MACHINE LEARNING ESTIMATION OF THE FUTURE CLIMATE RISK AMPLIFICATION OF FOOD SECURITY-INDUCED CONFLICT

Group 36

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CLIENT BREIF

- CSIRO, founded in 1916, conducts scientific research for national benefit and innovation.

- Some of its key contributions in this area include:
    - Climate Modeling
    - Carbon Accounting
    - Renewable Energy
    - Climate Policy Advice

PROBLEM STATEMENT

THE UNIVERSITY OF MELBOURNE

CSIRO

- Climate change and climate variability impact the food security across the globe
- It affects agricultural production, commodity prices, and trade between producing and consuming nations for the commodities that are key to food security

Aim is to visualise and model the **chain of influence between food security commodities (wheat, soy, rice) and climate teleconnections (Arctic Oscillation, El Nino Southern (ENSO) Oscillation, Southern Annual Mode etc.)**

DATA SOURCES

The Data was provided by the client and was received in the form of a zipped folder. Below is the brief summary of the data received.

- **World Bank Monthly Commodities Price:**
    - It contains monthly prices for various commodities
    - Source: https://www.worldbank.org/en/research/commodity-markets
    - Format: CSV
- **Climate Teleconnection Files:**
    - JRA55: (Japanese Reanalysis of the Atmosphere since 1955)
    - NNR1: (NCEP v1 Reanalysis)
    - Format: CSV

DATA SOURCES

The climate teleconnection files contains the information about various teleconnections stated below:

- AO.csv - Arctic Oscillation
- MEI.csv - Multivariate ENSO Index
- PSA.csv - Pacific South American
- PNA.csv - Pacific North American
- IOD.csv - Indian Ocean Dipole
- NHTELE.csv - Northern Hemisphere related teleconnections
- SAM.csv - Southern Annual Mode

OUR APPROACH

- Our approach is to examine ENSO and additional climate variables as external factors related to climate change and employ the **Auto-Regressive (AR) model** to explore the connection between **climate change and agricultural price fluctuations.**

- This project will focus on the reanalysis of coconut oil prices and build an AR model for other agriculture commodities' log return prediction.

- With this, our aim is to address the challenge of forecasting the effects of climate change on food security.

TIME-SERIES ANALYSIS

- A statistical technique for analyzing and modelling data that varies over time.

- **Data Stationarity:** We are using log returns instead of the actual prices. It gives us more information about the trend

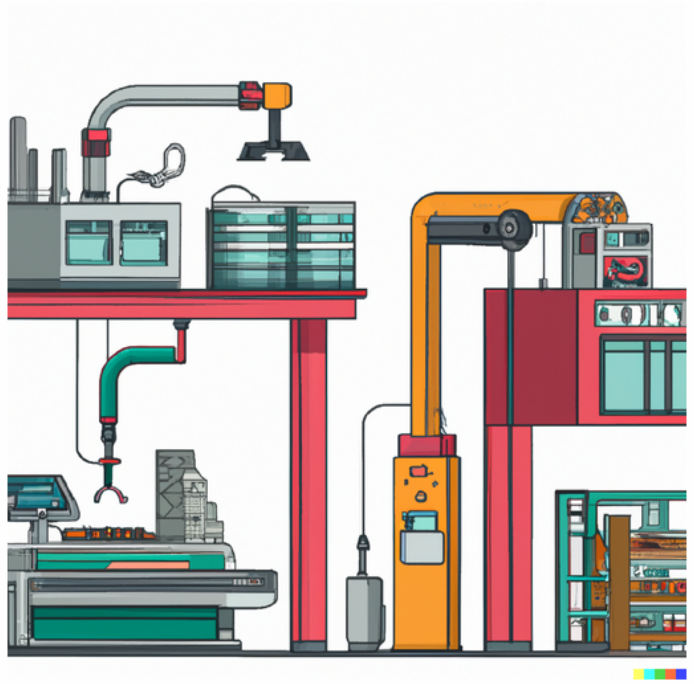
- Different types of time series models:
    - autoregressive (AR) models
    - moving average (MA) models
    - autoregressive integrated moving average (ARIMA)

HOW CLIMATE CHANGE IMPACT ON FOOD SECURITY

- Unfavorable for crop growth habit
- Reduced nutritional value
- Increased reliance on pesticides
- Potential impact on worldwide food security

FOOD SECURITY

Population



Production

Price

Trade

Source: https://openai.com/product/dall-e-2

WHY PRICE?

In developing a sustainable environment and society, agriculture also needs to remain sustainable. But, climate variability can have an impact on agricultural production and supply.

- **Sustainable Agriculture**
- **Producer decision**
- **Multidimensional research**
- **Direct impact on consumers**

ENSO-THE PHENOMENON

- **El Niño-Southern Oscillation (ENSO)** is a natural climate pattern that affects weather around the world, especially in the Pacific region.
- It involves the interaction between the ocean and the atmosphere
- It has two main phases:
  - El Niño (warmer than average sea surface temperatures)
  - La Niña (cooler than average sea surface temperatures)
- It affects global weather patterns, including droughts, floods, and changes in temperature and precipitation.

The phases of ENSO have heterogeneous impacts on rainfall, temperature, and potential economic activity.

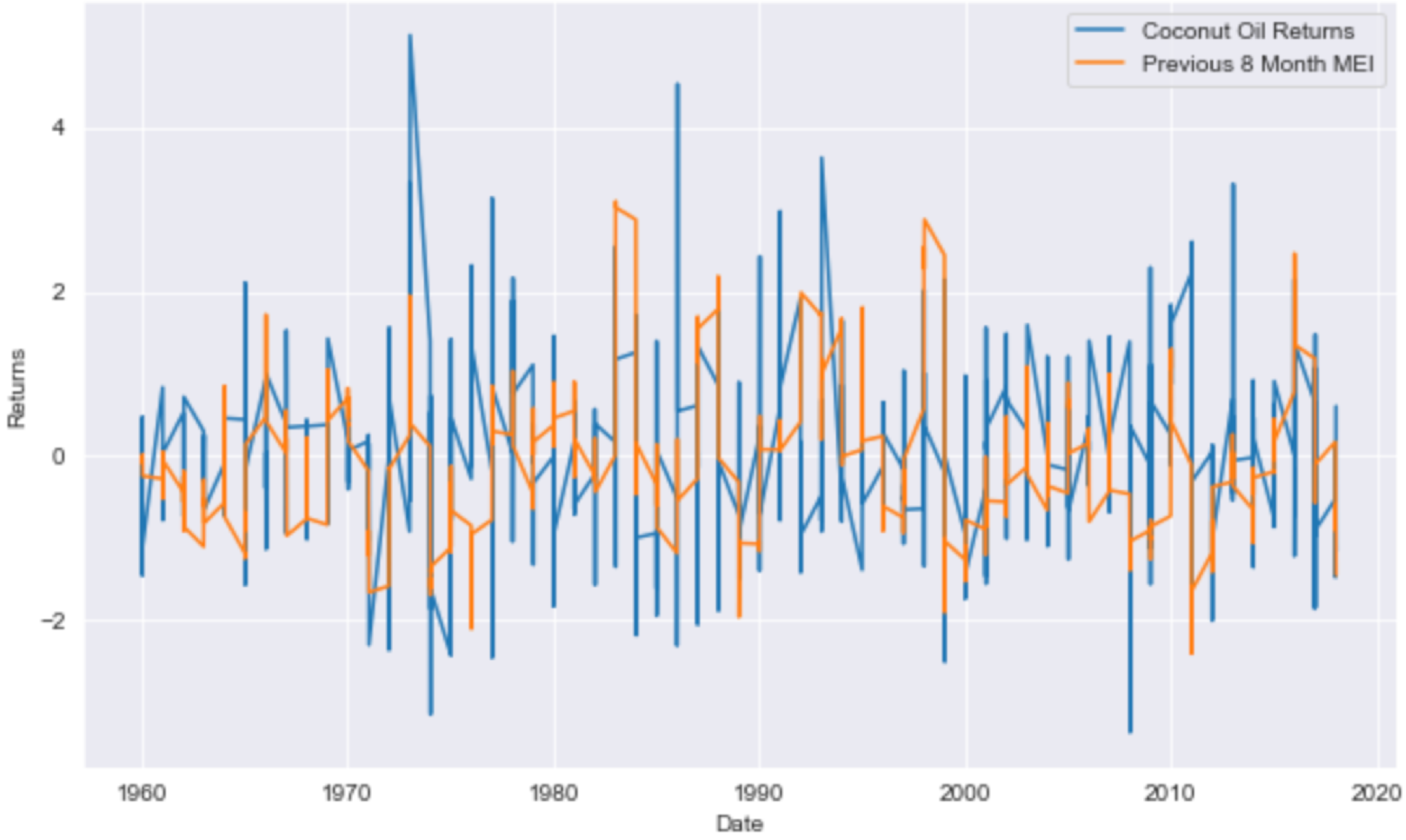
ENSO OBSERVATIONS

- We can calculate the phase and magnitude of ENSO using indices that are derived from sea surface temperature measurements in the equatorial Pacific Ocean.
- For our purposes, we explore the **Niño4 index and GCM-Niño4 index.**
- For both the indexes
  - positive values indicate warmer than average conditions (El Niño)
  - negative values indicate cooler than average conditions (La Niña) in the tropical Pacific.

We will use the GCM-Niño4 index in our study.
It is a standardized index that ranges between -1 and 1

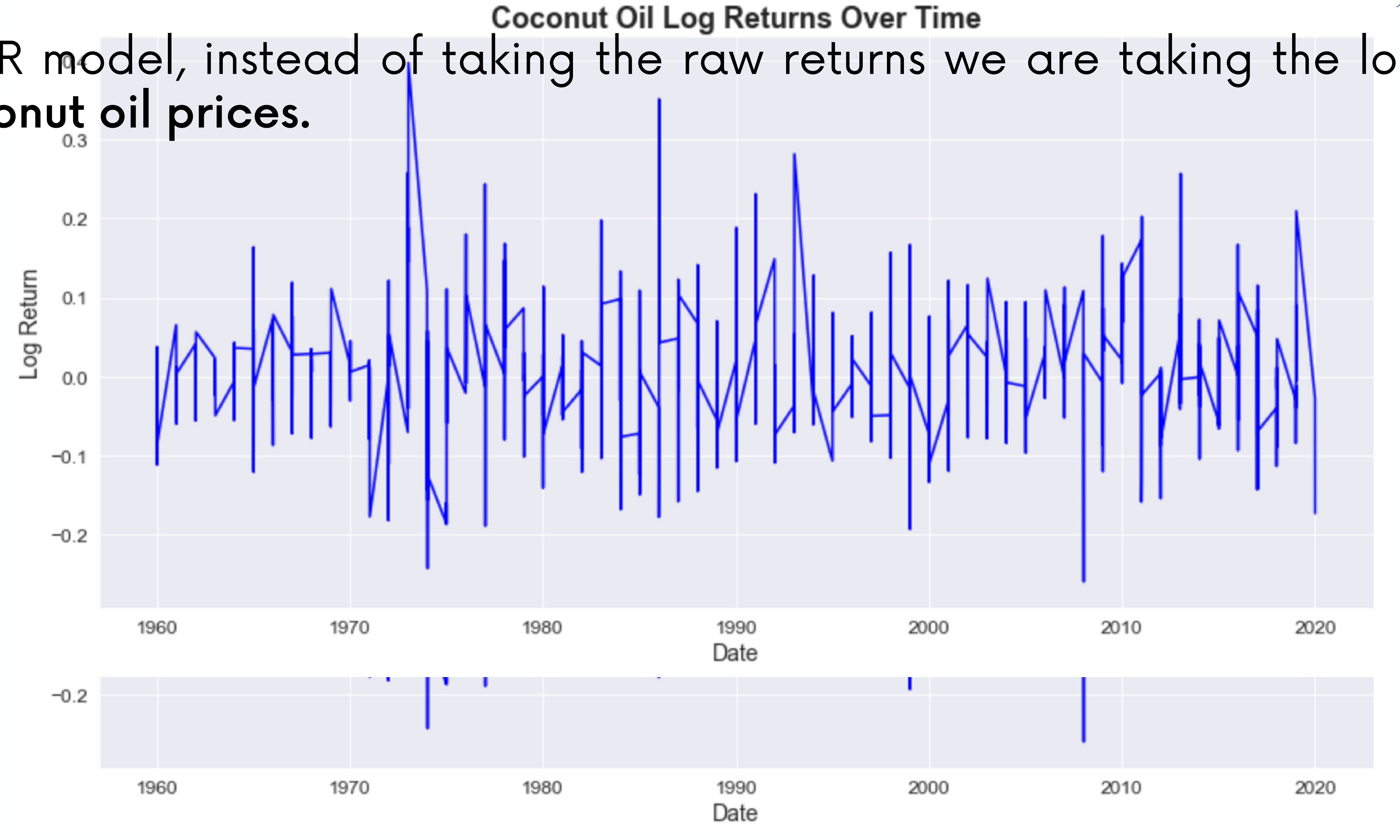
ENSO & VEGETABLE OILS

- As the first step of the project, we went through the relationship between ENSO factors and Coconut-Oil (A study conducted by our host)



LOG-RETURNS

- In our AR model, instead of taking the raw returns we are taking the log returns of the **coconut oil prices.**



Average log-return, : 0.0011

COMMODITY FORECASTING

$$p(t) = a^{pp} + \sum_{l=1}^{11} a_l^{pp} D_l(t) + \sum_{k \in I^{pp}} b_k^{pp} p(t-k) + \sum_{k \in I^{pE}} b_k^{pE} E(t-k)$$

- The real commodity log returns are calculated using the formula above
- This formula takes into account the factor of inflation and ENSO indexes

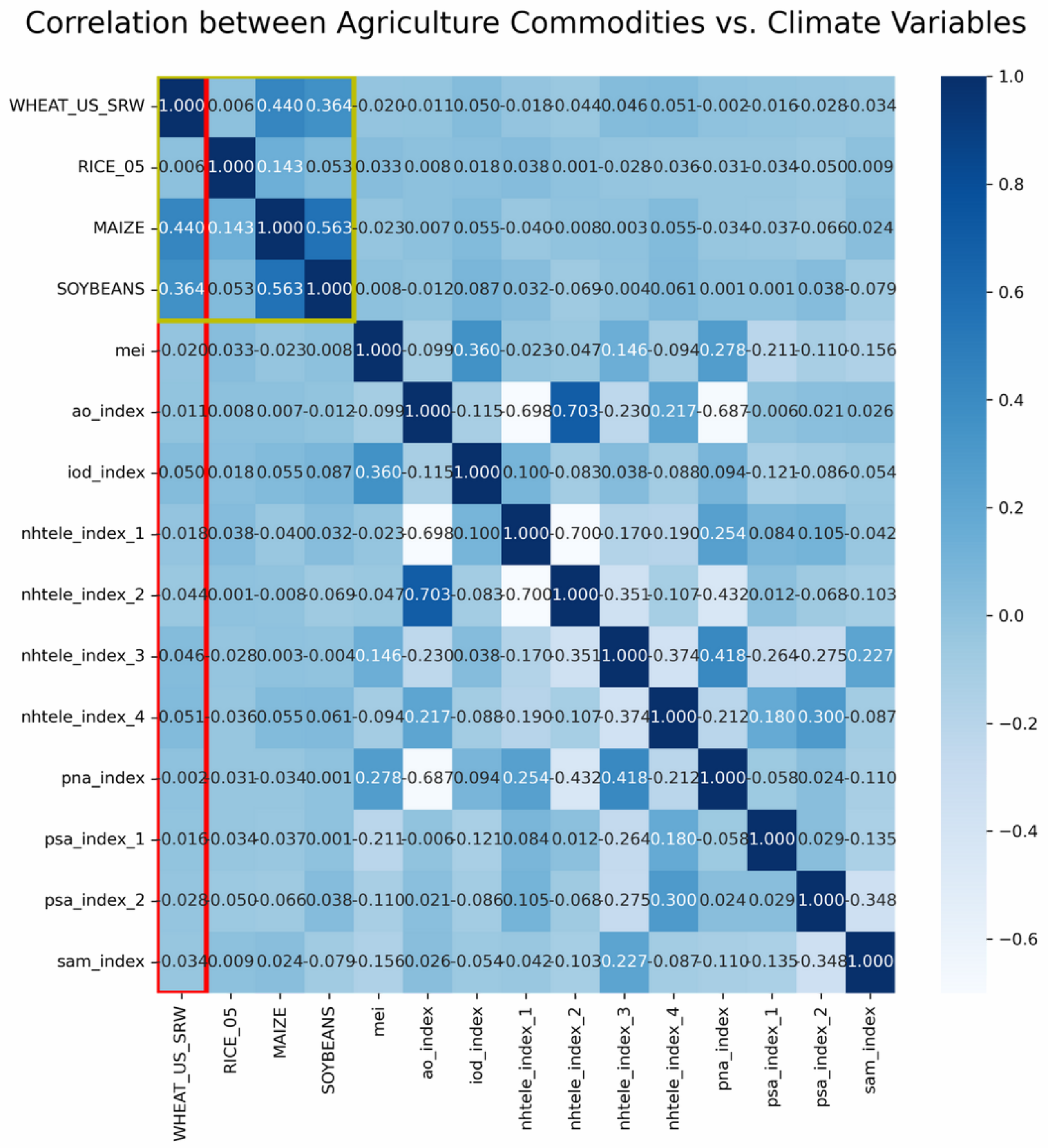
$p(t) = (1+i(t)) \times (1+\widetilde{p}(t)) - 1$	**real commodity log returns**
$\widetilde{p}(t) = \log(P(t)/P(t-1))$	**nominal rates**
$i(t) = \log(C(t)/C(t-1))$	**monthlty inflation rate**

- We will check the models for **serial correlation and heteroskedasticity**

WHEAT PRICE INFERENCE

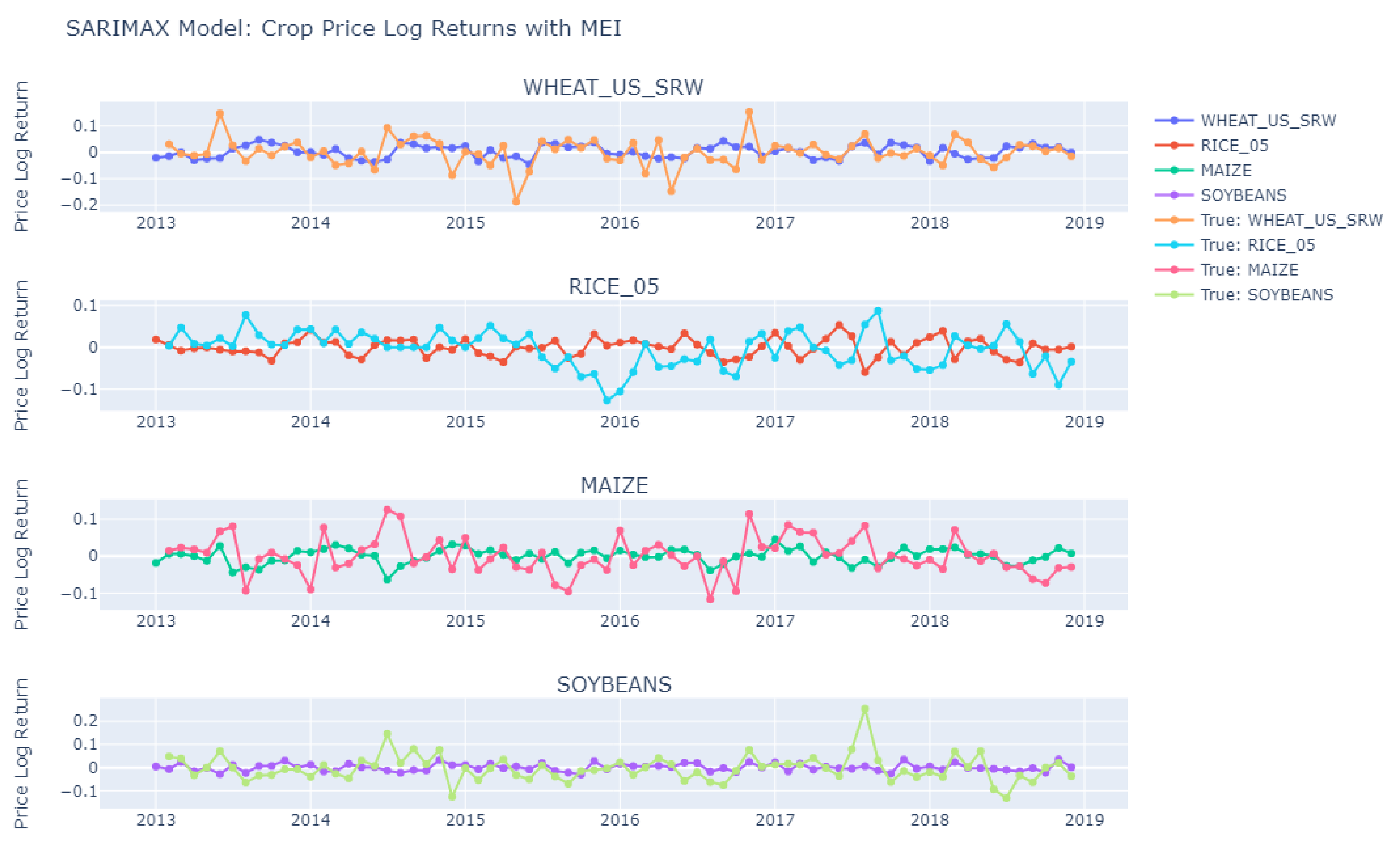
- Prior research indicates a negative linear correlation between MEI and coconut oil prices.
- Question: Is this relationship applicable to all agricultural commodities?
- Develop AR models focused on WHEAT prices and address the subsequent questions:
  - Does ENSO (MEI) significantly influence WHEAT price log return?
  - Can incorporating additional climate features enhance model performance?
- Example of WHEAT_US_SRW, RICE_05, MAIZE and SOYBEANS price log return predictions.

VARIABLE INSIGHTS



- Weak correlations were identified between the log returns of commodity prices and climate variables.
- There may be strong interconnections among different climate variables.
- The possibility of complex, non-linear relationships between climate variables should be considered.

AR WITH MEI FACTOR

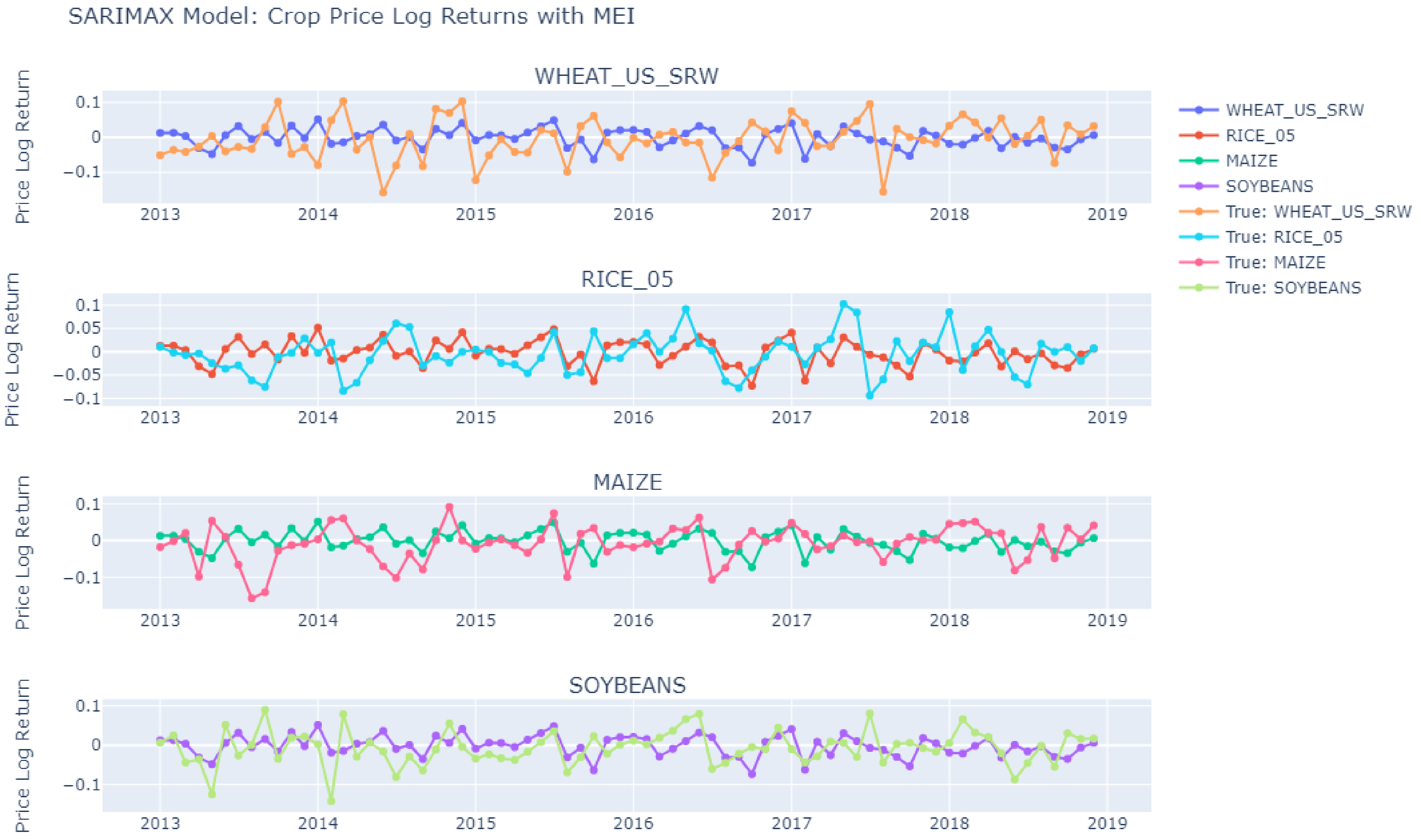


SARIMAX params: order=(6,1,0) and seasonal_order=(6,1,2,12))

SARIMAX WHEAT_US_SRW: BIC = -1124.849, RMAE = 0.220
SARIMAX RICE_05 : BIC = -1307.106, RMAE = 0.235
SARIMAX MAIZE : BIC = -1248.832, RMAE = 0.232
SARIMAX SOYBEANS : BIC = -1330.029, RMAE = 0.227

- The plot reveals a consistent trend across all four SARIMAX models.
- Incorporating ENSO may have a positive impact on predicting log returns for other agricultural commodities.
- However, the effect is not substantial due to the weak correlation observed earlier.
- All models exhibit RMSE values of approximately 0.2 and BIC scores around -1200, suggesting that AR models may be optimal when combined with ENSO.

AR WITH ALL FACTORS



- Hyperparameter settings significantly influence model inference capabilities.
- All SARIMAX models produce comparable RMSE values of approximately 0.2, with BIC scores increasing by around 300.
- Lower BIC scores indicate better model performance; thus, the previous model offers improved inference compared to others.
- Despite this, the current model captures trends more effectively and aligns more closely with the true log return when compared to previous models. This suggests a trade-off between BIC scores and trend alignment in model selection.

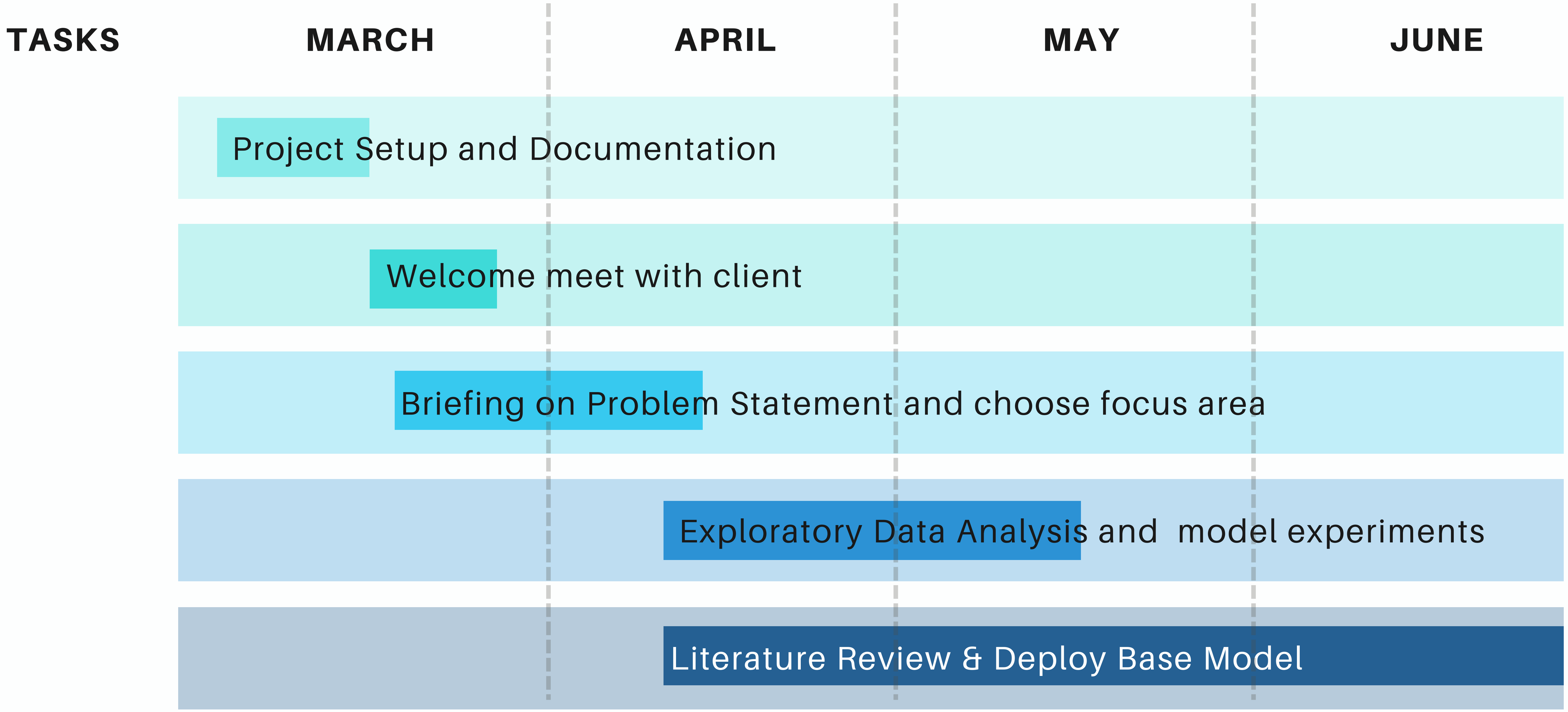
SARIMAX params for WHEAT_US_SRW: order=(8,2,2) and seasonal_order=(8,1,1,12))
SARIMAX params for RICE_05 : order=(8,1,3) and seasonal_order=(8,1,1,12))
SARIMAX params for MAIZE : order=(8,2,5) and seasonal_order=(8,1,1,12))
SARIMAX params for SOYBEANS : order=(8,1,4) and seasonal_order=(8,2,1,12))

SARIMAX WHEAT_US_SRW: BIC = -731.767, RMAE = 0.237
SARIMAX RICE_05 : BIC = -917.000, RMAE = 0.24
SARIMAX MAIZE : BIC = -841.786, RMAE = 0.255
SARIMAX SOYBEANS : BIC = -866.585, RMAE = 0.272

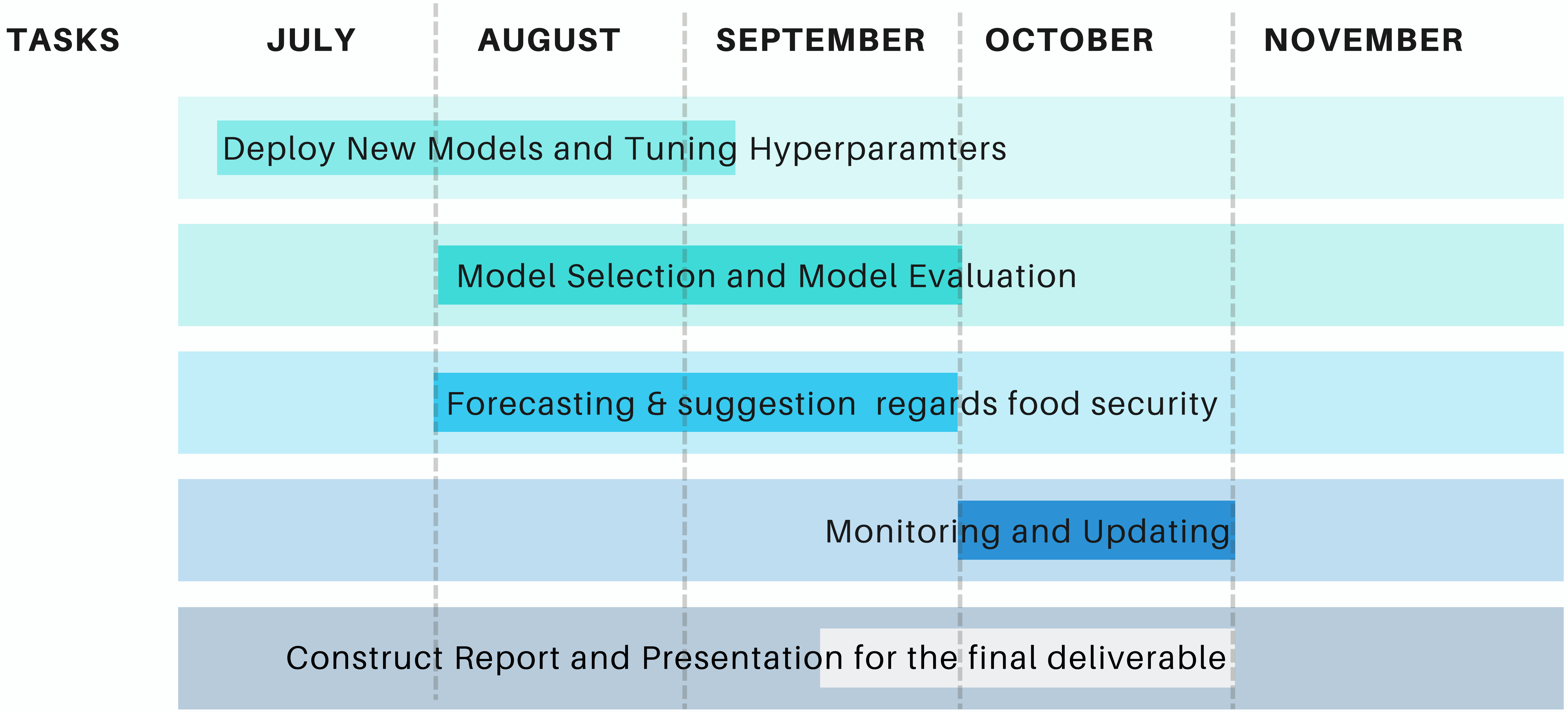
RESULTS TILL NOW

- Incorporating MEI alone does not significantly improve predictive performance.
- Constructing a comprehensive model using all factors leads to enhanced model capabilities.
- Although both models display similar RMSE values, the comprehensive model reveals a more precise seasonal pattern that aligns better with the true value.
- Possible Explanations:
  - Instead of exploring the price returns and teleconnections of the same time period, there might be a connection between the lagged values in past
  - A weak or nonlinear relationship may exist between wheat log return predictions and climate factors.
- **Considering these factors, the current AR model serves as an acceptable baseline model.**

PROJECT TIMELINE



PROJECT TIMELINE



NEXT STAGE

- Focus on the heteroskedasticity of our models and explore the Bayesian Information Criterion to select the most appropriate model
- Compare the findings that we got from **NNR1** with that of **JRA-55** teleconnections data

KEY CHALLENGES

- Discover other external climate factors that may possibly affect the price
- Tuning hyperparameters of the AR model for all the food security commodities

Q&A