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Risk and damage of southern pine beetle outbreaks under global climate change

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Abstract

This study, using the panel data modeling approach, investigates the relationships between climatic variables and southern pine beetle (SPB) (*Dendroctonus frontalis* Zimmermann) infestations and assesses the impact of global climate change on SPB infestation risk and damage. The panel data model alleviates possible collinearity among climatic variables, accounts for the effect of omitted or unobserved variables, and incorporates natural and human adaptation, thus representing a more robust approach to analyzing climate change impacts. SPB outbreaks in Louisiana and Texas appeared to move together; infestations in Alabama, Arkansas, Georgia, Florida, Mississippi, South Carolina, North Carolina, and Tennessee were highly correlated; and Virginia demonstrated its unique temporal pattern of SPB outbreaks. Salvage harvest was found to be helpful in lessening future infestation risk. Warmer winters and springs would positively contribute to SPB outbreaks with spring temperature showing a more severe and persistent impact than winter temperature; increases in fall temperature would ease SPB outbreaks; and summer temperature would have a mixed impact on SPB infestations. Compared to temperature, precipitation would have a much smaller impact on SPB infestations. While increases in the previous winter, spring, and fall precipitation would enhance SPB outbreak risk in the current year, a wetter summer would reduce infestations 3 years later. Global climate change induced by doubling atmospheric CO_2 concentration would intensify SPB infestation risk by 2.5–5 times. If the changes in the area and productivity of southern pine forests due to climate change are accounted for, SPB would cause even more severe damage, 4–7.5 times higher than the current value of trees killed annually.

Keywords: Southern pine beetle; Infestation risk; Climate change; Panel data

1. Introduction

The southern pine beetle (SPB) (*Dendroctonus frontalis* Zimmermann) is the most destructive insect to southern pine forests. From 1970 to 1996, trees killed by SPB were valued at nearly US$ 1.5 billion in the US south (Price et al., 1998). Among the factors that influence SPB infestations, climate is probably the most recognized and important one (Gagne et al., 1980; Ungerer et al., 1999). Due to increasing CO_2 concentration in the atmosphere, global climate is predicted to change at an unprecedented rate over the next century (IPCC, 2003). Changes in temperature and precipitation would influence SPB populations directly, through the physiological process of the insect, and indirectly, through its host trees and natural predators. Consequently, climate change could have profound effects on the distribution and abundance of SPB (Ayres and Lombardero, 2000), and thus the

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range (area) and intensity (risk) of SPB infestations. SPB outbreak areas are projected to expand and generally shift northward as temperature increases. The expansion of the projected infestation areas would be primarily due to the shifts in the distribution of southern pines resulting from climate change (Williams and Liebhold, 2002). However, the impact of climate change on the intensity of SPB infestations, particularly in terms of economic damage, has been relatively unexplored.

While the links between climate and SPB populations have long been recognized (Craighead, 1925; Beal, 1927), the efforts to date to quantify climate-SPB outbreak relationships have met with only limited success. Many agree that extremes in temperature and precipitation affect SPB populations and host trees, influencing SPB infestations. Cold winters and hot summers generally reduce SPB populations (Beal, 1929; Thatcher, 1960) while moisture deficits and surpluses could both contribute to SPB outbreaks (Kalkstein, 1974; Warning and Cobb, 1989). Attempts also have been made to develop the correlations between climatic/weather conditions and SPB outbreaks. Several studies were conducted to relate a variety of climatic variables to SPB outbreaks using multiple regressions (King, 1972; Kroll and Reeves, 1978; Campbell and Smith, 1980). However, the potential multicollinearity among the independent variables might introduce biases to the results (Kalkstein, 1981). As a result, findings from these studies are often confusing and contradicting with each other (Turchin et al., 1991). To avoid the multicollinearity problem, principal component analysis (PCA) was employed to establish regression relationships between climatic/weather conditions and SPB outbreaks (Kalkstein, 1981; Michaels, 1984; Michaels et al., 1986). In this approach, a series of independent linear combinations (principal components) of climatic data is generated, and then used to fit the regression model of SPB outbreaks. While the introduction of PCA alleviates multicollinearity, exclusion of other nonclimatic/weather factors creates new limitations and lessened the predictive capability of these models (Martinat, 1987; Turchin et al., 1991; McNulty et al., 1997). For this reason, their results are mostly qualitative rather than quantitative (Michaels, 1984). In addition, it becomes very cumbersome to separate or identify the effects of individual climatic factors like temperature and precipitation in a specific time period, because each principal component is related to many climatic factors in various time periods included in the model.

Moreover, these earlier models developed using time series data cannot account for natural and human adaptation to climate change. Incorporating natural and human adaptation is important in assessing climate change impacts because the impacts are complex and interrelated (Mendelsohn et al., 1994; Chen and McCarl, 2001; Lindner et al., 2002). Because global climate change would take place gradually over a long time period, the insect, its natural enemies, and host trees may adapt to the change. Meanwhile, climate change is likely to alter stand composition as it affects species distribution and abundance and forest landscapes due to natural and human adaptation (Davis and Zabinski, 1992; Bachelet and Neilson, 2000), which also could affect SPB outbreaks. Also, human beings may respond to SPB outbreaks by altering forest management practices and salvation efforts according to the severity of damage and timber market conditions (Hedden, 1978; de Steiguer et al., 1987). Because existing models are inappropriate for quantifying the impact of climate change and fail to account for natural and human adaptation, more robust approaches and models are needed for evaluating the risk and damage of SPB infestations resulting from climate change.

To overcome these deficiencies, the panel data modeling approach is used to assess the impact of climate change on SPB outbreak risk and the value of the damage caused by SPB due to climate change. Compared to the models using time series or cross-sectional data, panel data models can alleviate collinearity and are better able to control for the effect of missing or unobserved variables (Baltagi, 2001; Hsiao, 2003). This is particularly useful for fitting regression models associated with climatic variables that are often highly correlated and in the case of data limitations on some relevant variables. Because panel data share the features of both cross-sectional and time series data, this approach also is able to account for human and natural adaptation to climate change. Therefore, panel data modeling is an appropriate approach to assessing the impacts of climate change on SPB outbreaks. The estimated risk and damage of SPB outbreaks would be helpful in better understanding the potential impact of climate change on southern pine forests.

2. Methods

2.1. Model specification

A model for panel data can generally be expressed as

$$y_{it} = \alpha_i + \gamma_t + \beta' x_{it} + \varepsilon_{it} \tag{1}$$

where $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$; y the dependent variable; x a $k \times 1$ vector of explanatory variables; β a $k \times 1$ vector of constants; α the individual effect; γ the time effect and ε the error term.

If for some reason, some relevant variable z_{it} is omitted in Eq. (1), the effect of omitting z_{it} can be accounted for by the individual or/and time effects. For instance, if $z_{it} = z_i$ for all t, its effect will be incorporated into α_i. Similarly, if $z_{it} = z_t$ for all i, the effect will be incorporated into γ_t. Thus, Eq. (1) estimated using panel data can better control for the effect of omitting or unobserved variables than the models using time series or cross-sectional data alone.

Earlier studies have identified several factors that may be related to SPB outbreaks, including climate (as discussed earlier), previous SPB populations (Turchin et al., 1991), volume of host trees (Gumpertz et al., 2000), and control measures (Carter et al., 1991). Drawing on these existing findings, several variables were selected for inclusion in our model. The dependent variable was the risk of SPB infestation, measured by the proportion of the timber volume killed by SPB against the growing stock of all pine species at a given time for each state. The independent variables included seasonal average daily temperature and total precipitation, and the amount of the infested forest stock that was not salvaged. The spring season was from March to May; the summer from June to August; the fall from September to November; and the winter from December to February. SPB population and infestations have shown strong seasonal patterns. Winter climatic conditions are critical to SPB overwintering. Most of the SPB infestations as well as the growth of southern pines occur during the summer, while infestations can take place during the spring in the Gulf areas and during the fall in the Piedmont and Mountain regions (de Steiguer et al., 1987). In addition to the climatic variables, human intervention and infestation control measures also are likely to influence the risk of SPB infestations. To account for the effect of human intervention, the amount of unsalvaged infested timber, measured as percentage against the growing stock of pine trees, also was included in the model. The unsalvaged timber represents the SPB population remaining in the forest, which is likely to affect future infestations (Turchin et al., 1991; McNulty et al., 1997). On the other hand, it also relates to the efforts of salvage harvest, which is the most recommended direct control method for treating SPB infestations (Swain and Remion, 1981) and has largely replaced chemical and other treatments since the early 1970s (Price et al., 1998). Because climatic conditions also are likely to have lagged impacts on SPB infestations (Kroll and Reeves, 1978), lagged independent variables, which measure the past values of the variables, were included in the model as well. The empirical model can be written as

$$\begin{aligned} \mathrm{RISK}_{it} = \alpha_i + \gamma_t + \sum_{\rho=0}^{m} (&\beta_{0\rho}\,\mathrm{USV}_{i,t-\rho} + \beta_{1\rho}\,\mathrm{SPT}_{i,t-\rho} \\ &+ \beta_{2\rho}\,\mathrm{SMT}_{i,t-\rho} + \beta_{3\rho}\,\mathrm{FLT}_{i,t-\rho} \\ &+ \beta_{4\rho}\,\mathrm{WNT}_{i,t-\rho} + \beta_{5\rho}\,\mathrm{SPP}_{i,t-\rho} \\ &+ \beta_{6\rho}\,\mathrm{SMP}_{i,t-\rho} + \beta_{7\rho}\,\mathrm{FLP}_{i,t-\rho} \\ &+ \beta_{8\rho}\,\mathrm{WNP}_{i,t-\rho} + \varepsilon_{it}) \end{aligned} \tag{2}$$

where $i = 1, 2, \ldots, N$ (section/state); $t = 1, 2, \ldots, T$ (time/year); $\rho = 0, 1, \ldots, m$ (lags, i.e. the number of years lagged from the current year); RISK the risk of SPB outbreaks (the proportion of the timber volume killed by SPB in terms of the total pine growing stock); USV the proportion of unsalvaged volume in terms of the total pine growing stock; SPT the spring average daily temperature; SMT the summer average daily temperature; FLT the fall average daily temperature; WNT the winter average daily temperature; SPP the total spring precipitation; SMP the total summer precipitation; FLP the total fall precipitation; WNP the total winter precipitation and α, γ, and ε are the same as defined earlier in Eq. (1).

2.2. Data

The data on SPB outbreaks were obtained from Price et al. (1998). The total annual volume (including both pulpwood and sawtimber) killed by SPB was used. The data covered the period from 1973 to 1996 for 11 southern states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia. Seasonal temperature and precipitation were derived from the National Climatic Data Center (2003). The growing stock of pine forests was drawn from forest inventory data (Smith et al., 2001). Because the forest inventory data were compiled every 5–10 years, linear interpolations were employed to generate the annual series. The linear interpolations are justifiable because the growing stock at the state level generally changes gradually over time.

2.3. Model estimation

Estimation of the model involved a series of interactive procedures and tests, including the selection of variables (discussed in Section 2.1), lags, fixed or random effects, function form, and appropriate estimation methods. To determine the lag number, the process began with the 10th-order lags (10 years lagged from the current year) in Eq. (2), which, based on existing literature, should be able to capture the potential lagged impact of the explanatory variables on SPB infestations. Then, F-tests were performed to test the lower order restrictions of the 10th-order model. If a lower order restriction was able to be rejected, then an appropriate lag number was identified. To illustrate this process, let us begin with comparing the 9th-order model with the 10th-order model, if the restriction imposed on the 10th-order model for the 9th-order model (i.e. the hypothesis that the coefficient associated with the 10th lagged variable is equal to zero) is unable to be rejected, then the 10th lagged variables is statistically insignificant and can be removed from the model. Then the 8th-order model is tested against the 10th-order model. The same process continues until at a certain lag the restriction can be rejected, which implies that the variable with that lag is significant and should be included in the model. Another issue with panel data modeling is whether a fixed or random effects model is more appropriate. This is largely dependent on its error component. An F-test for fixed effects (Hsiao, 2003) and the Hausman test for random effects were conducted for this purpose.

Meanwhile, collinearity, heteroscedasticity, and serial correlation were checked. Collinearity was checked using the maximum condition index. Both the White's and Breush–Pagan–Godfrey (B–P–G) tests were conducted to detect heteroscedasticity. The Lagrange multiplier (LM) tests developed by Baltagi and Li (1995) were used to test autocorrelation in fixed or random effects models. Because fixed effects, heteroscedasticity, and autocorrelation were detected for the model associated with various lags tested, the fixed effects model was chosen and estimated using the Parks method. The Parks method is an efficient estimation method that can control for heteroscedasticity, autocorrelation, and contemporaneous correlation in panel data models (Parks, 1967). Finally, insignificant variables were dropped from the model using the backward stepwise method. Both linear and log-linear models were fit. However, the examination of the statistical significance of the power transformation parameters via the Box–Cox Transformation (Box and Cox, 1964) indicated that the log-linear model was better fit. Therefore, the log-linear model was selected.

For the final model, the F-tests rejected the null hypothesis of no one-way or two-way fixed effects at the 1% significance level ($P < 0.0001$). This indicates the existence of the fixed effects for both time and states. Thus, the fixed-effects model was an appropriate choice. Choosing the fixed-effects model also has other advantages over the random-effects model that may suffer from the inconsistency due to omitted variables and requires noncorrelations between the individual effects and other regressors (Greene, 2003). Both the White's and B–P–G tests suggested the rejection of homoscedasticity at the 5% level ($P = 0.0211$ for the White's test and $P = 0.0003$ for the B–P–G test). The calculated LM test statistics (7.04) led us to rejecting the null hypothesis of no autocorrelation at the 1% significance level. The estimated first-order autoregressive parameters ranged from -0.013 to 0.411. Also, several states have showed similar patterns of SPB outbreaks over time, suggesting potential correlations across states (to be further discussed later). Therefore, the Parks method was an appropriate estimation method for this model.

2.4. Assessment of climate change impacts

Due to the uncertainties of climate change, four climate change scenarios were developed and applied to the assessment of impacts on SPB outbreak risk.

Each climate change scenario was based on the simulation results from a specific General Circulation Model (GCM). The four scenarios correspond to four GCMs: the NASA Goddard Institute for Space Studies (GISS) model (Hansen et al., 1983), the Geophysical Fluid Dynamics Laboratory (GFDL) model (Manabe and Wetherald, 1987), the Oregon State University (OSU) model (Schlesinger and Zhao, 1989), and the United Kingdom Meteorological Office (UKMO) model (Wilson and Mitchell, 1987). These scenarios were parallel to those used in assessing the productivity and sustainability of southern forests by Cooter (1998). The seasonal temperature and precipitation changes in the southeastern United States predicted by these GCMs were directly applied to our regression model to simulate the potential impact of climate change on SPB outbreak risk in the region. For simplicity, it was assumed that the proportion of unsalvaged volume relative to the growing stock would remain the same in the future.

The value (V) of trees killed by SPB in the presence of global climate change was calculated by

$$V = PY\delta \qquad (3)$$

where P is the stumpage price (US\$/m^3); Y the volume of pine growing stock (m^3) and δ the SPB infestation risk under global climate change.

In estimating the damage value by SPB under global climate change, it was further assumed that the current shares of pulpwood and sawtimber in the total volume killed by SPB remain unchanged. The stumpage price represents the weighted average (in terms of the proportions of pulpwood and sawtimber killed by SPB) of the pulpwood and sawtimber prices reported in Louisiana (Howard, 2001). To avoid the effect of price fluctuations and inflation, the 10-year average price from 1990 to1999 measured in the 1992 constant dollars was used.

Climate change induced by elevated CO_2 concentration will not only affect SPB infestation risk but also forest stock as it would alter forest productivity and spatial distribution. Thus, the damage was evaluated under two situations: with and without consideration of forest stock changes due to climate change. The changes in southern pine forest area under climate change were derived from Bachelet and Neilson (2000). Miller and Haynes (1995) reported the mean percentage change in the net primary productivity for southern pines in the Southeast and South Central regions under the doubled CO_2 level. The weighted average (in terms of pine growing stock) of the change in the net primary productivity in these two regions was calculated and used in the analysis.

3. Results

3.1. Risk and spatial patterns of SPB infestations

Table 1 shows the average infestation rate and volume killed by SPB annually across states from 1973 to 1996. The volume includes both pulpwood and sawtimber. Again, the infestation rate or risk represents the proportion of the volume killed against the total pine growing stock. Of the 11 states, Alabama had the highest infestation rate and volume killed, while Florida had the lowest infestation rate and volume killed. Tennessee had the second higher SPB infestation rate, followed by South Carolina, Louisiana, Georgia, Texas, and North Carolina. Besides Alabama, other states that have an annual average volume killed exceeding 200,000 m^3 include Georgia, Louisiana, South Carolina, and North Carolina.

SPB infestations also show strong correlations across states (Table 2), suggesting comovements in SPB infestations among these states. The infestations

Table 1
Annual average infestation rates and volume killed by the SPB, 1973–1996[a]

State	Volume killed (1000 m^3)	Infestation rate (‰)
Alabama	561.7	1.816
Arkansas	33.7	0.147
Florida	17.4	0.091
Georgia	433.5	1.034
Louisiana	284.9	1.157
Mississippi	128.3	0.500
North Carolina	217.6	0.712
South Carolina	260.5	1.185
Tennessee	62.3	1.219
Texas	183.7	0.823
Virginia	102.5	0.607
Total	2286.1	0.845

[a] The infestation rate is measured as the proportion of the volume killed by SPB relative to the pine growing stock. Source: Price et al. (1998).

Table 2
Correlation coefficients of SPB infestations among states[a]

	AL	AR	FL	GA	LA	MS	NC	SC	TN	TX	VA
AL	1.000		0.456	0.634		0.474	0.461	0.412			
AR		1.000	0.443					0.631			
FL			1.000			0.603		0.600			
GA				1.000		0.424		0.439			
LA					1.000					0.791	
MS						1.000					
NC							1.000		0.665		
SC								1.000			
TN									1.000		
TX										1.000	
VA											1.000

[a] Only the correlations significant at the 5% level are shown here. AL, Alabama; AR, Arkansas; GA, Georgia; FL, Florida; LA, Louisiana; MS, Mississippi; SC, South Carolina; NC, South Carolina; TN, Tennessee; TX, Texas; and VA, Virginia.

in Alabama, Florida, Georgia, Mississippi, North Carolina, and South Carolina were significantly correlated; the infestations in Arkansas were related to those in Florida and South Carolina; and the outbreaks in Tennessee were linked to those in North Carolina. This implies that SPB outbreaks occurred simultaneously among these eight states. Interestingly, the infestations in Texas and Louisiana were highly correlated, but not related to other states. Thus, SPB outbreaks in Texas and Louisiana moved together, even though they might have different outbreak patterns from other states. Moreover, SPB infestations in Virginia were not related to those in any other states, suggesting a unique temporal pattern of SPB outbreaks in the state.

3.2. Regression results

The estimated regression model is shown in Table 3. Due to the long list of the dummy variables (representing the fixed effects), the estimated coefficients associated with them are not presented. The R^2 and adjusted R^2 indicate that the model is generally well fit. The maximum condition index suggests that there is no apparent collinearity among the regressors. Since it is a log-linear model, the coefficients in Table 3 represent elasticities, i.e. percentage changes in SPB infestation risk for a 1% change in a specific independent variable.

Climatic conditions significantly affected the risk of SPB outbreaks. Temperature and precipitation in all seasons either in the current or earlier year were related to SPB outbreaks. However, the magnitudes and directions of the impacts of seasonal temperature and precipitation varied across seasons. Increases in winter and spring temperatures would increase the risk of SPB outbreaks while rises in fall temperature would lessen the severity of infestations. The positive correlation between SPB outbreaks and winter temperature echoes earlier findings (Michaels, 1984). However, only the previous year's winter temperature had an impact on current SPB outbreak risk, and the magnitude (elasticity) of its impact was much smaller than that of other season's temperature. Therefore, a warmer winter might help SPB overwintering, leading to a higher risk of its outbreaks in the following year. But, its impact was relatively small compared to temperature changes in other seasons. For a 1% increase in the previous winter temperature, SPB outbreak risk in the current year would increase by only 0.53%. Warmer springs, particularly continuous warming in consecutive spring seasons, would tremendously increase the chance of SPB outbreaks. Spring temperatures in the current and past 3 years were all positively related to SPB outbreaks. The spring temperature elasticity of SPB outbreaks ranged from 8.79 to 14.87. The high sensitivity of SPB infestation risk to spring temperature may be partly because warmer springs coupled with abundant food as the host trees start to grow during the season would cause SPB populations to grow earlier and more rapidly. On the other hand, warmer falls in the current year and 2 years earlier would help alleviate SPB outbreak risk, with an elasticity of 13.85 and 9.10, respectively. Summer

Table 3
The estimated regression model describing the relationships between the risk of SPB outbreaks and climatic conditions

Independent variable	Estimated coefficient	P-value
ln SPT (spring temperature in the current year)	9.6332	0.0021
ln SMT (summer temperature in the current year)	−19.0138	0.0036
ln FLT (fall temperature in the current year)	−13.8521	0.0001
ln USV_{-1} (unsalvaged volume in the previous year)	0.2735	<0.0001
ln WNT_{-1} (winter temperature in the previous year)	0.5306	0.0133
ln SPT_{-1} (spring temperature in the previous year)	14.8663	<0.0001
ln SMT_{-1} (summer temperature in the previous year)	−19.6574	0.0023
ln WNP_{-1} (winter precipitation in the previous year)	−1.3903	0.0017
ln SPP_{-1} (spring precipitation in the previous year)	−1.0942	0.0141
ln FLP_{-1} (fall precipitation in the previous year)	−0.7764	0.0517
ln SPT_{-2} (spring temperature 2 years earlier)	12.9302	<0.0001
ln FLT_{-2} (fall temperature 2 years earlier)	−9.1044	0.0164
ln USV_{-3} (unsalvaged volume 3 years earlier)	−0.1383	0.0005
ln SPT_{-3} (spring temperature 3 years earlier)	8.7944	0.0056
ln SMT_{-3} (summer temperature 3 years earlier)	31.0637	<0.0001
ln SMP_{-3} (summer precipitation 3 years earlier)	3.8702	<0.0001
R^2	0.980	
Adjusted R^2	0.975	
Maximum condition index	12.76	

temperature had a mixed impact on SPB infestations. Warmer summers in the current or previous year would suppress SPB outbreaks while a rise in summer temperature 3 years earlier would contribute positively to current infestation risk. Although the negative impact of summer temperature in the current or previous year would be partially offset by the positive impact of a hotter summer 3 years earlier, overall continuing warming in summer would reduce SPB infestation risk.

SPB infestation risk would decrease as precipitation in the previous winter, spring, and fall increases or as summer precipitation 3 years earlier decreases. Except for winter, seasonal precipitation elasticities were smaller than seasonal temperature elasticities. Therefore, the magnitude of precipitation impacts on SPB infestations was in general much smaller than that of temperature impacts. A 1% increase in winter, spring, and fall precipitation in the previous year would reduce the risk of SPB outbreaks in the current year by 1.39, 1.09, and 0.78%, respectively. On the other hand, a 1% rise in summer precipitation 3 years earlier would increase the risk in the current year by 3.87%. This implies that a wet summer 3 years earlier would increase SPB outbreaks while moisture deficiencies (precipitation reductions) in the previous winter, spring, and fall would boot SPB infestation risk in the current year.

Many lagged seasonal temperature and precipitation variables were found significantly related to SPB outbreaks. Earlier studies also revealed that climatic conditions in the previous year significantly affected SPB outbreaks in the current year (Kroll and Reeves, 1978; Kalkstein, 1981). The lagged effects may be due to the response time needed for SPB populations to develop and reach an epidemic level. Such response time could be relatively long. In some cases, it could take up to 3 years or longer for SPB populations to develop into an epidemic level area wide (Turchin et al., 1991). Past climatic conditions also may have cumulative effects on the stress development of host trees or their resistance to SPB. In addition, short delays may occur in detecting the infested spots after trees were attacked by SPB (Kalkstein, 1974, 1976).

Unsalvaged timber also showed its significant impacts on SPB infestations. While an increase in the proportion of unsalvaged timber in the previous year would increase SPB infestation risk in the current year, a rise in the proportion of unsalvaged timber 3 years earlier would decrease the risk. Overall, unsalvaged timber would have a positive impact on SPB infestations. Thus, salvation of trees killed by SPB, in

Table 4
Climate change scenarios and resultant impacts on SPB outbreaks[a]

Variable	Climate change scenario (GCM)			
	I (GISS)	II (GFDL)	III (OSU)	IV (UKMO)
Change in winter temperature (°C)	4.6	4.0	3.5	6.7
Change in spring temperature (°C)	4.2	3.9	3.6	6.3
Change in summer temperature (°C)	4.1	4.1	3.6	6.5
Chang in fall temperature (°C)	4.4	4.1	3.5	6.7
Change in winter precipitation (%)	−11	11	−7	5
Change in spring precipitation (%)	5	15	−8	2
Change in summer precipitation (%)	15	2	12	0
Change in fall precipitation (%)	−2	5	2	−4
Increase in pine forest area (%)	57	25	41	25
Increase in SPB outbreak risk (%)	396	253	351	508
Estimated annual value of trees killed by SPB (without consideration of changes in pine forest area and productivity) (US$ mil.)	513.68	365.68	466.61	629.61
Estimated annual value of trees killed by SPB (with consideration of changes in pine forest area and productivity) (US$ mil.)	868.81	492.47	707.46	847.91

[a] GISS, the NASA Goddard Institute for Space Studies model; GFDL, the Geophysical Fluid Dynamics Laboratory model; OSU, the Oregon State University model and UKMO, the United Kingdom Meteorological Office model. The increase in pine forest area due to climate change was derived from Bachelet and Neilson (2000). The productivity for southern pines was assumed to increase by 7.6% under doubled atmospheric CO_2 concentration (Miller and Haynes, 1995).

general, would help reduce future infestation risk although the overall impact was relatively small. For a 1% reduction in the proportion of unsalvaged timber against the total growing stock, the overall future infestation risk would reduce by about 0.14%.

3.3. Climate change impacts

Table 4 shows the impact of climate change on the risk and damage of SPB infestations. Although the estimated SPB infestations varied across the climate change scenarios, SPB infestation risk was predicted to increase under the elevated CO_2 level. Under the four climate change scenarios, the risk of SPB outbreaks would increase by 2.5–5-fold from its current level. The magnitude of SPB outbreak risk was intensified by uneven percentage changes in temperature and precipitation across seasons, especially by the relatively high percentage changes in winter and spring temperatures. Even a uniform percentage increase in temperature or precipitation across the four seasons would tend to enhance SPB infestation risk. This is because the positive impacts of warmer winters and springs would outweigh the negative impacts of hotter summers and falls, leading to a higher risk of SPB outbreaks. And, increases in summer precipitation would drive infestation risk up more than the counter-effect imposed by increased precipitation in other three seasons.

The estimated annual average value of timber killed by SPB for all the 11 states would range from US$ 366 to 630 million, even without accounting for the potential expansion in pine forest areas and increases in forest productivity. Under the climate change scenarios as predicted by the four GCMs, the area of southern pine forests would increase by 25–57%. The productivity of southern pine was predicted to grow by 7.6% as atmospheric CO_2 concentration doubles. When the changes in pine forest area and productivity are incorporated, the value of damage would reach US$ 492–869 million annually, about 4–7.5 times higher than the current level. These damage values might be overestimated because the average infestation risk was applied to all areas of southern pine forests. The infestation risk in the new pine forest areas resulting from climate change could be lower than the average risk because the new pine forests would emerge in areas colder than where southern pine forests are currently located. Also note that the damage measures only the value of timber killed by SPB, not the value lost, which may be smaller because part of the infested trees would be salvaged. On the other hand, it does not account for the regeneration costs of infested spots and the delay in stand growth, nor measures the total welfare impact on producers and consumers.

4. Conclusions

This article assesses the impact of climate change on the risk and damage of SPB infestations via panel data modeling. This approach alleviates the collinearity problem usually associated with climatic variables and accounts for the effect of omitted or unobserved variables. As a result, it is more appropriate for estimating the effect of individual climatic variables on SPB outbreaks. In addition, the panel data model incorporates natural and human adaptation to climate change into the impact assessment. Therefore, it is a more robust method for predicting the impact of climate change on SPB infestations.

Historical data reveal the existence of potential spatial patterns of SPB outbreaks in the southern United States. SPB outbreaks in Louisiana and Texas were significantly correlated; infestations in Alabama, Arkansas, Florida, Georgia, Mississippi, South Carolina, North Carolina, and Tennessee seemed to move together; and Virginia displayed its unique temporal outbreak pattern. These patterns would have value for the prediction and control of future SPB outbreaks in the region. Our results also indicate the complexity of the impact of climatic factors on SPB outbreaks. Consistent with existing findings, winter temperature was found to be positively related to SPB infestations. However, its magnitude was much smaller than that of spring temperature, which was likely to have more severe and persistent impacts on SPB infestations. Summer temperature would have a mixed impact while a warmer fall would contribute negatively to SPB infestations. Compared to temperature, precipitation would have relatively small impacts. While increases in precipitation in the previous winter, spring, and fall would alleviate SPB infestation risk, too much rainfall in summer could stimulate SPB outbreaks. In addition, salvage harvest was found to have an overall negative impact on SPB outbreaks, suggesting its helpfulness in controlling SPB infestations.

Global climate change would intensify the risk of SPB outbreaks and cause more extensive and severe SPB damage to southern pine forests. On average, SPB infestation risk in the southern United States would increase by 2.5–5 times as atmospheric CO_2 concentration doubles. Because climate change also might increase the area and productivity of southern pine forests, the damage caused by SPB is likely to be even more severe. This could create a tremendous challenge for controlling SPB outbreaks in the future if the assumed global climate change under the doubled CO_2 level occurs.

In addition to climatic factors other variables like stand density also may affect SPB infestations. Unfortunately, existing data do not record stand density of the SPB infested spots. This creates difficulty in incorporating stand density in the regression model, resulting in potential biases to the estimated results. However, because of the unique features of the panel data model, the effects of omitted variables have been alleviated. This is an advantage of panel data modeling over other regression methods using time series or cross-sectional data alone. Furthermore, due to the uncertainties in climate change and its potential impacts, general caution should be taken in the interpretation and applications of the findings. More studies on this subject are strongly recommended to further clarify the impact of climate change on SPB infestations. Hopefully, this study has provided additional insights into existing knowledge of the relationship between climatic/weather factors and SPB infestations and the impact of climate change on SPB outbreaks.

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