



$$\sum_{k=1}^N [n_k \ln n_k]$$

By-Peril Predictive Modeling for Homeowners

MEASURE, MANAGE, & REDUCE RISKSM

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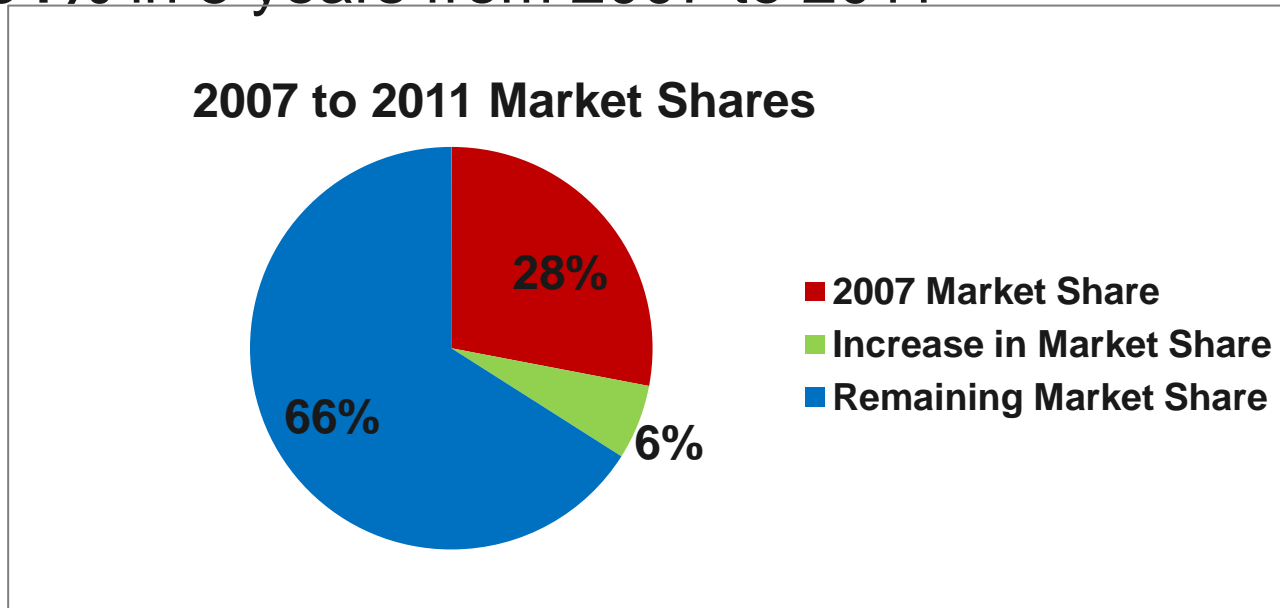
Opportunities in Predictive Modeling

- 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

Leading the Way With By-Peril Rating

- Market Share Benefits

- The 25 carriers using by-peril plans in 2011 have increased their combined market share from **28% to 34%** in 5 years from 2007 to 2011

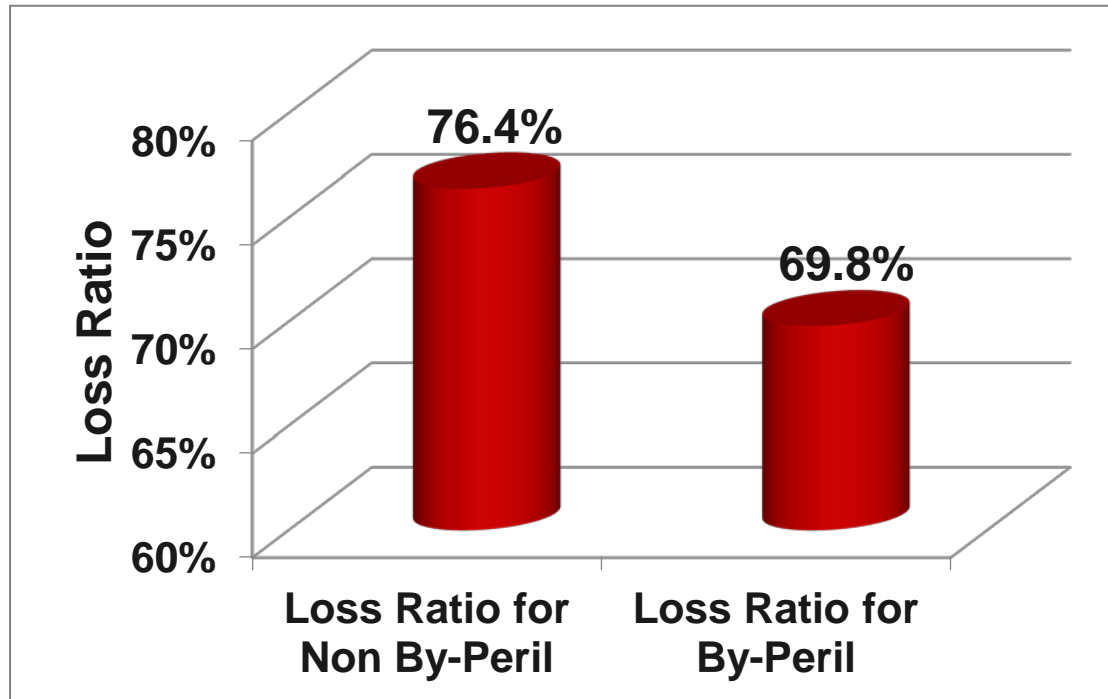


Source: ISO research using Perr & Knight filings and 2007-2011 AM Best Financials

Leading the Way With By-Peril Rating

• Loss Ratio Benefits

–The 25 companies rating by-peril have loss ratios **6.6** points lower than their competition in 2011



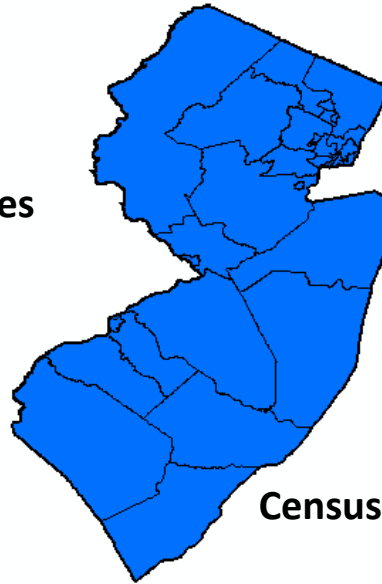
Source: ISO research using Perr & Knight filings and 2007-2011 AM Best Financials

Data Challenges With By-Peril Ratemaking

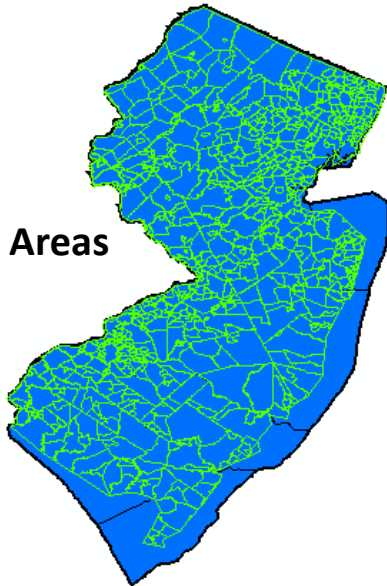
- Accurate by-peril Homeowners models require extensive data resources
 - Low frequency line – split further by peril
 - Severity is volatile and differs significantly by peril
- Level of peril detail available in claim records
 - More detail enables greater model refinement
 - Most carriers have limited detail in historical data

Geographic Refinement

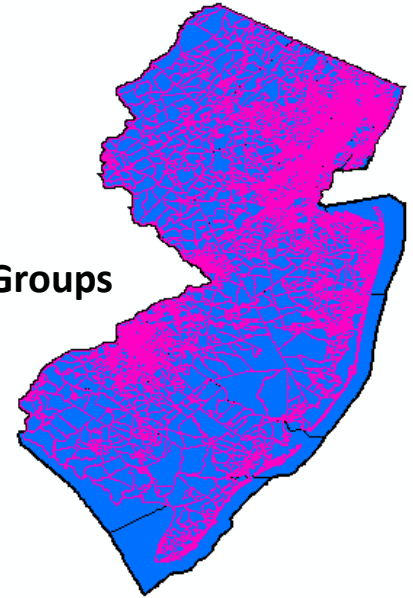
ISO Territories
26



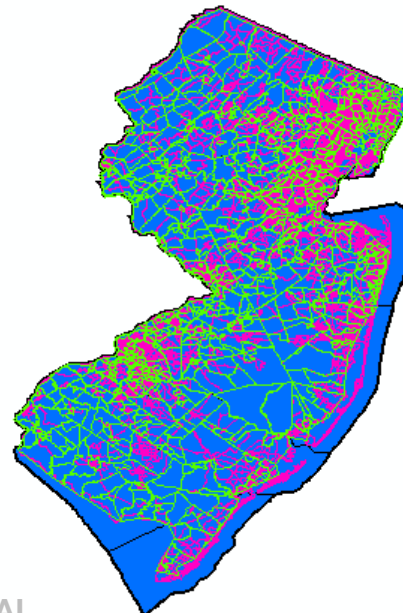
Fire Protection Areas
1,428







Census Block Groups
6,503



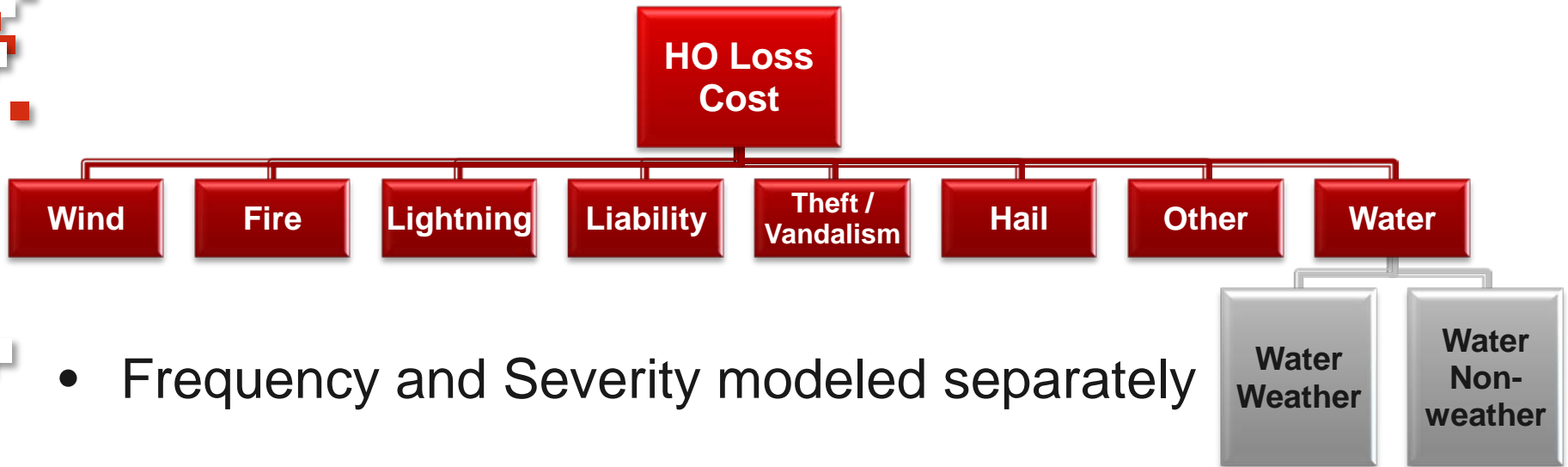
Fire Protection Areas &
Census Block Groups
7,042



-  New Jersey State Boundaries
-  New Jersey ISO Territories
-  New Jersey Census Block Groups
-  New Jersey Fire Protection Areas

Features of the Model

- Modeled by peril (excluding hurricane)



- Frequency and Severity modeled separately
- Combine to form 'all peril loss cost' – multiplied frequency and severity – added across perils
- Rating factors from Risk Analyzer used to modify the loss costs by peril to account for the effect of amount of insurance, deductible and age of construction.

The Environment is the Exposure



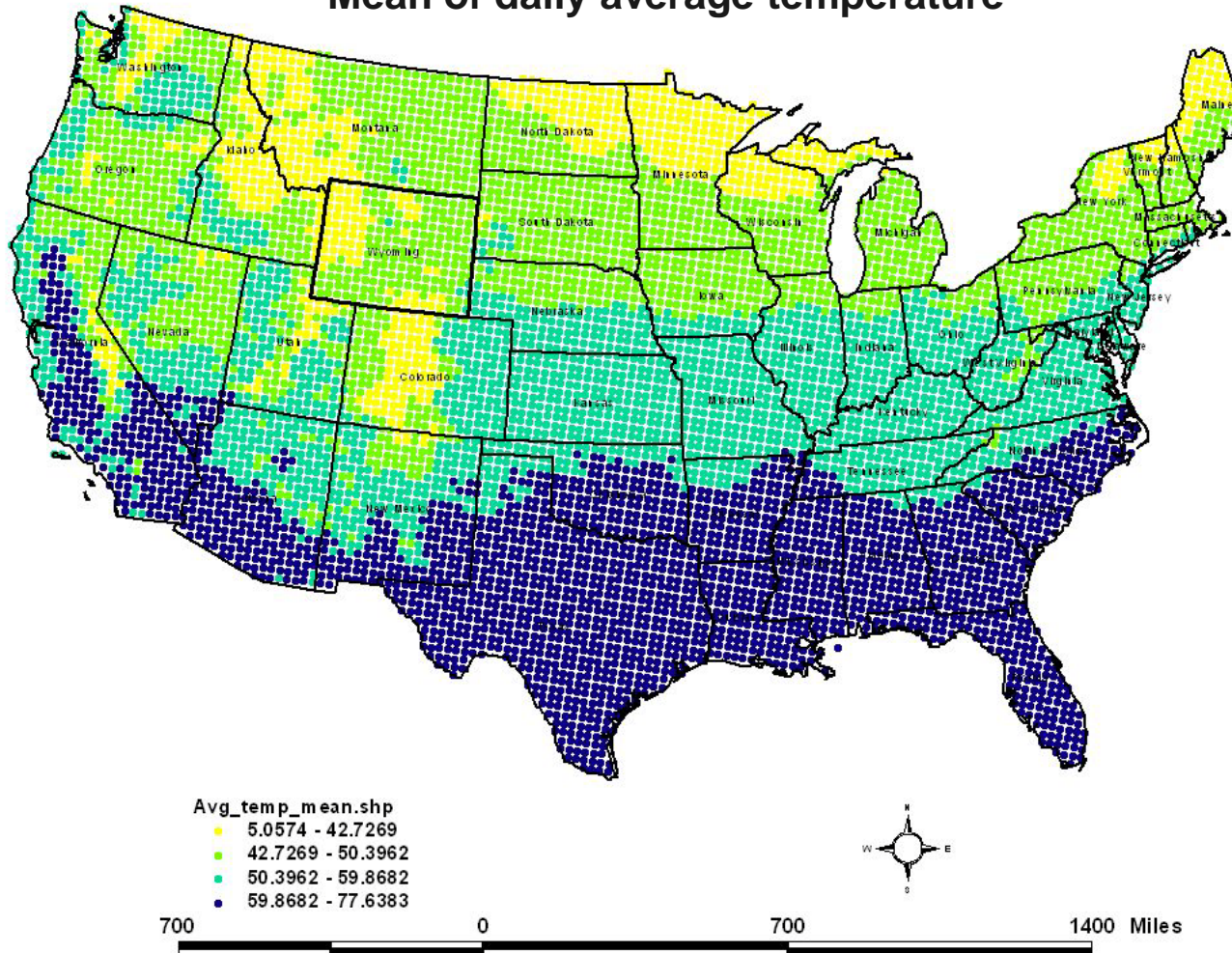
**Rating Factors
complement the
environment
predictions**

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

Mean of daily average temperature



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

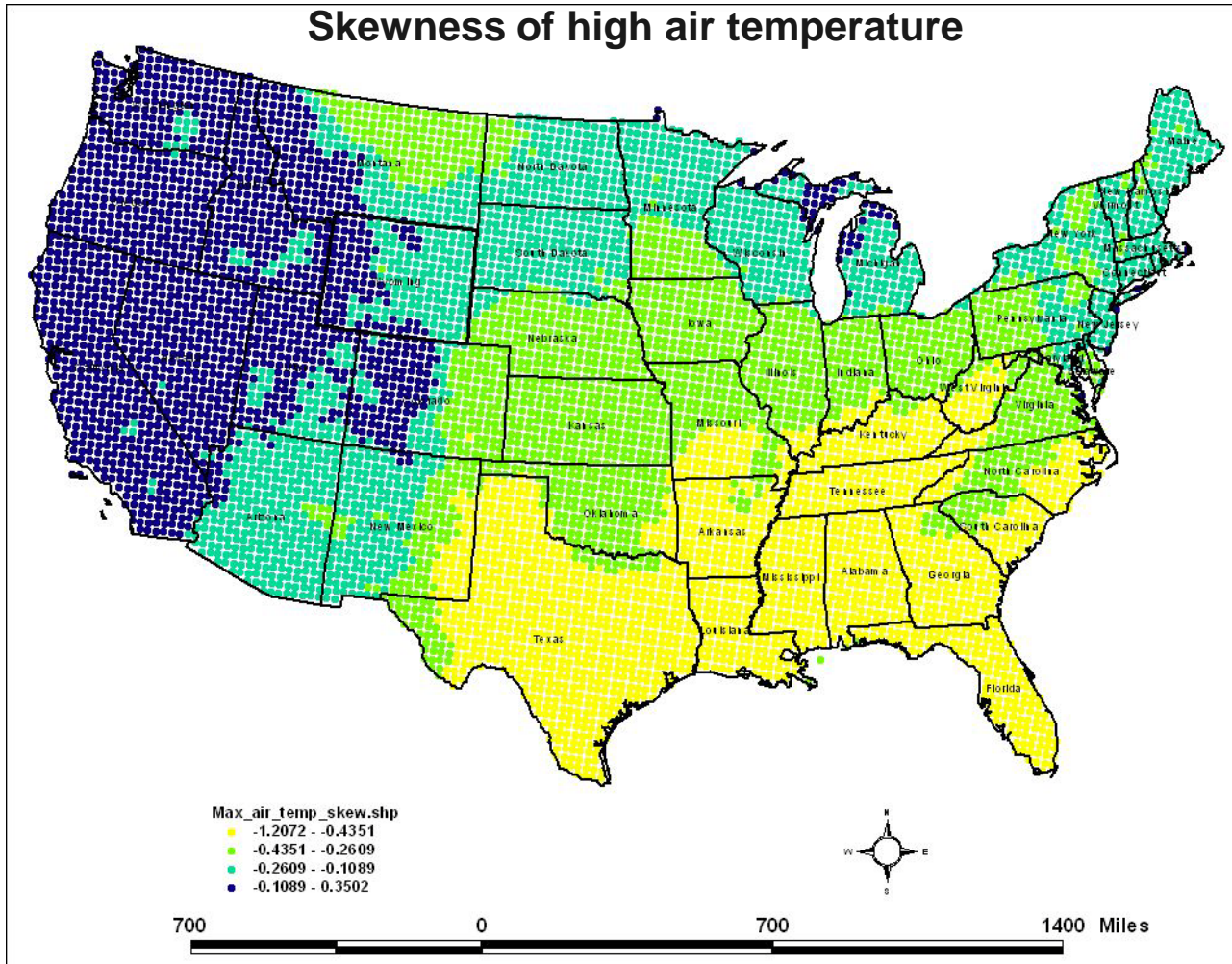
External Data – Weather

Derive Novel Data Features

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

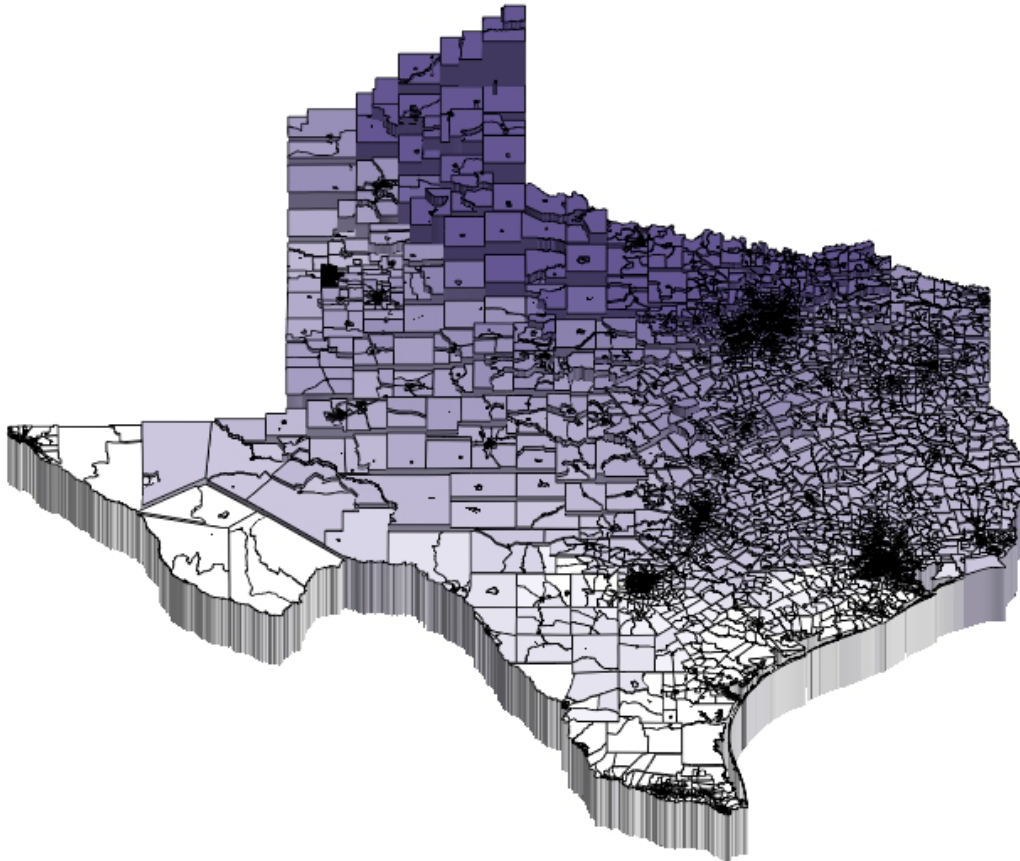
- Temperature
 - Below freezing / High temperatures
 - Variations / Average / min / max / deviation
- Precipitation, Wind and Snow
 - With / Without
 - Average / min / max / deviation
- Interactions
 - Weight of snow (snow + temp)
 - Ice (rain + temp)
 - Fire (no rain, high temp + high wind)
 - Blizzards (snow + wind)

External Data – Weather



Visualizing Weather Interactions

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



Positive coefficient in
Wind Frequency
model



Using SAS/Graph

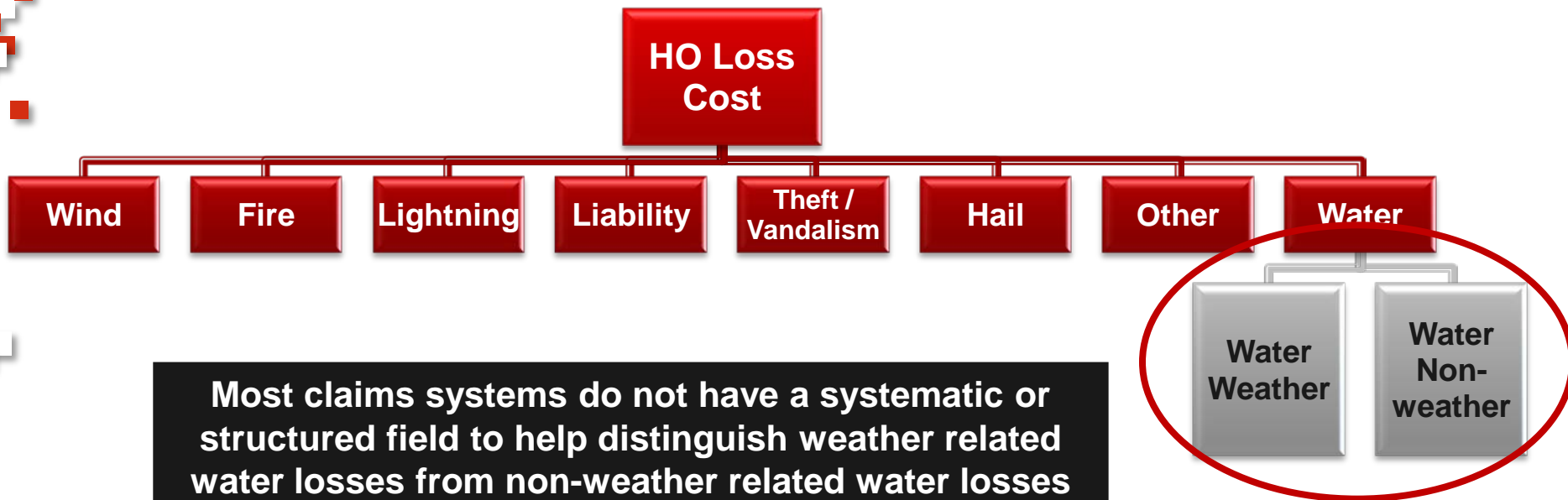
By-Peril Modeling – Serendipitous Discoveries

Weather & Elevation	FIRE	LIGHT	WIND	HAIL	WW	LIAB	THEFT
Elevation							
Temperature							
Precipitation							
Relative Humidity							
Snow							
Wind							
Ice Pellets							

External Validation:

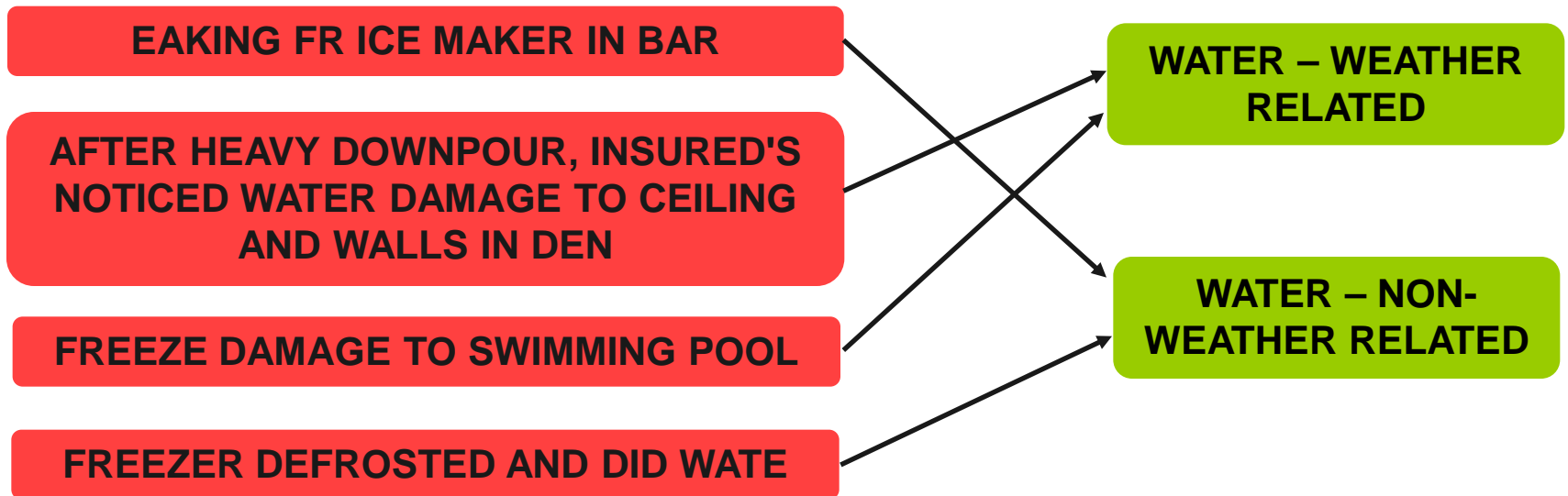
Ellen Cohn. "Weather and Crime". *The British Journal of Criminology* 30:51-64 (1990)

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



Public Protection Class (PPC)

- Derived from detailed review of local fire protection capabilities
- Applies within fire district boundaries, plus considerations of available water supply and fire station distance
- By-Peril Modeling allows PPC to be used differently than current Loss Costs

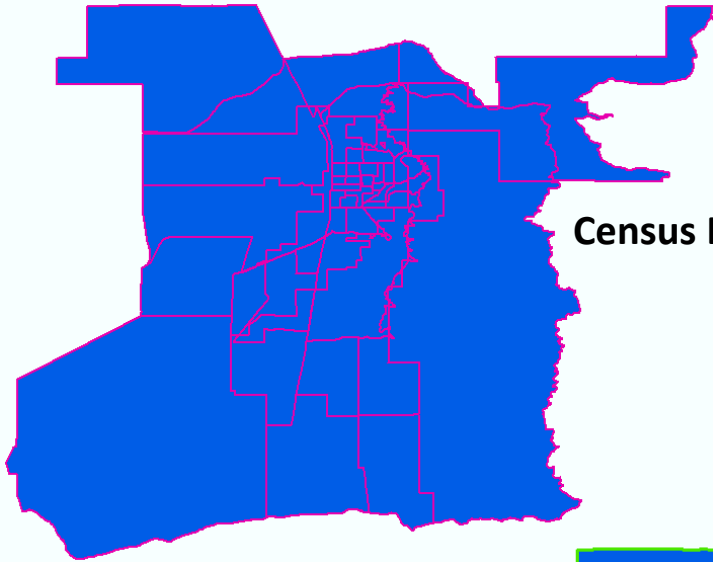
Current ISO Loss Costs

- Single factor applies to all-perils loss cost
- Only geographic refinement below Territory

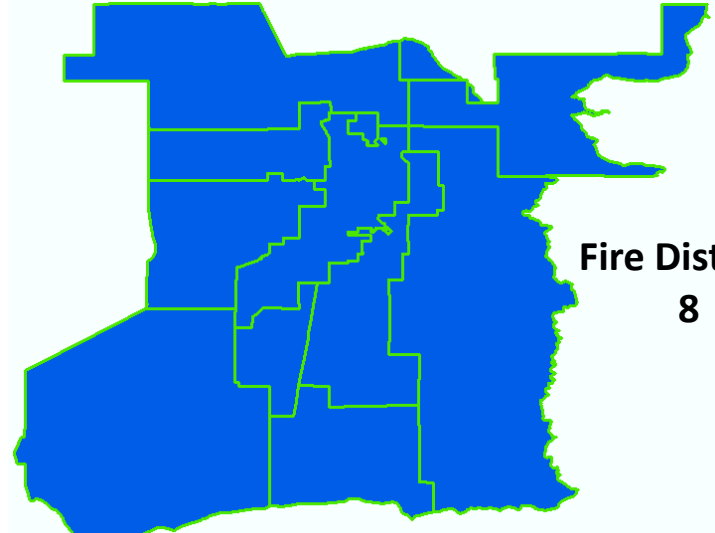
By-Peril Modeling

- Input variable in peril models
- Applies to perils where statistically significant
- Multivariate analysis with other geographic variables

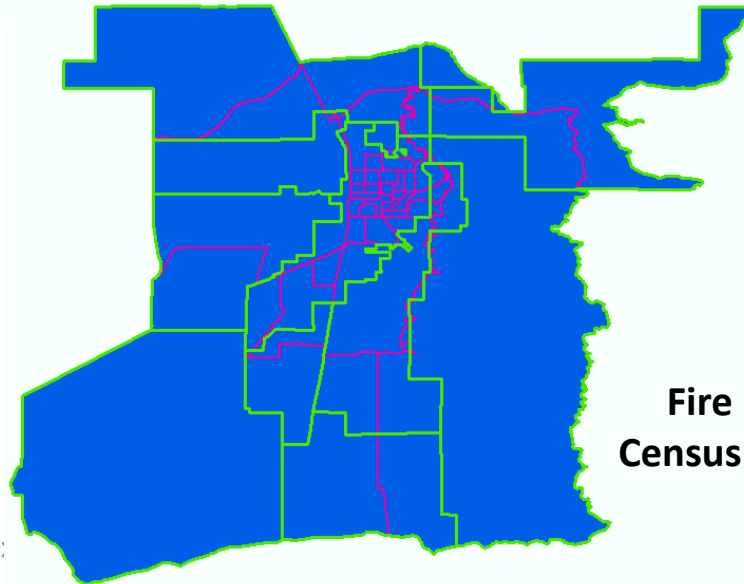
Geographic Units



Census Block Groups
73



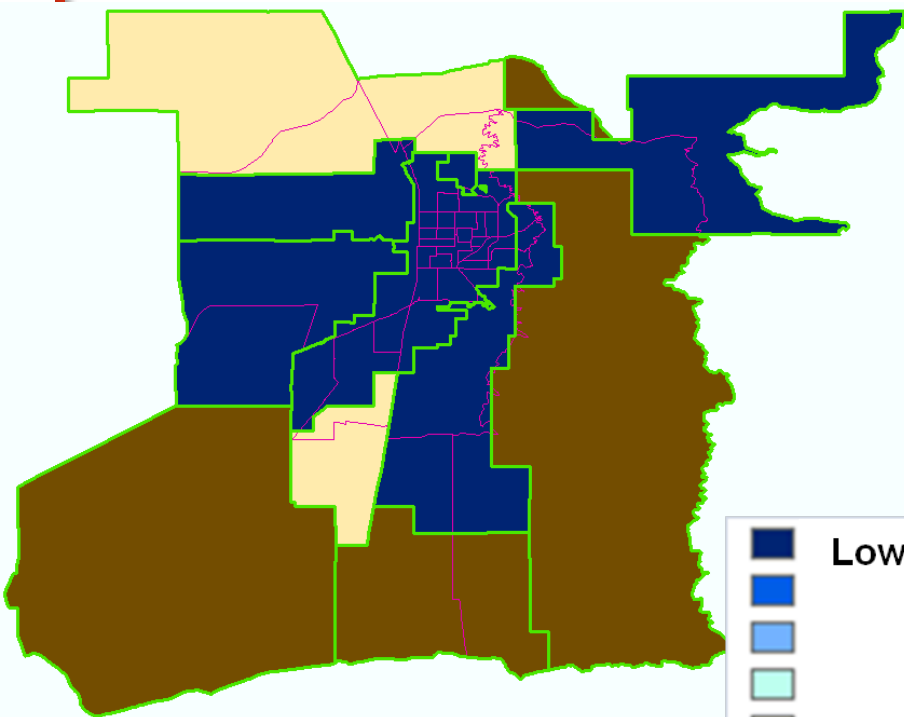
Fire Districts
8



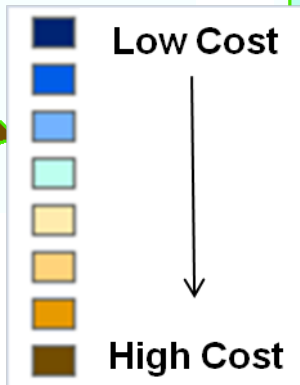
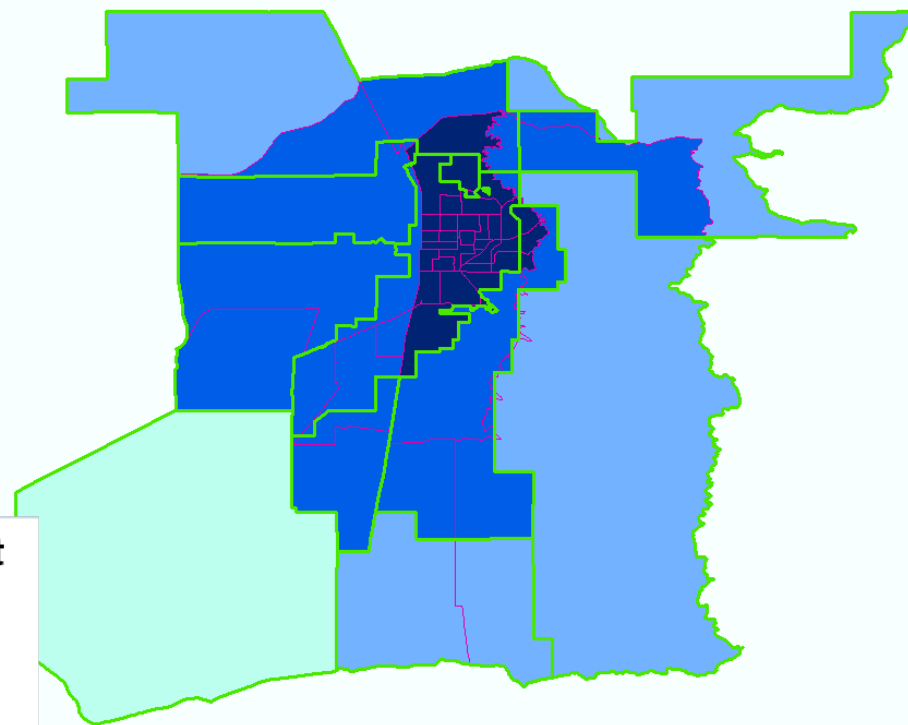
**Fire Districts &
Census Block Groups**
94

Geographic Units

ISO
TOTAL LOSS COST
WITH PPC



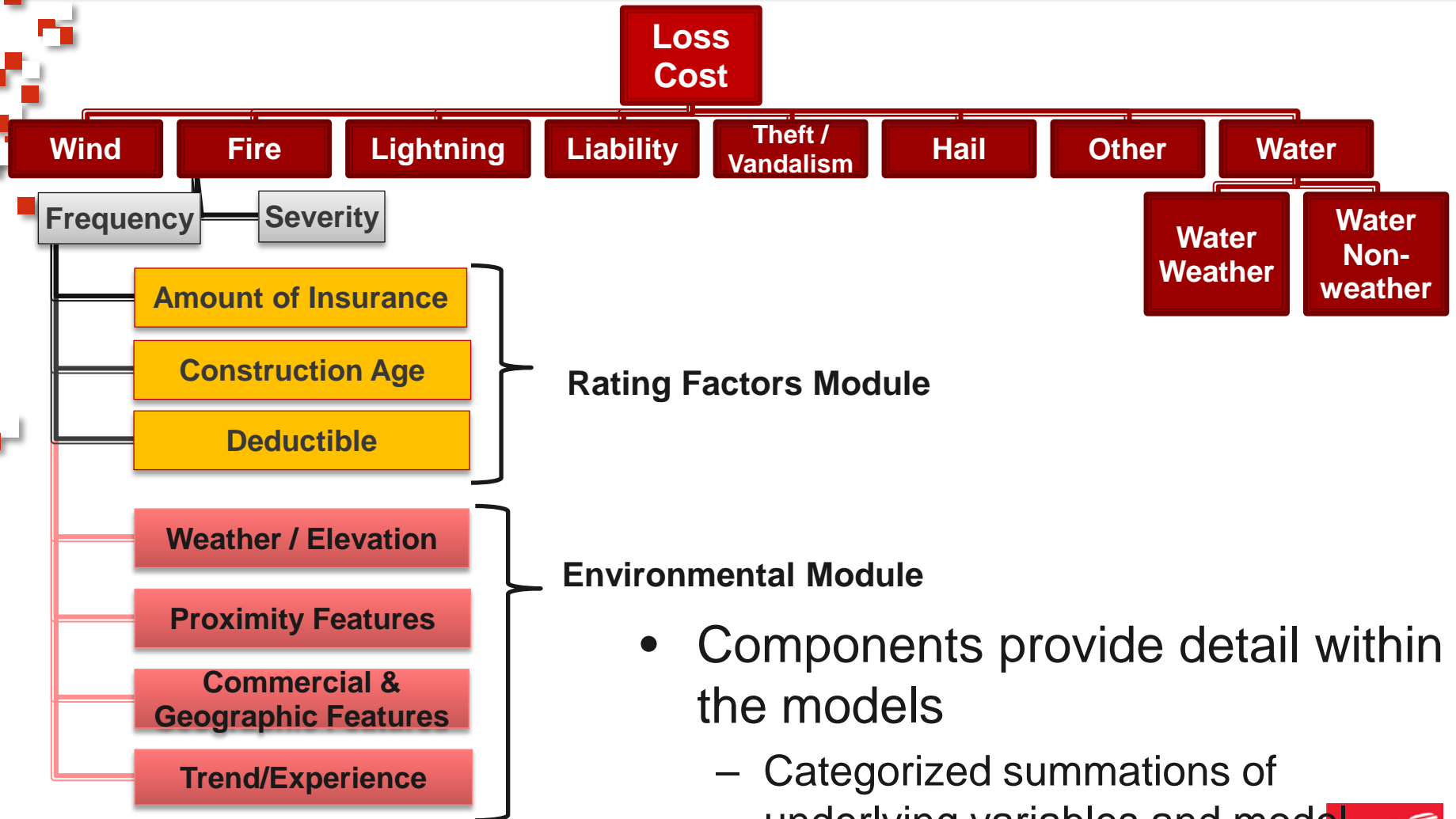
BY-PERIL MODEL
TOTAL LOSS COST
WITH PPC



Dealing with Data for By-Peril Modeling

- Accurate by-peril Homeowners models require extensive data resources
 - Low frequency line – split further by peril
 - Severity is volatile and differs significantly by peril
- Components create re-usable data features
 - Derived from modeling on larger datasets
 - Can be used directly as inputs into models on smaller datasets – Ensuring stable results without overfitting
- Components enable efficient modeling
 - Customized lift while short circuiting variable selection

Components



- Components provide detail within the models
 - Categorized summations of underlying variables and model parameters

Example of Variables

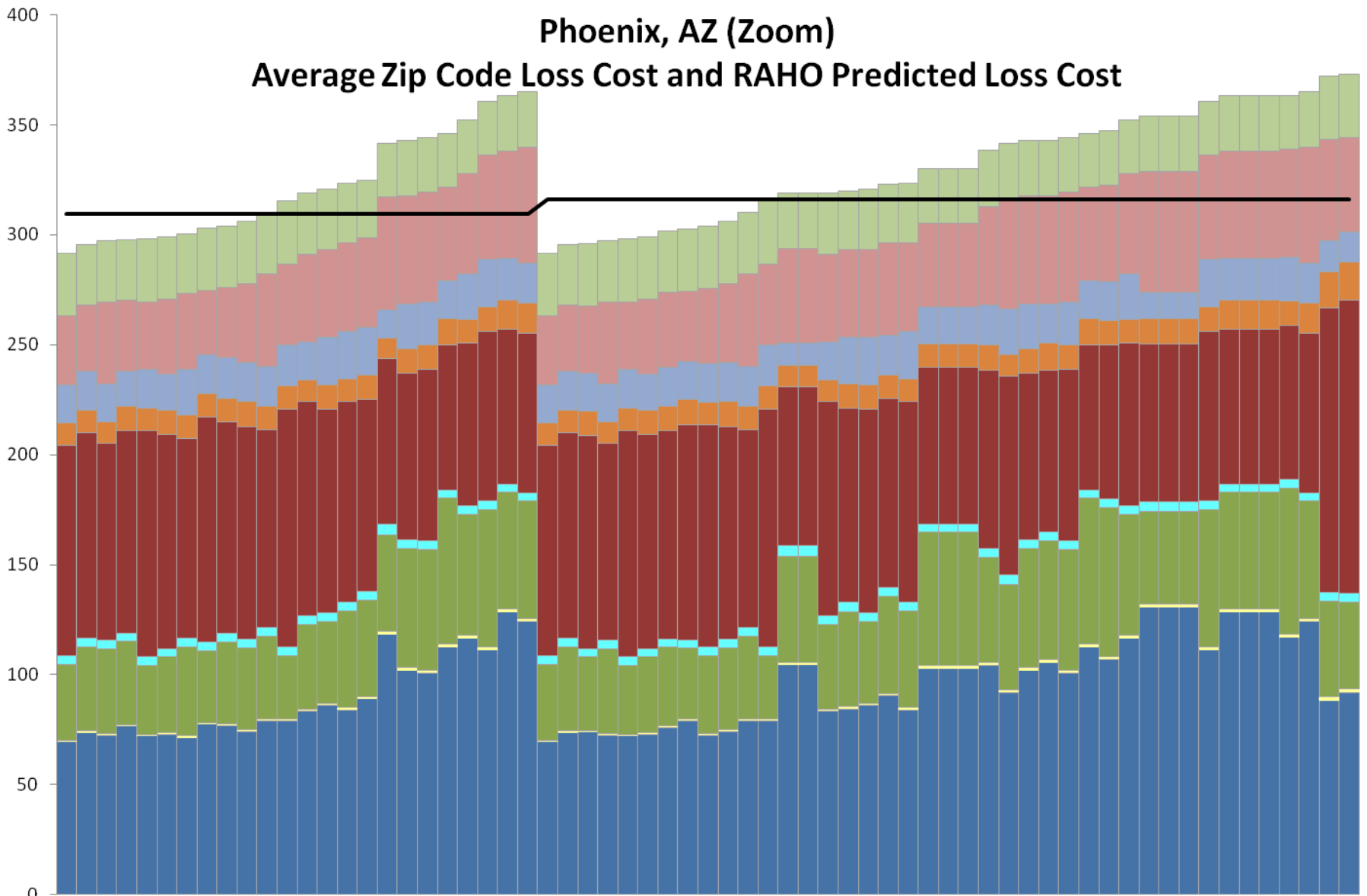
Environmental Components

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
 - Liability amount

Phoenix, AZ (Zoom)

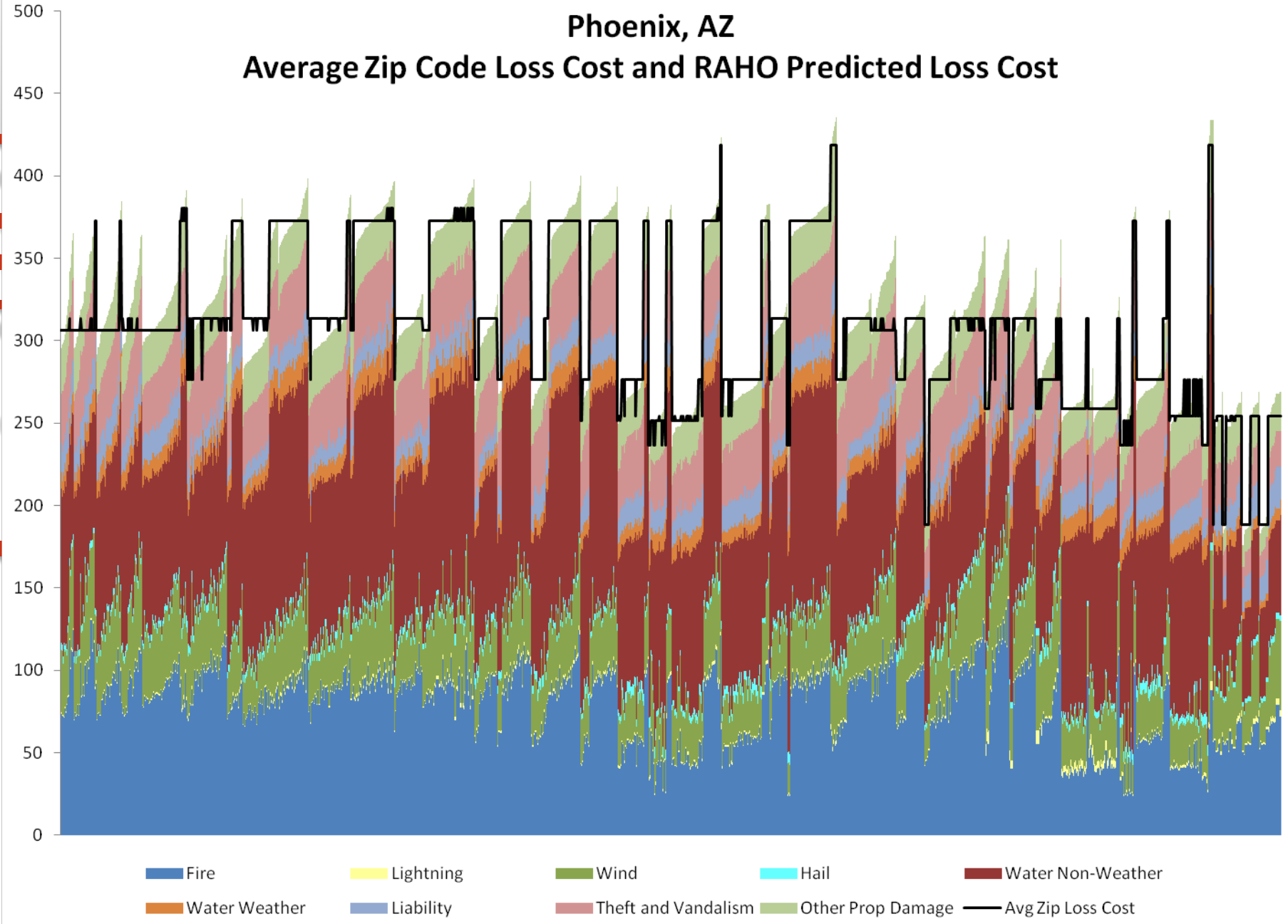
Average Zip Code Loss Cost and RAHO Predicted Loss Cost



Fire Lightning Wind Hail Water Non-Weather
Water Weather Liability Theft and Vandalism Other Prop Damage Avg Zip Loss Cost

Phoenix, AZ

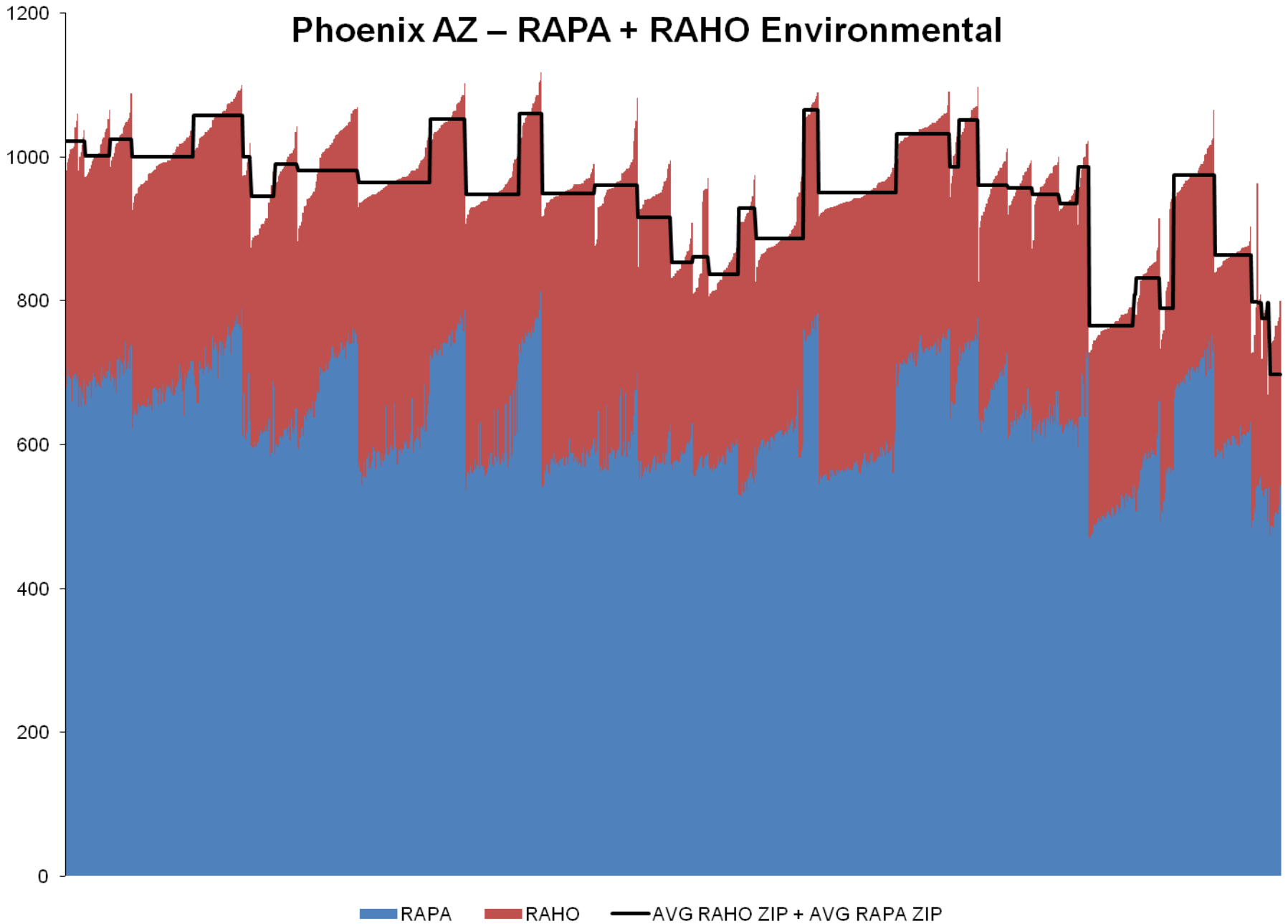
Average Zip Code Loss Cost and RAHO Predicted Loss Cost



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- Lightning
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- Water Non-Weather
- Water Weather
- Liability
- Theft and Vandalism
- Other Prop Damage
- Avg Zip Loss Cost

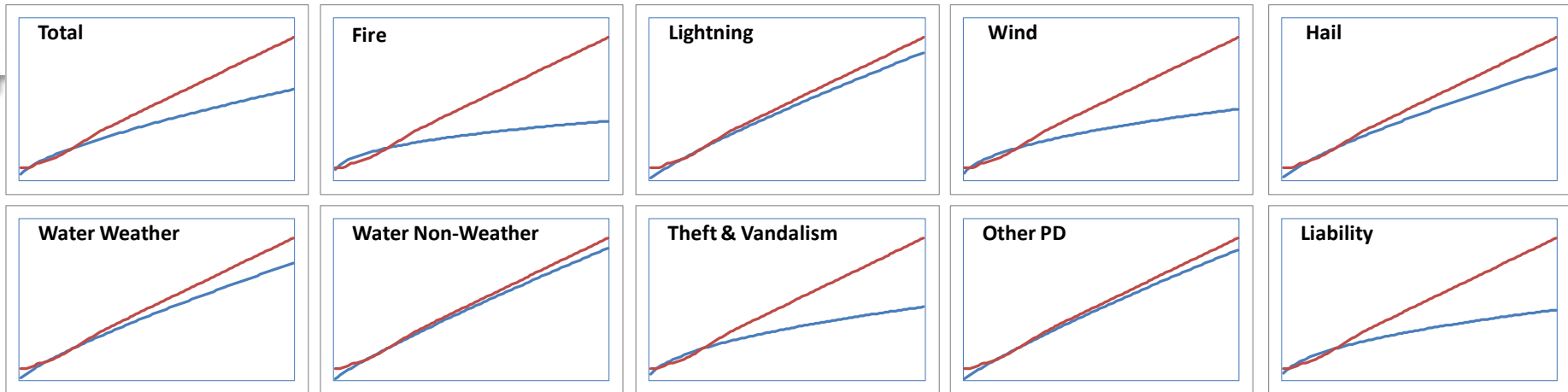
* Loss cost are calculated @ Territory Representative Risk

Phoenix AZ – RAPA + RAHO Environmental



By-Peril Rating Factors

- Modeled simultaneously with geographic variables
 - Amount of Insurance
 - Deductible
 - Age of Construction
- Produces a set of countrywide tables by peril for each rating factor



By-Peril Rating Factors + Environmental Factors

- Why are by peril rating factors more accurate?
 - By-peril rating factors allow for a more explicit recognition of the impact of perils *varying by location*
 - By-peril rating factors more dynamically react to changing peril contributions over time

Peril	Amount of Insurance Factor	Location A	Location B	Location C
Fire	1.5	30%	25%	50%
Wind	1.2	20%	25%	15%
Water	1.0	40%	25%	20%
Other	2.0	10%	25%	15%
All-Perils Factor	1.37	1.29	1.43	1.39

By-Peril Rating Factors + Environmental Factors

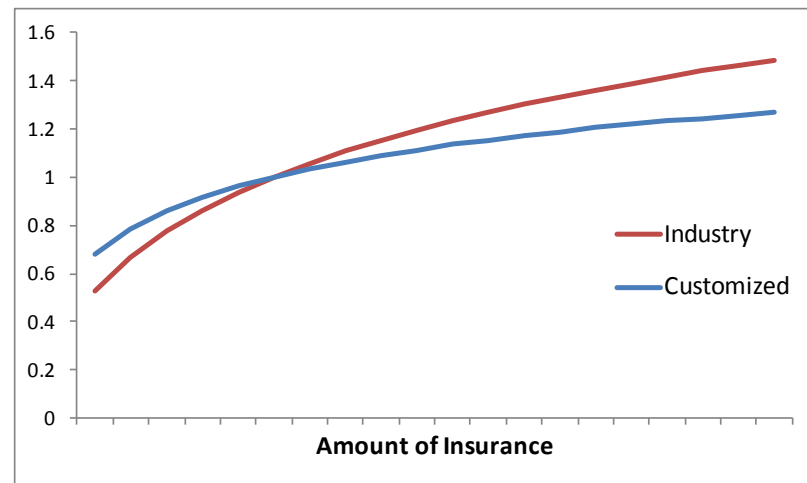
- Relativities that vary by peril provide lift
- Adds accuracy and complexity
 - All-peril relativities can be derived from peril-based relativities according to peril mix within the area
 - Local Prediction by peril results in varying peril loss costs at the address level
- Effectively produces all-peril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

Gaining Customized Lift Using RAHO By-Peril Rating Factors

- Step 1: Score your data using RAHO By-Peril Rating Factors
- Step 2: Fit your GLM using scored variable
 - Use continuous predictor (variate)
 - Apply transformations as needed
- Result:
 - Customized rating factor indication requiring less of your data
 - Avoids overfitting by preserving information from industry model

Policy Number	Amount of Insurance	RAHO AOI Factor (Fire Severity)
1	210,000	1.32
2	140,000	1.13
3	370,000	1.63

$$\dots + \beta \times (\text{RAHO AOI Factor}) + \dots$$



ISO Risk Analyzer® Homeowners

Perils

Fire	Light	Wind	Hail	Water Weather	Water Non Weather	Theft	Other PD	Liability
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Module

<p>Environmental</p> <ul style="list-style-type: none"> • Weather • Census • Commercial Features 	<p>Rating Factors</p> <ul style="list-style-type: none"> • Amount of Insurance • Age of Construction • Deductible 	<p>Building Characteristics</p> <ul style="list-style-type: none"> • Features • Dimensions • Layout
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Peril	AOI factor s
Fire	1.4
Wind	1.6
Hail	2.0



Building Characteristics Example

For illustrative purposes only



RAHO Environmental	Location	State B	State B
	PPC	5	5
RAHO By Peril Rating Factors	AOI	\$300,000	\$300,000
	Age of construction	25	25
	Deductible	\$1000	\$1000
ENV-BPR Loss Costs**		244	244
All perils combined factor		1.19	0.99
% Discount/Surcharge		+19	-1%
Building characteristics	Heating Code	Steam/Hot Water	Heat Pump
	Structure Code	Contemporary	Colonial
Top 3 Perils	Other PD	Water Weather	Wind

** ENV-BPR Loss costs – based on environmental and rating factors inputs

Roof is Asphalt and square feet is between 2500-3000 for both properties

Opportunities for Enhanced Segmentation

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

Questions?

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