Presented by Group 36

FUTURE CLIMATE RISK AMPLIFICATION OF FOOD SECURITY-INDUCED CONFLICT

MACHINE LEARNING ESTIMATION

University of Melbourne

Our Team

JIAQI HU

- Data Analyst

JIHANG YU

- Data Analyst

RITWIK GIRI

- Data Analyst
- Project Coordinator
- Meeting Facilitator
- Scribe

SUNCHUANGYU HUANG

- Data Analyst
- Documentation Specialist
- Meeting Organizer

XIANGYI HE

- Data Analyst
- Meeting Organizer
- Scribe

DR. VASSILI KITSIOS

Senior Research Scientist
CSIRO

DR. FENG LIU

Project Supervisor
University of Melbourne

MARIKA BENETTI-HILLE

Industry Consultant
University of Melbourne

THE UNIVERSITY OF MELBOURNE

Client Brief

- 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

Climate Changes

Victoria has also experienced an overall increase in the frequency of unusually hot days (Figure 7).

Extreme heat events already cost the Victorian economy on average $87 million a year, and this cost is projected to rise as heatwave events become more frequent (Natural Capital Economics, 2018)

Unusually hot weather

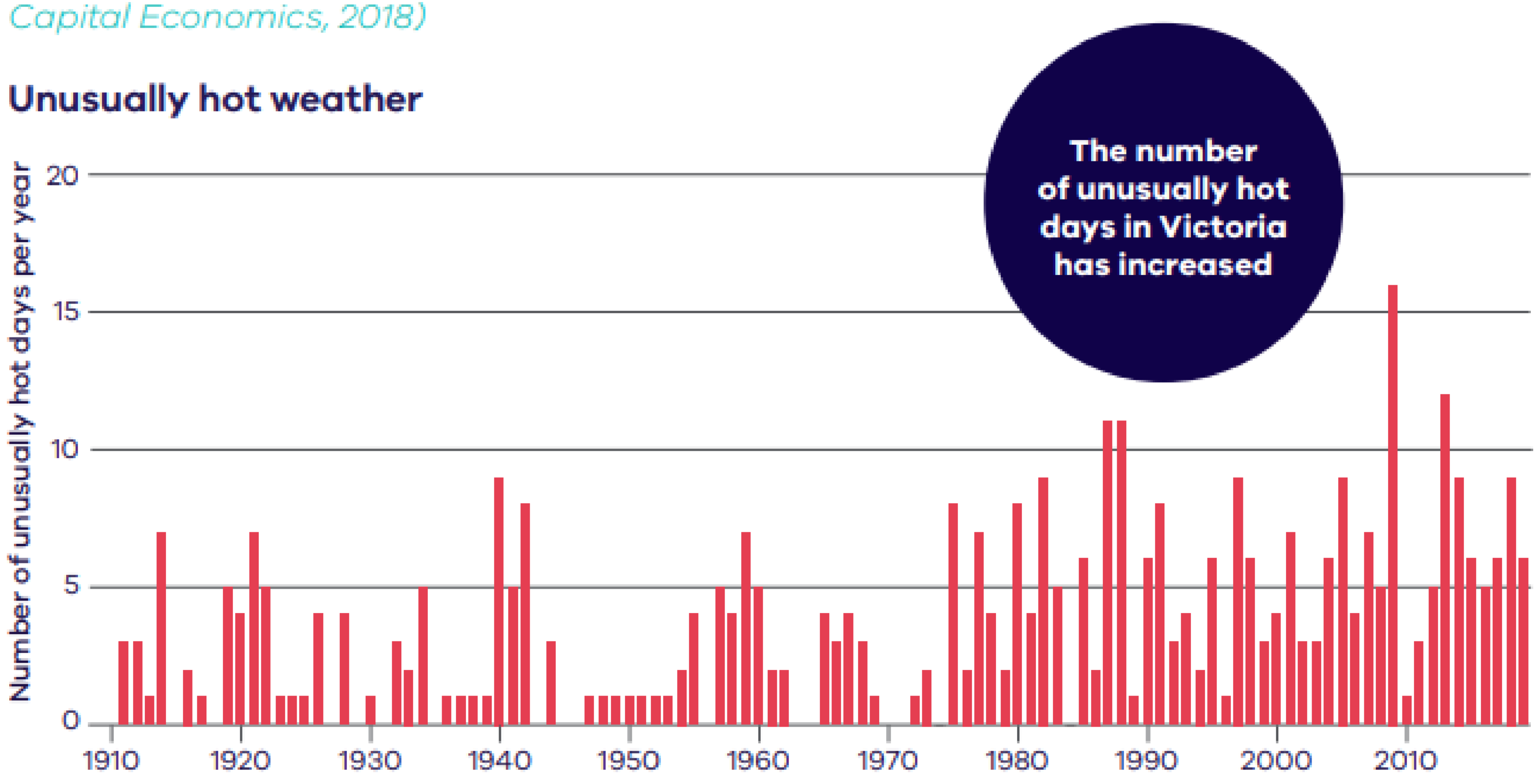


Figure 7: Days per year when Victorian average temperature is 'unusually hot'. Unusually hot days are those above the 99th percentile of each month from the years 1910 to April 2019 (BoM, 2019).

- The climate has changed significantly on a global scale
- An increase in the number of extreme weather events, as well as global warming and rising sea levels.
- In 2020, Europe saw frequent major storms and an increase in heat waves and wildfires.

THE UNIVERSITY OF MELBOURNE

The Problem

Climate change has the potential to destabilize global food security severely

It affects agricultural production, commodity prices, and trade between producing and consuming nations for the commodities that are key to food security

By 2023, **345 million people could face starvation** due to climate-induced land degradation

Regional drought and heatwaves have caused **20–50 per cent crop harvest losses**

THE UNIVERSITY OF MELBOURNE

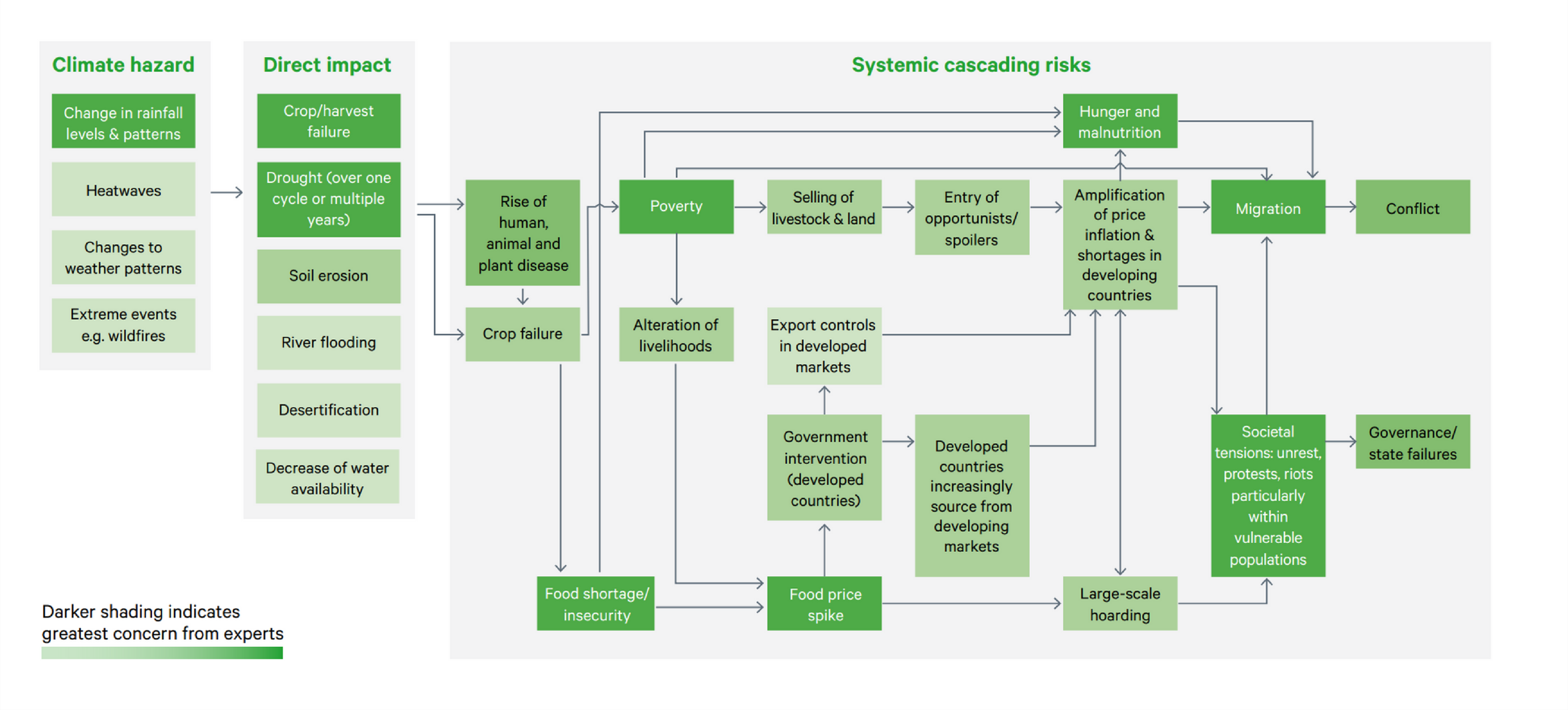
Food Insecurity across the Globe

The Global Food Crisis:

The 2007-08 global food crisis, driven by grain shortages and drought, led to a doubling of global food prices, export bans and food insecurity for importers. It led to mass protests in countries like Egypt and Indonesia.

Image Source: Food Tank

Indirect Impact



As shown in the figure, climate change doesn't directly impact commodity prices. There are various factors which are impacted by the climate change, which in turn **affect the supply-demand chain.**

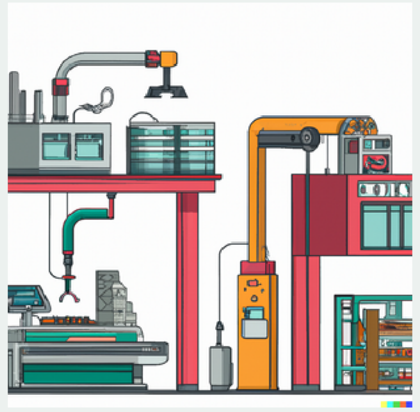
Climate Change Impact on food security

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

All these factors affect the commodity price market. It impacts:

- Sustainable Agriculture
- Producer/Consumer Decisions

Population



Production

Price

Trade

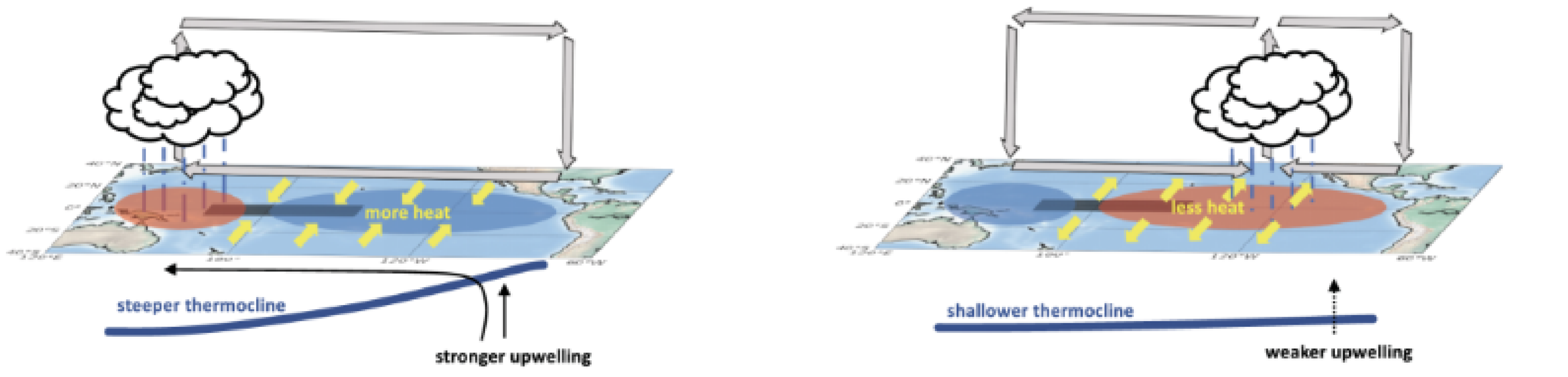
THE UNIVERSITY OF MELBOURNE

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

Objective

Examining the impact of climate variability on the prices of commodities is key to food security

ENSO Influencing Global Agriculture



(a) La Niña Phase (b) El Niño Phase

Two ENSO phases:

- **El Niño** (warmer than average sea surface temperatures in Eastern Pacific)
- **La Niña** (cooler than average sea surface temperatures in Eastern Pacific)

ENSO Influencing Global Agriculture

01.

ENSO: largest mode of climate variability

It has a direct and <u>profound</u> impact on our lives. ENSO events can disrupt weather patterns, leading to droughts, floods, and other extreme weather events.

02.

These disruptions, in turn, **ripple through various sectors**, from agriculture to economics, affecting food security, commodity prices, and even global supply chains.

03.

Understanding the impact of ENSO's influence on agriculture, we can better prepare for its effects, develop mitigation strategies, and ensure food stability in a changing climate.

Similar work

- Dr Vassili’s paper on forecasting prices for coconut oil, palm oil and soybean oil
- ENSO is designed as an exogenous factor in the research
- Log-returns of prices are calculated and used in modelling
- **Why log-returns?**

THE UNIVERSITY OF MELBOURNE

AutoRegressive (AR) Model

an Insightful Tool

The AR model is a fundamental tool in time series analysis

Captures the relationship between a variable and its past values

Widely used in finance, economics, and various fields for forecasting

Factors Considered

Main Factor:

- Endogenous: Commodity price log return values
- Exogenous: Climatic teleconnections (ENSO, SAM, AO)

Other factor:

- Seasonality in log return values
- Economics effects measured by Consumer Price Index (CPI)

python™

statsmodels

matplotlib

Customised AR model

THE UNIVERSITY OF MELBOURNE

One-Step-Ahead Forecasting

Adaptive modelling technique: accounts for the relationship between climate variability and commodity prices may change over time.

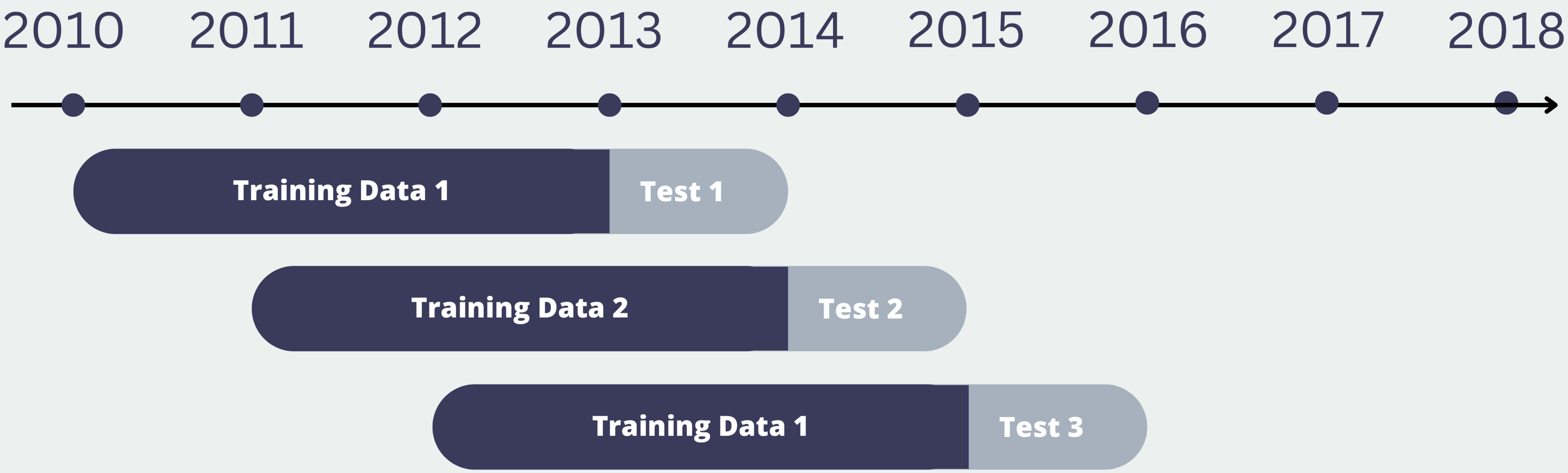
Initialization: Start with the past 60 months (5 years) of data to train an ARIMA model.

Loop for Forecasting: Within a loop, update the ARIMA model using the latest 60 months of data to predict the next month's commodity price.

THE UNIVERSITY OF MELBOURNE

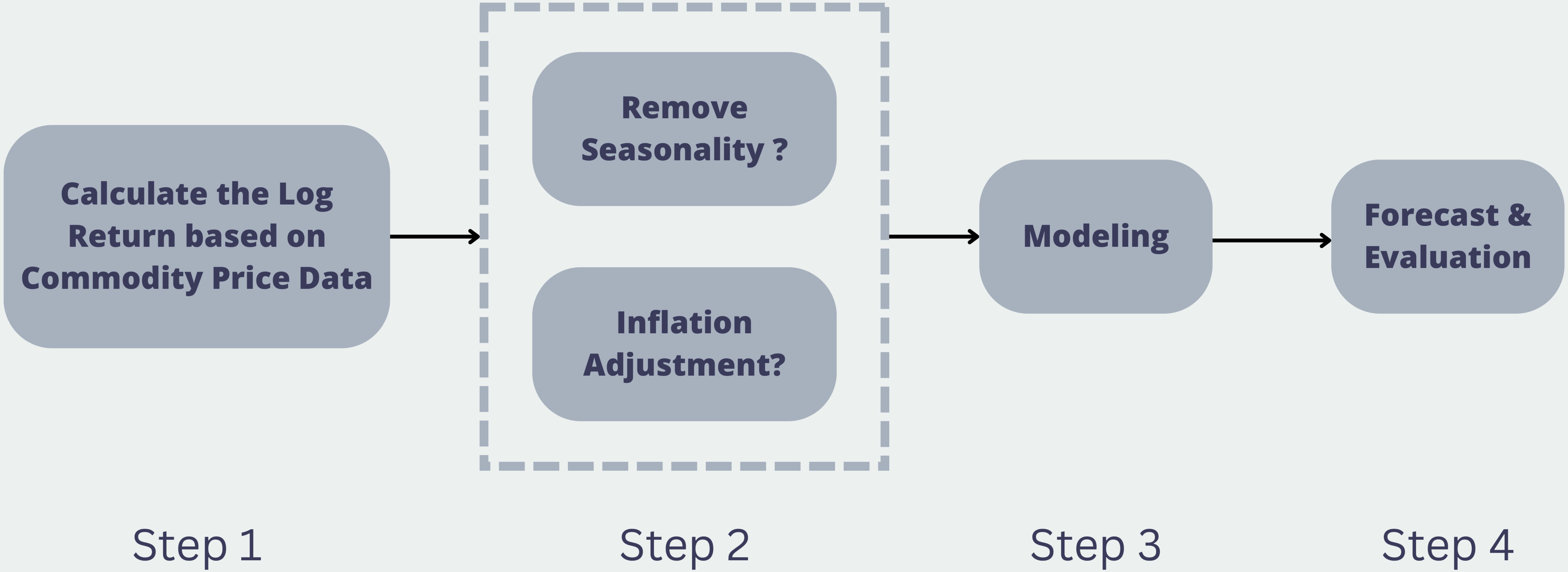
Rolling Window Approach

- Extensive use of the One-Step-Ahead method.
- Use a certain amount of data at a time to make our prediction.



THE UNIVERSITY OF MELBOURNE

Forecast & Evaluation Pipeline



Find the Optimal Model

- Find optimal lag values for Endogenous and Exogenous factors
    - RMSE and Correlation Coefficient

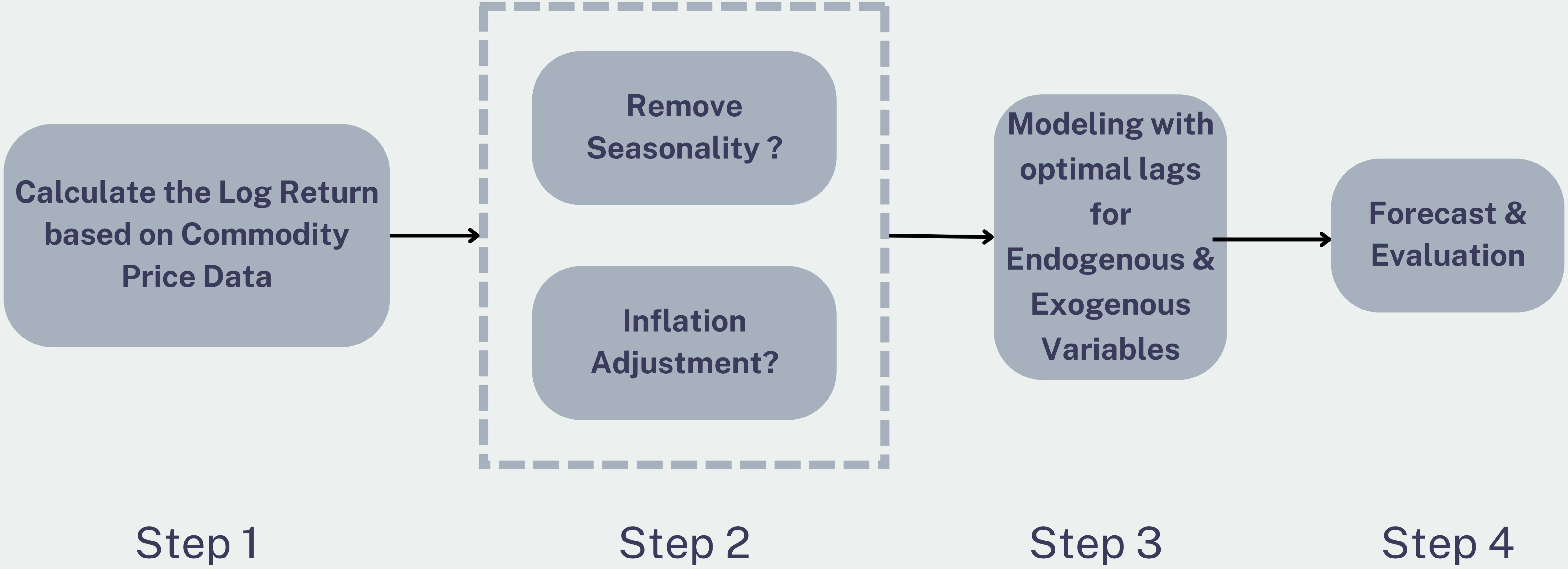
Find the optimal endogenous lag → **Find the optimal exogenous lag**

Step 1

Step 2

THE UNIVERSITY OF MELBOURNE

Forecast & Evaluation Pipeline



Climate Teleconnections

Climate teleconnections refer to significant and often long-distance linkages or relationships between climate phenomena in different parts of the world.

These connections can influence weather patterns, climate variations, and **even events in regions far from the initial source of the climate signal.**

01.

ENSO:
As we have already discussed in detail in our previous slides, it is one of the most important teleconnection.

02.

Arctic Oscillations (AO):
It can influence weather patterns, particularly in the **Northern Hemisphere.**
In the **positive phase**, it tends to bring milder and more stable conditions to regions like Europe and the eastern United States. In the **negative phase,** it can lead to colder and more variable weather.

03.

Southern Annular Mode (SAM):
It impacts weather and climate conditions in the **Southern Hemisphere.**
In the **positive phase**, tends to bring cooler conditions to southern Australia and parts of South America, while the **negative phase** is associated with drier and warmer conditions in these regions.

Results

Examined the influence of **ENSO**, SAM and AO on prices of commodities

(**Wheat**, Maize, Rice, Soybeans)

<u>These are the vital food security commodities</u>

Results

WHEAT

Type of Data		Best ENDO lag	Best EXO Lag	Correlation	RMSE
Seasoned Data	Without ENSO	2	-	0.16	0.07
	With ENSO	2	1	0.23	0.07
	Infl. Adjusted – W/o ENSO	2	-	0.14	0.07
	Infl. Adjusted – with ENSO	2	1	0.16	0.07
Deseasoned Data	Without ENSO	2	-	0.19	0.07
	With ENSO	2	1	0.25	0.07
	Infl. Adjusted – W/o ENSO	2	-	0.16	0.07
	Infl. Adjusted – with ENSO	2	1	0.18	0.07

Wheat from 2008-12-01 to 2018-12-01

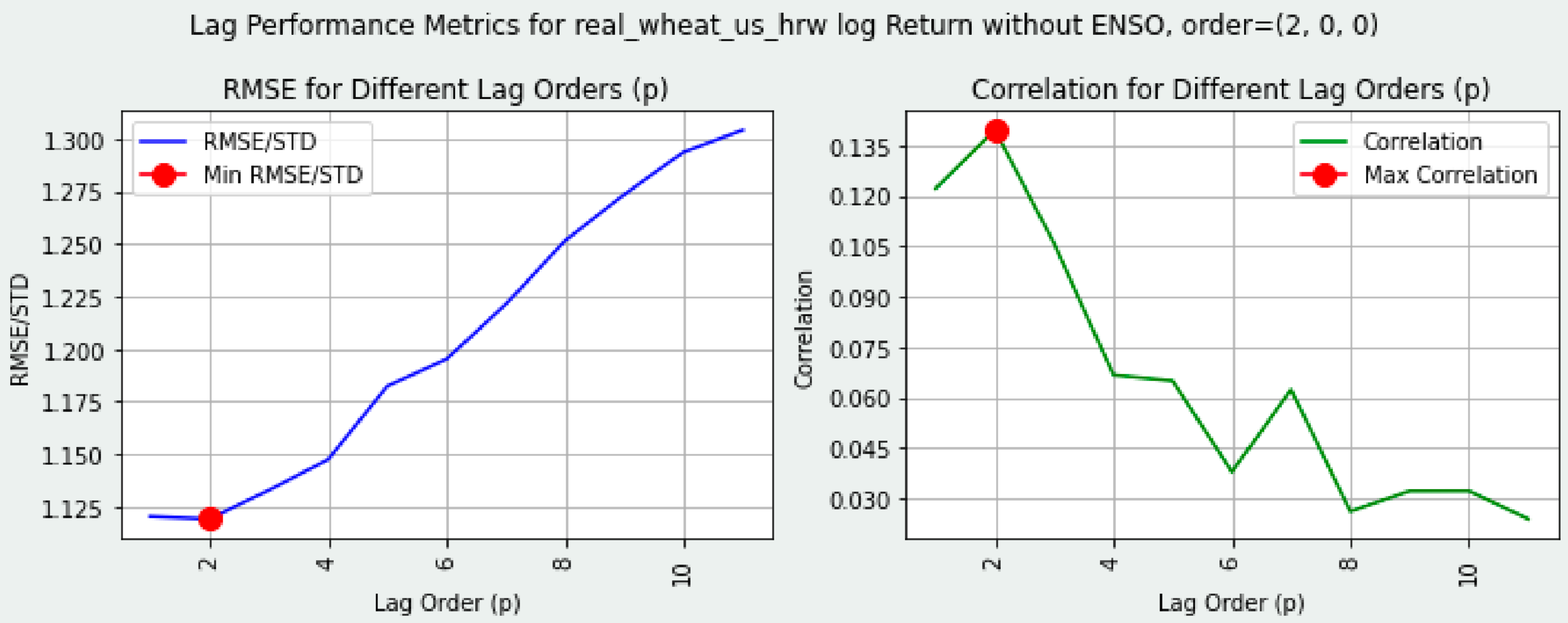
- **Decade: 2008-2018**
- Improvement in correlation **BUT** what about the lags?
    - **Best ENDO lag:** 2
    - **Best EXO lag:** 1

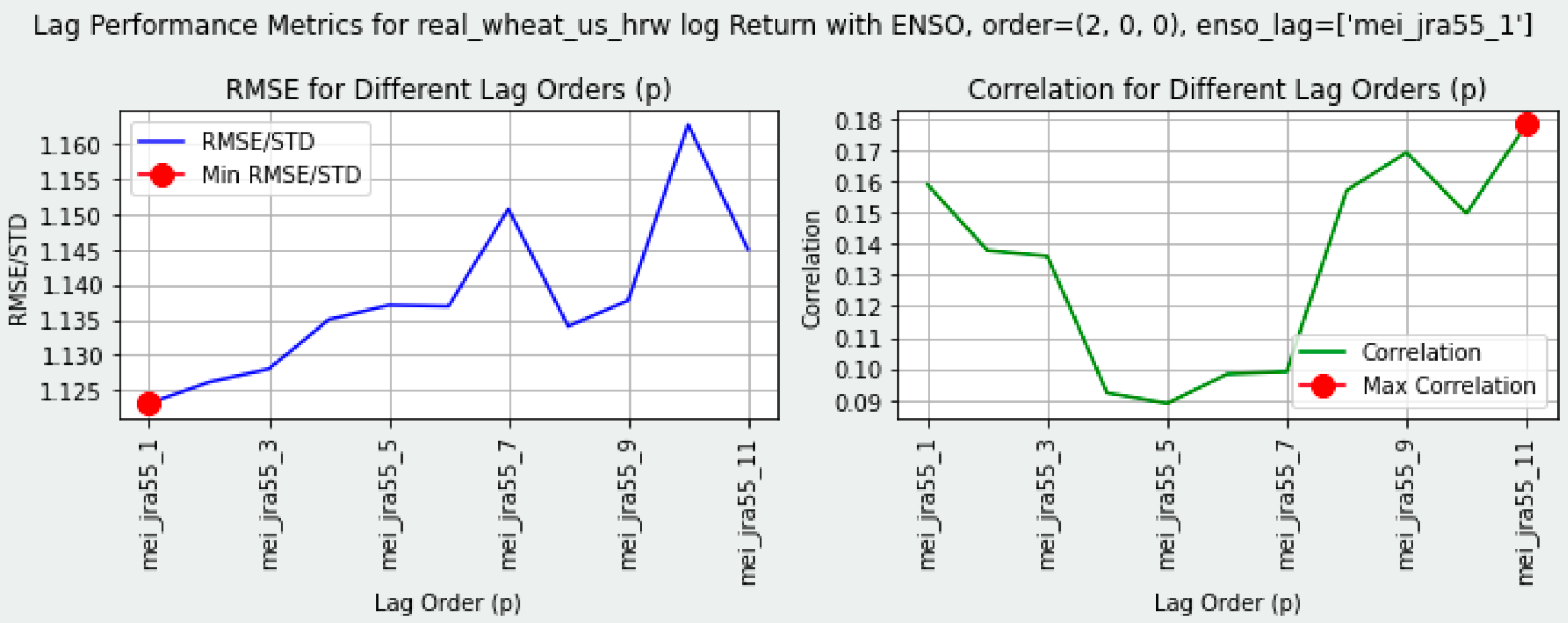
Exogenous variable used here is the ENSO Index

THE UNIVERSITY OF MELBOURNE

Results

WHEAT





Decade: 2008 - 2018

Best ENDO lag: 2 (Inflation Adj.)

Best EXO lag: 1

Exogenous variable used here is the ENSO Index

Results

WHEAT

Insights

- **Sensitivity of the model in the previous decades:**
  - 1988-1998: Improvement in the forecast is negligible
  - 1998-2008: Improvement was observed in the forecast, but the **optimal lag structure** has changed

- **Increased influence of climate on global agricultural production!!!**

Conclusion

So far..

- The ENSO factors significantly impact commodity prices for some period
- The different lag values have different impacts on the time-series analysis of the commodity prices

With the use of the AR predicting model, we can:

- Allow interventions and strategies to be planned ahead to prevent food scarcity for vulnerable populations by predicting shifts in commodity prices
- Help policymakers and stakeholders to implement measures to stabilize food markets, reduce social unrest, and maintain peace.
- Adapt to changing climate patterns, improve food supply chains, and foster global food security

THE UNIVERSITY OF MELBOURNE

Presented by Group 36

Thank you very much!

University of Melbourne

Reference

- Sharpe, S. (2019), ‘Telling the boiling frog what he needs to know: why climate change risks should be plotted as a probability over time, Geoscience Communication, 2(1), pp. 95–100, doi:10.5194/gc-2-95-2019 (accessed 13 Aug. 2021).
- https://www.chathamhouse.org/sites/default/files/2021-09/2021-09-14-climate-change-risk-assessment-quiggin-et-al.pdf

Results

WHEAT

Decade-wise
(1988-2018)

Type of Data		Best ENDO lag	Best EXO Lag	Correlation	RMSE
Seasoned Data	Without ENSO	1	-	0.29	0.04
	With ENSO	1	3	0.29	0.04
	Infl. Adjusted – W/o ENSO	1	-	0.31	0.04
	Infl. Adjusted – with ENSO	1	3	0.31	0.04
Deseasoned Data	Without ENSO	1	-	0.27	0.04
	With ENSO	1	3	0.26	0.05
	Infl. Adjusted – W/o ENSO	1	-	0.28	0.04
	Infl. Adjusted – with ENSO	1	3	0.27	0.04

```
date_range = {"start": "1988-12-01", "end": "1998-12-01"}
```

- **Decade: 1988 - 1998**
- Hardly any change in the correlation when ENSO is added

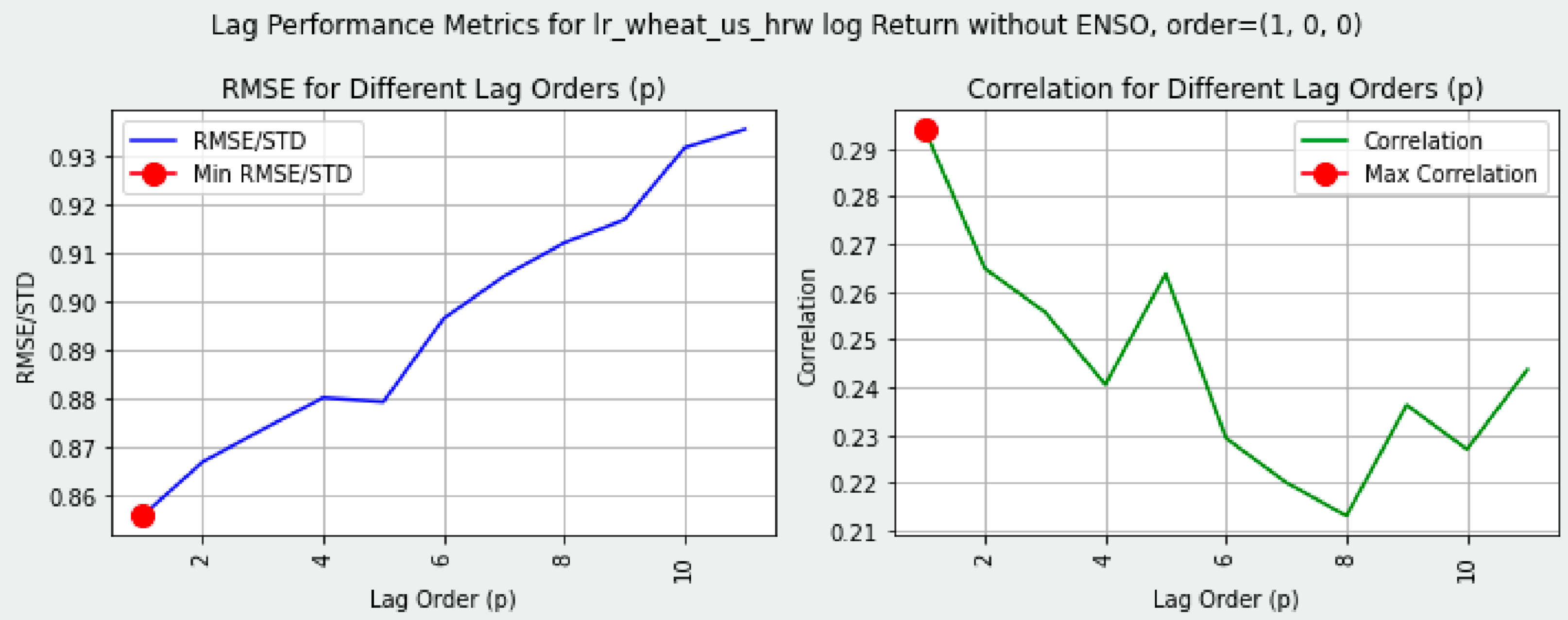
Exogenous variable used here is the ENSO Index

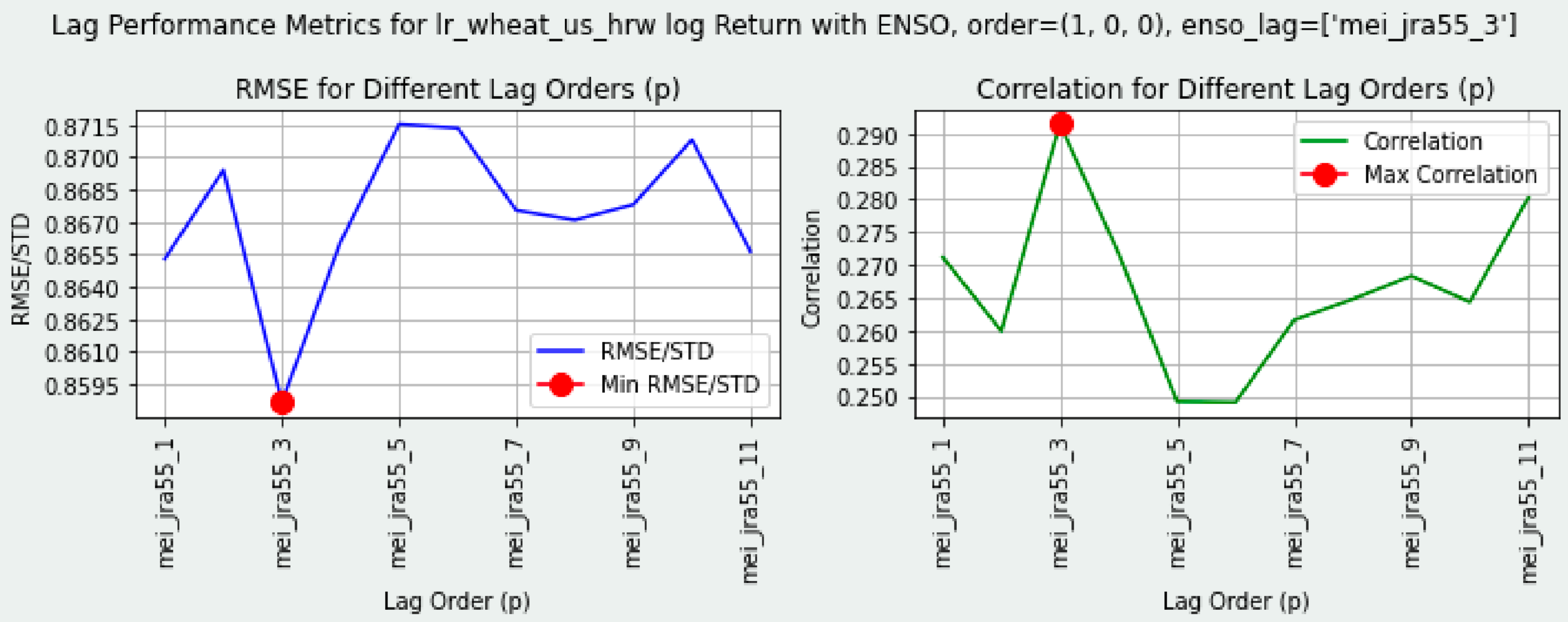
THE UNIVERSITY OF MELBOURNE

Results

WHEAT

Decade-wise
(1988-2018)





Decade: 1988 - 1998

Best ENDO lag: 1 (Inflation Adj.)

Best EXO lag: 3

Exogenous variable used here is the ENSO Index

THE UNIVERSITY OF
MELBOURNE

Results

WHEAT

Decade-wise
(1988-2018)

Type of Data		Best ENDO lag	Best EXO Lag	Correlation	RMSE
Seasoned Data	Without ENSO	1	-	0.18	0.04
	With ENSO	1	10	0.29	0.06
	Infl. Adjusted – W/o ENSO	7	-	0.22	0.05
	Infl. Adjusted – with ENSO	7	11	0.40	0.06
Deseasoned Data	Without ENSO	1	-	0.15	0.05
	With ENSO	1	10	0.28	0.04
	Infl. Adjusted – W/o ENSO	7	-	0.20	0.05
	Infl. Adjusted – with ENSO	7	10	0.34	0.06

```
date_range = {"start": "1998-12-01", "end": "2008-12-01"}
```

- **Decade: 1998 - 2008**
- ENSO Index significantly improves the correlations (**Why?**)
    - **Best ENDO lag:** 1,7
    - **Best EXO lag:** 10,11

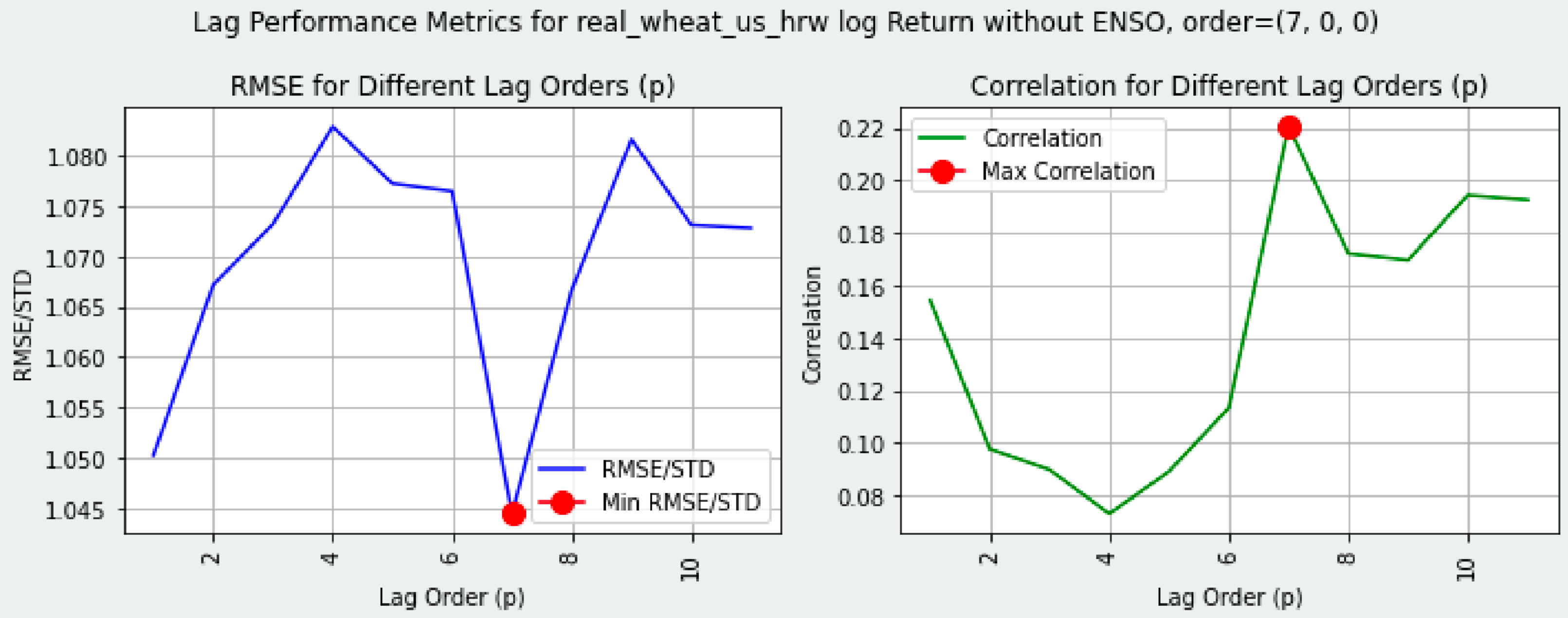
Exogenous variable used here is the ENSO Index

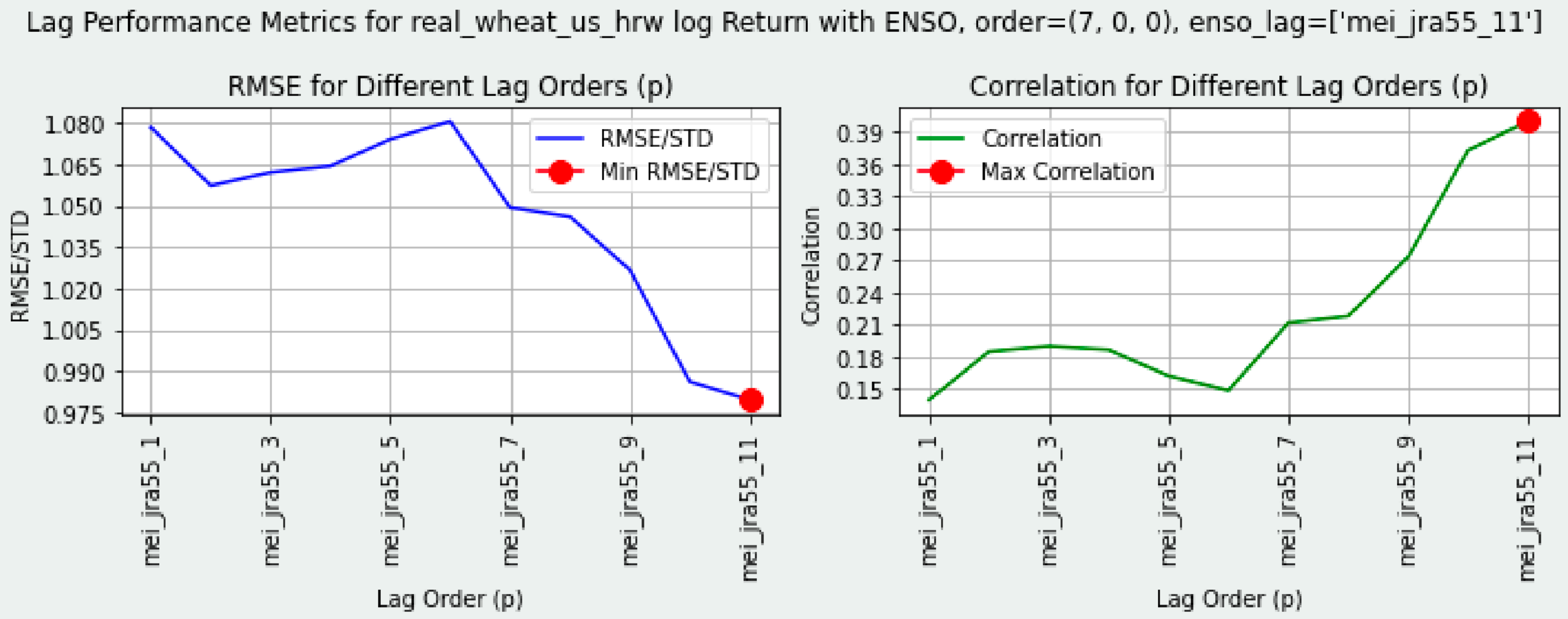
THE UNIVERSITY OF MELBOURNE

Results

WHEAT

Decade-wise
(1988-2018)





Decade: 1998 - 2008

Best ENDO lag: 7 (Inflation Adj.)

Best EXO lag: 11

Exogenous variable used here is the ENSO Index

THE UNIVERSITY OF
MELBOURNE

Results

WHEAT

(2008-2018)

Arctic Oscillation

Wheat

Type of Data		Best ENDO lag	Best EXO Lag	Correlation	RMSE
Seasoned Data	Without EXO	2	-	0.16	0.04
	With EXO	2	7	0.25	0.04
	Infl. Adjusted – W/o EXO	2	-	0.14	0.04
	Infl. Adjusted – with EXO	2	7	0.23	0.04
Deseasoned Data	Without EXO	2	-	0.19	0.04
	With EXO	2	7	0.25	0.04
	Infl. Adjusted – W/o EXO	2	-	0.16	0.04
	Infl. Adjusted – with EXO	2	7	0.23	0.04

Southern Annular Mode

Wheat

Type of Data		Best ENDO lag	Best EXO Lag	Correlation	RMSE
Seasoned Data	Without EXO	2	-	0.16	0.04
	With EXO	2	6	0.17	0.04
	Infl. Adjusted – W/o EXO	2	-	0.14	0.04
	Infl. Adjusted – with EXO	2	8	0.15	0.04
Deseasoned Data	Without EXO	2	-	0.19	0.04
	With EXO	2	6	0.21	0.04
	Infl. Adjusted – W/o EXO	2	-	0.16	0.04
	Infl. Adjusted – with EXO	2	6	0.18	0.04

Exogenous variable used here is the AO and SAM Index

ENSO is important... but

- How do we measure this impact?
- What can we learn from it?

Intuition

The risks of climate change can be understood more clearly when research starts by identifying what it is that we most wish to avoid and then assessing its likelihood as a function of time (Sharp, 2019)

Important Forecasting Tool:

- The AR model has demonstrated the impact of climate teleconnections in forecasting commodity prices.

- It provides a data-driven approach to understanding and predicting the impacts of climate variability on agricultural commodities.

THE UNIVERSITY OF MELBOURNE