# U.S. Storm Event Predictability

By Denise Macias

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# Purpose

The purpose of this project will be to determine the predictability of recent storm events in the U.S. through historical data.

# Data

- Source: National Climatic Data Center
- Original dataset:
  - 1,740,597 observations
  - 51 features
  - 70 event types
  - 1950-2022
- Cleaned dataset:
  - 1,740,597 observations
  - 17 features
  - 70 event types
  - 1950-2022



# Data Exploration

- **Target:** Magnitude
- **Focus:** Identify storm events that hold the most promise for a reliable magnitude forecast using the following criteria:
  - 1) Events for which magnitude is tracked
  - 2) Events with the highest event counts
  - 3) Events with the highest casualties

# Data Exploration: Events Identified

#### Thunderstorm Wind

- 484,908 events
- 11,609 injuries; 2,048 deaths; 15 billion in damages

#### Tornado

- 73,987 events
- 97,472 injuries; 12,230 deaths; 7 billion in damages

#### Hail

- 382,234 events
- 1,563 injuries; 30 deaths; 34 billion in damages

#### High Wind

- 79,894 events
- 1,986 injuries; 706 deaths; 16 billion in damages

# Data Exploration: Event Findings

#### • Thunderstorm Wind (1955-2022) → Contender

- Very chaotic from 1955-1996 and not representative of recent data
- Better consistency from 1996-2022
- Regions vary greatly from the national trend
  - % of data per region: South (48%), Midwest (36%), Northeast (11%), West (5%)
  - Midwest and West experience most severe thunderstorm wind events

#### Tornado (1950-2022) → Disqualified

- No records after 2006

#### • Hail (1955-2022) → Contender

- A little chaotic from 1955-2000 and not representative of recent data
- Better consistency from 2000-2022
- Regions do not vary as much from national trend
  - % of data per region: Midwest (44%), South (42%), West (9%), Northeast (4%)
  - Midwest and South experience most severe hail events

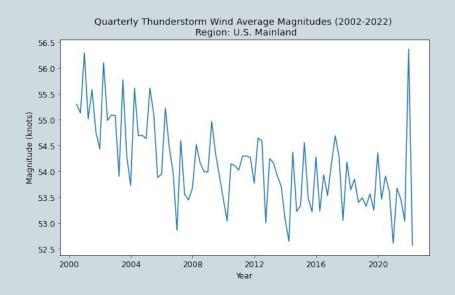
#### High Wind (1996-2022) → Disqualified

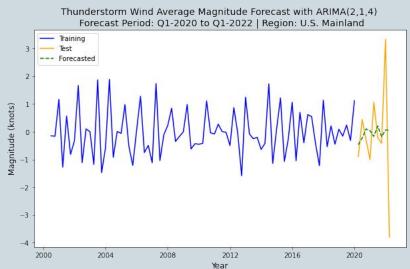
- Chaotic all throughout and no consistency

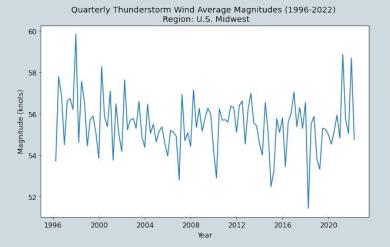


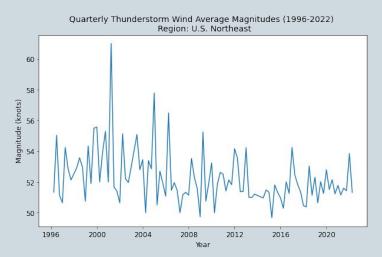
# Thunderstorm Wind

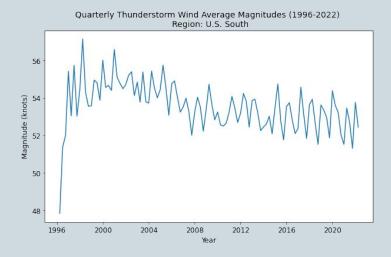
## **ARIMA Model Forecasts**

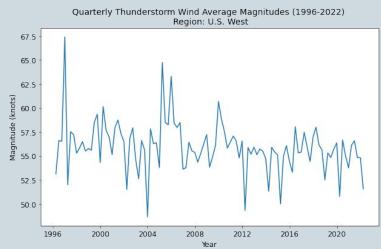


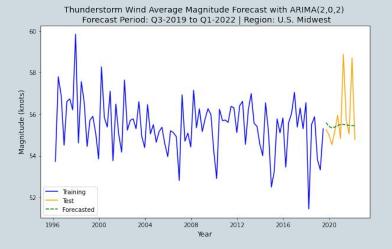


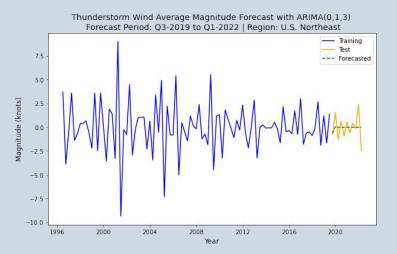


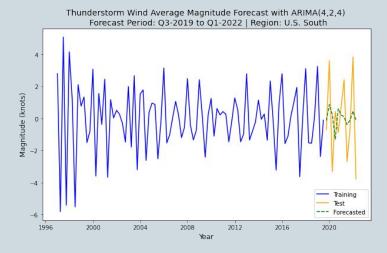


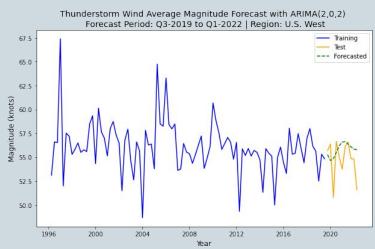












# ARIMA Model Findings

#### U.S. Mainland

- The ARIMA (2,1,4) model explained -2% of the variability
- Did not produce a reliable forecast → RMSE (1.80) > STD (0.98)

#### Midwest

- The ARIMA (2,0,2) model explained -4% of the variability
- Did not produce a reliable forecast → RMSE (1.49) > STD (1.32)

#### South

- The ARIMA (4,2,4) model explained 10% of the variability
- Did not produce a reliable forecast → RMSE (2.37) > STD (2.12)

#### Northeast

- The ARIMA (0,1,3) model explained 4% of the variability
- Produced a reliable forecast→ RMSE (1.28) < STD (1.52)

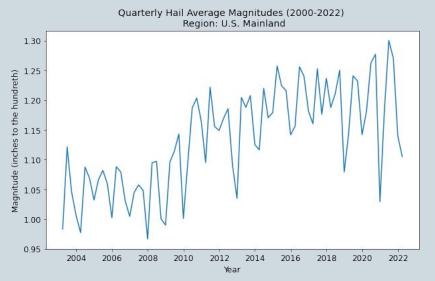
#### West

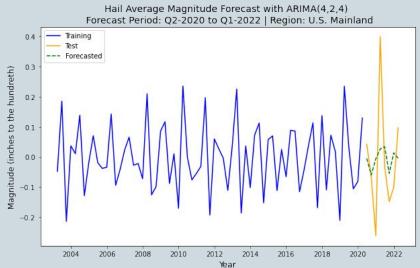
- The ARIMA (2,0,2) model explained -30% of the variability
- Produced a reliable forecast → RMSE (2.16) < STD (2.66)

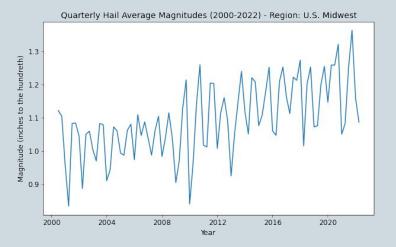
# Hail

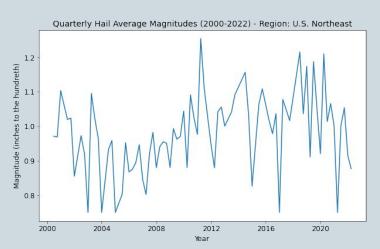


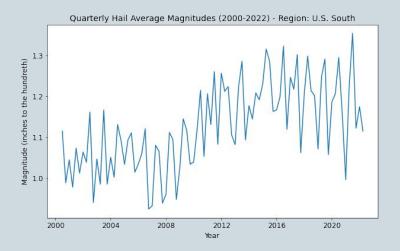
# **ARIMA Model Forecasts**

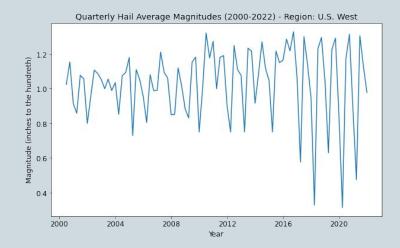


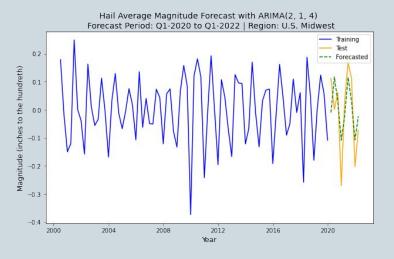


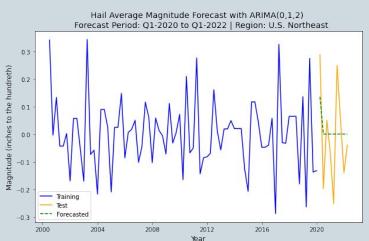


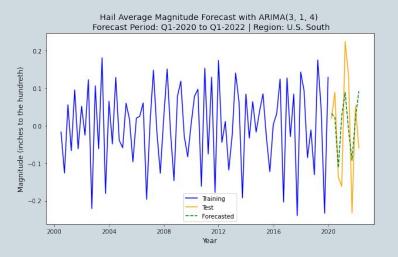


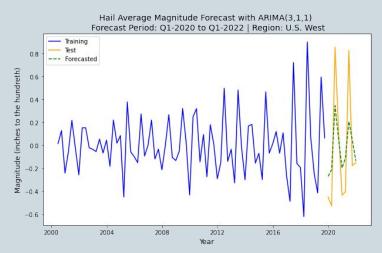












# ARIMA Model Findings

#### U.S. Mainland

- The ARIMA (4,2,4) model was able to explain 12% of the variability
- Did not produce a reliable forecast → RMSE (0.17) > STD (0.12)

#### Midwest

- The ARIMA (2,1,4) model was able to explain 55% of the variability
- Produced a reliable forecast → RMSE (0.09) < STD (0.12)

#### South

- The ARIMA (3,1,4) model was able to explain 31% of the variability
- Did not produce a reliable forecast → RMSE (0.118) > STD (0.114)

#### Northeast

- The ARIMA (0,1,2) model was able to explain 21% of the variability
- Did not produce a reliable forecast → RMSE (0.16) > STD (0.13)

#### West

- The ARIMA (3,1,1) model was able to explain 58% of the variability
- Did not produce a reliable forecast → RMSE (0.33) > STD (0.30)

# Conclusion

- Not very predictable on the regional or national level
- Removing outliers would create biased models that wouldn't necessarily translate into the real world

#### Next Steps:

- Changing the timeframe of the averages from quarterly to monthly
- Introducing exogenous variables
- Exploring other models such as SARIMA
- Exploring additional events



# Thanks!

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