# Spatio-Temporal Modeling of Lightning Fires on

# Forestland: A Compensation Scheme

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# Spatio–Temporal Modeling of Lightning Fires on Forestland: A Compensation Scheme

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**Abstract**

In the US forestry industry, wildfire has always been one of the leading causes of damage. This topic is of growing interest as wildfire has caused huge losses in recent years. Among all causes, lightning has always been the leading hazard. Unlike human related wildfires for which timber owners may be able to trace the responsible persons to claim losses, forestland owners essentially have no means to recover their losses against lightning–induced wildfire. In light of the fact that there are very few risk management instruments available to compensate timber losses. Following this line of inquiry, our paper studies risks of lightning induced wildfire, conditioning on crucial informational variables, across both spatial units and time periods. A non–parametric bootstrapping method is used to quantify the risks. Some relevant observable variables, such as environment and climate factors, are found to be statistically significant factors related to wildfire risks. A group index insurance scheme has been proposed and its associated actuarially fair premium rates have been estimated. Implications for wildfire management policies are also discussed.

KEY WORDS: lightning fire, index insurance, spatio-temporal correlation

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# 1    Introduction

Forests cover a large land area in the United States. Since the early twentieth century, the size of U.S. forestland area has been stable at around 746 million acres, comprising about one third of the total land of the United States. In a world context, the U.S. makes up about 10% of the world's total forestland, and its timber production for industrial products accounts for about one–fourth of the world's production (Brad and David, 2004). On average, three pounds of forestry industry products are consumed by each U.S. resident every day. This means that every year an amount equivalent to 100–foot tree will be consumed by each American (Bronson).

Although forest and timber industries play an important role in the U.S., they are constantly threatened by wildfire outbreaks. A wildfire is any uncontrolled fire in combustible vegetation that occurs in the countryside or in a wilderness area. The temperature of a wildfire could rise to 2,600 degrees Fahrenheit. Since such heat can even melt iron, properties and trees in the way are destroyed immediately. Wildfires usually spread rapidly over large areas. The forward blasts could be as wide as 60 feet and flames could rise up to 325 feet and move as fast as 100 miles per hour. This is especially true for violent crown fires – called "firestorms "or "blowups", that engulf the top of huge trees as they sweep across the landscape (Bronson). These characteristics make it difficult to contain a large wildfire within a small space and to extinguish it in a short period of time. The vector of wildfire transmission risks, involving significant weather events and idiosyncratic fuel buildups on the ground, makes containment a major challenge.

In December 2003, the Healthy Forest Restoration Act (Act, 2003) was signed by President George W. Bush with the aim of protecting land from wildfire disasters. Preceded by the two worst wildfire seasons (2000 and 2002) after World War II, this act stipulates that it will:

*"improve the capacity of the Secretary of Agriculture and the Secretary of the Interior to conduct hazardous fuels reduction projects on National Forest System land and Bureau of Land Management lands aimed at protecting communities, watersheds, and certain other at–risk lands from catastrophic wildfire, to enhance efforts to protect watersheds and address threats to forest and rangeland health, including catastrophic wildfire, across the landscape, and for other purposes."*

———Healthy Forest Restoration Act (Act, 2003, pp 108)

After the passage of this act, many more hazardous fuel reduction projects on federal lands have been expedited to protect forest–adjacent communities from wildfires. This act has proved to be a significant effort in wildfire prevention.

Among all sources of wildfire, lightning is the leading one for both outbreaks and damage (Figure 1). Unlike human related wildfires for which timber owners may be able to trace the responsible persons to claim losses, forestland owners essentially have no means to recover their losses against lightning–induced wildfire. Disaster relief, a form of *ad hoc* assistance, is often used to compensate property owners after disastrous wildfires. Some national organizations such as the American Red Cross offer immediate aid to victims after large wildfires. Other local non–profit programs, such as the Georgia Wildfire Relief Fund, provide assistance to affected residents and engage in local ecosystem restoration in the long term. In addition, affected private timber business owners are always highly dependent on government disaster relief programs. For example, southern California suffered from large wildfires in two consecutive years from 2007 to 2008. In 2007, the Internal Revenue Service (IRS) granted tax relief for Southern California wildfire victims. After the 2008 wildfire season, both the IRS and the California state government granted tax relief for affected business owners in Southern California.

Wide spread disasters such as lightning fire pose a significant hazard to timber production and assets, and thus warrant consideration of a relevant single–peril forest insurance product. First, such an approach can provide an actuarially fair rate by empirically quantifying risks, which may attract insurance companies and forest landowners to engage in a private insurance market. Further, the possibility of removing the government externality in the disaster payment market will likely result in a more efficient market scheme. Second, the potential economic benefits from mitigation and reduction of the further spread of lightning wildfire will be enhanced under such a specific–peril plan. Finally, quantification of wildfire risks may provide important benefits to local, state, and federal land managers, who must contemplate wildfire prevention and mitigation actions in advance of fires.

The first benefit stems from the notion that comprehension of a particular hazard and its spatio–temporal transmission mechanisms warrants the development of a class of single–peril insurance products that measure wildfire risks accurately. 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 insurance products once 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), development of private wildfire insurance products can lessen the government financial stress if *ad hoc* disaster relief eventually becomes unnecessary.

The second benefit stems from the notion that understanding the spatio–temporal aspects of wildfire risks and recognizing the potential spatio–temporal externalities can provide benefits to forest landowners, insurance companies, local and state governments and society in general. To fully capture those benefits, a comprehensive study of spatio–temporal relationships of wildfire risks, observable forest characteristics and environmental factors is required. In addition, a practical effective insurance policy needs to minimize adverse selection and moral hazard issues and should be able to induce incentive–compatible actions by forest landowners to prevent wildfire risks. A fair premium insurance plan also needs to evaluate compliance policies that decrease outbreak probabilities by reducing hazards in advance. Prescribed burning permits are an example of efforts made by forest landowners and governments to reduce wildfire risks.

The State of Florida, with a significant forest land portion of its total land area and a history of frequent lightning wildfire outbreaks, represents an ideal case–study for modeling losses associated with lightning fire risks. As many as 16 million acres of forest land cover almost half of Florida's total land area. Ranked among top four tree–planting states, Florida plants over 82 million trees every year, with 5 trees planted for each tree harvested. The forest and forest products industries have an economic impact of $16.5 billion, including 133,000 jobs (Bronson). At the same time, Florida suffers from over 1,200 lightning induced wildfire occurrences per year on average, with approximately 100,000 acres of forest land being burned in a typical year. Moreover, the fact that more than 300,000 private (non–industrial) landowners own half of Florida's forest land suggests a potentially significant demand for timber insurance product against lightning induced wildfire.

As broadscale lightning fire risks have rarely been studied before, our study provides a spatio–temporal model which is used to empirically evaluate lightning fire risks on forestland at the county–level and to develop an associated actuarially sound, single–peril insurance product. This paper studies the spatio–temporal correlated risks (see Figure 2 and Figure 3) of Florida lightning fires using data collected between 1981 and 2005. In addition to modeling the spatial and temporal aspects of lightning fires, it is also critical to understand their underlying causes. Our results suggest significant impacts on lightning fire risks by environmental factors and human interventions. We find that vegetation structures, climate variables and socioeconomic conditions are significant influences on the risks of fire. An annual county–level contract, which pays a pre–determined indemnity to all the insured in the event that the wildfire index exceeds a pre–specified level, is proposed. Statistical models are used to quantify lightning risks and to estimate associated insurance indemnities.

# 2 Risk Models and Insurance Contract

Although timber production and crop production share some similarities, forest insurance plans rarely exist while crop insurance policies are widely adopted in the agricultural sector. According to unpublished USDA statistics, total liability in the federal crop insurance program exceeded $113 billion in 2011.[1] Crop insurance programs have played an important role in U.S. agriculture for the last seventy–five years. This role has risen in prominence in recent years as programs expanded and government subsidies were increased. Multi–peril insurance policies, as well as single–peril insurance policies, have been popular among farmers. Because of the difficulties to accurately measure risks from all possible hazards, efforts to supply all risk (multiple–peril) insurance policies in the private market have typically turned out to be failures (Smith and Goodwin, 2011). As a matter of fact, the current existing multiple–peril insurance programs are all heavily subsidized by the federal government. Further, most all–peril crop insurance programs around the world are also highly dependent on government subsidies. Single–peril insurance policies, however, have been developed adequately well in the private market. One of the pioneer agriculture insurance policies was the hail insurance introduced to tobacco farmers in 1879. Ever since then, various kinds of single–peril agriculture insurance plans have been invented. For fire risks particularly, crop insurance the against single peril of fire was introduced by private companies at least as early as 1938 (Smith and Goodwin, 2011).

Although our goal is not to directly evaluate arguments in favor of or against government intervention in the provision of wildfire insurance, it is an issue that is relevant to the debate. Economists typically argue that such 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 countered 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 risk. Goodwin and Vado (2007) note that the case of an infectious disease may present such a situation. If government compensation for losses is provided when disease is provided, agents may have a greater incentive to report the threat. Likewise, if such compensation is provided to those who are at a greater risk of exposure, even if no losses are realized, mitigation efforts may be encouraged and the spread of the disease may be inhibited. In such a case, aggregate economic welfare may be enhanced by subsidized insurance since aggregate risk may be diminished by subsidized insurance.

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[1]See the online summary of business statistics at http://www.rma.usda.gov/data/sob.html.

Lightning fire risk provides a a potential example of such a risk. If lightning fire occurrences in a specific geographic area surpass a threshold, it is likely that those forest landowners in the area may face higher risks and thus may benefit from subsidized mitigation efforts. Indemnities provided under such a government program may be restricted by regulatory restrictions. Again, it is not our intent to address the rationale or necessity of such subsidized insurance, though many similarities to crop insurance can be identified. Accurate quantification of conditional risks and the provision of precise insurance premium rates is a necessary ingredient of any insurance program, whether subsidized or private. Our objective is to derive such measures to guide public policymakers and private insurance providers. The role of government in the provision and maintenance of such wildfire insurance remains an important topic for future policy deliberations and research.

Forest insurance plans against all risks, similar to those in agriculture production, can barely survive without government subsidies. In a global context, government financial support has helped expanding forest insurance coverage. 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 the premiums are subsidized for forest insurance. As a result, the plans have covered 18 million hectares, with the insurance subsidy totaling $17 billion by June 2010 (Petry, Zhang, and Zhang, 2010). In the U.S. forest sector, a very limited number of timber insurance programs against multiple perils are available in the private market. Examples include the Davis–Garvin Agency's standing timber insurance and the Outdoor Underwriters' standing timber insurance. These two programs offered all risk policies on a case by case basis in a couple of small regional markets. However, the overall nationwide forest landowners' insurance participation is infinitesimal and no single–peril forest insurance plan has been offered.

The almost total absence 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. It is in some sense too difficult to precisely measure all the associated risks from all possible hazards. In the case of inaccurately measured risks, insurance providers may face moral hazard and adverse selection problems. Moral hazard problems arise when agents assume more risks because they have been provided insurance. Such 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 may suffer actuarial losses. Index plans, such as those provided here, are generally more robust to such moral hazard concerns. If the actions

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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 diminished. The design of our proposed index plan offers such advantages.

Adverse selection occurs when high–risk agents tend to overinsure while low–risk agents underinsure. Such selection will lead to an adversely selected insurance pool. Precisely modeling and pricing risks is essential to avoid adverse selection problems. Compared with multi–peril insurance which is difficult to trace all risk sources, a single–peril insurance plan only requires considerations limited to risks associated with this specific hazard. An actuarially fair single–peril insurance plan can be more easily implemented, and therefore has the potential to increase insurance participation and to reduce adverse selection.

The central piece of any effective insurance scheme is a full understanding of all risks underlying the associated hazards. In insurance contracts, an actuarially fair insurance premium (or premium rate) is calculated 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 total indemnities. For example, if someone expects to pay $1,000 in a typical year on an insurance contract that covers up to $10,000 in total liability, the actuarially fair premium rate is 0.10 (or 10%).

A risk 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. One example is crop yield insurance. The focus in yield insurance modeling is to estimate probability densities describing crop yields. Suppose a farmer $i$ decides to insurance his crops in the coming year $t$, and his expected yield is $\mu$. He can choose a coverage level $\theta$ ($0 < \theta \leqslant 1$). In the case that the crop yield is below the pre–determined level $\theta\mu$, his loss will be compensated, which is the difference between his actual yield $y_{i,t}$ and the target level $\theta\mu$. Given the pre–determined target price $Price_t$, the indemnity is calculated as:

$$Indemnity_{i,t} = Price_t * max\{0, \theta\mu - y_{i,t}\}. \tag{2.1}$$

In some insurance programs, a loss is an all–or–nothing event. For example, life insurance policies will pay a fixed amount of money 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. Such insurance contracts are suitable to address 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, the actuarially fair premium is set equal to the expected loss, which is the product of the loss probability

and the conditional expected loss given the loss event occurs. If we denote $z = 1$ to be a loss event ($z = 0$ otherwise), the expected loss can be expressed as

$$E(Loss) = P(z = 1) * E(loss|z = 1). \tag{2.2}$$

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 $\beta$, i.e.

$$P(z = 1) = F(X\beta). \tag{2.3}$$

If the contract specifies a fixed indemnity amount in case of a loss event, i.e. $E(loss|z = 1) = Payment$, is predetermined, then a fair premium is equivalent to $E(Loss) = F(X\beta) * Payment$. The only remaining concern in deriving the actuarially fair premium rate is in how to model the loss probability.

Understanding factors that loss probabilities should be conditioned on is crucial in modeling risks. For example, in modeling life insurance, age and healthiness of the insured are always explicitly recognized when assessing death risks. As long as observable factors are pertinent to risks underlying an insurance contract, a more accurate actuarially fair premium can be constructed with these factors considered. For timber insurance against lightning fire risks, factors such as tree types, characteristics of forest land, weather and socio–economic classes are important risk determinants. We should model wildfire risks conditional on these factors to assess risks accurately.

A couple of operational issues should also be considered to design an insurance program. One important component of insurance provisions is the insurance period. For example, 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. 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. In lightning fire risk analysis, we assume with no loss of generality an insurance period corresponding to a calendar year. The other practical issue is that information about all the associated observable factors in the following year (the insurance period) is unavailable before the wildfire insurance contracts are signed. For example, drought is recognized as a significant predictor for fire hazard. However, even though they may be somewhat predictable by using various climate models, precipitation in year $t + 1$ is generally unknown in year $t$. In contrast, the precipitation records in year $t$ are available when insurance coverage for year $t+1$ is determined. Therefore, in our

analysis insurance parameters are always conditioned on variables that are observable in the prior year.

## 3 Empirical Analysis

### 3.1 Discussion of Data

The Florida fire occurrence data used in this study is obtained from Florida State Forestry Division. The data covers wildfire records for all the 67 Florida counties between 1981 and 2005. The details of each wildfire outbreak, such as cause, fuel type and duration are all reported. Of all the wildfire incidences, there are over 30,000 lightening–induced wildfire outbreaks on the forestland. Weather statistics for the same time period were collected from the National Climate Database Center (NCDC), maintained by National Oceanic and Atmospheric Administration (NOAA). Forest 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. Socio–economic statistics were collected from the Regional Economic Information System (REIS) data set assembled by the Bureau of Economics Analysis in 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 approach is general 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 lightning fire risks are unavailable at such a level of observation. Analysis at the county level, however, is more useful to measure lightning fire risks and develop an insurance plan. Wildfire, as a quickly transmitted disaster, can quickly spread over a large area. With large wildfires often crossing township boundaries, county level statistics about fire losses are more accurate. In addition to the size advantage, statistics at the county level are more abundant. Costs of insurance management, therefore, are usually less for county–level plans, as found in agriculture insurance adminstrations. Finally, premium calculations at the county level are able to smooth the premiums across different timber farms. A group (index) insurance plan, if conditioned on a county level index, can help alleviate moral hazard and adverse selection issues (Smith and Goodwin, 2011). As noted, moral hazard is diminished or eliminated when an individual insured is unable to significantly impact the index that determines losses. Spatial aggregation, say to a county level, provides such an index.

The dependant variable of our empirical analysis is the annual county–level burnt ratio, which is defined as the aggregate burnt area by lightning fire in proportion of the total forest land area within

a calendar year in each county. Wildfire suppression and management practices have discovered that several observable factors are relevant to future wildfire risks. For example, certain forest types, such as oak and hickory, are believed to be more resistant to wildfire spreading. Variables representing the shares of four groups of forest land types are considered here. These forest classifications include the group of longleaf slash pine forest lands and loblolly/shortleaf pine forest lands, the group of oak/pine forest lands and oak/hickory forest lands, and the group of oak/gum/cypress forest lands. We form an aggregate composite variable for the area in all other forest land types. Two crucial weather variables affect wildfire likelihoods – drought and temperature. We represent drought and temperature factors using the 12–month Standardized Precipitation (SP12) and Heating Degree Day (HDD) indexes, respectively. Hurricanes are a significant weather phenomenon hypothesized to be a factor influencing lightning induced wildfire risks. We measure hurricane risks by the historical annual frequency of hurricanes in a given location.[2] 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 suggested 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 definitions of measures of lightning fire risks and other relevant explanatory variables. Our analysis covers annual county–level observations for all 67 counties in Florida from 1981 to 2005. This results 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.

## 3.2 Regression Results

To model lightning fire risks, we apply the conditional probability model given by (2.3) to the available data. Two estimation approaches were considered. As the simplest and most common model, an OLS regression of $Y_{st}$ on $X_{s,t-1}$ is adopted

$$Y_{st} = X_{s,t-1}\beta + \epsilon_{st}, \tag{3.1}$$

where $Y_{st}$ is a lightning fire 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

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[2]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.

(Prestemon et al. 2002; Prestemon and Butry 2005). As a result, an OLS regression based solely on the independent variables may be insufficient to account for spatio–temporal autocorrelation.

An alternative approach is to include temporal lags of the dependent variable and the average of neighboring observations of the lagged dependent variable in order to correct for temporal and spatial autocorrelation. An example of such models, if only the first order temporal lag is included, can be expressed in the form of

$$Y_{st} = \rho Y_{\bar{s},t-1} + q Y_{s,t-1} + X_{s,t-1}\beta + \epsilon_{st}, \tag{3.2}$$

where $Y_{\bar{s},t-1}$ represents the average of all $\{Y_{i,t-1}\}$, given $i \in \Theta_s$ and $\Theta_s$ represents the set of all the spatial units bordered with the county $s$. A more general class of such models can also be written in a vector form like

$$Y_t = \rho W Y_{t-1} + q Y_{t-1} + X_{t-1}\beta + \epsilon_t; \tag{3.3}$$

where $Y_t$ represents a vector of observations of the dependent variable for all of the spatial units at time $t$, and $X_{t-1}$ represent one year lagged observable covariates. The equation (3.2) is a special case of the model (3.3) with a special spatial weight matrix $W$. Many models of this genre were developed by extending the conventional Box–Jenkins time series models (Box, Jenkins, and Reinsel, 1970) to an analogous spatio–temporal context (Haggett, Cliff, and Frey, 1977). The main advantage of this method, as noted by Ripley (1981), is its simplicity to apply. One of the implications underlying such models, though, is that spatial transmissions do not occur simultaneously. In scenarios for which the subscript $t$ corresponded to a short period of time, Upton and Fingleton (1985) promoted this model because such a lagged impact across spatial units is more reasonable than an instantaneous impact.

However, the response variable of our interest, either lightning fire frequency or propensity, is observed annually. While a wildfire rarely lasts longer than a month, spatial autocorrelation of regression residuals can barely be controlled. To recognize such disadvantage, we adopt a non–parametric method to estimate parameters parameters in equation (3.3) while successfully controlling the spatial autocorrelation.

Ever since Efron (1979) proposed the bootstrapping method, it has become a powerful statistical tool. Although the bootstrap (Efron, 1979) method can handle independent observations well, the strong spatio–temporal autocorrelation of lightning fire risks brings about a major challenge. Motivated by bootstrapping overlapping blocks method in the autoregressive time series scenario (Kunsch 1989) and block bootstrapping method of dependent data from a spatial map (Hall 1985), we have developed a method to bootstrap overlapping spatio-temporal blocks. By selecting an appropriate block size, the spatio-temporal correlation can be controlled.

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Table 2 presents the results of a simple ordinary least square regression (3.1) and the spatio–temporal linear regression (3.2) estimated by a block bootstrapping method. The OLS results suggest that climate factors, such as temperature and drought, affect lightning fires in the expected ways. Cold (HDD index) weather appears to reduce lightning fire risks. At the same time, the positive impact of population density verifies that human interventions are an important causal element of lightning fires. Regional factors related to the economic welfare of the population in a given county may also reflect other aspects of behavior. In particular, economic stresses may be related to deliberate acts of arson and other criminal activities. A high employment ratio could mitigate lightning fire risks, since employed persons have higher opportunities costs to commit criminal acts of arson.

Forest land characteristics affect lightning fires through a number of ways. A high private owners' share of forest lands always implies a higher lightning fire risk. As rangers and forest police work actively on public forest lands, private lands are expected to be more vulnerable in the face of lightning fire threats. The group of the longleaf/slash pine forest lands and loblolly/shortleaf pine forest lands appear to enhance fire risks while the combination of oak/pine forest lands and oak/hickory forest lands significantly lessen lightning fire risks. The oak/gum/cypress forest land group also appears to have higher burning risks. This reflects the fact that most swamp fires can be easily spread in this type of ecosystem.

Autocorrelation tests for the residuals in the OLS model, however, confirm our concerns. First, although temporal autocorrelation is successfully controlled,[3] neither model sufficiently corrects for spatial autocorrelation. In particular, the residuals are still autocorrelated in approximately one fourth of the observed years.[4] Secondly, compared with the OLS model, adding a lagged spatial dependent variable does not alleviate autocorrelation at all. This evidence suggests that the spatial linkages are more likely to exist simultaneously. This is less of a concern within the context of predicting the conditional probability of specific lightning fire risks but it does suggest that the models are inefficiently estimated and may result in misleading inferences.

The spatio–temporal model has produced similar results. The temporal dependence has been proven to be positive, while the lagged spatial dependence is demonstrated to be statistically insignificant and fairly weak in the magnitude. However, spatial autocorrelation among residuals has been reduced significantly, when compared with the results for the conventional models (i.e. the

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[3]The time series of each county is checked for first order autocorrelation using the Breusch–Godfrey test on the 5% significance level.

[4]The years in which residuals are spatially autocorrelated on the 5% significance level using Geary's $C$ index permutation test.

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percentage of years with spatially autocorrelated residuals decreased from around 25% to close to 12%). This is not surprising because the block bootstrapping method appears to have accounted for spatial interactions while the OLS models does not.

# 4   Indemnity and Premium Rates

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

$$E(loss_{st}) = \int E(Payment_{st}|Z_{st}, \Theta_{st}) * f(Z_{st}|\Theta_{st}) \, dZ_{st}, \tag{4.1}$$

where $Z_{st}$ is an indicator that one of the claim provisions has been triggered (i.e., that a loss event has occurred). $\Theta_{st}$ 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. If a fixed payment is made only if a specific outcome occurs, i.e. death in the life insurance contracts, the fair premium can be simplified as

$$E(loss_{st}) = Pr(Z_{st} = 1|\Theta_{st}) * Payment_{st}, \tag{4.2}$$

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

Similarly, for lightning fire risks, a comprehensive insurance scheme offered to an individual timber farmer can be expressed as

$$E(loss)_{st} = Pr(O_{st}|\Theta_{st}) * E(Payment_{st}|O_{st}, \Theta_{st}), \tag{4.3}$$

where $O_{st}$ is a lightning fire outbreak at the forest landowner's location $s$ in time $t$, and $Payment$ represents the compensation for the actual 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 lightning fire outbreaks are distributed fairly unevenly across space. Thus lightning fire outbreaks are too volatile to model accurately at the individual land parcel level of resolution. Secondly, there are also huge variations in the pricing of timber products. The prices of timber stock often are significantly different from one category to the other. Even for the same raw product, the seasonal price usually fluctuates

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drastically. Therefore, the transaction costs associated with assessing both individual outbreak risks and liability values may be too high to implement such a individual lightning fire insurance plan.

In contrast, 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. If homogeneous lightning fire risks are assumed across all relevant land in a county, the outbreak probability can be replaced by the burnt ratio. Therefore, the equation (4.3) can be written as

$$E(loss)_{st} = Z_{st} * E(Payment_{st}|Z_{st}, \Theta_{st}), \tag{4.4}$$

where $Z_{st}$ is the expected burnt ratio and $Payment$ is the fixed payout amount associated with $Z_{st}$. Our aforementioned models are able to forecast the burnt ratio for county $s$ in time $t$, which follows a lognormal distribution. However, results using the burnt ratio directly, such as (4.4), are not robust in our empirical models. Even though the logarithm of burnt ratio is normally distributed, its variations will be exponentially amplified when the logarithm form is converted back into the original form.

Our index insurance plans, however, are unaffected by these issues. In a hypothetical timber insurance program, the claim procedure could works as follows. Before the beginning of the insurance period, both insurance providers and forest landowners agree on a trigger 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 yearly burnt ratio for each county based on statistics. When the actual burnt ratio $Z_{st}$ in a county is more than 8%, all the insured forest landowners in this county will receive payments, even if some of them don't have any losses. Meanwhile, if the realized burnt ratio is smaller than 8%, then no one can claim payments. Therefore, if the predetermined percentage that will trigger claims is $\tilde{Z}_{st}$ (e.g., 8%), the actuarially fair premium equation can be written as

$$E(loss)_{st} = Pr(Z_{st} > \tilde{Z}_{st}|\Theta_{st}) * E(Payment_{st}|Z_{st} > \tilde{Z}_{st}, \Theta_{st}). \tag{4.5}$$

At the same time, the premium rate, which is the ratio of the premium to the liability, can be expressed as

$$Pr(Z_{st} > \tilde{Z}_{st}|\Theta_{st}) = 1 - \Phi((\ln \tilde{Z}_{st} - \mu_{st})/\sigma_{st}), \tag{4.6}$$

Summary statistics of the estimated premium rates with different trigger indices are presented in Table 4. Because a smaller trigger index is equivalent to a more comprehensive protection, premium rates are always going up as the trigger index declines. The estimated premium rates among spatio-temporal models are fairly close.

# 5    Conclusion

This analysis presents empirical models of the lightning risks in Florida. A brief overview of the U.S forest industry and existing lightning fire management instruments is provided. We also discuss the methodological issues related to the design of a single–peril fire insurance program in the U.S. forest sector. In our paper, we used a non–parametric estimation method intended to correct for spatio–temporal autocorrelation. Meanwhile, we examined important conditioning factors that could influence lightning fire outbreaks. The impacts of crucial informational covariates, such as environmental and climate factors, were assessed. A single–peril index insurance scheme was proposed and actuarially fair premium rates were estimated.

Our empirical models are based on a complete survey of Florida wildfire loss records from 1980 to 2005. To model the conditional probabilities, crucial relevant information, such as the National Forestry Inventory and Analysis (FIA) database, Regional Economic Information Systems (REIS) database and the National Climatic Data Center (NCDC) database were utilized. We used the logarithm of annual county-level burnt ratio by the lightning fires as the dependent variable and applied regression models from different classes. In light of the fact that lightning fire risks are spatio–temporally autocorrelated, we used a linear regression model with block bootstrapping method. The improvement in controlling spatial autocorrelation suggests that such a non–parametric modelling technique is more appropriate.

Our results reveal that almost all the conditioning variables, in most scenarios, exhibit positive relationships with lightning fire risks. For example, drought, temperature and human actions could enhance such hazards, while different components of forest land ecosystems also have influences on lightning fire risks. The results suggest potentially important policy implications, such as employing more rangers at the urban–forest interface, and encouraging expanding oak/gum/cypress forest composition because of its resistance to lightning fire hazard. Finally, an associated index insurance plan is proposed and associated premium rates are estimated.

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**Table 1. Definition and Statistics of Variables**

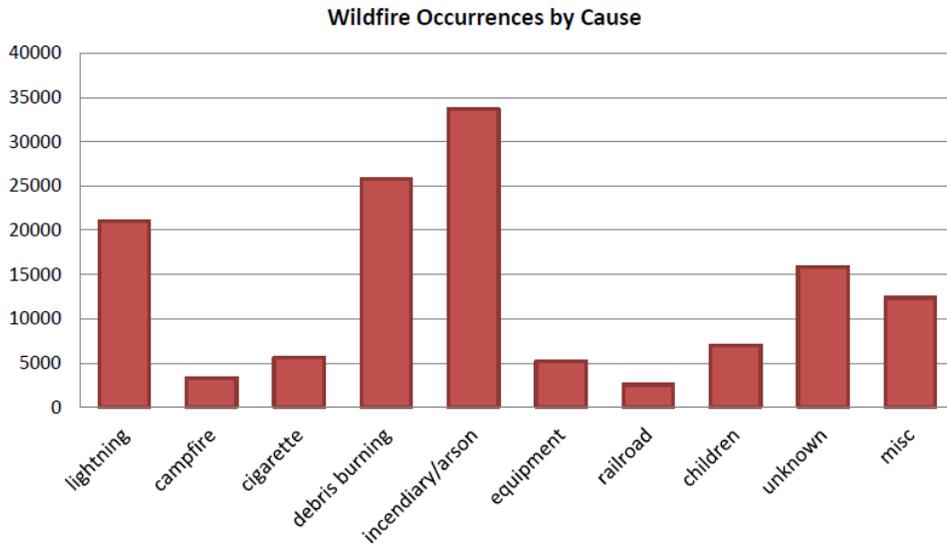| Variable(County Level) | Definition | N | Mean | Std. Dev. |
|---|---|---|---|---|
| Lightning Fire Burnt Ratio | Burnt forestland size/total forestland size | 1675 | 0.004 | 0.0211 |
| Forestland ratio | Total forestland area/county size | 1742 | 0.5168 | 0.2813 |
| Private share | Proportion of private 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 | Total of HDD index for a year divided by 365 | 1742 | 2.7920 | 1.4247 |
| December SP12 index | Probability of observing a given amount of precipitation | 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 |
| Employment Ratio | Percentage of workforce population | 1742 | 0.4253 | 0.1159 |

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**Table 2. Regression Results**

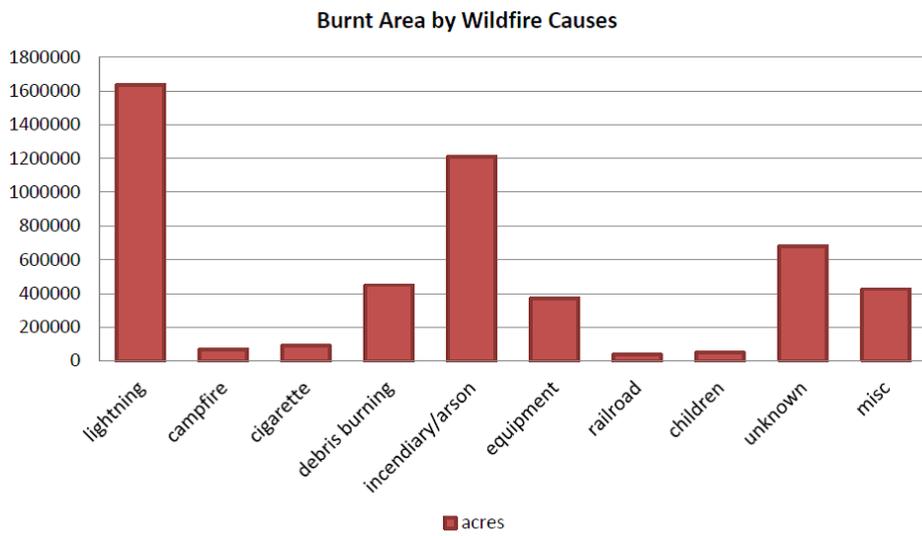| Parameter | OLS | | Spatio–Temporal Model | |
|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error |
| Spatial Dependence | | | -0.01034 | 0.03022 |
| Temporal Dependence | | | 0.06343 | 0.05634 |
| Intercept | 0.01102** | 0.00461 | 0.01069*** | 0.00463 |
| Forestland ratio | -0.00816* | 0.00458 | -0.00812* | 0.00459 |
| Private share | 0.00390 | 0.00384 | 0.00382 | 0.00385 |
| Longleaf /slash & loblolly /shortleaf | -0.00015423 | 0.00645 | -0.00005069 | 0.00646 |
| Oak/pine & oak/hickory | -0.01588** | 0.00640 | -0.01571* | 0.00641 |
| Oak/gum/cypress | -0.01134* | 0.00676 | -0.01114 | 0.00677 |
| Daily average of HDD index | -0.00031859 | 0.00099661 | -0.00026152 | 0.00099865 |
| December SP12 index | 0.00079243 | 0.00068214 | 0.00085611 | 0.00068494 |
| Hurricane incidences | -0.00513* | 0.00311 | -0.00502 | 0.00312 |
| Lightning density | 0.11758** | 0.05198 | 0.11456** | 0.05208 |
| Population density | 0.00032679 | 0.00114 | 0.00034683 | 0.00114 |
| Employment Ratio | -0.00713 | 0.00627 | -0.00723 | 0.00627 |
| Autocorrelation Test | | | | |
| Percentage of Years when Spatial Autocorrelation found in Residuals | 25% | | 11.94% | |
| Percentage of Counties where Temporal Autocorrelation found in Residuals | 12.50% | | 8.70% | |

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

**Table 4. Estimated Premium Rates given Different Trigger Indices**

| Model | Mean | Median | Std.Dev. | Max | Min |
|---|---|---|---|---|---|
| **Reimburse if Burnt Ratio > 0.1%:** | | | | | |
| OLS Model | 0.54794 | 0.53286 | 0.068544 | 0.75048 | 0.32278 |
| Spatio-Temporal Model | 0.54788 | 0.53248 | 0.069486 | 0.77146 | 0.32791 |
| **Reimburse if Burnt Ratio > 0.2%:** | | | | | |
| OLS Model | 0.53075 | 0.51535 | 0.069000 | 0.73631 | 0.30715 |
| Spatio-Temporal Model | 0.53070 | 0.51497 | 0.069962 | 0.75794 | 0.31219 |
| **Reimburse if Burnt Ratio > 0.3%:** | | | | | |
| OLS Model | 0.51349 | 0.49780 | 0.069330 | 0.72174 | 0.29187 |
| Spatio-Temporal Model | 0.51345 | 0.49743 | 0.070310 | 0.74400 | 0.29679 |
| **Reimburse if Burnt Ratio > 1%:** | | | | | |
| OLS Model | 0.39383 | 0.37698 | 0.068039 | 0.61030 | 0.19604 |
| Spatio-Temporal Model | 0.39389 | 0.37666 | 0.069111 | 0.63604 | 0.20004 |
| **Reimburse if Burnt Ratio > 10%:** | | | | | |
| OLS Model | .000015954 | .000009673 | .000015527 | .000117174 | .000000737 |
| Spatio-Temporal Model | .000016292 | .000009686 | .000016996 | .000153184 | .000000796 |

**Wildfire Occurrences by Cause**



(a) Outbreaks

**Burnt Area by Wildfire Causes**



■ acres

(b) Damage

Figure 1: Wildfires from Different Causes

(a) 1987

(b) 1988

(c) 1989

(d) 1990

(e) 1991

(f) 1992

(g) 1993

(h) 1994
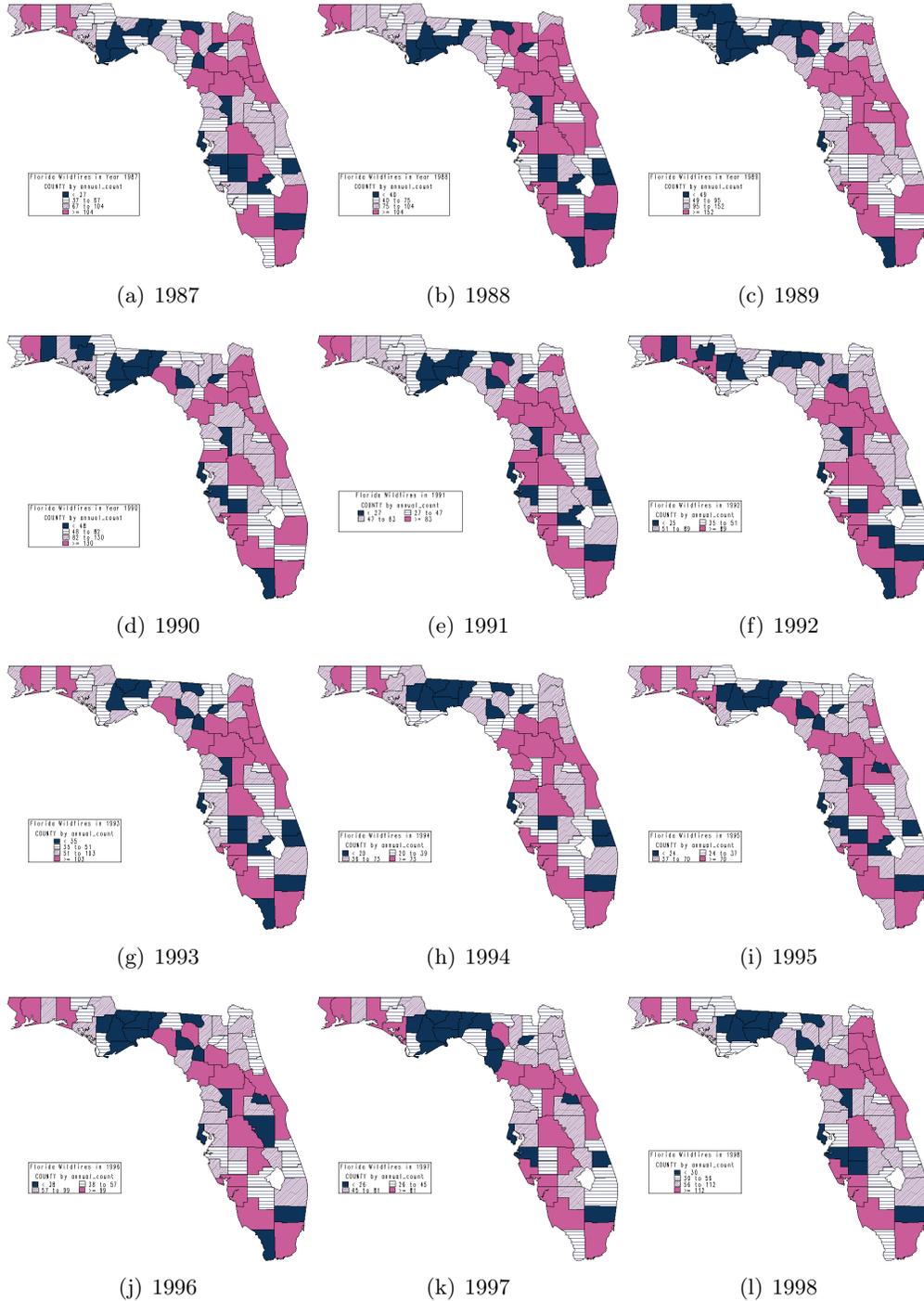
(i) 1995

(j) 1996

(k) 1997

(l) 1998

Figure 2: County–level Florida lightning induced wildfire outbreaks during 12 consecutive years: on each map, 4 different colors represent 4 levels of outbreaks separated by quartiles.