INTERNATIONAL JOURNAL OF FOREST ENGINEERING
https://doi.org/10.1080/14942119.2026.2646802

Responding to hurricane disruptions: salvage decisions under uncertain timber supply

Ian Pereira Sartorio[a], Bruno Kanieski da Silva[b], Shaun M. Tanger[c], Jesse D. Henderson[d], Mohammad Marufuzzaman[e], Yun Yang[f], Adam Polinko[g], and Christine Fortuin[g]

[a]Resource Management Service LLC, Birmingham, AL, USA; [b]Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA, USA; [c]Arkansas Center for Forest Business, University of Arkansas at Monticello, Monticello, AR, USA; [d]USDA Forest Service, Southern Research Station, Research Triangle Park, Raleigh, NC, USA; [e]Department of Industrial & Systems Engineering, Mississippi State University, Starkville, MS, USA; [f]College of Agriculture and Life Sciences, Cornell University, Ithaca, NY, USA; [g]Department of Forestry, Mississippi State University, Starkville, MS, USA

ABSTRACT

Hurricanes are increasingly frequent and intense disturbances that cause substantial economic and ecological damage to forested landscapes worldwide. Following such events, multiple stakeholders – including timberland owners, forest management organizations, logging and transportation providers, and wood-processing mills – face urgent salvage decisions under uncertain and spatially heterogeneous timber supply conditions. This study presents a scenario-based stochastic optimization framework for post-hurricane salvage logging that explicitly accounts for uncertainty in timber volume loss and quality degradation. Using Hurricane Michael (2018) as a case study in the southeastern United States, forest inventory data, remotely sensed damage indices, species-specific yield curves, and market information are integrated into a spatial optimization model that jointly determines salvage harvest locations and wood transportation decisions. Uncertainty in salvageable supply is represented through multiple simulated damage scenarios with varying levels of sawtimber downgrade to pulpwood. The framework compares risk-neutral and risk-averse strategies, including a mean – risk formulation based on Conditional Value-at-Risk (CVaR), and evaluates sensitivity to key economic and logistical parameters. Results indicate that risk-averse and performance-stable salvage strategies reduce transportation costs and mitigate losses in timber value relative to deterministic approaches, particularly under high uncertainty in damage severity and downgrade rates. Overall, the findings demonstrate that representing post-hurricane timber supply uncertainty through scenario-based simulations and evaluating alternative downgrade and risk preferences materially influence salvage location choices, transportation costs, and economic outcomes. The proposed framework provides a decision-support tool for assessing trade-offs between expected returns and downside risk across a wide range of plausible post-disturbance conditions.

ARTICLE HISTORY
Received 14 August 2025
Accepted 4 March 2026

KEYWORDS
Salvage logging; hurricane disturbance; timber supply uncertainty; stochastic optimization; risk-averse planning

Introduction

Hurricanes can have severe and far-reaching consequences for forests, impacting both ecological processes and forest market dynamics (Prestemon and Holmes 2000; Zampieri et al. 2020; Henderson et al. 2022; Worley et al. 2022). The aftermath of a hurricane often leaves behind damaged and downed trees that, if not salvaged efficiently, can exacerbate already significant economic losses for forest owners (Stanturf et al. 2007; Prestemon and Holmes 2010).

Extensive research has examined the effects of hurricanes and strong winds on forest ecosystems, documenting a wide range of physical, ecological, and economic impacts (Gao and Larjavaara 2024). At the stand and landscape levels, hurricanes cause substantial physical damage to trees, including windthrow, stem breakage, and crown loss (Oswalt and Oswalt 2008; Wang and Xu 2009; Rutledge et al. 2021). These structural impacts often trigger broader ecological disturbances, such as shifts in species composition, altered nutrient cycling, increased vulnerability to invasive species, and long-term changes in forest resilience (Lugo 2008; Xi et al. 2008; Kenney et al. 2021).

Beyond immediate damage, a growing body of literature highlights how forest degradation, land-use pressure, and intensive management can amplify disturbance severity and contribute to recurrent disturbance regimes (Peltola et al. 2010; Johnstone et al. 2016; Seidl et al. 2017; Ceccherini et al. 2020; de Pellegrin Llorente et al. 2023). These processes interact with market responses, leading to spatially heterogeneous damage patterns, temporal fluctuations in timber supply, and price volatility following major storm events (Prestemon and Holmes 2004, 2010; Stanturf et al. 2007; Sun 2016, 2020; Aghalari et al. 2021; Henderson et al. 2022). Although these consequences are reasonably well documented, the magnitude and interaction of these effects remain deeply uncertain. In part, this uncertainty arises from the uniqueness of individual storm events, as forest damage and welfare outcomes depend on the interaction of storm-specific and regional factors, including storm intensity, stand structure, ownership, infrastructure, and market dynamics (Stanturf et al. 2007; Petucco et al. 2020; Feng et al. 2021; Sartorio et al. 2024). These inherent uncertainties underscore the need for flexible and adaptive management strategies that respond to both ecological

CONTACT Ian Pereira Sartorio ips.forester@gmail.com Resource Management Service LLC, 31 Inverness Center Pkwy Suite 200, Birmingham, AL 35242, USA
Supplemental data for this article can be accessed online at https://doi.org/10.1080/14942119.2026.2646802.

and economic realities (de Pellegrin Llorente et al. 2023). When uncertainty is not explicitly acknowledged or is incorporated incorrectly, management decisions are more likely to be suboptimal. As Marshall (1987) noted, more rational and informed choices can emerge when uncertainty is explicitly recognized and integrated into decision-making processes.

Stochastic optimization encompasses a suite of mathematical optimization methods designed to address decision-making under uncertainty. Unlike deterministic optimization, which assumes all parameters are known with certainty, stochastic optimization typically represents uncertain parameters using probability distributions or discrete scenario sets (Kleywegt and Shapiro 2001; Powell 2019). The selection of an appropriate modeling framework depends on the characteristics of the problem, including its dynamics and the degree of uncertainty associated with key variables (de Pellegrin Llorente et al. 2023). When probability distributions are difficult to specify or subject to structural uncertainty, scenario-based approaches are commonly used to explore a range of plausible outcomes rather than to optimize for a single expected realization (Radke et al. 2017; Powell 2019; de Pellegrin Llorente et al. 2023; Eyvindson et al. 2024). In this context, strategies are often assessed based on their performance stability and exposure to unfavorable outcomes across scenarios, rather than through formal worst-case optimization over predefined uncertainty sets (Ben-Tal et al. 2009; Gabrel et al. 2014; Radke et al. 2017).

In forest management, research has focused on uncertainty related to forest growth, market conditions, and natural disturbances (Veliz et al. 2015; de Pellegrin Llorente et al. 2023). Studies evaluating uncertainty in timber supply have addressed inventory and growth model errors to improve short- and long-term management decisions (Zhou and Buongiorno 2004; Palma and Nelson 2014; Eyvindson and Kangas 2015; Kašpar et al. 2017), as well as the effects of climate change on forest regeneration and future supply (Schou et al. 2015; Daniel et al. 2017; Radke et al. 2017; De Pellegrin Llorente et al. 2022). These studies link climate change to increasing risks of natural hazards such as fire, drought, pests, and windthrow. Several models have incorporated such hazards explicitly to optimize harvest scheduling, including responses to pests (Sims 2011), wildfires (Ferreira et al. 2012), and stochastic wind events (Zhou and Buongiorno 2006; Eyvindson et al. 2024; Öhman et al. 2025).

Although studies have addressed forest management decisions under uncertainty related to natural disturbances and timber supply variability, limited research has explicitly focused on scheduling salvage operations under these conditions. Moreover, despite advances in estimating the extent and severity of forest damage, accurately quantifying salvageable timber stock remains challenging due to variability in timber quality and usability. As a result, simulation- and scenario-based approaches are particularly valuable for evaluating salvage strategies that must perform well across a wide range of plausible post-disturbance conditions.

The implications of improved salvage logging strategies extend beyond immediate economic gains. By collecting downed and damaged timber before continued biological and physical degradation occurs, effective salvage operations can help preserve higher-value timber, maintain regional market stability, and reduce the overall economic losses experienced by forest owners and rural communities. Moreover, evidence generated from salvage outcomes can inform forest management policies and planning frameworks aimed at enhancing long-term resilience to increasing natural disturbances.

To address these challenges, the objective of this study was to develop and evaluate a scenario-based stochastic optimization framework for post-hurricane salvage logging that accounts for uncertainty in timber supply and quality. Specifically, the study aims to: (1) Represent post-hurricane timber supply uncertainty through scenario-based stochastic simulations; (2) Combine multiple damage assessments to simulate salvageable timber stocks; (3) Evaluate how alternative assumptions regarding timber downgrade influence economic outcomes; (4) Incorporate a risk-averse mean – risk formulation using Conditional Value-at-Risk (CVaR) to limit exposure to unfavorable outcomes; and (5) Assess the stability of salvage strategies across a wide range of post-disturbance scenarios to support forest recovery planning.

Materials and methods

We developed a timber supply model focused on addressing the uncertainty surrounding salvageable timber stocks following Hurricane Michael (2018). Uncertainty in timber volume and quality was represented through scenario-based stochastic simulations derived from remotely sensed damage severity and forest inventory data. These simulations were integrated into a spatial optimization model to evaluate salvage harvest and transportation decisions under multiple post-disturbance realizations. We compared risk-neutral and risk-averse formulations to assess how downside-risk considerations influence salvage outcomes under uncertain timber supply conditions.

Figure 1 summarizes the overall workflow of the analysis. The following subsections describe the study area and timeframe, the assessment of hurricane damage using remotely sensed data, the estimation of pre-disturbance timber stocks from forest inventory and yield information, and the construction of post-hurricane timber supply scenarios, which are subsequently integrated into the spatial optimization model.

Study area and timeframe

The study area is located in northwest Florida (Figure 2), within the region potentially affected by sustained hurricane-force winds (Noaa 2024). The assessment period covers the first year following the hurricane, consistent with the typical timeframe for salvage logging activities (Sun 2020; Henderson et al. 2022). The analysis was restricted to softwood species, primarily Slash Pine (*Pinus elliottii*) and Loblolly Pine (*Pinus taeda*), because of their greater regional commercial importance (USDA Forest Service 2021), greater sampling frequency within the FIA database, and higher salvage rates compared to hardwoods (Brandeis et al. 2022).

Hurricane damage assessment

To estimate forest damage severity, we calculated the percent change in four key vegetation indices for each 30-meter forested pixel within the study area: NDVI (Normalized-Difference Vegetation Index), NDMI (Normalized-Difference Moisture Index), NBR (Normalized Burn Ratio), and LAI (Leaf Area Index). We utilized Google Earth Engine (GEE) to access Landsat 5, 7, and 8's collections, harmonize images, mask clouds

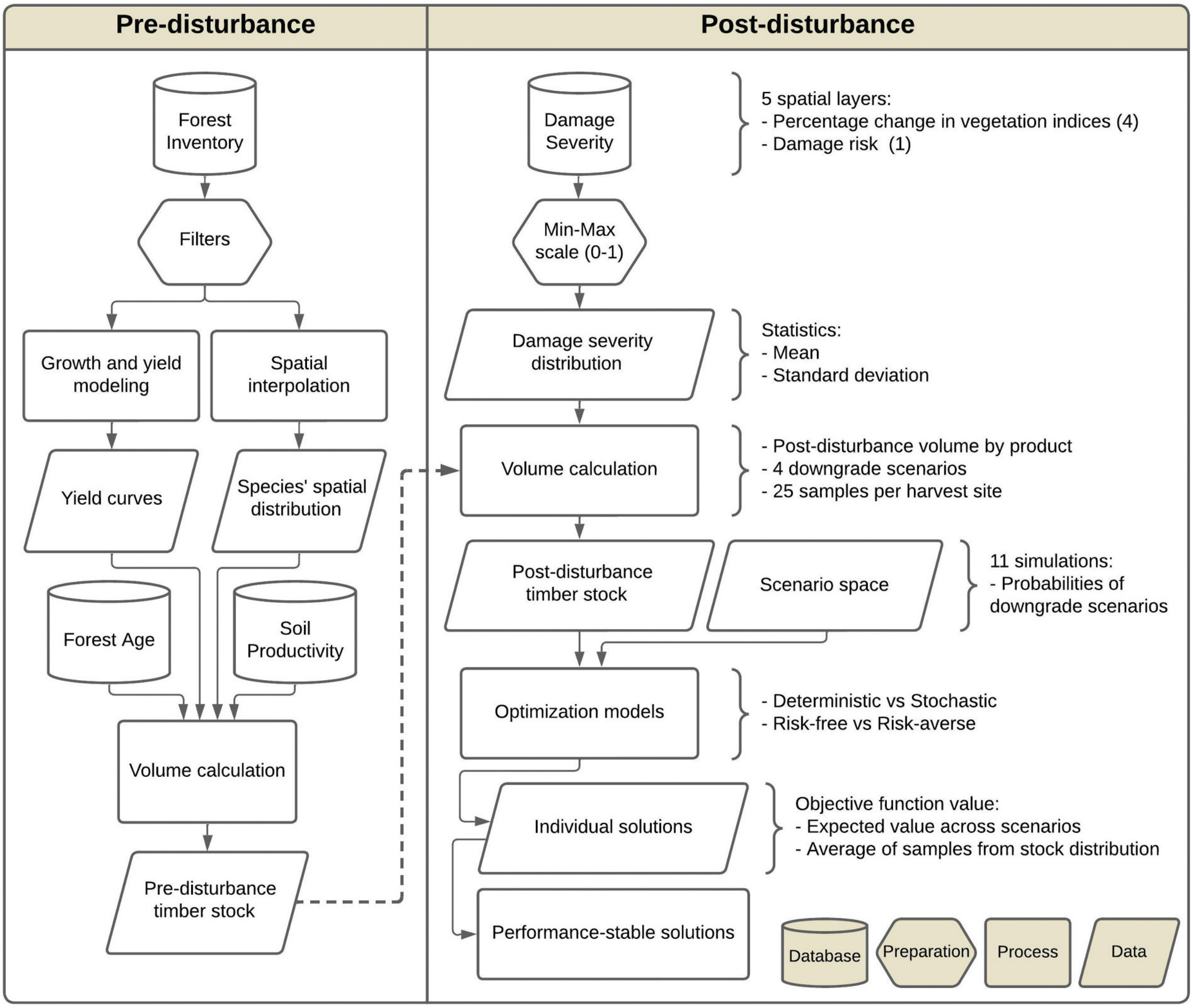

Figure 1. Overview of the scenario-based framework used to estimate pre- and post-disturbance timber stocks and evaluate salvage strategies. Optimization models are solved separately for each scenario, and resulting solutions are compared across scenarios to assess economic performance and stability under uncertainty.

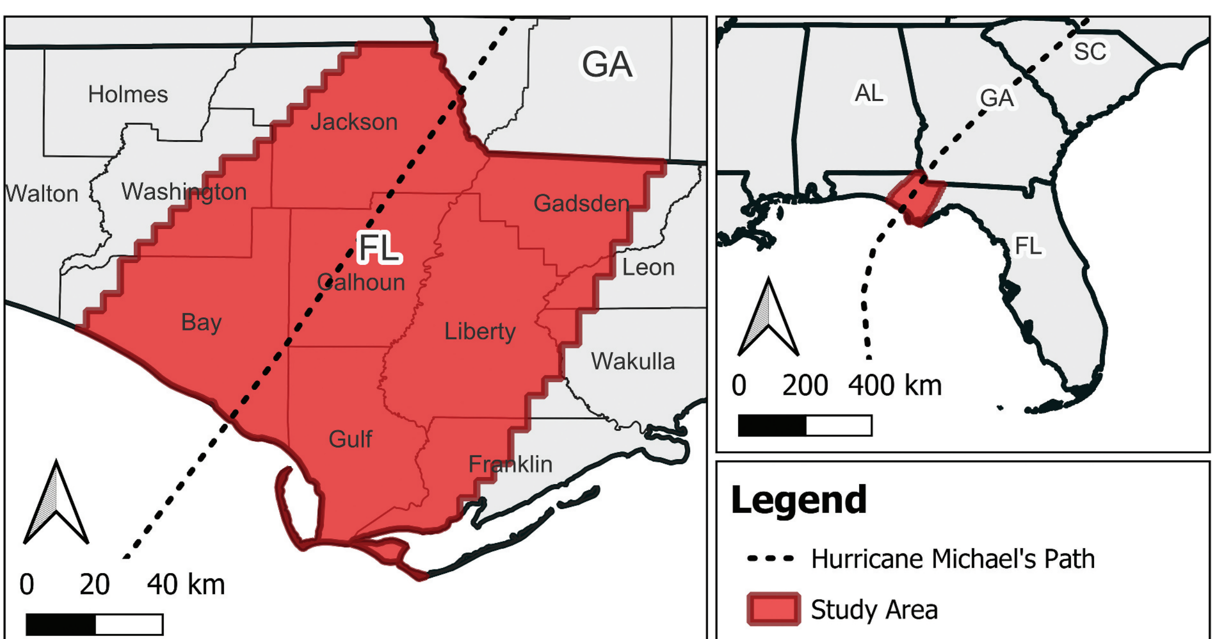

Figure 2. Study area in northwest Florida along the path of Hurricane Michael (2018), delimited by the area potentially affected by sustained hurricane-force winds (Noaa 2024). AL: Alabama, FL: Florida, GA: Georgia, SC: South Carolina.

and shadows, generate image mosaics, and compute time-series values and changes for NDVI, NDMI, and NBR. LAI values were obtained via GEE from the OpenET project, which integrates satellite-derived evapotranspiration estimates using multiple models (Melton et al. 2021). In addition, we utilized the USDA Forest Service's Storm Damage Viewer platform (USDA Forest Service 2024), which employs automated data processing and the ForestGALES model (Gardiner et al. 2008), to generate a tree damage risk metric based on the "wind sum" (a combination of wind speed and residence time). To ensure comparability across metrics, all five damage indicators were normalized to a common scale (from 0 to 1). We then computed the mean and standard deviation for each forested pixel to generate a composite "damage severity" score (see Supplementary Data – Figure S1). These severity values were subsequently used to estimate variations in post-hurricane timber stock (Figure 3(B)).

Timber stock estimation

To generate scenarios of salvageable timber stocks, we first calculated the pre-disturbance timber stocks through the following steps: (1) development of species- and site-specific yield curves relating timber volume per unit area to stand age and site productivity; (2) spatial overlay of species distribution, forest age, and site productivity maps to estimate timber volume at the pixel level using the corresponding yield curves. This calculation was restricted to areas classified as "Evergreen Forest" in the National Land Cover Database (NLCD) 2016 Land Cover map (Dewitz and U.S. Geological Survey 2021) consistent with the focus on softwood-dominated stands. All volumes are expressed in U.S. short tons (2,000 lb, or approximately 907 kg), consistent with standard U.S. forestry conventions and data sources.

Yield curves

We used the Forest Vegetation Simulator (FVS) to simulate 40 years of forest growth for each FIA inventory plot and fitted nonlinear models using the Chapman-Richards growth function (Pienaar and Turnbull 1973), stratified by species group and site class (see Supplementary Data – Figure S.2). Plots with a site index (base age 50) between 80 and 100 were classified as medium-quality sites, with low- and high-quality sites defined

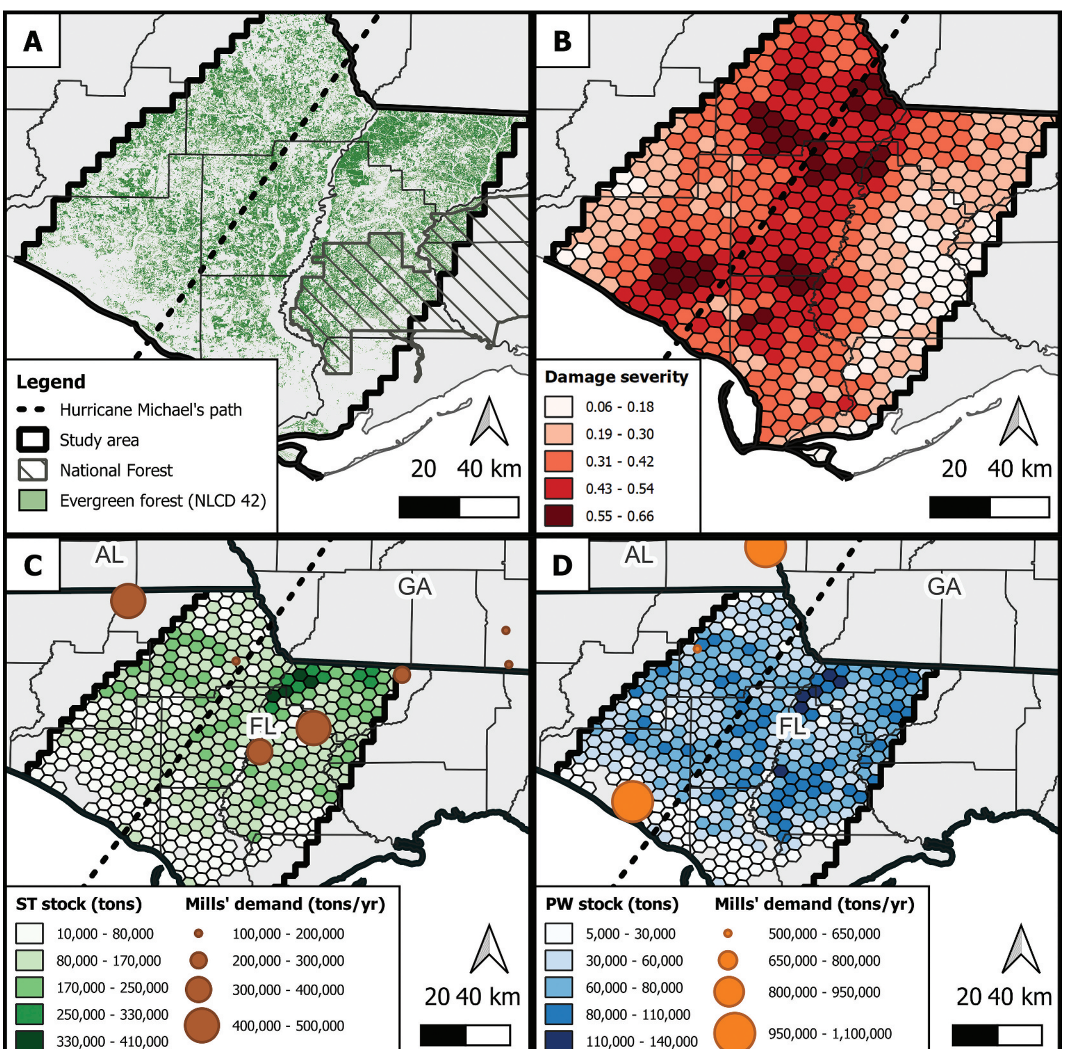

Figure 3. (A) Forested area, (B) Mean normalized damage severity per harvest site, (C) and (D) Pre-disturbance timber stock with mills' location and demand for Sawtimber (ST) and Pulpwood (PW), respectively. Source: NLCD 42: "Evergreen Forest" class (Dewitz and U.S. Geological Survey 2021). AL: Alabama, FL: Florida, GA: Georgia.

immediately below and above this range. For loblolly pine, a single yield curve was developed due to limited data. We modeled total merchantable and sawtimber volumes, calculating pulpwood volume as the difference between these two classes (see Supplementary Data – Figure S.3).

Species distribution, forest age, and site productivity

We developed a species distribution map using FIA data (USFS FIA 2024) from plots measured between 2014 and 2018. We calculated the basal area for pine individuals with a DBH over five inches, categorizing them by species into "Slash" and "Loblolly" groups. While the "Loblolly" group consisted solely of loblolly pine (*Pinus taeda*), the "Slash" group included slash pine (*Pinus elliottii*), longleaf pine (*Pinus palustris*), and sand pine (*Pinus clausa*), named after the dominant species in terms of basal area and timber volume. We computed the basal area proportions of each group within plots and applied an inverse distance weighted (IDW) interpolation method to assign values to all forested pixels (see Supplementary Data – Figure S.4), based on 216 FIA plot measurements.

Site productivity was represented using the Productivity Index (PI) map (Schaetzl et al. 2012), which ranks soils from 1 (least productive) to 19 (most productive) based on family-level soil taxonomy information. We classified productivity into three regional classes: low (PI < 2), medium (PI 2–4), and high (PI > 4), representing approximately 25%, 50%, and 25% of the landscape, respectively (see Supplementary Data – Figure S.5).

Forest stand age data was obtained from the CONUS Stocking-Age-Lorey's Height 2018 map (USFS FIA 2022). Using all compiled spatial layers, we calculated the pre-hurricane timber stock at the pixel level using the developed yield curves. To manage this data at a practical scale, we overlaid a hexagon grid across the study area and aggregated timber stocks within cells of approximately 6000 acres each (around 2430 hectares), following Brand et al. (2000). The study area comprised 550 grid cells, hereafter referred to as "harvest sites," each representing a potential salvage location with corresponding timber stock by product. Figure 3 summarizes the study area, showing the forest type under analysis (A), mean damage severity by harvest site (B), and pre-disturbance sawtimber (C) and pulpwood (D) stocks. The generation of post-hurricane timber stock scenarios is described in the following section.

Scenario design

Translating damage severity into salvageable timber volume poses challenges due to the existence of broken or damaged logs, variations in timber quality, and uncertainty in actual usability following a disturbance. To address these challenges, we linked damage severity values to sawtimber downgrades to pulpwood and represented post-hurricane timber supply uncertainty through a discrete set of downgrade scenarios. We defined four scenarios with varying maximum downgrade levels: 25%, 50%, 75%, and 100%. For example, under the 100% downgrade scenario, damage values ranging from 0 to 1 correspond to a proportional transition of sawtimber to pulpwood from 0% to 100%.

For each downgrade scenario, mean and standard deviation values of damage severity and downgrade rates were used to estimate post-hurricane salvageable timber stocks at the pixel level, which were subsequently aggregated to the harvest-site scale. Using the aggregated mean and standard deviation of timber volume for each harvest site, we sampled 25 realizations from the corresponding volume distribution. This sampling procedure captures within-site variability in salvageable timber stocks arising from spatial heterogeneity in damage severity. The number of samples was determined based on a sample average approximation analysis aimed at minimizing the optimality gap (Kleywegt et al. 2002; Eyvindson and Kangas 2015). Specifically, we evaluated convergence by jointly assessing the stability of the damage-weighted Net Present Value (NPV) objective value, changes in the unweighted NPV, and computational runtime as the number of samples increased, selecting a sample size beyond which further increases produced negligible improvements in solution quality relative to computational cost.

Despite these simulations, substantial uncertainty remains regarding the true likelihood of each downgrade scenario. In practice, reliable probability distributions for post-disturbance timber downgrade are rarely available. This situation corresponds to deep uncertainty, defined as circumstances in which decision-makers lack sufficient information to assign credible probabilities to future states of the system (Walker et al. 2010; Radke et al. 2017; de Pellegrin Llorente et al. 2023).

To explore how alternative beliefs about downgrade severity influence salvage decisions, we evaluated a set of probability-weighting assumptions applied to the downgrade scenarios. These include a baseline simulation ("00") that assigns equal probability (25%) to each downgrade scenario, as well as 10 additional simulations that progressively shift probability mass toward either more pessimistic or more optimistic outcomes (Table 1). Simulations with larger values in the left digit of their identifiers place increasing weight on higher downgrade scenarios, culminating in simulation "50," where the 100% downgrade scenario occurs with certainty. Conversely, simulations with larger values in the right digit emphasize lower downgrade scenarios, with simulation "05" assigning full probability to the 25% downgrade case.

Together, the combination of downgrade scenarios, probability-weighting assumptions, and sampled timber volumes defines the scenario space used to evaluate salvage decisions under deep uncertainty. While this scenario space is analogous to an uncertainty set in robust decision-making frameworks (Ben-Tal et al. 2009; Gabrel et al. 2014), decisions in this study are optimized separately for each probability simulation, rather than constrained to remain feasible or optimal across all scenarios simultaneously. Accordingly, robustness is assessed ex post, based on performance stability and downside outcomes across the scenario space, rather than through worst-case or uncertainty-set – protected optimization (Radke et al. 2017; Powell 2019).

Deterministic parameters

To estimate the timber demand for salvaged timber in each period, we used data from the 2021 RISI's Mill Asset Database (Fastmarkets 2021). All pine-consuming mills within a 100 km radius of the study area were included to account for timber demand both within and beyond the directly affected region.

Table 1. Probability distributions assigned to downgrade scenarios across 11 simulations. Each simulation represents a different belief about the likelihood of timber downgrade severity, ranging from pessimistic (simulation 50) to optimistic (simulation 05). Downgrade scenarios are proportional to mean damage severity, with S100 indicating 100% downgrade of sawtimber and S25 indicating only 25% downgrade.

	Probability (%)			
Simulation	Scenario S100	Scenario S75	Scenario S50	Scenario S25
50	100	–	–	–
40	75	25	–	–
30	50	50	–	–
20	50	25	25	–
10	25	50	25	–
00	25	25	25	25
01	–	25	50	25
02	–	25	25	50
03	–	–	50	50
04	–	–	25	75
05	–	–	–	100

This resulted in nine sawtimber mills and three pulpwood mills within this buffer zone. Considering increased production to accommodate the additional timber supply from salvage activities, we multiplied the mills' annual demands by 1.75. This adjustment was based on TPO (Timber Products Output) data (Forest Service 2024), which indicated a 75% increase in total production for the counties within the hurricane-impacted region in 2018 compared to the 2013–2017 average.

Quarterly timber demand was calculated by dividing the adjusted annual demand by four. We assumed that during the first quarter following the hurricane, mills would be willing to meet 50% of their demand with salvaged timber. This assumption is supported by estimates from Hurricane Katrina, where salvaged timber accounted for more than half of the total harvested volume (Carter 2017). For subsequent periods, we used the quarterly salvage intensity estimates from Sun (2020) and adjusted the demand values proportionally to the 50% value used in the first quarter (Table 2).

The logging capacity was determined using FIA 2018 data, calculating the average annual removal for the counties within the study region over the 5 years preceding the hurricane. This value was also increased by 75% to account for heightened salvage activity and then divided by four to determine the quarterly logging capacity.

Table 2. Deterministic parameters for timber prices, salvage rates, and demand over four quarters following hurricane Michael. Price drops are calculated relative to pre-hurricane delivered timber prices (excluding operational and fixed costs). Salvage rates reflect estimates of usable volume post-disturbance by quarter (Sun 2020), and salvaged timber demand from Q2 to Q4 is modeled as proportional to the Q1 demand and salvage rates.

	Period				
Metric	Pre-hurricane	Q1	Q2	Q3	Q4
Price drop (%)	–	50	40	30	1
Timber price ($/ton)					
Sawtimber	35.33	17.67	21.20	24.73	34.98
Pulpwood	17.41	8.70	10.44	12.18	17.23
Salvage rates (%)					
Sawtimber	–	40	32	23	5
Pulpwood	–	35	25	22	18
Salvaged timber demand (%)					
Sawtimber	–	50.00	40.00	28.75	6.25
Pulpwood	–	50.00	35.71	31.43	25.71

Regional timber prices by product (in US dollars per ton) and haul rates (in dollars per ton per loaded kilometer) were obtained from TimberMart-South (Foundation 2020). We used the average delivered prices for the first three quarters of 2018 for northwestern Florida. All monetary values presented are in US dollars. To accurately calculate revenues, these prices were adjusted by subtracting operational and fixed costs associated with forestry operations. Using stumpage and delivered prices, a transportation cost based on the average nearest distance to mills (50 km), and an assumed profit margin of 5%, we estimated that operational and fixed costs accounted for 25% of sawtimber revenues and 45% of pulpwood revenues. Consequently, we adjusted the delivered timber prices by deducting these percentages.

The adjusted timber prices served as the baseline for subsequent price fluctuations. Leveraging variations in timber prices documented in the literature for different hurricane events (Prestemon and Holmes 2010; Kinnucan 2016; Sun 2016, 2020; Carter 2017), we determined a "price drop" for each period, enabling the estimation of current timber prices post-hurricane (Table 2).

To calculate transportation costs, we computed distances between all harvest sites and timber-consuming mills. We established centroids within forested areas of each harvest site as origins and designated mills as destinations. The road network was delineated using the 2022 TIGER/Line Primary Roads National Shapefile (U.S. Census Bureau 2022). The unit transportation cost was based on the 2018 regional average haul rate of 0.093 dollars per ton per kilometer, converted from 0.15 dollars per loaded mile (Foundation 2020).

Finally, we conducted a comprehensive sensitivity analysis to evaluate the influence of deterministic parameters on model outcomes (see Supplementary Data – Figures S6 and S7). Each parameter was varied individually from 10% to 200% of its baseline value.

Mathematical optimization model

We approached the salvage planning problem from the perspective of a centralized decision-maker coordinating salvage operations across all sites. This abstraction simplifies real-world conditions involving multiple landowners and operational constraints, while allowing a transparent evaluation of how uncertainty in salvageable timber supply influences optimal decisions. The fundamental economic criterion guiding salvage decisions is whether the post-disturbance value of timber exceeds the costs of logging and transportation to market. If salvage operations yield a higher expected value than leaving damaged timber unharvested, timber recovery is economically justified (Prestemon and Holmes 2008).

The one-year timeframe was divided into four periods, corresponding to the quarters following the hurricane's landfall. The objective is to maximize the total NPV over this horizon. In order to isolate the effects of uncertainty in salvageable timber supply, only timber stock is treated as stochastic, while timber prices, demand, and operational parameters are assumed to be known with certainty. This modeling choice reflects a strong belief or prior knowledge about short-term market behavior following a major disturbance, and allows us to focus explicitly on the implications of deep uncertainty in timber volume and quality. While real-world decision-making may involve additional sources of uncertainty and adaptive behavior, the present framework evaluates how salvage strategies perform when uncertainty is concentrated in post-disturbance timber supply.

Sets

H: Harvest sites {h = 1, . . . , 550}
M: Mills {m = 1, . . . , 12}
P: Products {p = pulpwood (pw), sawtimber (st)}
T: Periods {t = 1, 2, 3, 4}
D: Downgrade scenarios {d = 1, 2, 3, 4}
S: Probability simulations {s = 1, . . . , 11}
N: Samples from timber stock distribution {n = 1, . . . , 25}
Ω: Combined scenario index (d, s, n), with ω =1, . . . , 1100

Deterministic parameters

DMG_h: *mean damage severity of harvest site "h" (0–1 scale)*
DR : decay rate (%)
$DMD_{p,m,t}$: *demand for product "p" in mill "m" at period "t" (tons)*
L: logging capacity (tons)
$OD_{h,m}$: *distance from harvest site "h" to mill "m" (km)*
C: unitary cost of transportation ($/ton/km)
$K_{p,t}$: *adjusted price of product "p" at period "t" ($/ton)*
$Pr^{d,s}$: *probability of the occurrence of downgrade scenario "d" in simulation "s" (%)*
δ: quarterly discount rate (%)
$\overline{RM}_p$: *maximum stock removal of product "p" (%)*
$\overline{pw}$: *maximum pulpwood demand satisfied with sawtimber (%)*

Scenario-dependent parameter

$Z^{d}_{p,h}$: *initial post-hurricane timber stock of product "p" at harvest site "h" under downgrade scenario "d" (tons)*

Decision variables

$X^{\omega}_{p,h,m,t}$: *quantity of timber product "p" salvaged at harvest site "h" and transported to mill "m" in period "t" under scenario ω.*
$Y^{\omega}_{h,m,t}$: *quantity of sawtimber salvaged at harvest site "h" and sold as pulpwood to mill "m" in period "t" under scenario ω*

Accounting variables

NPV^{ω}_{h} : *Net Present Value at harvest site "h" under scenario ω.*
$S^{\omega}_{p,h,t}$: *remaining stock of timber of product "p" at harvest site "h" in period "t" under scenario ω* $\Delta ST^{\omega}_{h,t}$: *sawtimber decayed stock at harvest site "h" in period "t" under scenario ω*

Baseline stochastic formulation (F1)

For each probability simulation *s*, we solved the optimization problem as defined by a series of equations described below. Decisions are optimized separately for each simulation, and expected values are computed using the corresponding probability weights assigned to downgrade scenarios. This structure allows us to evaluate how salvage decisions respond to alternative beliefs about downgrade severity, without imposing a single decision that must perform optimally across all scenarios.

The objective function maximizes the expected value of a damage-weighted NPV, averaged across downgrade scenarios and timber stock samples (Equation 1).

Objective function

$$\max \sum\nolimits_{\omega}^{\Omega} \sum\nolimits_{h}^{H} \mathrm{Pr}^{d,s} \left(NPV^{\omega}_{\mathrm{h}} \times DMG_{\mathrm{h}} \right) / \mathrm{N} \quad \forall\ s \in S \tag{1}$$

where NPV and transportation costs are defined as in Equations 2 and 3. Discounting is applied quarterly using a 1% rate, consistent with observed regional market conditions (Cubbage et al. 2022).

$$NPV^{\omega}_{h} = {}^{t}_{T} \left[\frac{\left(\sum\nolimits_{p}^{P} \sum\nolimits_{m}^{M} X^{\omega}_{p,h,m,t} \times K_{p,t} + \sum\nolimits_{m}^{M} Y^{\omega}_{h,m,t} \times K_{p=pw,t} - TC^{\omega}_{h,t} \right)}{(1+\delta)^{t}} \right] \tag{2}$$
$$\forall\ \omega \in \Omega,\ \ and\ h \in H$$

$$TC^{\omega}_{h,t} = {}^{p\ m}_{P\ M} \left(X^{\omega}_{p,h,m,t} +\ Y^{\omega}_{h,m,t} \right) \times C \times OD_{h,m} \tag{3}$$
$$\forall\ \omega \in \Omega,\ h \in H,\ and\ t \in T$$

Damage weighting prioritizes salvage from more severely affected sites, reflecting the higher urgency and faster degradation associated with greater damage severity.

Timber stock dynamics

Equations 4-7 describe the evolution of timber stocks over time. In the first period, available stocks ($S^{\omega}_{p,h,t}$) correspond to post-disturbance timber volumes derived from pre-hurricane stocks and damage severity (Equation 4). In subsequent periods, remaining stocks are updated based on previous removals and decay. Decayed sawtimber is downgraded to pulpwood (Equation 5), while decayed pulpwood is assumed to be abandoned (Equation 6).
for $t = 1$:

$$\mathrm{S}^{\omega}_{\mathrm{p,h,t}} =\ \mathrm{Z}^{\mathrm{d}}_{\mathrm{p,h}} \tag{4}$$
$$\forall \omega \in \Omega, \mathrm{d} \in \mathrm{D}, \mathrm{p} \in \mathrm{P}, \mathrm{h} \in \mathrm{H},\ and \mathrm{t} \in \mathrm{T}$$

for $t > 1$:

$$S^{\omega}_{p,h,t} = \left[S^{\omega}_{p,h,t-1} - \sum\nolimits_{M}^{m} \left(X^{\omega}_{p,h,m,t-1} + Y^{\omega}_{h,m,t-1} \right) \right] \times (1 - DR \times DMG_h) \tag{5}$$
$$\forall \omega \in \Omega,\ h \in H,\ t \in T,\ and\ p = st$$

$$S^{\omega}_{p,h,t} = \left[S^{\omega}_{p,h,t-1} - \sum\nolimits_{M}^{m} X^{\omega}_{p,h,m,t-1} \right] \times (1 - DR \times DMG_h) + \Delta \mathrm{ST}^{\omega}_{\mathrm{h,t}} \tag{6}$$
$$\forall \omega \in \Omega,\ h \in H,\ t \in T,\ and\ p = pw$$

where:

$$\Delta ST^{\omega}_{h,t} = \left[S^{\omega}_{p,h,t-1} - \sum\nolimits_{M}^{m} \left(X^{\omega}_{p,h,m,t-1} + Y^{\omega}_{h,m,t-1} \right) \right] \times DR \times DMG_h \tag{7}$$
$$\forall \omega \in \Omega,\ h \in H, t \in T,\ and\ p = st$$

We adopted a decay rate methodology inspired by Vanderschaaf et al. (2021), applying the double declining balance (DDB) method, commonly used for depreciating forestry equipment. This method doubles the normal straight-line depreciation rate. Given that damaged timber deteriorates rapidly and is typically salvageable only within the first year (Sun 2020; Henderson et al. 2022), we applied a linear depreciation rate of 25% per period (quarter of a year), resulting in a DDB rate of 50% per period. We further adjusted this method by scaling the DDB rate based on the mean damage value of individual harvest sites, reflecting higher decay rates in more severely damaged timber stocks.

Constraints

Equations 8-11 define the timber supply constraints. Although the maximum stock removal constraints (Equations 8 and 9) impose tighter site-level limits, the total stock removal constraints (Equations 10 and 11) are not redundant because they account for decay. In the final period, for example, complete removal of the remaining timber stock may still be lower than the maximum allowable harvest at a given site, as cumulative decay reduces the effective volume available for extraction.

(1) Maximum volume harvested by product, harvest site, and period

$$\begin{gathered}\textstyle\sum_{m}^{M} X_{p,h,m,t}^{\omega} \leq S_{p,h,t}^{\omega} \\ \forall \omega \in \Omega, h \in H, \quad t \in T, \ and\, p = pw\end{gathered} \tag{8}$$

$$\begin{gathered}\textstyle\sum_{M}^{m} \left(X_{p,h,m,t}^{\omega} + Y_{h,m,t}^{\omega} \right) \leq S_{p,h,t}^{\omega} \\ \forall \omega \in \Omega, h \in H, \ t \in T, \ and \ p = st\end{gathered} \tag{9}$$

(2) Total stock removal by product and harvest site

$$\begin{gathered}\textstyle\sum_{M}^{m} \sum_{T}^{t} X_{p,h,m,t}^{\omega} \leq Z_{p,h}^{d,n} \times \overline{RM}_{p} \\ \forall \ \omega \in \Omega, d \in D, n \in N, h \in H, \ and \ p = pw\end{gathered} \tag{10}$$

$$\begin{gathered}\textstyle\sum_{M}^{m} \sum_{T}^{t} \left(X_{p,h,m,t}^{\omega} + Y_{h,m,t}^{\omega} \right) \leq Z_{p,h}^{d,n} \times \overline{RM}_{p} \\ \forall \ \omega \in \Omega, d \in D, n \in N, h \in H, \ and \ p = st\end{gathered} \tag{11}$$

The maximum stock removal ($\overline{RM}_p$) used in Equations 10 and 11 was determined based on Brandeis et al. (2022), who found that post-Hurricane Michael, on average, 16.6% of tree volume was utilized across all damage severity zones, with nearly 40% utilization in catastrophic zones. Aligning with salvage rates from Henderson et al. (2022), we set maximum removal at 15% for both sawtimber and pulpwood.

Timber demand constraints are defined in Equations 12 and 13. These constraints are modeled as inequalities, reflecting that the problem considers only salvaged timber and that mill demand represents a willingness to accept this potentially lower quality material rather than a fixed procurement requirement.

(3) Maximum delivered timber by product, mill, and period

$$\begin{gathered}\textstyle\sum_{H}^{h} \left(X_{p,h,m,t}^{\omega} + Y_{h,m,t}^{\omega} \right) \leq DMD_{p,m,t} \\ \forall \omega \in \Omega, m \in M, t \in T, \ and\, p = pw\end{gathered} \tag{12}$$

$$\begin{gathered}\textstyle\sum_{H}^{h} X_{p,h,m,t}^{\omega} \leq DMD_{p,m,t} \\ \forall \omega \in \Omega, m \in M, t \in T, \ and\, p = st\end{gathered} \tag{13}$$

As described in the NPV_h^{ω} calculation (Equation 2), forest owners are allowed to sell some of the sawtimber volume to the pulpwood market when financially advantageous. However, this option is constrained by a certain arbitrary share ($\overline{pw}$ = 5%) of the mills' pulpwood demand (Equation 14), reflecting the limited capacity of pulp mills to accept oversize logs and to avoid unrealistic assumptions about market absorption. Logging capacity is defined by Equation 15.

(4) Maximum pulpwood demand satisfied with sawtimber by mill and period

$$\begin{gathered}\textstyle\sum_{H}^{h} Y_{h,m,t}^{\omega} \leq DMD_{p,m,t} \times \overline{pw} \\ \forall \omega \in \Omega, h \in H, t \in T, \ and\, p = pw\end{gathered} \tag{14}$$

(5) Logging capacity

$$\begin{gathered}\textstyle\sum_{P}^{p} \sum_{H}^{h} \sum_{M}^{m} \left(X_{p,h,m,t}^{\omega} + Y_{h,m,t}^{\omega} \right) \leq L \\ \forall \omega \in \Omega, \ and\, t \in T\end{gathered} \tag{15}$$

Alternative formulations

To contextualize results from the baseline stochastic formulation (F1), we evaluated two alternative models:

- Formulation Two (F2): Deterministic model, using pre-disturbance timber stocks without downgrade or stochastic variation.
- Formulation Three (F3): Mean-risk stochastic model, which balances expected economic returns with downside-risk mitigation.

These formulations provide benchmarks for evaluating how explicitly accounting for uncertainty and risk aversion influences salvage outcomes and site prioritization.

Risk-averse strategy (formulation F3)

In a risk-neutral strategy, models under formulation F1 and F2 focus exclusively on maximizing expected economic returns. While widely used, this approach does not account for variability in outcomes across scenarios and may expose decision-makers to substantial downside risk under adverse realizations (Alonso-Ayuso et al. 2014). To explicitly address this limitation, we incorporate Conditional Value-at-Risk (CVaR) into the stochastic framework.

CVaR, derived from Value-at-Risk (VaR), measures the expected value of outcomes in the lower tail of the objective distribution beyond a specified quantile and is a coherent risk measure widely used in stochastic optimization (Rockafellar and Uryasev 2000, 2002; Eyvindson and Cheng 2016). In a profit maximization context, CVaR captures the average economic performance under the most unfavorable outcomes, providing a coherent measure of downside risk.

To balance risk mitigation with expected economic performance, we integrate both objectives into a mean – risk formulation (Equations 16-18), adapted from Alonso-Ayuso et al.

(2018). The formulation follows the standard linear programming representation of CVaR, in which the Value-at-Risk threshold is endogenously determined, and downside deviations are captured through auxiliary shortfall variables (Rockafellar and Uryasev 2000; Alonso-Ayuso et al. 2014). The indices d, s, and n are shown explicitly (rather than being combined into a single index ω) to allow for the flexible summarization of any two indices when needed.

$$max\left[\begin{array}{c}\gamma\sum_S^s\sum_D^d\sum_N^n\sum_h^H \frac{Pr^{d,s}\left(NPV_h^{d,s,n}\times DMG_h\right)}{S\times N}+\\ \rho\left(\alpha-\frac{1}{\beta}\sum_S^s\sum_N^n\frac{v^{s,n}}{S\times N}\right)\end{array}\right] \tag{16}$$

st:

$$\alpha-\sum_D^d Pr^{d,s}\left(NPV^{d,s,n}\right)\leq v^{s,n}\quad \forall\, s\in S,\ n\in N \tag{17}$$

$$v^{s,n}\in\ \mathbb{R}_+\qquad \forall\, s\in S,\ n\in N \tag{18}$$

where S and N denote the number of probability simulations (11) and timber stock samples (25), respectively. The variable α represents the Value-at-Risk (VaR) cutoff, which is endogenously determined by the optimization at the specified tail probability level β. The auxiliary variables $v^{(s,n)}$ capture shortfalls of scenario outcomes below α and are strictly positive only when the realized NPV falls below this cutoff. The parameters γ and ρ control the relative weight assigned to expected performance and downside-risk mitigation.

The objective in Equation (16) therefore maximizes a weighted combination of (i) the expected damage-weighted NPV, used to prioritize salvage from more severely damaged locations, and (ii) a CVaR term computed on unweighted NPV, representing the mean economic performance of the worst-performing outcomes. In this study, the tail probability was set to $\beta = 0.10$, such that CVaR reflects the average NPV of the lowest 10% of outcomes, consistent with commonly used confidence levels in risk-averse planning (Alonso-Ayuso et al. 2018; Eyvindson et al. 2018). Initial values of γ and ρ were set to one, and alternative balances were explored to evaluate sensitivity to risk preferences.

Results

Post-hurricane timber stocks

Applying alternative downgrade scenarios—25%, 50%, 75%, and 100%—resulted in substantial differences in estimated salvageable timber volume across the landscape (Figure 4). For both sawtimber and pulpwood, the shift in total volume between successive scenarios is approximately 5 million tons, yielding a cumulative difference of roughly 15 million tons between the most optimistic (S25) and most pessimistic (S100) cases.

No harvest site experienced a complete downgrade of its sawtimber volume, even under the most pessimistic scenario (S100), because downgrade rates were applied proportionally to site-level damage severity. Although damage severity was calculated at the pixel level, values were aggregated to harvest sites of approximately 6000 acres for modeling. The highest observed mean damage severity among harvest sites was 66%, implying that, at most, 66% of sawtimber would be downgraded to pulpwood under S100 at any single site. Approximately half of all harvest sites exhibited mean damage severity values between 23% and 44%, with an overall average of 35% (Figure 4). As a result, under the S100 scenario, most sites experienced downgrades of approximately 35%.

Model solutions

Under the baseline stochastic formulation (F1), the optimal solution harvested the maximum allowable timber volume across all probability simulations, subject to logging capacity and mill demand constraints. As a result, total salvage revenues remained constant across simulations. However, because the spatial distribution of salvageable timber varied across simulations, the selection of harvest sites differed, leading to variation in total transportation costs and, consequently, total NPV (Figure 5).

Simulations with lower levels of sawtimber downgrade incurred higher transportation costs, with a maximum difference of approximately \$400 thousand between the most extreme simulations (S50 and S05). This effect is driven primarily by reduced pulpwood availability under low downgrade assumptions, which forces longer hauling distances to meet pulpwood demand. Although selling a limited share of sawtimber as pulpwood partially offsets this effect, this option is capped at 5% of pulpwood demand. Moreover, pulpwood mills account for 58% of total mill demand (compared to 42% for sawtimber), amplifying the influence of pulpwood supply constraints on system-wide transportation costs.

Comparisons between NPV and damage-weighted NPV provide insight into the spatial strategies adopted by the centralized planner. Under simulations with lower downgrade rates, harvest activity is concentrated in more severely damaged sites, resulting in higher damage-weighted NPV. However, these locations are often farther from mills, leading to increased transportation costs and lower overall economic returns. This highlights the trade-off between prioritizing severely damaged stands and minimizing logistical costs.

The deterministic formulation (F2) produced a total NPV of approximately \$32.2 million, which is lower than all outcomes under the stochastic formulation (F1). The largest observed difference between F1 and F2 was approximately \$800,000 (about 2.5% relative to F1 outcomes of roughly \$33 million), with F1 achieving an average NPV that was 1.6% higher than F2. These relatively modest differences reflect the abundance of timber supply relative to demand, particularly under reduced post-hurricane salvage demand. Nevertheless, despite similar aggregate economic outcomes, the spatial distribution of salvage activity and economic returns differs substantially across formulations (Figure 6).

Figure 6 is organized by rows: (DM) deterministic formulation without downgrade; (05) simulation emphasizing minimal downgrade; (00) equal-probability simulation; and (50) simulation emphasizing severe downgrade. Under low downgrade rates, salvaged sawtimber volumes are concentrated in fewer harvest sites, typically those closer to mills and more severely damaged. As downgrade severity increases, harvest activity becomes more spatially dispersed, with smaller volumes

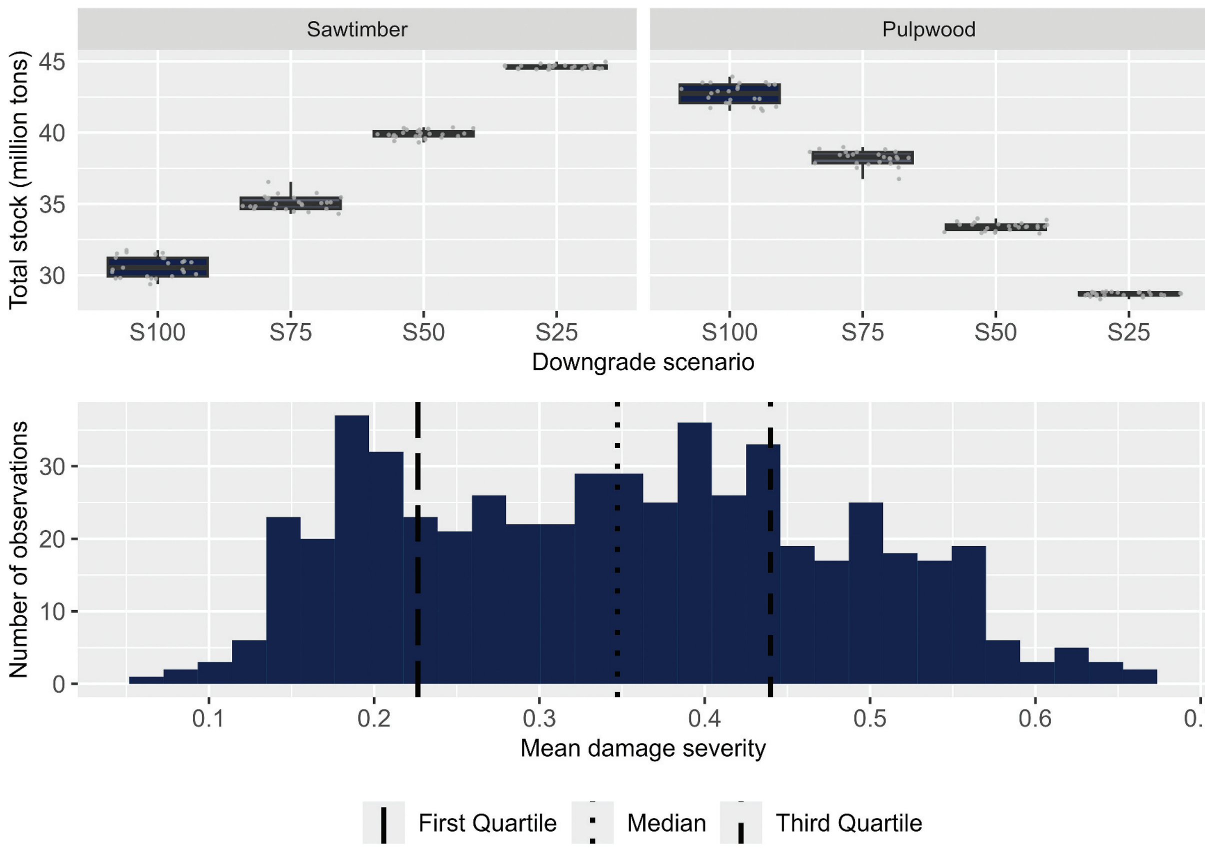

Figure 4. Total post-hurricane timber stock by product and scenario, with the frequency distribution of mean damage across harvest sites. Boxplot dots represent total stock values for individual samples. Scenarios abbreviations identify the percentage of sawtimber downgraded to pulpwood (25 to 100%).

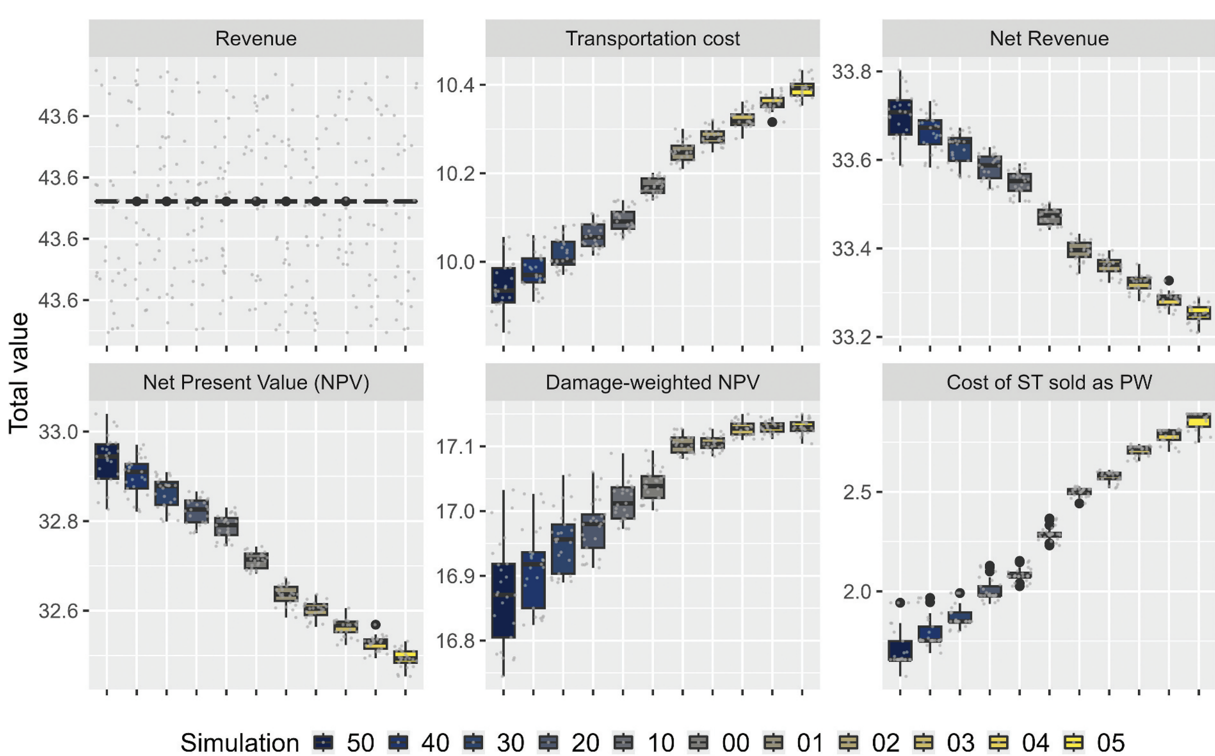

Figure 5. Optimization results for formulation F1. Values are shown in millions of dollars, including the damage-weighted NPV.

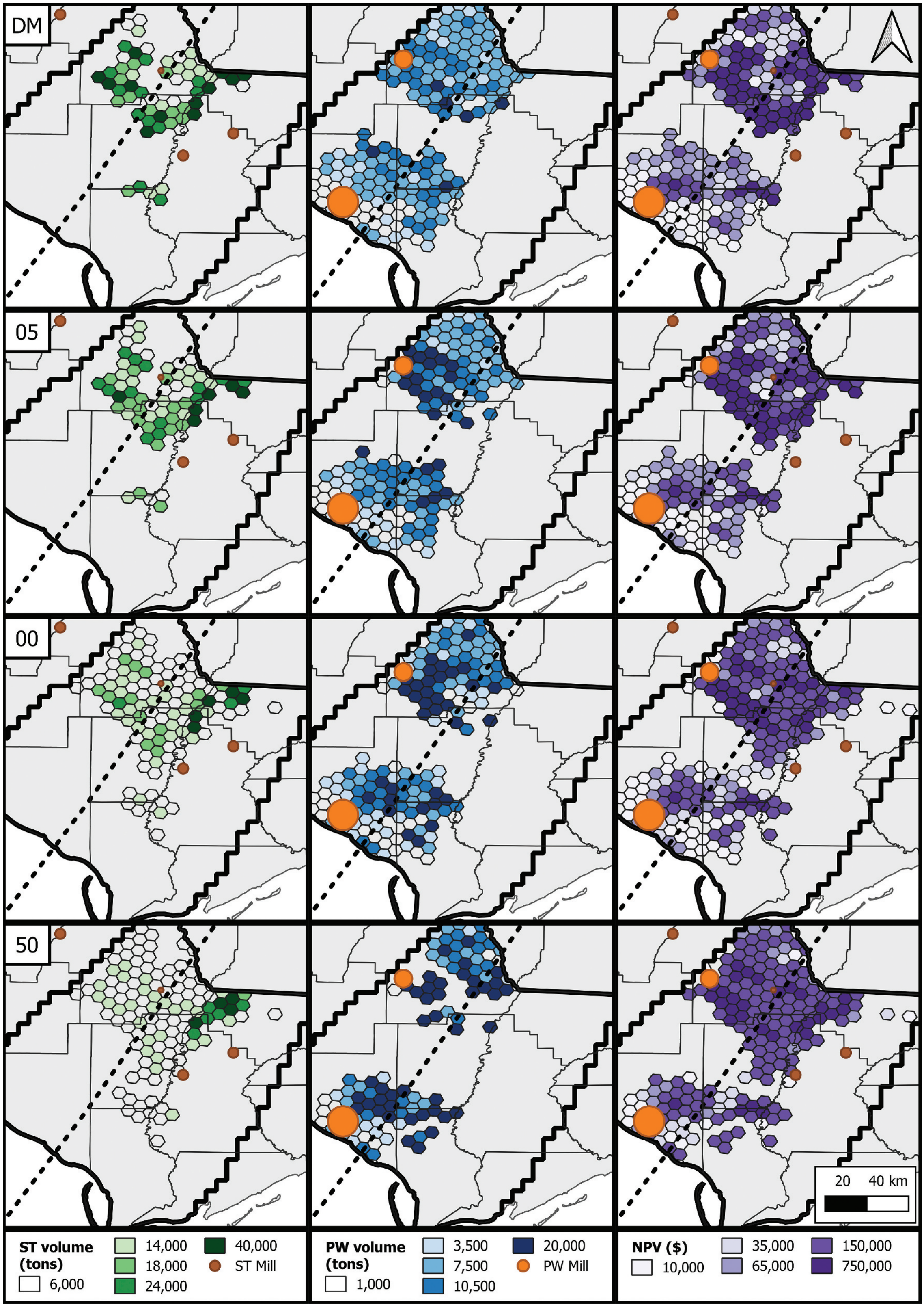

Figure 6. Spatial distribution of salvaged timber volume (sawtimber and pulpwood) and total net Present value (NPV), shown by quantile classes. DM: Deterministic formulation (F2); 05, 00, and 50: simulations for formulation F1.

recovered from a larger number of sites. Consequently, sawtimber transportation costs increase with higher downgrade severity, while pulpwood transportation costs decline as downgraded sawtimber increases pulpwood availability.

Results from simulation S05 closely resemble those from the deterministic formulation (F2), reflecting the low maximum downgrade rate (25%) in this case. Although economic returns vary spatially across simulations, no single spatial pattern

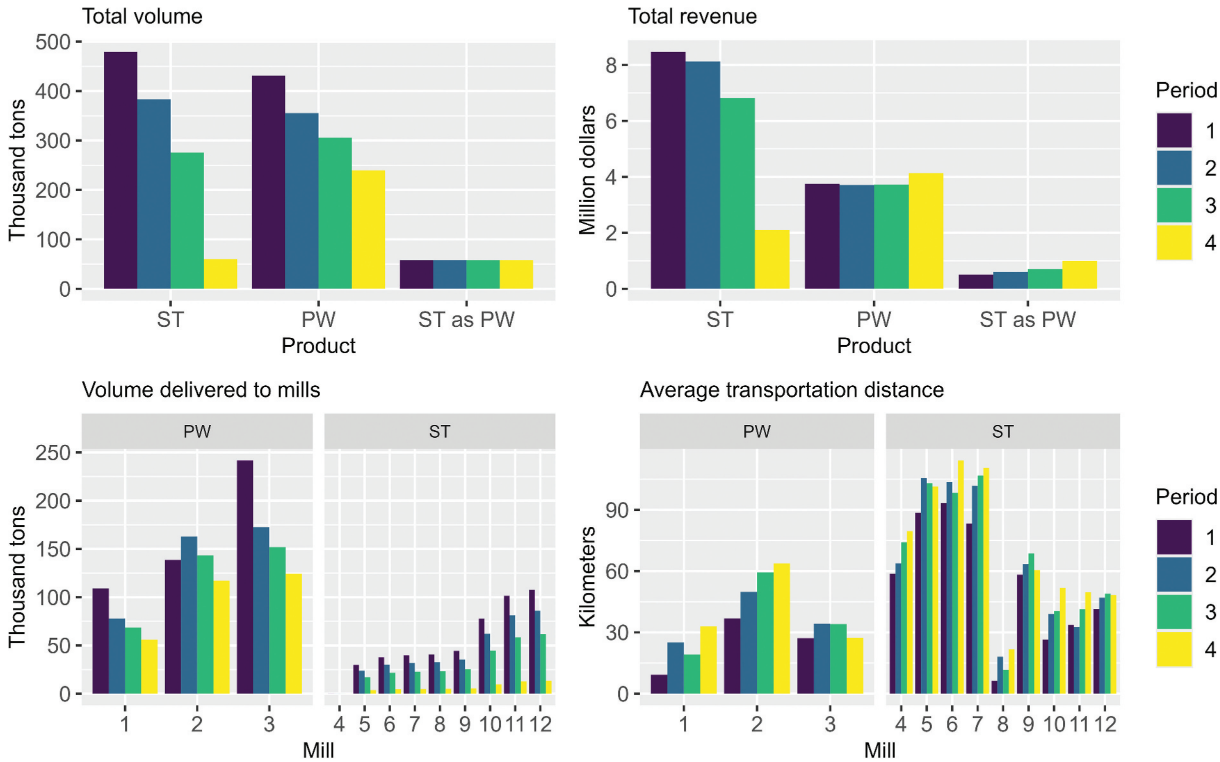

Figure 7. Optimization results for formulation F1 (simulation "00"), aggregated by product and period. ST: Sawtimber; PW: Pulpwood; ST as PW: Sawtimber sold as pulpwood. Downgrade scenarios have equal probability of occurrence in simulation "00".

dominates NPV outcomes due to the combined effects of sawtimber and pulpwood revenues.

The analysis of key results across the four periods provides additional insights into activity scheduling (Figure 7). By using delivered-timber prices and discounting transportation costs, we assumed forest owners and managers are responsible for delivering timber products to mills. This approach prioritizes shorter hauling distances during periods of low price, particularly in the first quarter post-hurricane when prices drop by 50%. As prices recover in later periods, salvage activity shifts farther from mills, allowing economic viable recovery from more remote sites.

Risk-averse results (formulation F3)

The mean – risk formulation (F3) incorporates CVaR to explicitly account for downside economic risk in salvage outcomes. Unlike the risk-neutral formulation (F1), which focuses solely on expected performance, F3 balances expected NPV with performance in the lower tail of the outcome distribution.

Relative to F1, results above the 10% quantile of the NPV distribution remain largely unchanged, with similar mean ($32.72 million) and standard deviation ($0.16 million) values. Differences between formulations emerge primarily in the lower tail of the distribution (Figure 8). The CVaR component shifts salvage activity away from scenarios with highly uncertain supply conditions, resulting in slightly lower damage-weighted NPV at the 10% quantile and a reduced emphasis on severely damaged but highly uncertain harvest sites.

Consistent patterns are observed for damage-weighted NPV: beyond the lower tail, distributions for the risk-neutral and risk-averse strategies are nearly identical, with mean values around 17.02 and standard deviations near 0.10. Sensitivity tests using alternative combinations of the weighting parameters γ and ρ produced only marginal changes in both central tendencies and dispersion. These findings indicate that, once downside-risk protection is incorporated, expected-value considerations dominate model outcomes and that the damage-weighted objective is relatively insensitive to moderate changes in the balance between return maximization and risk aversion.

Across all damage-severity and downgrade-probability scenarios, optimization results reveal consistent economic and spatial patterns. While total harvested volumes and aggregate NPVs differ only modestly across model formulations, the spatial allocation of salvage activity and associated transportation costs vary substantially. Scenario-based and risk-averse formulations reduce exposure to adverse outcomes under pessimistic downgrade assumptions by reallocating salvage activity away from locations with highly uncertain supply.

These results demonstrate that the primary value of incorporating uncertainty and risk considerations lies not in maximizing expected outcomes under a single scenario, but in improving the stability and resilience of salvage strategies across a wide range of plausible post-disturbance conditions.

Discussion

Scenario-based simulation approaches have been widely recognized as effective tools for supporting decision-making under deep uncertainty, particularly in post-disturbance contexts where reliable probability distributions are unavailable (Radke et al. 2017; Powell 2019; de Pellegrin Llorente et al.

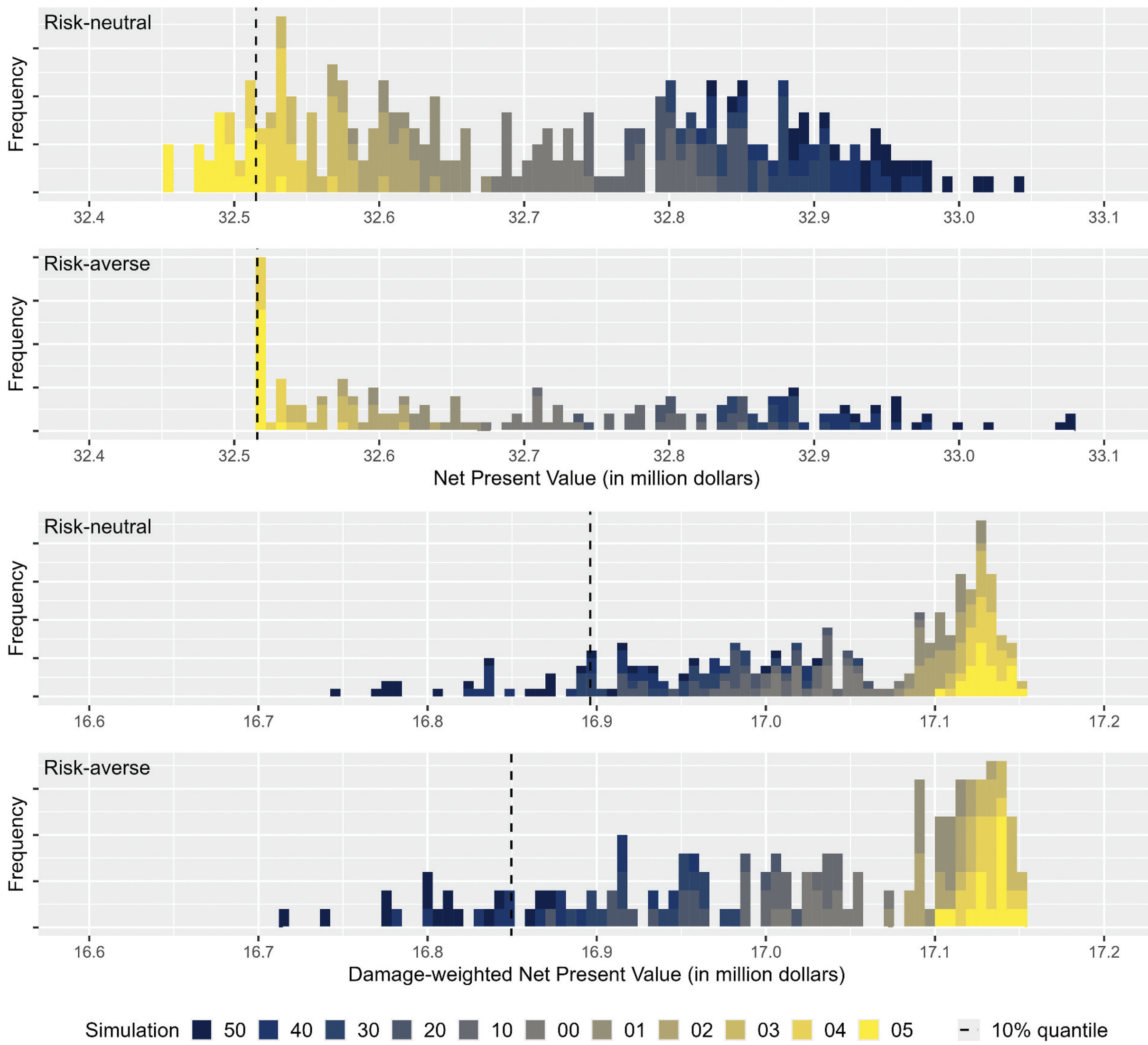

Figure 8. Optimization results for the risk-neutral (F1) and risk-averse (F3) formulations. Dashed lines indicate the 10% quantile of each distribution.

2023; Gao and Larjavaara 2024). In the context of salvage logging, such approaches allow management strategies to be evaluated across a broad range of plausible realizations of salvageable timber volume and quality, without relying on a single expected outcome. This framework is especially relevant following large-scale disturbances, where uncertainty arises from heterogeneous damage patterns, degradation dynamics, and market responses.

Although the stochastic optimization formulations (F1 and F3) provide a more explicit treatment of uncertainty, particularly with respect to downside risk, their aggregated outcomes were similar to those of the deterministic formulation (F2) in terms of total harvested volume and total NPV. Several factors contributed to this convergence. First, timber supply in the study area was abundant relative to mill demand, limiting the marginal influence of alternative downgrade and decay assumptions. Second, downgrade and decay effects were scaled by site-level damage severity (on a 0–1 scale), moderating their influence in moderately damaged areas. Third, all formulations prioritized more severely damaged sites through the use of damage-weighted NPVs. While this design avoided selecting undamaged stands near mills, it may have constrained model flexibility and biased site selection toward damage severity.

Despite similarities in aggregated outcomes, the spatial allocation of salvage activities and associated economic returns varied substantially across simulations, particularly when comparing different probabilities for downgrade scenarios. This spatial heterogeneity has important implications given the diverse characteristics of forestlands within the study area. For example, forests are under distinct ownership types, including family-owned, corporate, and public. The decision for a specific salvage location may prioritize a small number of corporate owners to the detriment of more numerous non-industrial private forest landowners. Ecological aspects are also relevant at a landscape level and thus impacted by changes in salvage location. These ecological characteristics may include the presence of river streams, endangered species habitats, and connectivity corridors. Concentrating salvage operations in ecologically sensitive areas could disrupt key ecological processes and affect biodiversity and ecosystem services (Lindenmayer et al. 2008; Leverkus et al. 2018).

The centralized planner perspective adopted in this study should be interpreted as a normative benchmark rather than a literal representation of post-disturbance decision-making. In practice, salvage operations involve multiple independent actors, including landowners, logging contractors, transportation providers, and mills, each operating under distinct objectives and constraints. In such decentralized systems, the primary value of the proposed framework lies in its ability to reveal system-level trade-offs, spatial inefficiencies, and risk-sensitive salvage priorities that may not be apparent when decisions are made independently.

Model outputs can be operationalized through decision-support tools, coordination mechanisms, or policy interventions that facilitate information sharing and strategic alignment among stakeholders. For example, regional planners or industry associations could use scenario-based results to identify priority salvage zones, anticipate transportation bottlenecks, or evaluate the economic consequences of alternative salvage intensities under uncertainty. Similarly, mills and landowners could use these insights to inform contracting strategies, pricing negotiations, and risk-sharing arrangements without requiring centralized control. In this way, the framework supports improved decentralized decision-making by providing a consistent analytical basis for coordination. Given the well-documented economic consequences of salvage decisions (Prestemon and Holmes 2004, 2010; Sun 2020) and associated ecological trade-offs (Royo et al. 2016; Leverkus et al. 2021), future models could incorporate ownership categories and ecological constraints through explicit weights or penalties. Such additions would enable more equitable and sustainable planning by balancing economic efficiency with social and environmental objectives.

Future research could also explore uncertainty in additional parameters, such as timber prices, mill demand, or transportation constraints, as well as operational limitations related to storage, road access, and intertemporal harvest adjacency. Extending the framework to incorporate mill procurement objectives explicitly could further improve realism. For instance, while current results favor shorter transportation distances during low-price periods, mills may strategically procure timber from more distant locations when prices are depressed, reserving nearby stocks for higher-price periods. Similarly, pessimistic sawtimber downgrade scenarios may benefit pulpwood production, highlighting trade-offs between product classes that could be addressed through product-specific or stakeholder-specific optimization. As wind disturbances are projected to increase in frequency and intensity, recent studies emphasize the growing need for spatially explicit, optimization-based decision-support frameworks that can evaluate such trade-offs under deep uncertainty (Öhman et al. 2025).

With respect to risk management, the mean – risk formulation (F3) effectively reduced exposure to unfavorable outcomes in the lower tail of the NPV distribution. However, this improvement was achieved primarily by reallocating salvage activity away from the most severely damaged but highly uncertain sites toward less affected areas. Identifying an appropriate balance between expected economic performance and downside-risk mitigation ultimately depends on decision-makers' risk preferences and tolerance levels, consistent with prior applications of CVaR in forest planning under uncertainty (Eyvindson and Cheng 2016; Eyvindson et al. 2024). Because risk attitudes vary across stakeholders, individual assessments may be as important as collective evaluations. Incorporating such perspectives can support more resilient salvage strategies capable of navigating post-disturbance uncertainty while managing trade-offs between economic performance, equity, and ecological impact.

Conclusions

This study developed a scenario-based, spatially explicit optimization framework to support post-hurricane salvage logging decisions under uncertainty in timber supply and quality. The framework integrates forest inventory data, remotely sensed damage assessments, and market information to capture heterogeneous damage patterns and evaluate salvage strategies across a wide range of plausible damage and timber downgrade conditions.

Results indicate that explicitly modeling uncertainty influences spatial harvest allocation, transportation costs, and exposure to unfavorable economic outcomes. While aggregate harvested volumes and total NPV were similar across deterministic and stochastic formulations under conditions of abundant timber supply, stochastic, and mean – risk approaches altered the distribution of returns and reduced vulnerability to lower-tail losses. The risk-averse formulation mitigated extreme negative outcomes primarily by reallocating salvage activity away from highly uncertain, severely damaged sites. Sensitivity to alternative downgrade probability assumptions further underscores the importance of accurately representing post-disturbance timber quality uncertainty.

The framework provides a flexible decision-support tool that improves salvage efficiency and strengthens economic resilience following extreme wind disturbances. Although the model adopts a centralized planning perspective, its outputs remain relevant for decentralized systems by identifying priority salvage areas, potential logistical bottlenecks, and risk-sensitive trade-offs faced by landowners, managers, and wood-processing facilities.

By linking damage heterogeneity, timber quality uncertainty, and risk preferences within a spatial optimization, this study model strengthens the analytical foundation for post-disturbance salvage planning. As wind disturbances are projected to increase in frequency and intensity, scenario-based stochastic and mean – risk approaches offer a robust pathway for enhancing economic resilience and adaptive forest recovery strategies. Future research should extend this framework to incorporate ecological constraints, ownership heterogeneity, dynamic price responses, and decentralized decision structures to further broaden its applicability.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by a joint venture agreement between the Mississippi State University and the U.S. Forest Service – Hurricane Salvage and Supply Chains: Welfare and Carbon Outcome (21-JV -11330180-098).

ORCID

Ian Pereira Sartorio http://orcid.org/0009-0009-9140-330X

References

Aghalari A, Marufuzzaman M, Aladwan BS, Tanger S, Da Silva BK. 2021. A bilevel model formulation for solving a post-hurricane damaged timber management problem. Comput Ind Eng. 162:107726. https://doi.org/10.1016/j.cie.2021.107726

Alonso-Ayuso A et al. 2014. Medium range optimization of copper extraction planning under uncertainty in future copper prices. Eur J Oper Res. 233(3):711–726. https://doi.org/10.1016/j.ejor.2013.08.048

Alonso-Ayuso A, Escudero LF, Guignard M, Weintraub A. 2018. Risk management for forestry planning under uncertainty in demand and prices. Eur J Oper Res. 267(3):1051–1074. https://doi.org/10.1016/j.ejor.2017.12.022

Ben-Tal A, El Ghaoui L, Nemirovski A. 2009. Robust optimization. Angew Chem Int Ed. 6(11):27–65.

Brand GJ, Nelson MD, Wendt DG, Nimerfro KK. 2000. The hexagon/panel system for selecting FIA plots under an annual inventory. In McRoberts RE, Reams GA, Van Deusen PC editors. Proceedings of the First Annual Forest Inventory and Analysis Symposium; Gen. Tech. Rep. NC-213 , U.S. Department of Agriculture, Forest Service, North Central Research Station, San Antonio, TX. p 8–13. http://www.fia.fs.fed.us/library/sampling/docs/supplement1_121704.pdf

Brandeis T, Turner J, Baeza Castro A, Brown M, Lambert S. 2022. Assessing forest resource damage following natural disasters using national forest inventory plots. Research Paper SRS-65R. https://doi.org/10.2737/SRS-RP-65

Carter J. 2017. How have recent Gulf Coast hurricanes affected stumpage price? Forest2Market. https://www.forest2market.com/blog/how-have-recent-gulf-coast-hurricanes-affected-stumpage-price

Ceccherini G et al. 2020. Abrupt increase in harvested forest area over Europe after 2015. Nature. 583(7814):72–77. https://doi.org/10.1038/s41586-020-2438-y

Cubbage F et al. 2022. Comparative global timber investment costs, returns, and applications, 2020. J For Bus Res. 1(1):90–121. https://doi.org/10.62320/jfbr.v1i1.16

Daniel CJ, Ter-Mikaelian MT, Wotton BM, Rayfield B, Fortin MJ. 2017. Incorporating uncertainty into forest management planning: timber harvest, wildfire and climate change in the boreal forest. For Ecol Manage. 400:542–554. https://doi.org/10.1016/j.foreco.2017.06.039

de Pellegrin Llorente I et al. 2023. Perceptions of uncertainty in forest planning: contrasting forest professionals' perspectives with the latest research. Can J Res. 53(6):391–406. https://doi.org/10.1139/cjfr-2022-0193

De Pellegrin Llorente I, Hoganson HM, Windmuller-Campione MA. 2022. Recognizing uncertainty in forest planning: a decomposition model for large landscapes. For Sci. 68(2):200–213. https://doi.org/10.1093/forsci/fxab061

Dewitz J, U.S. Geological Survey. 2021. National land cover database (NLCD) 2019 products (ver. 2.0, June 2021). U.S. Geological Survey (USGS). https://doi.org/10.5066/P9KZCM54

Eyvindson K, Cheng Z. 2016. Implementing the conditional value at risk approach for even-flow forest management planning. Can J Res. 46(5):637–644. https://doi.org/10.1139/cjfr-2015-0270

Eyvindson K, Hartikainen M, Miettinen K, Kangas A. 2018. Integrating risk management tools for regional forest planning: an interactive multiobjective value-at-risk approach. Can J Res. 48(7):766–773. https://doi.org/10.1139/cjfr-2017-0365

Eyvindson K, Kangas A. 2015. Evaluating the required scenario set size for stochastic programming in forest management planning: incorporating inventory and growth model uncertainty. Can J Res. 46(3):340–347. https://doi.org/10.1139/cjfr-2014-0513

Eyvindson K, Kangas A, Nahorna O, Hunault-Fontbonne J, Potterf M. 2024. Integrating wind disturbances into forest planning: a stochastic programming approach. Silva Fenn (Hels). 58(4):23044. https://doi.org/10.14214/sf.23044

Fastmarkets. 2021. Risi mill asset database [data set]. Fastmarkets. https://www.fastmarkets.com/forest-products/mill-data-and-costs

Feng Y, Negrón-Juárez RI, Chambers JQ. 2021. Multi-cyclone analysis and machine learning model implications of cyclone effects on forests. Int J Appl Earth Observ Geoinf. 103:103. https://doi.org/10.1016/j.jag.2021.102528

Ferreira L, Miguel F, Jose G, Garcia-Gonzalo J. 2012. A stochastic dynamic programming approach to optimize short-rotation coppice systems management scheduling: an application to eucalypt plantations under wildfire risk in Portugal. For Sci. 58(4):353–365. https://doi.org/10.5849/forsci.10-084

Gabrel V, Murat C, Thiele A. 2014. Recent advances in robust optimization: an overview. Eur J Oper Res. 235(3):471–483. https://doi.org/10.1016/j.ejor.2013.09.036

Gao W, Larjavaara M. 2024. Wind disturbance in forests: a bibliometric analysis and systematic review. For Ecol Manage. 564:122001. https://doi.org/10.1016/j.foreco.2024.122001

Gardiner B et al. 2008. A review of mechanistic modelling of wind damage risk to forests. Forestry. 81(3):447–463. https://doi.org/10.1093/forestry/cpn022

Henderson JD, Abt RC, Abt KL, Baker J, Sheffield R. 2022. Impacts of hurricanes on forest markets and economic welfare: the case of Hurricane Michael. For Policy Econ. 140:140. https://doi.org/10.1016/j.forpol.2022.102735

Johnstone JF et al. 2016. Changing disturbance regimes, ecological memory, and forest resilience. Front Ecol Environ. 14(7):369–378. https://doi.org/10.1002/fee.1311

Kašpar J, Hlavatỳ R, Kuželka K, Marušák R. 2017. The impact of assumed uncertainty on long-term decisions in forest spatial harvest scheduling as a part of sustainable development. Forests. 8(9):335. https://doi.org/10.3390/f8090335

Kenney G et al. 2021. Hurricane Michael altered the structure and function of longleaf pine woodlands. J Geophys Res Biogeosci. 126(12). https://doi.org/10.1029/2021JG006452

Kinnucan HW. 2016. Timber price dynamics after a natural disaster: hurricane Hugo revisited. J Econ. 25:115–129. https://doi.org/10.1016/j.jfe.2016.09.002

Kleywegt AJ, Shapiro A. 2001. Stochastic optimization. In: Salvendy G, editor. Handbook of industrial engineering. ed.3rd John Wiley and Sons Inc. p 2625–2649. https://doi.org/10.1002/9780470172339.ch102

Kleywegt AJ, Shapiro A, Homem-de-Mello T. 2002. The sample average approximation method for stochastic discrete optimization. SIAM J Optim. 12(2):479–502. https://doi.org/10.1137/S1052623499363220

Leverkus AB et al. 2021. Tamm review: does salvage logging mitigate subsequent forest disturbances? For Ecol Manage. 481(2020):118721. https://doi.org/10.1016/j.foreco.2020.118721

Leverkus AB et al. 2018. Salvage logging effects on regulating and supporting ecosystem services — a systematic map. Can J Res. 48(9):983–1000. https://doi.org/10.1139/cjfr-2018-0114

Lindenmayer DB, Burton PJ, Franklin JF. 2008. Salvage logging and its ecological consequences. Island Press. https://books.google.com/books?id=9HX56iaZuncC&printsec=frontcover#v=onepage&q&f=false

Lugo AE. 2008. Visible and invisible effects of hurricanes on forest ecosystems: an international review. Austral Ecol. 33(4):368–398. https://doi.org/10.1111/j.1442-9993.2008.01894.x

Marshall PL. 1987. Sources of uncertainty in timber supply projections. Forestry Chron. 63(3):165–168. https://doi.org/10.5558/tfc63165-3

Melton F, Huntington J, Allen R Anderson M, Fisher JB, Kilic A. 2021. OpenET: filling a critical data gap in water management for the western United States. J Am Water Resour Assoc. 57(6):933–957. https://doi.org/10.1111/1752-1688.12956

NOAA NHC. 2024. NHC data in GIS formats: advisory wind field and forecast wind radii, preliminary best track [data set]. National Oceanic and Atmospheric Administration (NOAA), and National Hurricane Center (NHC). https://www.nhc.noaa.gov/gis/

Foundation N. 2020. TimberMart-South quarterly price data for Florida [data set]. University of Georgia.

Öhman K et al. 2025. Integrating wind damage vulnerability into long-term forest planning: an optimisation-based model for spatial decision support. Trees People. 20:100870. https://doi.org/10.1016/j.tfp.2025.100870

Oswalt SN, Oswalt CM. 2008. Relationships between common forest metrics and realized impacts of Hurricane Katrina on forest resources in Mississippi. For Ecol Manage. 255(5–6):1692–1700. https://doi.org/10.1016/j.foreco.2007.11.029

Palma CD, Nelson JD. 2014. A robust model for protecting road-building and harvest-scheduling decisions from timber estimate errors. For Sci. 60(1):137–148. https://doi.org/10.5849/forsci.12-090

Peltola H et al. 2010. Impacts of climate change on timber production and regional risks of wind-induced damage to forests in Finland. For Ecol Manage. 260(5):833–845. https://doi.org/10.1016/j.foreco.2010.06.001

Petucco C, Andrés-Domenech P, Duband L. 2020. Cut or keep: what should a forest owner do after a windthrow? For Ecol Manage. 461:461. https://doi.org/10.1016/j.foreco.2020.117866

Pienaar LV, Turnbull KJ. 1973. The Chapman-Richards generalization of Von Bertalanffy's growth model for basal area growth and yield in even-aged stands. For Sci. 19(1):2–22. https://doi.org/10.1093/forestscience/19.1.2

Powell WB. 2019. A unified framework for stochastic optimization. Eur J Oper Res. 275(3):795–821. https://doi.org/10.1016/j.ejor.2018.07.014

Prestemon JP, Holmes TP. 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 JP, Holmes TP. 2004. Market dynamics and optimal timber salvage after a natural catastrophe. For Sci. 50(4):495–511. https://doi.org/10.1093/forestscience/50.4.495

Prestemon JP, Holmes TP. 2008. Timber salvage economics. Econ For Disturbances Wildfires Storms Invasive Species. 167–190. https://doi.org/10.1007/978-1-4020-4370-3_9

Prestemon JP, Holmes TP. 2010. Economic impacts of hurricanes on forest owners. General Technical Report PNW-GTR-802. 2 (September):207–221. http://www.srs.fs.usda.gov/pubs/36650

Radke N, Yousefpour R, von Detten R, Reifenberg S, Hanewinkel M. 2017. Adopting robust decision-making to forest management under climate change. Ann For Sci. 74(2). https://doi.org/10.1007/s13595-017-0641-2

Rockafellar RT, Uryasev S. 2000. Optimization of conditional value-at-risk. J Risk. 2(3):21–41. https://doi.org/10.21314/JOR.2000.038

Rockafellar RT, Uryasev S. 2002. Conditional value-at-risk for general loss distributions. J Bank Financ. 26(7):1443–1471. https://doi.org/10.1016/S0378-4266(02)00271-6

Royo AA, Peterson CJ, Stanovick JS, Carson WP. 2016. Evaluating the ecological impacts of salvage logging: can natural and anthropogenic disturbances promote coexistence? Ecology. 97(6):1566–1582. https://doi.org/10.1890/15-1093.1

Rutledge BT, Cannon JB, McIntyre RK, Holland AM, Jack SB. 2021. Tree, stand, and landscape factors contributing to hurricane damage in a coastal plain forest: post-hurricane assessment in a longleaf pine landscape. For Ecol Manage. 481:118724. https://doi.org/10.1016/j.foreco.2020.118724

Sartorio IP et al. 2024. Understanding hurricane effects on forestlands: land cover changes and salvage logging. For Ecol Manage. 569:122132. https://doi.org/10.1016/j.foreco.2024.122132

Schaetzl RJ, Krist FJ, Miller BA. 2012. A taxonomically based ordinal estimate of soil productivity for landscape-scale analyses. Soil Sci. 177 (4):288–299. https://doi.org/10.1097/SS.0b013e3182446c88

Schou E, Thorsen BJ, Jacobsen JB. 2015. Regeneration decisions in forestry under climate change related uncertainties and risks: effects of three different aspects of uncertainty. For Policy Econ. 50:11–19. https://doi.org/10.1016/j.forpol.2014.09.006

Seidl R et al. 2017. Forest disturbances under climate change. Nat Clim Change. 7(6):395–402. https://doi.org/10.1038/nclimate3303

Sims C. 2011. Optimal timing of salvage harvest in response to a stochastic infestation. Nat Resour Model. 24(3):383–408. https://doi.org/10.1111/j.1939-7445.2011.00096.x

Stanturf JA, Goodrick SL, Outcalt KW. 2007. Disturbance and coastal forests: a strategic approach to forest management in hurricane impact zones. For Ecol Manage. 250(1–2):119–135. https://doi.org/10.1016/j.foreco.2007.03.015

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. 2020. Timber price dynamics after a natural disaster: a reappraisal. J Econ. 35(4):397–420. https://doi.org/10.1561/112.00000520

U.S. Census Bureau. 2022. 2022 Tiger/Line shapefiles: roads [data set]. U.S. Census Bureau, Geography Division. https://www2.census.gov/geo/tiger/TIGER2022/ROADS/

USDA Forest Service. 2021. Timber product output and use for Florida, *2020*. Resource update FS-348. https://doi.org/10.2737/FS-RU-348

USDA Forest Service. 2024. Storm damage viewer [data set]. U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center. https://apps.fs.usda.gov/lcms-viewer/storm-model.html

Forest Service USDA. 2024. Timber products output (TPO) interactive reporting tool [data set]. U.S. Department of Agriculture, Forest Service. https://www.fs.usda.gov/research/products/dataandtools/tools/timber-products-output-tpo-interactive-reporting-tool

USFS FIA. 2022. Conus stocking-age-loreys height 2018 [data set]. USDA Forest Service, Forest Inventory and Analysis. https://usfs.maps.arcgis.com/home/item.html?id=73b9ca41aa5e4b05b9f45cd3875f65c9

USFS FIA. 2024. USDA Forest Service, Forest Inventory and Analysis. FIA DataMart v2.0.01. Retrieved 01 06 2024. https://apps.fs.usda.gov/fia/datamart/datamart.html

Veliz FB, Watson JP, Weintraub A, Wets RJB, Woodruff DL. 2015. Stochastic optimization models in forest planning: a progressive hedging solution approach. Ann Oper Res. 232(1):259–274. https://doi.org/10.1007/s10479-014-1608-4

Walker WE, Marchau VAWJ, Swanson D. 2010. Addressing deep uncertainty using adaptive policies: introduction to section 2. Technol Forecast Soc. 77 (6):917–923. https://doi.org/10.1016/j.techfore.2010.04.004

Wang F, Xu YJ. 2009. Hurricane Katrina-induced forest damage in relation to ecological factors at landscape scale. Environ Monit Assess. 156 (1–4):491–507. https://doi.org/10.1007/s10661-008-0500-6

Worley E et al. 2022. Impacts of hurricane Michael on watershed hydrology: a case study in the southeastern United States. Forests. 13(6):904. https://doi.org/10.3390/f13060904

Xi W, Peet RK, Urban DL. 2008. Changes in forest structure, species diversity and spatial pattern following hurricane disturbance in a Piedmont North Carolina forest, USA. J Plant Ecol. 1(1):43–57. https://doi.org/10.1093/jpe/rtm003

Zampieri NE, Pau S, Okamoto DK. 2020. The impact of hurricane Michael on longleaf pine habitats in Florida. Sci Rep. 10(1). https://doi.org/10.1038/s41598-020-65436-9

Zhou M, Buongiorno J. 2004. Nonlinearity and noise interaction in a model of forest growth. Ecol Modell. 180(2–3):291–304. https://doi.org/10.1016/j.ecolmodel.2004.04.023

VanderSchaaf CL, McConnell TE, Tanger SM. 2021. Estimated impacts of Emerald Ash Borer on Ash timber supply in Texas, Usa. J Forestry Span. 119(1):45–61. https://doi.org/10.1093/jofore/fvaa043

Zhou M, Buongiorno J. 2006. Forest landscape management in a stochastic environment, with an application to mixed loblolly pine-hardwood forests. For Ecol Manage. 223(1–3):170–182. https://doi.org/10.1016/j.foreco.2005.10.068