Claims modelling for climate risk

Ronald Richman

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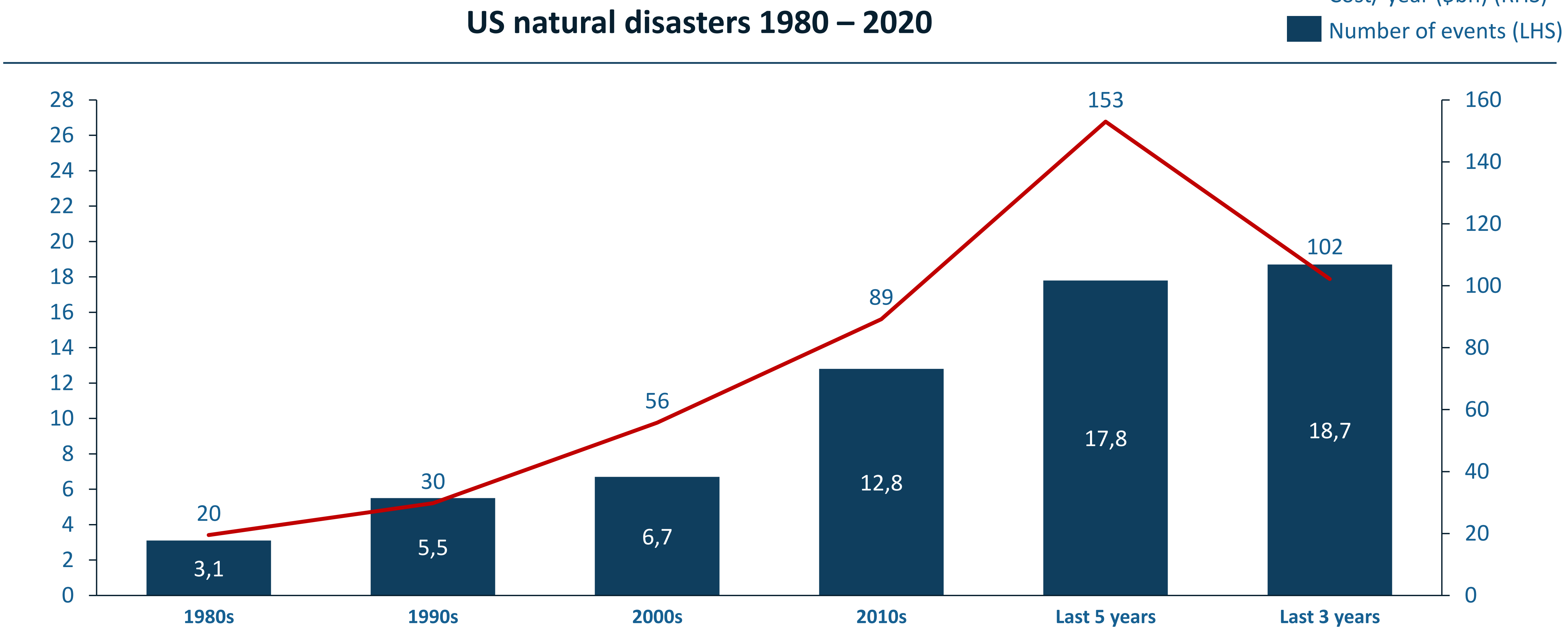
Insurance Data Science

Background

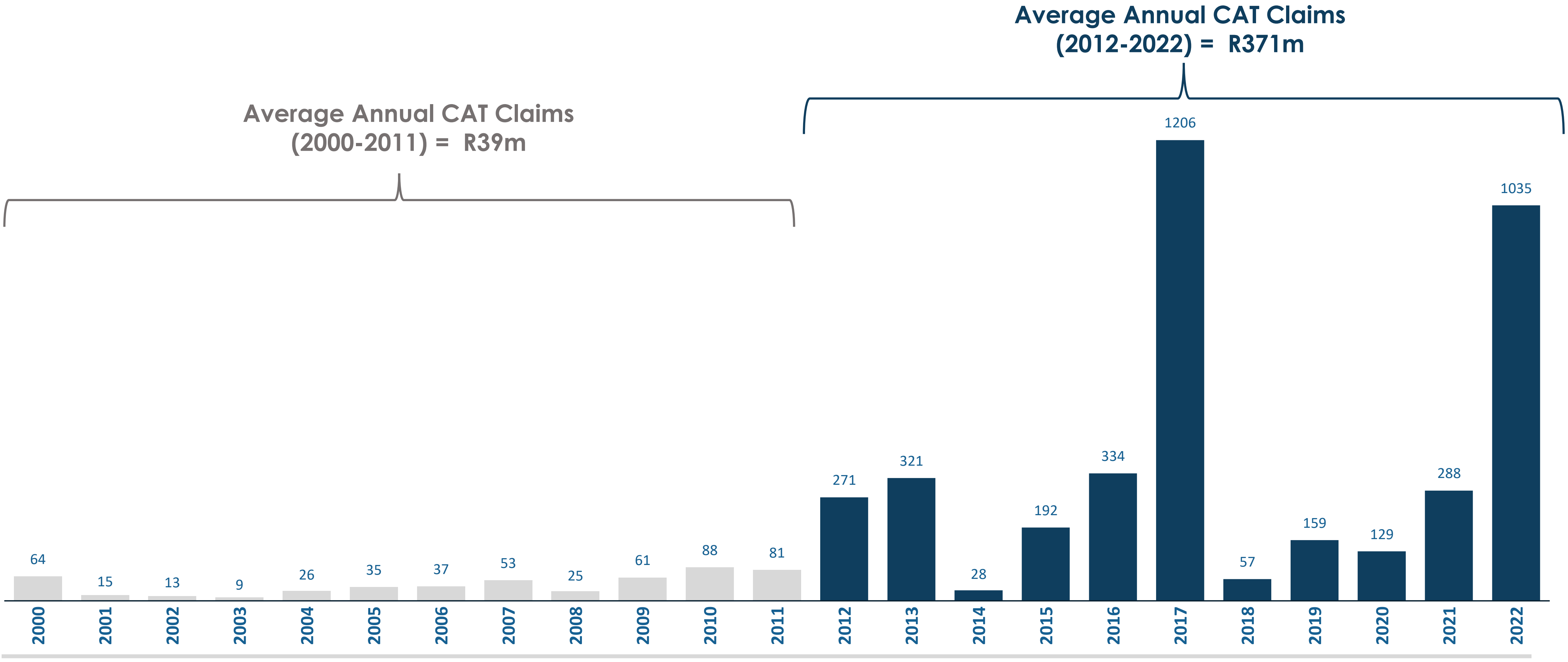
There has been an increase in both frequency and severity of natural disasters globally



Source: NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2022)

Severity Impact

Severity of weather-related claims has increased 10-fold over last decade



Source: Old Mutual Insure pricing data (inflation- and exposure-adjusted weather catastrophe claims) R'mil

Macro and Micro Modelling

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Macro view

- Pre-existing models of shocks to short-term insurance portfolio:
  - Earthquake
  - Hail
  - Wildfire
  - Flood
  - Windstorm
- Models calibrated to recent experience of these perils
- Run at a portfolio level
- <u>Can we modify these models to take climate change into account?</u>

Micro view

- Pricing data links individual policies in portfolio to claims data
- Can also acquire climate data looking at experience at granular level…
- … e.g. precipitation data in small areas for a long period
- <u>Can we link climate data to our traditional pricing to quantify effect of climate change?</u>

Micro - Short-term Weather Forecasting

- **Project aim**
  - Can we link climate data to our traditional pricing to quantify effect of climate change?
  - Incorporate highly granular precipitation data, curated by meteorologists, into traditional short-term pricing datasets.
  - Fit statistical models to observe predictive value of this addition.
  - Quantify the potential impact of using future predicted precipitation levels in rating processes
  - Quantify the impact of increased precipitation (driven by climate change and La Nina weather system) on insurance risk
- **Project with support from:**
  - University of the Witwatersrand (Prof. Rendani Mbhuva, Adam Balusik)
  - University of Pretoria (Prof. Willem Landman)
  - ETH Zürich (Prof. Dr. Mario V Wüthrich)
  - OMI Catastrophe & Climate Modelling (Caesar Balona)
- **Working paper in progress**

Micro - Short-term Weather Forecasting

- **Overview of steps taken**
  - Select one line of business
  - Geolocate LoB pricing file using external service provider
  - Obtained CHIRPS precipitation dataset
  - Created precipitation grid across SA at a 0.05’ longitude by 0.05’ latitude level of granularity (~25km^2)
  - Mapped geolocated pricing file to the precipitation grid
  - Fit Gradient Boosted Machines (GBMs) model to predict claims experience using factors used in the current pricing environment, with and without precipitation
  - Fit a Neural Net to disperse overall South African rainfall forecasts to a grid level
  - Refit models using forecasted rainfall
  - Analyzed model results on an actual and forecasted basis
    - Feature importance
    - Dependence plots
    - Predicted loss experience by yearly rainfall experience (actual and forecasted basis)

Geolocation – Data Engineering

- **Data Considerations**
  - Geolocated LOB pricing file
    - ~ 13mil rows and many columns
  - CHIRPS precipitation dataset
    - ~ 19.5mil rows and 4 columns
  - Memory management and optimisation becomes very important
    - Python – Pandas
      - Batch processing
      - Memory efficient data storage
      - Minimum viable datatypes
      - Use vectorized operations where possible
      - Utilize GPU for modelling

Precipitation – CHIRPS Overview

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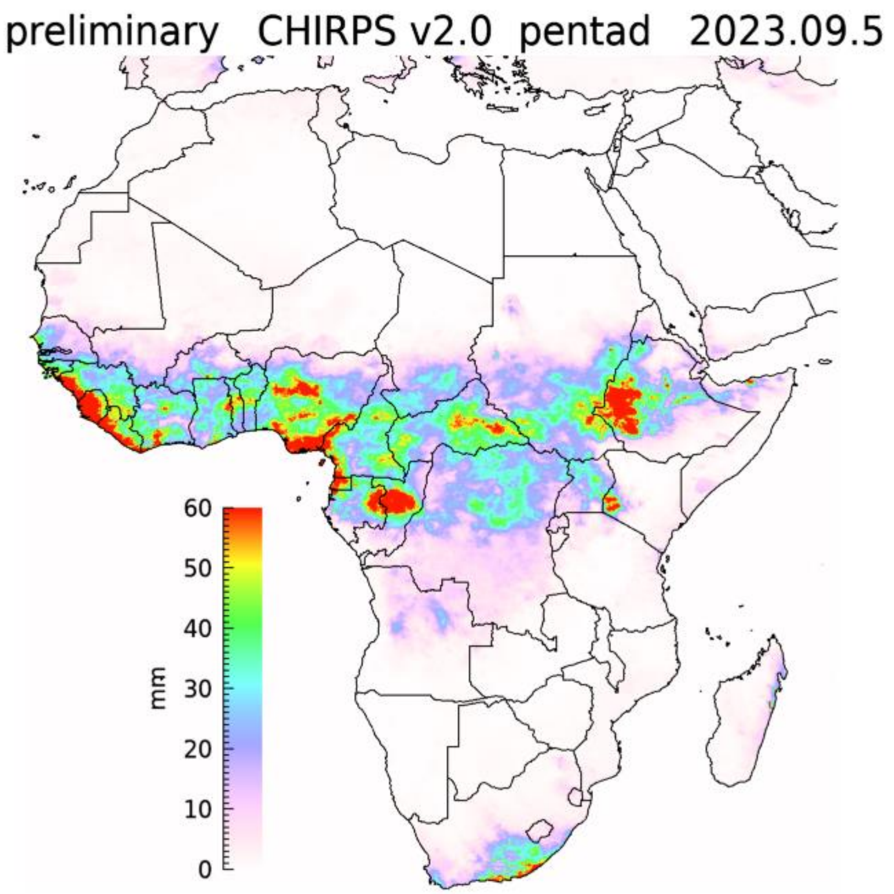
- **CHIRPS Dataset**
  - Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 35+ year quasi-global rainfall data set.
  - Spanning 50°S-50°N (and all longitudes) and ranging from 1981 to near-present.
  - CHIRPS incorporates in-house climatology, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring.



Precipitation – CHIRPS Visualisation

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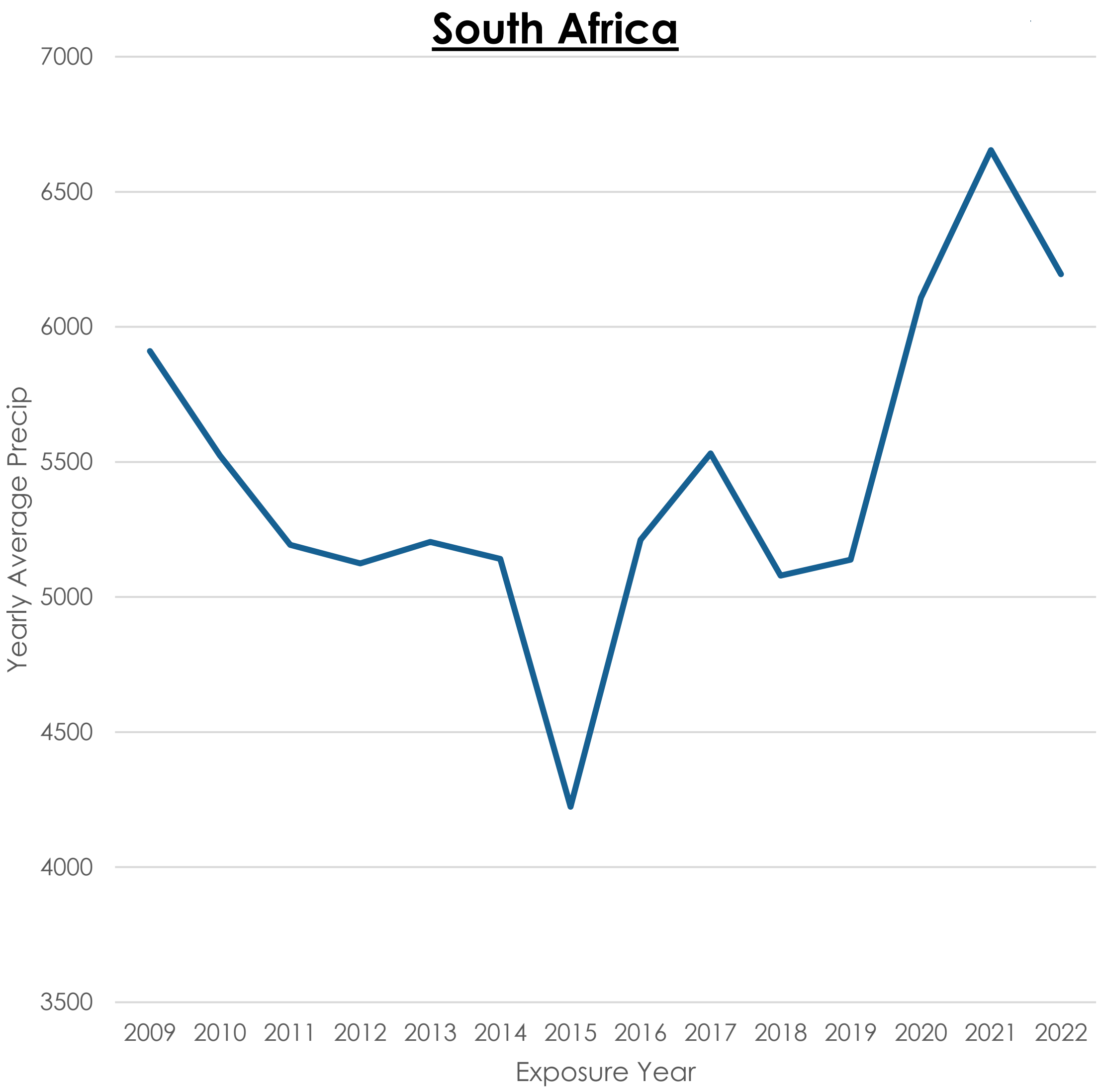
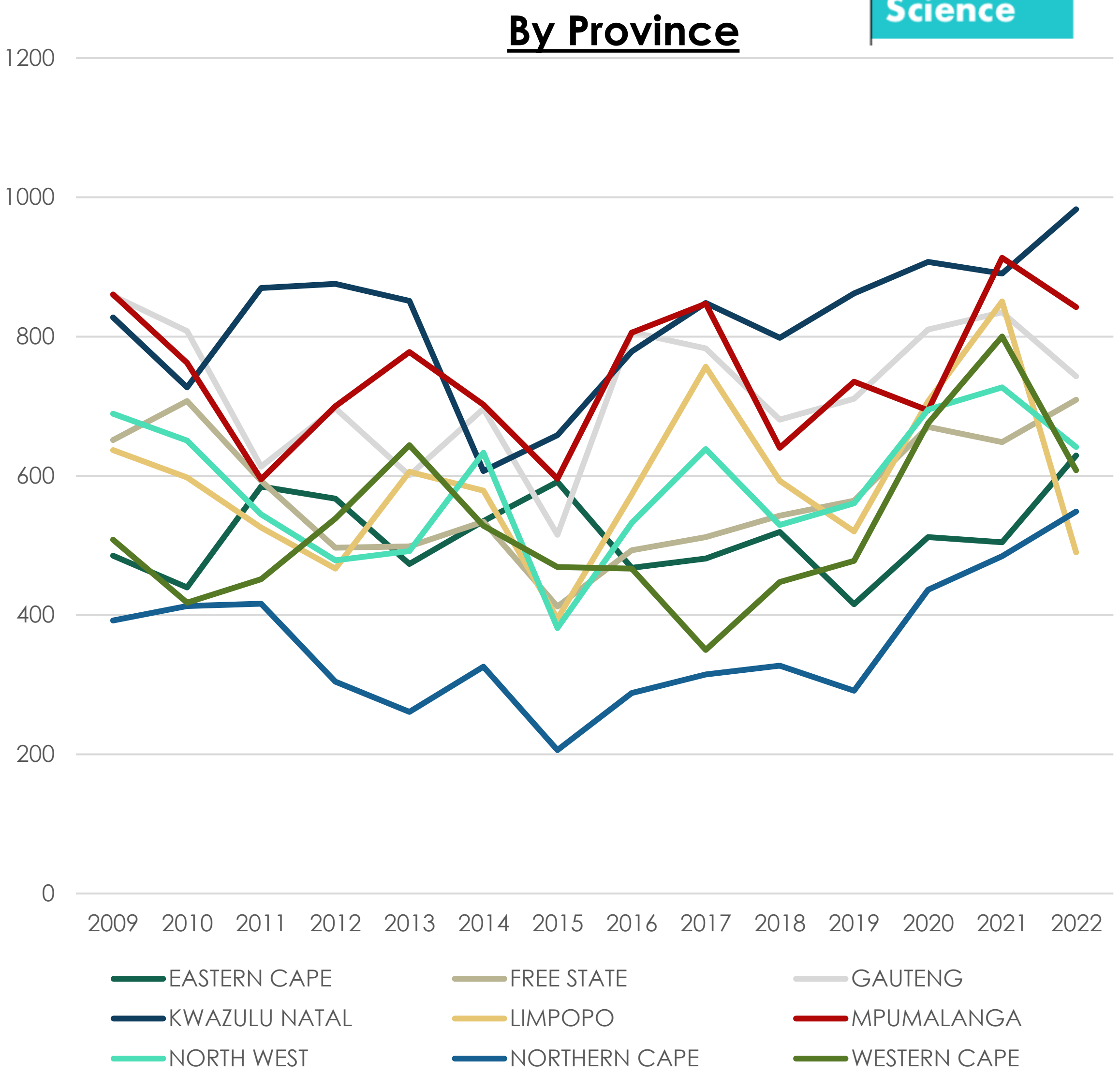
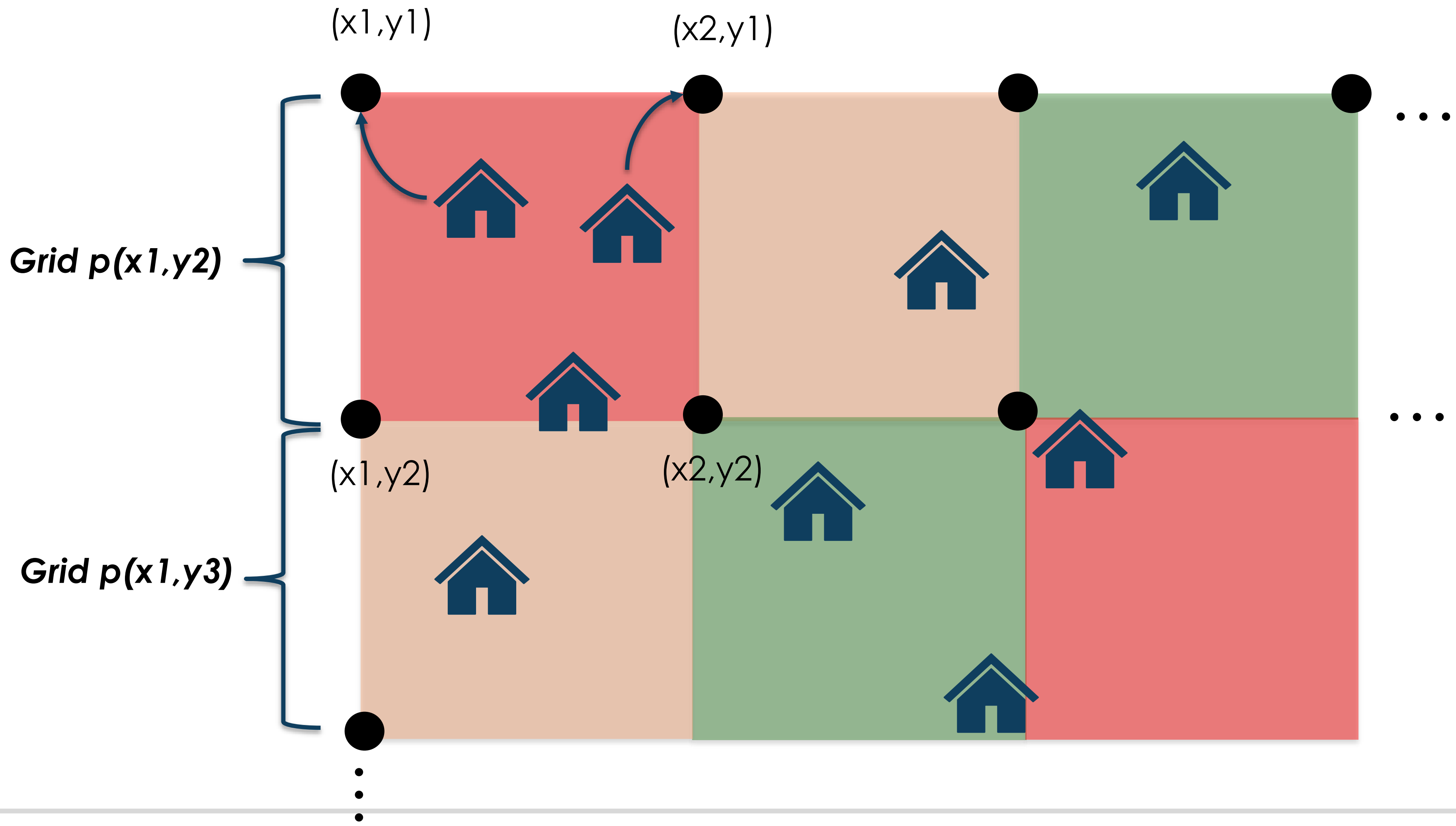




Linking Exposure to Precipitation – Join Logic



Linking Exposure to Precipitation - Visualisation

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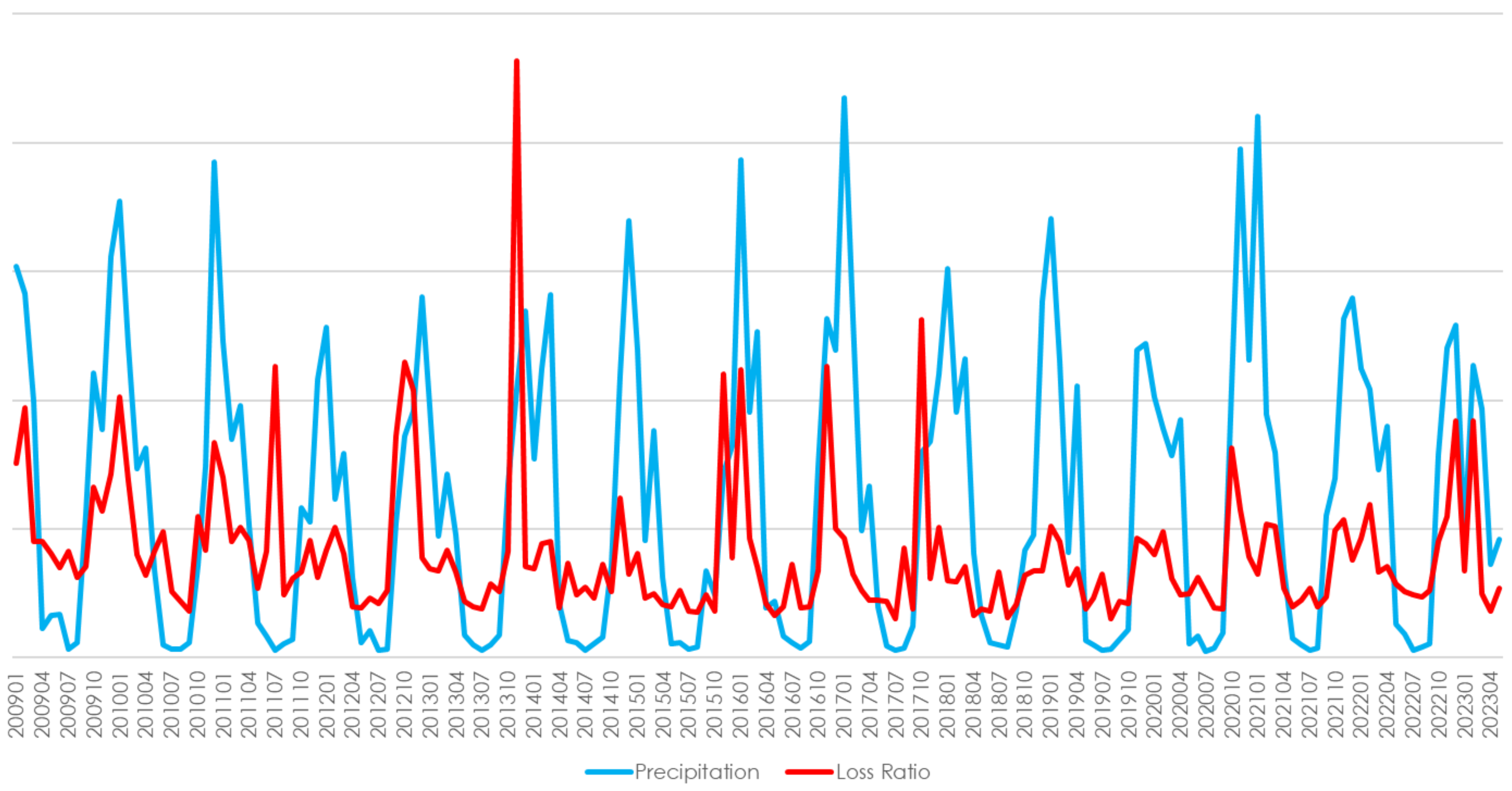
Gauteng - Precipitation vs Loss Ratio



Modelling Implementation

Loss prediction given precipitation experience

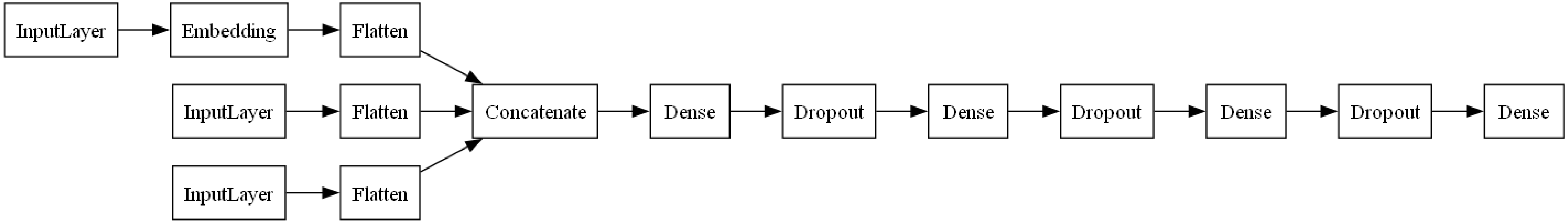
Frequency GBM	
Model	Gradient Boosted Machine
Form	Poisson Regression
Algorithm	LightGBM
Train/Test Split	Time-based
Loss function	Poisson Negative Log-Likelihood
Inputs	Traditional rating factors +- (Grid Precipitation)
Weight	Exposure
Output	Frequency
Validation score	Poisson Mean Deviance

Severity GBM	
Model	Gradient Boosted Machine
Form	Gamma Regression
Algorithm	LightGBM
Train/Test Split	Time-based
Evaluation metric	Gamma Negative Log-Loss Likelihood
Inputs	Traditional rating factors +- (Grid Precipitation)
Weight	Exposure
Output	Severity
Validation score	Gamma Mean Deviance

Modelling Implementation

Forecasting precipitation

Grid Dispersion NN	
Model	Neural Net
Form	Poisson Regression
Algorithm	Keras
Train/Test Split	Random
Loss function	Mean Squared Error
Inputs	Grid cell bounds, Overall precipitation prediction*, Calendar month
Output	Per grid cell precipitation
Validation score	MSE



Modelling Results

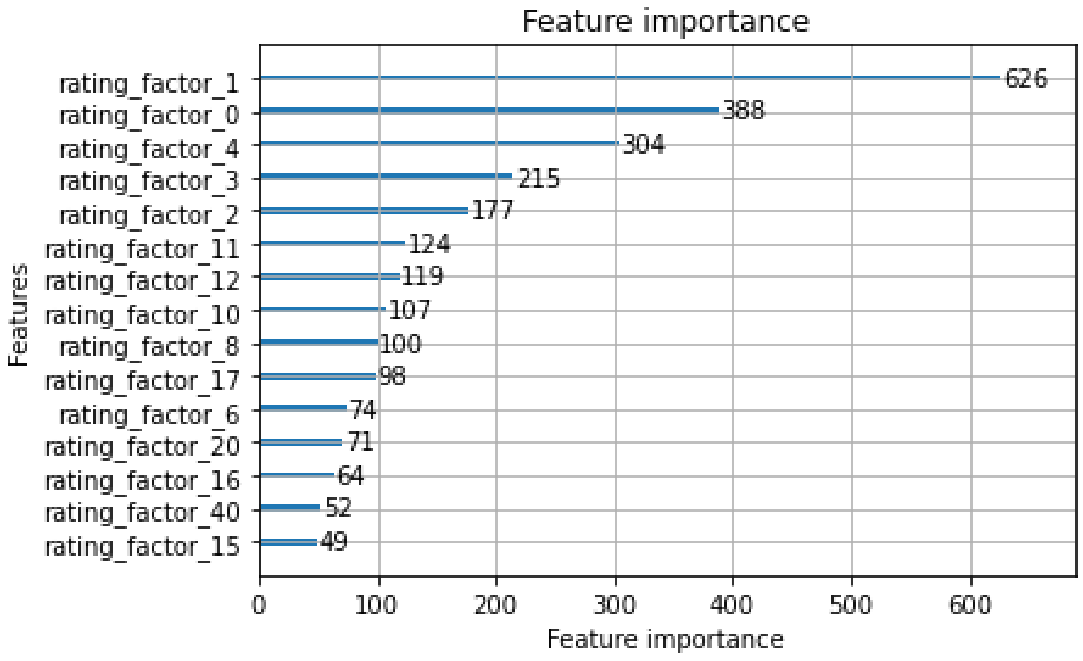
Out-of-sample validation scores

Model	Poisson/Gamma Deviance
Frequency GBM w/o precipitation	0.1687
Frequency GBM w/ actual precipitation	0.1679
Frequency GBM w/ forecasted precipitation	0.1683
Severity GBM w/o precipitation	1.7833
Severity GBM w/ actual precipitation	1.7465
Severity GBM w/ forecasted precipitation	1.7775

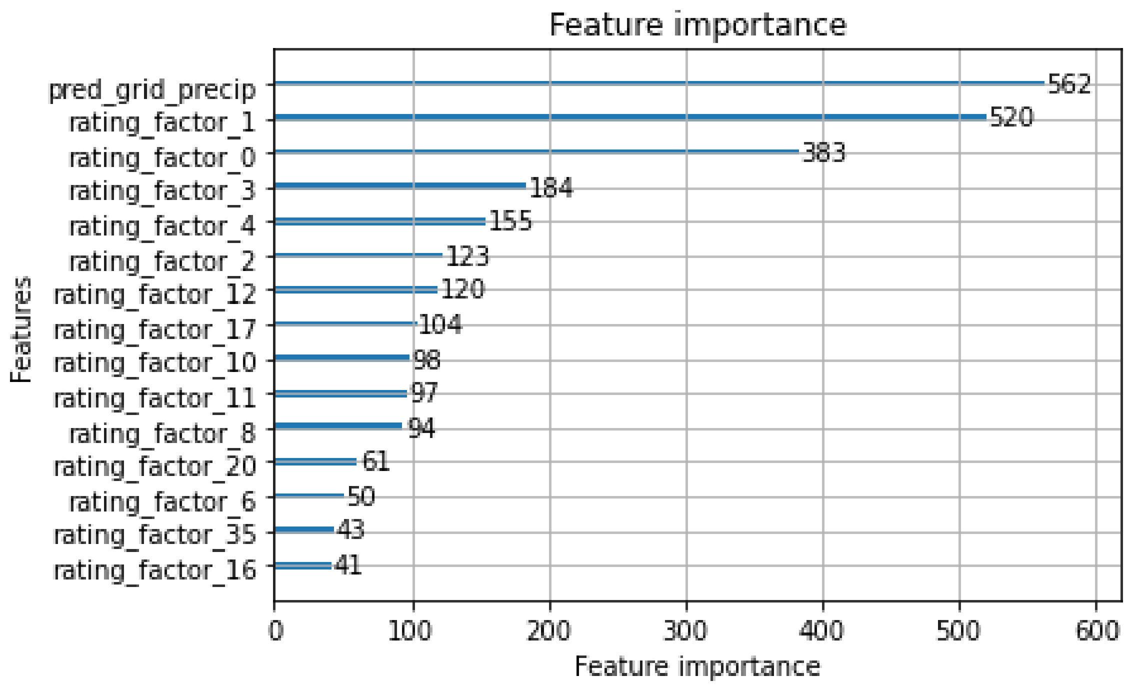
Modelling Results

Frequency GBM Implementation

Traditional Pricing Dataset



With Forecasted Precipitation Data



Modelling Results

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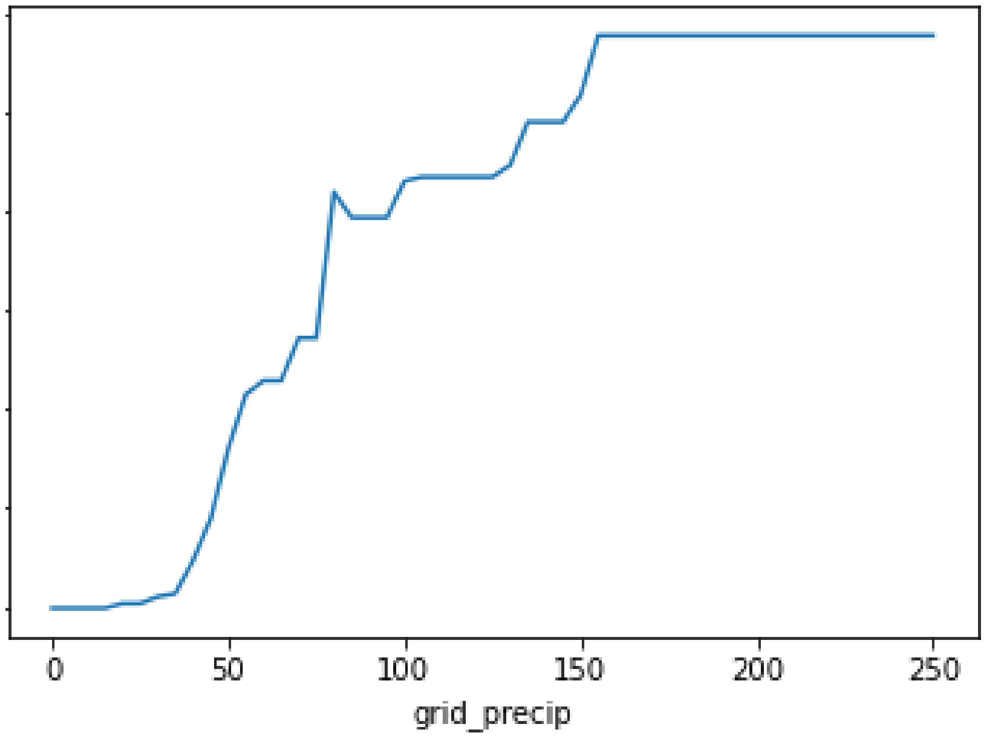
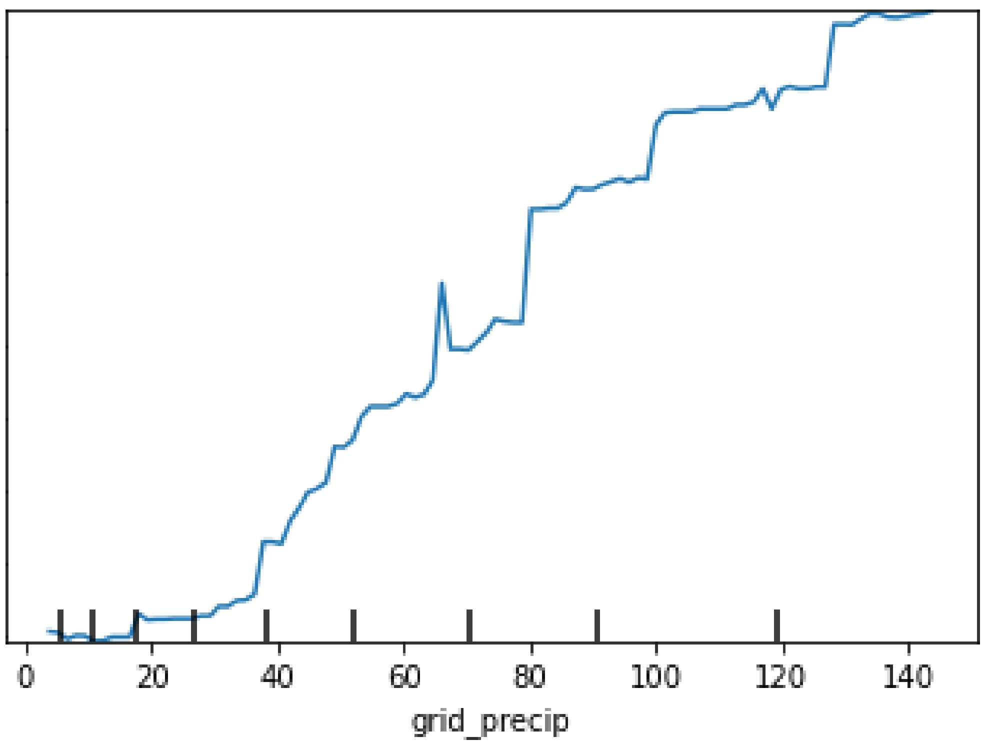
Frequency GBM Implementation

Sample P/H Sensitivity (Base Risk Profile)



Partial Dependency Plot



Modelling Results

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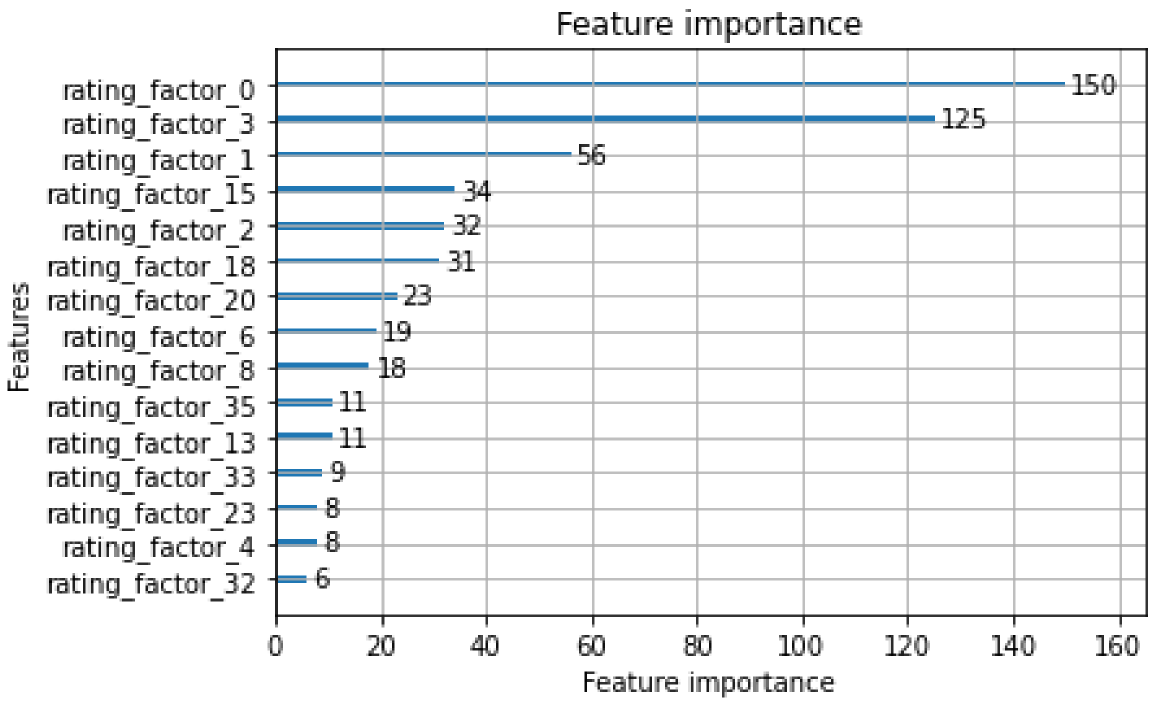
Severity GBM Implementation

Traditional Pricing Dataset



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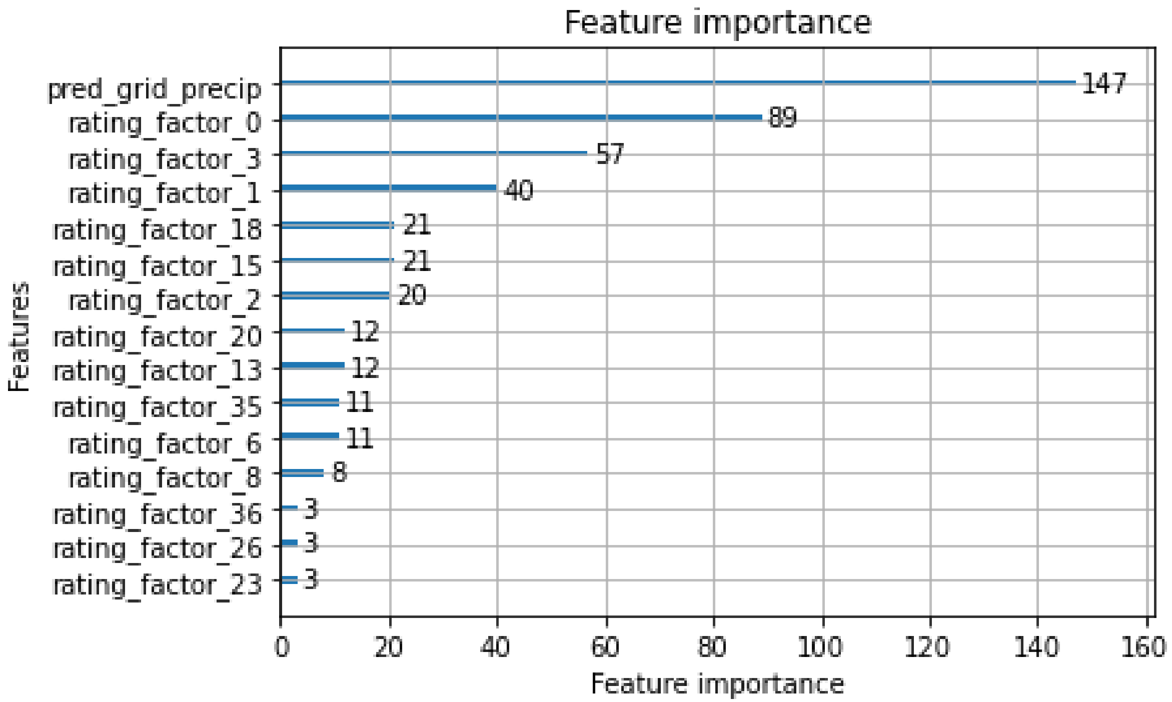
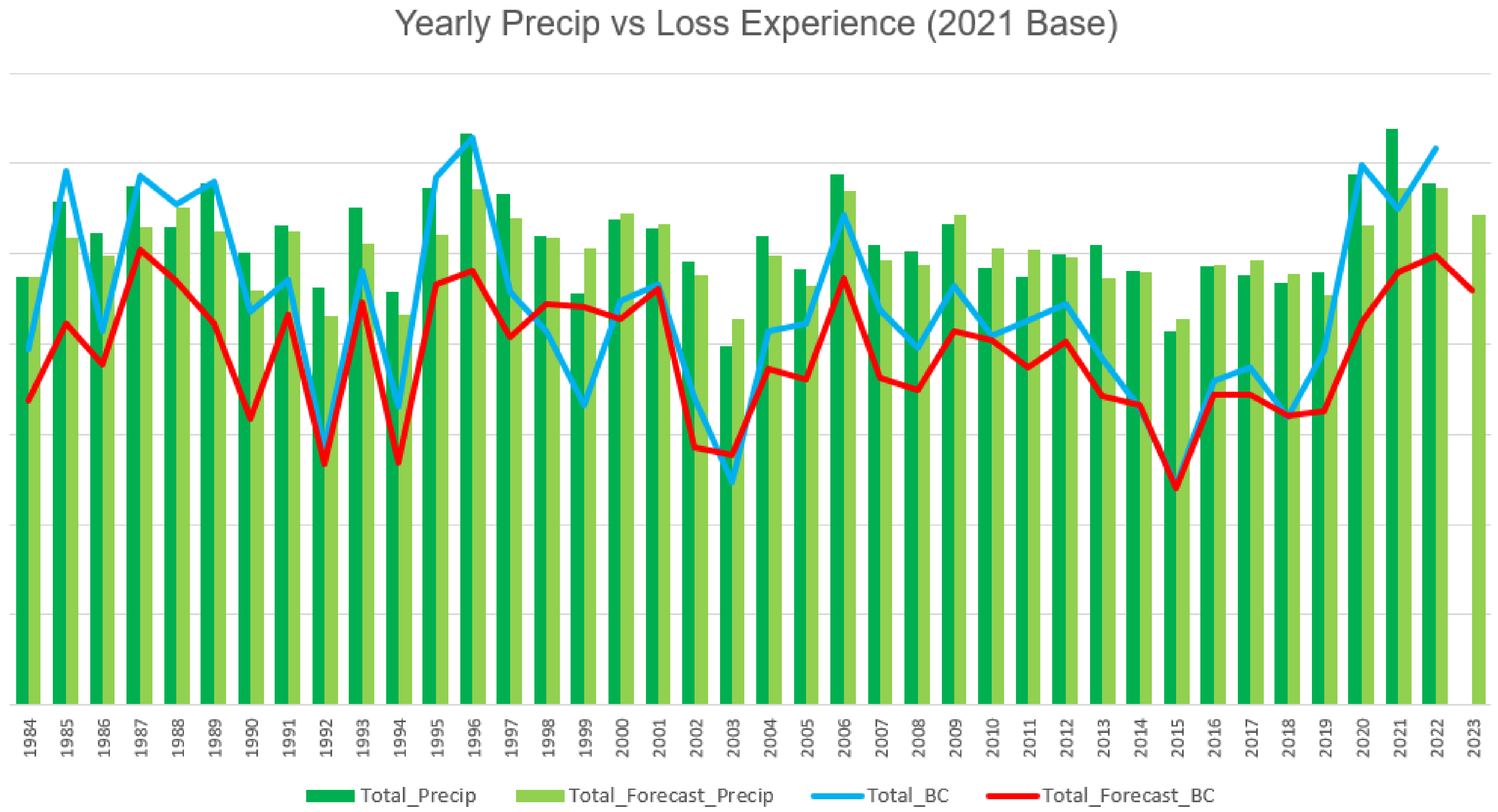


Modelling Results

Overall Book Sensitivity to Yearly Precipitation Experience (2021 Base)

Loss Experience



Precipitation induced volatility on loss experience was calculated to equal **61%** of the associated SAM measure of volatility.

Conclusion

- **Conclusions**
    - Shown that traditional short-term pricing datasets can be linked to open-source highly granular precipitation data
    - Demonstrated that precipitation data is a highly predictive factor when modelling insurance risk
    - Demonstrated the relationship between changes in actual precipitation and frequency and severity
    - Obtained precipitation forecasts that may be used for practical implementations (pricing/proactive risk management)
    - Demonstrated that precipitation forecasts provide similar predictive value
    - Obtained distribution of loss experience given differing years of precipitation experience for proactive risk management.