Modernizing homeowners rate plans in the age of changing risk

Commissioned by ZestyAI

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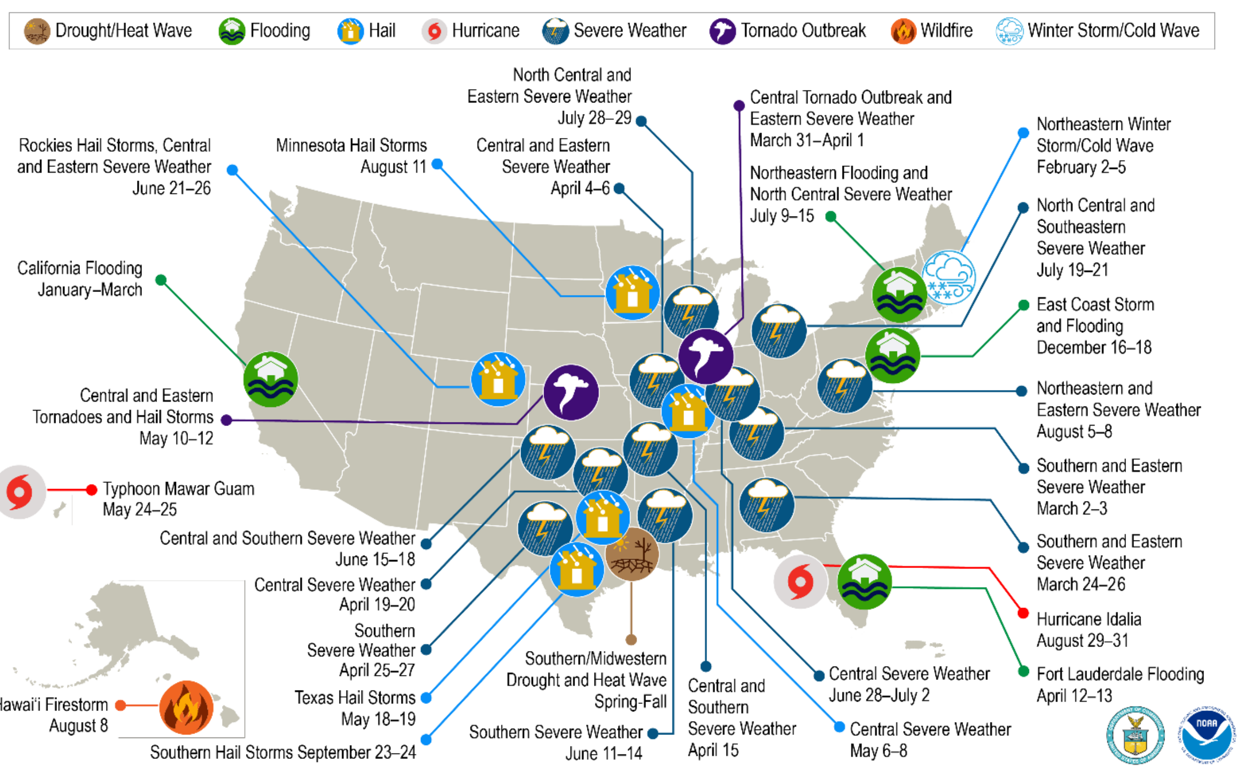
Executive summary

The U.S. homeowners insurance market is facing challenges from catastrophe events, inflation, increasing reinsurance cost, climate change, and many other emerging risks. This paper explores methods for insurance companies to modernize their homeowners rate plans by improving risk segmentation and pricing sophistication, presents important considerations for these methods, and outlines a case study about ZestyAI's Z-HAIL model.

Introduction

FIGURE 1: U.S. 2023 BILLION-DOLLAR WEATHER AND CLIMATE DISASTERS



*This map denotes the approximate location for each of the **28 separate billion-dollar weather and climate disasters that impacted the United States in 2023.***

Source: NOAA

The year 2023 was another record-setting year in the number of climate disasters across the world. The United States experienced 28 weather and climate disasters, each exceeding $1 billion in losses.[1] The increase in frequency and severity of catastrophic weather events creates challenges for the homeowners insurance industry, exacerbated by rising costs to rebuild properties[2] and soaring reinsurance costs for catastrophe exposed lines.[3] Insurance companies have sought rate increases to cover these rising costs. When adequate rate increases are not possible, some have decided to reduce their exposure to catastrophe exposed properties through tighter underwriting eligibility guidelines or by leaving catastrophe exposed states altogether.[4] Other companies improve underwriting and rating sophistication to allow them to better identify the high-cost risks and charge an adequate rate.

Although it is much simpler to prepare the regulatory support and implement a simple statewide base rate increase to account for the higher catastrophe costs, this may result in cross-subsidization across segments of policyholders, and adverse selection[5] in the market may occur from competitors utilizing multi-peril rating, risk segmentation tools, and other pricing and underwriting sophistication.

Improving risk segmentation

Improved risk segmentation enables insurance companies to charge rates that are more commensurate with the risk being insured. Simply put, by introducing rating factors that either increase or decrease the premium based on whether the segment has a higher or lower expected loss cost, companies can increase their profitability without the need for overly restrictive underwriting criteria. Companies may also use property-level risk-segmentation tools within underwriting to accept catastrophe-exposed properties that meet certain catastrophe-mitigation requirements, such as roof ties and window shutters to protect against hurricanes. Pricing and underwriting sophistication allows insurance companies to use a more targeted approach when accepting and rating risks, rather than a heavy-handed approach of not accepting any catastrophe-exposed properties, which leads to availability issues in the market (i.e., uninsured properties).

One common method for companies to make their rating algorithms more sophisticated is to switch from single-peril pricing, where there is a combined base rate that covers all perils, to multi-peril pricing, where the premium is determined for each peril independently. This allows the insurance company to apply discounts or surcharges related to specific perils, such as applying a wildfire-mitigation discount only to the wildfire component of the premium, rather than applying it to premium that includes unrelated perils.

Another way for companies to improve risk segmentation is by introducing rating variables that consider the risk characteristics about the individual property, such as a wildfire risk score that considers vegetation directly surrounding a property. In order to develop factors for these new rating variables, companies may use their historical exposure and loss experience data or rely on publicly available competitor information from approved regulatory filings. The advantage of using a company's own historical exposure and loss experience is that the data is readily available. However, due to the random nature of insurance losses, that data may not be sufficiently credible.[6] It may also be limited to risk attributes already used in rating and may not have information about new rating attributes that the company is considering adding, such as fire-resistant eaves or windows. On the other hand, it is quick and easy to rely on competitor data for companies without credible exposure or loss experience. However, there are various adjustments that may be required if there are significant differences in expenses, business strategy, risk profiles, and other considerations between the competitor program and the proposed program. Failing to reflect these material differences may lead to unexpected results such as higher loss ratios or combined ratios, and profitability challenges for specific risk segments as well as the program as a whole.

1 National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). Retrieved from: https://www.ncei.noaa.gov/access/billions/.

2 The cost to rebuild increased 13.4% in 2021, 9.3% in 2022, and continued to increase 9.1% in 2023 according to the DGS California Construction Cost Index CCCI. California Department of General Services. Retrieved from: https://www.dgs.ca.gov/RESD/Resources/Page-Content/Real-Estate-Services-Division-Resources-List-Folder/DGS-California-Construction-Cost-Index-CCCI.

3 Reuters (2024). U.S. property reinsurance rates rise by up to 50% on Jan 1-broker says. Retrieved from: https://www.reuters.com/markets/us/us-property-reinsurance-rates-rise-by-up-50-jan-1-broker-says-2024-01-02/.

4 Jacobson, L. (February 2024). Insurers such as State Farm and Allstate are leaving fire- and flood-prone areas. Home values could take a hit. CNBC. Retrieved from: https://www.cnbc.com/2024/02/05/what-homeowners-need-to-know-as-insurers-leave-high-risk-climate-areas.html.

5 Adverse selection occurs when a policyholder chooses a company over another because that company's rates do not account for risk characteristics that are present in other rate plans, usually leading to poorer loss experience and decreased profitability.

6 Credibility refers to the predictive utility of a body of data, especially as it compares to its intended use.

Risk models

With the development of modern technologies, some companies are shifting to incorporating risk models for natural and other hazards into their insurance programs for rating and underwriting. A risk model can predict future outcomes such as loss frequency, severity, or loss cost for the purposes of ratemaking or underwriting. Examples include catastrophe models that produce average annual losses (AAL), wildfire models that are used to quantify the relative riskiness of properties with respect to their propensity to be damaged by wildfires, and roof models that classify the quality of roofs and their ability to mitigate loss. Risk models may also incorporate climatological, environmental, geospatial, and other data specific to properties or very granular regions to allow for powerful rate segmentation, especially when coupled with modern machine learning and artificial intelligence models.

We were commissioned by ZestyAI to perform a case study of the hail risk model developed by ZestyAI, called Z-HAIL™, to determine how it could be used in rating to improve an insurance company's ability to predict loss and classify risk. The Z-HAIL model uses a variety of climatological data and property-specific attributes developed through high-resolution aerial imagery to understand and measure a property's exposure to hail risk. For each scored property, Z-HAIL provides:

- Z-HAIL Claim Frequency Score, representing the annual likelihood of a hail claim being filed, ranging from 1 to 10, with 1 being the lowest expected frequency risk segment and 10 being the highest expected frequency risk segment.

- Z-HAIL Claim Severity Score, representing the total cost of a hail claim as a proportion of the insured property's Coverage A[7] limit, given that a hail claim is filed on the property, ranging from 1 to 5, where 1 is the lowest expected damage ratio segment and 5 is the highest expected damage ratio segment of risk.

The following summarizes the results of the case study using data from an insurance carrier (Carrier 1) that writes homeowners and dwelling fire insurance in Texas.

Case study

The street address for each property insured under policies with effective dates from January 1, 2016, to December 31, 2021, were sent to ZestyAI. ZestyAI then calculated the following for each property at the beginning of each policy term and appended to the data:

- Z-HAIL Claim Frequency Score
- Z-HAIL Claim Severity Score
- Combined Hail Risk Score, which is based on probabilities underlying the Z-HAIL Claim Frequency and Z-HAIL Claim Severity Scores

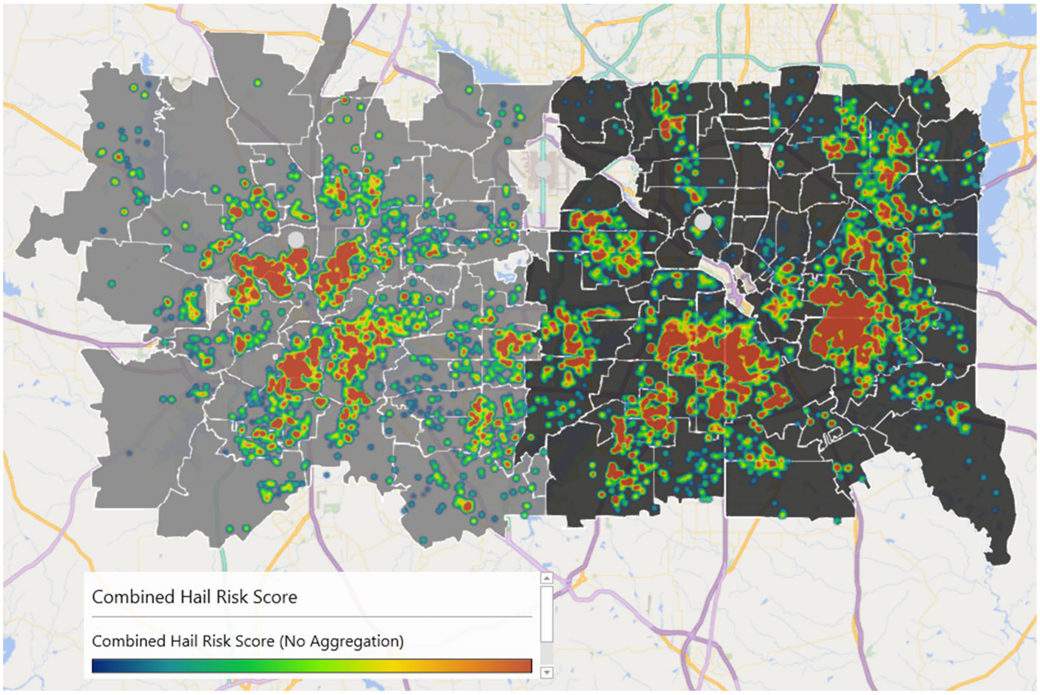
We then appended other details about the policy such as the earned premium as well as the loss experience during the policy term, valued at June 30, 2022.[8]

Analysis

Figure 2 is a map of Carrier 1's in-force exposures on December 31, 2021, in Tarrant County on the left in light grey and Dallas County on the right in dark grey. ZIP Codes are outlined in white. Exposures are color-coded according to the Combined Hail Risk Score as defined above, where blue represents the lowest risk, green indicates moderate risk, and red indicates the highest risk.

[7] Coverage A provides property insurance for a house and its attached structures, including the roof.
[8] Reported losses are net of salvage and subrogation and exclude loss adjustment expenses (LAE), incurred but not reported (IBNR), and loss development. Reported loss ratio calculated as reported hail loss divided by policy earned premium.

FIGURE 2: COMBINED HAIL RISK SCORE – TARRANT AND DALLAS COUNTY



Figures 3 and 4 provide a closer view of ZIP Code 75116 in Dallas County and ZIP Code 76111 in Tarrant County, respectively. As shown in the figures, the Combined Hail Risk Score varies significantly within individual ZIP Codes, which illustrates that the risk model provides more granular classification than the county and ZIP-Code-based territory definitions currently utilized by Carrier 1. When companies use county or ZIP-Code-based territory definitions without any other type of risk scores in the rate plan, all risks in the same broad region will be assigned the same territory factor despite properties within the region having very different risk exposure (such as the roof type, the age of the property, or the condition of the roof or of the property). Using a property-level risk model can improve segmentation and recognize the difference in risk exposures even in small geographical areas.

FIGURE 3: COMBINED HAIL RISK SCORE – DALLAS COUNTY, ZIP CODE 75116

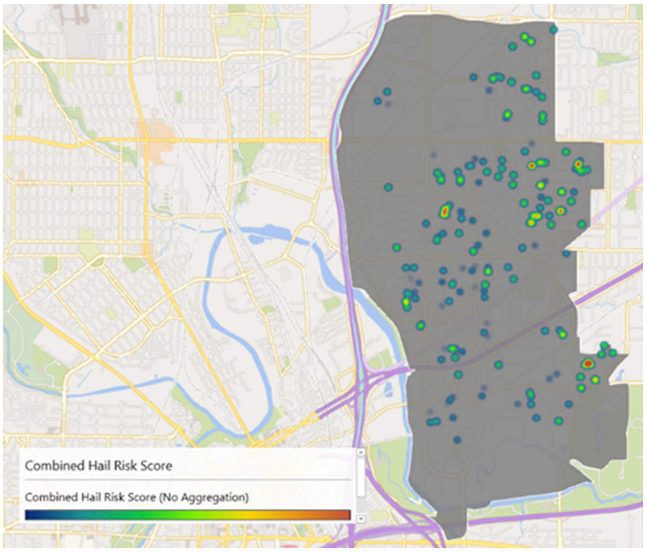
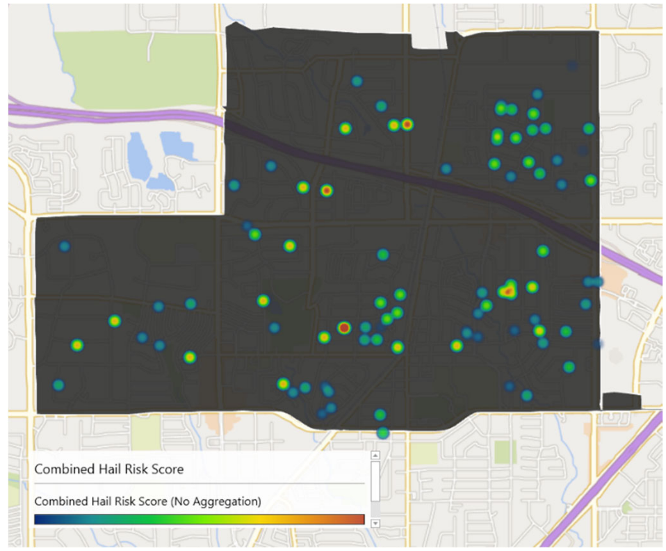


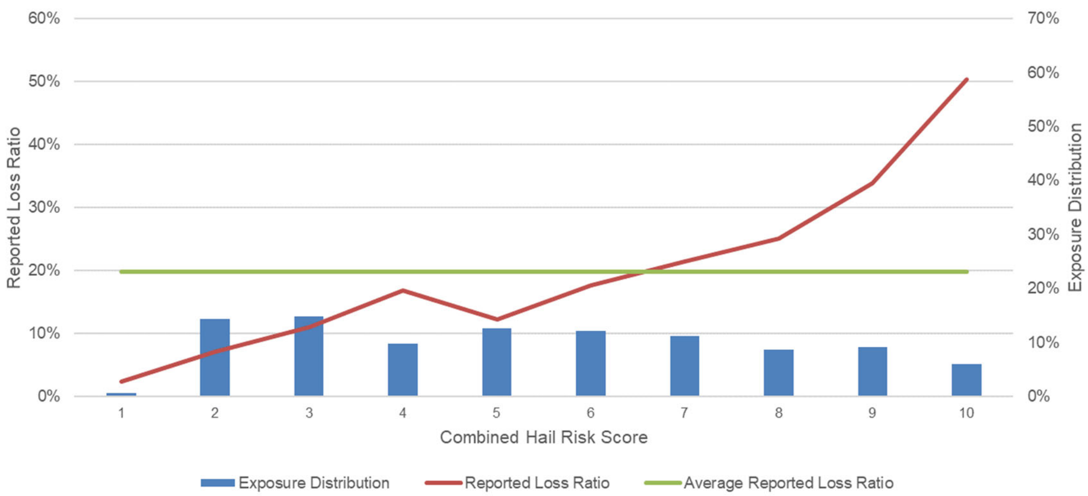
FIGURE 4: COMBINED HAIL RISK SCORE – TARRANT COUNTY, ZIP CODE 76111



To understand the predictive power of the Combined Hail Risk Score, Figure 5 plots Carrier 1's five-year exposure distribution (blue bar) and loss ratio (red line) by Combined Hail Risk Score sorted into 10 groups of increasing risks. Each group on the x-axis contains five distinct Combined Hail Risk Scores. The average loss ratio across the entire experience period and all Combined Hail Risk Scores is plotted as the green horizontal line. Figure 5 illustrates a reversal between groups 4 and 5, where the reported loss ratio decreases as the risk increases to group 5, and consistently increases thereafter. The reported loss ratio of 50.4% for Combined Hail Risk Score group 10 divided by the reported loss ratio of 2.4% for Combined Hail Risk Score group 1 results in a lift of about 21[9] (e.g., 50.4% / 2.4% ≈ 21). Because the metric being measured is loss ratio, the lift measures how well the model segments risks considering both frequency and severity over the property characteristics already present in Carrier 1's current rate plan. When risk models are implemented in production settings, their results are analyzed to understand inconsistencies, such as reversals, and other potential issues to ensure that they perform as expected, and insurance programs should be monitored and maintained as experience data is collected.

[9] The lift calculated within this analysis may be distorted because ZestyAI's Z-HAIL modeling dataset overlaps with Carrier 1's experience period, though ZestyAI did not use Carrier 1 experience for training, testing, or validating Z-HAIL.

FIGURE 5: REPORTED LOSS RATIO BY COMBINED HAIL RISK SCORE



The above results demonstrate how a risk model can be evaluated to determine how well it improves segmentation in insurance programs. The risk scores can be used to develop more refined territories or a new rating variable by risk score groups, or to classify the risk of a particular property for purposes of underwriting and calculating premium.

When utilizing an external risk model, insurance companies are responsible for developing rate relativities for the risk score groups. It is important that the actuary considers how correlation between existing variables in the rate plan and the new risk model are accounted for. In addition to considering correlation with existing rating variables, companies need to consider regulatory requirements. Depending on state regulations, models used in underwriting eligibility and rating may need to be filed for regulatory review. For example, models used in either underwriting eligibility or rating of an admitted insurance program are required to be filed for regulatory review and approval in California.[10] In addition to documentation required by Actuarial Standards of Practice (ASOPs), states such as California and Florida require documentation about the model, such as a data dictionary of the variables considered by the model, how it was developed, and how it is intended to be used, as well as validation statistics and other details. Ensuring that the intended use is consistent with the actual use is an important consideration. If a risk model was trained on data that did not include insurance losses, it is important for companies to consider how to adjust the data or model to be appropriate for the intended use and demonstrate how the model output is reasonably correlated with insurance frequency, severity, loss cost, or some other insurance metric. Furthermore, to the extent that companies value fully explainable model results, companies may want to evaluate how the output can be communicated to policyholders to satisfy consumer notification requirements, or in the event of a consumer inquiry or complaint as the result of a declination of coverage, non-renewal, or premium increase.

Other considerations are the costs associated with developing or licensing the model, processing and storing the data in a manner that satisfies the company's documentation requirements, and the IT and other department resources needed to implement the model. Costs can be examined to understand the difference between developing an in-house model versus licensing a model. The cost to develop a company-specific model includes the cost to obtain data, prepare the data, develop the model, and maintain the model. If development cost and effort or speed to market are important to the company, the company may consider licensing a risk model from a third-party vendor.

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[10] California Department of Insurance. Model Checklist. Retrieved from: https://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0200-prior-approval-factors/upload/Model-Checklist.pdf.

Conclusion

Risk models are generally built upon a much larger set of data that is not limited to a single insurance company's historical exposure and loss experience, which addresses the lack of credibility that a single company may experience when analyzing its own data. Risk models that utilize property-level characteristics can produce more granular risk segmentation than traditional risk group definitions, especially for weather perils where location, surrounding conditions, and property features are important components affecting the frequency and severity of claims. For companies introducing risk models that have already been approved under a rating service organization (RSO) or similar entity that files the model for approval by state regulators for later adoption by insurance companies, this can significantly shorten the regulatory review time to limit the review to the intended use of the model, rather than a complete review of the model that was already performed in the RSO filing.

As discussed above, it is important to understand the intended use of risk models, including how they operate, their pros and cons, and how the results can be communicated to non-technical audiences. For companies looking to better respond to changing climate risks and emerging risks, utilizing a risk score or other insurance pricing sophistication techniques may enable an insurance company to better understand, measure, and price risk. This segmentation sophistication may in turn alleviate some of the pressure with a market experiencing availability issues or higher risk costs that aren't yet adequately accounted for in underwriting and pricing.

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