Understanding California wildfire risk, part 2: Zesty.ai risk score model

Annie Shen, ACAS
Sheri L. Scott, FCAS, MAAA, CSPA
Katherine Dalis, ACAS, MAAA, CCRMP

This article is the second in a series of articles examining California wildfire risk and tools that could be used to identify, quantify, and mitigate this risk. Since our previous white paper in this series, "Understanding California Wildfire Risk," the California Department of Forestry and Fire Protection (CAL FIRE)[1] has updated its wildfire statistics, summarized in Figure 1.

FIGURE 1: CAL FIRE CALENDAR YEAR STATISTICS

Year	Number of Wildfires	1,000 Acres Burned	Structures Damaged/ Destroyed	1,000Acres Burned per Fire	Structures per 1,000 Acres
2013	9,907	602	456	0.06	0.76
2014	7,233	626	471	0.09	0.75
2015	8,283	881	3,159	0.11	3.59
2016	6,954	670	1,274	0.10	1.90
2017	9,270	1,548	10,280	0.17	6.64
2018	7,948	1,975	24,226	0.25	12.27
2019	7,860	260	732	0.03	2.82

As illustrated in Figure 1, the number of acres burned per wildfire and the structures damaged per acre burned have increased since 2013. Relentless years of devastating wildfires are stretching the California homeowners insurance industry to its limits, with insured losses of $37 billion outpacing premiums of $32 billion since 2016.[2]

In response to the increased wildfire losses that appear to be the new normal, insurance companies have been filing for rate increases with the California Department of Insurance. Although the California rate template allows insurance companies some recognition of the cost of capital for catastrophic wildfire insurance, it does not permit consideration of the net cost of reinsurance.[3] As further described in our prior white paper, reinsurance rates have dramatically increased in the wake of several years of devastating global catastrophes.

Faced with the inability to cover all the costs of insuring California wildfires, the California admitted insurance market has been reducing its wildfire exposure. Stricter underwriting eligibility guidelines and higher rates for wildfire-exposed properties have pushed more policyholders into secondary markets, such as the California Fair Access to Insurance Requirements (FAIR) Plan.

The FAIR Plan is designed to accept properties that are having difficulty finding insurance in the voluntary market and does not decline risks due to wildfire exposure. The FAIR Plan's recent rate filings help explain how the tightening admitted market has driven a large volume of homeowners with wildfire-exposed properties into its portfolio. Because the California Department of Insurance has recently taken the position that the FAIR Plan cannot include any cost of capital in its premiums, the FAIR Plan is struggling to prevent its rates in wildfire-exposed areas from becoming lower than the admitted market.[4] All else equal, not permitting the FAIR Plan to include the cost of capital, which the admitted market is permitted to include, results in lower FAIR Plan rates relative to the admitted market. As a result, there has been an influx of homeowners moving to the FAIR Plan simply because they can get a lower premium. This is expanding the FAIR Plan from being the market of last resort to a competitive provider of wildfire insurance in the state.

1 California fires of 10 or more acres from CAL FIRE as of January 6, 2021. See https://www.fire.ca.gov/incidents/.

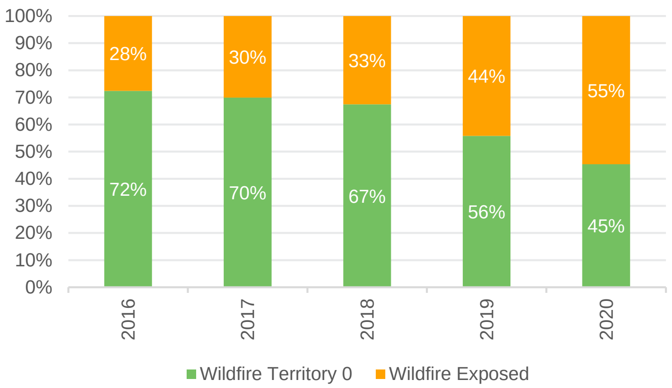
2 S&P Global, National Association of Insurance Commissioners (NAIC) Annual Statement, Statutory State Page, Line 4: Homeowners, Direct Incurred Losses and Direct Earned Premium, calendar years 2015 to 2019, as of September 28, 2020.

3 California Insurance Code (CIC) Section 2644.25 and the CA Rate Template only permit net cost of reinsurance to be considered for medical malpractice or earthquake. CIC Section 2644.15-16 permits a rate of return (ROR) between the risk-free ROR and 6% higher than the risk-free ROR, and an additional 2% at the Commissioner's discretion based on market conditions. The ROR range could be used to consider the higher cost of capital to provide catastrophe coverage.

4 FAIR Plan California rate filings 19-4339 and 20-2965, where the California Department of Insurance did not permit consideration of net cost of reinsurance nor any cost of capital.

Figure 2 illustrates that FAIR Plan properties located in wildfire-exposed territories ("Wildfire Exposed") have doubled from 28% in 2016, to 55% in 2020, shifting the FAIR Plan's footprint across the state to higher wildfire-exposed areas.[5] "Wildfire Territory 0" denotes the FAIR Plan's lowest wildfire-rated territory.

FIGURE 2: FAIR PLAN DISTRIBUTION BY WILDFIRE EXPOSURE



To better understand its exposure to wildfire, the FAIR Plan asked Zesty.ai, Inc. (Zesty.ai), a company that provides a wildfire risk score model, to score the FAIR Plan properties relative to wildfire risk. Zesty.ai calculated that 4% of all residential properties in California are heavily exposed to wildfire, compared to 21% of FAIR Plan properties.[6]

WILDFIRE EXPOSURE MEASUREMENT TOOLS

Insurance companies and reinsurance companies have been early adopters of property-level wildfire risk models to assess a property's wildfire risk level and help understand and manage their overall wildfire risk. As discussed in our previous paper, traditional wildfire risk models consider the following:

1. **Fuel**: The grass, trees, dense brush, and vegetation that feed wildfires.
2. **Slope**: Steeper slopes of the surrounding terrain increase the speed of wildfire and affect reconstruction costs.
3. **Access**: Dead-end roads and areas that are difficult to access impede firefighting equipment.

Modern computing power and technological advancements have enabled companies to create more sophisticated models that consider more granular property-level data.

According to documentation provided by Zesty.ai, its Z-FIRE wildfire risk model is unique in that it uses high resolution satellite imagery along with climate and other data sources to provide two layers of information about a property's wildfire exposure. The first layer (L1) provides the annualized probability of the property being within the perimeter of a wildfire by identifying the type and proximity of fuel source, precipitation, temperature, and other geospatial variables. The second layer (L2) provides the conditional probability of the property being destroyed in the event of a wildfire by using high-resolution satellite imagery to identify specific details about the property such as how close certain types of vegetation are to the structure, whether there are tree branches overhanging the roofline, whether fire-resistant building materials are used, and other details about the building. The homeowner can influence the L2 probability of destruction by clearing brush within the property perimeter, trimming tree branches hanging over the roofline, upgrading to modern building materials such as fire-resistant roofs, and other home-hardening measures.

In this paper we use the Zesty.ai Z-FIRE model L1 and L2 probabilities to assess exposure to wildfire and how the insurance industry and homeowners can use wildfire risk models to better understand, assess, and mitigate wildfire risk. This case study was performed independently, and not commissioned by Zesty.ai, FAIR Plan, or any other company.

Case study

PORTFOLIO OF PROPERTIES

The FAIR Plan's portfolio of properties is uniquely suitable for evaluating a wildfire model and wildfire exposure because it has sufficient properties with varying levels of wildfire exposure.

To start the analysis, FAIR Plan residential properties insured between January 1, 2016, through September 30, 2020, were sorted in order of FAIR Plan wildfire territory, and then the territories were grouped into five groups of increasing wildfire exposure. Group 1 contains the lowest wildfire exposure territory that couldn't be further segmented, while Group 5 represents properties in territories currently classified as having the highest wildfire risk under the FAIR Plan's current approved rate plan.

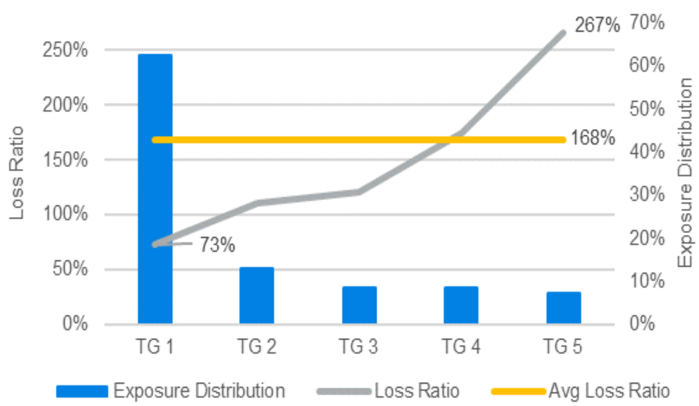
Figure 3 summarizes the distribution of earned exposures and reported loss ratio for each group of FAIR Plan territories. The loss ratio for a territory group was calculated as the sum of each property's reported wildfire loss and defense and cost containment (DCCE) in the territory group, divided by the earned premium for each property in the territory group during the experience period.[7].

[5] Effective January 1, 2021, FAIR Plan Territory 0 was split into True 0 and 0 as detailed in CA filing 20-2965. Because the reallocation of properties into True 0 and 0 has not been completed on policies that have not yet renewed since the territory split, Territory 0 includes True 0 and 0.

[6] Heavily exposed defined as Zesty Z-FIRE L1 x L2, very high-risk score groups, using FAIR Plan residential dwelling policies in force on December 31, 2019.

[7] Reported loss and DCCE for accidents January 1, 2016, through September 30, 2020, valued as of September 30, 2020, without expected future development or

FIGURE 3: WILDFIRE REPORTED LOSS RATIO BY FAIR PLAN TERRITORY GROUP

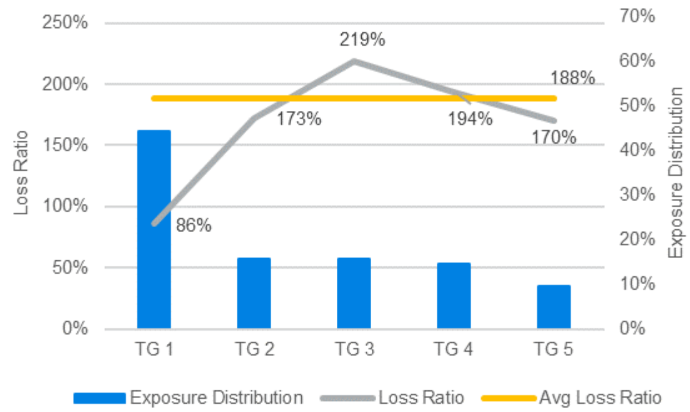


The orange line is the average loss ratio across all territory groups combined, which is 168%. This means that during the experience period, for every $100 in premium collected, $168 in losses was reported by the FAIR Plan. The area between the orange line and the gray line represents the cross-subsidization that occurred. The area below the orange line, down to the gray line, represents the subsidization that properties in the less risky FAIR Plan wildfire territory groups provided to properties in the very high-risk territory group. The amount of subsidy that the very high-risk territory group received is the area below the gray line, down to the orange line.

Because the FAIR Plan's footprint is shifting toward more wildfire-exposed areas, using historical experience without adjustment can underestimate the wildfire loss ratio. Also, because catastrophe losses widely fluctuate from year to year, modern insurance ratemaking techniques generally rely on stochastic catastrophe modeling to estimate the average annual loss (AAL) on in-force properties instead of historical experience losses. For these reasons, this case study also performs a similar review of modeled AAL from a widely used industry stochastic catastrophic model applied to FAIR Plan policies in force on December 31, 2019.[8]

Figure 4 summarizes the distribution of in-force properties and modeled loss ratio for each FAIR Plan territory group. The loss ratio was calculated as the sum of each property's wildfire AAL in the territory group, divided by on-level premium for each property in the group.

FIGURE 4: WILDFIRE AAL LOSS RATIO BY FAIR PLAN TERRITORY GROUPS



The shift of FAIR Plan policies into higher territory groups, which have higher loss ratios, is driving up the overall FAIR Plan wildfire loss ratio. The average statewide loss ratio is 188%, using AAL on in-force policies as the measurement of expected annual losses. All territory groups except TG 0 have a loss ratio above 100%, which means that the rates need to be increased to simply cover the expected loss costs for properties in these territory groups. Compounding the influx of more wildfire-exposed properties into the FAIR Plan is the inability to cover all the costs to insure wildfire-exposed properties, creating market conditions and a deterioration of the FAIR Plan's rate adequacy.

One way to reduce the subsidies in Figures 3 and 4 is to adjust the current FAIR Plan rating factors to better match rate to risk. That means increasing the rating factors applied to risks in territory groups above the orange line, and reducing rating factors for territory groups below the orange line, to achieve the same loss ratio across all territory groups. This would eliminate the subsidy within the FAIR Plan's insurance program but may not improve the overall loss ratio of the entire program, represented by the orange line. To improve the overall average loss ratio, the combined impact of all the rate increases would need to be greater than the rate decreases. The FAIR Plan may also need to increase its overall base rates for wildfire across all territories in order to reduce the overall loss ratio and collect sufficient premium to cover all the costs of insuring wildfire. In recent rate filings, the FAIR Plan has indicated that it plans to take smaller annual rate increases to move toward the fully indicated wildfire rate level, rather than taking the fully indicated rate change at once. This approach manages the impact of rate changes on the FAIR Plan's current policyholders. It will take several years of smaller rate adjustments to eliminate the

incurred but not reported (IBNR). Earned premium calculated by rerating each policy during the experience period, using rates current on September 30, 2020.

[8] AAL was from a widely used industry stochastic catastrophe model and does not include DCCE. For consistency with the experience period analysis, the in-force analysis used rates current on September 30, 2020.

subsidies in Figures 3 and 4 and bring the wildfire rates to an actuarially sound rate level.

STRATIFY RISK WITH A WILDFIRE RISK SCORE MODEL

To further assess its wildfire risk, the FAIR Plan asked Zesty.ai to provide its Z-FIRE L1 and L2 probabilities for each property, which were multiplied together to arrive at a combined Z-FIRE wildfire risk score (WRS) for each property. To mimic underwriting, characteristics about each property immediately before the experience period were used to calculate the WRS. After calculating each property WRS, properties were then sorted into five groups of increasing WRS, of roughly equal size.

Figure 5 summarizes the distribution of FAIR Plan residential dwelling fire properties in force on December 31, 2019, by current FAIR Plan wildfire territory group and WRS group.

FIGURE 5: DISTRIBUTION BY WRS GROUP

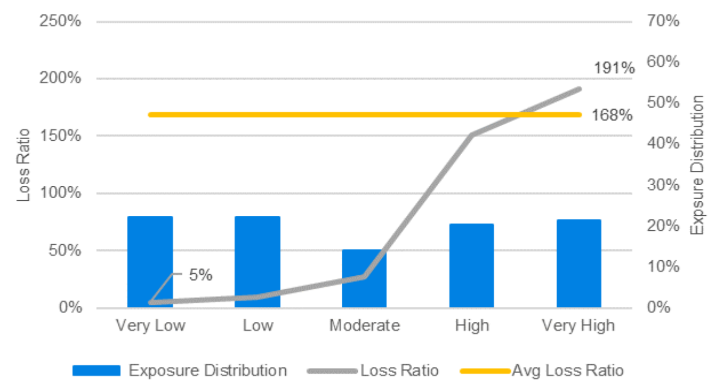
		WRS Group					
		Very Low	Low	Moderate	High	Very High	Total
Current Wildfire Territory Group	TG 1	20.1%	18.4%	5.3%	0.3%	0.1%	44.3%
	TG 2	0.4%	1.1%	6.0%	4.5%	3.7%	15.7%
	TG 3	0.0%	0.2%	3.7%	5.8%	6.0%	15.8%
	TG 4	0.0%	0.1%	2.8%	5.2%	6.4%	14.6%
	TG 5	0.0%	0.0%	1.4%	3.6%	4.7%	9.7%
	Total	20.5%	19.8%	19.2%	19.4%	21.0%	100.0%

The diagonal of the above matrix, outlined in gold, represents properties where wildfire risk was classified similarly by both the current territory group assignment and WRS group. Below the diagonal represents properties the WRS classified as lower risk than the current rate plan. For example, the WRS used additional characteristics specific to each of the 9.7% of properties in the FAIR Plan's highest wildfire territories (TG 5), to reclassify some of these properties into less risky WRS groups, leaving only 4.7% classified as very high risk. Above the diagonal represents properties the WRS classified as higher risk than the current rate plan.

HISTORICAL EXPERIENCE PROPERTIES

After a WRS group was assigned to each property, the FAIR Plan's actual wildfire reported loss experience ratio was calculated for each WRS group.[9] Figure 6 summarizes the reported loss ratio by WRS group.

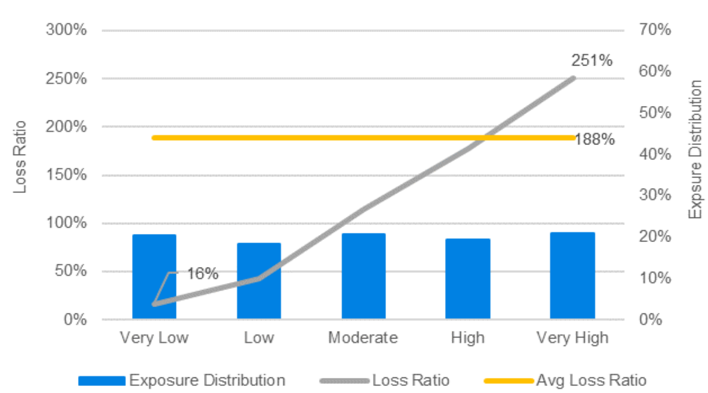
FIGURE 6: WILDFIRE REPORTED LOSS RATIO BY WRS GROUP



The orange line is the average loss ratio across all territory groups combined. The area below the orange line, down to the gray line, represents the subsidization that properties in the less risky WRS groups provided to properties in the very high-risk WRS group. The amount that the very high-risk WRS group obtained in subsidy is the area above the orange line and up to the gray line. To achieve an overall loss ratio of 75% across all WRS groups, the average premium in the very low, low, and moderate WRS groups would need to decrease by 93%, 88%, and 64%, respectively, and the high and very high WRS groups would need to increase rates by 101% and 156%, more than doubling their current average premium. These indicated rate changes help explain the magnitude of the inadequacy of the FAIR Plan rates for wildfire-exposed properties, using reported loss experience as the measure for indicated rate level.

To evaluate the FAIR Plan's growing wildfire exposure, a similar review using AAL on in-force policies is summarized in Figure 7.

FIGURE 7: WILDFIRE AAL LOSS RATIO BY WRS GROUP



[9] First properties were sorted in ascending order of WRS and then grouped into five WRS groups of roughly equal earned exposure. Because many properties had identical WRS it was not possible to achieve exactly equal earned exposure in each WRS group. Undeveloped reported loss and DCCE for the accident period and earned premium using rates on-level to September 30, 2020, for the period January 1, 2016, to September 30, 2020.

Figures 6 and 7 are called lift charts, where the upward-sloping gray line is a measurement of how well the model classifies risk into increasing WRS groups. The overall lift in Figure 7 is calculated as the 251% loss ratio in the very high-risk WRS group divided by the 16% loss ratio in the very low-risk WRS group, which equals 15.5. An upward-sloping gray line with a lift of 15.5 indicates that the Z-FIRE model is able to stratify risk between the very high-risk and very low-risk wildfire properties.

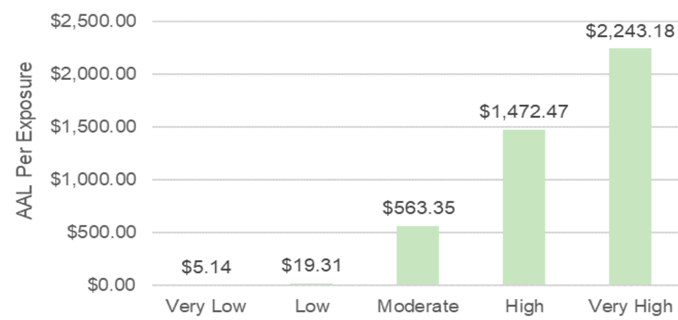
The data summary that is often used to determine the indicated rate factors for individual WRS groups compares loss costs instead of loss ratios. The average reported loss and DCCE per exposure in each WRS group was plotted as green bars in Figure 8.

FIGURE 8: WILDFIRE AVERAGE REPORTED LOSS PER EXPOSURE BY WRS GROUP

The very high-risk WRS group average wildfire loss cost of $1,986.78 is nearly three times the overall average of $662.58, while the loss cost for the very low-risk group of $0.87 is a fraction of the overall average. Note that while our analysis was conducted using a different source of data than that used in building the Z-FIRE model, it is likely there is overlap in the exposures and events included.[10] As models tend to perform better on data they have "seen" than new data, the lift achieved for future exposures may be lower than the differentiation shown in Figure 8.

To create a lift chart using purely "unseen" data, we plotted the AAL per exposure by WRS group using data from a catastrophe model that was not used to train the Z-FIRE model.

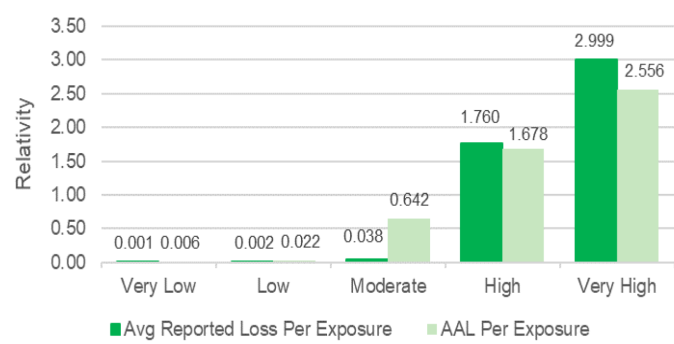
FIGURE 9: WILDFIRE AAL PER EXPOSURE BY WRS GROUP



The AAL per exposure in Figure 9 in the very high-risk WRS group of $2,243.18 is more than 2.5 times the overall average AAL per exposure of $887.56, while the AAL per exposure for the very low-risk group of $5.14 is a fraction of the overall average.

To calculate the indicated rating factors for the WRS groups, the losses per exposure in Figures 8 and 9 are converted into relativities compared to the overall average loss per exposure. Figure 10 plots the relativity of the average reported loss and DCCE per exposure in each of the WRS groups to the overall average of $662.58 in the dark green bars, and the relativity of the AAL per exposure in each of the WRS groups to the overall average of $887.56.

FIGURE 10: RELATIVITY OF WILDFIRE REPORTED LOSS PER EXPOSURE AND AAL PER EXPOSURE TO OVERALL AVERAGE BY WRS GROUP

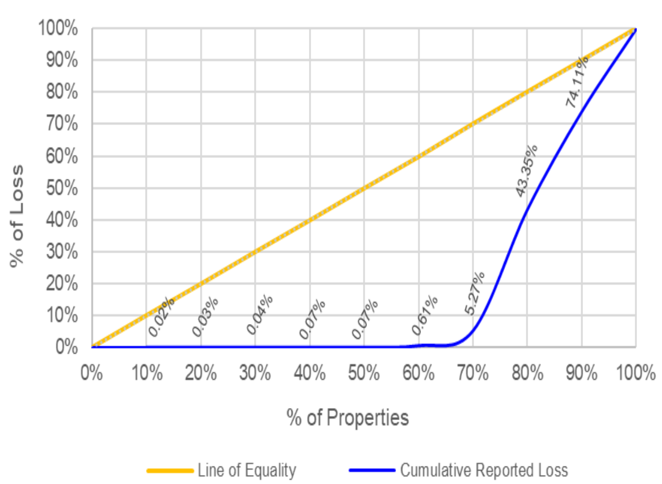


The relativities represent the indicated factors that the FAIR Plan could use to differentiate its rates between the different WRS groups using the Z-FIRE model. The dramatic difference between the very high-risk WRS group and the very low-risk WRS group in Figures 8, 9, and 10 demonstrate the predictive power of the Z-FIRE model without using premium or relying on the current FAIR Plan territories.

[10] The FAIR Plan 2016 to 2020 reported loss and DCCE used in the Figure 8 lift chart likely includes properties that were also included in the data used by Zesty to train Z-FIRE™, which included 20 years of wildfires through 2019.

Please note that a lift chart is simply one method that can be used to assess the model. There are other model validation techniques, such as a Lorenz curve. Lorenz curves are commonly used to demonstrate a model's ability to sort a data set by a metric, in this case the risk of wildfire loss. To create a Lorenz curve, the properties were sorted from lowest to highest WRS. The cumulative percentage of properties was plotted in deciles on the x-axis and the cumulative historical reported wildfire loss and DCCE for each of these properties plotted on the y-axis. The resulting blue line in Figure 11 is called a Lorenz curve.

FIGURE 11: LORENZ CURVE OF CUMULATIVE WILDFIRE REPORTED LOSS

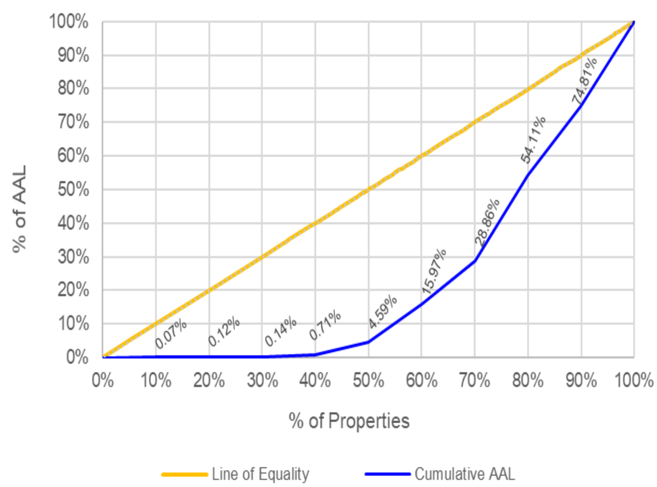


The straight orange line is called the line of equality and represents the situation where the model does not sort any better than a random sort. The more the Lorenz curve bows out away from the line of equality, toward the bottom right, the better the model's ability to sort risk. From the Lorenz curve the Gini coefficient can be calculated as twice the area between the Lorenz curve and the line of equality. The Gini coefficient is a value between zero and one and quantifies the amount by which the model outperforms a random sort, where a random sort has a Gini coefficient of 0.00. The best model performance has a Gini coefficient of 1.00. The Gini coefficient in Figure 9 is 0.653.

As with lift charts, Lorenz curves that use historical reported loss and DCCE experience require a sufficient volume of wildfire losses to produce stable results that can be relied upon. Some insurance companies with restricted eligibility for wildfire-exposed properties may not be able to produce meaningful results from a Lorenz curve due to an insufficient volume of historical wildfire loss and DCCE data. As with lift charts, a Lorenz curve can also be created using modeled AAL based on the insurance company's current portfolio of properties or a hypothetical portfolio of properties that doesn't require a sufficient volume of historical loss experience.

In Figure 12, the cumulative AAL on each property, grouped into deciles, is plotted on the y-axis, and the distribution of properties on the x-axis.

FIGURE 12: LORENZ CURVE USING CUMULATIVE WILDIFRE AAL



Similar to evaluating the historical loss experience, the predictive ability of the catastrophe model to sort risk is depicted by the blue Lorenz curve that bows out away from the orange line of equality. The Gini coefficient for Figure 12 is 0.541.

To calculate the lift charts in Figures 8 through 10 and the Lorenz curves in Figures 11 and 12, property addresses, historical loss, and DCCE as well as AAL were provided by the FAIR Plan. The Z-FIRE WRS on each FAIR Plan address was provided by Zesty.ai. None of the analysis in Figures 8 through 12 used FAIR Plan premium or territories. Furthermore, no data from any other third parties was used, relied upon, or referenced in the calculation of the any of the lift charts, Lorenz curves, or analysis throughout this white paper.

Lift charts and Lorenz curves are only two of the statistical methods used to measure a model's ability to predict loss and segment risk. There are many other statistical tools, such as a mean squared error (MSE) approach. The statistical methods used depend on the data available and the intended purpose of the analysis. The intended purpose of the analysis in this white paper was to provide the insurance industry with an overview of two statistical methods that could be used to review the ability of a wildfire model to measure and sort wildfire risk.

Summary

The above analysis demonstrates how insurance companies can use modern WRS models to assess and manage wildfire risk. Having access to modern WRS models is only half the battle. Updating California regulations to enable insurance companies and the FAIR Plan to cover the full cost of wildfire exposure, including the net cost of reinsurance and the cost of capital related to providing catastrophic coverage, could help reverse the trend of reduced availability in the voluntary market. Coupling that with facilitating the use of WRS models to introduce discounts that encourage home hardening or other wildfire risk improvement measures taken by homeowners and communities could help mitigate escalating wildfire costs. The industry, regulators, communities, and homeowners can work together to use the insights and modern techniques that the insurance industry has developed to assess and mitigate wildfire exposure, such as wildfire risk scoring models, to better understand and reduce the impact from California wildfires.

CONTACT

Sheri L. Scott, FCAS, MAAA, CSPA

sheri.scott@milliman.com