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How to fight against southern pine beetle epidemics: An insurance approach

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Abstract
The southern pine beetle (SPB) is among the leading biological agents killing southern pine species in the eastern United States. In light of recognized spatiotemporal autocorrelation in SPB outbreaks, we devise a spatiotemporal block bootstrapping method that can be applied to analyze spatiotemporally dependent infestations. We also identify the relevant risk determinants and evaluate their impacts on the frequency of SPB outbreaks. For example, we find forest type, climate, and natural disasters like storm and forest management are all significantly associated with SPB risks. Using the results of a statistical model, we design a county-level group index insurance plan that generates estimates of actuarially fair premium rates for timber stands containing southern pine species. Given that no government-provided compensation scheme for SPB epidemics currently exists, application of this new insurance product could reduce forest owners losses. Our study offers an approach to analyzing and protecting against risks of other destructive pests affecting the timber sector.

KEYWORDS
index insurance, southern pine beetle, timber, spatiotemporal correlation

Le dendroctone méridional du pin (DMP) est l'un des principaux agents biologiques tuant les pins dans l'Est des États-Unis. À la lumiére de l'autocorrélation spatio-temporelle des épidémies de DMP, nous avons mis au point une méthode d'amorçage en bloc (bootstrapping) spatio-temporel qui peut être utilisée pour analyser les infestations qui sont spatio-temporellement dépendantes. Nous identifions également les déterminants de risque pertinents et évaluons leurs impacts sur la fréquence des épidémies de DMP. Par exemple, nous constatons que le type de forêt, le climat, les catastrophes naturelles telles que les tempêtes et la gestion des forêts sont tous significativement associés aux risques de DMP. À l'aide des résultats d'un modéle statistique, nous concevons un régime d'assurance de type indexé sur les groupes au niveau du comté qui génére des estimations des taux de prime équitables sur le plan actuariel pour les peuplements de bois contenant des espéces de pins du sud. Étant donné qu'il n'existe actuellement aucun systéme d'indemnisation fourni par le gouvernement pour les épidémies de DMP, l'application de ce nouveau produit d'assurance pourrait réduire les pertes des propriétaires forestiers. Notre étude propose une approche pour analyser et protéger contre les risques d'autres ravageurs nuisibles affectant le secteur du bois.

1 | INTRODUCTION

The southern pine beetle (SPB) (*Dendroctonus frontalis* Zimmermann) is among the most destructive pests in the U.S. forest sector (Pye, Holmes, Prestemon, & Wear, 2011). Since record keeping began on SPB outbreaks,[1] scientists have observed that SPB outbreaks occur, on average, every 10–12 years (Billings & Upton, 2010). In the Southern United States, the development of the second generation of commercial forest systems in the United States (i.e., wide adoption of pine trees) provided a suitable environment for SPB inhabitation. As both the size and the density of pine forests increase, SPB outbreaks have been observed more frequently. This topic is of growing interest especially because SPB outbreaks have increased from near undetectability in the 1960s to more widespread epidemics in recent years (Aukema et al., 2011; Gumpertz, Wu, and Pye, 2000; Mawby & Gold, 1984).

Scholars from different scientific backgrounds have done extensive research on infestation, spread, and outbreak patterns of SPB. Biologists (Hofstetter, Cronin, Klepzig, Moser, & Ayres, 2006; Vasanthakumar et al., 2006) have studied the individual SPB infestation behavior, while forest entomologists (Fargo, Coulson, Pulley, Pope, & Kelley, 1978; Staeben, Sullivan, Nowak, & Gandhi, 2015; Strom, Meeker, Bishir, Roberds, & Wan, 2016) have studied the SPB outbreaks at the stand scale. In addition, SPB outbreaks across tree stands and at the landscape level have been evaluated (Niemiec, Lutz, & Howarth, 2014; Nowak, Meeker, Coyle, Steiner, & Brownie, 2015). However, not until recently have the broadscale SPB outbreaks been recognized as an important indicator to measure the SPB hazard for large spatial units, such as a county. Such a class of studies focused on studying the SPB outbreak probabilities to evaluate the associated economic losses. Most such literature focused on whether an SPB outbreak would occur in a county, no matter how big or small the potential damages. In other words, a modest endemic and a destructive epidemic were treated indifferently. For example, Zhu, Huang, and Wu (2005) used spatiotemporal Bayesian statistical methods to estimate the county-level probability of SPB outbreaks in North Carolina. They employed a binary-dependent variable that measures SPB risk. That is whether there were any SPB spot[2] found in a county, regardless of the intensity of SPB outbreaks.

Although broadscale probabilities of SPB infestations in the southern states have already been studied with spatiotemporal models (Pye, Price, Clarke, & Huggett, 2004), the frequencies of SPB outbreaks at the aggregate level (e.g., county) have less often been investigated. It is observed that the economic costs vary dramatically when the SPB activity fluctuates (Pye et al., 2004). It is found that the economic costs of SPB infestations are more closely related to their intensities rather than their probabilities. For example, an SPB epidemic generally costs much more than an endemic infestation does.[3] Although timber losses are directly related to the severity of outbreaks, the broadscale intensities of SPB outbreaks have almost not been evaluated before. Our study focuses on the broadscale intensity (frequency) of SPB outbreaks, that is, on the county level, in the aim of providing a better tool to analyze and forecast broadscale SPB risks and associated economic costs.

At the same time, although SPB has been considered the primary mortality agent of southern pine forests (Thatcher, 1981), no associated compensation mechanism exists. The only assistance available to southern pine owners is by claiming an Internal Revenue Service (IRS) tax credit due to a casualty loss. However, such an ex-post approach is not a form of compensation scheme in the sense that it can only reduce income tax burden. In addition, since tax deductions can only be granted after disasters, they have limited influence on risk profiles.

Although tax and insurance-based incentives for compensating for SPB related losses are limited or nonexistent, government programs exist that help timberland owners reduce SPB-related natural peril. The Southern Pine Beetle Prevention Program, supported by the USDA Forest Service provides subsidies for prevention and restoration efforts.[4] It offers partial cost reimbursement or incentive payments for pulpwood thinning, prescribed burning, planting longleaf pine, and mechanical underbrush treatments, even if no SPB spots have been recently identified on the landowner's property. This program has treated more than one million acres of forest lands since its inception in 2003. However, its efficiency is still questionable since this program may distort timber markets by providing timber owners nonmarket payment for their essential treatment while costing in total nearly $110 million of government subsidies. Some states have their own SPB prevention programs. A notable example is the Texas cost sharing program. It provides state subsidies through cost sharing. Nevertheless, its utility for many timberland owners is limited by restrictions and subsidy limits. For example, the Texas program only applies to the forest landowners whose share

[1] Hereafter, "SPB" refers to southern pine beetle.

[2] A SPB spot is defined as a multiple-tree mortality center caused by SPB (Billings, 2011).

[3] As pointed out by an anonymous reviewer, economic cost of an SPB epidemic is not always larger than that of an endemic. Such costs will also be related to intensity and spatial scale of an epidemic/endemic.

[4] For details, see https://www.srs.fs.usda.gov/compass/2016/12/20/southern-pine-beetle-prevention-program/

of acreage in loblolly or slash pine types is more than 70%. The program also puts a cap on a landowner's total claim (i.e., total cost shares must not exceed $8,500 per landowner or $17,000 for a partnership).

In economics, researchers often place pest control efforts in one of two categories: self-protection and self-insurance (Carlson, 1979). In practice, self-protection refers to measures taken to reduce the probability that a loss event happens. Applications of pesticides, herbicides or insecticides fall into this category. The Southern Pine Beetle Prevention Program is an example of a self-protection. SPB protection programs mainly focus on taking proactive steps to protect forests from SPB attacks and are not targeted at active infestations. Self-insurance refers to the measures to put aside a pool of funds that one could use if economic losses occur. Such funds can be corporate or personal assets. Yet to what extent and by how much an individual timber landowner should be self-insured can be a difficult financial decision, given the unpredictable and potentially disastrous financial losses caused by SPB.

A practical alternative against such type of infrequent hazards would be commercial insurance. In the United States, several classes of insurance plans, including both multiperil and single-peril plans, are currently available to lessen pest damage in agriculture. In the timber industry, however, insurance instruments against SPB are almost nonexistent. A timber insurance plan, if available, would provide several advantages. First, from an economics' perspective, a financial arrangement that internalizes risks is the most efficient way to compensate losses caused by disasters, such as SPB. Second, the development of timber insurance products can attract both timber owners and financial institutions to share the risks associated with timber production. Furthermore, if compensation provisions for mitigation costs are also stipulated in insurance contracts, government support may become unnecessary in the future. In all, given that widespread financial losses occur on a regular basis, it makes sense that demand for a fairly priced insurance product would be enthusiastically received by a significant segment of the timberland owning population in affected regions.

Currently, almost all the timber insurance products available worldwide are all-risk plans. However, such a class of insurance plans can barely survive without government subsidies. In Brazil, most commercial forest owners were unwilling to buy insurance until 2004, when the Brazilian authorities started to subsidize forest insurance premiums. In 2009, the estimated value of these subsidies reached almost $100 million (Kunzemann, 2009). In China, 50% of forest insurance premiums are subsidized. As a result, the plans have covered 18 million hectares of forests, with the insurance subsidy totaling $17 billion by June 2010 (Petry, Zhang, & Zhang, 2010). In the U.S. forest sector, without government support, the overall nationwide forest landowners' insurance participation is close to zero.

The failures of all-risks timber insurance plans without government support may come from adverse selection and moral hazard issues, both of which are due to the asymmetric information between the insured and insurance providers. Adverse selection is caused by miscalculations of insurance premium rates for insurance policy buyers. Since a multiperil timber insurance plan has to quantify the risks of all sources hazards, tangible, and intangible, insurance companies may lack sufficient data for accurately computing an actuarially fair premium. As a result, high-risk agents are more willing to purchase insurance products than low-risk ones, which leads to an adversely selected insurance pool. In contrast, single-peril insurance plans only require considerations limited to risks associated with a specific hazard (e.g., SPB). An actuarially fair single-peril insurance plan can be more easily implemented and therefore has the potential to increase insurance participation and reduce the likelihood of adverse selection.

A moral hazard problem refers to insured agents efforts to increase the risks of losses, knowing that the potential costs of such risks will be borne by insurance providers. Moral hazard actions may range from simple mismanagement of properties to intentional fraud. If the insurer is unable to monitor such behavior on an individual basis, the insurance program may be distorted and suffers the risk of actuarial losses. As existing multiperil timber insurance policies are all individual policies with high monitoring and administration costs, it becomes fairly difficult to eliminate moral hazard issues. However, index plans are generally more robust to such moral hazard concerns. If the actions of individual agents are unable to significantly affect the aggregate index or index threshold that governs coverage and establishes losses, issues associated with moral hazard may be minimized. Moreover, as aggregate (e.g., county level) statistics on SPB outbreaks are available from government reports, the administration costs can be much smaller. In addition, the information that an index insurance program is based upon is often publicly available. Asymmetry in information among all the parties involved in the insurance contract can be minimized. Therefore, a single-peril index insurance product against SPB hazard could be an ideal financial instrument for SPB risk management. Though index insurance programs are not currently available in the forest sector, index insurance scheme has been frequently studied and continuously offered in the agricultural sector (Farrin & Miranda, 2015; Giné, Menand, Townsend, & Vickery, 2012; Karlan, Osei, Osei-Akoto, & Udry, 2014; Miranda, 1991; Miranda & Farrin, 2012; Miranda & Gonzalez-Vega, 2010). For example, the rainfall index (RI) insurance program is available for farmers to hedge the drought risks. It works as follows. The index is based on weather data collected and maintained by NOAAs Climate Prediction Center, which reflects relative precipitation is received compared to the long-term average for a specified area and time frame. Every year, USDA Risk Management Agency

(RMA) issues base values of this index of each county. Farmers in a county, if such a program is offered, can purchase this insurance product by choosing a prespecified RI level associated with RMA base value of this index. If county-wide realized rainfall, which is observed by NOAA, exceeds the selected level, all the insured will get paid. Otherwise, the insured will not receive indemnity payment.

A similar group index insurance plan for timber should be able to address the potential needs of single-peril timber insurance contracts against SPB in the southern states. It is noted that private markets for single-peril insurance contracts (i.e., hail) currently exist in the agricultural sector but not in forestry due to several factors. First, failure to offer timber insurance, both single-peril and multiperil, is partially due to the lack of the specialized forestry knowledge required to generate the actuarial information. Such knowledge includes an understanding of the long timber production process and how biological and physical variables interact to generate such perils for each individual timber stands. Those information is often complicated and difficult to comprehend. Our proposed index insurance scheme, on the contrast, should be able to overcome such difficulty since it is mostly based upon public information that is easy to obtain. Second, a primary factor influencing offerings of an insurance coverage against a certain peril at the individual level is the extent to which the relevant risk is systemic. A primary example of systemic risk in property insurance is that of flooding. A flood is likely to impact a wide area (be systemic) and thus most individual-level commercial policies exclude flood coverage. In agriculture, a fluid market for individual-level single-peril coverage of hail has existed for over a hundred years. Hail risks tend to be localized and thus nonsystemic. In the case of SPB, epidemic outbreaks sometimes cause catastrophic and widespread damage (Holmes, 1991), making the risks systemic, at least during catastrophic infestations. Similar to the recent development of flood index insurance products, our proposed broadscale group index insurance plan against SPB may be more appropriate than individual plans. Third, one potential block of customers for such insurance - timber investment management organizations and real estate investment trusts, are spatially diversified and own large timber tracts, which allows them to self-insure, and may reduce the incentives for insurance companies to invest in knowledge generation for timber insurance. Yet, these organizations and trusts always have to bear financial losses if SPB-caused damages occur. Therefore, an instrument to hedge the SPB risks may still be appealing to them, especially if such risks could be systematic (i.e., if most of one's land is in the southern United States). In addition, the majority of timberland in the south is owned by private owners (Chen, Goodwin, & Prestemon, 2013), which warrants demand for a timber insurance product against SPB.

Another advantage that index insurance plans provide is that they can condition purely on pest damages (Carlson, 1979). Similar to crops, timber losses may be complicated for various reasons. An individual insurance plan against SPB is difficult to operate in the sense that it is almost impossible to separate insured damage from uninsured damage in some cases. For example, if a timber stand experiences both SPB and wildfire (potentially connected to SPB-killed trees) within the same year, the timber value losses attributable to SPB are difficult to quantify. While individual plans heavily rely on a case-by-case assessment, an index plan solely depends on the aggregate index, such as the extent or existence of county-level SPB outbreaks.

Our study focuses on SPB outbreaks in the southern United States. Since SPB outbreaks are found to be spatially and temporally autocorrelated (Figures 1 and 2), it is necessary to accommodate their autocorrelations using appropriate econometric methods. In our paper, a block bootstrapping method with zero-inflated estimation has been proposed to construct statistical models that include exogenous covariates while adjusting for spatial and temporal autocorrelation. With this approach, the statistical models that we produce allow for inferences on the effects of covariates, generating conclusions about the influences of environmental factors on SPB outbreaks, which have implications for southern pine timber management in the subject region. Almost all the explanatory variables, including soil moisture, temperature, tree species, and hurricane occurrences, are found in our models to have significant impacts. Soil moisture is found to be negatively related to SPB outbreaks, while temperature is positively related. Forest type is found to be a significant factor related to the probability of SPB outbreaks: loblolly shortleaf and oak-pine types are positively related to SPB infestation (outbreak) probability, while longleaf-slash and oak-gum-cypress types are negatively related. Size of a forestland parcel and the government share of forestland are significantly positively correlated with the likelihood of an SPB outbreak. An unexpected finding is that hurricanes are found to lessen SPB outbreaks, ceteris paribus. By combining current environmental information, as measured by the included covariates, with the spatiotemporal patterns identified by our statistical models, our method offers a way to forecast the frequency of future SPB outbreaks.

This study makes two primary contributions to the literature. First, we apply a novel modeling approach, using a block-bootstrapping method combined with zero-inflated count models, to characterize broadscale SPB outbreaks at the county level. Second, we outline, using the statistical results, a new and potentially viable financial instrument that timberland owners could use to hedge against SPB risks.

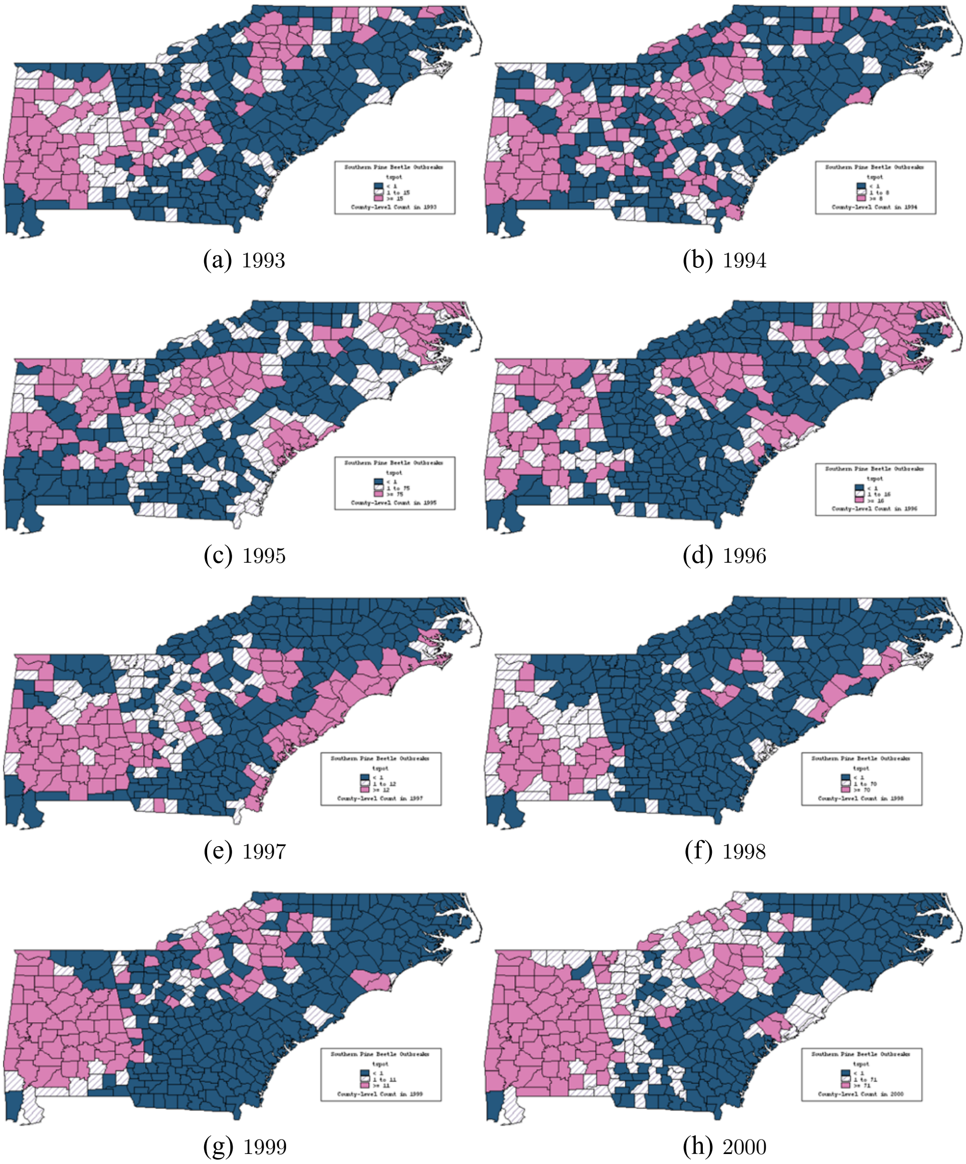


FIGURE 1 County-level SPB outbreaks during eight consecutive years in AL, GA, SC, and NC: on each map, three different colors represent three levels of outbreaks (i.e., no SPB spot finds, less than the median of positive finds, and no less than the median)

2 | RISK MODELS AND INSURANCE CONTRACTS

As mentioned above, contagious pests such as SPB pose significant hazards to timber stands and thus warrant a consideration of single-risk index insurance plans. Such plans may supply several benefits. First, actuarially fair timber insurance programs may result in a free private market for risk sharing against the SPB hazard. Second, if carefully designed, the development of such programs can provide an instrument to mitigate SPB risks and further lessen its spread.

In insurance contracts, an actuarially fair insurance premium (or premium rate) is calculated based upon knowledge of risks. Any effective insurance scheme relies on a full comprehension of all underlying risks associated with potential loss events. The actuarially fair rate is the rate (expressed in terms of total premium as a percentage of total liability) that sets total premiums equal to expected total indemnities. For instance, if someone expects to pay \$10,000 in a typical year on an insurance contract that covers up to \$200,000 in total liability, the actuarially fair premium rate is 0.05 (or 5%).

To measure the actuarially fair premium rate, we always model the conditional probability density or a cumulative distribution function that underlies the risks associated with possible outcomes. In some occasions, a loss is an all-or-nothing event. If such

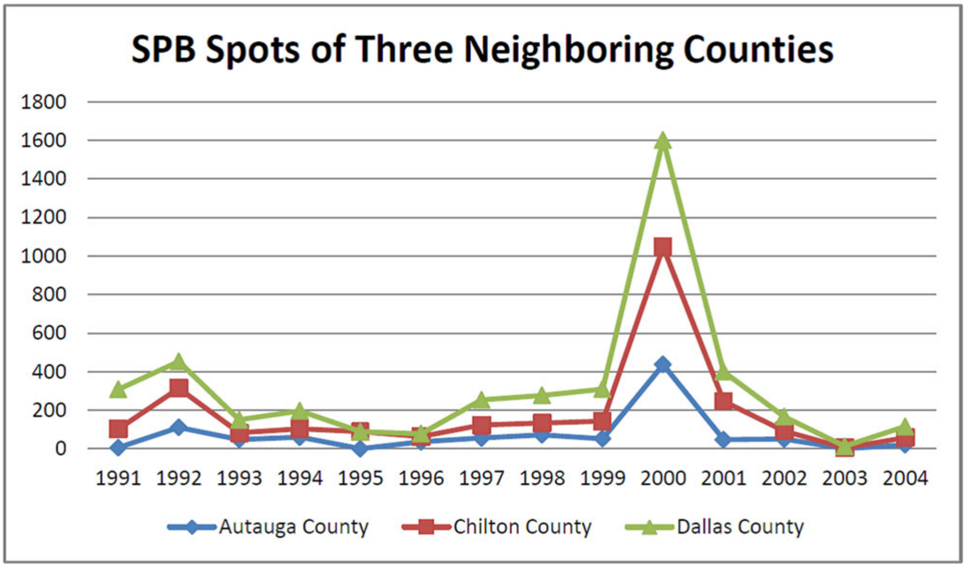


FIGURE 2 Southern pine beetle spots in three neighboring counties from 1991 to 2004

a loss event is denoted as z = 1, the probability of this loss event is usually modeled as a function that is conditional on a vector of observable covariates X and the associated parameter estimates vector β, that is,

$$P(z = 1) = F(X\beta) \tag{1}$$

Life insurance policies are such an example, when a financial indemnity will be paid only upon death of the insured. This kind of insurance scheme simplifies the premium calculation, because the payout amount is predetermined, and an actuarially fair premium rate is equivalent to the conditional probability that a loss event occurs. The expected loss can be expressed as

$$E(Loss) = P(z = 1) * E(loss|z = 1) \tag{2}$$

If the contract specifies a financial indemnity in case of a loss event (i.e., $E(loss|z = 1) = Payment$ is predetermined), then a fair premium is equivalent to

$$E(Loss) = F(X\beta) * Payment \tag{3}$$

and the actuarially fair premium rate is equal to the probability of loss.

However, such insurance products may not accommodate SPB hazards well, since an SPB attack does not always imply a total loss. The pulp yields from SPB killed pines are only slightly lower than green-cut pines. For paper quality, even for SPB-killed pines dead for more than 90 days, over 80% of veneer volume, over 60% of grade C and better veneer, and over 75% of wide veneer can be recovered. Surprisingly, for gluing quality, panels from beetle-killed pines dead for 45 days only fail all grading requirements by a narrow margin, while trees dead for 180 days can pass requirements (Insect & Management, 1979). Further, because of the marks left on the outer surface of usable wood caused by SPB inhabitation, sometimes beetle-killed trees are highly marketable.

A more general form of the actuarially fair premium can be expressed as the expected loss conditional on all possible loss outcomes,

$$E(loss_{st}) = \int E(Payment_{st}|z_{st}, \Theta_{st}) * f(z_{st}|\Theta_{st})\, dz_{st} \tag{4}$$

where z_{st} is an indicator that in county s during year t, one of the claim provisions has been triggered (i.e., that a loss event has occurred). Θ_{st} represents the prior information set of conditioning variables that are conceptually relevant to the risks, and $f(z_{st})$ represents the corresponding probability density function of the loss event. Since such an insurance scheme can compensate any losses caused by SPB infestations, if calculated accurately, it might provide a comprehensive protection for individual pine owners against the SPB hazard. However, there are at least two difficulties that may complicate the implementations of such insurance products. First, the magnitude of a southern pine loss, equivalent to $E(Payment_{st}|z_{st})$, is strictly related to the severity of SPB infestations, z_{st}. In other words, the two terms in the integral are correlated. Thus, an accurate calculation requires a further investigation of such correlation. Second, even if we can identify the timber loss as a closed functional (or estimated) form of SPB severity, high spatiotemporal variability of SPB infestations (Figures 1 and 2) makes it costly to monitor and measure such risks at an individual level.

A group insurance plan at the county level may be able to overcome the loss-severity correlations and the high spatiotemporal variability. One advantage of group insurance plans is that they can smooth risks across the whole county by basing coverage on an aggregate index. In addition, when the indemnity payments are explicitly predetermined, the actuarially fair premiums can be easily computed, as long as the density distribution of the index is accurately estimated. A plausible index can be based on annual SPB outbreaks (measured by identified spots) within a county. In a hypothetical timber insurance program, the claim procedure could work as follows. Before the beginning of the insurance period, both insurance providers and pine owners agree on an indemnity trigger index of SPB spot finds say $\tilde{z}_{st} = 100$, and the insured agents pay premiums to insurance companies. At the end of the insurance period, the federal or state authority publishes the observed SPB spot finds for each county. When the actual SPB outbreaks z_{st} in a county exceed the threshold stipulated in the contract, say 100 spots, every insured pine owner in this county will receive a fixed payment. Note that payments are made to all the insured, regardless of whether they experience SPB induced losses or not. Such is the nature of index coverage. Meanwhile, if the realized SPB spots are smaller than 100, then no one receives a payment. Therefore, if the predetermined SPB spot finds that will trigger claims is $\tilde{z}_{st}$ (e.g., 100), the actuarially fair premium can be written as

$$E(loss)_{st} = \Pr(z_{st} > \tilde{z}_{st}|\Theta_{st}) * E(Payment_{st}|z_{st} > \tilde{z}_{st}, \Theta_{st}). \tag{5}$$

At the same time, the premium rate, which is the ratio of the premium to the liability, is the term $\Pr(z_{st} > \tilde{z}_{st}|\Theta_{st})$ on the right-hand side. Such a premium rate is also equivalent to the loss probability that the loss event happens. More specifically, the loss probability is the probability that realized SPB spot finds z_{st} surpasses the prespecified threshold $\tilde{z}_{st}$.

The central piece of any insurance contract is to precisely model the loss probabilities, which is $\Pr(z_{st} > \tilde{z}_{st}|\Theta_{st})$ in Equation (5) for an index insurance program, conditional on relevant information. Therefore, understanding factors on which loss probabilities should be conditioned is crucial. For example, in modeling automobile insurance, age and education of the insured are usually explicitly recognized when assessing risks of accidents. As long as observable factors are pertinent to the risks underlying an insurance contract, a more accurate actuarially fair premium can be constructed if these factors are considered. Thus, it becomes very important to select an appropriate group of independent variables. In SPB prevention practice, it is found that several environmental factors are crucial risk contributors. For SPB insurance, factors such as tree types, characteristics of forest land, and weather are important risk determinants.

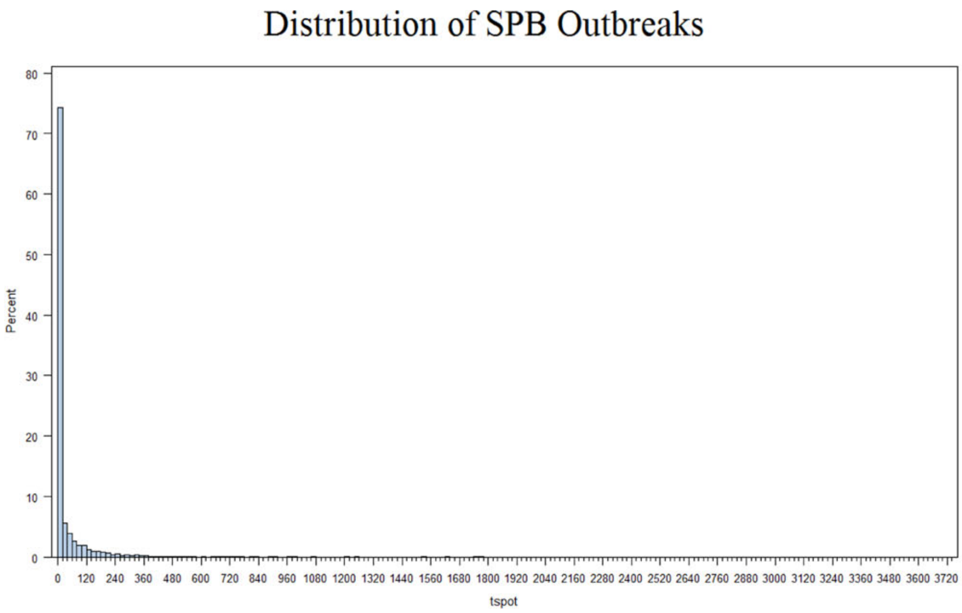
In the design of an insurance program, some operational issues should also be considered. One crucial component of insurance provisions is the insurance period. In agricultural insurance contracts, the insurance period is usually specified on a calendar year or crop season basis. The insurance protection covers associated risks from the beginning of the insurance period until the end of the insurance period. With no loss of generality, we also assume an insurance period corresponding to a calendar year in this study. It is important to identify insurance periods because risks can only be conditioned (i.e., modeled) upon information available prior to the beginning of an insurance period. For example, temperature is significantly related to SPB survival rates. However, temperature records in year t are not available until insurance coverage for year $t + 1$ is determined. Therefore, in our analysis, insurance parameters are always conditioned on lagged variables that are observable in the prior year before the terms of coverage are determined.

3 | EMPIRICAL ANALYSIS

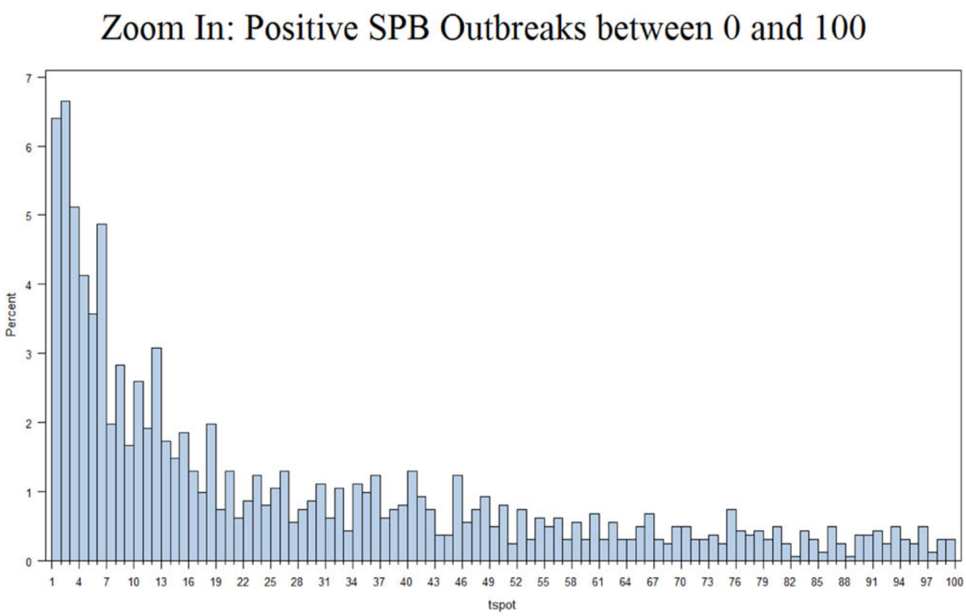
3.1 | Econometric specifications

A major challenge arises from the fact that the SPB spots distribution has a heavy weight on zeros (Figure 3). To accommodate this issue, we propose using zero-inflated count models. One candidate is the zero-inflated Poisson (ZIP) model (Lambert, 1992), where the discrete density function can be written as

$$\Pr(Y_{st} = y_{st}) = \begin{cases} \omega_{st} + (1 - \omega_{st})\exp(-\lambda_{st}), & y_{st} = 0 \\ (1 - \omega_{st})\exp(-\lambda_{st})\lambda^{y_{st}}/y_{st}!, & y_{st} > 0 \end{cases} \tag{6}$$



(a) Distribution of SPB spots



(b) Zoom in: positive SPB spots under 100

FIGURE 3 Distributions of SPB spots

In this paper, we assume that the parameters λ_{st} and ω_{st} both depend on the same set of covariates $X_{s,t-1}$. Accordingly, the link functions are expressed as

$$\log(\lambda_{st}) = X'_{s,t-1}\beta \tag{7}$$

$$\log(\omega_{st}/(1-\omega_{st})) = X'_{s,t-1}\gamma \tag{8}$$

Similarly, we apply another zero-inflated count model, which is the zero-inflated negative binomial (ZINB) model (Ridout, Hinde, & DemeAtrio, 2001) with a probability function as

$$\Pr(Y_{st} = y_{st}) = \begin{cases} \omega_{st} + (1-\omega_{st})(1+\alpha\lambda_{st})^{-1/\alpha}, & y_{st} = 0 \\ (1-\omega_{st})\frac{\Gamma(y_{st}+\alpha^{-1})}{y_{st}!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_{st}}\right)^{\alpha^{-1}}\left(\frac{\lambda_{st}}{\alpha^{-1}+\lambda_{st}}\right)^{y_{st}}, & y_{st} > 0 \end{cases} \tag{9}$$

where $\alpha(\geq 0)$ is a dispersion parameter not dependent on covariates. The link functions are same as the ZIP models. Compared with the ZIP model whose scale of the distribution is assumed to be one, the ZINB model allows for overdispersion of the scale. Hence, the latter model may have more flexibility in addressing overdispersed observations.

Research has shown that SPB outbreaks are spatially and temporally autocorrelated. Pheromone attractants, which individual SPBs use to communicate with others, can attract nearby beetles to inhabit newly infected trees. For example, SPB spots grow continuously and colonizations are spatially concentrated. Migration of SPB within forests can occur over either long distances or short distances. Particularly, the long-distance migration is evidenced by Borden (1974) and Hedden and Billings (1977). It is found that the SPB population density follows spatiotemporal patterns during each stage of SPB life history, that is, colonization (Fargo et al., 1978), reemergence (Coulson et al., 1978), survivorship (Coulson et al., 1979), and emergence (Coulson, Pulley, Foltz, Martin, & Kelley, 1977). In addition, research on broadscale SPB risks also found spatiotemporal patterns of probabilities of SPB outbreaks (e.g., Gumpertz, Wu, and Pye, 2000; Pye et al., 2004; Zhu et al., 2005). Therefore, to analyze the spatiotemporally correlated SPB outbreaks, we consider including both temporal and spatial lags of the dependent variable in order to control spatiotemporal autocorrelation. Thus, we include these two regressors $y_{\bar{s},t-1}$ and $y_{s,t-1}$ in analysis, where $y_{\bar{s},t-1}$ represents the average of all $\{y_{i,t-1}\}$, given $i \in \Theta_s$ and Θ_s represent the set of all spatial units bordering county s.

To further control for the spatiotemporal autocorrelation of SPB risks, we adopt a block bootstrapping method. Ever since Efron (1979) proposed the bootstrapping method, it has become a powerful statistical tool. Although the original bootstrapping method can only handle independent observations well, the strong autocorrelation of SPB outbreaks brings about a major challenge. Motivated by the method to bootstrap overlapping blocks in the autoregressive time-series scenario (Kunsch, 1989) and block bootstrapping methods designed for modeling dependent data from a spatial map (Hall, 1985), we utilize a spatiotemporal block bootstrapping approach. First of all, we attribute all the county-year observations into predetermined spatiotemporal blocks. Each block contains several observations that are adjacent either spatially or temporally. Second, we randomly sample the blocks with replacement. After sampling N blocks, we perform statistical analysis for all the observations contained in these N blocks and obtain the estimates of our interest. Still, to recognize that quite a few observations are zeros, the zero-inflated models are again applied during the estimation stage. Then, we repeat the second step by B times in order to construct nonparametric distributions of the estimates. By selecting an appropriate block size, spatiotemporal correlation can be minimized.

3.2 | Discussion of data

Our study focuses on SPB outbreaks in the southern states. The SPB database was obtained from the USDA Forest Service, Southern Research Station.[5] It contains the county-level records of SPB spots found every year in 10 southern states. As observations from different states have different time spans, for consistency, we use a subset of this database, which includes the records of all the counties of North Carolina, South Carolina, Georgia, and Alabama from 1991 to 2004.[6] In addition, the national Forest Inventory and Analysis (FIA) database (Woudenberg et al., 2010) and the NOAA national weather database[7] have supplied ecological information of forestland and weather condition, respectively. The dependent variable in this study is the annual county-level SPB spots found.[8] As mentioned above, distribution of the dependent variable is extremely right-skewed, with a heavy weight on zeros. In addition, its time series (Figure 1) and spatial maps (Figure 2) exhibit an obvious spatiotemporal pattern.

Previous studies have found some causal factors that are related to SPB outbreaks. We carefully selected a set of relevant regressors in this study. Forest management practice and previous research have found that several observable

[5] For details, see https://www.srs.fs.usda.gov/sustain/data/spb/

[6] Such a time span is determined by the availability of observations. Although the original data dated back to 1960s, observations before 1991 contain a significant amount of missing values.

[7] For details, see https://www.ncdc.noaa.gov/

[8] Observations of this variable may contain measurement errors due to different sampling methods. However, as this variable is the only variable that we can obtain to describe the intensities of SPB outbreaks, we still decide to use it while controlling for the measurement errors.

factors are associated with SPB risks. Since poor tree vigor is a main factor for SPB attacks (Hicks, Howard, Coster, & Watterston, 1978), soil moisture directly impacts tree susceptibility. For example, J. Lorio and Peter (1968), Bennett (1968), and Belanger, Hatchell, and Moore (1976) reported that infestations are more likely to occur on wet or moist sites than dry sites. However, Moore and Thatcher (1973) , Craighead (1925), and Beal and Massey (1945) found a positive relationship between SPB epidemics and drought. In our study, we use the SP12 index in December[9] to measure soil moisture. Its impact will be examined.

It was recognized that management of a stands tree species composition offers one method for reducing losses by SPB (Belanger, Osgood, & Hachell, 1979). Specifically, certain forest types are generally more resistant to SPB infestations than others. For example, Longleaf and slash pines produce more resin than loblolly or shortleaf pines. Such resin flow not only reduces the likelihood of an SPB attack, but it can also crystalize adults and eggs within galleries. As a result, loblolly and shortleaf pines are regarded as more susceptible host tree species, and the SPB Prevention Program suggests planting longleaf or slash pines as a proactive preventative method. Acreages of stand forest types are included as covariates to measure their various impacts. They are loblolly-shortleaf pine, longleaf-slash pine, oak-pine, oak-hickory, and oak-gum-cypress.[10]

Temperature is considered as the greatest single abiotic influence in every life stage of SPB (Fronk, 1947; White & Franklin, 1976). Temperature extremes affect beetle activity and survival (Moore & Thatcher, 1973), meaning that both hot and cold weather can be fatal to SPB. On the one hand, insect survival is directly affected by high temperatures, because the longevity of adult SPB is limited under hotter weather (Coulson et al., 1980). For example, Beal (1933) found that an exposure to 44 degrees centigrade for about 2 hours is fatal to all SPB life stages. Also, high temperatures can shorten adult SPB longevity when they migrate between trees. Tree evapotranspiration potential, which is found to be a significant factor in explaining SPB infestation (Kalkstein, 1976), is also related with temperature. In addition, SPBs communications by pheromones and attractants are impacted by high temperatures in the summer (Fares, Sharpe, & Magnuson, 1980). On the other hand, low temperatures can limit the flight capacity of SPB. Franklin (1970) found that SPB adult flight activity is inhibited when temperatures drop below 10 ºC . To measure year-long temperatures, we use the daily average of the Heating Degree Day[11] (HDD) index.

Natural disturbances, such as hurricanes and lightning, are hypothesized to be causal factors of SPB outbreaks. Since tree vigor is crucial for SPB host selection, weakened or dying trees, especially downed trees caused by such disturbances, are favorite targets of SPB attack. Even the affected standing trees, if still alive, will become much less vigorous (Thatcher, 1981). High winds have been generally associated with SPB outbreaks (P. Lorio & Bennett, 1974), additional circumstantial evidence that hurricanes, in particular, could be connected to outbreaks, as well. Data on hurricane frequency, the covariate employed in our models, were obtained from NOAA National Hurricane Center.[12] In addition, as an important hazard source for timber losses, lightning (Clarke, Riggins, & Stephen, 2016) is also evaluated in this study and associated lightning data were obtained from NOAA.[13]

Human intervention always plays an important role in pest control. In agricultural practice, to reduce pest damage to crops, farmers usually adopt field scouting at the beginning of the crop season to decide whether to apply pesticides. Similarly, timberland owners may also use such preventive methods. Although detailed data on such prevention efforts are unavailable, a proxy for human activities on the forest land is considered. Ownership of forestland, either private or public, may reflect the associated management styles (Bergmann & Bliss, 2004), and thus should be linked to preventive actions. In this study, the area occupied by federally owned forest is included among the covariates. Although in some states, forest agencies are authorized by the state laws to practice SPB controls on affected lands regardless of its ownership (Thatcher, 1981), different forestland owners may still have varying management objectives (i.e., logging vs. recreation) and therefore have diversified levels of concern for SPB control. For example, logging is viewed as a causal factor for beetle outbreaks since logging residues provide a comfortable environment for beetle brood (Schmid, 1977). In addition, SPB outbreaks can occur or worsen in situations where no control is

[9] SP12 index is Standardized Precipitation of the past 12 months (including the current month). Thus, a December SP12 index is a measure of annual precipitations.

[10] Stand density, in particular, overstocking, is an important causal factor of beetle epidemics. Schenk, Moore, Adams, and Mahoney (1977) found that trees are fairly susceptible to beetle attacks when intertree competition is intense. In this study, acreages of different forests are used as a proxy to measure overstocking.

[11] Heating Degree Day is a measurement of cold weather that quantifies the demand for energy needed to heat a building. In this study, it is calculated as outside temperature (T) relative to 65 °F. For example, HDD is equal to $65 - T$ if $T < 65$, and 0 if $T > 65$. We found such a measure more closely associated with SPB outbreaks than annual average temperature.

[12] For details, see http://www.nhc.noaa.gov/data/

[13] For details, see https://www.ncdc.noaa.gov/data-access/severe-weather/lightning-products-and-services

TABLE 1 Definition and statistics of variables

Variable(county level)	Definition	N	Mean	Median	Min	Max	Std. Dev.
SPB spots	Total finds of southern pine beetle spots	5,208	47.9247	0	0	3736	175.5377
Loblolly/shortleaf pine forestland	Size of loblolly/shortleaf pine forestland (measured by 100,000 acres)	4,836	0.6427	0.5120	0	3.1911	0.5141
Long/slash pine forestland	Size of long/slash pine forestland (measured by 100,000 acres)	4,836	0.1492	0	0	2.8126	0.3449
Oak/pine forestland	Size of oak/pine forestland (measured by 100,000 acres)	4,836	0.3229	0.2538	0	1.6833	0.2471
Oak/hickory forestland	Size of oak/hickory pine forestland (measured by 100,000 acres)	4,836	0.6171	0.5097	0	3.6393	0.4872
Oak/gum/cypress forestland	Size of Oak/gum/cypress forestland (measured by 100,000 acres)	4,836	0.2589	0.1386	0	1.7272	0.3140
National forestland	Total size of all national forests (measured by 100,000 acres)	4,836	0.0801	0	0	1.9467	0.2201
Daily average of HDD Index	Sum of daily Heating Degree Day indices within a year divided by 365	4,836	7.6697	7.4959	3.6932	14.8986	1.9793
December SP12 index	Next year's probability of observing a given amount of precipitations	4,836	0.2400	0.3300	−2.4200	2.5200	0.9044
Lightning incidences	Annual count of lightning strikes (measured by100,000 strikes)	4836	0.0612	0.0485	0.0035	0.6208	0.0482
Hurricane incidences	Annual count of hurricane strikes within 40 miles of a county's centroid	4,836	0.0275	0	0	2	0.1746

practiced and can easily cause further losses on adjacent lands. Therefore, it is essential to include forestland ownership data as a proxy to measure human interventions[14].

Other than aforementioned underlying factors, measurement errors of the response variable in this study, though easy to ignore, are also of great concern. The survey method to evaluate SPB outbreaks varies from one state to another. Some states use field-scouting methods. They randomly choose some sampling sites, inspect the SPB damage, and estimate the overall infestations. In some other states, inspectors take aircrafts over a large area of forests to find out whether an SPB epidemic takes place. As a result, the SPB spots reported from different states may be substantially influenced by the inspection methods that they choose. To accommodate this issue, state indicators are adopted in the covariates to measure these fixed effects.

Summary statistics and definitions of SPB outbreaks and explanatory variables are presented in Table 1. This study utilizes annual county-level observations for all 372 counties in Alabama, Georgia, South Carolina, and North Carolina between 1991 and 2004. This results in 5,208 county-year observations. All independent variables are lagged one year[15] because conditional information is only available prior to the insurance period.

[14] As one anonymous referee pointed out, there might be other measures that may more accurately reflect forest management objectives. However, due to the availability of such data, we decide to adopt forest ownership as a proxy measure of human interventions in this study.

[15] Also, by doing so, we are able to control for the potential endogeneity since lagged exploratory variables are exogenous (or at least weakly exogenous) to current years SPB outbreaks.

TABLE 2 Estimates and statistics from preliminary regressions: Count models

Parameter	Poisson model Estimate	Poisson model Std Err	Negative binomial Estimate	Negative binomial Std Err
$Y_{\bar{s},t-1}$	0.0002***	0.0000	0.0020***	0.0007
Y_{t-1}	0.0005***	0.0000	0.0030***	0.0006
Intercept	4.2403***	0.0174	2.7403***	0.3338
Loblolly/shortleaf pine	0.2891***	0.0048	0.9334***	0.1406
Long/slash pine	−2.0170***	0.0208	−0.9348***	0.1655
Oak/pine forestland	0.9556***	0.0114	0.1645	0.2973
Oak/hickory pine	0.3159***	0.0061	0.3868**	0.1555
Oak/gum/cypress	−1.2892***	0.0106	−1.2201***	0.2103
National forestland	0.5708***	0.0072	0.4702**	0.2269
Daily average HDD	−0.0909***	0.0021	−0.0027	0.0392
December SP12 index	−0.6034***	0.0023	−0.2281***	0.0472
Lightning incidences	1.2776***	0.0662	1.9710	1.6129
Hurricane incidences	−0.3877***	0.0217	−0.5632**	0.2341
GA	−1.0579***	0.0088	−0.8064***	0.1699
NC	−0.8907***	0.0096	−0.6476***	0.1828
SC	0.7195***	0.0069	0.2203	0.1827
Scale	1			
Dispersion			8.1652	0.2086
	Autocorrelation test			
Percentage of Years when Spatial Autocorrelation found in Residuals	100%		76.92%	
Percentage of Counties where Temporal Autocorrelation found in Residuals	2.42%		4.84%	

NOTE: *, ** and *** represent significance at 10%, 5%, and 1% respectively.

3.3 | Results

For the purpose of comparison, we first run the Poisson regression and negative binomial regressions, both of which are widely used to analyze count data, including observations with counts of 0. The results are presented in Table 2. The results suggest that almost all the conditioning explanatory variables have statistically significant impacts on SPB outbreaks, except for very few covariates, such as the hurricane frequency measure in some occasions. In addition, spatial dependence is found to be significantly positive, which makes more sense as the SPB hazard is contagious. However, autocorrelation tests for the residuals strongly challenge the validity of these two models. Although temporal autocorrelation is successfully controlled for, neither model sufficiently corrects for spatial autocorrelation.[16] Spatial autocorrelation is found in most years, that is, over three quarters of the time span. Such a disappointment may still come from the inaccurate modeling specifications. Although the Poisson and the negative binomial models both allow for observations of zeros, they cannot adequately address the scenarios when a preponderance of zeros are observed in the distribution (Figure 3).

Tables 3 and 5 present the results of the ordinary zero-inflated models and their variant versions with block bootstrapping methods. The estimates of most parameters are consistently significant in these four models. Also, as we mentioned earlier, significant estimates of the state dummies suggest that there exist differences in how SPB spots are reported in each state.

Land characteristics affect SPB risks through various ways. First of all, human intervention, which is implied by the ownership types, matters. National forests are susceptible to SPB infestations. Unlike a typical private timberland owner, whose timberland extent might be relatively low and hence easier to monitor, the federal government is not expected to be able to closely monitor properties all the time. Second, different forest lands have heterogeneous risk exposures. As the host type for SPB inhabitation, loblolly-shortleaf forest has a significant impact on the magnitude of SPB outbreaks. Similarly, oak-pine forest and oak-hickory

[16] Each county is checked for first-order autocorrelation using the Breusch–Godfrey test at the 5% significance level. Spatial autocorrelation is checked using Geary's *C* index permutation test at the 5% significance level every year.

TABLE 3 Estimates and statistics from ordinary zero-inflated models

Parameter	Zero-inflated Poisson		Zero-inflated negative binomial	
	Estimate	Std Err	Estimate	Std Err
	Logit selection			
$Y_{\bar{s},t-1}$	−0.0030***	0.0007	−0.0053***	0.0017
Y_{t-1}	−0.0052***	0.0007	−0.0432***	0.0068
Intercept	0.0537	0.2524	0.3045	0.3298
Loblolly/shortleaf pine	−0.9352***	0.1104	−0.9684***	0.1523
Long/slash pine	0.7968***	0.1577	0.8233***	0.1960
Oak/pine forestland	−0.4359*	0.2376	−0.3777	0.3096
Oak/hickory pine	−0.0384	0.1144	0.0931	0.1510
Oak/gum/cypress	0.9224***	0.1757	1.1497***	0.2281
National forestland	−0.9114***	0.1728	−0.9225***	0.2490
Daily average HDD	−0.0310	0.0281	−0.0453	0.0351
December SP12 index	0.2803***	0.0384	0.2719***	0.0475
Lightning incidences	1.3609	1.1828	−2.1935	1.5931
Hurricane incidences	0.4586**	0.2170	0.6323**	0.2665
GA	1.1026***	0.1383	0.9114***	0.1971
NC	1.7140***	0.1451	1.6545***	0.2029
SC	1.2354***	0.1552	1.4944***	0.2192
	Positive finds			
$Y_{\bar{s},t-1}$	0.0002***	0.0000	0.0002	0.0003
Y_{t-1}	0.0004***	0.0000	0.0013***	0.0003
Intercept	4.9745***	0.0178	4.6511***	0.2846
Loblolly/shortleaf pine	0.0824***	0.0049	0.2359**	0.1010
Long/slash pine	−1.1217***	0.0196	−0.7357***	0.1503
Oak/pine forestland	0.6231***	0.0115	0.4934**	0.2171
Oak/hickory pine	0.2771***	0.0062	0.3330***	0.1170
Oak/gum/cypress	−0.8390***	0.0107	−0.7575***	0.1704
National forestland	0.2497***	0.0073	0.2361	0.1520
Daily average HDD	−0.1120***	0.0021	−0.1240***	0.0334
December SP12 index	−0.4648***	0.0023	−0.2352***	0.0390
Lightning incidences	1.2716***	0.0707	0.0966	1.2054
Hurricane incidences	−0.1481***	0.0216	−0.0747	0.2584
GA	−0.6322***	0.0088	−0.5317***	0.1237
NC	−0.2455***	0.0096	0.0439	0.1438
SC	0.9297***	0.0068	0.8368***	0.1330
Dispersion (Scale)	1		2.5274***	0.1047
	Autocorrelation test			
Percentage of years when spatial autocorrelation found in residuals	84.62%		69.23%	
Percentage of counties where temporal autocorrelation found in residuals	2.42%		4.84%	

NOTE: *, ** and *** represent significance at 10%, 5%, and 1% respectively.

forest are vulnerable to SPB hazard. At the same time, longleaf-slash forest can significantly reduce the SPB risks, which supports the SPB Prevention Programs suggestions. The presence of timberland covered by the oak-gum-cypress forest type is also associated with lower SPB infestation occurrence.

Climatic factors, such as temperature and drought, are expected to significantly influence the frequencies of SPB outbreaks. Although both low (Franklin, 1970) and high (Fares et al., 1980) temperatures are reported as fatal factors to SPB, in this study,

TABLE 4 Model comparisons

Model comparison	Vuong's test: Preferred model	Vuong's test: AIC statistics	Clarke's sign test: Preferred model	Clarke's sign test: AIC statistics
Poisson vs. Negative Binomial	Negative binomial	−23.8178 (<.0001)	Negative Binomial	−1911 (<.0001)
Zero-inflated Poisson vs. Negative Binomial	Negative binomial	−24.2704 (<.0001)	Zero-inflated Poisson	177 (<.0001)
Zero-inflated negative binomial vs. Negative Binomial	Zero-inflated negative binomial	19.5991 (<.0001)	Zero-inflated negative binomial	1,172 (<.0001)
Zero-inflated Poisson vs. Zero–inflated negative binomial	Zero-inflated negative binomial	−24.4142 (<.0001)	Zero-inflated negative binomial	−1,638 (<.0001)

it is found that cold weather plays a more significant role in alleviating the SPB activities. Similarly, addressing the question about whether dry or wet sites are more susceptible to SPB infestations, our results indicate that SPB risks are more closely related to drought.

The likelihoods of fire and hurricane disturbances, though sometimes not statistically significant, affected SPB activities in different ways. On the one hand, lightning is found to intensify SPB outbreaks, that is, its estimates are positive in the regressions on the positive counts of SPB spots. Yet, how lightning can affect the probabilities of SPB outbreaks remains unclear; its estimates are unstable in sign and sometimes insignificant in the Logit selection equation of the zero-inflated count model. On the other hand, contrary to our conjecture, in most scenarios, hurricane incidences are negatively associated with SPB hazard. A possible explanation is that other than leave downed timbers untreated on the ground, timberland owners in the south region usually manage to quickly salvage valuable timber and remove other downed trees in order to reestablish new stands following hurricanes (Stanturf, Goodrick, & Outcalt, 2007). Such poststorm management may therefore counteract elevated infestation likelihood associated with the hurricane, although this remains a hypothesis to be tested in further research.

In addition, to verify the improvement made by the zero-inflated models, we adopt two tests for model comparisons. The models under scrutiny consist of count models and zero-inflated models. As not all the models are nested within each other, we adopt two types of likelihood ratio tests applicable for nonnested model selections. One is Vuong's test (Vuong, 1989) and the other is Clarke's sign test (Clarke, 2007). The null hypothesis of the latter is

$$H_0 : \Pr_0\left[\ln\frac{f(Y_i|X_i;\beta_*)}{g(Y_i|Z_i;\gamma_*)} > 0\right] = 0.5 \tag{10}$$

and the test statistic can be expressed as

$$M = \sum_{i=1}^{n} I_{(0,+\infty)}\left\{ln\frac{f(Y_i|X_i;\hat{\beta}_*)}{g(Y_i|Z_i;\hat{\gamma}_*)}\right\} \tag{11}$$

where $M \sim B(n, 0.5)$. The results (Table 4) reveal that in this study, the zero-inflated models perform better, especially the ZINB model.[17]

Finally, one bit of evidence supporting zero-inflated modeling specifications is that spatial autocorrelation among residuals has been reduced. Even for the ordinary ZIP and ZINB models, there is less spatial autocorrelation found in the residuals. This suggests that using zero-inflated models to account for excessive zeros in the observations provides better statistical analysis. Moreover, spatial autocorrelation is further reduced by block bootstrapping methods (i.e., the percentage of years with spatially autocorrelated residuals drops from around 80% to close to 50%). This improvement suggests that such nonparametric methods may be extended to other situations where spatiotemporal autocorrelation concerns.

4 | INSURANCE PREMIUMS

The primary goal of our empirical analysis has been to construct models that can precisely estimate actuarially fair premiums conditional on observable covariates. An actuarially fair premium that abstracts from administrative and operating costs

[17] Block bootstrapping results are not checked since they are derived from nonparametric methods and the tests are only applicable to parametric models.

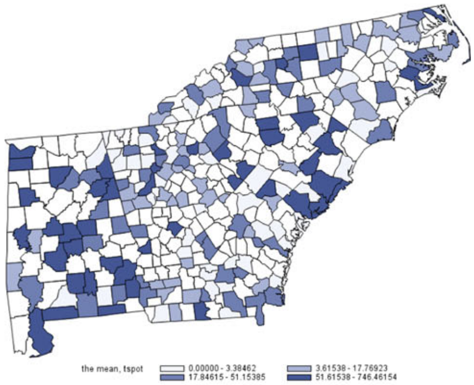
TABLE 5 Estimates and statistics from block bootstrapping methods

Parameter	Block ZIP Estimate	Block ZIP Std Err	Block ZINB Estimate	Block ZINB Std Err
	Logit selection			
$Y_{\bar{s},t-1}$	−0.0047***	0.0009	−0.0089***	0.0030
Y_{t-1}	−0.0069***	0.0013	−0.0506***	0.0122
Intercept	0.6168**	0.2554	1.1844***	0.3224
Loblolly/shortleaf pine	−0.9157***	0.1141	−1.0126***	0.1435
Long/slash pine	0.5638***	0.1668	0.3283*	0.1723
Oak/pine forestland	−0.4178*	0.2383	−0.4040	0.3633
Oak/hickory pine	0.0066	0.1211	0.1313	0.1664
Oak/gum/cypress	0.7857***	0.2383	1.0051***	0.2478
National forestland	−0.8471***	0.1936	−0.4450	0.3000
Daily average HDD	−0.0890***	0.0275	−0.1522***	0.0339
December SP12 index	0.1807***	0.0361	0.1584***	0.0483
Lightning incidences	1.7329	1.3303	−0.1147	1.6863
Hurricane incidences	0.2005	0.1745	0.1807	0.2395
GA	1.0572***	0.1240	0.8591***	0.1747
NC	1.5173***	0.1580	1.5378***	0.1957
SC	−1.2686	3.9211	−3.0388	6.4594
	Positive finds			
$Y_{\bar{s},t-1}$	0.0001	0.0003	0.0002	0.0003
Y_{t-1}	0.0010***	0.0003	0.0022***	0.0003
Intercept	5.1837***	0.2067	4.3323***	0.2704
Loblolly/shortleaf pine	0.0210	0.0912	0.1495	0.0929
Long/slash pine	−1.2617***	0.2126	−0.9565***	0.1426
Oak/pine forestland	0.5409***	0.1991	0.3322	0.2058
Oak/hickory pine	0.1954**	0.0836	0.2685**	0.1090
Oak/gum/cypress	−0.7421***	0.1968	−0.9054***	0.1776
National forestland	0.5436***	0.1347	0.6519***	0.1405
Daily average HDD	−0.1635***	0.0223	−0.1101***	0.0319
December SP12 index	−0.2552***	0.0364	−0.1371***	0.0385
Lightning incidences	3.3559***	0.9726	3.9363***	1.1539
Hurricane incidences	−0.3914***	0.1220	−0.3126**	0.1452
GA	−0.4812***	0.0956	−0.4383***	0.0994
NC	0.1411	0.1155	0.1992**	0.1178
SC	0.9565***	0.2676	0.8631***	0.3027
Dispersion (Scale)	1		2.5675***	0.1169
	Autocorrelation test			
Percentage of years when spatial autocorrelation found in residuals	53.84%		61.54%	
Percentage of counties where temporal autocorrelation found in residuals	6.65%		4.84%	

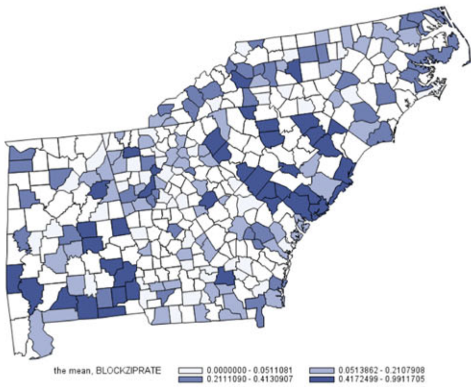
NOTE: *, ** and *** represent significance at 10%, 5%, and 1% respectively.

(including any return to capital) associated with the program should be set equal to the expected loss. Since the indemnity payment of index insurance plans is usually a predetermined fixed amount, an actuarially fair premium (Equation (5)) can be rewritten as

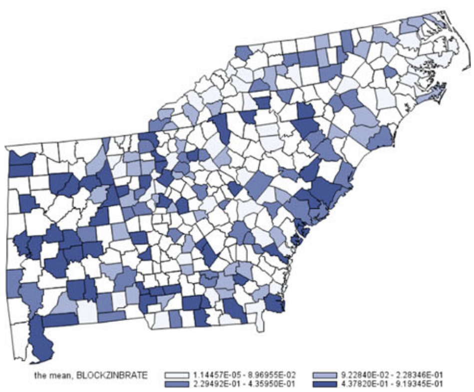
$$Premium_{st} = E(loss_{st}) = Payment_{st} * \Pr(Z_{st} > \tilde{Z}_{st} | \Theta_{st}) \tag{12}$$



(a) Actual SPB Spots



(b) Average Premium Rates by Block Bootstrapping ZIP



(c) Average Premium Rates by Block Bootstrapping ZINB

FIGURE 4 Quartile distributions of average SPB spots and estimated premium rates for SPB epidemics: 1991–2003

where $Z_{st} > \tilde{Z}_{st}$ denotes that the trigger index $\tilde{Z}_{st}$ has been surpassed, meaning that the loss event occurs. Such a predetermined payment $Payment_{st}$ can be a function of either the realized index Z_{st} or the trigger index. The latter is widely adopted in agricultural insurance such as RI plans. If the indemnity payment is independent of realized index, the only focus is to model the probability of the loss event, which is equivalent to the premium rate.

The indemnity payment, however, is still of great importance since an effective compensation scheme is crucial for insurance programs to sustain in the long run. As a timber insurance product, its indemnities should closely reflect the value losses of timber properties caused by SPB infestations. There are four popular treatment methods for SPB-killed timber, including (1) removal and salvage (cut-and-remove), (2) cut-and-leave or cut-and-top, (3) fell and spray with insecticides (cut-and-spray), and (4) fell, pile, and burn (pile-and-burn). Among all these four options, salvage remains the most economic method to treat epidemic infestations (Swain & Remion, 1980). Yet, since SPB infestations are usually small and scattered, it is almost impossible to completely salvage SPB-infested timbers. It is reported that once a pine is infested, the economic loss will be at least 50% of its timber value (Thatcher, 1981). A reasonable indemnity amount may be calculated based on such an estimate.

Further, a carefully designed insurance scheme in compliance with policy goals may benefit society in general. For contagious hazards like SPB, if mitigation actions can be compensated through insurance programs, overall risk profile may be affected toward a desirable direction. Thus, one possible plan would be

$$Payment_{st} = (Insured Acres)_{st} * [(Pine\ Value\ Per\ Acre)_{st} * 50\% + (Mitigation\ Cost)] \tag{13}$$

given that SPB epidemics occur. Mitigation costs are used to compensate forest owners' mitigation actions against SPB, such as timber thinning and prescribed burning.[18] If such a program becomes available, the government may choose to encourage mitigation actions by subsidizing premiums to reduce wildfire in the long run. Although such mitigation actions have already been subsidized by the government through the SPB Prevention Program, a subsidy based on market behavior might be more efficient. For instance, insurance purchasing decisions are more closely tied to underlying risk profiles, which might be unobservable. However, the focus of this study is not to make arguments in favor of or against government intervention. Even if no subsidy is provided, as long as the distribution of SPB outbreaks is accurately measured, the premium charge will be actuarially fair.

Given SPB epidemics occur, mitigation costs are used to compensate forest owners' mitigation actions against SPB, such as timber thinning and prescribed burning. If such a program becomes available, the government may choose to encourage mitigation actions by subsidizing premiums to reduce wildfire in the long run.[19] Although such mitigation actions have already been subsidized by the government through the SPB Prevention Program, a subsidy based on market behavior might be more efficient.[20] An example of the latter would be subsidized insurance premiums offered to offset forest owners' spending on mitigation efforts. However, the focus of this study is not to make arguments in favor of or against government intervention, or to argue about which form of government interventions would be more effective. Even if no subsidy is provided, as long as the distribution of SPB outbreaks is accurately measured, the premium charge will be actuarially fair. In addition, whether or not to keep mitigation incentive in the insurance scheme (Equation (13)) will not affect the actuarial fairness of the program given, the loss probabilities are accurately estimated.

In SPB control practice, the SPB intensity (density) is measured by the number of spots per thousand acre host pine. An epidemic is deemed as more than one multiple-tree spot per thousand acres of host type.[21] Hence, for simplicity, we define the loss event to be an SPB epidemic. In other words, the condition to trigger indemnity payments, expressed as $Z_{st} > \tilde{Z}_{st}$, is equivalent to $Z_{st} > Host\ Acres/1,000$. Thus, the trigger index can be written as $\tilde{Z}_{st} = Host\ Acres/1,000$. Since the distribution density of SPB spots can be estimated, the premium rate (or loss probability) can be conveniently obtained.

Summary statistics of the estimated premium rates using zero-inflated models are presented in Table 6. As noted above, these estimated premium rates are equivalent to the predicted probabilities that SPB epidemics occur within a county. First of all, the overall results obtained from the four models are similar, while the results obtained from ZINB models are less extreme.[22] Second, the smallest difference in the premium rates between the models is found in the state of Alabama. The main reason behind this is that Alabama has the most outbreaks and the variation pattern should be more close to the whole map. With the same reason, the premium rates in Alabama remain highest. Third, the premium rates in North Carolina are relatively smaller. This coincides our previous finding that the low temperature will limit SPB infestations. Fourth, the difference in premium rates between different models is relatively larger in South Carolina. The South Carolina difference implies that there may exist some idiosyncratic attributes of the SPB infestation pattern in this state different from others.

[18] Even unaffected timber owners can ask the SPB Prevention Program to subsidize mitigation actions such as thinning and logging if they find their trees susceptible to SPB attacks, but mitigation actions are not mandatory. For example, even though overstocking may potentially cause SPB inhibitions, not all the timber owners with this issue will do thinning.

[19] For this index insurance product, to encourage such mitigation actions should reduce the overall SPB risks in each county if the participation rate is high enough. However, if not, subsidized mitigation actions such as thinning by an insured timber owner will likely inflate the SPB risks of his uninsured neighbors who do not perform mitigation actions.

[20] As suggested by one anonymous referee, mitigation is a weak-link public good. A market-based scheme may not induce mitigation effort to achieve the socially optimal level.

[21] In our study, “host-type” refers to the loblolly-shortleaf pine type only.

[22] As pointed out by one anonymous referee, ZIP model may sometimes produce too extreme values and unrealistic estimates. For example, the maximum premium rate could be as large as 1, meaning insured needs to pay as much as agreed indemnity amount as premium. The minimum premium rate could be as low as 0, meaning associated insurance policy could be offered for free. Both suggested another evidence that ZINB models are preferred.

TABLE 6 Estimated premium rates for SPB epidemics

Model	Mean	Median	Std.Dev.	Max	Min
Overall:					
Zero-inflated Poisson	0.2422	0.1712	0.2790	1	0
Block bootstrapping ZIP	0.2882	0.1978	0.3181	1	0
Zero-inflated negative binomial	0.2454	0.1678	0.2364	0.9980	7.7703E-09
Block bootstrapping ZINB	0.2862	0.2082	0.2614	0.9999	9.6134E-13
Alabama:					
Zero-inflated Poisson	0.3942	0.3895	0.3789	1	0
Block bootstrapping ZIP	0.3974	0.4117	0.3760	1	0
Zero-inflated negative binomial	0.4249	0.4041	0.2649	0.9980	9.9634E-05
Block bootstrapping ZINB	0.4469	0.4387	0.2894	0.9999	1.2030E-04
Georgia:					
Zero-inflated Poisson	0.1606	0.0529	0.1968	0.9629	0
Block bootstrapping ZIP	0.1523	0.0842	0.1882	0.9856	0
Zero-inflated negative binomial	0.2600	0.1962	0.2214	0.9841	1.2419E-04
Block Bootstrapping ZINB	0.2758	0.2131	0.2292	0.9910	1.0124E-04
North Carolina:					
Zero-inflated Poisson	0.1956	0.1829	0.1969	0.9905	0
Block bootstrapping ZIP	0.2418	0.2330	0.2159	0.9991	0
Zero-inflated negative binomial	0.1295	0.0789	0.1612	0.9851	9.2149E-06
Block bootstrapping ZINB	0.1486	0.0934	0.1716	0.9982	4.7327E-06
South Carolina:					
Zero-inflated Poisson	0.4047	0.3308	0.3387	1	0
Block bootstrapping ZIP	0.7003	0.8411	0.3650	1	0
Zero-inflated negative binomial	0.1856	0.1076	0.2084	0.9607	7.7703E-09
Block bootstrapping ZINB	0.3872	0.3387	0.3097	0.9920	9.6134E-13

Figure 4 compares the map of average SPB spots (Figure 4a) with maps of the estimated average premium rates using block bootstrapping zero-inflated models (Figures 4b–c). The overall resemblance between all the maps suggests an adequate modeling specification, including an appropriate selection of covariates and fitting methods.

5 | CONCLUSION

Without viable financial instruments to hedge against risks brought about by pervasive hazards such as SPB, timberland owners are vulnerable to potentially high-consequence economic losses and limited government assistance in the aftermath. Our study, however, suggests a potential approach to compensate their losses at no cost in terms of overall social welfare. A single-peril index insurance scheme against SPB risks is proposed, and associated actuarially fair premium rates are estimated.[23] Hypothetically, if such an insurance program becomes available, a private market for risk sharing of pest damages and cost sharing of pest control will emerge. Compared with a direct subsidy from the government that is completely exogenous and usually results in a welfare loss, such a market mechanism should be more efficient in pricing risks. The main subject in this study, unlike previous research, is the broadscale frequency of SPB infestations, that is, county-level spot finds. Such a choice is dictated by the fact that economic losses caused by this pest are more related to its intensities rather than probabilities. Therefore, this study should aid in the identification of patterns of SPB infestations and in generating precise estimates of their associated costs. The distribution of the SPB outbreak count variable, however, is extremely right-skewed, with excessive zeros. In order to better

[23] All commercial lines of insurance require a loading factor that serves to cover operating costs, build reserves, and provide a return to capital. However, the first step in nearly all lines of insurance is to carefully quantify the risk—that is, by measuring the actuarially fair premium rate. This rate is a starting point for the commercial insurer, who then applies loading factors to cover these other factors.

estimate its probability densities, we adopted zero-inflated count models. Particularly, a ZINB model fit best. As a pest with adequate mobility, SPB is generally viewed as a contagious hazard and their infestations are usually found to be spatially and temporal correlated. To control for spatiotemporal autocorrelation of SPB risks, a nonparametric block bootstrapping method was used. The estimation results suggest some potentially important forest management implications. Most covariates are found to be statistically significant causal factors for SPB risks. For example, drought and high temperatures appear to enhance SPB hazard significantly. Another prominent finding is that different tree species can affect SPB hazard in distinct ways. Thus, timber owners and forest agencies may take preventive actions to protect pine properties against SPB by managing forests appropriately, such as to expand the establishments of certain types of tree stands, like long/slash pines.

Furthermore, we have designed an insurance plan to compensate the losses caused by SPB epidemics. Such an index program is based upon county-level statistics. An indemnity payment is triggered when an epidemic occurs. Associated actuarially fair premium rates are calculated and mapped. Since SPB risks are spatiotemporally correlated, mitigation actions might introduce positive externalities, which might lessen the transmission of SPB hazard. Thus, it is suggested that an indemnity payment consists of both timber loss and mitigation costs. From the government's perspective, such a hypothetical insurance program may become an alternative outlay for the SPB mitigation subsidy funds. The government and the society, in general, may benefit from such an approach since insurance may be more widely available and high-risk agents are more easily targeted. However, risk profiles may evolve after insurance adoption, and strong spatiotemporal dependence of SPB risks may also cause moral hazard issues. Therefore, this study only focuses on modeling SPB risks and estimating associated actuarially fair premium rates with proposed index insurance products. The necessity and effectiveness of possible government's involvement in the SPB disaster payment markets remains open for future research.

REFERENCES

Aukema, J. E., Leung, B., Kovacs, K., Chivers, C., Britton, K. O., Englin, J., … Von Holle, B. (2011). Economic impacts of non-native forest insects in the continental united states. *PLoS One*, *6*(9), e24587.

Beal, J. (1933). Temperature extremes as a factor in the ecology of the southern pine beetle. *Journal of Forestry*, *31*(3), 329–336.

Beal, J., & Massey, C. (1945). *Bark beetles and ambrosia beetles (Coleoptera: Scolytoidea), with special references to species occurring in North Carolina*. Volume 10. Durham, NC : Duke University.

Belanger, R., Hatchell, G., & Moore, G. (1976). Soil and stand characteristics related to southern pine beetle infestations: A progress report for Georgia and North Carolina. In *Proceedings of the 6th Southern Forestry Soils Workshop at Charleston, SC held October*, (pp. 19–21).

Belanger, R., Osgood, E., & Hachell, G. (1979). *Stand, soil, and site characteristics associated with southern pine beetle infestations in the southern Appalachians*, volume 198. Asheville, NC: Department of Agriculture, Forest Service, Southeastern Forest Experiment Station.

Bennett, W. (1968). Timber management and southern pine beetle research. *Forest Farmer*, *27*(9), 12–13.

Bergmann, S. A., & Bliss, J. C. (2004). Foundations of cross-boundary cooperation: Resource management at the public–private interface. *Society & Natural Resources*, *17*(5), 377–393.

Billings, R. F. (2011). Aerial detection, ground evaluation, and monitoring of the southern pine beetle: State perspectives. In R. N. Coulson & K. D. Klepzig (Eds.), *Southern Pine Beetle II* (Gen. Tech. Rep. SRS-140, Vol. 140, pp. 245–261). Asheville, NC: US Department of Agriculture Forest Service, Southern Research Station.

Billings, R. F., & Upton, W. W. (2010). A methodology for assessing annual risk of southern pine beetle outbreaks across the southern region using pheromone traps. In J. M. Pye, H. M. Rauscher, Y. Sands, D. C. Lee, & J. S. Beatty (Tech. Eds.), *Advances in threat assessment and their application to forest and rangeland management* (pp. 73–85). Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations.

Borden, J. (1974). Aggregation pheromones in the scolytidae. In M. C. Birch (Ed.), *Pheromones* (pp. 135–160). Amsterdam: North-Holland.

Carlson, G. (1979). Insurance, information, and organizational options in pest management. *Annual Review of Phytopathology*, *17*(1), 149–161.

Chen, X., Goodwin, B. K., & Prestemon, J. P. (2013). Is timber insurable? A study of wildfire risks in the us forest sector using spatio-temporal models. *American Journal of Agricultural Economics*, *96*(1), 213–231.

Clarke, K. A. (2007). A simple distribution-free test for nonnested model selection. *Political Analysis*, *15*(3), 347–363.

Clarke, S. R., Riggins, J. J., & Stephen, F. M. (2016). Forest management and southern pine beetle outbreaks: A historical perspective. *Forest Science*, *62*(2), 166–180.

Coulson, R., Fargo, W., Pulley, P., Foltz, J., Pope, D., Richerson, J., & Payne, T. (1978). Evaluation of the re-emergence process of parent adult dendroctonus frontalis (coleoptera: Scolytidae). *Canadian Entomologist*, *110*(5), 475–486.

Coulson, R., Fargo, W., Pulley, P., Pope, D., Foltz, J., & Bunting, A. (1979). Spatial and temporal patterns of emergence for within-tree populations of dendroctonus frontalis (coleoptera: Scolytidae). *Canadian Entomologist*, *111*(3), 273–287.

Coulson, R., Pope, D., Gagne, J., Fargo, W., Pulley, P., Edson, L., & Wagner, T. (1980). Impact of foraging by monochamus titillator [col.: Cerambycidae] on within-tree populations of dendroctonus frontalis [col.: Scolytidae]. *BioControl*, *25*(2), 155–170.

Coulson, R., Pulley, P., Foltz, J., Martin, W., & Kelley, C. (1977). Survival models for within-tree populations of dendroctonus frontalis (coleoptera: Scolytidae). *Canadian Entomologist*, *109*(8), 1071–1077.

Craighead, F. (1925). Bark-beetle epidemics and rainfall deficiency. *Journal of Economic Entomology*, *18*(4), 577–586.

Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *The annals of Statistics*, *7*(1), 1–26.

Fares, Y., Sharpe, P., & Magnuson, C. (1980). Pheromone dispersion in forests. *Journal of Theoretical Biology*, *84*(2), 335–359.

Fargo, W., Coulson, R., Pulley, P., Pope, D., & Kelley, C. (1978). Spatial and temporal patterns of within-tree colonization by dendroctonus frontalis (coleoptera: Scolytidae). *Canadian Entomologist*, *110*(11), 1213–1232.

Farrin, K., & Miranda, M. J. (2015). A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *Journal of Development Economics*, *116*, 199–211.

Franklin, R. T. (1970). Southern pine beetle population behaviour. *Journal of the Georgia Entomological Society*, *5*(3), 175–82.

Fronk, W. (1947). *The southern pine beetle: Its life history*, volume 108. Blacksburg, VA: Virginia Agricultural Experiment Station.

Giné, X., Menand, L., Townsend, R., & Vickery, J. (2012). Microinsurance: A case study of the Indian rainfall index insurance market. In C. Ghate (Ed.), *Handbook of the Indian economy*, (pp. 167–194). Oxford: Oxford University Press.

Gumpertz, M. L., Wu, C. T., & Pye, J. M. (2000). Logistic regression for southern pine beetle outbreaks with spatial and temporal autocorrelation. *Forest Science*, *46*(1), 95–107.

Hall, P. (1985). Resampling a coverage pattern. *Stochastic Processes and their Applications*, *20*(2), 231–246.

Hedden, R., & Billings, R. (1977). Seasonal variations in fat content and size of the southern pine beetle in East Texas. *Annals of the Entomological Society of America*, *70*(6), 876–880.

Hicks, J. R., Howard, J., Coster, J., & Watterston, K. (1978). The role of tree vigor in susceptibility of loblolly pine to southern pine beetle. In *Proceedings of the 5th North American Forest Biology Workshop*, (p. 171–181).

Hofstetter, R. W., Cronin, J. T., Klepzig, K. D., Moser, J. C., & Ayres, M. P. (2006). Antagonisms, mutualisms and commensalisms affect outbreak dynamics of the southern pine beetle. *Oecologia*, *147*(4), 679–691.

Holmes, T. P. (1991). Price and welfare effects of catastrophic forest damage from southern pine beetle epidemics. *Forest Science*, *37*(2), 500–516.

Insect, U. S. F., & Management, D. (1979). *Use of beetle-killed timber for pulp, plywood, and paneling*, volume 15. Atlanta, GA: US Dept. of Agriculture, Forest Service, Forest Insect and Disease Management.

Kalkstein, L. (1976). Effects of climatic stress upon outbreaks of the southern pine beetle. *Environmental Entomology*, *5*(4), 653–658.

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics*, *129*(2), 597–652.

Kunsch, H. (1989). The jackknife and the bootstrap for general stationary observations. *Annals of Statistics*, *17*(3), 1217–1241.

Kunzemann, T. (2009). Forest insurance in Brazil. *Website news*, Allianz Knowledge Site.

Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics*, *34*(1), 1–14.

Lorio, J., & Peter, L. (1968). Soil and stand conditions related to southern pine beetle activity in Hardin County, Texas. *Journal of Economic Entomology*, *61*(2), 565–566.

Lorio, P., & Bennett, W. (1974). *Recurring southern pine beetle infestations near Oakdale, Louisiana*, volume 95. New Orleans, LA: Southern Forest Experiment Station, Forest Service, US Dept. of Agriculture.

Mawby, W., & Gold, H. (1984). A reference curve and space-time series analysis of the regional population dynamics of the southern pine beetle (Dendroctonus frontalis Zimmermann). *Researches on Population Ecology*, *26*(2), 261–274.

Miranda, M. J. (1991). Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics*, *73*(2), 233–242.

Miranda, M. J., & Farrin, K. (2012). Index insurance for developing countries. *Applied Economic Perspectives and Policy*, *34*(3), 391–427.

Miranda, M. J., & Gonzalez-Vega, C. (2010). Systemic risk, index insurance, and optimal management of agricultural loan portfolios in developing countries. *American Journal of Agricultural Economics*, *93*(2), 399–406.

Moore, G., & Thatcher, R. (1973). *Epidemic and endemic populations of the southern pine beetle*, volume 111. Asheville, NC: US Dept. of Agriculture, Forest Service, Southeastern Forest Experiment Station.

Niemiec, R. M., Lutz, D. A., & Howarth, R. B. (2014). Incorporating carbon storage into the optimal management of forest insect pests: A case study of the southern pine beetle (Dendroctonus frontalis Zimmermann) in the New Jersey pinelands. *Environmental management*, *54*(4), 875–887.

Nowak, J. T., Meeker, J. R., Coyle, D. R., Steiner, C. A., & Brownie, C. (2015). Southern pine beetle infestations in relation to forest stand conditions, previous thinning, and prescribed burning: Evaluation of the southern pine beetle prevention program. *Journal of Forestry*, *113*(5), 454–462.

Petry, M., Zhang, L., & Zhang, S. (2010). *China - Peoples Republic of Forest Products Annual Report 2010* (Gain Paper CH100042). USDA Foreign Agriculture Service, Global Agriculture Information Network.

Pye, J. M., Price, T., Clarke, S., & Huggett Jr., R. (2004). A history of southern pine beetle outbreaks in the southeastern united states through 2004. Web publication. http://www.srs.fs.usda.gov/econ/data/spb/index. htm.

Pye, J. M., Holmes, T. P., Prestemon, J. P., & Wear, D. N. (2011). Economic impacts of the southern pine beetle. In R. N. Coulson & K. D. Klepzig (Eds.), *Southern Pine Beetle II* (Gen. Tech. Rep. SRS-140, Vol. 140, pp. 213–222). Asheville, NC: US Department of Agriculture Forest Service, Southern Research Station.

Ridout, M., Hinde, J., & DemeAtrio, C. G. (2001). A score test for testing a zero-inflated poisson regression model against zero-inflated negative binomial alternatives. *Biometrics*, *57*(1), 219–223.

Schenk, J., Moore, J., Adams, D., & Mahoney, R. (1977). A preliminary hazard rating of grand fir stands for mortality by the fir engraver. *Forest Science*, *23*(1), 103–110.

Schmid, J. (1977). *Guidelines for minimizing spruce beetle populations in logging residuals*. Fort Collins, CO: Rocky Mountain Forest and Range Experiment Station.

Staeben, J. C., Sullivan, B. T., Nowak, J. T., & Gandhi, K. J. (2015). Enantiospecific responses of southern pine beetle (dendroctonus frontalis) and its clerid predator, thanasimus dubius, to α-pinene. *Chemoecology*, *25*(2), 73–83.

Stanturf, J. A., Goodrick, S. L., & Outcalt, K. W. (2007). Disturbance and coastal forests: A strategic approach to forest management in hurricane impact zones. *Forest Ecology and Management*, *250*(1), 119–135.

Strom, B., Meeker, J., Bishir, J., Roberds, J., & Wan, X. (2016). Southern pine beetle in loblolly pine: Simulating within stand interactions using the process model SPBLOBTHIN. In *Proceedings of the 18th Biennial Southern Silvicultural Research Conference ()p. 614.*

Swain, K., & Remion, M. (1980). *Direct control methods for the southern pine beetle*. Washington, DC: US Government Printing Office.

Thatcher, R. (1981). *The southern pine beetle* (Number 4). US Dept. of Agriculture, Expanded Southern Pine Beetle Research and Applications Program, Forest Service, Science and Education Administration.

Vasanthakumar, A., Delalibera, I., Handelsman, J., Klepzig, K. D., Schloss, P. D., & Raffa, K. F. (2006). Characterization of gut-associated bacteria in larvae and adults of the southern pine beetle, Dendroctonus frontalis Zimmermann. *Environmental Entomology*, *35*(6), 1710–1717.

Vuong, Q. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, *57*, 307–333.

White, R., & Franklin, R. (1976). Activity of the southern pine beetle in response to temperature. *Journal Georgia Entomological Society*, *11*(4), 370–372.

Woudenberg, S. W., Conkling, B. L., O'Connell, B. M., LaPoint, E. B., Turner, J. A., & Waddell, K. L. (2010). *The forest inventory and analysis database: Database description and users manual version 4.0 for phase 2* (General Technical Report RMRS-GTR-245). USDA Forest Service.

Zhu, J., Huang, H., & Wu, J. (2005). Modeling spatial-temporal binary data using Markov random fields. *Journal of Agricultural, Biological, and Environmental Statistics*, *10*(2), 212–225.

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