Predictive Modeling for Homeowners

011011

NAI

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Lessons from Personal Auto

- Major innovations in historically static rate plan
- Increased competition
- Profitable growth for adopters of advanced analytics
- Hunger for the next innovation
- In comparison, much less modeling has been done in Homeowners
- Translates into greater opportunity
- By peril modeling is an important tool



ISO's approach to predictive modeling

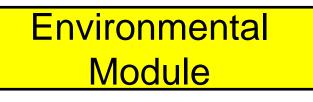
- Highly qualified modeling team
- Technical staff has more than 25 advanced degrees in math/statistics/computer science
- State of the art statistical/data mining approaches
- Enabling company customization
- Not a "one size fits all" solution
- De-mystifying the "black box"



ISO Risk Analyzer[®] - Homeowners Framework

Traditional Rating Plan New By Peril Rating

- Territory
- State
- Construction
- Protection
- Amount of Ins



Risk Characteristics

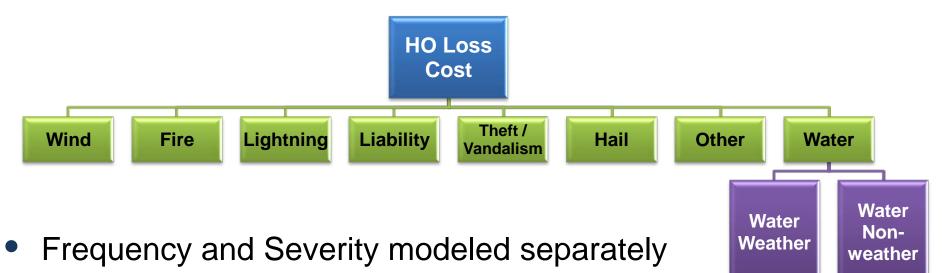
- Prior Claims
- Demographics
- Credit

Human Factors

Total Policy Risk Interactions of all indicators

Features of the Model

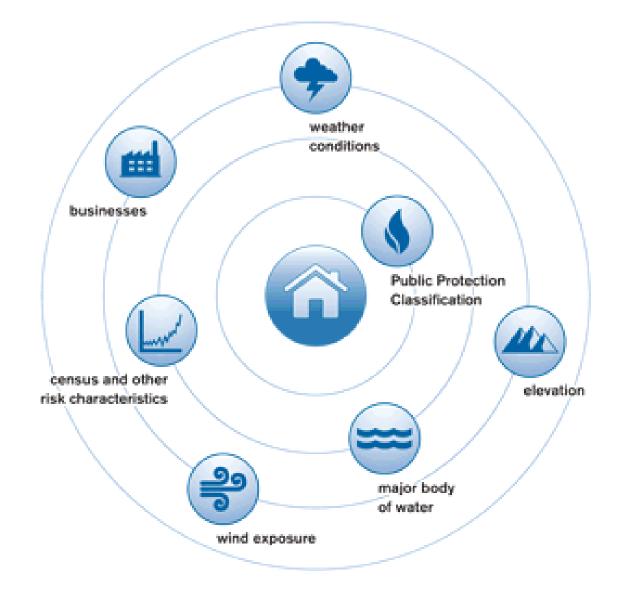
Modeled by peril (excluding hurricane)



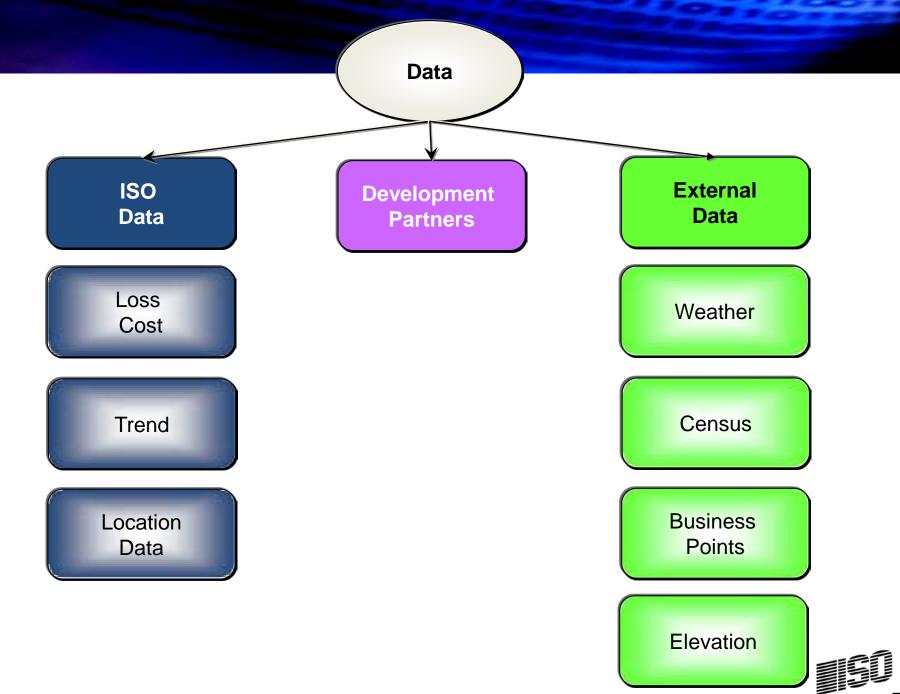
Combine to form 'all peril loss cost' – multiplied frequency and severity – added across perils



The Environment is the Exposure





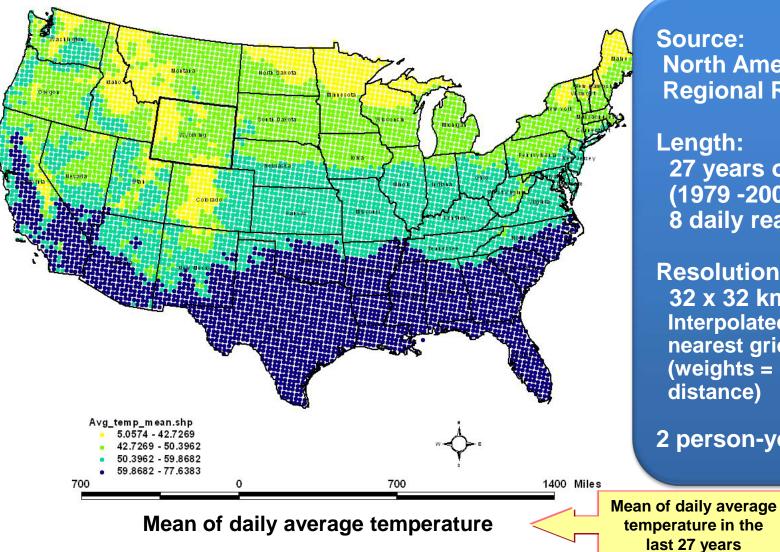


Modeling Techniques Employed

- Variable Selection univariate analysis, transformations, known relationship to loss
- Sampling
- Regression / general linear modeling
- Sub models/data reduction splines, principal component analysis, variable clustering
- Spatial Smoothing



External Data – Weather



Source: **North America Regional Reanalysis**

Length: 27 years of data (1979 - 2005) 8 daily readings

Resolution: 32 x 32 km **Interpolated using 4** nearest grid centroids (weights = inverse distance)

2 person-years work

External Data – Weather Derive Novel Data Features

(Indicators, daily, consecutive days, number of days)

Temperature

- Below freezing / High temperatures
- Variations / Average / min / max / deviation

Precipitation, Wind and Snow

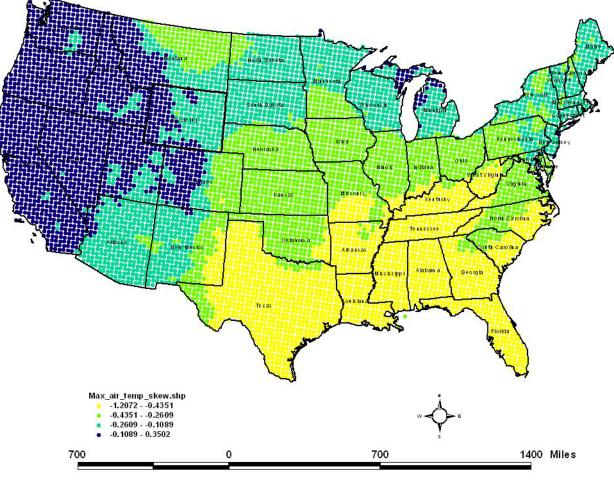
- With / Without
- Average / min / max / deviation

Interactions

- Weight of snow (snow + temp)
- Ice (rain + temp)
- Fire (no rain, high temp + high wind)
- Blizzards (snow + wind)



External Data – Weather

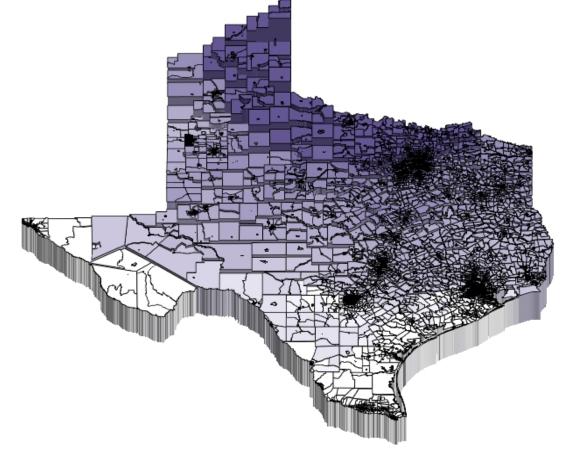


Skewness of high air temperature



Visualizing of Weather Interactions

% of days with High < 32 and % of days with Low > 72 (Texas)



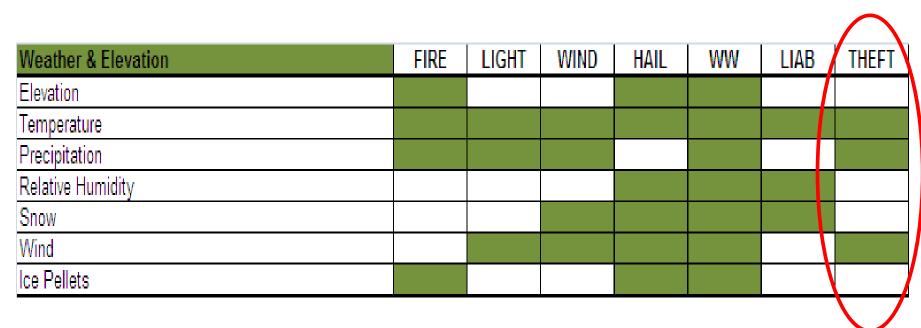
Positive coefficient in Wind Frequency model

Using SAS/Graph



value -1.05 - -1.01 - -1.01 - -0.99 - -0.99 - -0.99 - -0.99 - -0.98 - -0.98 - -0.97 - -0.97 - -0.91 - -0.91 - -0.91 - -0.79 -0.79 - -0.65 - -0.65 - -0.52 - -0.52 - -0.34 - -0.34 - -0.26 - -0.20 - -0.20 - -0.13 - -0.13 - -0.13 - 1.20

By-Peril Modeling – Serendipitous Discoveries

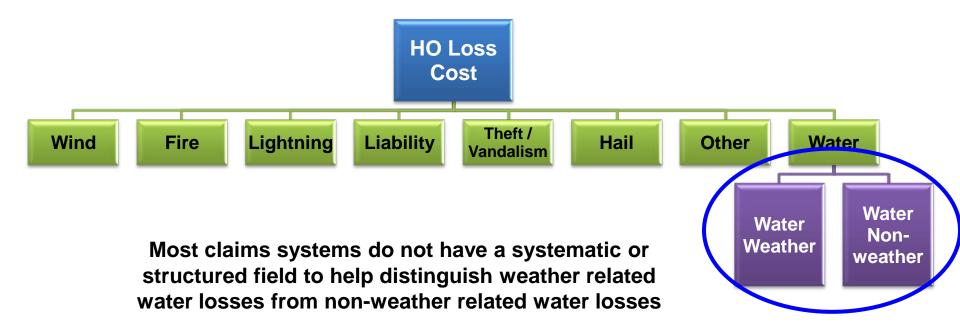


External Validation:

Ellen Cohn. "Weather and Crime". The British Journal of Criminology 30:51-64 (1990)



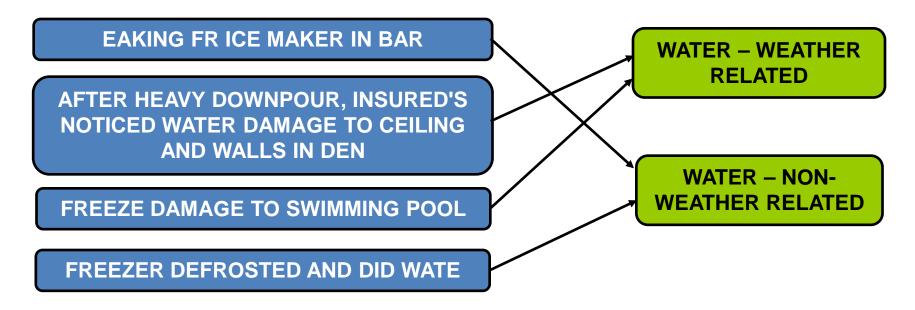
Decomposing Water Losses





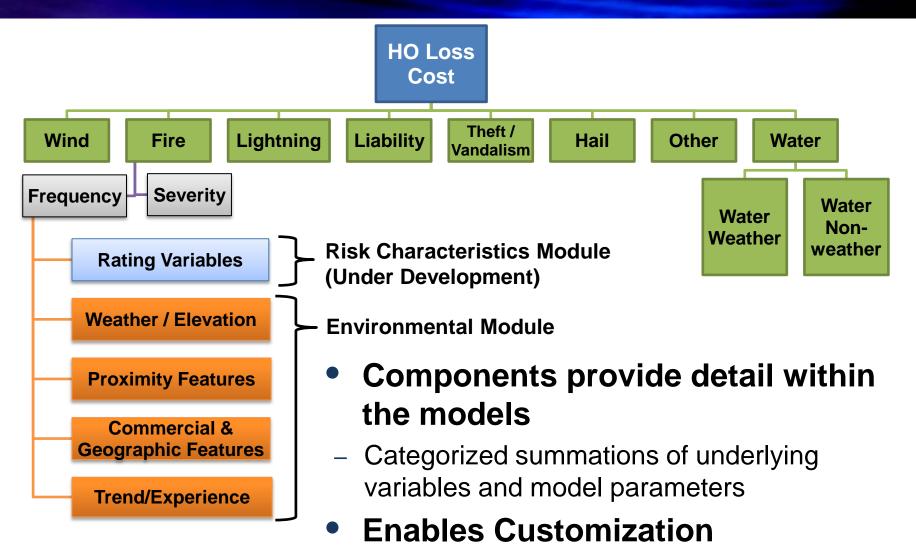
Text Mining for Cause-Of-Loss

- Rich information buried in Unstructured data, such as Loss Descriptions or Adjuster Notes
- E.g., Extracting the "Type of Loss" from the Loss Description





Components



- Short circuiting the variable selection process



Example of Variables in Components

Unique for each peril model (freq/severity)

- Weather / Elevation:
- Elevation
- Measures of Precipitation
- Measures of Humidity
- Measures of Temperature
- Measures of Wind

• **Proximity**:

- Commuting patterns
- Population variables
- Public Protection Class

Commercial & Geographic Features:

- Distance to coast
- Distance to major body of water
- Local concentration of types of businesses (i.e. shopping centers)

- Trend / Experience
- Peril's proportion of ISO Loss Cost
- Trend
- Base Level parameters for:
 - HO Form
 - Construction type
 - Amount of insurance
 - Liability amount
 - Deductible amount
 - Wind and hail deductible
 - Construction age
 - Risk Characteristics Module (Under Development)



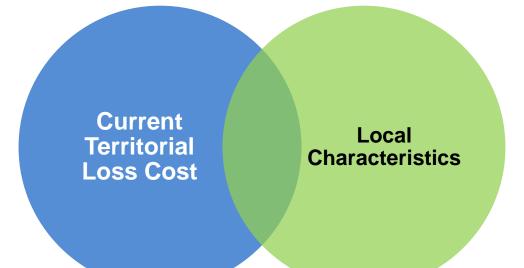
Improving Accuracy by Combining Geographic Ratemaking Methods

- Use traditional territorial loss cost as predictor variable in models
- Enables model to capture effects not identified by other predictor variables
- Helps to "true up" model predictions with traditional estimates
- Need to be aware that some effects of predictor variables may already be embedded in current territory loss costs



Improving Accuracy by Combining Geographic Ratemaking Methods

Shared Predictive Effects

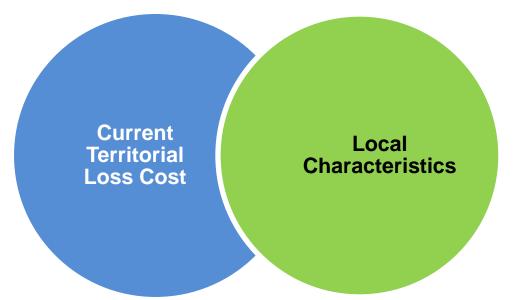


 Multivariate methods can address the overlap without double counting



Improving Accuracy by Combining Geographic **Ratemaking Methods**

Separated Predictive Effects – Same Prediction



- Estimate the portion of current loss cost not explained by other predictors
- Use "Loss Cost Residual" as predictor

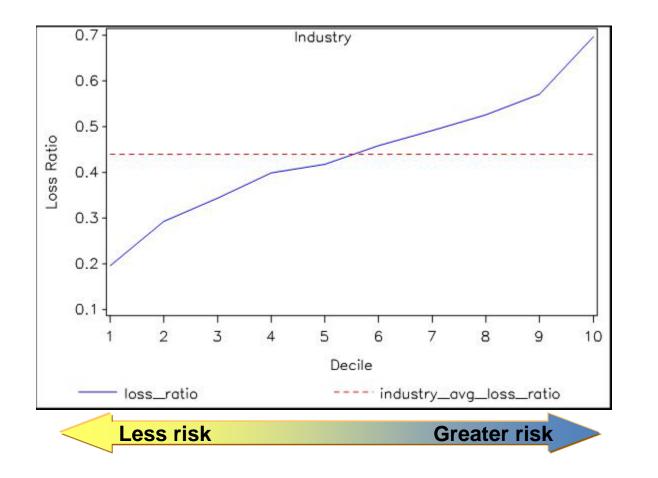


Model Testing

- Validation of model performance on hold-out dataset
- Look at results on maps
- Statistical reports to quantify the effect of changes
- Examine adjacent loss cost differences
- Compare to current territorial base rates
- Examine largest changes from current loss costs
- External review

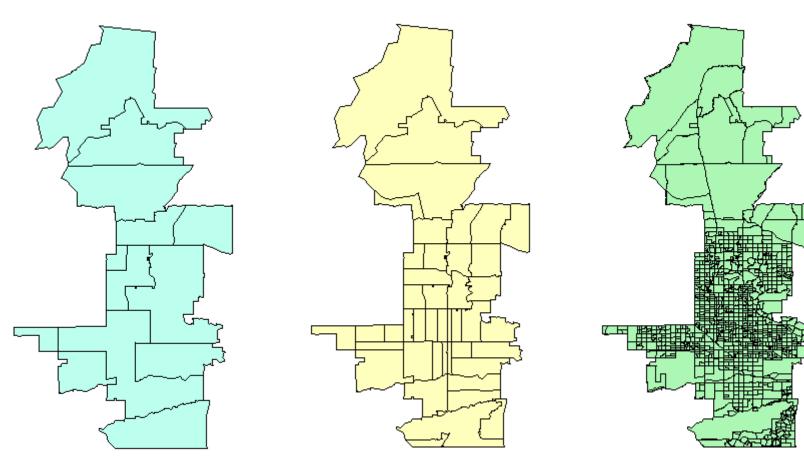


Industry Total Loss Cost Loss Ratio by Premium Decile





Phoenix, AZ Geographic Area

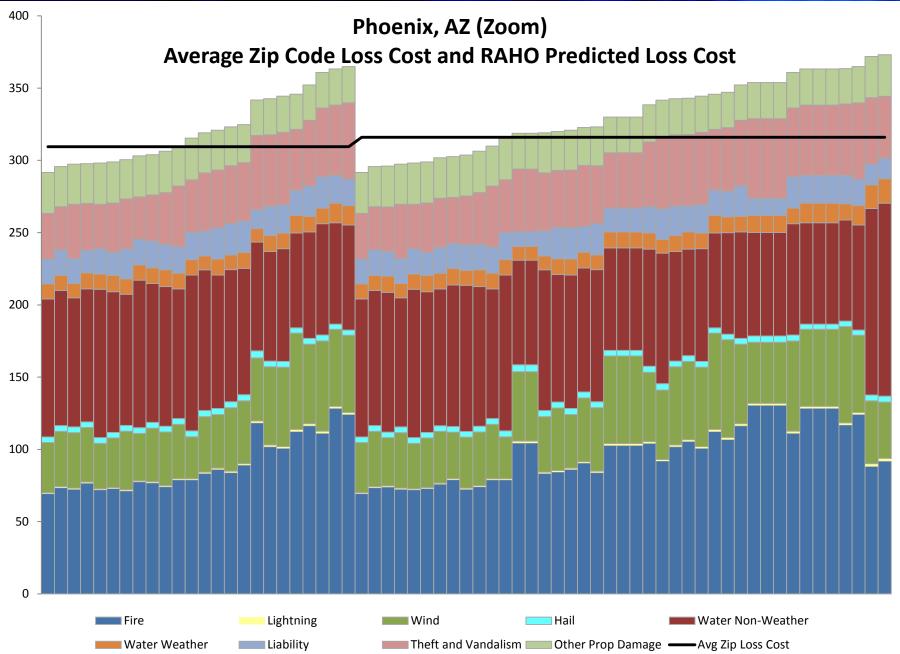


ISO Territories: 9

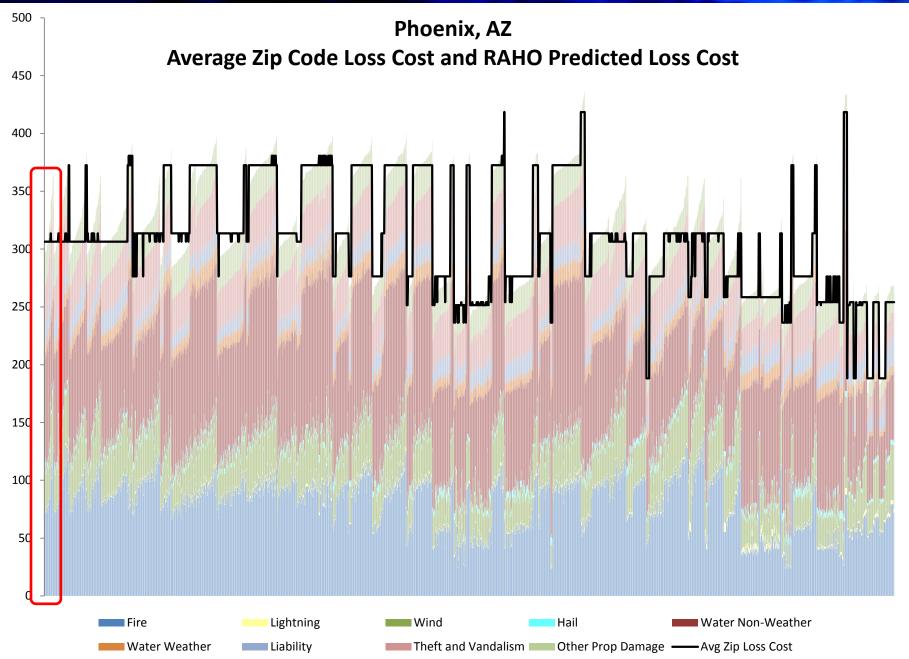
Zip Codes: 80

RAHO: 1309



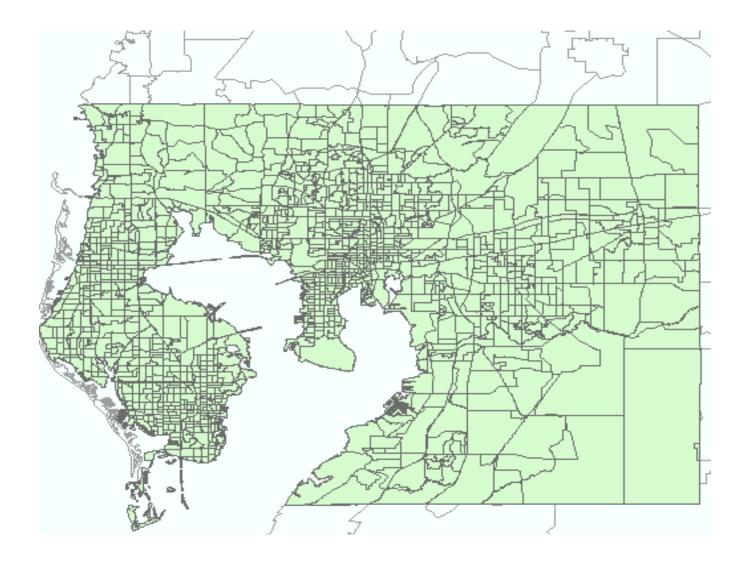


* Loss cost are calculated @ Territory Representative Risk

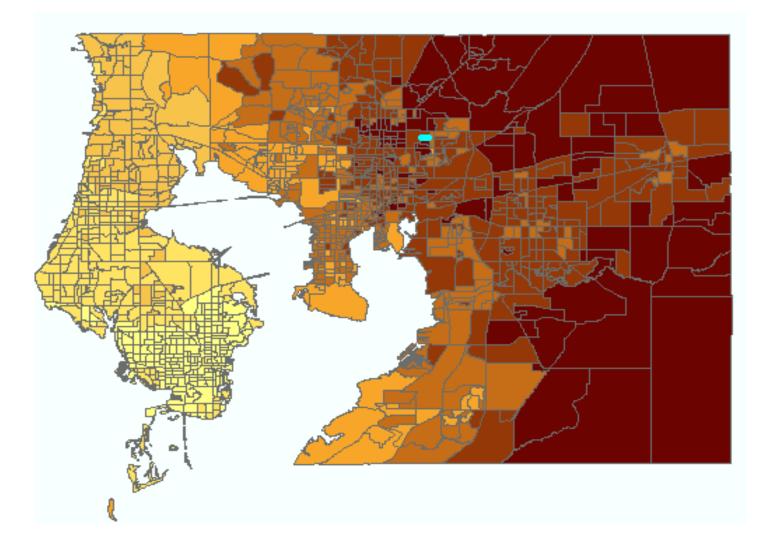


* Loss cost are calculated @ Territory Representative Risk

Tampa Bay, FL Area



Tampa Bay Area Detailed Loss Costs (Non-Hurricane)



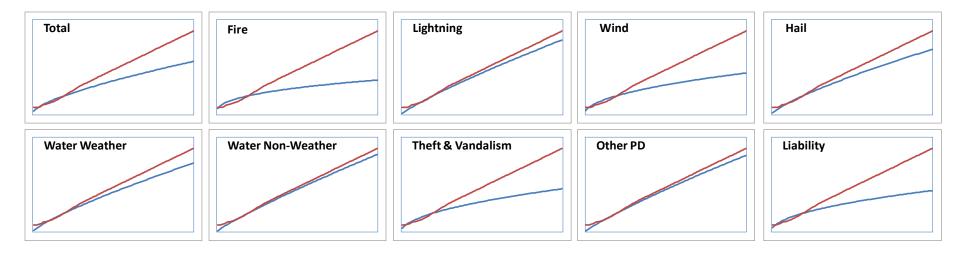


Opportunities for Enhanced Segmentation

- Use sum-of-peril loss cost estimates
- Build new territories
- Refine existing territories
- Use peril-specific models to break apart allperil rating
- Geographic exposures and rating variables
- Using components as input to models
- Incorporate new predictive data with simpler sourcing, preparing, and selecting of variables



Rating Variable Impact by Peril



—Model by Peril Relativity —Current Relativity

- Significant variation by peril
- Enhanced accuracy of loss prediction



Rating Variable Relativities by Peril

- Relativities that vary by peril provide lift
- Adds accuracy and complexity
- All-peril relativities can be derived from peril-based relativities according to peril mix within the area
- Local Prediction by peril results in varying peril loss costs at the address level
- Effectively produces all-peril amount relativities that vary at the address level



Questions?

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