Analyzing Impact of Weather on Commodity Prices

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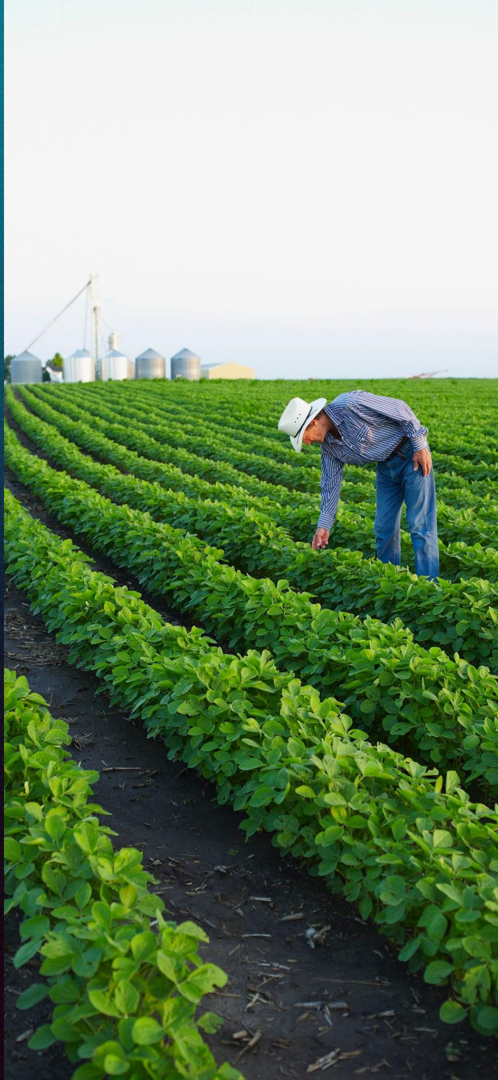
IST 707 - Applied Machine Learning

PRESENTATORS: Aaron Rofe, Nick Rovelli, Sean Madden, Semi Babafemi

Problem and Main Stakeholders

- The Problem
    - We are trying to solve is predicting the price of select common crops, using weather
- Main Stakeholders
    - Farmers
        - Need to adapt to changing climates
    - Governments
        - Efficiently use resources
    - Insurance companies
        - Better understanding of how to protect clients
    - Commodity traders and investment firms
        - Use data backed investment decisions
    - Consumers
        - Able to make more informed purchases
    - Supply Chain Management Companies
        - Accurately placed resources



Envisioned Solution

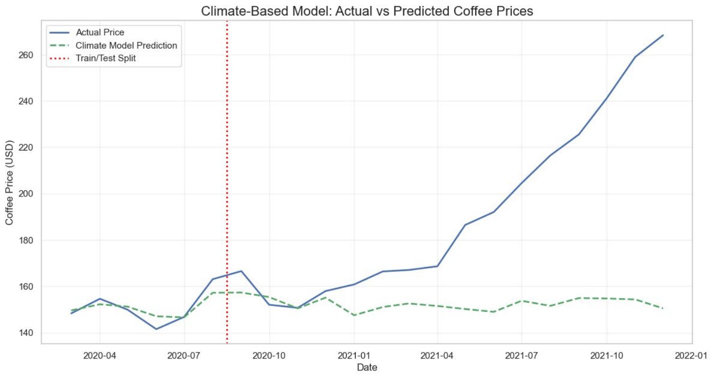
- Predict crop prices using weather and climate data
- Train Random Forest model on 6 years of monthly data
- Add Markovian Momentum Model (MMM) to detect shocks
- MMM monitors price spikes, volatility, and surprise errors
- Blend base model + MMM for more reliable forecasts
- Adapts to real-world disruptions like COVID or supply chain issues

Data

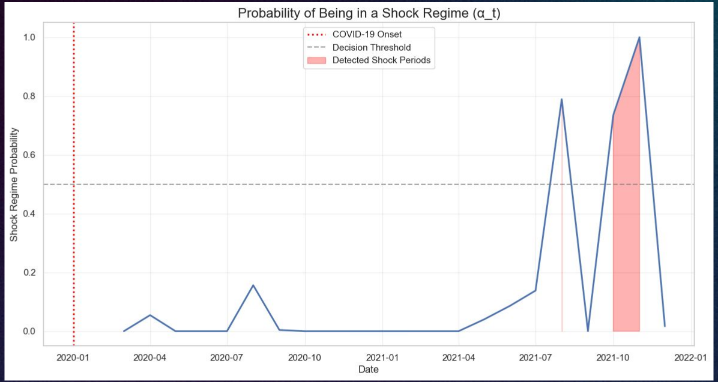
- Commodity pricing data came from the Federal Reserve Bank of St. Louis. Contains monthly pricing data on 7 selected common commodities such as wheat, corn, coffee, and cotton.
- Weather data came from the ERA5-Land dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF). Contains granular weather measurements such as precipitation, temperature and humidity.
- For each of the seven commodities, we linked the weather data to the region with the highest level of global production.

Caleb Lohner, Utah #241

Initial Results



Model trained using climate variables from pre-COVID period only



Meta-Model trained that detects when the market enters a shock-regime based on price momentum, shipping indicators, and residuals from the base model

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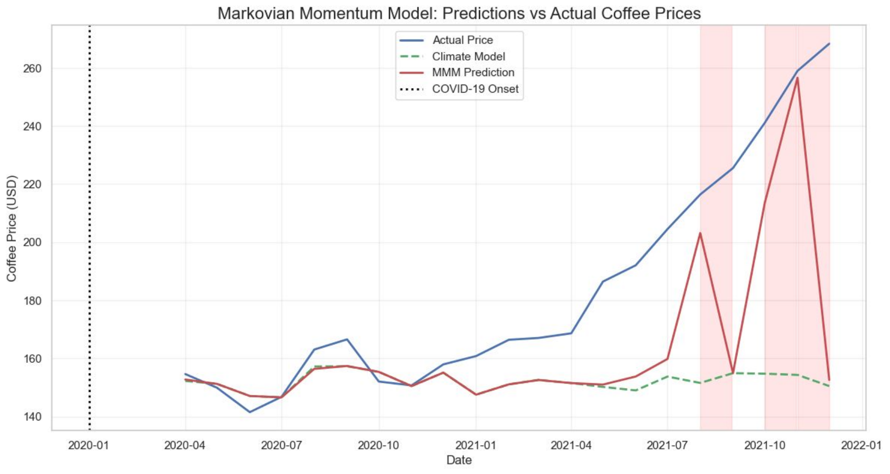
Initial Results

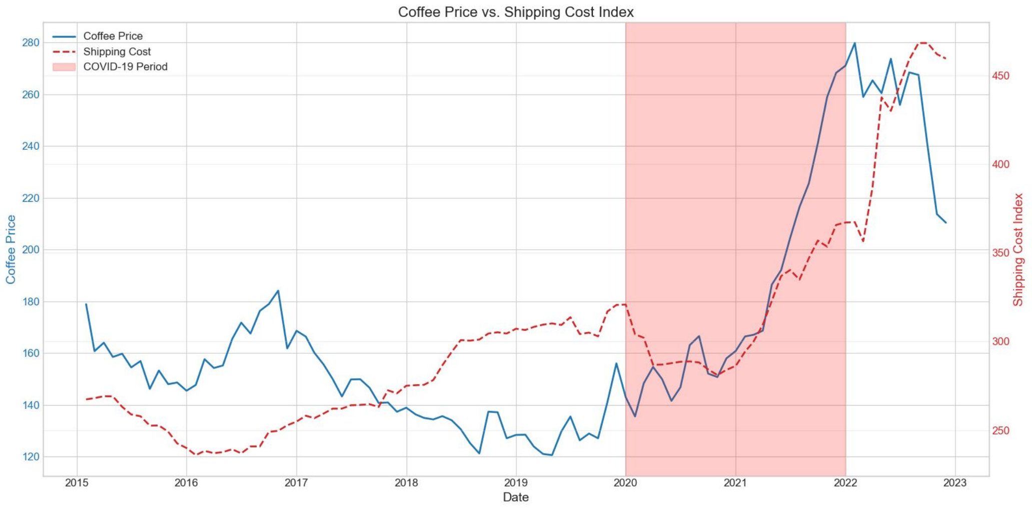


Markovian Momentum Model that blends the climate model with a momentum-based model, weighted by the shock probability

Challenges

Traditional climate-based forecasting models tend to fail under extreme conditions—such as the COVID-19 pandemic

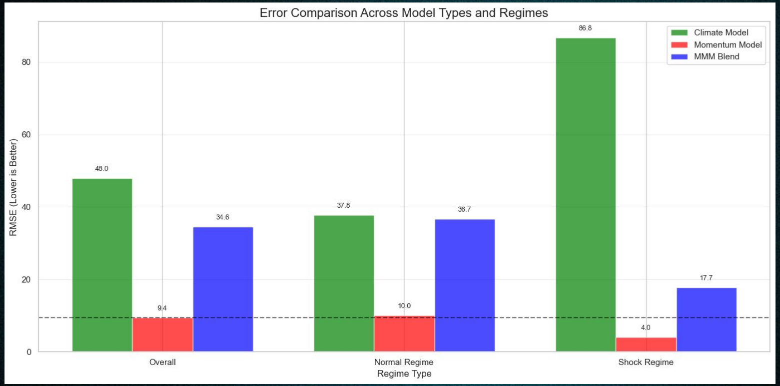
To improve the model's ability to recognize when climate-driven pricing breaks down—especially during periods of global disruption—we added a bootstrapped approach that adds external economic signals to our dataset.



- Global shipping costs (FRED: Deep Sea Freight Index)
- Price momentum and acceleration
- Rolling price volatility and changes

Why Moving to Log Returns Makes Sense for This Project

Plan & Goals



More Stability, Less Noise

- Raw commodity prices are volatile, with large random jumps—even during calm periods.
- **Log returns** (i.e., the change in the logarithm of prices) naturally smooth out the scale of extreme movements.
- This makes it easier for the model to **detect true patterns** driven by climate or shocks, without getting overwhelmed by random price noise.