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Objective

Develop a quantitative model that predicts weekly price movements of major commodities such as Brent Crude, Henry Hub Natural Gas, ERCOT Power, RBOB Gasoline, Copper, and Corn by integrating satellite-based weather anomalies with EIA supply-demand fundamentals. The goal is to identify how extreme weather events influence production, storage, demand, and consumption, and translate those disruptions into measurable market returns using advanced machine-learning and statistical techniques.

Core Concept

Construct a multi-commodity Supply-Stress Index (SSI) that quantifies each commodity's sensitivity to extreme weather across key producing and consuming regions. The SSI will serve as the central explanatory variable for forecasting price direction and magnitude.

Data Sources

- NASA POWER API – Weather data (temperature, precipitation, radiation, wind speed)
- EIA Open Data API – Supply-demand fundamentals (stocks, storage, utilization)
- Yahoo Finance / Quandl – Market data for front-month futures
- NOAA / VisualCrossing / CPC / WeatherAPI – Validation and event tracking
- **Might Implement:**
    - ERCOT temperature, load, and power generation data for regional validation
    - Political and macroeconomic news feeds for contextual risk factors

Features

- Weather anomaly z-scores vs historical baseline
- Rolling 7, 14, and 30-day averages for temperature and precipitation
- Degree-days for heating/cooling intensity
- Weekly EIA deltas (inventory, production, utilization)
- Interaction features (e.g., Weather Anomaly × Power Demand)
- Supply-Stress Index: Principal Component Analysis (PCA) combining weather and EIA metrics
- Retrospective analysis of past weather anomalies and their effect for demand

Modeling Approach

- **Models:** Ridge Regression, Random Forest, XGBoost, and optional LSTM for temporal dependencies
- **Targets:** Next-week return direction and magnitude
- **Validation:** Rolling window cross-validation with walk-forward retraining

Backtesting Framework

- Convert forecasts into long/short trading signals
- Include transaction costs and position limits
- Evaluate with Sharpe ratio, drawdown, hit ratio, and turnover
- Stress test performance across major market events:
  - 2020 COVID crash
  - 2021 Texas freeze
  - 2022 Ukraine conflict

Visualization & Deliverables

- Time-series dashboard of weather anomalies vs price or power movements
- Geographic map of producing regions colored by Supply-Stress Index
- Performance dashboard with equity curves and key metrics

Flask Web Application

A Flask-based web dashboard will make the model's results interactive and user-friendly.

- **Features include:**
  - Real-time forecasts and SSI values for each commodity or power hub
  - Comparison of predicted vs actual weekly returns
  - Weather anomaly maps for ERCOT and major commodity-producing regions
  - Buttons to trigger model retraining or run scenario simulations
- **Tech setup:**
  - Backend: Flask REST API serving model predictions
  - Frontend: React + Plotly/Dash for visualization

    - Deployment: AWS cloud access or Docker for containerization

Expected Outcomes

- Quantitative link between weather variability and commodity/power price risk
- Multi-commodity Supply-Stress Index for early warning of disruptions
- Validated backtesting results with trading and operational performance metrics
- Scalable, web-based forecasting and visualization platform

Tools & Tech Stack

- **Programming:** Python (Pandas, NumPy, Scikit-learn, XGBoost, Plotly, Requests)
- **APIs:** NASA POWER, EIA Open Data, Yahoo Finance, ERCOT Data Portal
- **Environment:** Jupyter, GitHub
- **Web:** Flask + Plotly Dash for interactive dashboard