By-Peril Predictive Modeling for Homeowners

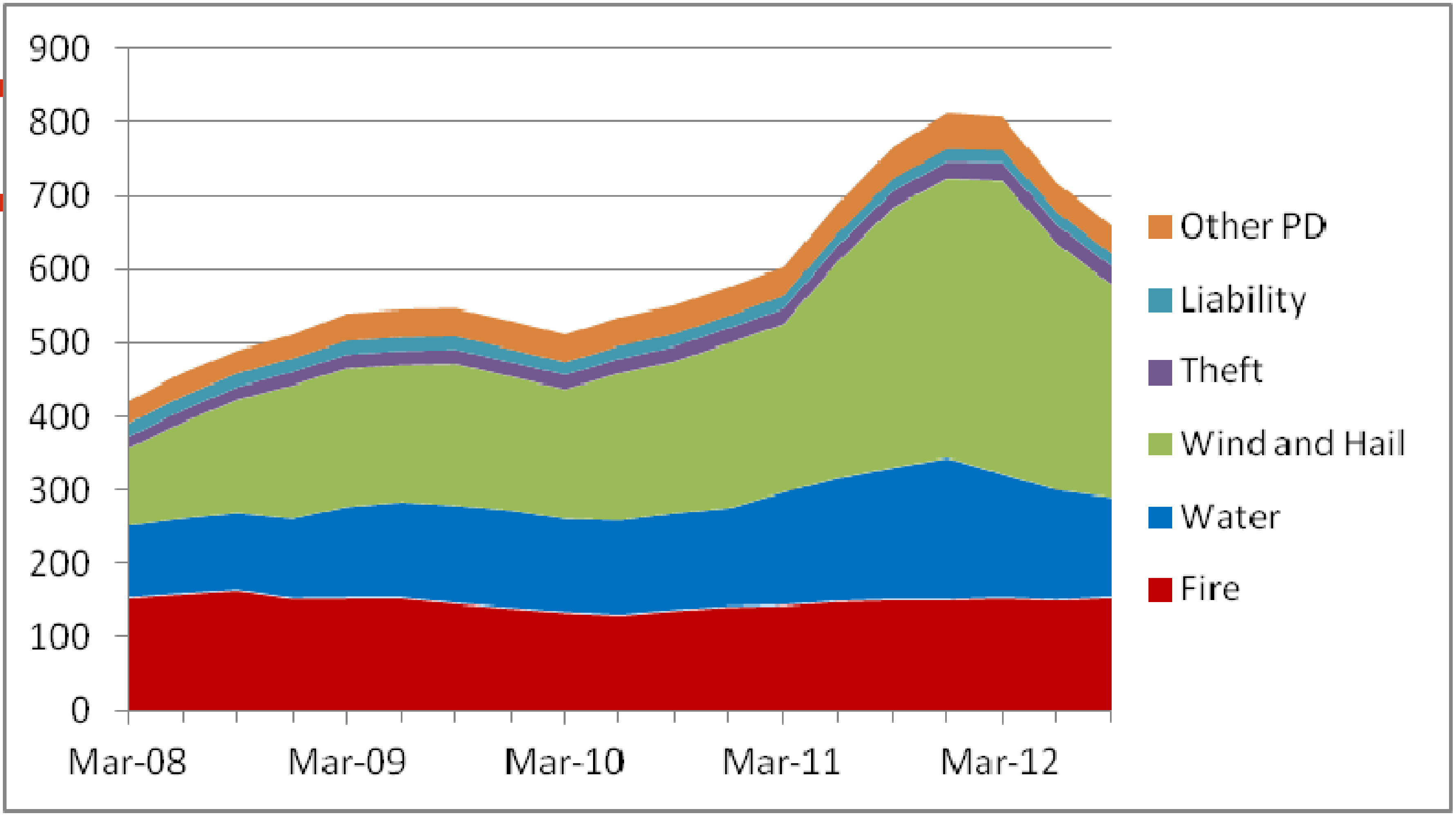
MEASURE, MANAGE, & REDUCE **RISK**[SM]

David Cummings
Senior VP – Personal Lines & Analytics

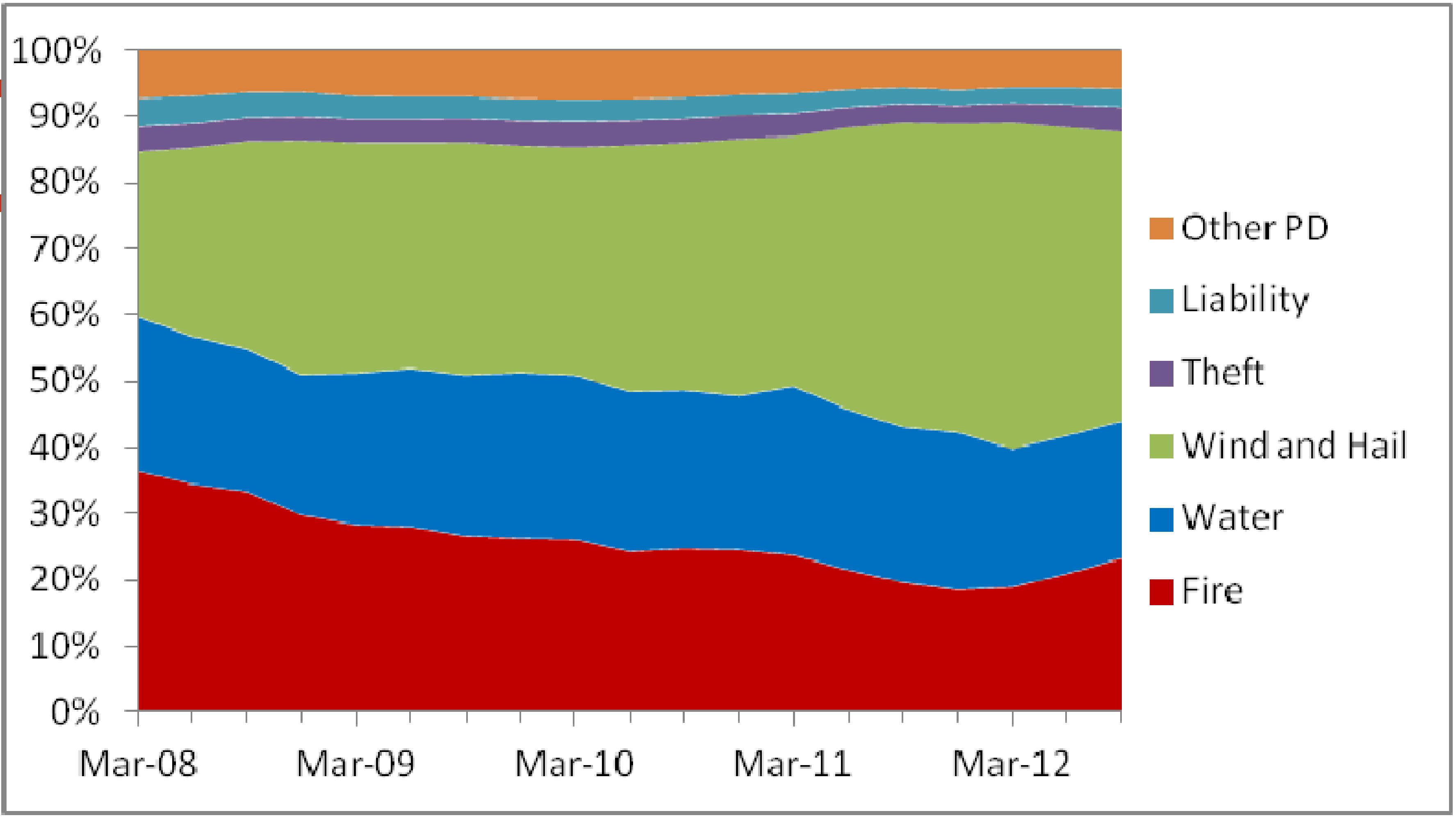
Opportunities and Challenges in By-Peril Modeling

- 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

Peril Trends Over Time

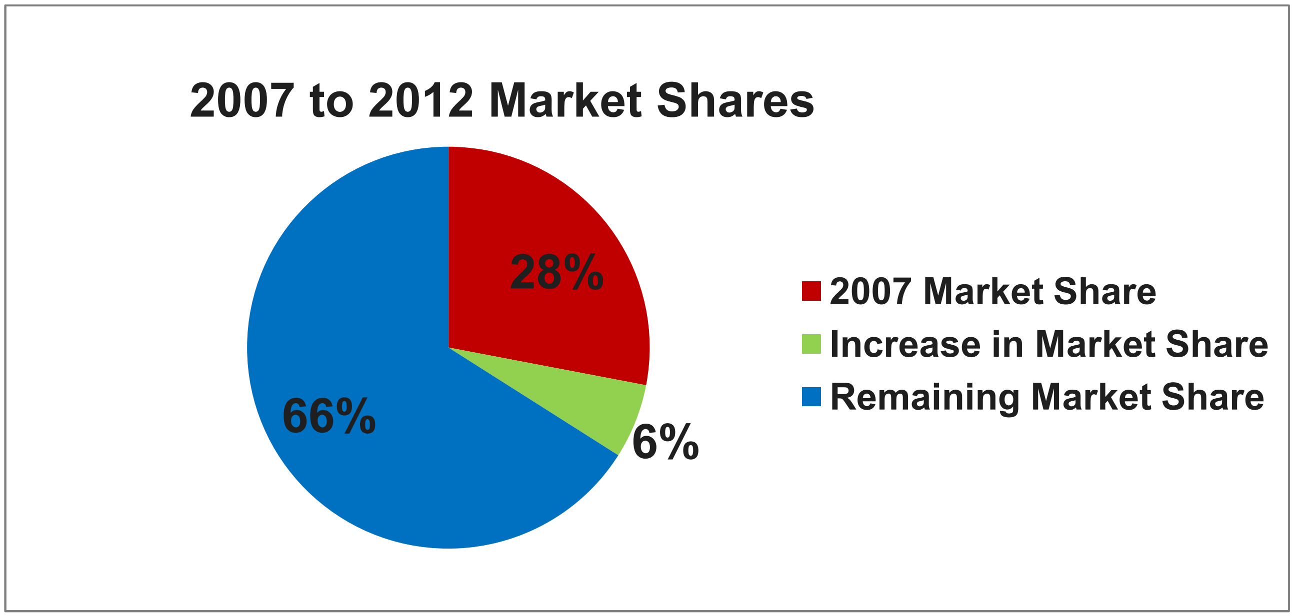


Peril Distribution Over Time



Leading the Way With By-Peril Rating

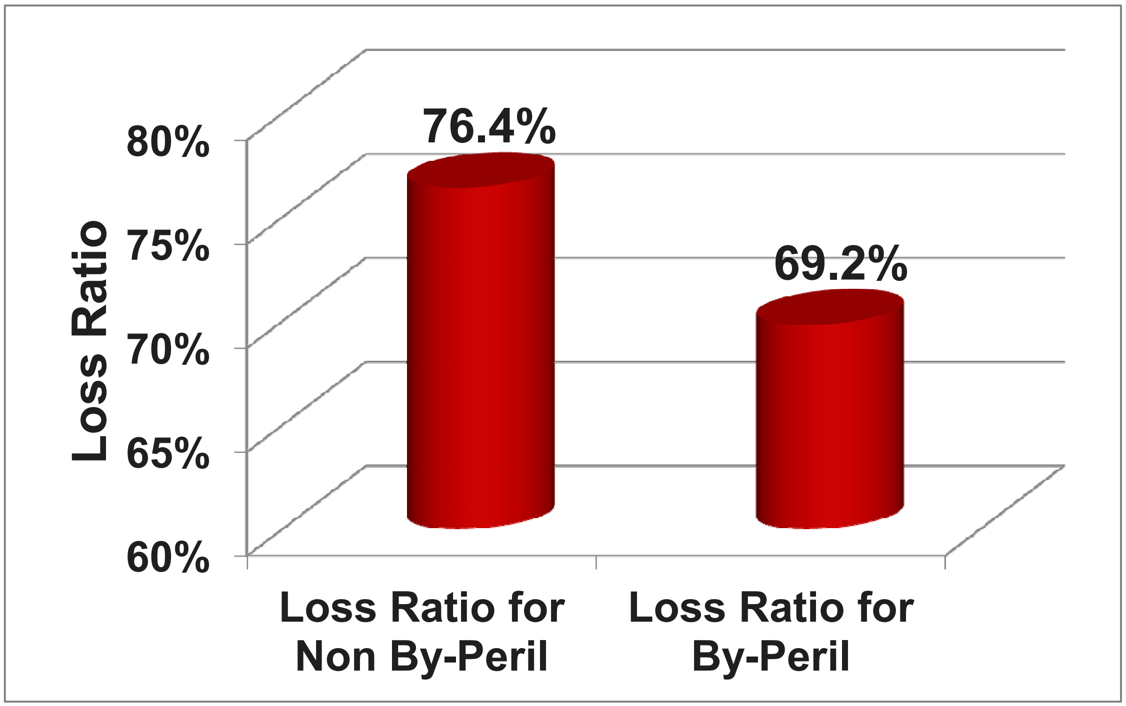
- Market Share Benefits
  - The 25 carriers using by-peril plans in 2011 have increased their combined market share from **28% to 34%** in 5 years from 2007 to 2012



Source: ISO research using Perr & Knight filings and 2007-2012 AM Best Financials

Leading the Way With By-Peril Rating

- Loss Ratio Benefits
  - The 25 companies rating by-peril have loss ratios **7.2** points lower than their competition in 2012

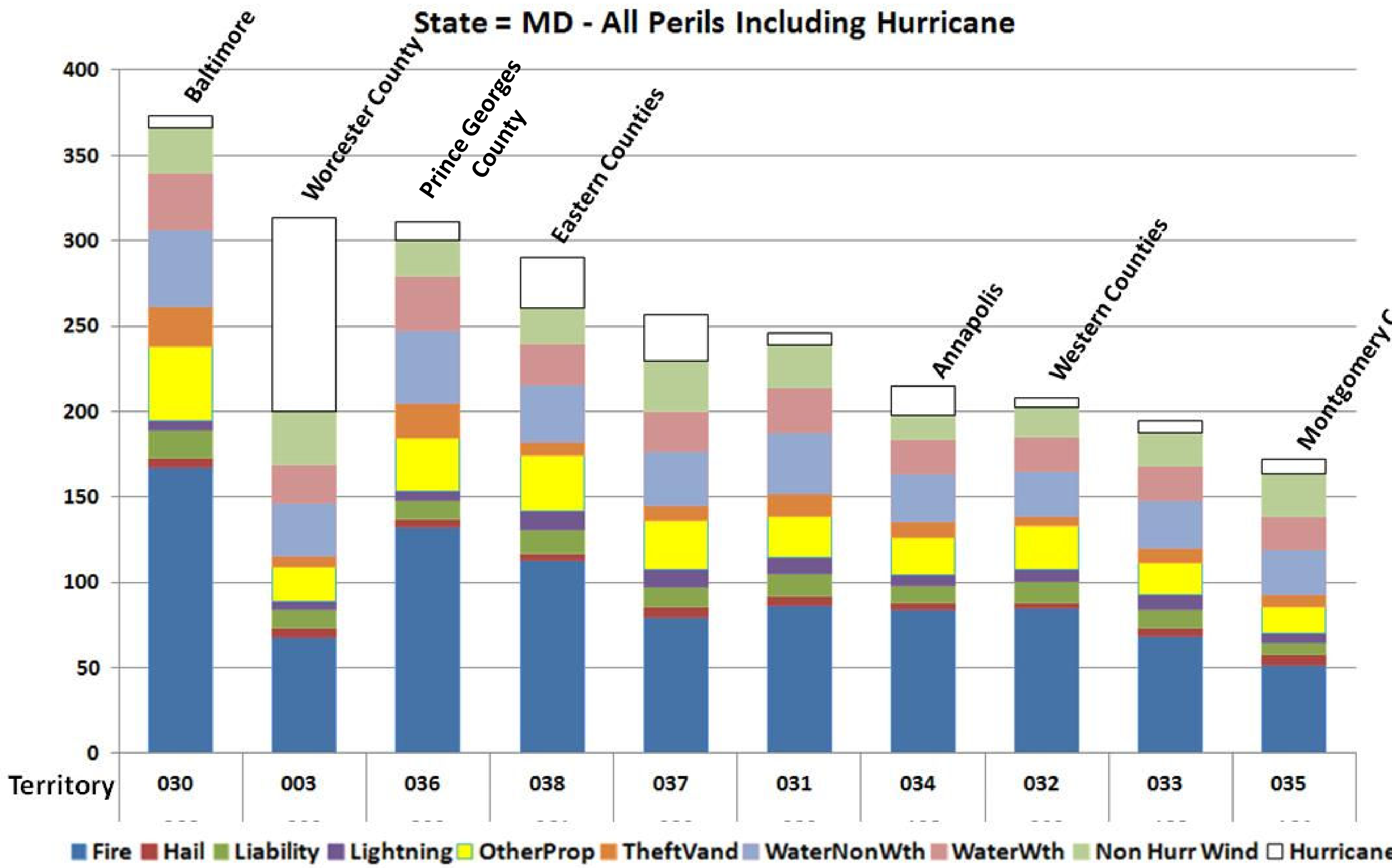


Source: ISO research using Perr & Knight filings and 2007-2012 AM Best Financials

Opportunities for By-Peril Modeling

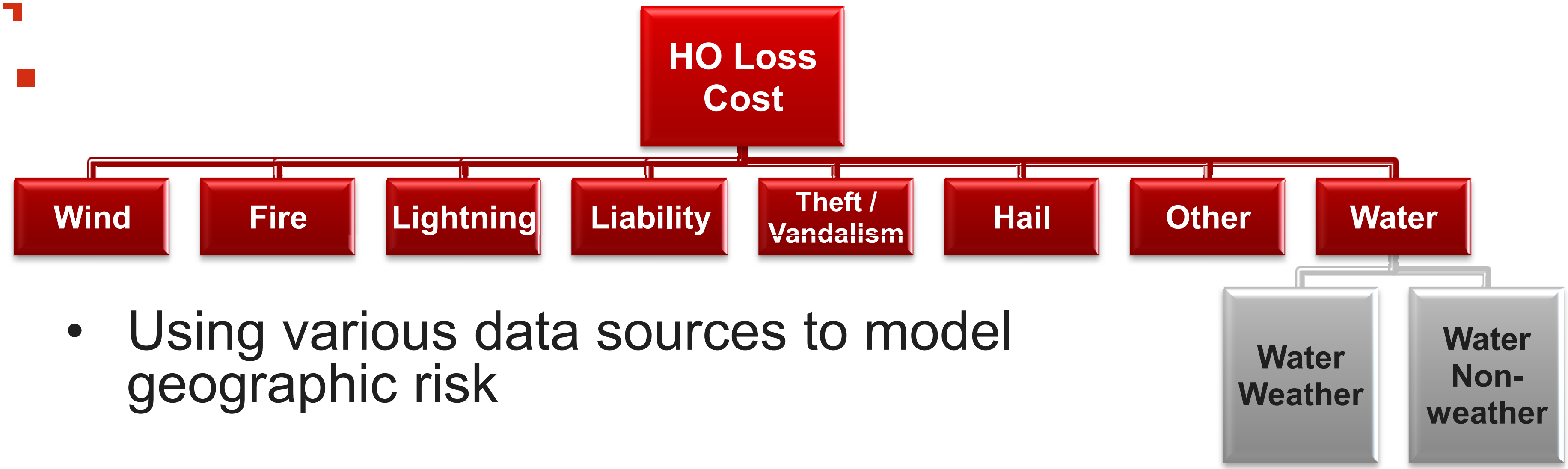
- Geographic Refinement
- Traditional Rating Factors
- Building Characteristics

Implied By-Peril Loss Costs for Standardized Risk



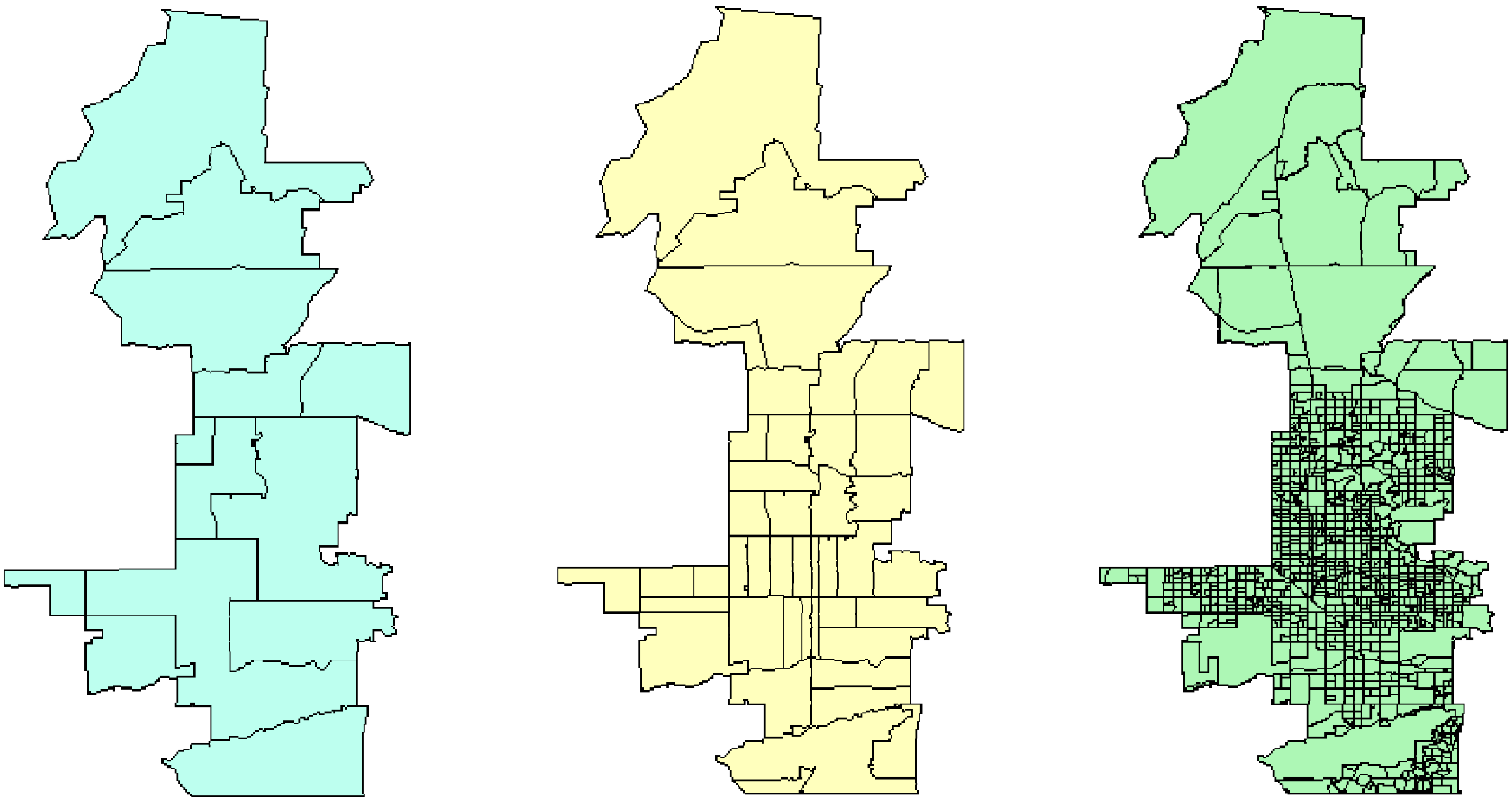
Modeling Approach

- Modeled by-peril (excluding hurricane)



- Using various data sources to model geographic risk
- Frequency and Severity modeled separately
- Combine to form ‘all peril loss cost’ – multiplied frequency and severity – added across perils

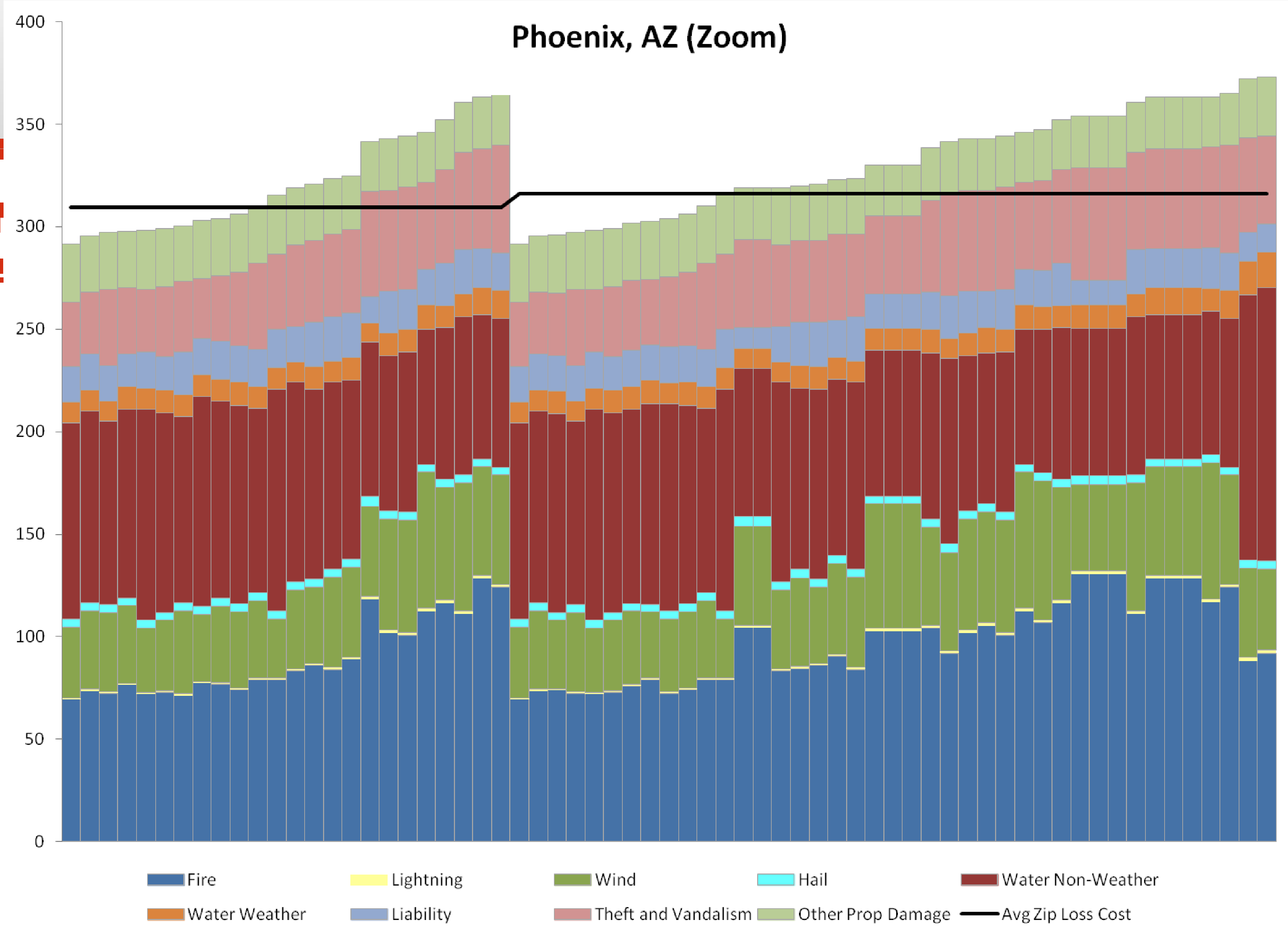
Phoenix, AZ Geographic Area



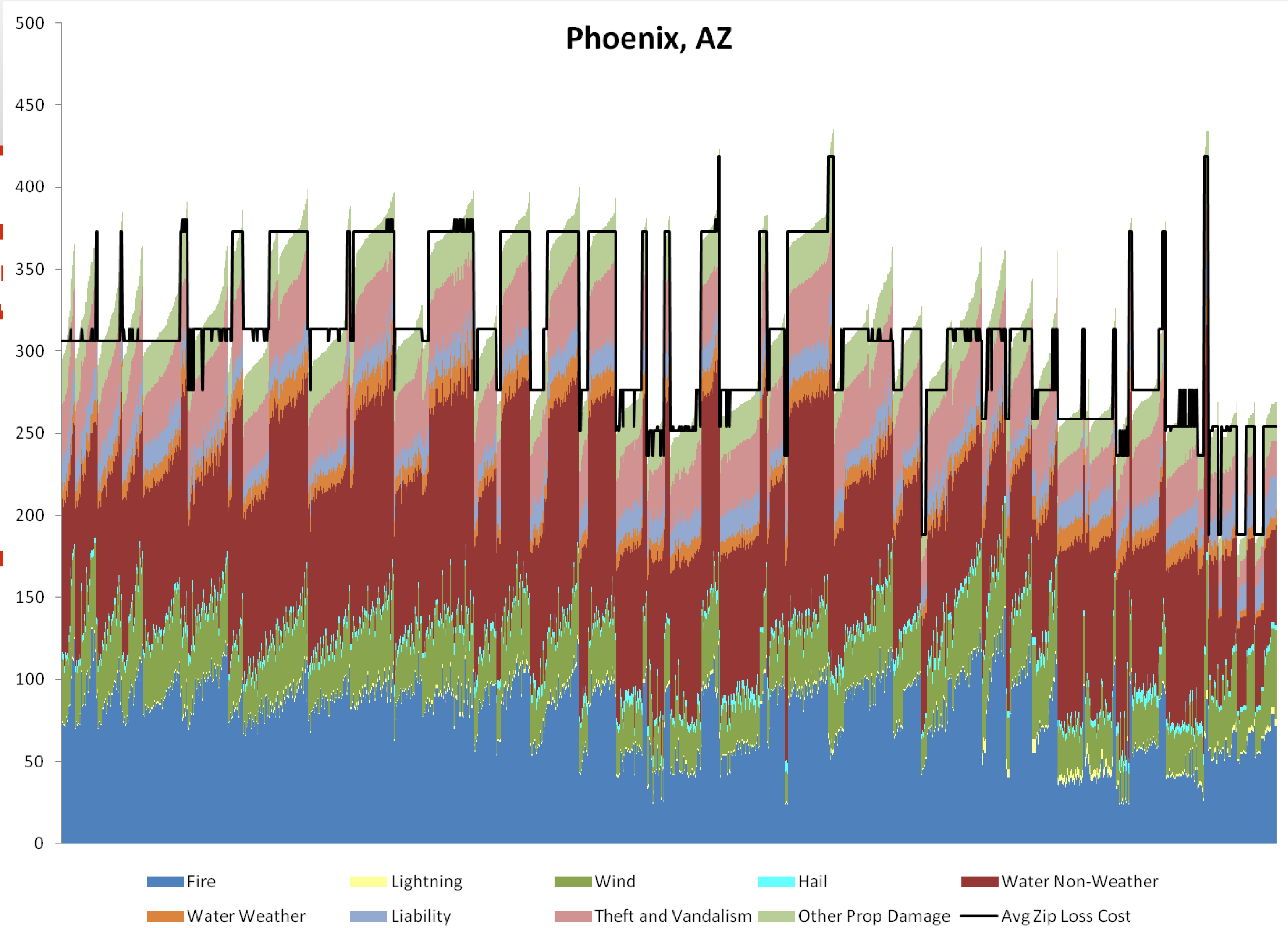
ISO Territories: 9

ZIP Codes: 80

RAHO: 1309



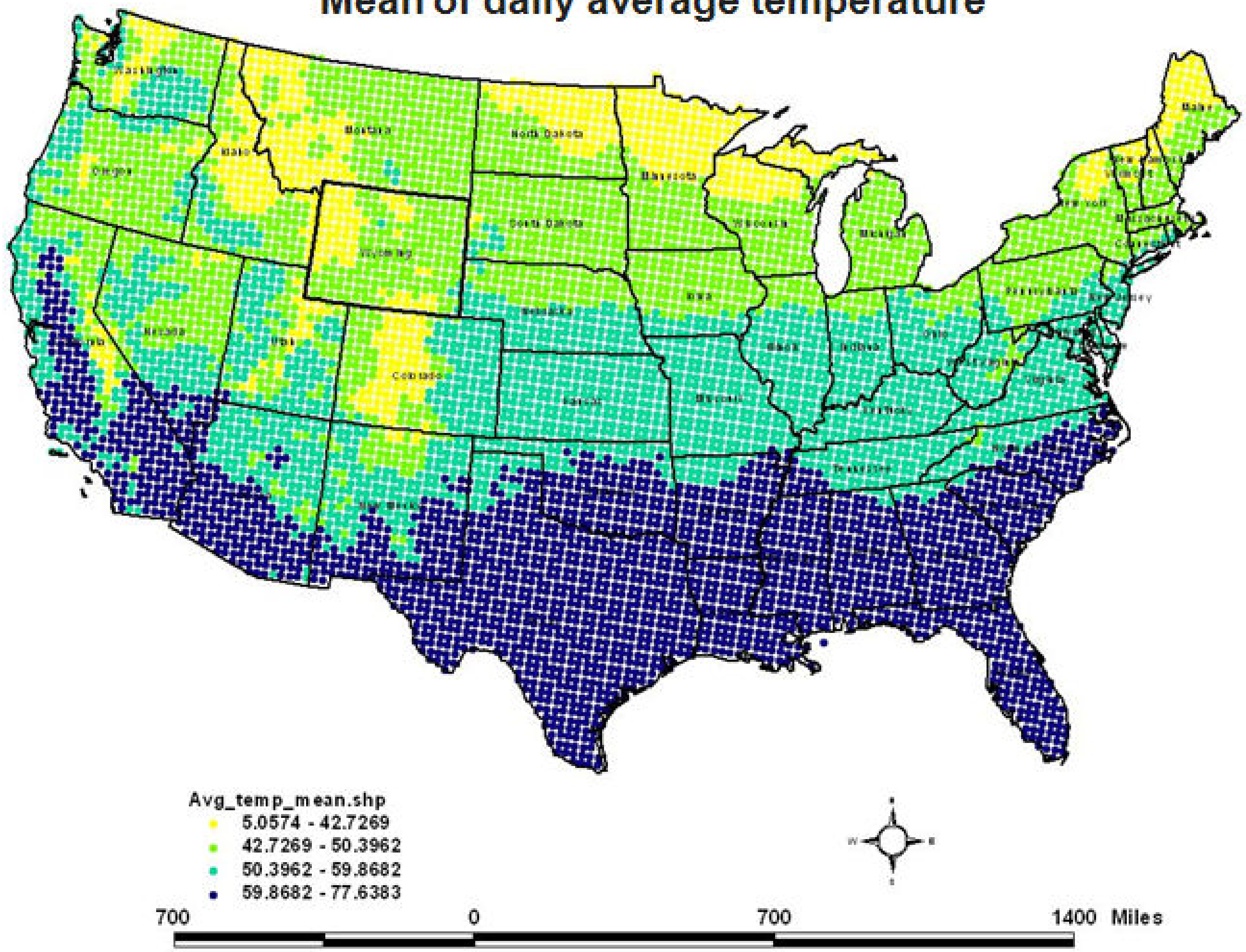
Phoenix, AZ (Zoom)
400
350
300
250
200
150
100
50
0
Fire
Lightning
Wind
Hail
Water Non-Weather
Water Weather
Liability
Theft and Vandalism
Other Prop Damage
Avg Zip Loss Cost



*** Loss cost are calculated @ Territory Representative Risk**

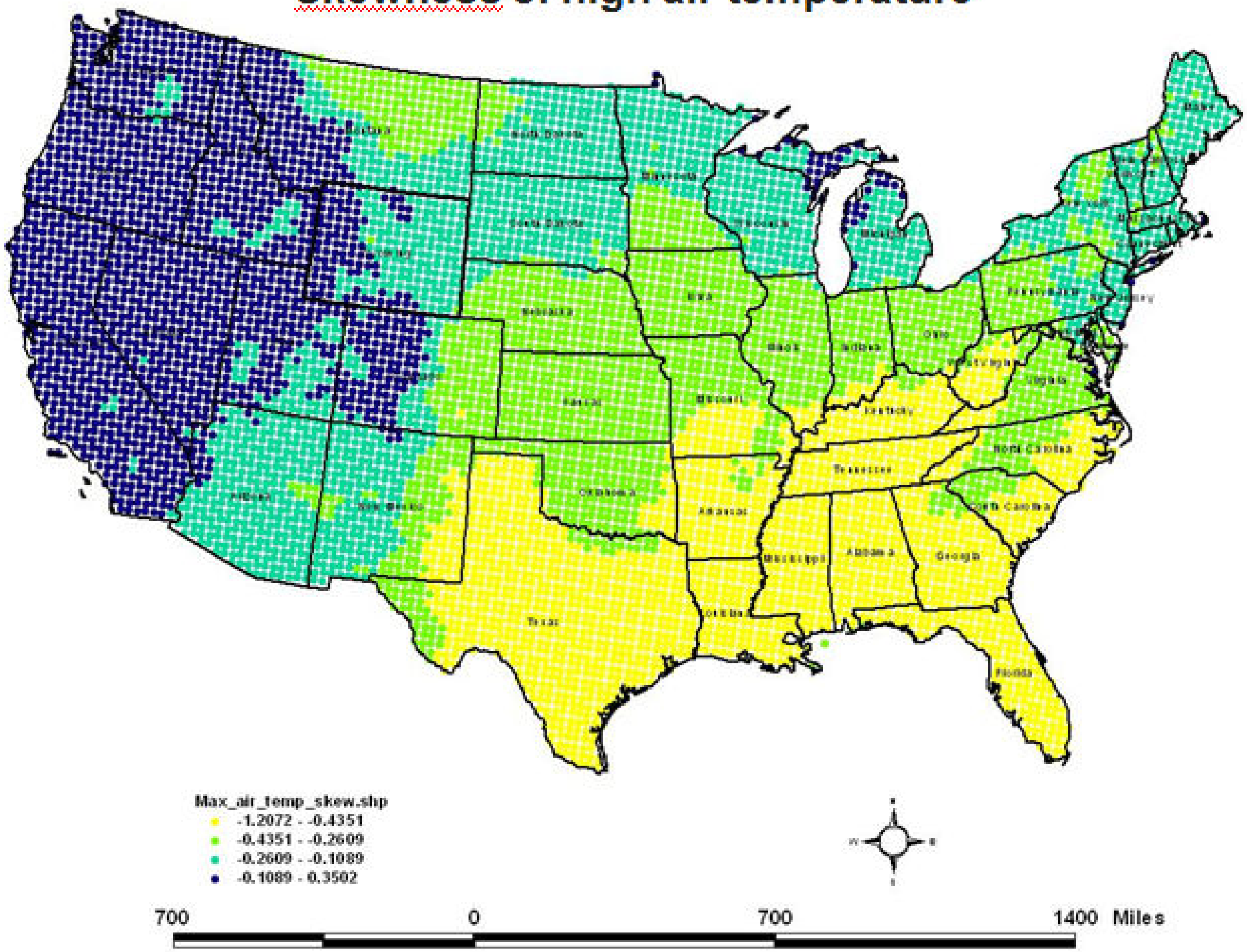
External Data – Weather

Mean of daily average temperature



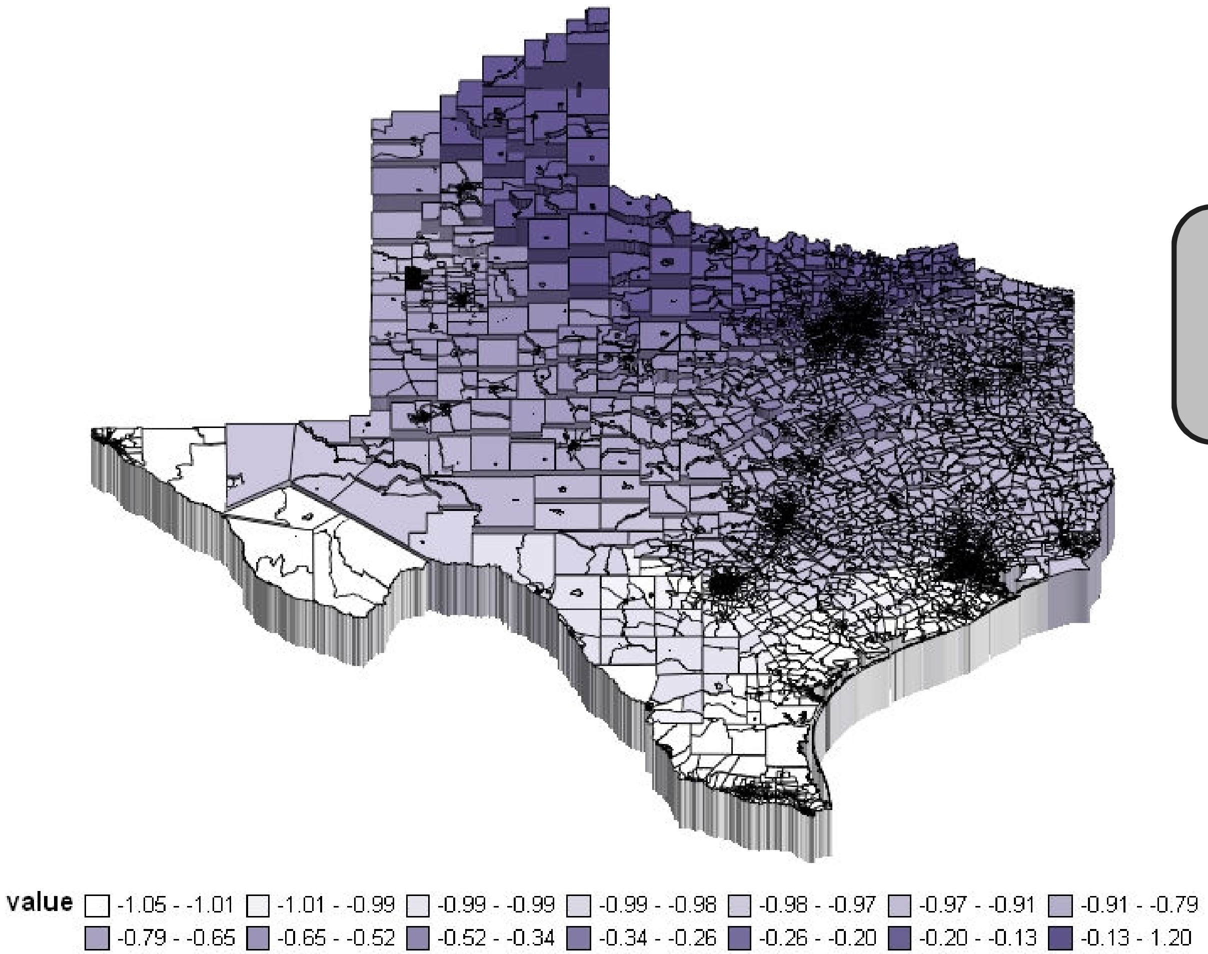
External Data – Weather

Skewness of high air temperature



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

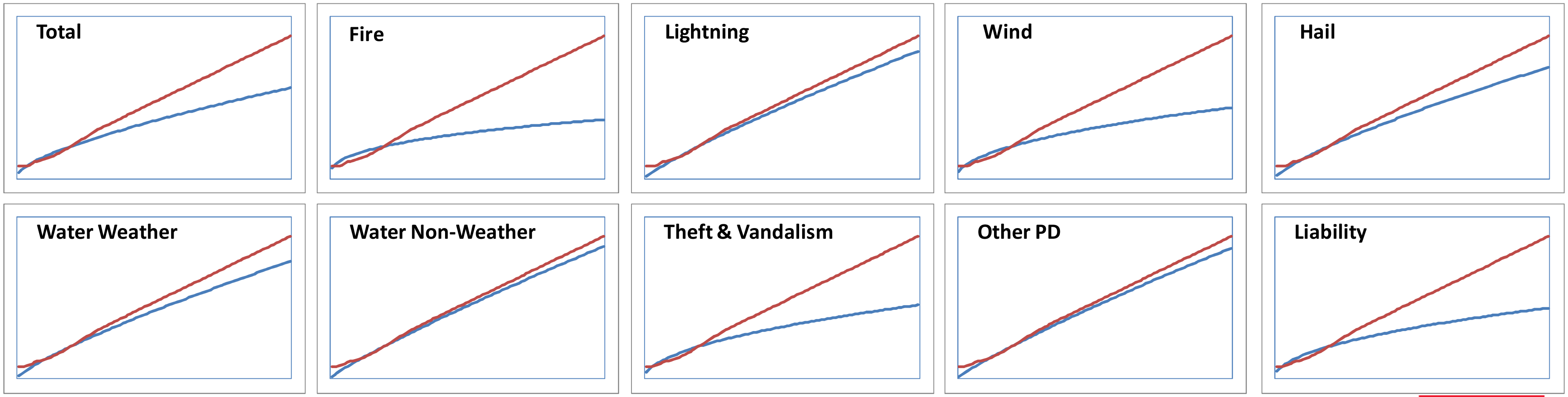
Weather & Elevation	FIRE	LIGHT	WIND	HAIL	WW	LIAB	THEFT
Elevation							
Temperature							
Precipitation							
Relative Humidity							
Snow							
Wind							
Ice Pellets							

External Validation:

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

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

Building Characteristics Overview

Use specific building and property features:

- Construction style & material
- Roof age & material
- Square footage, lot size, # of bedrooms / baths / stories
- Heating and cooling systems
- Garage and basement information
- Etc…..

Building Characteristics Illustration

Both houses are in the same ZIP Code and have $300k ITV
Same year of construction and in same PPC

3000 sq foot 4 bed, 3.5 bath colonial
Brick exterior, attached 2 car garage

2500 sq foot 3 bed, 2.0 bath ranch
Wood siding, 2 car carport

Building Characteristics Illustration

3000 sq foot 4 bed, 3.5 bath colonial
Brick exterior, attached 2 car garage

- Multiple stories have higher water non-weather losses
- 3.5 baths and two stories leads to higher water claims
- Attached garage lowers fire and wind exposure
- Fireplace increases hail exposure
- Brick construction lowers weather claims

- All peril factor: 1.165
  - Hail: 1.258
  - Water Non-Weather: 1.309
  - Liability: 0.859
  - Fire: 0.908

Building Characteristics Illustration

- Larger floor plan has greater weather exposure
- Fewer bathrooms decreases water non-weather losses
- Pool increases wind and liability exposure
- Composite shingles lowers weather claims
- Single story increases theft/vandalism

- All peril factor: 0.950
  - Hail: 0.605
  - Water Non-Weather: 0.905
  - Liability: 1.162
  - Theft & Vandalism: 1.373

2500 sq foot 3 bed, 2.0 bath ranch
Wood siding, 2 car carport

Building Characteristics Summary

- All peril factor: 1.165
  - Hail: 1.258
  - Water Non-Weather: 1.309
  - Liability: 0.859
  - Fire: 0.908

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Data Challenges in By-Peril Predictive Modeling

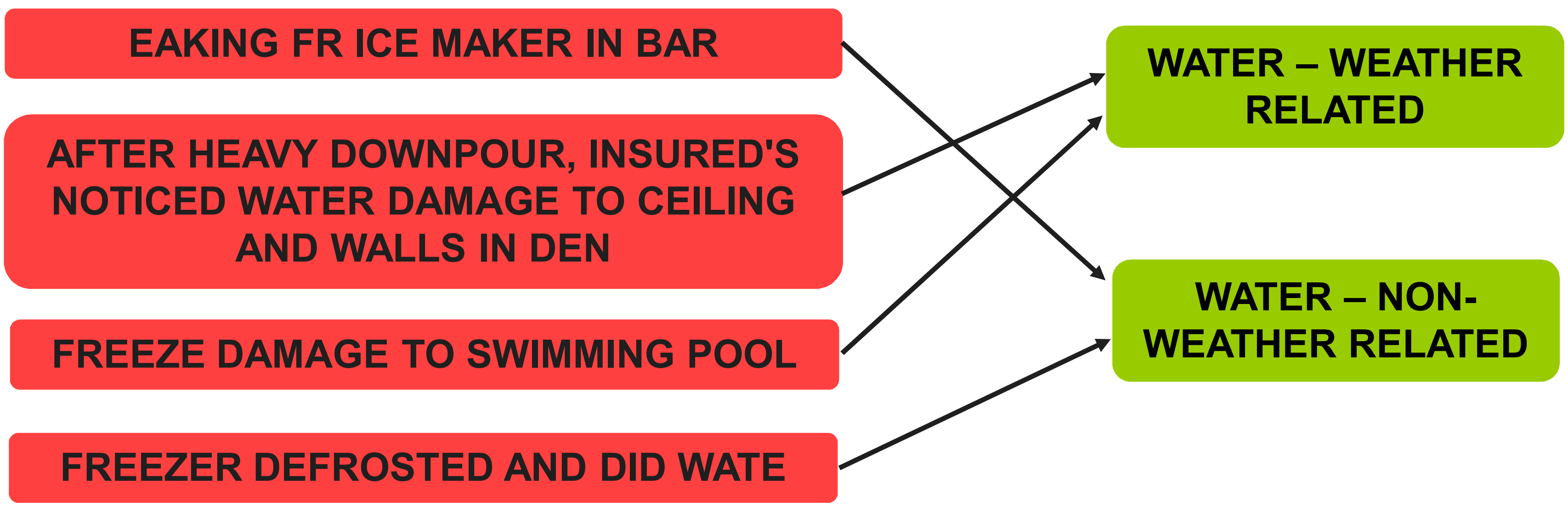
- Data Preparation
  - Splitting losses by peril
- Data Volume
  - Separating the signal from the noise in each peril

Decomposing Water Losses

Most claims systems do not have a systematic or structured field to help distinguish weather related water losses from non-weather related 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



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

- Solution: 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

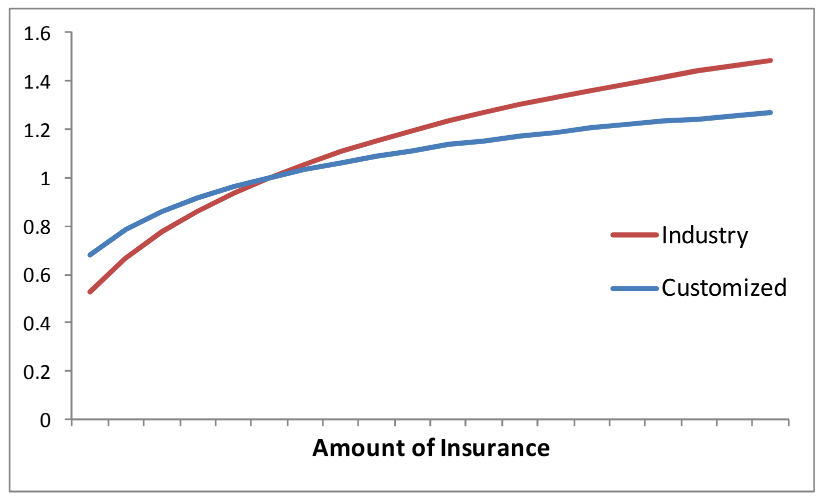
Gaining Customized Lift
With Re-Usable Data Features

- Step 1: Score your data using results from "larger" model

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

- Step 2: Fit your GLM using scored variable
  - Use continuous predictor (variate)
  - Apply transformations as needed

$$\cdots + \beta \times (\text{AOI Fire Severity Factor}) + \cdots$$



- Result:
  - Customized rating factor indication requiring less of your data
  - Avoids overfitting by preserving information from "larger" model

Be Careful with Binned Variables

- Without enough data, binned variables ignore known relationship to loss – can lead to overfitting

Variable Treatment	Gini
Continuous	38.05
5 bins – equal exposures	37.77
10 bins – equal exposures	33.78
20 bins – equal exposures	31.72

Data with 1,400 claims

Variable Treatment	Gini
Continuous	29.18
5 bins – equal exposures	28.93
10 bins – equal exposures	29.31
20 bins – equal exposures	30.12

Data with 6,300 claims

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?

David Cummings
dcummings@iso.com