Is Timber Insurable? A Study of Wildfire Risks in the U.S. Forest Sector Using Spatio-temporal Models

Xuan Chen, Barry K. Goodwin, and Jeffrey P. Prestemon

In the U.S. forest products industry, wildfire is one of the leading causes of damage and economic losses. While individual wildfire behavior is well studied, new literature is emerging on broad-scale (e.g., county-level) wildfire risks. Our paper studies wildfire risks using crucial informational variables across both spatial units and time periods. Several statistical models are used to quantify the risks. We develop several maximum likelihood estimation methods to account for spatio-temporal auto-correlation in conditional risks. A group index insurance scheme is proposed, and its associated actuarially fair premium rates are estimated and presented. Implications for wildfire management policies are also discussed.

Key words: wildfire, index insurance, spatio-temporal correlation.

JEL codes: G22, Q23.

The U.S. timber products sector is the world's largest in both market value and volume, and accounted for 24% of total world output and 23% of total world consumption from 2000 to 2010 (Department of Commerce 2012). A large portion of the timber industry is based on natural and planted forests that cover one-third of the U.S. landscape. Further, 57% of all U.S. production is based on timber harvested from southern U.S. forests (Smith et al. 2010), large segments of which are prone to damaging wildfires (Malamud et al. 2005). Hence, land owners and managers take steps to reduce expected damages by preventing fire occurrence (Prestemon et al. 2010) by managing fuels so that they burn less intensely and less frequently (Cleaves et al. 2000) and by suppressing fires when they occur. The USDA Forest Service and the Department of the Interior spent a combined average of $1.4 billion/year from 2000 to 2011 in inflation-adjusted 2011 dollars (USDA Forest Service 2011; Department of the Interior 2012) on mitigating losses through timber salvage (Prestemon et al. 2006). However, limited efforts are made to provide private landowners with financial instruments that mitigate expected losses from wildfires. This is surprising, given their potential to help alleviate private losses (e.g., Butry et al. 2001; Kent et al. 2003).

After wildfires, private landowners and other affected residents are often assisted in an ad hoc fashion. Often, non-profit organizations such as the American Red Cross extend aid that addresses personal needs. Other local non-profit programs, such as the Georgia Wildfire Relief Fund (State of Georgia 2008), provide assistance to affected residents and engage in local ecosystem restoration over the long term.

Government assistance after wildfires is typically delivered in the form of tax credits and government-subsidized low-interest loans. In 2007, the Internal Revenue Service (IRS) and the California state government granted tax relief for Southern California wildfire victims following large wildfires in 2007 and 2008 (Internal Revenue Service 2007, 2008; State of California 2008). Often, assistance from the government requires that a wildfire be large and particularly damaging. When juxtaposed with the reality that most fires are small, a significant number of landowners affected by wildfire are not

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included in coordinated federal or state actions to aid victims, and therefore effective risk management instruments are lacking.[1]

Real-world experience with forest insurance has a mixed record. In the United States, a very limited number of timber insurance programs addressing multiple perils are available on the private market. Examples include the Davis-Garvin Agency's standing timber insurance and the Outdoor Underwriters' standing timber insurance. These two programs offer all-risk insurance policies on a case-by-case basis in a few small regional markets. However, the overall nationwide forest landowners' insurance participation is very small.

The paucity of multi-peril forest insurance plans in private markets implies a high cost that results from the difficulties associated with monitoring and administering multi-peril insurance. In some sense it may be too difficult to precisely measure risks from all possible hazards. In the case of inaccurate monitoring or poorly measured risks, insurance providers may face moral hazard and adverse selection problems, which arise when agents assume more risks because they have insurance. Such moral hazard actions may range from simple mismanagement of property to intentional fraud.

Adverse selection occurs from inaccurate rates when high-risk agents are more likely to purchase insurance than low-risk agents, thus leading to an adversely-selected insurance pool. Precisely modeling and pricing risks is essential for avoiding adverse selection. Compared with multi-peril insurance, for which it may be difficult to trace all risk sources, a single-peril insurance plan only requires consideration of the limited risks associated with the specific hazard. An actuarially fair single-peril insurance plan can be more easily implemented, and therefore has the potential to increase insurance participation and reduce adverse selection.

In most fire-prone regions of the United States, wildfire is the most significant hazard faced by timberland owners. There are thus at least two benefits to be gained from developing a timber insurance product. First, such a product could empirically quantify risks and potentially attract insurance companies and forest landowners to engage in a private insurance market for risk sharing. Second, such a product could provide a baseline estimate of the timber-related net benefits of wildfire risk mitigation (prevention, fuels management, suppression) for individual landowners, policy makers, and public land managers.

The first benefit stems from the notion that recognition of a particular hazard and its spatio-temporal transmission mechanisms may warrant the development of single-peril insurance products that accurately measure wildfire risks. Given the fact that wildfire risks are usually catastrophic, if actuarially fair rates can be implemented in a single-peril insurance plan, risk-averse forest landowners will purchase such products if they are offered by insurance companies. Such a private insurance market can ease the destructive losses of forest landowners, even in the absence of government intervention. Furthermore, as forest disaster relief is becoming a fast-growing burden for governments worldwide (Holecy and Hanewinkel 2006), developing private wildfire insurance products can lessen the financial stresses associated with taxpayer-funded support, and make ad hoc disaster relief unnecessary.

The second benefit of developing a timber insurance product stems from the notion that understanding the causal factors associated with wildfire could result in broader welfare gains to society. Understanding how wildfire risks are propagated spatio-temporally and how they depend on inputs can lead to more rational public policies and private landowner decision making. However, wildfire production is complicated by the existence of both purchased and free inputs that need to be jointly considered in the statistical models required to generate a fair insurance scheme (e.g., Prestemon, Mercer, and Pye 2008). Another complication is that a practical, effective insurance policy needs to minimize adverse selection and moral hazard distortions, and should be able to induce incentive-compatible actions by forest landowners to prevent wildfire risks (e.g., Amacher, Malik, and Haight 2006; Crowley et al. 2009). A fairly-priced insurance plan also needs to evaluate compliance policies that decrease outbreak probabilities by reducing hazards in advance. Prescribed burning is an example of efforts made by

[1] Individuals and businesses can claim wildfire losses as a deduction in their income taxes. However, in the case of timber, these casualty losses are only on the basis (investment costs). For federal taxes, only casualty losses, net of any income obtained from timber salvage, that exceed 7.5% of taxable income can be claimed. For state taxes, these losses may not be claimed at all, particularly in states without income taxes.

forest landowners and governments to reduce wildfire risks (e.g., Cleaves et al. 2000; Mercer et al. 2007).

The State of Florida provides a natural setting for evaluating a wildfire timber insurance product. Nearly half of the state's 35 million acres of land—16.1 million acres—is forested (Smith et al. 2010). Florida ranks among the top five tree-planting states in the United States, with one-third of its forests covered in pine plantations. Thus, Florida's forest products sector is heavily dependent on the fire-prone and fire-vulnerable investment of private landowners. Florida's timber products sector is an important income and employment generator, with annual income ranging from \$2 billion to \$4 billion/year, and employment ranging from 35,500 to 61,400 people from 1990–2010. The sector also generated nearly 1% of the state's income in 2010 (Department of Commerce 2012). At the same time, Florida experiences over 4,000 wildfire occurrences per year, on average, with approximately 200,000 acres of forest land being burned in a typical year. Moreover, the fact that 70.7% of Florida's forests are privately held by 509,000 non-industrial landowners (Butler 2008) suggests that a potentially significant demand for forest wildfire insurance protection could exist in the state.[2]

This paper studies spatially and temporally correlated wildfire risks in Florida using data covering 1981 to 2005.[3] We evaluate many of the underlying causal factors (purchased or free inputs) associated with wildfire risks. We find that vegetation types, climate, and socioeconomic conditions have significant influences on the probability of fire occurrence. An annual county-level contract, which pays a pre-determined indemnity to all those insured in an affected county in the event that a wildfire index exceeds a pre-specified level, is proposed. Statistical models are used to quantify wildfire risks at the county-level and to estimate expected insurance indemnities. A key component of the insurance modeling involves the estimation of several spatio-temporal, lattice models. Implications for wildfire management policies are also discussed.

[2] Similar arguments could be made for other fire-prone states in the region (e.g., Georgia, Mississippi, Alabama, Texas) where timber values are high, wildfires are frequent, and forest ownership is dominated by private landowners.

[3] The Florida wildfire data set provided by the Florida Forest Service was only available for this time period.

Risk Models and Insurance Contracts

The central tenet of any effective insurance scheme is a full understanding of all risks underlying the associated hazards. An actuarially fair insurance premium (or premium rate) is based upon knowledge of risks; 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.

A model measuring the actuarially fair premium rate is usually expressed in terms of a conditional probability density or a cumulative distribution function that underlies the risks associated with possible outcomes. In some insurance programs, such as life insurance, a loss is an all-or-nothing event. In this case, because the payout amount is predetermined, an actuarially fair premium rate is equivalent to the conditional probability that the loss event occurs. Such insurance contracts are appropriate for wildfire risks, where any exposure to wildfire for properties within a small site usually results in a total loss. For an insurance contract underwriting a total loss event, if we denote $z = 1$ to be a loss event ($z = 0$ otherwise), the expected loss can be expressed as:

$$(1) \qquad E(Loss) = P(z = 1)E(loss|z = 1).$$

The probability of a loss event is usually given as a function that is conditional on a vector of observable covariates, X, and the associated parameter estimates vector β, that is,

$$(2) \qquad P(z = 1) = F(Xb).$$

When the contract specifies a fixed indemnity in case of a loss event (i.e., $E(loss|z = 1) = Payment$ is predetermined), then the fair premium is equivalent to $E(Loss) = F(X\beta)^{*}Payment$, and the actuarially fair premium rate is thus equal to the probability of loss.

Combining the aforementioned risk function and the theoretical discussions in Prestemon et al. (2002), we construct a model to describe broadscale wildfire risks. Wildfire hazards arise from different sources, such as lightning and arson. Hence, a broadscale wildfire risk function (Prestemon et al. 2002) can be written as:

$$(3) \quad B_{st} = \sum_{i} B_{i,s,t},$$

where B_{st} is the ratio of total burned area by wildfire to the total forestland area of county s in year t, and $B_{i,s,t}$ represents the burnt ratio caused by hazard source i. On an aggregate level, the burnt ratio is equivalent to the wildfire risk probability.[4] Therefore, the wildfire damage function of the burnt ratio caused by hazard i can be written as:

$$(4) \quad B_{i,s,t} = F_i(X_{st}\beta),$$

where X_{st} is a vector of observable variables associated with wildfire hazards.

Understanding factors that determine loss probabilities is crucial for modeling risks. For forest wildfire insurance, factors such as tree types, characteristics of forest land, weather, and socio-economic factors are potentially important risk determinants.[5]

Further operational issues should also be considered when designing an insurance program. One important component of insurance provisions is the insurance coverage period. For example, in agricultural insurance contracts, the insurance period is usually specified on a calendar year or crop season basis. We assume an insurance period corresponding to a calendar year with no loss of generality. It is also important to identify insurance periods because risks can only be conditioned on information available prior to the beginning of an insurance period. For example, although drought is a significant cause of wildfires and may be predictable, precipitation in year $t+1$ is generally unknown in year t. Therefore, our insurance parameters are always conditioned on variables that are observable in the year before the terms of coverage are determined.

Empirical Analysis

We use fire occurrence data collected by the Florida State Forestry Division from 1981–2005. A total of 132,371 individual fires were recorded over this period, and each record describes characteristics of an individual wildfire. The initial time, township ID, cause, fuel type, spread speed, duration, and acreage burned are documented. Weather statistics for the same period were collected from the National Climate Database Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). Land characteristics were obtained from the Forest Inventory and Analysis Database (FIADB), which is administrated by the USDA's Forest Inventory and Analysis National Program.[6] Socio-economic statistics were collected from the Regional Economic Information System (REIS) data set assembled by the Bureau of Economic Analysis of the U.S. Department of Commerce.

In our analysis, the unit of observation is a county. This choice is dictated by our available data, though the analytical approach is applicable to any geographic or temporal unit of observation for which suitable data exist. Although the fire data consist of township-level records, detailed information for many of the factors suspected to be relevant to wildfire risks are only available at the county level. Wildfire can spread quickly over a large area spanning township boundaries, so county-level statistics about wildfire losses may be more accurate and useful. Finally, premium calculations at the county level smooth the premiums across different timber farms without inducing adverse selection. A group (index) insurance plan, if conditioned on a county-level index, can also help alleviate moral hazard and adverse selection (Smith and Goodwin 2011).

The dependent variable in our analysis is the annual county-level burnt ratio (burnt area as a proportion of the total forest area). As illustrated in figure 1.a, the distribution of this variable is highly right-skewed, suggesting that conventional risk modeling approaches that assume normality may not

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[4] Divide the land of a county into n equally sized small sites. The probability that one small site is burned within a time period is denoted as $P(Z=1)$. If we assume homogeneous broadscale risk within a county, following the law of large numbers, the burnt ratio B, which is the number of burned sites divided by n, converges to $P(Z=1)$ as n goes to infinity.

[5] Fuel management and suppression effort may also be related with wildfire risks. However, our focus is to produce an actuarially fair insurance product, and wildfire prevention/suppression actions are endogenously determined by environmental factors. As long as the variables included in our statistical model have adequately accounted for the varying rates of prevention/suppression effort and fuel management, our modeling should be sufficient to estimate and forecast a fair premium.

[6] The FIADB county-level observations are generated from measurements of fixed-location plots. These plots are visited on a periodic basis (every few years) to gather information in the form of tree volumes by species and product classes, among other variables.

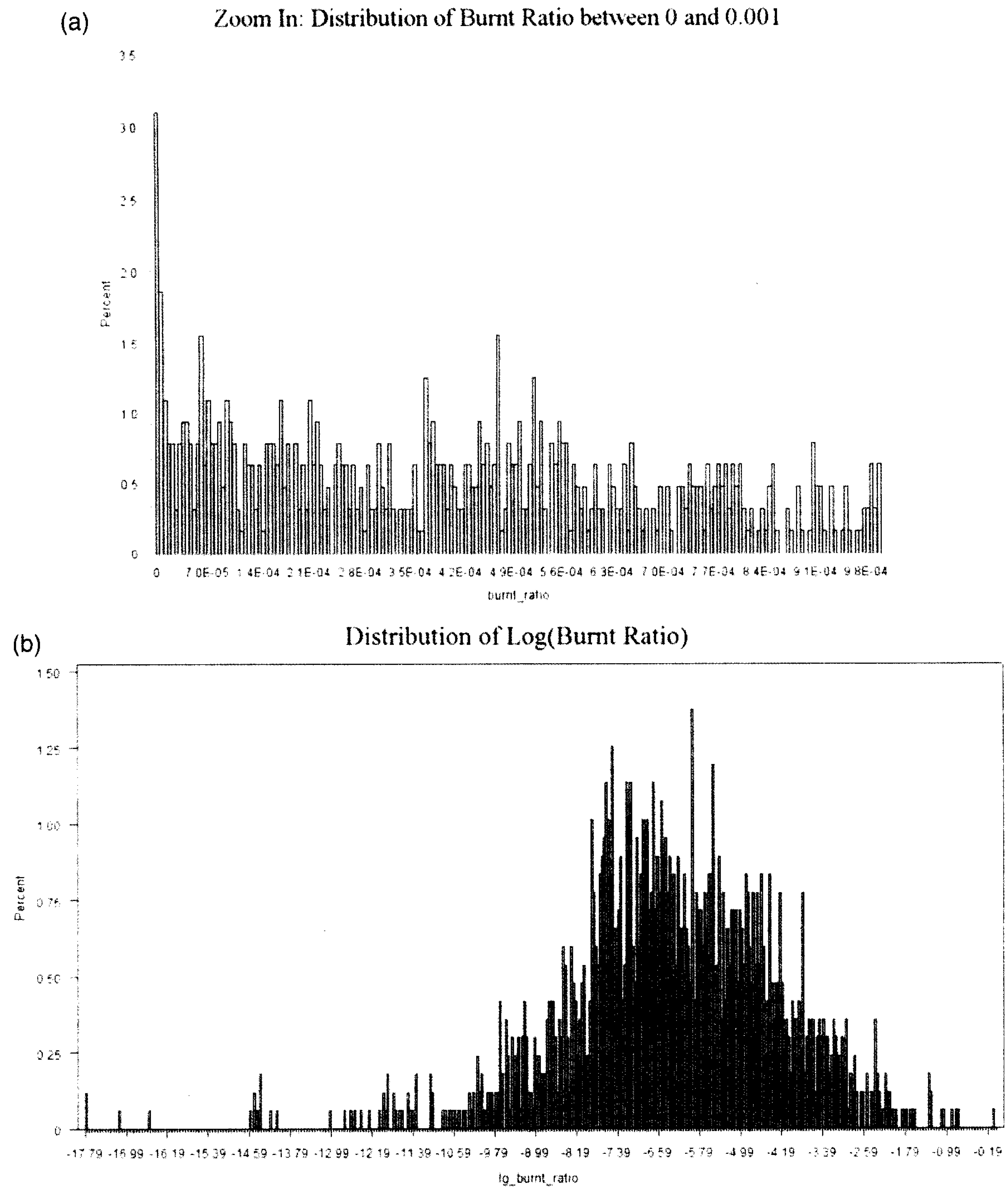

Figure 1. Distributions of burnt ratio and its logarithm

be appropriate. We therefore use as our response variable a log-transformation of the burnt ratio that smoothes the burnt ratio (all observations are positive), and yields a distribution that is much closer to normal (figure 1.b).

Several observable factors are relevant to wildfire risks. For example, certain forest types such as oak and hickory are believed to be more resistant to wildfire spread. Variables representing the shares of several groups of forest lands are considered here, including the group of long-leaf slash pine forests and loblolly/shortleaf pine forests, the group of oak/pine forests and oak/hickory forests, and the group of oak/gum/cypress forests. We form an aggregate composite variable for the area comprised of all other forest land types.[7] Two crucial weather variables affect wildfire likelihoods, that is, drought and temperature. We represent drought and temperature factors using the 12-month Standardized Precipitation (SP12) index and the Heating Degree Day (HDD) index, respectively. Hurricanes are also a significant weather phenomenon that hypothetically influence wildfire risks (Myers and van Lear 1998; Chen and Goodwin 2011). We measure hurricane risks by using the historical annual frequency of hurricanes at a given location.[8] Human intervention, including deliberate or accidental incendiary events, are represented by population, employment, and the proportion of forest land that is privately-owned. These factors have been identified as potentially relevant causal factors of arson and other crimes (see Becker 1968), and their empirical significance has been verified by existing research (Prestemon et al. 2002).

Table 1 presents summary statistics and variable definitions for wildfire risks and relevant explanatory factors.[9] Our analysis utilizes annual county-level observations for all 67 counties in Florida from 1981 to 2005, resulting in 1,675 county-year combinations. To recognize the need for conditioning information to be available prior to the provision of insurance, all covariates are lagged one year in the empirical models.

Several estimation approaches to estimating the conditional probability model were considered. As the simplest and most common model, an ordinary least squares (OLS) regression of y_{st} on $X_{s,t-1}$ was adopted:

$$(5) \qquad y_{st} = X_{s,t-1}\beta + \epsilon_{st},$$

where y_{st} is a wildfire risk indicator and $X_{s,t-1}$ is a vector of lagged observable covariates. However, existing research has found that wildfire risks are both spatially and temporally autocorrelated (Prestemon et al. 2002; Prestemon and Butry 2005). As a result, an OLS regression based solely on the independent variables may not account for spatio-temporal autocorrelation.

An alternative approach includes temporal lags of the dependent variable and the average of neighboring observations of the lagged dependent variable to correct for temporal and spatial autocorrelation. For example, if only the first-order temporal lag is included, the model can be expressed as:

$$(6) \qquad y_{st} = \rho y_{\bar{s},t-1} + q y_{s,t-1} + X_{s,t-1}\beta + \epsilon_{st},$$

where $y_{\bar{s},t-1}$ is the average of all $\{y_{i,t-1}\}$, given $i \in \Theta_s$, and Θ_s represents the set of all spatial units bordering county s. A more general class of such models can be written in a vector form as:

$$(7) \qquad Y_t = \rho W Y_{t-1} + q Y_{t-1} + X_{t-1}\beta + \epsilon_t,$$

where Y_t is a vector of observations of the dependent variable for all of the spatial units at time t, and X_{t-1} represent the lagged covariates. Equation 6 is a special case of equation 7, but with a spatial weight matrix W. Elements of the spatial weight matrix W are defined as $W_{ij} = 1/$(*the number of county i's neighbors*) if counties i and j are neighbors, and is zero otherwise. This method simplifies estimation, but does imply that spatial transmission does not occur contemporaneously (see Ripley 1981).

The response variable of our interest—either wildfire frequency or propensity—is observed annually. While a wildfire rarely lasts longer than a month, simultaneous spatial interactions within a year are more likely to underlie the truth. Therefore, we have also developed a regression model with autoregressive, spatio-temporal dependence, in the form of

$$(8) \qquad Y_t = \rho W Y_t + q Y_{t-1} + X_{t-1}\beta + \epsilon_t.$$

The differences between the two aforementioned models (equations 6 and 8) are not limited to the fact that ρ is a simultaneous spatial dependence parameter in equation 8, while ρ is a lagged spatial dependence parameter in equation 6. Unlike the model represented by equation 6, for which it is convenient to adopt OLS estimation

[7] As suggested by an anonymous referee, a significant portion of timber plantations in Florida are intensively managed with short rotations, which may affect wildfire risks. We considered alternative models that accounted for pine plantations. The resulting models suffered from multi-collinearity problems, and thus our final specification did not include plantation shares. These alternative results are available upon request.

[8] Future research may benefit from a consideration of temporally-variable hurricane risk measures that reflect long-run weather cycles. The accuracy and utility of such measures remains open to debate, and these factors are not used in this analysis.

[9] Ground fuel is related to wildfire risks. In this study, forestland ratio is used to represent such information. We found that this proxy is more desirable than other alternatives such as biomass density, living tree density, and tree mortality in terms of the goodness of fit. In addition, adding any of the abovementioned alternative variables did not improve the results, and led to multi-collinearity problems.

Table 1. Definition and Statistics of Variables

Variable (County Level)	Definition	N	Mean	Std. Dev.
Burnt ratio	Burnt forestland size/total forestland size	1675	0.0109	0.0392
Log (Burnt ratio)	Logarithm of burnt ratio	1675	−5.6251	1.8754
Forestland ratio	Total forestland area/county size	1742	0.5168	0.2813
Private share	Proportion of private owners' forestland	1742	0.7434	0.2585
Longleaf /slash pine and loblolly /shortleaf pine share	Proportion of longleaf /slash pine forestland and loblolly / shortleaf pine forestland	1742	0.4144	0.1840
Oak/pine and oak/hickory share	Proportion of oak/pine forestland and oak/hickory forestland	1742	0.2076	0.1243
Oak/gum/cypress share	Proportion of oak/gum/cypress forestland	1742	0.2209	0.1241
Daily average of HDD Index	Sum of daily Heating Degree Day indices within a year divided by 365	1742	2.7920	1.4247
December SP12 index	December's probability of observing a given amount of precipitation for next 12 months	1742	0.2531	0.9798
Hurricane incidences	Annual count of hurricane strikes within 40 miles of a county's centroid	1742	0.1819	0.4777
Population density	No. of residents per acre of county land	1742	0.3887	0.6928
Log(population density)	Logarithm of population density	1742	−1.8720	1.3548
Employment ratio	Percentage of workforce population	1742	0.4253	0.1159

techniques, the spatio-temporal autoregressive model (equation 8) may present estimation challenges. In particular, it may be difficult to estimate parameters when the weight matrix W appears iteratively in the log-likelihood function.

Another challenge is how to incorporate the temporally-lagged dependent variable. As Cliff and Ord (1975) noted, the lagged dependent variable Y_{t-1} can be treated as an independent variable, as long as Y_{t-1} is independent of current errors ϵ_t. In addition, if the assumption that errors $\{\epsilon_t\}$ are serially independent is satisfied, the estimation method for simultaneous equations systems is applicable (Johnston 1972). Cliff and Ord (1975) devised a maximum likelihood estimation method for models with spatial dependence, and proved that an OLS regression approach will not produce consistent estimates in that scenario. Therefore, we modified their method to accommodate the spatio-temporal modeling context and developed a similar maximum likelihood estimation method.[10]

[10] For further information, please see the supplementary appendix online.

In addition to scenarios where the dependent variable is autocorrelated, researchers have often built empirical models in which autocorrelation exists among errors. Such an idea comes from the notion that if the independent covariates are not comprehensive enough, the unexplained parts of the dependent variable are still likely to have spatio-temporal interaction. Therefore, we modified the maximum likelihood estimation method of Ord (1975), and constructed a model with spatio-temporal autocorrelated errors in the form of

$$(9) \qquad Y_t = X_{t-1}\beta + U_t,$$

and

$$(10) \qquad U_t = \rho W U_t + q U_{t-1} + \epsilon_t .$$

Our estimation methods have important advantages in the presence of spatial and temporal correlation. The simultaneous spatial dependence parameter ρ is an important factor to be estimated. Although conventional models such as equation 7 allow for lagged spatial interaction, the potential for simultaneous transmission in a broad time

Table 2. Estimates and Statistics from Conventional Regressions Parameter

	OLS Model		Conventional S-T Model	
	Estimate	Std. Error	Estimate	Std. Error
$Y_{\bar{s},t-1}$			−0.0292	0.0349
Y_{t-1}			0.2643***	0.0264
Intercept	−4.4674***	0.2875	−3.6629***	0.3189
Forestland ratio	−3.5721***	0.2802	−2.6151***	0.2946
Private share	1.4833***	0.2392	0.9049***	0.2384
Longleaf /slash & loblolly /shortleaf	3.2207***	0.3878	2.9126***	0.3939
Oak/pine & oak/hickory	−1.7279***	0.3834	−0.7750**	0.3789
Oak/gum/cypress	2.0596***	0.4157	1.7687***	0.4151
Daily average of HDD index	−0.3193***	0.0532	−0.3094***	0.0540
December SP12 index	−0.2757***	0.0413	−0.1121**	0.0448
Hurricane incidences	−0.1118	0.2069	−0.1649	0.1988
Log(population density)	0.3627***	0.0442	0.2650***	0.0449
Employment Ratio	−2.2862***	0.4367	−1.5802***	0.4350
Summary Statistics				
$\hat{\sigma}^2$	2.6798		2.4659	
R^2	0.4091		0.4446	
Max. VIF	3.6447		4.4866	
Max. condition index	23.9007		28.9506	
Autocorrelation Test				
Percentage of years when spatial autocorrelation found in residuals	24.00%		29.17%	
Percentage of counties where temporal autocorrelation found in residuals	5.97%		10.45%	

Note: Asterisks *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

scale has been ignored. In some cases, if the spatial dependence within the same period does indeed exist, misspecification of the model may lead to estimation biases.

Table 2 presents the results of a simple OLS regression (equation 5) and the conventional spatio-temporal linear regression (equation 6). The OLS results suggest that all of the conditioning explanatory variables, except for the hurricane frequency measure, have statistically significant impacts on wildfire risks.[11] The conventional spatio-temporal model produces similar results, except that the coefficient of the HDD index is not statistically significant. Temporal dependence is shown to be positive and significant, while the lagged spatial dependence is not statistically significant and is small in magnitude.[12] Overall, the specification of the models and the choice of explanatory variables appears to receive strong empirical support.

Autocorrelation tests for the residuals, however, confirm our concerns. Although temporal autocorrelation is successfully controlled for, neither model sufficiently corrects for spatial autocorrelation.[13] The residuals are autocorrelated in approximately one-quarter of the years, and adding a lagged dependent variable does not alleviate autocorrelation, suggesting that spatial linkages are more likely to exist simultaneously. This is less of a concern within the context of predicting the conditional probability of specific wildfire risks, but it does suggest that the models are inefficiently estimated and may result in misleading inferences.

The difference between the magnitudes of coefficients in these two models also suggests possible misidentification by the OLS model. The estimated coefficients of observable variables in the OLS model are always larger

[11] Other variables may also be relevant. Examples include wildfire prevention/suppression effort, law enforcement, and road densities. We considered these factors and found that they were correlated with other included variables and that their inclusion did not change the overall results. Further, some data do not cover the entire time span from 1981 to 2005. Results using these variables are not presented here, but are available upon request.

[12] Both the variance inflation index (VIF) and condition index are small, which suggests that no multi-collinearity exists among the covariates.

[13] 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. Statistics of Spatio-Temporal Autoregressive Regressions

	S-T Auto. Dep.[a]		S-T Auto. Err.[b]	
Parameter	*Estimate*	Std. Error	*Estimate*	Std. Error
Spatial dependence	0.2813***	0.0269	0.3445***	0.0288
Temporal dependence	0.2489***	0.0244	0.2495***	0.0241
Intercept	−2.4588***	0.3063	−4.9675***	0.3987
Forestland ratio	−1.9814***	0.2784	−2.8695***	0.4221
Private share	0.7071***	0.2264	0.9400***	0.3321
Longleaf/slash & loblolly/shortleaf	2.5052***	0.3757	3.5459***	0.5583
Oak/pine & oak/hickory	−0.7039*	0.3599	−0.5574	0.6093
Oak/gum/cypress	1.4335***	0.3961	3.0884***	0.5990
Daily average of HDD index	−0.1991***	0.0517	−0.4627***	0.0896
December SP12 index	−0.0379	0.0405	−0.0528	0.0868
Hurricane incidences	−0.0883	0.1887	0.5003	0.4336
Log(population density)	0.1969***	0.0426	0.3686***	0.0649
Employment Ratio	−0.9281**	0.4117	−1.7992***	0.5565
		Summary Statistics		
$\hat{\sigma}^2$	2.2252		2.1991	
		Autocorrelation Test		
Percentage of years when spatial autocorrelation found in residuals	12.50%		8.70%	
Percentage of counties where temporal autocorrelation found in residuals	11.94%		11.94%	

Note: Asterisks *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.
[a]The autoregressive model with spatio-temporally autocorrelated dependent variables (see equation 8).
[b]The autoregressive model with spatio-temporally autocorrelated dependent error terms (see equations 9-10).

than those in the spatio-temporal model. This is not surprising, because the spatio-temporal model has taken temporal and neighboring county impacts into consideration, while the OLS regression only models wildfire risks conditional on independent variables. If spatio-temporal autocorrelation indeed exists, influences of covariates may be exaggerated by the OLS model, and thus lead to inaccuracies in insurance design and the mismanagement of wildfire control programs.

Table 3 presents the results of the spatio-temporal autoregressive model and the model with spatio-temporal autocorrelated errors. Similar to the conventional models (table 2), most parameter estimates suggest statistically significant influences. Climate factors, such as temperature and drought, affect wildfires as expected. Cold weather (represented by the HDD index) appears to significantly reduce wildfire risks. The significant impact of population density again verifies that human intervention is an important causal element of wildfire s. Factors related to the economic welfare of the population in a given county may also reflect economic stresses related to deliberate acts of arson (Prestemon and Butry 2005). High employment significantly mitigated wildfire risks, since employed persons have higher opportunity costs of time and are less likely to commit arson.

Private ownership of forests always implies a significantly higher wildfire risk. Since rangers and forest police work actively on public forest lands, private lands are expected to be more vulnerable to wildfire threats. The group of longleaf/slash pine, loblolly/shortleaf pine, and oak/gum/cypress forests have significantly higher fire risks. The latter result reflects the fact that swamp fires are easily spread.

Contrary to expectations, the SP12 index, which represents drought conditions, is not statistically significant in these two models. Likewise, oak/pine and oak/hickory forests are not significant in the model with autocorrelated errors. The direction of the impacts from these two variables, though, are still as expected. With the exception of the hurricane index, coefficients of other covariates are all statistically significant with the anticipated signs.[14]

[14] As noted by an anonymous referee, lightning is also an important causal factor for wildfire. Results that included lightning were similar to those presented in the paper and reflected

Another important implication of our results is that spatial dependence is now statistically significant, which is in contrast to estimates of the conventional spatio-temporal model. This finding confirms suspicions that the conventional spatio-temporal modeling specifications neglected to consider contemporaneous spatial linkages between wildfire risks within a given year. Further, spatial autocorrelation among residuals has been reduced significantly relative to the results for the conventional models. The percentage of years with spatially autocorrelated residuals decreases from around 25% to close to 10%. This is not surprising since the methods account for simultaneous spatial interactions, while conventional models only consider lagged spatial interactions. These improvements confirm that these models are superior for evaluating spatio-temporal autocorrelated wildfire risks. Finally, since the smaller estimated variance of errors implies a better fit, these two models provide a more desirable tool for predicting wildfire risks.

The primary goal of our empirical analysis is to construct models that precisely estimate conditional wildfire probabilities to determine actuarially fair insurance premium rates. An actuarially fair premium that abstracts from administrative and operating costs (including any return to capital) associated with the program should be set equal to the expected loss. The expected loss is usually expressed as:

$$(11) \quad E(loss_{st}) = \int E(Payment_{st}|z_{st}, \Theta_{st}) \times f(z_{st}|\Theta_{st})dz_{st},$$

where z_{st} is an indicator that one of the claim provisions has been triggered (i.e., that a loss event has occurred). Further, Θ_{st} represents the conditioning variables that are conceptually relevant to the risks, and $f(z_{st})$ represents the corresponding probability density function of the loss event. When a fixed payment is made only if a specific outcome occurs (e.g., death in the case of life insurance contracts), the fair premium can be simplified to:

$$(12) \quad E(loss_{st}) = Pr(z_{st} = 1|\Theta_{st}) \times Payment_{st},$$

where $Pr(z_{st})$ represents the corresponding actuarially fair insurance premium rate. As noted, it is also a conditional probability that can be empirically estimated using the aforementioned models.

Similarly, for wildfire risks, expected losses for a comprehensive insurance scheme that can be offered to an individual timber owner can be expressed as:

$$(13) \quad E(loss)_{st} = Pr(o_{st}|\Theta_{st}) \times E(Payment_{st}|o_{st}, \Theta_{st}),$$

where o_{st} represents a loss event caused by wildfire at location s in time t, and *Payment* represents compensation for the loss. However, in light of the problems associated with adverse selection and moral hazard outlined above, such an insurance plan would not be expected to be viable in the forest industry. The first difficulty comes from the fact that wildfire outbreaks are distributed unevenly across space and are too volatile to model accurately at the individual land parcel level of resolution. Second, the value of timber ranges widely across stands and over time, due to variations across stands in species and qualities of the timber products they contain. Therefore, the transaction costs associated with assessing both individual risks and liability values may be too high to implement such an individual wildfire insurance plan, potentially causing moral hazard and adverse selection.

A group insurance plan at the county level may be able to overcome such complications. 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, if the actions of individual agents do not significantly affect the aggregate index or index threshold that governs coverage, moral hazard is diminished. We can use the burnt ratio to represent the fire probability as

$$(14) \quad E(loss)_{st} = z_{st} \times E(Payment_{st}|z_{st}, \Theta_{st}),$$

where z_{st} is the expected burnt ratio. Our models forecast the burnt ratio for county s in time t, which we assume follows a log-normal distribution conditional on information available at time t-1. However, results using the burnt ratio directly, such as equation 14, are not robust in our empirical models. Even though the logarithm of burnt

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substantial multi-collinearity with other climate measures such as precipitation and temperature.

ratio is normally distributed, its variations will be exponentially amplified when the logarithmic form is converted back into the original level.

Our index insurance plans, however, are unaffected by these issues. In a hypothetical timber insurance program, the claim procedure could work as follows. Before the beginning of the insurance period, both insurance providers and forest landowners agree on an indemnity trigger for the burnt ratio index, say $\tilde{z}_{st} = 8\%$, and the insured agents pay premiums to insurance companies. At the end of the insurance period, the federal or state authority issues a final burnt ratio for each county based on statistics documenting fire occurrences. When the actual burnt ratio z_{st} in a county exceeds the threshold stipulated in the contract, say 8%, every insured forest landowner in this county will receive a fixed payment. Note that in such index plans, payments are made to all insuring landowners regardless of whether they experienced fire losses. Thus, in our example, the actuarially fair premium is:

$$(15) \quad E(loss)_{st} = Pr(z_{st} > \tilde{z}_{st} | \Theta_{st}) \times E(Payment_{st} | z_{st} > \tilde{z}_{st}, \Theta_{st}).$$

The premium rate, which is the ratio of the premium to the liability, is:

$$(16) \quad Pr(z_{st} > \tilde{z}_{st} | \Theta_{st}) = 1 - \Phi((\ln \tilde{z}_{st} - \mu_{st})/\sigma_{st}),$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, and $z_{st} \sim \ln N(\mu_{st}, \sigma_{st}^2)$. The mean μ and the standard error σ are estimated by our models. Since the mean burnt ratio is approximately 0.1% (table 1), we consider triggers of 10%, 1%, 0.15%, 0.1%, 0.05%, 0.01%, and 0.001%.

Summary statistics of the estimated premium rates for different triggers are presented in table 4. Because a smaller trigger provides more comprehensive protection, premium rates increase as the trigger level declines. Premium rates among spatio-temporal models are fairly similar. In contrast, the OLS regression, which ignores spatio-temporal autocorrelation, generally produces much higher premium rates. This indicates that premium rates may be overestimated if one does not consider spatio-temporal autocorrelation. Recall that the effects of observable covariates on risks are overestimated when spatio-temporal correlation is ignored (table 2). This also suggests that the resulting higher rates will likely discourage participation in the insurance plans. Further, if information is not perfectly symmetric, overestimating premium rates will result in an adversely-selected pool of insured agents, which may endanger the sustainability of such programs.

Figure 2 and online supplementary figure compare the average actual burnt ratio between 1983 and 2005 (figure 2) to the average estimated premium rates using different models for the same time period (online supplementary figure). The overall similarities of the maps suggest an appropriate selection of covariates. Although the visual differences between the four maps of premium rates are not substantial, the mosaic patterns generated by the preferred models are closer to the actual burnt ratio map than those of the conventional models, which suggests a better fit.

An important function of any insurance program is accurately calculating premiums. The total premium depends on the premium rate and the expected payout. The $Payment_{st}$ in equation 15, which is the product of insured acres and the indemnity payment per acre, can be set exogenously in accordance with various policy goals. For example, given that the payment will be made to all insured timber owners if the threshold is surpassed, the indemnity amount may be set at a level that corresponds to the cost of desired fire risk mitigation actions that may be taken in response to localized fire outbreaks. For example, payments may be set as:

$$(17) \quad Payment_{st} = (Insured\ Acres)_{st} \times [(Timber\ Value\ Per\ Acre)_{st} \times (Actual\ Loss\ Ratio)_{st} + (Prevention\ Cost)],$$

where $(Actual\ Loss\ Ratio)_{st}$ is equivalent to the burnt ratio z_{st} in equations 15 and 16. Since county-level timber volume and regional timber prices are readily available, it is straightforward to estimate the average timber value per acre in each county.[15]

[15] Timber loss values are not limited to the values of trees. For example, even a young stand of trees too small to be commercially

Table 4. Estimated Premium Rates Given Different Trigger Indices

Model	Mean	Median	Std. Dev.	Max.	Min.
Reimburse if burnt ratio > 10%:					
OLS Model	0.0296	0.0048	0.0546	0.4595	2.2380E-6
Conventional spatio-temporal model	0.0249	0.0031	0.0471	0.3582	3.2602E-9
Model with dependent responses	0.0242	0.0027	0.0467	0.3641	1.8989E-9
Model with dependent errors	0.0239	0.0033	0.0420	0.2874	2.4611E-9
Reimburse if burnt ratio > 1%:					
OLS Model	0.2059	0.1176	0.2062	0.9040	7.3282E-4
Conventional spatio-temporal model	0.1946	0.1019	0.2059	0.8650	7.2380E-6
Model with dependent responses	0.1938	0.0998	0.2093	0.8729	5.3640E-6
Model with dependent errors	0.1971	0.1075	0.2029	0.8171	5.9200E-6
Reimburse if burnt ratio > 0.15%:					
OLS Model	0.5189	0.4888	0.2642	0.9931	2.1562E-2
Conventional spatio-temporal model	0.5079	0.4749	0.2757	0.9896	8.7885E-4
Model with dependent responses	0.5051	0.4779	0.2841	0.9910	7.5272E-4
Model with dependent errors	0.5139	0.4859	0.2768	0.9827	7.6228E-4
Reimburse if burnt ratio > 0.1%:					
OLS model	0.5935	0.5869	0.2535	0.9967	3.7963E-2
Conventional spatio-temporal model	0.5835	0.5775	0.2665	0.9949	2.0512E-3
Model with dependent responses	0.5803	0.5811	0.2749	0.9957	1.8007E-3
Model with dependent errors	0.5893	0.5865	0.2671	0.9911	1.7999E-3
Reimburse if burnt ratio > 0.05%:					
OLS model	0.7136	0.7399	0.2187	0.9991	8.8282E-2
Conventional spatio-temporal model	0.7058	0.7379	0.2337	0.9987	7.5751E-3
Model with dependent responses	0.7026	0.7429	0.2408	0.9989	6.9019E-3
Model with dependent errors	0.7109	0.7457	0.2328	0.9975	6.7755E-3
Reimburse if burnt ratio > 0.01%:					
OLS model	0.9108	0.9481	0.1059	0.9999	3.5634E-1
Conventional spatio-temporal model	0.9073	0.9517	0.1235	0.9999	8.0182E-2
Model with dependent responses	0.9063	0.9549	0.1239	0.9999	7.7763E-2
Model with dependent errors	0.9102	0.9536	0.1187	0.9999	7.4655E-2
Reimburse if burnt ratio > 0.001%:					
OLS model	0.9939	0.9988	0.0133	1.0000	0.8504
Conventional spatio-temporal model	0.9928	0.9991	0.0254	1.0000	0.5249
Model with dependent responses	0.9932	0.9993	0.0238	1.0000	0.5281
Model with dependent errors	0.9934	0.9992	0.0232	1.0000	0.5109

Prevention costs are used to compensate forest owners' preventive actions that may be taken once a fire occurs in a given county. Such steps include building fire breaks and removing excess fuels. In the case of contagious (spatio-temporally correlated) risks, preventive actions may provide positive externalities across spatial units and across time periods. This occurs if payments permit costly risk mitigation efforts that reduce the risks of wildfire spread. Non-insured timber owners, neighbors, and the local community may realize benefits from the decreased risks that result from mitigation efforts. Therefore, such an insurance scheme may help to mitigate overall wildfire risks and thus enhance social welfare. The realization of such externality benefits may require compensated timber owners to undertake mitigation efforts.

Insurance provisions sometimes require specific actions following a claim. If the

valuable may still have a non-zero loss value due to stand re-establishment costs and delayed rotations, as determined by the insurance adjuster.

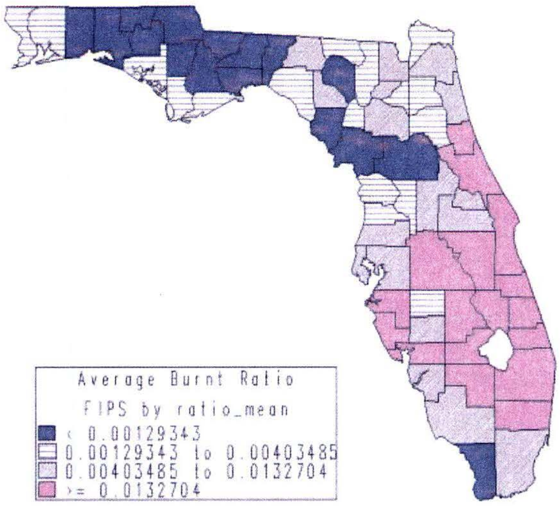

Figure 2. Average burnt ratio between 1983–2005

trigger index is surpassed, the expected indemnity in equation 15 can be expressed as

$$(18)\quad E(Payment_{st}|z_{st} > \tilde{z}_{st}, \Theta_{st})$$
$$= (Insured\ Acres)_{st}$$
$$\times\ E\left\{\left[(Timber\ Value\ Per\ Acre)_{st} \times z_{st} + (Prevention\ Cost)|z_{st} > \tilde{z}_{st}, \Theta_{st}\right]\right\}$$
$$= (Insured\ Acres)_{st} \times (Timber\ Value\ Per\ Acre)_{st} \times E(z_{st}|z_{st} > \tilde{z}_{st}, \Theta_{st})$$
$$+\ (Prevention\ Cost),$$

where

$$E(z_{st}|z_{st} > \tilde{z}_{st}, \Theta_{st}) = \exp(\mu_{st} + \sigma^2_{st}/2) \times \Phi((\mu_{st} + \sigma^2_{st} - \ln \tilde{z}_{st})/\sigma_{st})/[1 - \Phi((\ln \tilde{z}_{st} - \mu_{st})/\sigma_{st})],\ \text{given } z_{st} \sim \ln N(\mu_{st}, \sigma^2_{st}).$$

The actuarially fair premiums are:

$$(19)\quad Premium_{st} = E(loss)_{st}$$
$$= E(Payment_{st}|z_{st} > \tilde{z}_{st}, \Theta_{st}) \times (Premium\ Rate)_{st}$$
$$= \left\{(Timber\ Value\ Per\ Acre)_{st} \times \exp(\mu_{st} + \sigma^2_{st}/2) \times \Phi((\mu_{st} + \sigma^2_{st} - \ln \tilde{z}_{st})/\sigma_{st})\right.$$
$$\left.+\ (Prevention\ Cost) \times [1 - \Phi((\ln \tilde{z}_{st} - \mu_{st})/\sigma_{st})] \times (Insured\ Acres)_{st}\right\}.$$

The trigger index of the burnt ratio $\tilde{z}_{st}$ is predetermined and has no influence on the conditional wildfire probability. Hence, as long as the probability of a fire (i.e., the distribution of burnt ratio $z_{st} \sim \ln N(\mu_{st}, \sigma^2_{st})$) can be conditioned using relevant information, the premium paid by the insured should be actuarially fair.

We consider a validation study to simulate the viability of this insurance plan. Because actuarial fairness only depends on the conditional probabilities, the choices of *Timber Value Per Acre* and *Prevention Cost* will not affect program performance. Thus, we assume for simplicity, but without loss of generality, that the average timber value is identical for all counties and years in Florida, which is estimated to be $983 per acre (Bronson). Fire prevention cost is assumed to be $112 per acre, which roughly corresponds to the labor costs (valued at minimum wage) of removing excess fuel on a 2,000 square foot plot.

An important operational issue involves specifying the trigger index. Since the typical burnt ratio fluctuates dramatically across counties, timber owners from different counties might be unwilling to buy an insurance policy with a universally constant trigger. Therefore, we assume an insurance plan whose provisions are attached to the expected burnt ratio. For example, if the predicted burnt ratio is estimated to be $\hat{z}_{st} = 10\%$[16] and the target coverage level is $C = 80\%$, the trigger index will be $\tilde{z}_{st} = C \times \hat{z}_{st} = 8\%$. The associated actuarially fair premium (equation 19) can then be

[16] The expected burnt ratio $\hat{z}_{st}$ is given by $\hat{z}_{st} = \exp(\mu_{st} + \sigma^2_{st}/2)$, given $z_{st} \sim \ln N(\mu_{st}; \sigma^2_{st})$.

simplified as:

$$(20)\quad Premium_{st} = \{(Timber\ Value\ Per\ Acre)_{st} \times \exp(\mu_{st} + \sigma_{st}^2/2) \times \Phi(\sigma_{st}/2 - \ln C/\sigma_{st}) + (Prevention\ Cost) \times [1 - \Phi(lnC/\sigma_{st} + \sigma_{st}/2)] \times (Insured\ Acres)_{st}.$$

Such a plan more closely reflects expected wildfire risks and thus should be more widely accepted. In our validation experiments, we assume full participation and use parameter estimates from each model to forecast annual wildfire risks. In each experiment, a fixed coverage level of protection is offered. For example, if *Coverage* = 120%, a forest landowner can only claim an indemnity payment if the actual burnt ratio z_{st} in his county exceeds 120% of the expected burnt ratio, $\hat{z}_{st}$. Premiums are assessed using equation 20, and indemnities are determined by equation 17.

Summary statistics of simulated premiums and indemnities for several insurance plans are presented in table 5. The loss ratio, which should be one for an actuarially fair plan, is defined as the ratio of total indemnities to total premiums. Ignorance of spatio-temporal autocorrelation may cause overestimation of premiums, which is confirmed (table 5) since the programs derived from the OLS model consistently collect much higher profits than others. Within all four modeling specifications, the most desirable result (i.e., the loss ratio is closest to one) is always generated by one of the two preferred models. This verifies our contention that the spatial correlation of wildfire risks is more likely to be contemporaneous. Although both premiums and indemnities rise as the level of protection becomes more comprehensive (with a lower coverage value), the loss ratio eventually approaches one and is stabilized when target coverage is below 1.5%.[17] One implication is that they are better able to represent the entire distribution rather than just the right part of the distribution. This is reasonable because the log-normal distribution of the burnt ratio is extremely right skewed. The other implication is that a target coverage level as low as 1% is small enough to compensate most wildfire occurrences. The validation results therefore support the viability of this index insurance scheme. Over half of the policies will not make reimbursements if the target coverage is more than 50%. This reflects the fact that the standard deviation of errors σ_{st} is between 1.5 and 1.6 (tables 2 and 3). An alternative would be to use the predicted median of the burnt ratio instead of the expectation as the benchmark score.[18]

Conclusion and Discussion

Society has long had to deal with natural disasters using both ad hoc compensation and more formal institutional arrangements. While the latter may be best represented by the largely private sector effort to provide insurance to property owners, timberland owners have generally lacked insurance. We evaluate an insurance instrument that protects timber owners against wildfire risks. A single-peril index insurance scheme is proposed and associated actuarially fair premiums are estimated. A validation study representing the operation of such a plan supports the viability of such index insurance plans—at least from the perspective of insurance providers.

In this paper, we identified spatio-temporal dependence for wildfire risks in Florida. To this end, we developed two new structural models that revised the spatial autocorrelation models of Ord (1975) to explicitly address the spatio-temporal aspect of this problem; contemporaneous spatial dependence was incorporated and parameters were estimated using maximum likelihood methods. Our empirical analysis was based on a complete survey of Florida wildfire loss records from 1981 to 2005, as well as data drawn from the National Forestry Inventory and Analysis (FIA) database, the Regional Economic Information System (REIS) database, and the National Climate Data Center (NCDC) database. The results confirmed that our proposed statistical models offer advantages over conventional models when recognizing spatio-temporal autocorrelation and when calculating premiums.

Our analysis also suggests potentially important forest management implications.

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[17] Premiums and indemnities are also stabilized when coverage <1:5%, according to statistics for a target coverage below 1.5%, some of which are not presented in table 5, but are available upon request.

[18] $Median(z_{st}) = \exp(\mu_{st})$, given $z_{st} \sim \ln N(\mu_{st}, \sigma_{st}^2)$.

Table 5. Validation Study of Index Insurance Programs with Different Coverage Levels

Model	Premium Per Acre					Indemnity Per Acre					Loss Ratio[c]
	Mean	Median	Min.	Max.	Std. Dev.	Mean	Median	Min.	Max.	Std. Dev.	
Coverage = 200%:											
OLS model	22.11	15.55	12.13	219.71	16.83	11.20	0	0	1001.68[d]	53.69	0.6395
Conventional spatio-temporal model	20.72	15.20	12.34	133.30	13.09	12.45	0	0	1001.68	54.99	0.7167
Model with dependent responses	20.40	15.20	12.42	131.76	12.45	13.32	0	0	1001.68	56.05	0.7512
Model with dependent errors	20.48	15.25	12.34	99.23	11.65	13.23	0	0	1001.68	56.07	0.7179
Coverage = 150%:											
OLS model	27.11	19.92	16.18	243.55	18.44	13.73	0	0	1001.68	56.63	0.6078
Conven-tional spatio-temporal model	25.90	19.80	16.65	150.26	14.47	16.66	0	0	1001.68	59.13	0.7256
Model with dependent responses	25.68	19.89	16.76	149.06	13.80	17.31	0	0	1001.68	59.78	0.7520
Model with dependent errors	25.72	19.91	16.60	112.81	12.90	16.99	0	0	1001.68	59.60	0.6929
Coverage = 120%:											
OLS model	31.50	23.87	19.89	261.34	19.58	17.88	0	0	1001.68	60.06	0.6813
Conventional spatio-temporal model	30.48	23.97	20.61	163.25	15.44	19.96	0	0	1001.68	61.92	0.7194
Model with dependent responses	30.35	24.16	20.75	162.32	14.77	21.50	0	0	1001.68	62.99	0.7573
Model with dependent errors	30.36	24.14	20.52	123.41	13.80	20.50	0	0	1001.68	62.35	0.7068
Coverage = 100%:											
OLS model	35.41	27.44	23.29	275.29	20.44	21.87	0	0	1001.68	63.05	0.7198
Conventional spatio-temporal model	34.59	27.77	24.24	173.67	16.18	24.20	0	0	1001.68	64.73	0.7597
Model with dependent responses	34.55	28.05	24.39	172.96	15.50	26.75	0	0	1001.68	66.27	0.8210
Model with dependent errors	34.51	28.00	24.08	132.04	14.47	24.53	0	0	1001.68	65.13	0.7305

(Continued)

Table 5. Continued

Model	Premium Per Acre					Indemnity Per Acre					Loss Ratio[c]
	Mean	Median	Min.	Max.	Std. Dev.	Mean	Median	Min.	Max.	Std. Dev.	
Coverage = 80%:											
OLS model	40.57	32.24	27.90	291.54	21.38	27.68	0	0	1001.68[d]	66.79	0.7538
Conventional spatio-temporal model	40.03	32.87	29.16	186.08	16.99	30.06	0	0	1001.68	67.98	0.7951
Model with dependent responses	40.11	33.25	29.32	185.64	16.30	32.57	0	0	1001.68	68.99	0.8540
Model with dependent errors	40.03	33.22	28.90	142.48	15.22	29.92	0	0	1001.68	68.02	0.7664
Coverage = 50%:											
OLS model	52.61	43.65	38.98	322.54	23.00	41.65	0	0	1001.68	72.28	0.8580
Conventional spatio-temporal model	52.72	44.98	40.97	210.64	18.37	46.96	0	0	1001.68	73.28	0.9498
Model with dependent responses	53.09	45.57	41.13	210.72	17.67	48.77	0	0	1001.68	73.54	0.9712
Model with dependent errors	52.89	45.54	40.48	163.73	16.49	45.75	0	0	1001.68	73.08	0.8987
Coverage = 10%:											
OLS model	96.10	86.20	81.04	394.48	25.42	97.40	113.38	0	1001.68	62.83	1.0706
Conventional spatio-temporal model	97.31	88.72	84.27	272.59	20.39	103.07	113.46	0	1001.68	58.77	1.0906
Model with dependent responses	98.09	89.75	84.00	273.24	19.66	103.44	113.49	0	1001.68	58.48	1.0785
Model with dependent errors	97.72	89.59	83.04	220.78	18.35	101.76	113.44	0	1001.68	59.79	1.0574
Coverage = 1%:											
OLS model	124.89	114.85	109.62	427.16	25.75	118.65	113.57	0	1001.68	41.89	0.9832
Conventional spatio-temporal model	123.46	114.76	110.26	300.88	20.64	119.45	113.57	0	1001.68	40.67	0.9895
Model with dependent responses	123.19	114.87	110.41	300.54	19.86	119.45	113.57	0	1001.68	40.67	0.9898
Model with dependent errors	123.23	114.88	110.21	247.94	18.51	119.31	113.57	0	1001.68	40.89	0.9856

Notes: [c]Defined as the total indemnities divided by the total premiums.
[d]This maximum amount paid out in indemnity corresponds to a total loss of 17,201 acres of forest land burnt by wildfire in Broward County in 1989, which is equivalent to approximately 91% of its entire forest land area. Since the expected burnt ratio for that year was only between 0.58% and 0.65%, unless the coverage level is larger than 13.845%, this indemnity payment is always triggered. This maximum value is unaffected by model specifications, as the indemnity per acre is calculated by equation 17: Timber Value Per Acre × Actural Burnt Ratio + Prevention Cost = $983 \times 0.905086 + 112 \approx 1;001:68$.

Our results identify important causal factors related to wildfire risks. These factors include drought, high temperatures, and human actions, all of which appear to enhance wildfire hazards significantly. Components of forest land ecosystems also have significant influences on fire risks. Thus, the government and timber owners may consider actions to reduce wildfire hazards, such as concentrating fire suppression resources on certain types of forestland and in high unemployment areas. In addition, spatial and temporal spillover effects of wildfire are confirmed. This suggests that efforts to reduce the ignition and spread of wildfires may imply positive externalities, which may have important policy implications.

Economists typically argue that government intervention reduces overall economic welfare unless a specific failure of the market exists. Many arguments pointing to market failures are advanced by proponents of subsidized insurance, and most such arguments are refuted by empirical evidence (Smith and Goodwin 2011). However, one persuasive case favoring government support for specific peril or multiple peril insurance exists when such insurance may be used to encourage mitigation efforts by those threatened by contagious risk (Goodwin and Vado 2007). If subsidized compensation for losses is provided when such a hazard is present, mitigation efforts may be encouraged and the spread of the hazard may be inhibited. In such a case, aggregate economic welfare could potentially be enhanced by subsidized insurance. Subsides might also serve to mitigate free-rider problems and the distortions that they entail.

From the government's perspective, such insurance may provide a useful financial instrument to compensate wildfire losses and alleviate wildfire risks. Compared to ad hoc disaster relief, timber wildfire insurance plans may have several advantages. First, the coverage of insurance might be much wider than that of disaster relief. Indeed, disaster relief usually ignores small-scale wildfires, which comprise a dominant share of all wildfires. Such index insurance programs may also help wildfire suppression. Since indemnities are directly attached to a wildfire index, insured forest landowners have strong incentives to report a wildfire despite its scale. Thus, suppression actions can be taken in a timely manner and the spread of wildfire may be inhibited. At the same time, because an individual fire likely cannot influence the aggregate index directly, moral hazard issues are diminished.

The government can also more actively engage in wildfire management with this insurance instrument. Disaster relief, which is usually only granted after very large wildfires, has almost no impact on reducing wildfire risks. Because wildfire risks are positively correlated in both space and time, mitigation actions should reduce neighboring and future wildfire hazards. An insurance scheme that supports preventive actions may lower wildfire risks and associated future premiums, and a lower premium will raise insurance participation and encourage even more preventive actions.[19] Such reciprocal arrangements will likely alleviate wildfire risks in the long term. Further, unlike ad hoc disaster payments, subsidies may be a more fiscally stable instrument for the government.

Our main focus is to propose a risk-management instrument for timber owners. The accurate quantification of conditional risks and insurance premium rates are necessary ingredients of any insurance program, whether subsidized or private. Our objective is to derive such measures to guide public policymakers and private insurance providers. In this study it is not our intent to quantitatively verify the rationale or necessity of the aforementioned subsidized scheme. Indeed, the role of government in the provision and maintenance of such wildfire insurance remains an important topic for future policy deliberations and research. Other important problems relating to the dynamic behavior of landowners and insurers also remain of interest. If insurance induces more risk mitigation, risk profiles may evolve over time along with insurance participation.

[19] To ensure subsidized mitigation actions are performed, restrictive insurance provisions and monitoring steps may be required. As a reviewer correctly notes, the benefits of index coverage may be diminished if individual monitoring is required. However, validating mitigation is quite distinct from the range of underwriting and data requirements necessary to adequately price and loss-adjust policies offering individual coverage. Further, if the subsidy for the insured is so big that the spillover benefits to the uninsured neighbors can reduce expected losses of the uninsured by a significant amount, free riding by the uninsured may arise, which could result in a suboptimal Nash equilibrium. To prevent such cases, a careful evaluation of the optimal subsidy amount may be necessary. The goal of our research is not to evaluate insurance subsidies in detail, but rather to discuss the modeling and pricing of fire risks. The role of subsidies is an important topic for future research.

Supplementary Material

Supplementary material is available at the American Journal of Agricultural Economics online at www.oxfordjournals.org/our_journals/ajae.

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