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Understanding the labor supply for conducting wildfire hazardous fuel reduction treatments

Jaana Korhonen [a,*], Jeffrey P. Prestemon [b]

[a] *Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA, USA*
[b] *USDA Forest Service Southern Research Station, Forestry Sciences Laboratory, 3041 E. Cornwallis Road, Durham, NC 27713, USA*

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ABSTRACT

It is becoming increasingly critical for societies to understand how costs and benefits associated with natural disasters and their mitigation activities are allocated across economic actors. Although higher rates of wildfire hazard mitigation would be expected to increase jobs in the forestry and logging sector, scientific examination of the magnitude of such impacts has been scarce. This research helps to close this research gap by evaluating how labor markets in Western U.S. counties have responded to the mechanical wildfire hazardous fuel reduction treatments carried out on national forests in 10 states. Econometric analysis of quarterly data, 2018–2022, suggest that these treatments generate statistically significant and positive, but limited, impacts on jobs in the forestry and logging sector and in the wood products sector in the U.S. West. The positive effects partially offset the overall long-run decline in forestry and logging sector jobs. Given that the employment impacts of mechanical treatments vary geographically, our results imply that strategies could be developed that maximize the positive job effects of treatments by varying investment levels across regions.

1. Introduction

Every year, homes, income, and lives are lost to destructive wildfires. These losses are anticipated to increase in parallel with intensifying wildfires due to unpredictable weather patterns, drier conditions, and heatwaves (Davis et al. 2014; Mazdiyasni and AghaKouchak, 2015; Schiermeier, 2018; Natole et al., 2021; Yu et al., 2023). Prestemon et al. (2024), for example, projected that area burned on national forests of the U.S. West each year may nearly double by mid-century. Expansion in wildfires in private lands can be expected, as the recent fire seasons have been characterized by high total area burned and also periods of rapid growth and very large single-day wildfire spread events (Coop et al. 2022). Large-scale wildfires act as economic shocks to local and regional economies by, for example, destroying timber, decreasing water quality (Butry et al., 2001; Prestemon et al., 2006, 2012; Bousfield et al. 2025), damaging infrastructure (Prestemon et al., 2006; Hjerpe et al. 2024), reducing recreation opportunities (Gellman et al., 2022), and increasing health costs, e.g., due to smoke exposure (Kochi et al. 2010; Burke et al. 2022; Bayham et al., 2022; Borgschulte et al., 2022).

In 2022, the USDA Forest Service launched a 10-year effort, “The Wildfire Crisis Strategy” (WCS), to undertake actions on the ground to mitigate wildfire hazard, restore ecosystems to more fire-resilient conditions, and protect communities (USDA FS, 2022). Initial actions focus on 21 spatially delineated geographic areas of special concern, or “landscapes,” where wildfires pose the most immediate threats to communities. In 2024, the agency announced a $500 million investment to reduce wildfire risk to communities,

* Corresponding author.
E-mail address: jaana.korhonen@uga.edu (J. Korhonen).

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critical infrastructure, and natural resources through the Inflation Reduction Act (P.L. 117–58[1]) and the Infrastructure Investment and Jobs Act (P.L. 117–58[2]). Of this funding, approximately $400 million was allocated to federal treatment and restoration efforts in the WCS landscapes in the western U.S., while there were plans for an additional $100 million to be allocated through a collaborative process involving Tribes, communities, and partners reliant upon the multitude of ecosystems services provided by forests.

Hazardous fuel treatments—such as prescribed burns, mechanical thinning, and chemical treatments—are the primary options for achieving hazardous fuel reductions (Mercer et al. 2007; Stephens et al. 2012; Prestemon et al. 2012; Vaillant and Reinhardt 2017; Hunter & Robles, 2020; Hessburg et al. 2021; Prichard et al., 2021; Daum et al., 2024). The choice of the most suitable method is made by evaluating the costs, benefits, operational limits, and risks of implementing each treatment type. Prescribed burns, for example, carry risks, such as smoke exposure and the potential for escape, and they necessitate specific environmental conditions that are sometimes difficult to secure (Yoder 2008; Williamson et al. 2016; Jones et al. 2022; Frey, 2024; Li et al. 2025). Thus, federal fire management policy currently allows limited use of prescribed fire, provided liability and risks are thoroughly reviewed (Frey, 2024). In turn, although mechanical treatment strategies may bring with them particular operational challenges and legal scrutiny, their execution time window is less constrained (Chiodi et al., 2018; Miller et al., 2020).

Mechanical hazardous fuel reduction treatments, in particular, are typically labor-intensive, meaning that new employment opportunities may be created. However, there may be a wide gap between the number of workers needed to carry out a land manager's plans, and the number available locally to employ. Research has established that such gaps are widespread in the forestry and logging sector (Conrad et al., 2018; Conrad and Blinn, 2024). The nation's logging industry is said to face multiple challenges, including an ageing workforce, low profitability, an unskilled workforce, and rising costs (Conrad and Blinn, 2024; He et al., 2021; Ellis et al., 2024; Conrad et al., 2018). Nonetheless, the research on the labor impacts triggered by wildfire mitigation activities in public lands remains limited.

To narrow the research gap, we developed econometric and data science techniques to analyze the labor market impacts of hazardous fuel treatments in the forestry and logging sector during 2018–2022. In this study, we advanced two complementary objectives. First, we established a theoretical framework for analyzing labor supply dynamics in the context of mechanical hazardous fuel treatments on public lands. We then assessed employment impacts empirically across states that intersect with WCS landscapes. Equation estimates allow an assessment of the marginal effects of treatments on employment. Second, we conducted a counterfactual analysis to estimate nonmarginal effects of varying hypothetical hazardous fuel reduction treatment and wage levels on employment across different regional contexts. Our research contributes to the evolving literature on the economic costs and benefits of hazardous fuel reduction treatments and ecological restoration in fire-prone landscapes, offering novel insights from a labor market perspective. These findings give insights into labor dynamics that can inform wildfire management strategies and policy discussions. In particular, our analysis can be used to assess the prospects of job creation of the increased investment in wildfire hazardous fuel reduction treatments, including as being carried out in the WCS landscapes.

2. Theory and empirical approach

From the perspective of established theory in wildfire economics (e.g., Donovan and Rideout, 2003), a wildfire manager seeks to identify the optimal level of hazardous fuel treatments. The manager's goal is to maximize the effectiveness of these treatments over time and across diverse geographical contexts. At the societal level, the objective is to allocate funding for hazardous fuel management activities so that treatments are neither over- nor under-funded (Donovan and Rideout 2003; Hjerpe et al., 2024). Under this framework, as environmental conditions favorable to wildfire ignition and spread rise, the economically optimal level of treatment investment is expected to increase.

Public funding and policy incentives offer the opportunity to perform wildfire hazardous fuel reduction treatments in remote or low-population areas that lack a competitive labor market. Thus, the cost-benefit analysis of these interventions is an important societal question (Hjerpe et al., 2024), which extends to these markets impacting communities residing adjacent to the WCS landscapes. Proponents argue that expanding hazardous reduction treatments will create rural jobs in sectors such as logging, equipment operation, and landscape monitoring. For instance, the Public Land Management Act of 2009 (P.L. 111–11[3]) and the Infrastructure Investment and Jobs Act of 2021 (P.L. 117–58) emphasized creating local employment and training opportunities through grants and contracts for restoration work. A more recent executive order (Exec. Order No. 14,123) (Executive Office of the President, 2025) aimed to expand timber utilization and reduce wildfire damage by offering market-based incentives for biomass removal. While forest restoration, hazardous fuel treatments, and timber management are not synonymous, they have convergence and overlap in the many fire-prone forests of the American West (Reinhardt et al., 2008; Stephens et al., 2021).

2.1. Labor supply and demand

The employment impacts of hazardous fuel treatments are derived from a reduced-form expression of equilibrium labor supply and labor demand:

[1] https://www.congress.gov/117/plaws/publ58/PLAW-117publ58.pdf [Last accessed 05/2025].
[2] https://www.congress.gov/117/plaws/publ169/PLAW-117publ169.pdf [Last accessed 05/2025].
[3] https://www.congress.gov/bill/111th-congress/house-bill/146/text [Last accessed 05/2025].

$$\begin{aligned} Y^S &= f(W, H) \\ Y^D &= g(W, Q, \mathrm{R}, M) \end{aligned} \tag{1}$$

where Y^s is the quantity of labor supplied, Y^D is the quantity of labor demanded, W is the wage rate, H are exogenous supply factors affecting labor supply, Q quantifies exogenous labor demand factors, R is a vector of time-invariant regional demand factors, and M indexes a programmatic shift in demand due to the implementation of the WCS.

The employment response to hazardous fuel reduction treatments is illustrated in Fig. 1, describing equilibrium labor quantities and equilibrium wage rates and their changes given a shift in the labor demand function under conditions of a market with either an inelastic or elastic labor supply function.

Because equilibrium wages are determined at the intersection of labor supply and labor demand, labor demand econometric equation estimation requires controlling for the endogeneity of wages in equation (1),

$$Y^D = h(W(H, Q, R, M), Q, R, M) \tag{2}$$

Wooldridge (2015) and Heckman and Robb (1985) offer a method to account for endogeneity of a variable in econometric specifications of equations by using a control function. The control function method allows for endogeneity control in the context of nonlinear equation estimates, such as in Poisson and Zero-Inflated Poisson models. The control function method has two stages: (i) estimate a least squares regression of the endogenous explanatory variable on all exogenous variables of the main model and at least one exogenous instrumental variable related to the endogenous variable that is not found in the main model, and save the vector of residuals; (ii) include the residuals from the first equation estimate as an additional regressor, including the endogenous variable, in the main model (e.g., the Poisson or Zero-Inflated Poisson (ZIP) model). Upon estimation of the main model, the added residual variable controls for the endogeneity of the endogenous explanatory variable—and the significance of the control function residuals in the main model equation estimate amounts to a test of the statistical significance of the variable's endogeneity. In the case of empirical estimation of labor demand, the parameter estimate for the endogenous wage variable is a consistent estimator of the marginal effect of wage on labor demand.

2.2. Empirical estimation of hazardous fuel reduction effects on employment

We apply a Zero-Inflated Negative Binomial (ZINB)[4] regression model to quantify the equilibrium employment level (e.g., $E_{1\_elastic}$ or $E_{1\_inelastic}$ from Fig. 1), compared to the no-treatment counterfactual of E_0, given a labor demand shift (Fig. 1). The ZINB model involves two components: i) a negative binomial specification quantifying the expected count (i.e., the employment level), and ii) a logit model quantifying the probability of having zero employment (i.e., a structural zero).

In the Negative Binomial (NB) model (i), the employment level Y_{it} for county i in year t, where $Y_{i,t} = \{0,1,2\ldots\}$, is:

$$Y_{i,t} | \mathrm{X}_{i,t} \sim NB(\mu_{i,t}, \alpha) \tag{3}$$

The expected count $\mu_{i,t}$ is modeled as:

$$\mu_{i,t} = \exp\left(\beta_0 + \sum_{k=1}^{K} \beta_i \ln(\mathrm{X}_{k,i,t}) + \beta_6 \widehat{\varepsilon}_{i,t} + \delta_7 \mathrm{R}_{2i} + \delta_8 \mathrm{R}_{3i} + \delta_9 \mathrm{WCS}_i + \gamma_t Year_t\right) \tag{4}$$

Eq. (4) states that the level of employment in the forestry and logging sector in county i in year t is an exponential function of the following predictors. First are the $k = 1\ldots,K$ variables represented by $\mathrm{X}_{k,\ldots}$: acres treated in county i in year t; the wage rate paid in the sector (as represented by the wage rate in Forestry and Logging, NAICS 113) in that county in that year; the squared NAICS 113 wage rate for that county and year; and the level of NAICS 321 (Wood Product Manufacturing) employment in that county and year. Next is a set of shifters: two regional indicators (dummy variables) (R_{2i}, R_{3i}, with region 1 as the reference[5]); a WCS_i dummy, where $\mathrm{WCS}_i = 1$ if the county intersects with a WCS landscape and 0 if the county does not intersect; and Year_t, a dummy capturing a time fixed-effect. Finally, $\widehat{\varepsilon}_{it}$ is the residual from the linear control function addressing potential endogeneity using real dollar county level personal income (U.S. Bureau of Economic Analysis, 2025a) and its squared value as exogenous instruments. The wage variables among the $\mathrm{X}_{k,.}$ are deflated by the U.S. GDP deflator (2025b). See Tables 1 and 2 for summary statistics.

For the zero-inflation equation of the ZINB model, we use NAICS 321 employment (Z) as an inflation variable, assuming that a higher NAICS 321 employment level corresponds with a lower probability of a structural zero in forestry and logging employment:

$$\pi_{i,t} = \exp(\gamma_0 + \gamma_1 \ln(\mathrm{Z}_{i,t}) + \delta_7 \mathrm{R}_{2i} + \delta_8 \mathrm{R}_{3i} + \delta_9 \mathrm{WCS}_i + \gamma_t Year_t) / [1 + \exp(\gamma_0 + \gamma_1 \ln(\mathrm{Z}_{i,t}) + \delta_7 \mathrm{R}_{2i} + \delta_8 \mathrm{R}_{3i} + \delta_9 \mathrm{WCS}_i + \gamma_t Year_t)] \tag{5}$$

[4] A likelihood ratio test comparing the Poisson and negative binomial (NB) models supported the use of the NB model (LR $\chi^2 = 35{,}834.1$, $p < 0.01$). Additionally, AIC and BIC values indicated a better fit for the zero-inflated negative binomial (ZINB) model compared to the NB model. We also found that the NB model predicted significantly fewer zero counts than observed (811 vs. 2,994).

[5] The regions designated for this study do not correspond to USDA FS regions as defined in the national forest system. Instead, our regions are three different groupings of whole states.

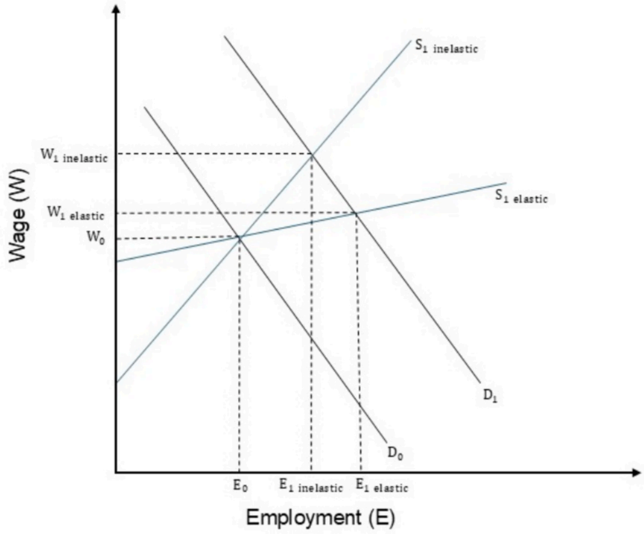

Fig. 1. Illustration of the labor market response to a public investment in cases of either inelastic or elastic labor supply. The shift in demand for labor, from D_0 to D_1, represents increased funding for wildfire hazardous fuel reduction treatments. Under an inelastic labor supply, the initial equilibrium shifts from E_0, W_0 to a new equilibrium at E_1_inelastic, W_1_inelastic. Under an elastic labor supply, the new equilibrium shifts to $E_{1\_elastic}$, $W_{1\_elastic}$.

Table 1
Summary statistics for county-level quarterly data, 2018–2022. The table reports the mean, standard deviation, minimum, and maximum for key outcome and explanatory variables (ln-transformed and level) per million acres. Wages are in real (2020) U.S. dollars.

Variable	Mean	Std. Dev	Min	Max
Employment (NAICS 113)	39.5	128.4	0	1934.2
Ln(Wages in NAICS 113)	1.1	6.8	−4.8	18.1
Ln(Wages in NAICS 113)^2	45.1	80.9	−2.3	326.2
Ln(Empl. in NAICS 321)	0.3	3.7	−4.2	8.2
Ln(Empl. in NAICS 321)^2	14.1	14.4	0	67.3
Ln(Acres treated)	−1	3.5	−4.9	9.2
Ln(Income)	9.5	0.4	−2.3	10.4
Ln(Income)^2	90.3	5.4	5.3	108.5

Table 2
Mean values for key outcome and explanatory variables (ln-transformed) by year and by region. Values are scaled per million acres. Wages are in real (2020) U.S. dollars.

	Mean Ln. Acres treated	Mean Ln. Empl. (NAICS 113)	Mean Ln.Wages (NAICS 113)	Mean Ln. Wages^2 (NAICS 113)	Mean Ln. Empl. (NAICS 321)	Mean Ln. Empl.^{2} (NAICS 321)	Mean Ln. Income	Mean Ln. Income^2
2018	−0.8	38	1.2	46.1	0.3	14	9.4	89.3
2019	−0.9	40.1	1	44.3	0.3	14	9.5	89.9
2020	−1.1	38.8	1	43.7	0.3	14.1	9.5	90.3
2021	−1.1	40.9	1.2	46.6	0.3	14.2	9.5	90.7
2022	−0.9	39.9	1.1	44.9	0.3	14.3	9.5	91.2
Average	−1	40.0	1.1	45.1	0.3	14.1	9.5	90.3
Region 1	−1.6	15.8	−0.6	22.2	−0.4	10.5	9.5	89.8
Region 2	0	97.9	5.6	96.1	2.3	21.5	9.6	92.2
Region 3	−1.3	3.7	−1.7	15.8	−1	10.1	9.4	88.9
Non-WCS region	−1.6	32.9	0.1	34.2	−0.3	12.4	9.5	89.8
WCS region	0.6	55	3.6	70.5	1.7	18.1	9.5	91.4

*Region 1 = Arizona, Colorado, Idaho, Region 2 = California, Oregon, Washington, Region 3 = Montana, Nevada, New Mexico, Utah. “non-WCS region” denotes counties with no overlap, whereas WCS region denotes counties intersecting with WCS landscapes.

where π_i is the probability that the value of the dependent variable in county i at time t is a structural zero.

The full ZINB model combines both parts:

$$P(Y_{i,t} = y) = \begin{cases} \pi_{i,t} + (1 - \pi_{i,t}) \bullet P_{NB}(Y_{it} = 0|\mu_{i,t}, \alpha), if y = 0 \\ (1 - \pi_{i,t}) \bullet P_{NB}(Y_{i,t} = y|\mu_{i,t}, \alpha), if y > 0 \end{cases} \tag{6}$$

where $P_{NB}(Y_i = y|\mu_i, \alpha)$ is the negative binomial probability mass function for the count process and π_i accounts for the zero-inflation process.

Furthermore, we conducted a marginal effects analysis for hypothetical 25 % and 50 % average increases in treatment levels, as well as 10 % and 30 % increases in wages, while holding other variables constant using post-estimate commands for the ZINB model in STATA.

2.3. Model robustness assessment

We used quarterly data due to the unavailability of monthly wage data, though we acknowledge that finer temporal scales might yield more precise results as shown in the studies focusing on employment impacts after a wildfire. For instance, Luo (2023) observed a slight drop in employment immediately following a large wildfire, but recovery occurred within the same quarter. Furthermore, we included a variable for burned acres, but its inclusion did not significantly improve the model, conceivably due to data frequency limitations. In general, previous research has articulated that wildfire events increase labor market variability, with larger fluctuations in employment (Nielsen-Pincus et al., 2013), which vary by sector (Luo, 2023; Prudencio et al., 2018; Davis et al., 2014).

We tested the ZINB model with finer regional scales and longer time periods, starting in 2010. In these models, we incorporated state fixed effects for individual states and counties. However, these models were less stable due to significant variations in ecological and economic conditions that the model was unable to capture, as well as differences in data quality across states and counties. For example, states like Oregon and California dominated forestry and logging employment, leading to inflated IRRs in the state level fixed-effects models. In practice, national forest hazardous fuel reduction treatments and forest industry practices are coordinated at the landscape level, not by individual states. In our analysis, however, the regions were divided based on how each state intersected with WCS landscapes. Regional models were more stable, reducing overfitting and improving the generalizability of results across counties with similar hazardous fuel reduction treatment and forest industry characteristics. Furthermore, we applied our estimated statistical model to quantify the county-level employment impacts of simulated 25 % and 50 % increases in treatment for the years 2018, 2020, and 2022. The visualizations suggested that increases in employment in certain counties are likely to coincide with reductions in neighboring counties, with some geographical and temporal variation. The results indicated that the most positive job gains are predicted in coastal Oregon, where major wood product processing facilities and relatively strong markets for biomass are located (Appendix B).

Overall, the ZINB model was a good fit for the data. It accounted for the zero-bound in forestry and logging sector employment. These zeros occurred due to geographic or structural factors, normal economic or seasonal variation, or data suppression for confidentiality, according to Bureau of Labor Statistics' reporting protocols. The FACTS data included information about the type of workforce associated with the individual treatment activities, although no data about the number of employees were available. We tested the model with controls for part-time employment and for contractor activities, including logging, road building, trucking, milling, and biomass utilization, but such statistical controls provided no additional value to the analysis.

To account for the different temporal and spatial impacts, we tested several alternative model specifications, including a dynamic panel least squares regression model, a difference-in-difference (DID) linear regression model, a spatial panel regression model, and panel regression models with multiple controls such as forest cover, wildfire occurrence, and population size. Although the results were consistent with those reported in this study, models were unstable, probably due to the prevalence of zero values or other data limitations. For instance, the continuing nature of hazardous fuel reduction treatments across counties meant that we could not set a specific point for DID treatment levels. We also estimated the model separately for each quarter, and results were similar. These estimates are available upon request.

To assess heteroscedasticity, we plotted Pearson residuals and predicted values, detecting no unexpected patterns or outliers. There was no indication of over-prediction of zeros (Appendix C), and we evaluated variance patterns across regions (Appendix D). While we made efforts to control for heteroscedasticity, we acknowledge it may still be an issue. In Region 3, some Pearson residuals deviated from predicted values, suggesting that the model underpredicts these values. The model also underpredicted counts in Regions 1 and 2.

We analyzed the association between hazardous fuel reduction treatment costs and forestry and logging employment, including both field treatments and on-site biomass handling costs in real (2020) U.S. dollars using the GDP deflator (U.S. Bureau of Economic Analysis, 2025b). The total cost coefficient was slightly lower than that for acres treated, meaning that the employment impact associated with a cost increase is smaller than the relative increase in acreage treated. The interpretation was, however, more challenging due to the high variability of costs across different landscapes. Therefore, we focused on area-based estimates.

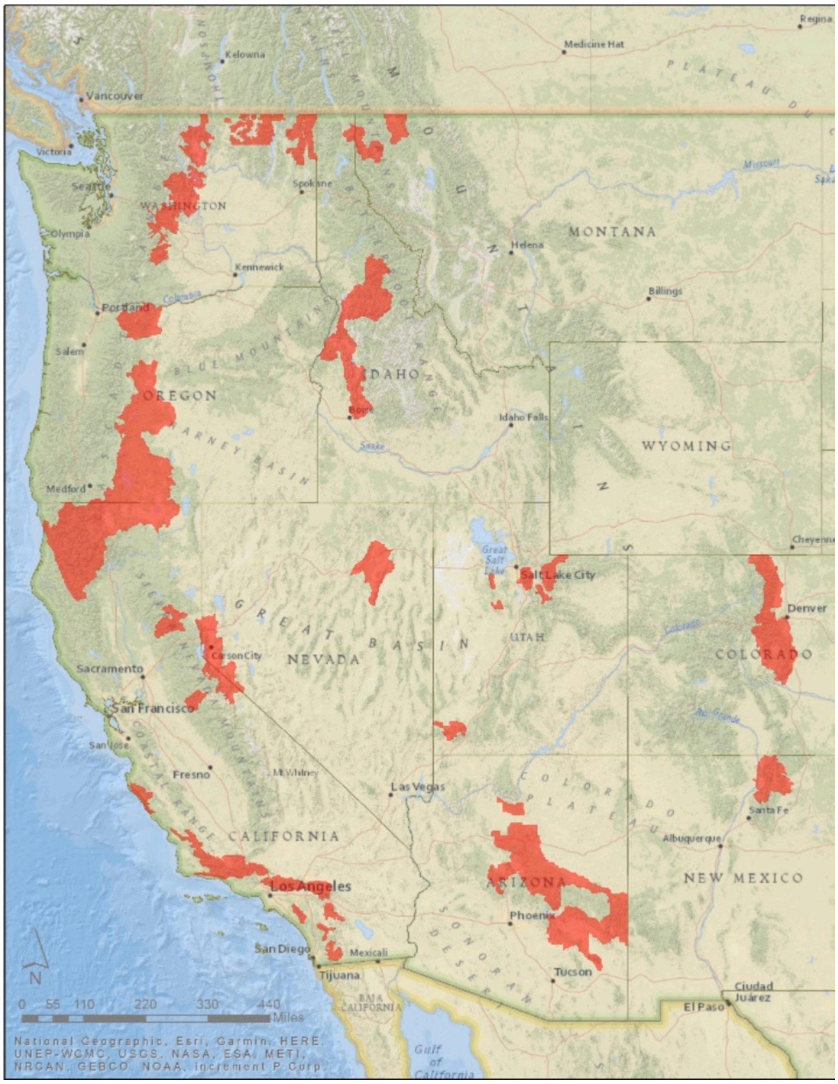

Fig. 2. WCS landscapes and States.

3. Data

Our study context is 391 counties in those states that are potentially impacted by hazardous fuel reduction treatments carried out on the 21 WCS landscapes. These landscapes are found across 10 states and are targets for reducing the natural accumulation of hazardous fuels over time (Fig. 2). Our analysis relies on data from multiple publicly available data sources for these counties and states. The states were divided into three regions based on the authors' judgment on the location, area and connectivity of these WCS landscapes within the states: Region 1 includes Arizona, Colorado, Idaho; Region 2 includes California, Oregon, Washington; and Region 3 includes Montana, Nevada, New Mexico, Utah. We reiterate that the region numbers in our study do not align with the USDA Forest Service's region numbers.

3.1. *Wildfire hazardous fuel reduction treatments data*

The hazardous reduction treatments data are obtained from the USDA FS Activity Tracking System (FACTS) database, which contains information on where specific forest resource activities occur nationwide (USDA FS, 2025). By definition, the wildfire hazardous fuel reduction treatments must comply with the following definition to be so-labeled in FACTS: "Vegetative manipulation designed to create and maintain resilient and sustainable landscapes, including burning, mechanical treatments, and/or other methods that reduce the quantity or change the arrangement of living or dead fuel so that the intensity, severity, or effects of wildfire are reduced within acceptable ecological parameters and consistent with land management plan objectives, or activities that maintain desired fuel conditions. These conditions should be measurable or predictable using fire behavior prediction models or fire effects

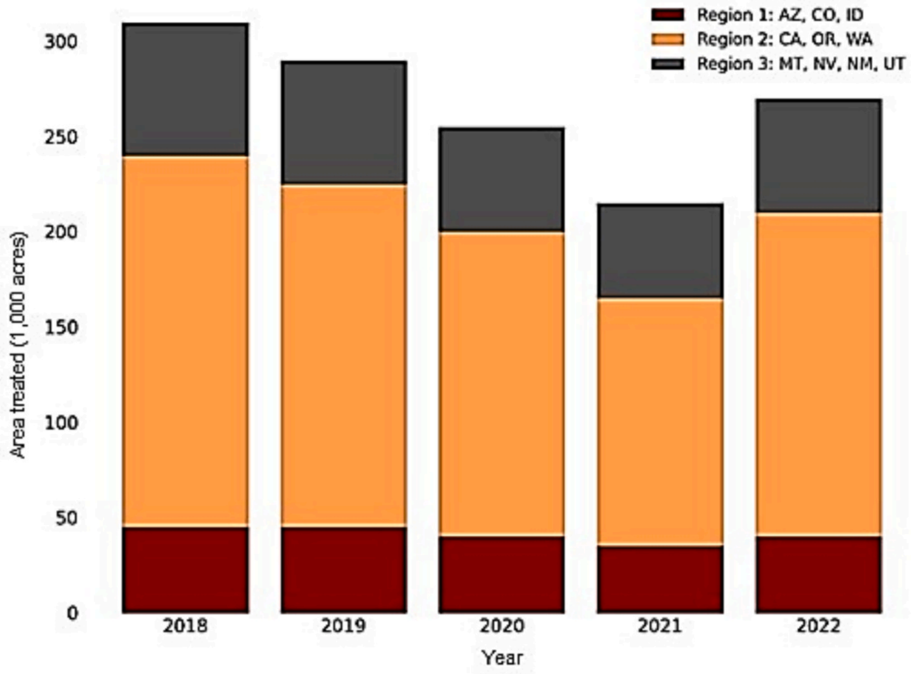

Fig. 3. Mechanically treated area (acres) by year and regions, 2018–2022. .
Source: USDA FS (2025). Region 1 includes Arizona, Colorado, Idaho; Region 2 includes California, Oregon, Washington; and Region 3 includes Montana, Nevada, New Mexico, Utah

models." (USDA FS, 2025).

We focused on the wildfire hazardous fuel reduction treatments that are classified as mechanical treatments and include only those treatments that were classified as accomplished by the time the data were collected in January 2025. Based on the data, we constructed two variables that were tested for estimating the impact of the hazardous fuel treatments on employment, but since the cost-based estimates proved less stable and more difficult to interpret in the study context, they are not reported. To avoid double-counting treated acres, we omit the biomass handling activities. The data for biomass handling activities overlapped with the areas where mechanical treatments were conducted. Fig. 3 portrays mechanically treated acreages by year and State 2018–2022. Fig. 4 illustrates the variability in mechanical treatments in WCS and non-WCS intersecting counties, 2010–2023.The specific mechanical treatment activities included in this study are described in Appendix A. Summary statistics for the data used in the analysis are shown in Tables 1 and 2.

3.2. Employment and wage data

3.2.1. Employment data

We compiled employment data for two sectors or industries connected to the production and consumption of biomass produced by hazardous fuel reduction treatments carried out on national forests of the United States. For forestry and logging, we combined two datasets. For both the forestry and logging industry and the wood products industry, we collected employment and wage data for NAICS 113 and 321, respectively, from the Quarterly Census of Employment and Wages (QCEW) (U.S. Bureau of Labor Statistics, 2025a), which reports monthly employment levels and total quarterly wages for establishment with paid employees covered under the unemployment insurance program. These data contain employment in private, federal, state, and local government, including all wage earners and part-time workers. Quarterly employment levels were calculated as the average employment across the three months of each quarter. Wage data are reported only quarterly, so no monthly averaging was needed. QCEW program data censor information from counties where the number of employees is very small compared to the establishments. In these counties, data cannot be reported due to the need to protect confidentiality of data (U.S. Bureau of Labor Statistics, 2025a).

To more fully account for employment in the forestry and logging sector, we collected data for nonemployer businesses, self-

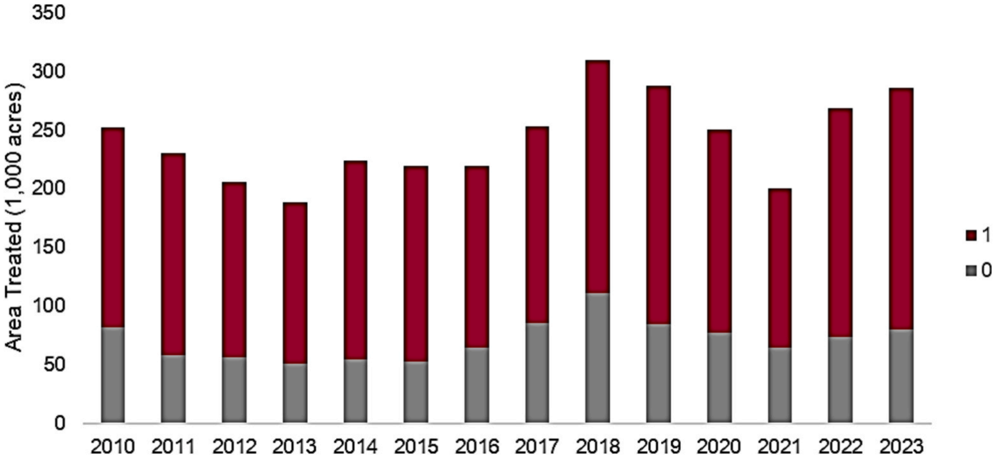

Fig. 4. Acreages of mechanical wildfire hazardous fuel reduction treatments in WCS counties (indicated in red, "1") and non-WCS counties (indicated in gray, "0") on average by year, 2010–2023. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

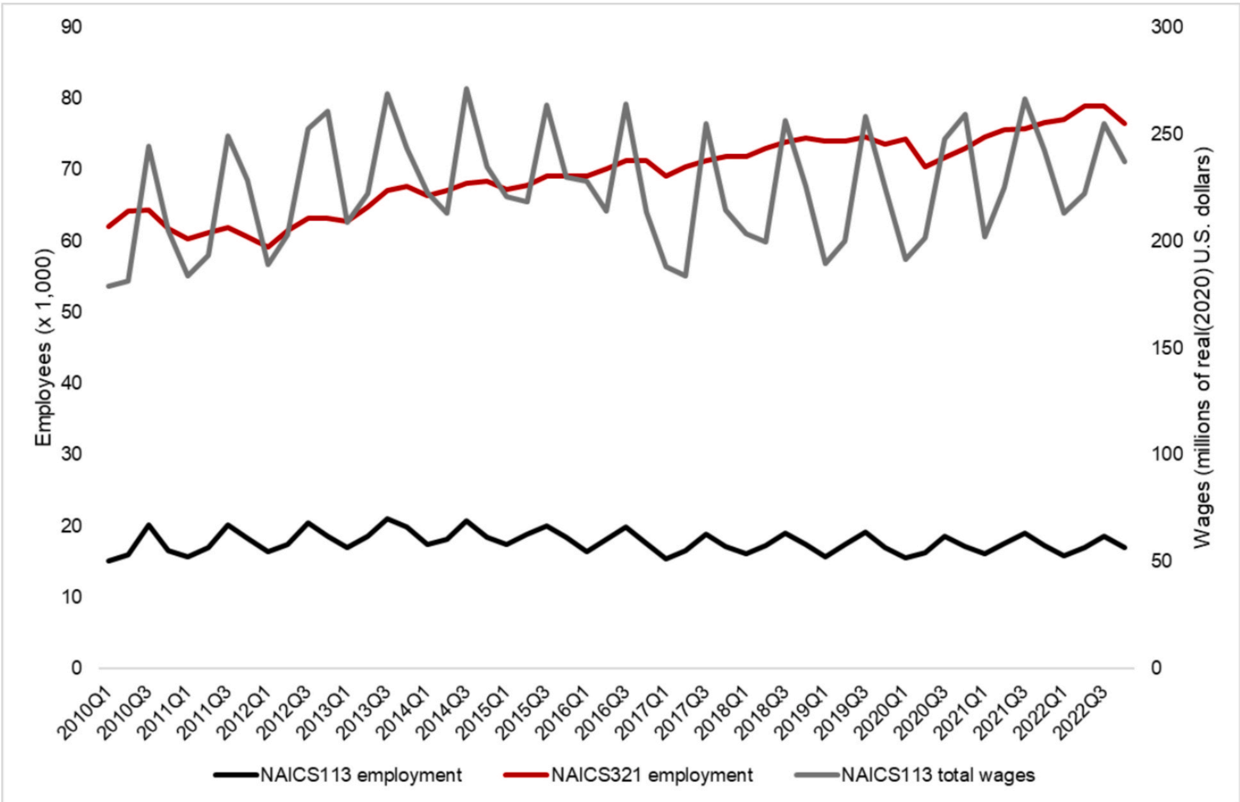

Fig. 5. Average wage and employment, 2018Q1–2022Q4 (). NAICS 113 (Forestry and Logging), NAICS 321 (Wood Product Manufacturing).
Source: U.S. Bureau of Labor Statistics (2025a)

Table 3
Results from the ZINB mode. N = 7820, non-zero observations n = 4826, zero observations n = 2994.

	Coefficient (Standard Error)
Ln(Acres treated)	1.16 (0.01)***
Ln(Wages)	0.73 (0.01)***
$Ln(Wages)^2$	1.02 (0.001)***
Ln(Employment321)	1.02 (0.01)**
$Ln(Employment321)^2$	1.05 (0.002)***
residuals	1.25 (0.02)***
Regional controls	
Region 2	2.77 (0.16)***
Region 3	0.50 (0.02)***
WCS_dummy	1.11 (0.04)**
Cons	1.69 (0.13)***
Inflate	
Ln(employment321)	−0.67 (0.04)**
cons	−2.04 (0.13)***
Ln(alpha)	−0.55 (0.04)***
Alpha	0.58 (0.02)

*** significant at the 1 % level, ** at 5 %, * at 10 %
Note: Time fixed effects were initially included but are not shown for brevity. A test of the significance of the time fixed effects failed to reject the null of no time fixed effect ($Chi^2(19) = 18.57$, p-value 0.48). Hence, time fixed effects were not included in the final model. A Wald test on the joint non-significance of the total model was rejected, with $Chi^2(35) = 22{,}888.61$, p-value of 0.00.

employed individuals and sole proprietors operating small businesses from the nonemployer statistics (NES) offered by the U.S. Census Bureau (2025a). The program covers those entities that have no paid employees and are subject to the federal income tax. The annual data were converted to quarterly using seasonality parameters that we calculated based on data spanning the same time frame that quantified the quarterly fluctuations in establishments and wages from the employee business quarterly data.[6] We then added the constructed quarterly NES NAICS 113 forestry and logging employment data to the QCEW NAICS 113 Forestry and Logging employment data. Fig. 5 pictures average wage and employment, 2010 Quarter 1 (January-March) – 2022 Quarter 4 (October-December). In the figure, the forestry and logging employment levels are the total of QCEW and NES data.

3.2.2. *Wage data*

QCEW wage data represent the total compensation paid during the calendar quarter, regardless of when the services were performed. A few state laws, however, specify that wages be reported for or be based on the period during which services are performed rather than the period during which compensation is paid. Under most state laws or regulations, wages include bonuses, stock options, severance pay, the cash value of meals and lodging, tips and other gratuities. In some states, wages also include employer contributions to certain deferred compensation plans, such as 401(k) plans, as described by the U.S. Census Bureau (2025a).

The receipts used for self-employed people include gross receipts, as reported on annual business income tax returns (U.S. Census Bureau, 2025b). These data were only available on an annual basis and were imputed to a quarterly frequency by first dividing the annual total receipts by four, and then applying a seasonal pattern identical to the one observed in wage data for employee businesses in the QCEW over the same time period (calculated as described in footnote 2).

The total wages for NAICS 113 in our empirical model included the QCEW-reported wages plus the receipts for self-employed people for NAICS 113 from the NES through the end of 2022. The average quarterly employment and wage trends over time are presented in Fig. 5.

4. Results

The full equation estimate of the ZIP model (Table 3) shows statistical significance for nearly all variables and for the model. Confirming the existence of wage endogeneity and the importance of controlling endogeneity in estimation to ensure statistically consistent parameter estimates, the parameter estimate for the control function residuals was significant at the 1 % level.

Our analysis indicated an average 0.16 % increase in the NAICS113 employment count for an additional 1 % increase in treated area (Ln(Acres treated), IRR = 1.16), which was significantly different from zero at the 1 % level (Table 3). Furthermore, our results showed a nonlinear, U-shaped relationship between NAICS 113 employment and wages. A 1 % increase in wages initially leads to a 0.27 % decline in employment (Ln(Wages), IRR = 0.73), reaches a minimum point, and then employment increases with further wage

[6] Seasonality values were calculated quarterly each year by determining the proportion of employer business establishments in Forestry and Logging (NAICS 113) for each quarter (quarterly establishment count divided by the total annual establishment count). These proportions were then used to adjust the nonemployer business establishment counts in the sector by multiplying them by the corresponding quarterly share.

growth (Ln(Wages)^2, IRR = 1.02).

At lower levels, the effect of a 1 % increase in NAICS 321 employment is associated with about a 0.02 % increase in NAICS 113 employment, but as the wood products industry grows, as measured by the coefficient on the Ln(employment)^2 variable, the impact on NAICS113 employment accelerates to a 0.05 % increase.

The employment impacts were estimated to be 2.77 times higher in Region 2 and 0.50 times higher in Region 3, compared to Region 1. In counties intersecting with WCS landscapes, the impact was 1.11 times higher compared to counties that do not intersect with these landscapes. The regional coefficients reflected structural effects, not treatment effects. The differences can be explained by timber harvest activity, larger treatable areas, and regional policies or industry infrastructure that we could not control for in detail, potentially causing heterogeneity issues in the model, which are discussed in the limitations.

The coefficient of the inflation variable (−0.67) indicated that a one-unit increase in NAICS 321 employment reduced the odds of having zero NAICS 113 employment by 0.67. This translated to a roughly 49 % lower probability of zero employment if industry employment increased by 1 % (calculated as percent change = $(e^{-0.67} - 1) \times 100$).

4.1. Marginal effects analysis for wildfire hazardous fuel reduction treatments and wage increases

The results indicated that increasing the treated area by 25 %, holding other variables constant, corresponded with an average 3.5 % increase in NAICS113 employment, while a 50 % increase corresponded to a 6.5 % increase in NAICS113 employment. These results are consistent with an inelastic labor supply. Consistent with the inelastic marginal result, we find that a 10 % and 30 % increase in wages, holding other variables constant, was associated with a 3.2 % and 7.9 % decline in employment, respectively. Furthermore, our analysis indicates that wages would need to increase by about 453 % from current levels to reverse the decline in logging employment in our study area.

5. Discussion and conclusions

In this article, we demonstrated the impact of mechanical wildfire hazardous fuel reduction treatments on employment in the forestry and logging sector (NAICS 113), using multiple modeling approaches. Our findings contribute to ongoing discussions about the societal benefits of public land wildfire management and the socioeconomic impacts of natural disaster policies. To our knowledge, this is the first study to evaluate the benefits of wildfire hazardous fuel reduction treatment investments on public lands from a labor market perspective. Our results may inform decisions on treatment investment allocations across the national forest system, considering varying job creation potential across the WCS landscapes.

Previous literature has highlighted a lack of cohesive vision regarding the intensity, location, and preferred method of hazardous fuel removal—whether mechanical, prescribed burning, chemical, or a combination thereof—across diverse landscapes and forest types (Toman et al., 2013; Stephens et al., 2014; Paveglio and Edgeley, 2023). A responsive labor supply would facilitate a faster or larger expansion of treatments, relative to goals on the geographic scale or the aggregate of treatment costs. However, our results demonstrate that labor markets in forestry and logging are relatively inelastic. This finding is also consistent with the observation that an aging and consolidating workforce would represent an operational as well as a budgetary challenge as agencies consider expanded wildfire hazardous fuel reduction treatment activities (Conrad et al., 2018; Conrad and Blinn, 2024).

Results from the ZINB model suggested that a 1 % increase in acres treated is associated with a 0.16 % increase in NAICS 113 employment, on average. Additionally, our marginal effects analysis predicted a 3.5 % increase in NAICS 113 employment for a hypothetical 25 % increase in hazardous fuel reduction treatment levels. The greater the treatment quantities carried out on western forests, the higher the marginal cost of labor, implying that large treatment programs, including those contemplated under the WCS, may encounter operational and budgetary limits related to the availability of workers. Although the quadratic specification mathematically implies a reversal in the employment effect at extremely high wage levels, this turning point occurs at more than four times (453 % increase) the current wage level. In practice, such wages would be implausibly high, given current labor market structure and treatment resource availability. Furthermore, even while logging is considered a very demanding, high-risk occupation, salaries for new employees in the logging sector have generally reflected the averages in the manufacturing industry (Blinn et al., 2015; He et al., 2021). In other words, this analysis highlights the difficulty of reversing the secular decline in the size of the forestry and logging workforce through typical demand-driven processes in the labor market.

While our data and models approached labor in forestry and logging in aggregate, this sector includes a variety of job types and work activities. It is likely that the employment impact differs by role. For example, the increased need for logging workers may be more pronounced than for administrative positions or in other subcategories of the sector, highlighting the need for a more in-depth, job-type-specific analysis that was beyond the scope of this study due to the data limitations. At the 2023 employment level of 49,800 loggers in reporting establishments (U.S. Bureau of Labor Statistics, 2025b), a 3.5 % increase in NAICS 113 sector employment would mean nearly 1700 additional workers employed by those establishments—slightly less than the projected decline of 2200 logging jobs between 2023 and 2033.

The goal of this research was to gain insights into the relationship between hazardous fuel treatments and labor supply, with the assumption that the analysis would help evaluate the impacts and workforce demands of WCS implementation. That said, the study did not explicitly focus on treatments currently occurring on WCS landscapes. Because the landscapes do not perfectly align with county boundaries or other units that correspond to available labor data, our county-level analysis of the labor market accounts for landscape presence only identifying their overlap with a county. Furthermore, because the WCS was introduced in 2022, corresponding with the end of our time series of treatment and employment observations, it is unlikely that the number of employees would have adjusted sufficiently after implementation for our model to capture such effects, even if the data were available. As hours worked per employee have been increasing (Federal Reserve Bank of St. Louis, n.d.), it is likely that, in the short term, the increased need for the logging workforce has been met by adjusting work hours rather than the number of employees. Insights into more structural, long-term adjustments (e.g., impacts from business generation) are left for future research.

Despite the outlined limitations, our results offer quantitative insights into the workforce impacts and requirements associated with hazardous fuel reduction treatments, as well as the potential distribution of labor markets both within and beyond WCS landscapes. Additionally, our results provide insight into the spatial impacts and economic interactions associated with increased hazardous reduction treatments. Our findings suggest that these treatments do have positive effects on jobs in the forestry and logging sector, although effects are limited by an inelastic labor supply. Investment in these treatments, on the other hand, could help offset the secular decline in employment in that sector.

The geographic differences may have been driven by economic, ecological, or geographic factors specific to the wildfire hazardous fuel reduction treatment locations. Regional differences were captured by regional indicator variables (dummies), implying an assumption that such factors are time-invariant, while they may not be truly time-invariant. Moreover, our analysis did not account for variables influencing labor supply conditions or potential displacement effects from other sectors—both of which are critical to understanding workforce availability for wildfire hazardous fuel reduction treatments. Incorporating institutional (e.g., minimum wage regulations), technology and innovation investment, and contextual infrastructure, demographic and geographic variables (e.g., housing availability, school quality, urban vs. rural classification, occupational safety, mobility, immigration) could enable a more nuanced and robust analysis. Some of these variables may have been partially captured through the geographic controls that we included in our models, while others would require more sophisticated and granular quantitative approaches. Future analyses could explore these dynamics —particularly with respect to heteroscedasticity and wildfire hazardous reduction treatment capacity—if more comprehensive datasets become available.

Furthermore, previous research has highlighted that the economic feasibility of wildfire hazardous fuel reduction treatments depends on the involvement of the private sector's long-term value creation process (Wear et al. 2024). This issue is particularly relevant in the context of hazardous fuel reduction treatments, as mechanical thinning and small-diameter wood processing face economic challenges (Hjerpe and Mottek-Lucas, 2018; Wear et al., 2024). The potential for utilizing biomass from these wildfire hazardous fuel reduction treatments is influenced by various values, including biodiversity (Moskwa et al., 2016; Western et al., 2017), as well as the economic feasibility of commercial biomass use (Nicholls et al., 2018). Stephens et al. (2021) suggested that wildfire hazardous fuel reduction treatments may provide more co-benefits for long-term conservation than previously anticipated, but the quantification of these possible co-benefits with employment was not addressed in our study. Indeed, more research is warranted to find strategies that simultaneously account for diverse forest management objectives, available product markets, and labor supply.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work Dr. Korhonen used Grammarly in order to enhance the clarity and readability. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRediT authorship contribution statement

Jaana Korhonen: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jeffrey P. Prestemon:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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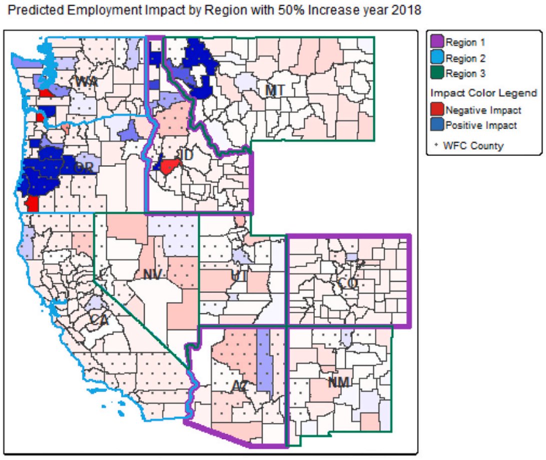
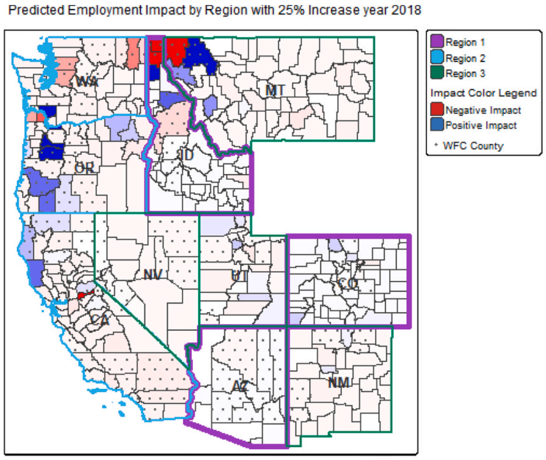
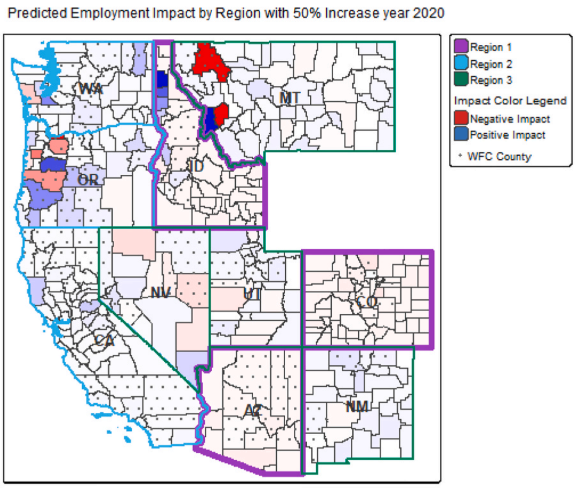
Appendix A. Activities included in the data

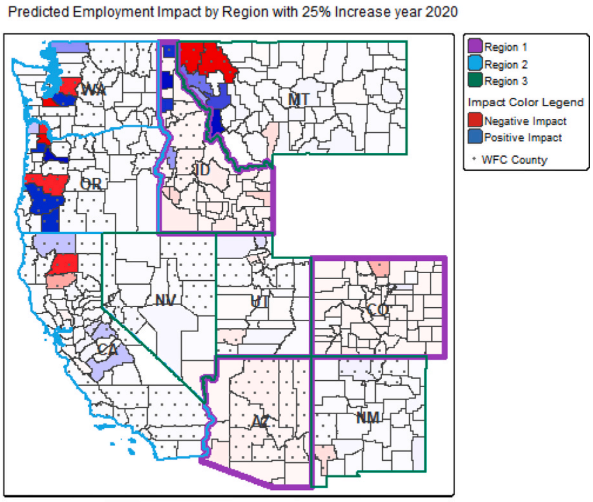
ACTIVITY_C.	ACTIVITY.
1160.	Thinning for Hazardous Fuels Reduction.
3370.	Precommercial thinning for visual.
4111.	Patch Clearcut (EA/RH/FH)
4113.	Stand Clearcut (EA/RH/FH)
4115.	Patch Clearcut (w/ leave trees) (EA/RH/FH)
4117.	Stand Clearcut (w/ leave trees) (EA/RH/FH)
4121.	Shelterwood Preparatory Cut (EA/NRH/NFH)
4122.	Seed-tree Preparatory Cut (EA/NRH/NFH)
4131.	Shelterwood Establishment Cut (with or without leave trees) (EA/RH/NFH)
4132.	Seed-tree Seed Cut (with and without leave trees) (EA/RH/NFH)
4141.	Shelterwood Removal Cut (EA/NRH/FH)
4142.	Seed-tree Final Cut (EA/NRH/FH)
4145.	Shelterwood Removal Cut (w/ leave trees) (EA/NRH/FH)
4146.	Seed-tree Removal Cut (w/ leave trees) (EA/NRH/FH)
4151.	Single-tree Selection Cut (UA/RH/FH)
4175.	Two-aged Patch Clearcut (w/res) (2A/RH/FH)
4177.	Two-aged Stand Clearcut (w/res) (2A/RH/FH)
4183.	Two-aged Seed-tree Seed and Removal Cut (w/res) (2A/RH/FH)
4192.	Two-aged Preparatory Cut (w/res) (2A/NRH/NFH)
4193.	Two-aged Shelterwood Establishment and Removal Cut (w/ res) (2A/RH/FH)
4194.	Two-aged Shelterwood Establishment Cut (w/res) (2A/RH/NFH)
4196.	Two-aged Shelterwood Final Removal Cut (w/res) (2A/NRH/FH)
4231.	Salvage Cut (intermediate treatment, not regeneration)
4232.	Sanitation Cut.
4241.	Special Products Removal.
4270.	Permanent Land Clearing.
4521.	Precommercial Thin.

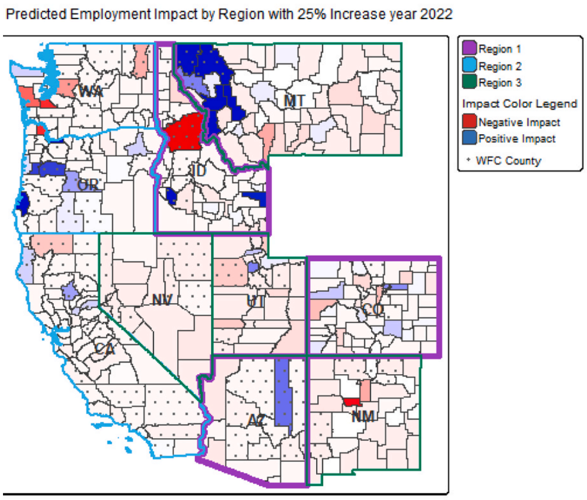
Appendix B Predicted forestry and logging sector employment impacts from simulated 25 % and 50 % treatment increases in 2018, 2020, and 2022, based on the model estimate reported in Table 3 of this article. Impacts are regionally standardized so that the maximum impact is three times the regional average. Variation between years reflects differences in treatment levels during each year. Darker color indicates more negative and positive impacts.

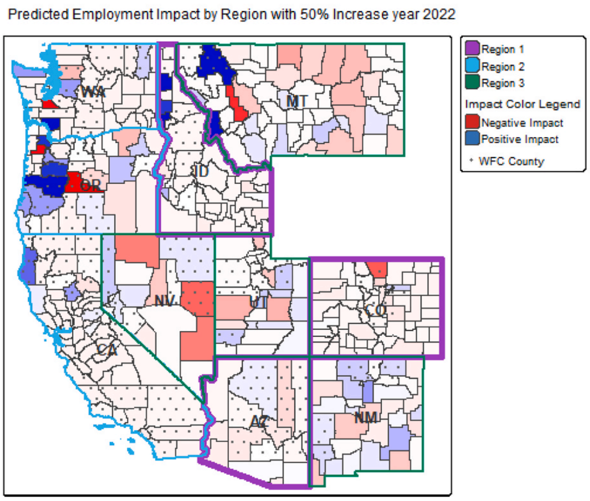




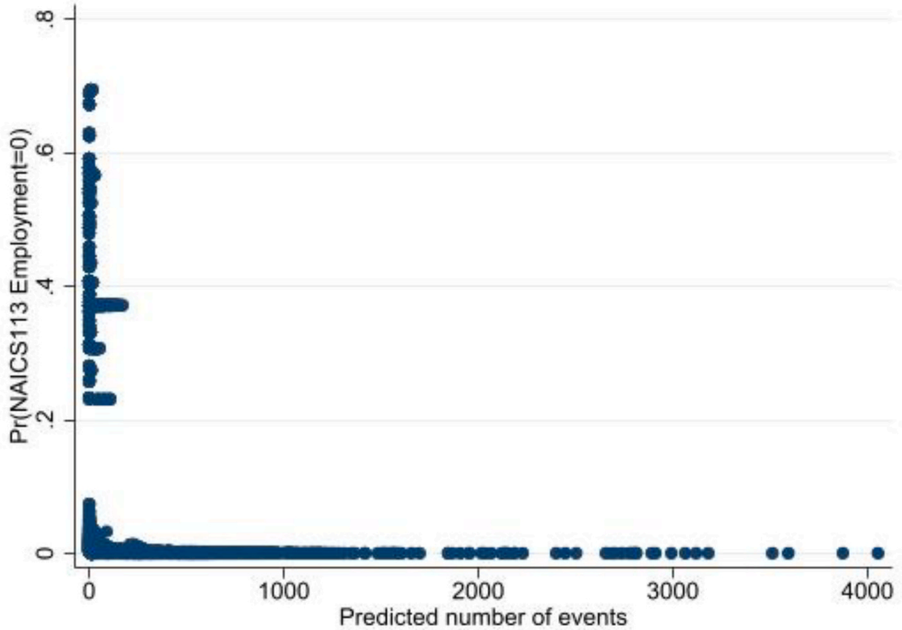








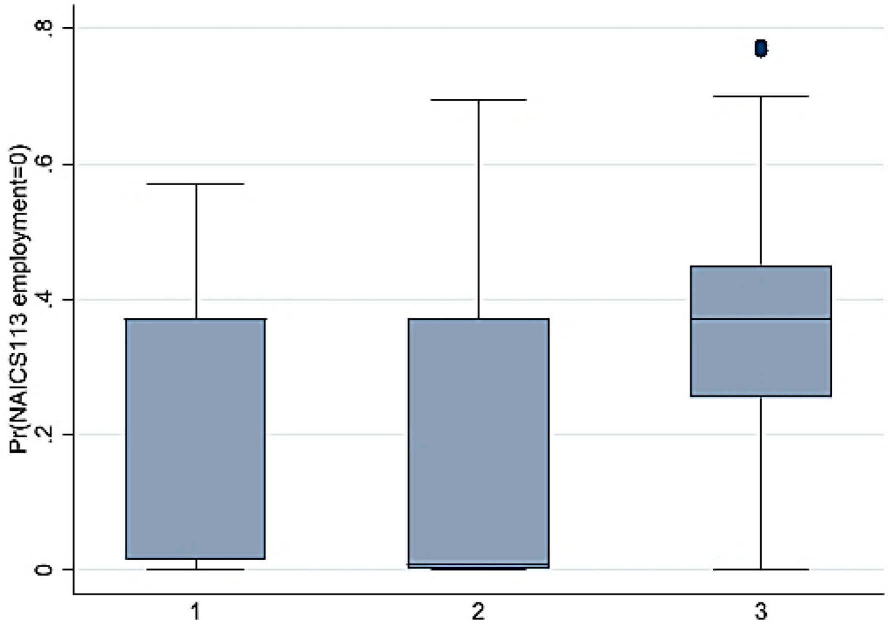
Appendix C Pearson residuals (Pr) vs. predicted values after a zinb model.



The vertical line at y = 0 indicates many predicted values are near zero, which is common when using the ZINB model to data exhibiting excess zero outcomes.

The horizontal line at residual = 0 represents observations where the prediction matches the actual value (i.e., the Person residual is zero).

Appendix D Box-whiskers plots of Pearson residuals across regions.



Data availability

Data will be made available on request.

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