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Research Article

Keywords: wildfire, exposure, southwestern, community

Posted Date: January 11th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1171350/v1>

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Future property risk estimation for wildfire in Louisiana, USA

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Keywords: Wildfire, Natural hazards, Population projections, Forest resources, Vulnerability, Resilience, Environmental change, Climate change, Burn probability

Abstract

Background

Wildfire is an important but understudied natural hazard. As with other natural hazards, wildfire research is all too often conducted at too broad a spatial scale to identify local or regional patterns. This study addresses these gaps by examining the current and future wildfire property risk at the census-block level in Louisiana, a U.S. state with relatively dense population and substantial vulnerability to loss from this hazard, despite its wet climate. Here wildfire risk is defined as the product of exposure and vulnerability to the hazard, where exposure is a function of the historical and anticipated future wildfire frequency and extent, and the latter is a function of population, structure and content property value, damage probability, and percent of property damaged.

Results

Historical (1992–2015) average annual statewide property loss due to wildfire was \$5,556,389 (2010\$), with the greatest risk to wildfire in southwestern inland, east-central, extreme northwestern, and coastal southwestern Louisiana. Based on existing climate and environmental model output, this research projects that wildfire will increase by 25 percent by 2050 in Louisiana from current values. When combined with projections of population and property value, it is determined that the geographic distribution of risk by 2050 will remain similar to that today – with highest risk in southwestern inland Louisiana and east-central Louisiana. However, the magnitude of risk will increase across the state, especially in those areas. Projected annual loss will be \$11,167,496 by 2050 (2010\$) due to population growth, intensification of development at the wildland-urban interface, and climate change. The wildfire-induced property damage is notable because it is projected to increase by 101 percent. These values do not include

crop, forestry, or indirect losses (e.g., cost of evacuation and missed time at work), which are likely to be substantial.

Conclusions

The results suggest that increased efforts are needed to contain wildfires, to reduce the future risk. Otherwise, wildfire managers, environmental planners, actuaries, community leaders, and individual property owners in Louisiana will need to anticipate and budget for additional efforts to mitigate the economic (and presumably other) impacts associated with a substantial and increasing hazard that often goes underestimated.

Background

Although weather-related disasters cause extensive and rapidly increasing damage worldwide, efforts to understand the holistic risk from these hazards are still in progress. While a growing amount of research is focusing on assessing risk due to flood (e.g. Mostafiz et al. 2021c, 2021d), hurricane (e.g. Emanuel et al. 2006), tornado (e.g. Masoomi and Van de Lindt 2017), and extreme weather events (e.g. Rocchetta et al. 2015), the risk of wildfire – combustion in a natural setting, marked by flames or intense heat, ranging in coverage from less than 20 hectares to over 3 million hectares – is lesser-studied, with research largely limited to the regions that are more susceptible to extreme economic loss. Although natural and human-prescribed fire is often healthy (Hamilton and Salerno 2020, Hood et al. 2020) as a mechanism for restoring nutrients to the soil and providing new niches while often leaving native species unharmed or resilient to the disturbance (Binkley et al. 2007), for combatting pests, diseases, and fungal growth, and for allowing for the post-fire regrowth to establish hardier individuals, the hazardous aspects of wildfire deserve more attention in risk assessments. The risk of wildfire is particularly important to understand near the wildland-urban interface (WUI; Radeloff et al. 2005) – the area where development meets wildland vegetation, with both providing fuel for fires, leaving more natural ecosystems, people, and property exposed to wildfire danger (Theobald and Romme 2007). Because wildfire is a critical ecosystem process influenced by a combination of natural and human factors (Lasslop and Kloster 2017) and because its presence and intensity can be modified by climate change (Piñol et al. 1998, Malamud et al. 2005, Mokhov et al. 2006, Cannon and DeGraff 2009, Flannigan et al. 2009, Marlon et al. 2009, Moritz 2012, Enright and Fontaine 2014), it must be considered in environmental risk assessment.

The impacts of wildfire are three-fold: environmental, health, and property. In recent decades, studies on environmental impacts of wildfire have emphasized the role of wildfire dynamism and variability at the regional level (Morgan et al. 2001, Vázquez et al. 2002, Cleland et al. 2004, De la Riva et al. 2004, Schoennagel et al. 2004, Malamud et al. 2005, Moreira et al. 2009, de Zea Bermudez et al. 2010, Aldersley et al. 2011, Garcia-Gonzalo et al. 2014; Ferreira et al. 2014, 2015, Marques et al. 2017, Strydom and Savage 2017, Colantoni et al. 2020), in part because climate change implications on ecosystems (Davis et al. 2019) present unique challenges for hazard management in each wildfire regime (Pacheco et al. 2015). Regarding human health impacts of wildfire, the southeastern U.S. has been found to be most affected by hospital admissions and premature deaths due to wildfire events in the U.S.A. (Fann et al. 2018), in addition to generally unhealthy conditions due to wildfire-related smoke (Kaulfus et al. 2017, Sorensen et al. 2021). From a property loss perspective, wildfire impacts have been substantial, especially at the WUI. In a holistic cost-benefit or “hedonic” approach, Hansen et al. (2014) found a negative effect of wildfire on property values in California, Colorado, and Montana, with less conclusive evidence from research based elsewhere in Colorado and in Alaska. Further work showed that home prices and sales rates in the Front Range of Colorado are influenced by wildfire risk and risk perceptions (McCoy and Walsh 2018). Other research has examined the impacts of wildfire risk on residential property values in the Netherlands (Magnée 2020). Property damage in northeastern Florida due to wildfires in the El Niño year of 1998 was estimated at \$10–12 million (Butry et al. 2001). And more recently, programs like FireSmart (Ergibi and Hesseln 2020) provide homeowners in the WUI with information to make more informed decisions for protecting their property from the wildfire hazard.

Several recent studies have evaluated wildfire probabilities or associated migration and adaptive capacities, with the goal of enhanced understanding of the risk. Li et al. (2009) used an artificial neural network approach for modeling the impact of population density and weather parameters such as average relative humidity, wind velocity, and daily sunshine hours to forest fire risk in Japan. Thompson et al. (2013) introduced a polygon-based spatially explicit burn probability model to assess exposure of resources to wildfire. Incorporating both natural and anthropogenic ignitions, Ager et al. (2013) proposed a wildfire simulation model which characterizes potential wildfire behavior in terms of annual burn probability and flame length by analyzing a set of social and ecological parameters in the Oregon and Washington national forests. Ager et al. (2014) examined the spatiotemporal patterns of the wildfire occurrence in Sardinia, Italy, and characterized the outcomes of both the probability of ignition and large fire in terms of weather, land use, anthropogenic features, and time of year. Based on wildfire likelihood and intensity over the 1992 to 2010 period, Dillon et al. (2015) developed a broad-scale wildfire potential map for the contiguous U.S.A. that can be used to analyze wildfire threat or risk to structures or power lines. Short et al. (2016) created national burn probability (BP) and conditional fire intensity level (FIL) estimates at a 270-m grid resolution over the contiguous U.S. using the U.S. Forest Service Missoula Fire Sciences Laboratory's geospatial Fire Simulation system (FSim), which includes scenarios for generating wildfire-conducive weather, wildfire occurrence, fire growth, and fire suppression. Based on the minimum travel time algorithm, Alcasena et al. (2016) developed a fire simulation model to analyze the wildfire exposure of highly valued resources and assets in a 28,000 ha area in central Navarra, Spain. Bui et al. (2017) generated a GIS-based novel hybrid artificial intelligence approach to model spatial susceptibility of the wildfire hazard in the central highland forest region of Vietnam. Papakosta et al. (2017) built a probabilistic model for predicting wildfire housing loss at the mesoscale (1 km²) level using Bayesian network analysis, enabling the construction of an integrated model based on causal relationships among the influencing parameters jointly with the associated uncertainties. Hong et al. (2019) predicted the spatial pattern of wildfire susceptibility in Huichang County, China, by using the integrated probabilistic "weights-of-evidence" and knowledge-based "analytical hierarchy process" models. Jaafari et al. (2019a) developed a wildfire prediction model incorporating ten geophysical and climatological parameters to investigate the spatial distributions of wildfire probabilities from 32 fire events at the Zagros ecoregion of Iran. In recent years, use of rigorous data interpretation techniques such as geographical information systems (GIS), and statistical and machine learning approaches have resulted in various prediction models of wildfire probability (Preisler et al. 2004; Catry et al. 2010; Silva et al. 2015; Bui et al. 2017; Tutmez et al. 2018; Jaafari et al. 2018, 2019a, 2019b; Hong et al. 2019; Botequim et al. 2013, 2017, 2019).

Because of its vulnerability to the hazard, most of the existing wildfire research in the U.S.A. focuses on the West (Cannon and DeGraff 2009, Ager et al. 2013, Dennison et al. 2014, Holden et al. 2018, Ager et al. 2021). The historical record shows that the western U.S.A. has generally experienced increasing wildfire frequency and intensity over time (Running 2006, Westerling et al. 2006, Dennison et al. 2014, Higuera et al. 2015, Abatzoglou and Williams 2016, Westerling 2016, Holden et al. 2018). Despite earlier research that suggested that wildfire occurrence in Mississippi had decreased since the 1920s (Grala and Cooke 2010), the volume of wildfire risk-related research on the U.S. Southeast deserves more attention, especially because of the

droughts in recent years (Schubert et al. 2021), dense population, the aforementioned concentration of human health impacts in that region, and high probability of risk from other wildfire-related hazards. Louisiana is particularly understudied regarding wildfire, especially in light of the suggestion of Fann et al. (2018) that PM_{2.5} concentrations in Louisiana attributed to wildfire exceeded that of any other state except California in 2008, and the property vulnerable to fire.

This research presents a census-block-level property risk assessment for wildfire in Louisiana, U.S.A. The three primary objectives are to: 1) characterize the historical wildfire burn probability; 2) project the future wildfire burn probability; and 3) assess the future property loss in Louisiana due to wildfire. Integration of natural and social science approaches as shown in the three objectives here are needed to understand more fully the property risk of wildfire, especially in light of climate change concerns (Ayres et al. 2016). The contribution of the paper is to provide a more complete understanding of the wildfire risk, at the census block level, by extending previous innovative geospatial approaches to overlaying fire extent with infrastructure (e.g., Marques et al. 2011) quantitatively and by incorporating changes in population, property value, and climate, along with the historical wildfire burn probability, damage probability, and percent of damaged property as components of the property risk. The results will benefit foresters, property owners, and mitigation specialists within and beyond Louisiana as they seek new and improved ways to characterize and prepare for the wildfire hazard.

Louisiana is selected as the focus of this research for several reasons. Despite abundant rainfall, the state can be subjected to periods of drought (Bushra et al. 2019) and therefore wildfire, which can have disproportionate impacts because of the heavy reliance of wet-environment land uses, such as rice farming, industrial applications, and recreation. Moreover, as will be shown later, the future frequency of such periods of wildfire is expected to increase in Louisiana as in much of the rest of the United States. Furthermore, the state is relatively densely populated compared to most of the wildfire-vulnerable Western U.S., causing anthropogenic activity to contribute substantially to the intensifying hazard and its human impacts. Finally, Louisiana-based studies on wildfire to date are largely limited to environmental (Haywood et al. 2000, Drewa et al. 2002, Jones and Chamberlain 2004, Haywood 2011, Stambaugh et al. 2011, Yeldell et al. 2017, Jones et al. 2020, Simmons and Bossart 2020), with substantially less work on risk assessment to property.

Over the 2007 to 2016 period, an annual average of 1,431 wildfires burned 14,950 acres of forestland in Louisiana, with most of these fires caused by arson or human negligence, exacerbated by human confrontation with nature (Louisiana Department of Agriculture & Forestry (LDAF) 2021). Likewise, lightning was found to be a minor cause of wildfire in nearby Mississippi compared to anthropogenic causes (Grala and Cooke 2010). Using the customary categorization of U.S. wildfires as large (> 300 acres) or small (< 300 acres), Louisiana wildfires tend to be small, averaging about 10 acres in size (LDAF 2021). Wildfire as tabulated here do not include prescribed burns (Penman et al. 2020) or fires started in a building.

Methods

Data

Because wildfire outside but near Louisiana can endanger the state, a 50-km buffer to include adjacent Texas, Arkansas, and Mississippi is analyzed along with Louisiana. To address the first objective – characterizing the historical wildfire probability – historical wildfire occurrence data from 1992 to 2015 from Short (2017) and large wildfire burn probability from Short et al. (2020) are used. The second objective – projecting the future wildfire probability – relies on information from the fourth National Climate Assessment (U.S. Global Change Research Program (USGCRP) 2017). USGCRP (2017) follows the method of the Intergovernmental Panel on Climate Change (IPCC) by running fossil fuel emission scenarios termed “representative concentration pathways” (RCPs), with the scenarios numbered based on the amount of radiative forcing (in W m^{-2}) anticipated in the year 2100, such that RCP8.5 is the most severe scenario. As in the vast majority of contemporary climate change-based research, the model results using the RCPs are based on the Coupled Model Intercomparison Project (CMIP; Meehl et al. 2014). Results from IPCC’s fifth assessment report are available in USGCRP (2017). Other scenarios account for changes in economic growth, environmental values, globalization, and regionalization.

To address the objective of assessing the future property loss in Louisiana due to wildfire considering anticipated changes to climate and population, Louisiana census-block shapefiles are downloaded from the U.S. Census Bureau (2010). Likewise, population projections are based on data from U.S. Census Bureau (2021). LDAF detailed fire summary data for Louisiana (2007–2017; Bret Lane, personal communication, 4/9/2018) serve as a baseline for future property loss due to wildfire.

Assessing historical wildfire burn probability

A method of computing both large and small fire probabilities is necessary here because FSim focuses on large (> 300 acres) fires (Dillon et al. 2015) and fires in and near Louisiana are primarily classified as “small.” The wildfire probability calculation follows the method of Dillon et al. (2015), which uses large fire (i.e., > 300 acres) probability from FSim (Finney et al. 2011) supplemented by a collection of small fire (i.e., < 300 acres) probabilities from the Fire Protection Agency (FPA) fire occurrence data (Short 2013). The total probability is calculated as the sum of large and small fire probability.

Large wildfire burn probability raster files are downloaded from U.S. Department of Agriculture (Short et al. 2020). Then, the “Extract by Mask” tool in ArcGIS® is used to delineate the large fire probabilities in Louisiana and surroundings (50-km buffer). To extract the small fire probabilities, the nationwide fire occurrence point-based shapefiles (1992–2015) from U.S. Department of Agriculture (Short 2017) are downloaded, and fires larger than 300 acres are removed. Small wildfire occurrence are then extracted for Louisiana and surroundings using the “clip” tool in ArcGIS. A total of 73,501 small fire records exist in the study area. Planar kernel density analysis (Silverman 1986) is then performed for the small fire data, to produce a spatial distribution of fire density, with cell size set to 270 m, to correspond to that used in the FSim layer, and a kernel size of 50 km (Dillon et al. 2015). The cell area ($270 \text{ m} \times 270 \text{ m} = 72,900 \text{ m}^2$)

is then multiplied by the resulting kernel density of fire. To identify the small fire probability over the smoothed surface, the total number of fires (73,501) is divided by the kernel density, and this value for each pixel is divided by 24 to compute the historical (1992–2015) annual probability. To calculate total fire annual probability, this small fire probability is added to the large fire probability from FSim. The 50-km buffer is then removed by masking with the Louisiana boundary. Finally, the wildfire burn probability of each census block $p(f)_i$ is extracted from the raster files at the centroid of each census block.

Assessing future wildfire burn probability

The first step in determining future wildfire burn probability is to quantify the wildfire hazard for Louisiana. Liu et al. (2009) modeled seasonal changes to the Keetch-Byram Drought Index (KBDI; Pharo and Croom 1971), which has been used commonly to assess wildfire probability (e.g., Gannon and Steinberg 2021), at the global scale. The A2a economic or environmental or globalization or regionalization scenario, which assumes that global population surpasses 10 billion by 2050, with relatively slow economic and technological development, has been found to create global CO₂ mixing ratios of 575 parts per million (ppm) by 2050 and 870 ppm by 2100 (Liu et al. 2009), compared to the current 418 ppm. Thus, it is not surprising that models consistently project a warming global atmosphere (Wehner et al. 2017), which would seemingly increase wildfire probability.

Nevertheless, such a projection of the future wildfire hazard intensity is not straightforward. Anticipated water scarcity and intensifying insect infestations, such as by the southern pine beetle in Louisiana (Coleman et al. 2008) in a warming world may mitigate the wildfire hazard by reducing fuel from trees that are stunted or killed (Prestemon et al. 2016, Wehner et al. 2017). Other factors that might at first glance seem to mitigate future wildfire occurrence may actually exacerbate the wildfire hazard. For example, although daily precipitation totals are projected to increase by 9–13 percent for Louisiana by 2050 amid a generally more extreme precipitation climate nationwide by 2100 (Wehner et al. 2017), the enhanced “per event” precipitation and sharp increase in the frequency of days having a greater than 90th percentile of precipitation are accompanied by substantially more frequent “zero precipitation days” and small precipitation totals that would fall within today’s zero-to-tenth-percentile (Wehner et al. 2017). This is because the temporally warming atmosphere would require more atmospheric moisture before saturation is reached, and therefore before precipitation could occur. Thus, the anticipated increased precipitation totals could result in an enhanced wildfire hazard for Louisiana. Furthermore, the anticipated weakening of steering circulation (Vautard and Yiou 2009) that moves frontal and tropical weather systems will leave longer interarrival times between intense precipitation events. Such changes in both precipitation intensity and interarrival times would reduce soil moisture, which in turn would increase wildfire burn probability.

Wehner et al. (2017) acknowledges that projections of seasonal precipitation deficits lack confidence, particularly regarding extratropical precipitation extremes (e.g., O’Gorman and Schneider 2009) and that resulting wildfire occurrence is likely to display great local and regional spatial heterogeneity. The interplay between modeled trends in individual variables that may have compensating effects in their influence on future wildfire intensity and probability also complicate regional generalizations. Nevertheless, Wehner et al. (2017) recognize that the preponderance of evidence suggests that enhanced evapotranspiration caused by increased

temperatures will outpace the projected increasing precipitation totals. The net result is likely to be soil desiccation through this century over much of the continental U.S., at least under the RCP8.5 scenario.

At the regional scale, Prestemon et al. (2016) used three general circulation models and three IPCC-based emission scenarios to conclude that median annual area of the U.S. Southeast affected by lightning-ignited wildfire will increase by 34 percent, human-ignited wildfires will decrease by 6 percent, and total wildfire will increase by 4 percent by 2056–60 compared with the years 2016–2020. Such results are corroborated by USGCRP (2017), which suggests an increase in lightning-ignited wildfire by 2050 in the U.S. Southeast, including Louisiana (Wehner et al. 2017).

The Wehner et al. (2017) projection for Louisiana is for small soil moisture decreases in autumn relative to natural variability but large decreases relative to natural variability in the other three seasons by mid-century, with a “medium” degree of confidence (Wehner et al. 2017). The earlier KBDI work by Liu et al. (2009; their Figure 5) estimated similarly for Louisiana, but with more precise soil moisture forecasted decreases of 50–150 mm per three-month period in autumn and winter (September through February) and decreases of 200–250 mm per three-month period in March through May and June through August. The midpoint of the time series of the Liu et al. (2009) projection is 2085, so our current research assumes that half of the projected changes will occur by 2050. Thus, decreases of 25–75 mm per three-month period (or 8–25 mm per month, with 17 mm per month as the midpoint) are projected for each month from September through February in Louisiana by 2050. Decreases of 100–125 mm per three-month period (or 33–42 mm per month, with 38 mm per month as the midpoint) are projected for each month from March through August in Louisiana by 2050.

To provide more detail for Louisiana based on these results from Liu et al. (2009), mean monthly precipitation data for 31°N, 91.5°W (the nearest available data point to the center of the state) are input into the Web-based, Water-Budget, Interactive, Modeling Program (Willmott et al. 1985, WebWIMP 2021). WebWIMP calculates decreases in soil moisture in the upper-layers of 12.2 percent (February) to 46.1 percent (August). Thus, a 25 percent decrease in available moisture in the organic matter and uppermost soil layers, and a 25 percent increase in wildfire susceptibility across Louisiana by 2050 ($F_{2050} = 1.25$) is projected here. These calculations are not without their caveats. For example, these changes do not take into account projected changes in global air temperature. According to Frankson et al. (2017), historically unprecedented warming is to be expected in Louisiana under a higher emissions pathway by 2100.

Projecting population

The method of projecting population (P) at the census-block (i) scale by the year 2050 follows that of Mostafiz et al. (2020a; 2020b; 2021a; 2021b). Because annual census-block level population estimates are unavailable, the process begins with parish- (i.e., county-) wide annual growth rate calculations. For each of Louisiana’s 64 parishes (j), the average of the annual population growth rate (r_j) for the n -year (i.e., 40) period for which available annual U.S. Census Bureau (2021) estimates exist (i.e., 1980–2020) is calculated, beginning in year y , as described by Equation 1:

$$r_j = \frac{\sum_y^{y+n} \left[\frac{(P_{j,y+1} - P_{j,y})}{P_{j,y}} \right]}{n} \quad (1)$$

After r_j is determined for each of Louisiana's 64 parishes, future population change is downscaled to the census block (i), assuming that r_j is the same for each census block in its parish. Future population is then projected for each census block, assuming that currently unpopulated census blocks remain uninhabited through 2050. For each i , the 2010 population is used as the base (i.e., $P_{0,i} = P_{2010,i}$) and future population is projected out to 2050 (i.e., $P_{f,i} = P_{2050,i}$), given a n -year period within which the population changes (t), as shown in Equation 2:

$$P_{f,i} = P_{0,i} e^{r_j t} \quad (2)$$

This approach outperforms other methods that were tested. Specifically, the extension of a trend line of parish-level population into the future proved impractical because several parishes show an insignificant trend line and low explained variance. A second methodology tested is the extension of the growth rate trend line to approximate the 2050 population, but this proved problematic for the same cause. The abrupt, sizeable, and temporary population redistributions both within and beyond Louisiana in the wake of significant hurricanes (most notably Katrina in 2005) are likely contributors to the low explained variance. The procedure selected is least sensitive to these concerns and was also implemented effectively in Mostafiz et al. (2020a; 2021a; 2021b).

Assessing structure and content value

To evaluate current and future structure value (SV) in each census block, the total number of buildings in each census block in 2010 ($N_{2010,i}$) is acquired from the U.S. Census Bureau (2010) by summing the buildings constructed during each time interval as reported in the shapefiles (Mostafiz et al. 2021a). Then this value is multiplied by the mean building value in 2010 in a given census block ($MV_{2010,i}$) to give the total SV in that census block ($SV_{2010,i}$), as shown in Equation 3:

$$SV_{2010,i} = N_{2010,i} \times MV_{2010,i} \quad (3)$$

The number of buildings in 2050 in a census block ($N_{2050,i}$) is assumed to change proportionately to population, so the population projection described above is used to scale the building inventory. Total SV in 2050 in a census block ($SV_{2050,i}$) is then calculated as the product of $SV_{2010,i}$ and the ratio of 2050 population to 2010 population.

$$SV_{2050,i} = SV_{2010,i} \times \frac{P_{2050,i}}{P_{2010,i}} \quad (4)$$

The economic but not sentimental worth of items on the damaged property is known as content value (CV ; Mostafiz et al. 2021b). U.S. Army Corps of Engineers (USACE; 2019) calculates CV by multiplying SV by a structure-to-content value ratio according to the type of occupancy, in its National Structure Inventory version 2.0 (i.e., NSI 2.0). CV is presumed to be equal to SV for residential, commercial, and industrial structures in NSI 2.0 (USACE 2019). USACE (2019) recommends that CV be assumed to be 50 percent of SV when its official depth-damage functions are unavailable, and FEMA (2013, pp. 6–9) suggests assuming that CV is half of SV for all residential structures. As this research includes only residential structures, here the midpoint of these two estimates is taken, or

$$CV = 0.75 SV \quad (5)$$

The property value (PV) is the sum of SV and CV , or

$$PV = SV + CV \quad (6)$$

Projecting future property loss

Because LDAF records show that from 2007 to 2017, 389 of the 12,979 Louisiana residences that were threatened by fire were damaged (Bret Lane, personal communication, 4/9/2018), a conditional probability of damage $p(d|f_i)$ of 0.03 is assumed. Then, the probability of damage $p(d)_i$ is calculated as shown in Equation 7:

$$p(d)_i = p(f)_i \times p(d|f_i) \quad (7)$$

Based on LDAF advice, each damaged building is assumed to have a loss of 5 percent of the PV (Bret Lane, personal communication, 4/9/2018); thus, d is 0.05. Future property loss due to wildfire (L) in census block i is calculated as shown in Equation 6:

$$L_{2050,i} = PV_{2050,i} \times p(d)_i \times d \times F_{2050,i} \quad (8)$$

All losses are expressed in 2010\$. Because of uncertainties in these assumptions, a sensitivity analysis is conducted to demonstrate the impact of model assumptions regarding F_{2050} , SV to CV ratio, $p(d|f_i)$ and d . More specifically, each of these assumed values was changed by + 50 percent, to give a range of values for $L_{2050,i}$.

Note that the calculation for historical annual property loss ($\bar{L}_{1992-2015,i}$) is simply

$$\bar{L}_{1992-2015,i} = PV_{2010,i} \times p(d)_i \times d \quad (9)$$

with the 2010 property value being used at each census block $PV_{2010,i}$. Annual per capita and per building property loss in 2010 and 2050 by census block are calculated by dividing by the population and building count, respectively.

Results

Historical wildfire probability

Historical (1992–2015) wildfire burn probability ranges from 0 in coastal southeastern census blocks to 7.7 percent at a point in Cameron Parish (Appendix A), in the extreme coastal southwest (Figure 1A). The west-central, east-central, and extreme northwestern and southwestern parts of the state have the highest burn probability for wildfire (Figure 1A). For parish-level planning purposes, it is also worthwhile to note that Washington (the northeasternmost parish north of New Orleans and Lake Pontchartrain) is the most vulnerable parish, where the mean historical wildfire burn probability is 4.1 percent (Appendix A).

Figure 1 | Wildfire burn probability: (A) historical (1992–2015), and (B) projection for 2050.

Projected future wildfire probability

By 2050 projected wildfire burn probability is anticipated to range from 0 on the southeastern coast to 9.6 percent at a point in Cameron Parish (Figure 1B; Appendix B). The highest wildfire burn probability among census block centroids is expected to be 8.6 percent in census block 221179501012000 in Washington Parish. Washington will be the most vulnerable parish, where the mean projected wildfire burn probability is 5.2 percent (Appendix B). Washington, St. Helena, Beauregard, Allen, Tangipahoa, St. Tammany, Vernon, Rapides, Livingston, and Calcasieu are the top ten most vulnerable parishes in Louisiana (Appendix A-B), whereas St. Mary, Iberia, Terrebonne, Assumption, and Lafourche are the least vulnerable parishes (Appendix A-B). In general, the wildfire hazard is likely to remain concentrated in the same

geographical areas of the state as in the historical record, but burn probabilities are likely to increase (Figure 1A-B).

Projected future population

Using the values calculated in Equations 1 and 2, and assuming that the 102,781 census blocks in Louisiana that were inhabited in 2010 (from among the 203,447 total) will remain the only blocks inhabited in 2050, the 2050 population density projection is generated. Population is most densely concentrated around New Orleans, Baton Rouge, and Shreveport, the state's three largest cities (Figure 2A). By 2050, the population will remain concentrated in largely the same areas, but with increasing density around Lafayette, Baton Rouge, and north of New Orleans and Lake Pontchartrain (Figure 2B). Population density decreases are expected throughout northeastern Louisiana, along the Red River Valley from Shreveport to the area southeast of Alexandria, in the New Orleans area, and elsewhere (Figure 2B). Appendix C shows these values by parish.

Figure 2| Population density by census block: (A) 2010, and (B) change in population density from 2010 to 2050.

Historical and projected future property loss

The wildfire risk will increase statewide by 2050 due to intensifying negative impacts of climate change statewide, and increasing population and development in many parts of the state. The historical (1992–2015) average annual statewide property loss due to wildfire was \$5,556,389 (2010\$). Projected annual loss will be \$11,167,496 by 2050 (2010\$; Appendix D). This absolute annual total for 2050 is small compared to property losses due to other hazards in Louisiana, such as expansive soils (\$91.8 million; Mostafiz et al. 2021a), tornadoes (\$24.3 million; Mostafiz et al. 2020a), extreme cold (\$23.2 million; Mostafiz et al., 2020a), and wind (\$20.5 million; Governor's Office of Homeland Security and Emergency Preparedness 2019). However, the wildfire-induced property damage is notable because it is projected to increase by 101 percent. Furthermore, the wildfire hazard is anticipated to exceed that for the hazards of lightning (\$4.3

million; Mostafiz et al. 2020a), hail (\$2.5 million Mostafiz et al. 2020a), and sinkholes (\$0.3 million; Mostafiz et al. 2021b). Note that these values do not include crop, forestry, or indirect losses (e.g., cost of evacuation, missed time at work, etc.), which are likely to be high for wildfire as well. Thus, the loss estimates here are conservative.

The maximum estimated property losses will remain concentrated near their present locations, namely east-central, southwestern, and northwestern Louisiana (Figure 3A-B). On a per capita basis, the historical (1992–2015) average annual per capita property loss due to wildfire was only \$1.23 (2010\$) in Louisiana (Appendix D). Projected per capita property loss is \$1.97 by 2050 (2010\$), giving an increase in annual per capita property loss of 61 percent (Appendix D). The same general spatial distribution of per capita property losses (Figure 4A-B) occurs (and is projected to occur by 2050) as was shown for absolute losses. The historical average annual per building property loss was \$2.83 (2010\$) whereas the projected loss will be \$4.63 (2010\$) by 2050 (Appendix D). Thus, the annual per building property loss will increase by 64 percent in Louisiana. Again, the spatial distribution remains similar (Figure 5A-B).

Figure 3| Estimated annual property loss (2010\$) due to wildfire by census block: (A) historical (1992–2015), and (B) 2050.

Figure 4| Estimated annual per capita property loss (2010\$) due to wildfire by census block: (A) historical (1992–2015), and (B) 2050.

At the parish level, St. Tammany (immediately north of Lake Pontchartrain and New Orleans in east-central Louisiana) had the highest historical (1992–2015) overall wildfire annual property loss (\$1,560,580), per capita property loss (\$6.68), and per building property loss (\$16.36) among the parishes (Appendix D). Changes in the wildfire burn probability and expansion of population are projected to change wildfire risk by 2050. Nevertheless, the greatest annual wildfire property loss (\$4,633,439), per capita property loss (\$8.34), and per building property loss (\$20.45) are expected to remain in St. Tammany Parish (Appendix D).

At the census-block level, the highest historical average annual property loss due to wildfire was in block 221030408035041 of St. Tammany Parish (\$18,837). The highest historical (1992–2015) average annual per building property loss (\$37.35) was in census block 221030407061032, also in St. Tammany Parish. The highest historical annual per capita property loss in the state was \$354.83 in census block 220919511002011, in St. Helena Parish (east-central Louisiana, northwest of St. Tammany).

By 2050, the greatest annual property loss due to wildfire is projected to be in census block 221030408035041, in St. Tammany Parish (\$55,950). The highest annual per capita property loss (\$443.54) will be in census block 220919511002011 of St. Helena Parish. The highest annual per building property loss (\$46.68) will be in census block 221030407061032, in St. Tammany Parish.

Figure 5 | Estimated annual per building property loss: (A) historical (1992–2015), and (B) 2050 by census block in Louisiana (2010\$).

Sensitivity Analysis

If the wildfire burn probability in 2050 increases by 12.5 percent (i.e., $F_{2050} = 1.125$) or 37.5 percent from the present (i.e., $F_{2050} = 1.375$), rather than the 25 percent increase (i.e., $F_{2050} = 1.25$) currently assumed, the result would change by ± 10.0 percent (Table 1). If CV would be taken to be only 37.5 percent of SV or 112.5 percent of SV , instead of the model-estimated 75 percent of SV , the sensitivity is approximately ± 21.4 percent (Table 1). However, the model is much more sensitive to variations in the other two variables included. Specifically, the greatest sensitivity in model assumptions is that for $p(d|f_i)$, which is derived as the conditional probability of damage (0.03). If $p(d|f_i)$ would actually be 0.015 or 0.045, the modeled annual loss in 2050 would change by 50 percent (Table 1). Same as sensitive is the percent of property damage (d). If 2.5 or 7.5 percent of the property is damaged, rather than the 0.05 assumed in the model, the annual loss in 2050 would change by 50 percent (Table 1).

Table 1. Sensitivity analysis of 2050 projections of Louisiana statewide annual property loss (i.e., risk) due to wildfire, by parameter (2010\$).

Parameter	Low Scenario	Modeled (Equation 6)	High Scenario	Difference from Equations 8 (%)
Future Condition (F_{2050})	\$10,050,746 (+12.5%)	\$11,167,496 (+25%)	\$12,284,245 (+37.5%)	± 10.0

Content to Structure Value Ratio (CV/SV)	\$8,774,461 $CV = 0.375 SV$	\$11,167,496 $CV = 0.75 SV$	\$13,560,530 $CV = 1.125 SV$	± 21.4
Conditional Probability of Damage $p(d f_i)$	\$5,583,748 $(p(d f_i) = 0.015)$	\$11,167,496 $(p(d f_i) = 0.03)$	\$16,751,244 $(p(d f_i) = 0.045)$	± 50.0
Percent of Property Damage (d)	\$5,583,748 $(d = 0.025)$	\$11,167,496 $(d = 0.05)$	\$16,751,244 $(d = 0.075)$	± 50.0

Discussion

While it is tempting to overlook the wildfire hazard in a state that receives abundant rainfall, is susceptible to so many other, more calamitous hazards, and often suffers from other more pressing economic hardships, the wildfire hazard in Louisiana is formidable and is expected to become more challenging in coming decades. Thus, adequate resources should be devoted to preventing and mitigating the hazard, including but not limited to, educating the public on the dangers of carelessness with managed fires. Additional resources will be needed to combat the anticipated increased risk, in places where population is expected to increase. The mean annual loss of \$11.2 million statewide by 2050 is likely skewed by major fires, which suggests that resources must be on hand to address them.

The implications of the sensitivity analysis are that investment in improved warning and response systems, which would reduce $p(d|f_i)$, and the development of fire-retardant structure and content materials, which would reduce d , would seem to be wise mitigation measures. Such strategies would likely overcome or at least strongly buffer any higher-than-anticipated climate change-driven increases to the wildfire hazard, at least in Louisiana. The hope is that any reductions in ability to acquire resources to prevent or mitigate the hazard are offset by improvements and innovations in technology to detect and combat the fires. If the risk does indeed remain roughly proportionate to the population increase, resources to combat the risk should be available, assuming that other economic and demographic factors also change proportionately. For example, the vulnerability to wildfire under the uncertain and complex conditions of response during the COVID-19 pandemic would almost certainly exacerbate losses (Thompson et al. 2021).

As in any research, this work has some caveats that should be acknowledged. The lack of consideration of some natural features can limit the reliability of the findings. For example, this work does not consider vegetation type, fuel load, land use, or disturbance patterns, which might change the future potential destructiveness of the fires. Recent research (Krueger et al. 2017) suggests that the fraction of available water (FAW) is a better predictor of large growing-season wildfires than the KBDI. FAW is calculated as the ratio of plant available water to soil water capacity. But FAW has not yet been projected as confidently to 2050 as precipitation, and until it can be predicted better, soil moisture projections are limited those using the KBDI.

Another set of limitations involves the population projection methodology, which ignores abrupt changes in the future, such as migrations prompted by hurricanes or other natural disasters, economic depression, or other extreme events. Another limitation is the assumption, necessitated by data availability, of equal population growth rates for every census block within a parish. Census-block-level population data are only available at the decennial census; interim estimates are not provided at the census block level. Therefore, we project the population of a census block assuming that its population grows at the same rate as the parish in which it resides. This assumption is reasonable because in most cases, the inhabited sections of a parish are small and the census blocks therein are clustered. These small, clustered areas are likely to be affected similarly by economic conditions, natural hazards, and other factors that would cause population changes. Therefore, it is likely that the growth rate is similar. In addition, population growth may not follow an exponential growth curve. This research also does not consider changes in economic and demographic characteristics by 2050, which might alter the ability for taxes to cover additional mitigation and prevention strategies. Unfortunately, the absence of reliable demographic projections for Louisiana based on more elaborate modeling makes these assumptions necessary. As the spatial patterns of population change, therefore, one would expect the spatial patterns of human-caused ignitions and fire likelihood to shift as well. These dynamics are not represented in the current effort; however, improvements and refinements in these assumptions can be directly used in the developed methodology.

Furthermore, the loss calculations are limited by many assumptions. For example, building replacement cost rather than building value could have given additional information that would have assisted in some aspects of planning, such as for setting fire insurance premiums. Likewise, inclusion of industrial and commercial structures, crop value, and especially timber resource value would have given a much more accurate estimate of the total direct economic impact of wildfire.

Finally, in a more general sense, this research is limited by its focus on the data-driven approach to property loss. Community-level wildfire risk analysis is necessary to improve wildfire mitigation planning (Ager et al. 2015), so that non-quantifiable features and assets can be considered and protected accordingly. Likewise, losses to human health are not considered here, but are important, particularly given previous research that demonstrates the health impacts of wildfire-induced air quality concerns in the U.S. Southeast.

Conclusion

This research has developed a method for analyzing historical and future property losses to wildfire in Louisiana, a U.S. state with relatively dense population, abundant infrastructure, and a likely increasing susceptibility to long periods without rainfall. In contrast to most work on spatial distribution of hazards, the analysis is done at the census-block level, which provides a more suitable areal unit of analysis than the parish (i.e., county) because of the wide disparities in population, property, and (in some cases) natural vulnerability to the hazard. The results suggest that the present areas of maximum risk – west-central, east-central, and extreme northwestern and southwestern coastal Louisiana – will remain the most vulnerable areas to this often-overlooked hazard in 2050. However, annual loss, both on an absolute and per capita basis,

are expected to increase substantially, as the population grows, development along the WUI intensifies, and amplified climatic changes combine to exacerbate the risk.

Wildfire risk assessment can be enhanced in future research by using ignition location modeling or similar techniques to align future wildfire with shifts in population, especially as population changes align with land use land cover types. In addition, crop and forestry loss assessment due to wildfire could be conducted, particularly because these are of such high value in many places, including Louisiana.

Future research should also be conducted to extend a similar methodology to other hazards in other places, such as earthquakes, sinkholes, lightning, and hail. In a more general sense, improved population, economic, and demographic forecasts are needed, so that current and future risk to natural hazards, including wildfire, can be assessed more accurately. As the accuracy of climate models improves, the reliability of future projections for natural hazard risk will advance in their mission of protecting lives and property.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

This project resulted from the 2019 Louisiana State Hazard Mitigation Plan update, for which CF and RR received funding from FEMA, via Louisiana's Governor's Office of Homeland Security and Emergency Preparedness (GOHSEP), grant number: 2000301135. Any opinions, findings, conclusions, and recommendations expressed in this manuscript are those of the authors and do not necessarily reflect the views of FEMA or GOHSEP.

Authors' contributions

RM developed the methodology, collected and analyzed the data, and developed the initial text. CF provided original ideas and advice on the overall project methodology and edited the text. RR developed the atmospheric projections and edited early and late drafts of the text. NB expanded the literature review and provided oversight on analysis, particularly regarding the population projections.

Acknowledgments

Publication of this article was subsidized by the LSU Libraries Open Access Author Fund. The authors warmly appreciate the assistance and support of Jeffrey Giering of GOHSEP for overall project support, and David Dunaway of LSU Libraries for assistance in acquiring population data. Bret Lane of Louisiana Department of Agriculture and Forestry provided wildfire damage data.

Abbreviations

CV: Content value

d: Property damage percentage

F_{2050} : Future adjustment factor of wildfire burn probability in 2050

FAW: Fraction of available water **FSim:** Fire Simulation system

GIS: Geographical information systems

i: Census-block

IPCC: Intergovernmental Panel on Climate Change

j: Parish

KBDI: Keetch-Byram Drought Index

$\bar{L}_{1992-2015,i}$: Historical (1992-2015) annual property loss by wildfire at census block i

$L_{2050,i}$: Projected property loss due to wildfire in 2050 at census block i

LDAF: Louisiana Department of Agriculture & Forestry

$MV_{2010,i}$: Mean building value in 2010 at census block (i)

$N_{2010,i}$: Total number of buildings at census block (i) in 2010

NSI: National Structure Inventory

P: Population

$p(d)_i$: Probability of damage at census block (i)

$p(d|f)_i$: Conditional probability of damage

$p(f)_i$: Wildfire burn probability of census block (i)

PV: Property value

r_j : Average annual population growth rate of parish (j)

RCP: Representative concentration pathway

SV: Structure value

USGCRP: U.S. Global Change Research Program

USACE: U.S. Army Corps of Engineers

WUI: Wildland-urban interface

y: Year

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Supplementary materials

Appendix A: Historical (1992–2015) Wildfire Burn Probability (%), by Louisiana Parish.

Parish	Point-based		Parishwide	
	Min	Max	Mean	Standard Deviation
Acadia	0.01	1.18	0.16	0.18
Allen	1.20	6.22	3.77	1.28
Ascension	0.01	1.04	0.36	0.24
Assumption	0.00	0.05	0.01	0.01
Avoyelles	0.06	1.23	0.29	0.21
Beauregard	2.01	5.39	3.87	0.47
Bienville	0.82	1.52	1.17	0.14
Bossier	0.71	2.06	1.14	0.24
Caddo	0.65	3.20	1.59	0.56
Calcasieu	0.13	6.48	1.82	1.07
Caldwell	0.45	1.64	0.99	0.27
Cameron	0.00	7.70	1.52	1.61
Catahoula	0.07	1.24	0.53	0.31
Claiborne	1.11	1.56	1.37	0.11
Concordia	0.06	0.46	0.18	0.08
De Soto	0.61	1.72	0.83	0.20
East Baton Rouge	0.05	2.92	0.64	0.54
East Carroll	0.06	0.36	0.21	0.07
East Feliciana	0.15	3.67	1.72	0.86
Evangeline	0.25	5.23	1.73	1.06
Franklin	0.07	0.78	0.24	0.14
Grant	1.18	2.07	1.74	0.20
Iberia	0.00	0.02	0.00	0.00
Iberville	0.00	0.36	0.03	0.04
Jackson	0.84	1.22	1.03	0.08
Jefferson	0.00	0.93	0.13	0.18
Jefferson Davis	0.04	2.52	0.72	0.56
Lafayette	0.01	0.09	0.02	0.01
Lafourche	0.00	0.08	0.01	0.01
LaSalle	0.32	2.01	1.45	0.37
Lincoln	0.85	1.33	1.07	0.12
Livingston	0.51	4.41	2.15	0.95
Madison	0.06	0.33	0.13	0.06
Morehouse	0.30	0.96	0.64	0.14

Natchitoches	0.82	1.74	1.13	0.15
Orleans	0.08	2.31	0.93	0.54
Ouachita	0.37	0.89	0.64	0.13
Plaquemines	0.00	0.24	0.03	0.05
Pointe Coupee	0.03	0.17	0.08	0.03
Rapides	0.47	6.13	2.43	1.46
Red River	0.65	1.03	0.83	0.08
Richland	0.22	0.67	0.34	0.07
Sabine	0.81	2.16	1.35	0.30
St. Bernard	0.00	2.00	0.24	0.21
St. Charles	0.00	0.49	0.05	0.06
St. Helena	2.17	4.75	3.97	0.48
St. James	0.01	0.50	0.10	0.10
St. John the Baptist	0.01	1.47	0.46	0.37
St. Landry	0.03	0.76	0.17	0.13
St. Martin	0.00	0.06	0.01	0.01
St. Mary	0.00	0.01	0.00	0.00
St. Tammany	0.92	5.60	3.15	0.89
Tangipahoa	1.22	4.76	3.55	0.96
Tensas	0.06	0.68	0.18	0.12
Terrebonne	0.00	0.02	0.00	0.00
Union	0.65	1.22	0.89	0.12
Vermilion	0.00	0.53	0.04	0.06
Vernon	1.34	6.11	3.08	1.12
Washington	3.19	6.93	4.14	0.69
Webster	0.97	1.54	1.34	0.10
West Baton Rouge	0.02	0.19	0.07	0.04
West Carroll	0.19	0.56	0.39	0.07
West Feliciana	0.06	1.39	0.34	0.26
Winn	1.10	1.98	1.48	0.21

Appendix B: Projected Wildfire Burn Probability (%) in 2050, by Louisiana Parish.

NAME	Point-based		Parishwide	
	Min	Max	Mean	Standard Deviation
Acadia	0.01	1.47	0.20	0.22
Allen	1.50	7.77	4.71	1.60
Ascension	0.02	1.30	0.45	0.30
Assumption	0.00	0.06	0.01	0.01
Avoyelles	0.08	1.54	0.36	0.26
Beauregard	2.51	6.73	4.83	0.59
Bienville	1.03	1.89	1.47	0.17
Bossier	0.89	2.57	1.43	0.31
Caddo	0.81	4.00	1.99	0.70
Calcasieu	0.16	8.10	2.28	1.33
Caldwell	0.56	2.05	1.23	0.33
Cameron	0.00	9.62	1.90	2.01
Catahoula	0.09	1.55	0.67	0.38
Claiborne	1.39	1.95	1.71	0.14
Concordia	0.08	0.58	0.22	0.10
De Soto	0.77	2.15	1.03	0.24
East Baton Rouge	0.06	3.65	0.80	0.67
East Carroll	0.07	0.45	0.26	0.09
East Feliciana	0.18	4.58	2.15	1.08
Evangeline	0.31	6.54	2.16	1.32
Franklin	0.08	0.98	0.29	0.17
Grant	1.47	2.59	2.17	0.25
Iberia	0.00	0.02	0.00	0.00
Iberville	0.01	0.45	0.04	0.05
Jackson	1.05	1.53	1.29	0.10
Jefferson	0.00	1.16	0.16	0.23
Jefferson Davis	0.05	3.15	0.89	0.69
Lafayette	0.01	0.11	0.03	0.02
Lafourche	0.00	0.10	0.01	0.01
LaSalle	0.40	2.51	1.81	0.47
Lincoln	1.06	1.67	1.34	0.16
Livingston	0.64	5.52	2.69	1.18
Madison	0.08	0.41	0.16	0.07
Morehouse	0.38	1.20	0.80	0.18
Natchitoches	1.02	2.18	1.42	0.18
Orleans	0.10	2.89	1.16	0.67
Ouachita	0.46	1.12	0.80	0.16

Plaquemines	0.00	0.31	0.04	0.06
Pointe Coupee	0.04	0.22	0.09	0.03
Rapides	0.59	7.66	3.04	1.83
Red River	0.81	1.29	1.04	0.10
Richland	0.27	0.83	0.43	0.09
Sabine	1.02	2.70	1.69	0.37
St. Bernard	0.00	2.50	0.30	0.26
St. Charles	0.00	0.61	0.07	0.08
St. Helena	2.71	5.94	4.96	0.60
St. James	0.01	0.62	0.13	0.12
St. John the Baptist	0.01	1.84	0.57	0.47
St. Landry	0.04	0.95	0.21	0.16
St. Martin	0.00	0.07	0.02	0.01
St. Mary	0.00	0.02	0.00	0.00
St. Tammany	1.15	7.01	3.94	1.11
Tangipahoa	1.52	5.95	4.44	1.20
Tensas	0.08	0.85	0.23	0.15
Terrebonne	0.00	0.03	0.01	0.00
Union	0.81	1.52	1.11	0.15
Vermilion	0.00	0.66	0.05	0.08
Vernon	1.68	7.64	3.85	1.40
Washington	3.99	8.67	5.18	0.87
Webster	1.21	1.93	1.67	0.13
West Baton Rouge	0.03	0.24	0.08	0.04
West Carroll	0.24	0.70	0.49	0.09
West Feliciana	0.08	1.74	0.43	0.32
Winn	1.38	2.47	1.85	0.27

Appendix C: Louisiana Parish Population in 2010, Projected Population by 2050, Density in 2010, Projected Density by 2050, and Projected Change in Population Density.

Parish	Population (2010)	Population (2050)	Density (per km ²) (2010)	Density (per km ²) (2050)	Density Change (2010–2050) (per km ²)
Acadia	61,773	67,309	36.3	39.5	3.3
Allen	25,764	30,554	13.0	15.4	2.4
Ascension	107,215	278,635	136.7	355.3	218.6
Assumption	23,421	22,875	24.8	24.2	(0.6)
Avoyelles	42,073	40,710	18.8	18.2	(0.6)
Beauregard	35,654	45,242	11.8	15.0	3.2
Bienville	14,353	11,471	6.7	5.4	(1.4)
Bossier	116,979	183,706	52.1	81.8	29.7
Caddo	254,969	238,795	105.1	98.4	(6.7)
Calcasieu	192,768	233,579	68.0	82.4	14.4
Caldwell	10,132	9,248	7.2	6.6	(0.6)
Cameron	6,839	5,253	1.4	1.0	(0.3)
Catahoula	10,407	7,741	5.4	4.0	(1.4)
Claiborne	17,195	15,467	8.7	7.8	(0.9)
Concordia	20,822	17,145	10.8	8.9	(1.9)
De Soto	26,656	28,631	11.5	12.4	0.9
East Baton Rouge	440,171	526,522	361.4	432.3	70.9
East Carroll	7,759	4,397	6.8	3.8	(2.9)
East Feliciana	20,267	20,074	17.2	17.0	(0.2)
Evangeline	33,984	33,924	19.3	19.3	(0.0)
Franklin	20,767	17,005	12.6	10.3	(2.3)
Grant	22,309	29,701	13.0	17.3	4.3
Iberia	73,240	78,687	27.4	29.5	2.0
Iberville	33,387	33,263	19.7	19.7	(0.1)
Jackson	16,274	14,727	10.8	9.8	(1.0)
Jefferson	432,552	409,450	260.1	246.2	(13.9)
Jefferson Davis	31,594	30,585	18.5	17.9	(0.6)
La Salle	14,890	13,171	8.7	7.7	(1.0)
Lafayette	221,578	361,856	317.8	519.0	201.2
Lafourche	96,318	112,609	25.3	29.6	4.3
Lincoln	46,735	54,630	38.2	44.6	6.5
Livingston	128,026	314,726	71.5	175.7	104.3
Madison	12,093	8,268	7.2	4.9	(2.3)
Morehouse	27,979	19,510	13.4	9.3	(4.1)
Natchitoches	39,566	37,548	11.8	11.2	(0.6)
Orleans	343,829	310,135	379.5	342.3	(37.2)

Ouachita	153,720	167,523	93.9	102.4	8.4
Plaquemines	23,042	21,107	3.5	3.2	(0.3)
Pointe Coupee	22,802	20,338	14.9	13.3	(1.6)
Rapides	131,613	125,227	37.3	35.5	(1.8)
Red River	9,091	7,174	8.7	6.9	(1.8)
Richland	20,725	18,611	14.2	12.7	(1.4)
Sabine	24,233	22,705	9.2	8.7	(0.6)
St. Bernard	35,897	59,835	6.4	10.7	4.3
St. Charles	52,780	74,669	51.3	72.6	21.3
St. Helena	11,203	11,570	10.6	10.9	0.3
St. James	22,102	21,233	33.1	31.8	(1.3)
St. John the Baptist	45,924	60,827	43.3	57.3	14.0
St. Landry	83,384	80,465	34.3	33.1	(1.2)
St. Martin	52,160	68,297	24.7	32.3	7.6
St. Mary	54,650	41,198	18.8	14.2	(4.6)
St. Tammany	233,740	555,517	82.4	195.8	113.4
Tangipahoa	121,097	204,995	55.4	93.8	38.4
Tensas	5,252	2,529	3.2	1.5	(1.6)
Terrebonne	111,860	129,437	20.7	24.0	3.3
Union	22,721	23,720	9.7	10.1	0.4
Vermilion	57,999	70,768	14.5	17.7	3.2
Vernon	52,334	47,403	15.1	13.6	(1.4)
Washington	47,168	48,685	26.9	27.8	0.9
Webster	41,207	35,843	25.9	22.5	(3.4)
West Baton Rouge	23,788	33,301	45.1	63.1	18.0
West Carroll	11,604	9,567	12.4	10.2	(2.2)
West Feliciana	15,625	19,823	14.2	18.0	3.8
Winn	15,313	12,352	6.2	5.0	(1.2)
Louisiana	4,533,372	5,661,868	33.4	41.7	8.3

Appendix D: Historical (1992–2015) Annual Average and 2050-Projected Property Loss, per Capita Property Loss, and per Building Property Loss, by Louisiana Parish 2010\$).

Parish	Annual Property Loss		Annual Per Capita Property Loss		Annual Per Building Property Loss	
	Historical (1992–2015)	Projected (2050)	Historical (1992–2015)	Projected (2050)	Historical (1992–2015)	Projected (2050)
Acadia	5,834	7,939	0.09	0.12	0.23	0.29
Allen	70,484	104,389	2.74	3.42	7.24	9.05
Ascension	79,001	256,591	0.74	0.92	1.94	2.42
Assumption	166	203	0.01	0.01	0.02	0.02
Avoyelles	13,541	16,395	0.32	0.40	0.75	0.94
Beauregard	132,231	209,560	3.71	4.63	8.79	10.99
Bienville	14,537	14,661	1.01	1.28	1.88	2.36
Bossier	151,806	297,915	1.30	1.62	3.08	3.84
Caddo	355,593	416,460	1.39	1.74	3.17	3.97
Calcasieu	262,914	398,089	1.36	1.70	3.20	4.00
Caldwell	9,166	10,486	0.90	1.13	1.84	2.29
Cameron	11,858	11,474	1.73	2.18	3.30	4.10
Catahoula	4,405	4,104	0.42	0.53	0.90	1.13
Claiborne	18,779	21,171	1.09	1.37	2.42	3.02
Concordia	4,071	4,208	0.20	0.25	0.43	0.54
De Soto	22,093	29,624	0.83	1.03	1.80	2.25
East Baton Rouge	318,443	476,118	0.72	0.90	1.70	2.12
East Carroll	774	555	0.10	0.13	0.27	0.33
East Feliciana	33,236	41,186	1.64	2.05	4.15	5.19
Evangeline	36,540	45,596	1.08	1.34	2.49	3.11
Franklin	3,602	3,702	0.17	0.22	0.40	0.50
Grant	33,168	55,078	1.49	1.85	3.73	4.67
Iberia	273	367	0.00	0.00	0.01	0.01
Iberville	1,412	1,759	0.04	0.05	0.11	0.14
Jackson	18,581	21,103	1.14	1.43	2.42	3.02
Jefferson	103,818	122,841	0.24	0.30	0.55	0.69
Jefferson Davis	12,467	15,121	0.39	0.49	0.94	1.17
La Salle	19,561	21,701	1.31	1.65	2.98	3.72
Lafayette	7,293	14,887	0.03	0.04	0.08	0.10
Lafourche	397	580	0.00	0.01	0.01	0.01
Lincoln	54,301	79,338	1.16	1.45	2.79	3.49
Livingston	321,625	987,898	2.51	3.14	6.41	8.01
Madison	831	717	0.07	0.09	0.17	0.22

Morehouse	15,877	13,870	0.57	0.71	1.28	1.60
Natchitoches	47,276	56,097	1.19	1.49	2.54	3.18
Orleans	226,704	255,825	0.66	0.82	1.19	1.49
Ouachita	114,107	155,416	0.74	0.93	1.77	2.21
Plaquemines	3,075	3,524	0.13	0.17	0.32	0.40
Pointe Coupee	2,493	2,779	0.11	0.14	0.22	0.28
Rapides	267,425	318,269	2.03	2.54	4.80	6.00
Red River	6,534	6,460	0.72	0.90	1.58	1.98
Richland	4,960	5,580	0.24	0.30	0.58	0.72
Sabine	42,303	49,748	1.75	2.19	2.99	3.75
St. Bernard	12,487	25,996	0.35	0.43	0.74	0.93
St. Charles	1,623	2,869	0.03	0.04	0.08	0.10
St. Helena	49,864	64,279	4.45	5.56	9.68	12.10
St. James	2,187	2,627	0.10	0.12	0.26	0.32
St. John the Baptist	9,400	15,556	0.20	0.26	0.54	0.67
St. Landry	13,271	16,020	0.16	0.20	0.37	0.46
St. Martin	994	1,625	0.02	0.02	0.05	0.06
St. Mary	44	41	0.00	0.00	0.00	0.00
St. Tammany	1,560,580	4,633,439	6.68	8.34	16.36	20.45
Tangipahoa	630,169	1,332,887	5.20	6.50	12.58	15.73
Tensas	1,809	1,109	0.34	0.44	0.54	0.67
Terrebonne	117	169	0.00	0.00	0.00	0.00
Union	21,337	27,811	0.94	1.17	1.88	2.35
Vermilion	650	988	0.01	0.01	0.03	0.03
Vernon	117,933	133,743	2.25	2.82	5.50	6.88
Washington	198,893	256,359	4.22	5.27	9.45	11.82
Webster	51,412	55,964	1.25	1.56	2.66	3.32
West Baton Rouge	2,469	4,319	0.10	0.13	0.26	0.33
West Carroll	3,879	4,006	0.33	0.42	0.77	0.96
West Feliciana	7,375	11,668	0.47	0.59	1.45	1.82
Winn	16,342	16,634	1.07	1.35	2.26	2.82
Louisiana	5,556,389	11,167,496	1.23	1.97	2.83	4.63