences between the market conditions at the time of Hurricane Hugo in 1989 and Hurricane Michael in 2018. These differences include factors such as the acceleration of markets, increased frequency of operation, and improved data availability. These advancements have likely facilitated innovations and more efficient market dynamics, leading to a faster recovery in timber prices after Hurricane Michael compared with previous events.

Sensitivity analysis

In Figure 11, we delve into the results of our first sensitivity analysis, which sheds light on the varying impacts of ±5 percent, ±10 percent, and ±15 percent price variations in the previous TMS quarter report before the event for different

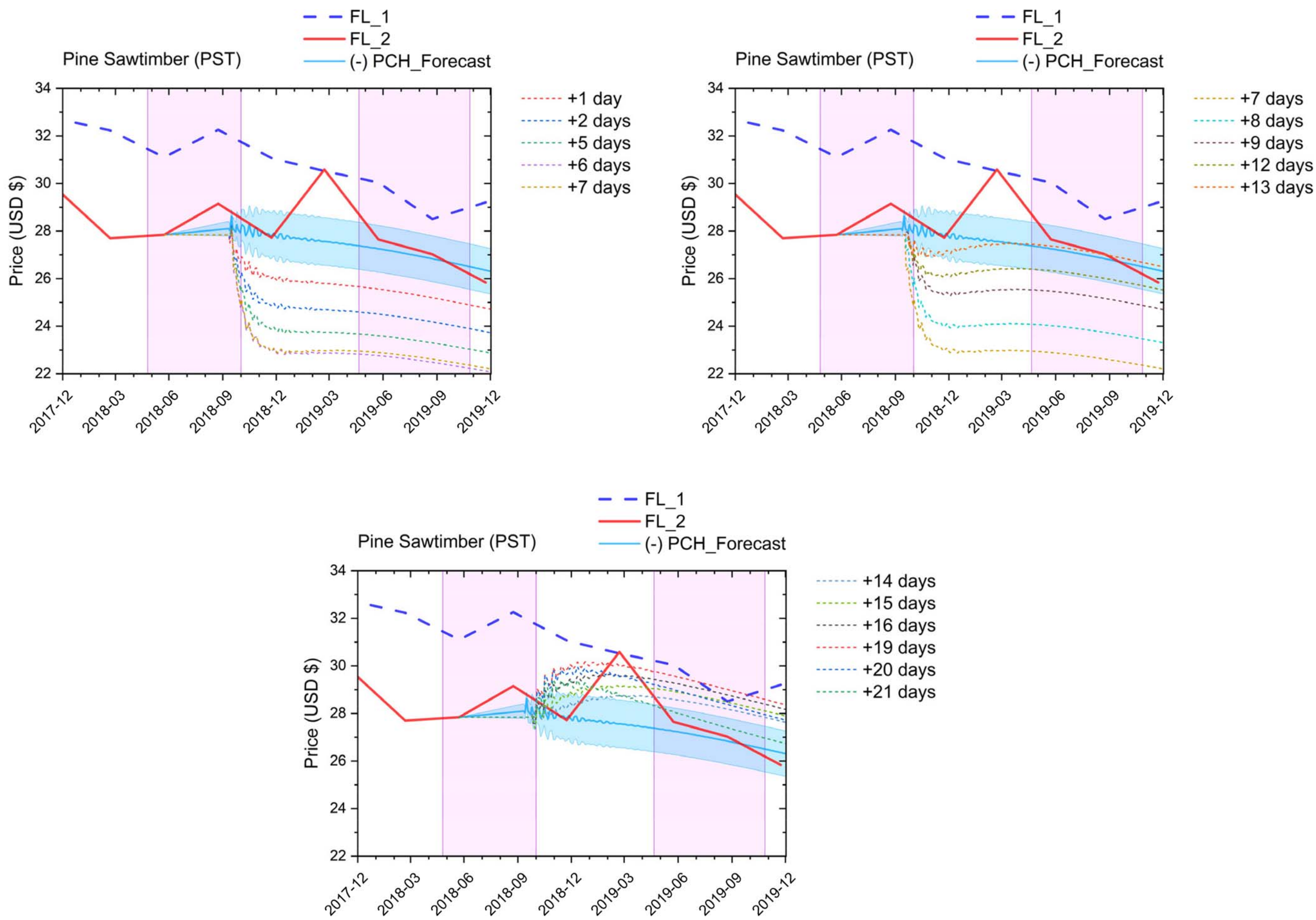

Figure 12.—Florida pine sawtimber (PST) forecasting sensitivity analysis. The forecast center line corresponds to the average of the four series used (open, high, low, close). Sensitivity analysis has been conducted with the assumption of a variation of the last cut-off day after hurricane Michael made landfall. This test represents the variation in price of the open market index due to the news and updates of the damage originated by the hurricane.

timber products: PST, CNS, and PPW. For PST, a deviation of −10 percent proves to be a threshold, leading to long-term discrepancies between the forecasted and actual prices later reported by TMS. In this case, the forecast produced with −10 percent stays below the TMS price reported after 1 year of the event and outside of the original probability cone (±1 standard deviation). In contrast, a +10 percent variation aligns closely with the maximum price reported by TMS two quarters post-hurricane. The CNS product showcases unique characteristics. A ±10 percent variation in CNS prices coincides with both the minimum and maximum prices reported by TMS, occurring one and two quarters after the hurricane. On the other hand, ±5 percent variations in CNS remain in good agreement with the original forecast behavior, highlighting their resilience to minor changes. In the case of PPW, a ±5 percent price variation continues to demonstrate alignment with the original forecast behavior. A +10 percent variation exceeds the forecast range, while even a substantial −15 percent change is insufficient to predict the minimum reported by TMS two quarters after the hurricane's landfall. These findings emphasize the unique sensitivity of PPW forecasts to price variations, especially on the lower end of the scale.

Figure 12 specifically focuses on the model's response when the forecast is rerun daily after Hurricane Michael's landfall. The results reveal an intricate and dynamic price forecast pattern in the aftermath of the hurricane, reflecting the sensitivity forecasts to frequent updates. At the outset, we observe a downward trend in the forecast that extends over the initial 6 days after the hurricane's landfall, resulting in a significant −17.9 percent price downturn. This downturn underscores the immediate impact of the hurricane on timber prices, aligning with the real-time market dynamics in the wake of the disaster. However, a recovery phase emerges around day 13, with the forecast showing a bounce-back. By day 19, the model reaches its maximum forecasted price, marking an +8.3 percent price increase from the last reported TMS quarter before the hurricane. This resurgence reflects the resilience of the forestry market and its ability to rebound in response to postdisaster market dynamics. Ultimately, by around day 21, the forecast model steadies, returning to a pattern that closely mirrors the original forecast. By evaluating our model under these assumptions, we gained valuable insights into its adaptability and robustness in the face of changing variables and evolving market dynamics.

Conclusions

In this study, wavelet coherence analysis provided additional insights into the relationship between the TMS data and the market indices. It facilitated the detection of patterns of similarity, periodicity, or relationships that may not have been apparent through traditional correlation analysis alone. The ability to capture both amplitude and phase information allowed for a more nuanced understanding of the coherence between the time series, providing valuable information on the potential impacts of hurricanes on stumpage prices.

The combination of traditional correlation analysis and wavelet coherence analysis enhanced the statistical analysis in this study, offering a comprehensive examination of the relationship between the TMS data and the market indices. Together, these analytical approaches provided a robust foundation for understanding the dynamics of the timber market and the potential effects of hurricanes on timber prices.

Overall, the combination of correlation and coherence analysis allows us to uncover different aspects of the relationships between the indices. Although correlation coefficients capture the broad linear associations, coherence coefficients provide a more nuanced understanding of the subtle differences and commonalities in their fluctuations. This comprehensive analysis enhances our ability to discern the intricate dynamics of the price data and offers valuable insights into the interconnectedness of the indices at various levels of aggregation.

By considering the CPI's geographic and item structures, as well as the specific delimitations for the South region and major metropolitan areas, this study ensures a comprehensive and accurate assessment of price changes and their potential impact on the timber market.

The faster recovery observed in this study suggests a more accelerated rebound in prices following the hurricane's impact. This disparity in findings highlights the importance of considering various factors, such as market dynamics, local conditions, and specific characteristics of the hurricane event, when analyzing the impact on timber prices. The market's ability to quickly adapt and respond to the impact of natural disasters may have played a significant role in the observed faster recovery in timber prices.

These findings highlight the importance of considering the specific context and characteristics of each hurricane event when analyzing the impact on timber markets. The dynamic nature of markets, coupled with advancements in technology and data availability, have likely contributed to the observed differences in the recovery patterns of timber prices.

Furthermore, it is important to highlight that the programming of the forecasting technique used in this study can be updated on a daily basis following a catastrophic event. This real-time updating capability enables timely adjustments to the forecast based on the latest available data, allowing for a more accurate assessment of the postevent market conditions. The results from the sensitivity analysis underscore the importance of accurate and timely market data in fine-tuning forecasting models and anticipating price movements following natural disasters.

By continuously integrating new data and adjusting the forecasts, decision-makers can monitor the recovery progress, identify any deviations from the expected trajectory, and make necessary adjustments to their strategies or interventions. This dynamic and adaptive approach to forecasting helps to ensure that the decision-making process remains responsive to the changing market conditions in the aftermath of a natural disaster.In conclusion, the TMS quarterly reports play a vital role in providing accurate and comprehensive timber price information in the US South. The collaboration among stakeholders, the data collection process, and the categorization of prices based on product types and diameter thresholds ensure a valuable resource for analyzing market trends and informing decision-making in the forestry and natural resource management sectors. While acknowledging the limitations and variations in reported prices, the TMS reports remain a valuable tool for understanding the dynamics of the timber market in the southeastern United States.

Finally, we acknowledge the importance of addressing the limitations and potential challenges associated with the application of wavelet analysis and the Wavelet-ARIMA model in our study. With the inclusion of 10 Consumer Price Indices (CPIs), 7 Producer Price Indices (PPIs), 30 state-wide Timber Market Survey indices, 54 subregions, and 24 open market series, the number of unique correlations pairing combinations alone could reach an overwhelming number. These computations require significant computational resources and time to yield meaningful results. As with any analytical method, they come with their own set of limitations and assumptions. One of the primary challenges associated with wavelet analysis is the selection of appropriate wavelets and scales (Guo et al. 2022). In general, a mother wavelet is expected to possess specific properties, including orthogonality, compact size, limited support, symmetry, and vanishing moments (Rhif et al. 2019). Furthermore, the interpretation of wavelet results may not always be straightforward (De Moortel et al. 2004).

One major limitation of ARIMA models is their presumed linear form of the associated data (Khandelwal et al. 2015). In the context of the timber market, the effectiveness of the Wavelet-ARIMA model may vary based on the characteristics of the data set, the market's inherent complexity, and the presence of external factors not considered in the model. For example, the influence of factors such as government policies, supply chain disruptions, or changing consumer preferences could introduce additional complexities that may not be fully captured by the model (Vahid 2011). Nevertheless, the extensive efforts undertaken in this study contribute to a more comprehensive understanding of the relationships and dynamics within the data sets, providing valuable insights into the effects of hurricanes on stumpage prices in the Southern US region.

Acknowledgments

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