International Institute for Applied Systems Analysis
IIASA www.iiasa.ac.at

Comprehensive Method for Medium-Term Analysis and Forecast of Agricultural Commodity Prices

CMAF

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Advancing Systems Analysis (ASA)

Program research goals

- Identify, develop and deploy **new systems-analytical methods, tools, and data**
- Address the most pressing global sustainability challenges
- Find **solutions** to those challenges that are **both realistic and appropriate**

ASA Research Groups

Group Leader:
Sebastian Poledna

EM

Exploratory Modeling of Human-Natural Systems

SYRR

Systemic Risk and Resilience

Group Leader:
Reinhard Mechler

NODES

Novel Data Ecosystems for Sustainability

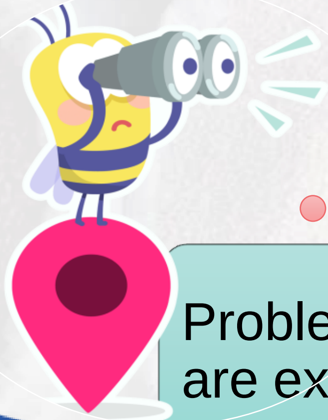
Group Leader: Ian McCallum

CAT

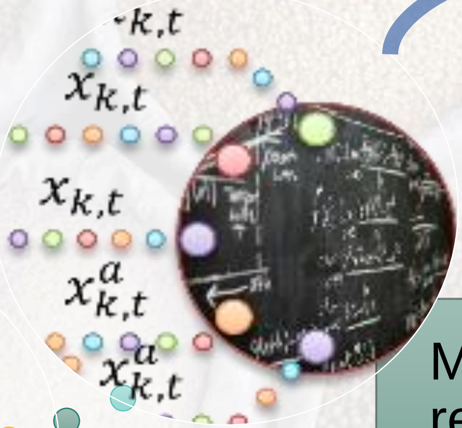
Cooperation and Transformative Governance

Group Leader:
Nadezhda Komendantova

CMAF



Problem: Food prices are extremely volatile



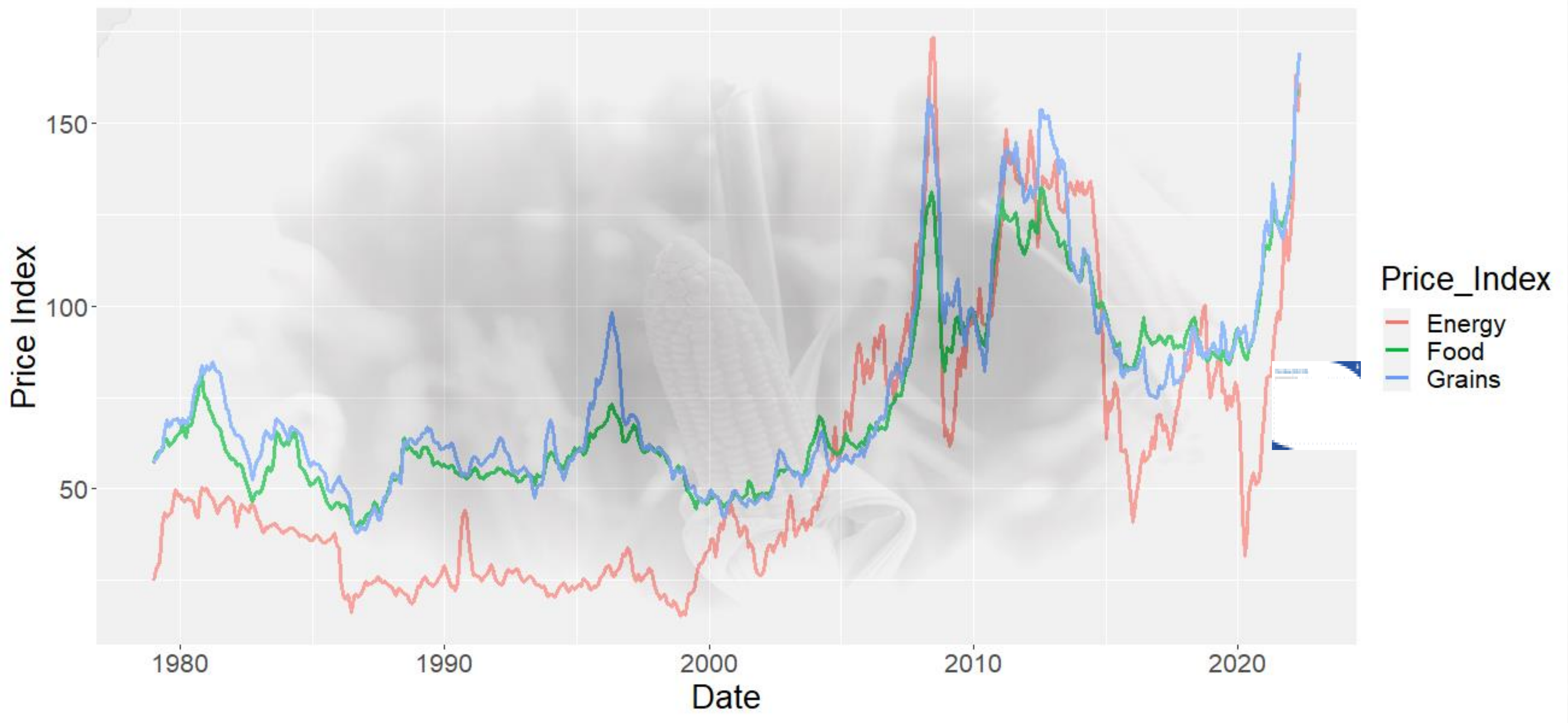
Many possible reasons/Data to use

Studying the problem using econometric & ML models

Model agnostic

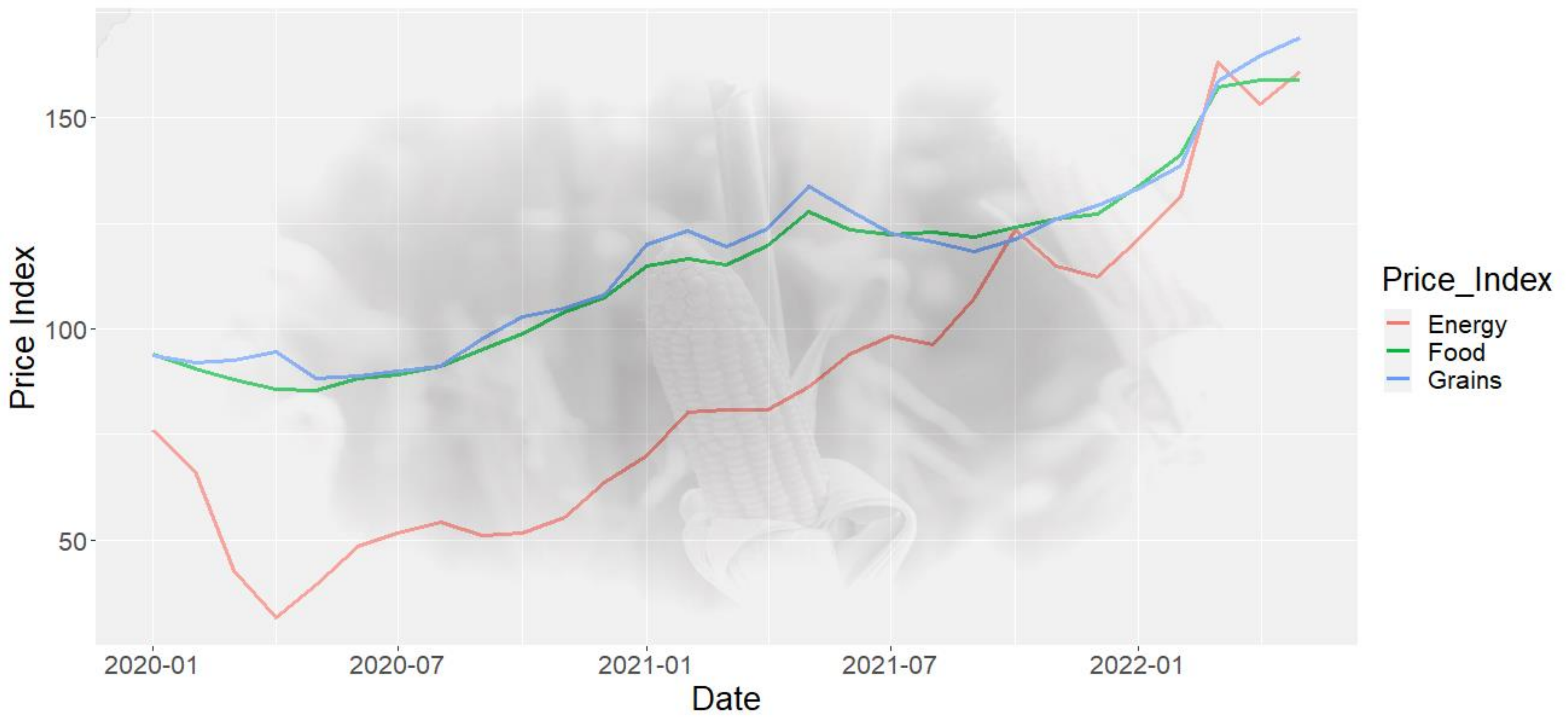
Everyone can understand

Price indices – High correlation



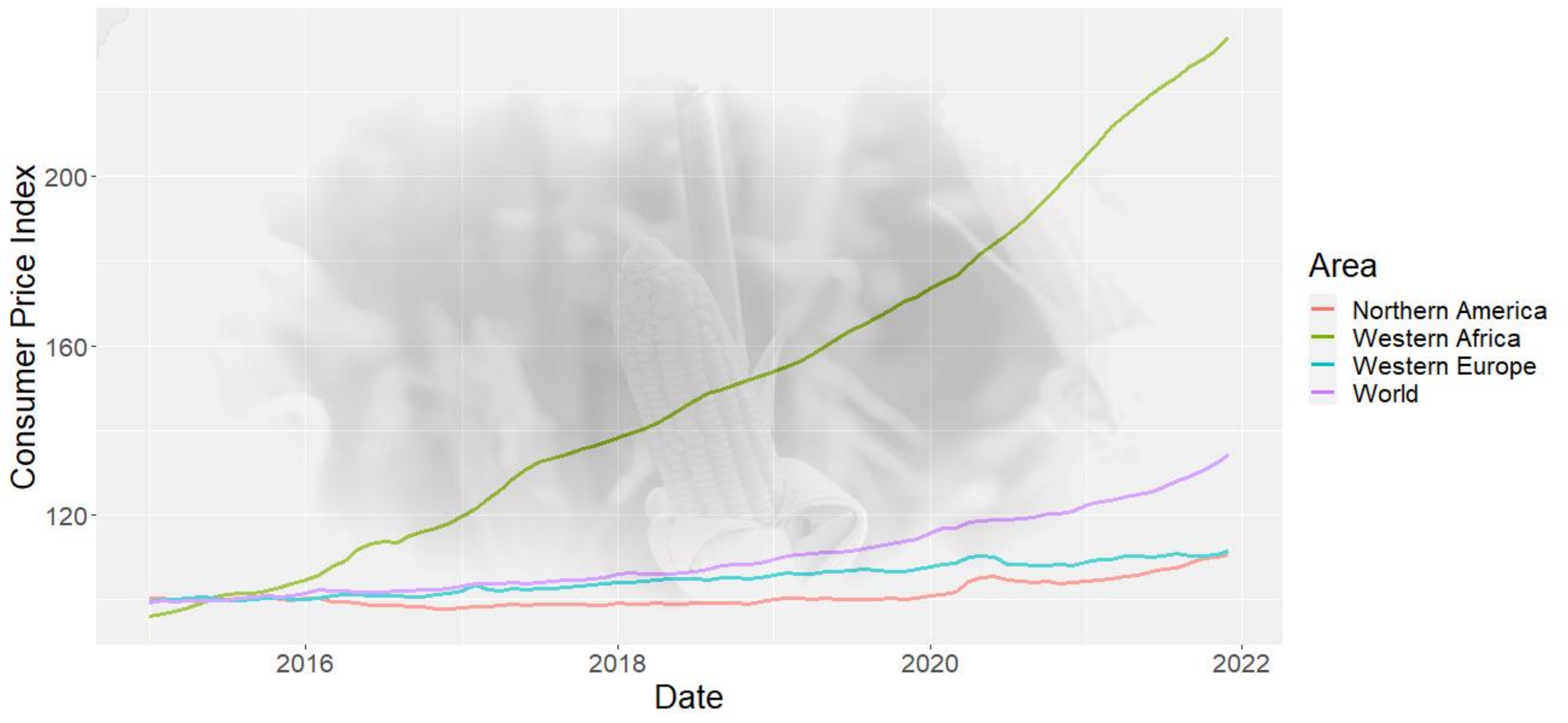
Source: the World Bank

Price indices (2010=100)

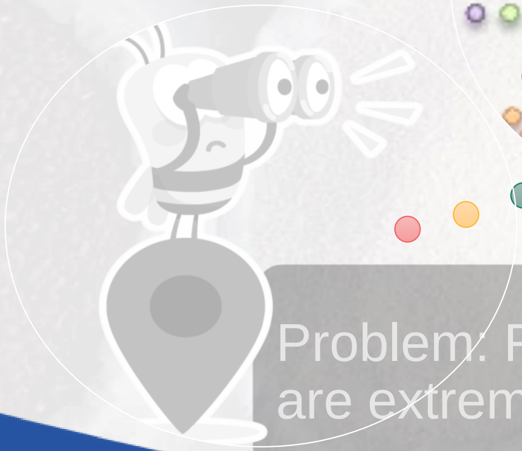


Source: the World Bank

Consumer Food Price index (2015=100)



Source: FAO Stat



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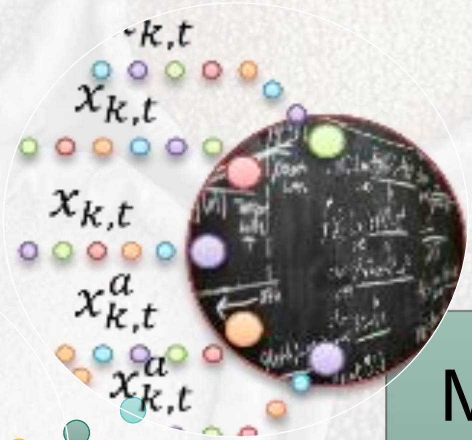

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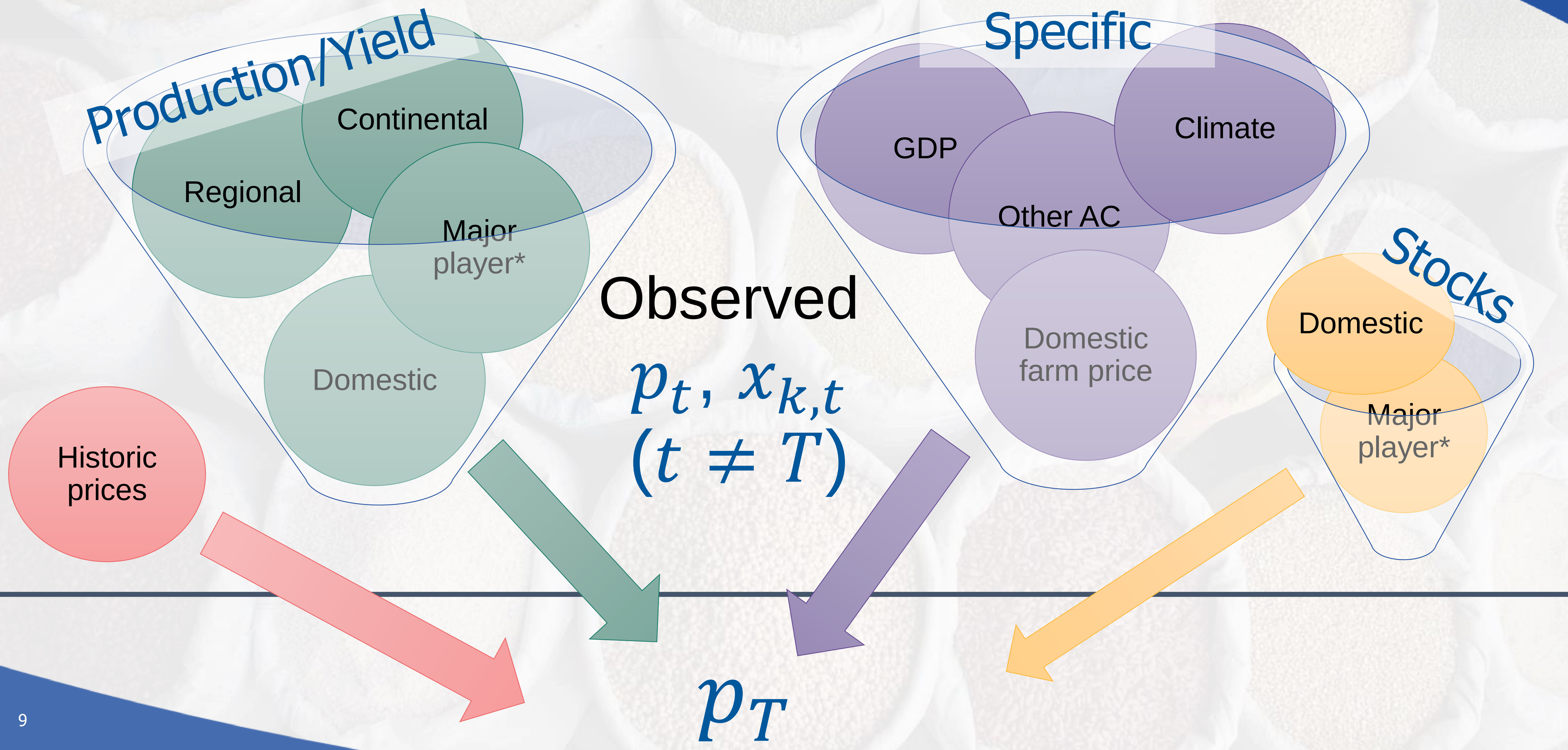
Model overview

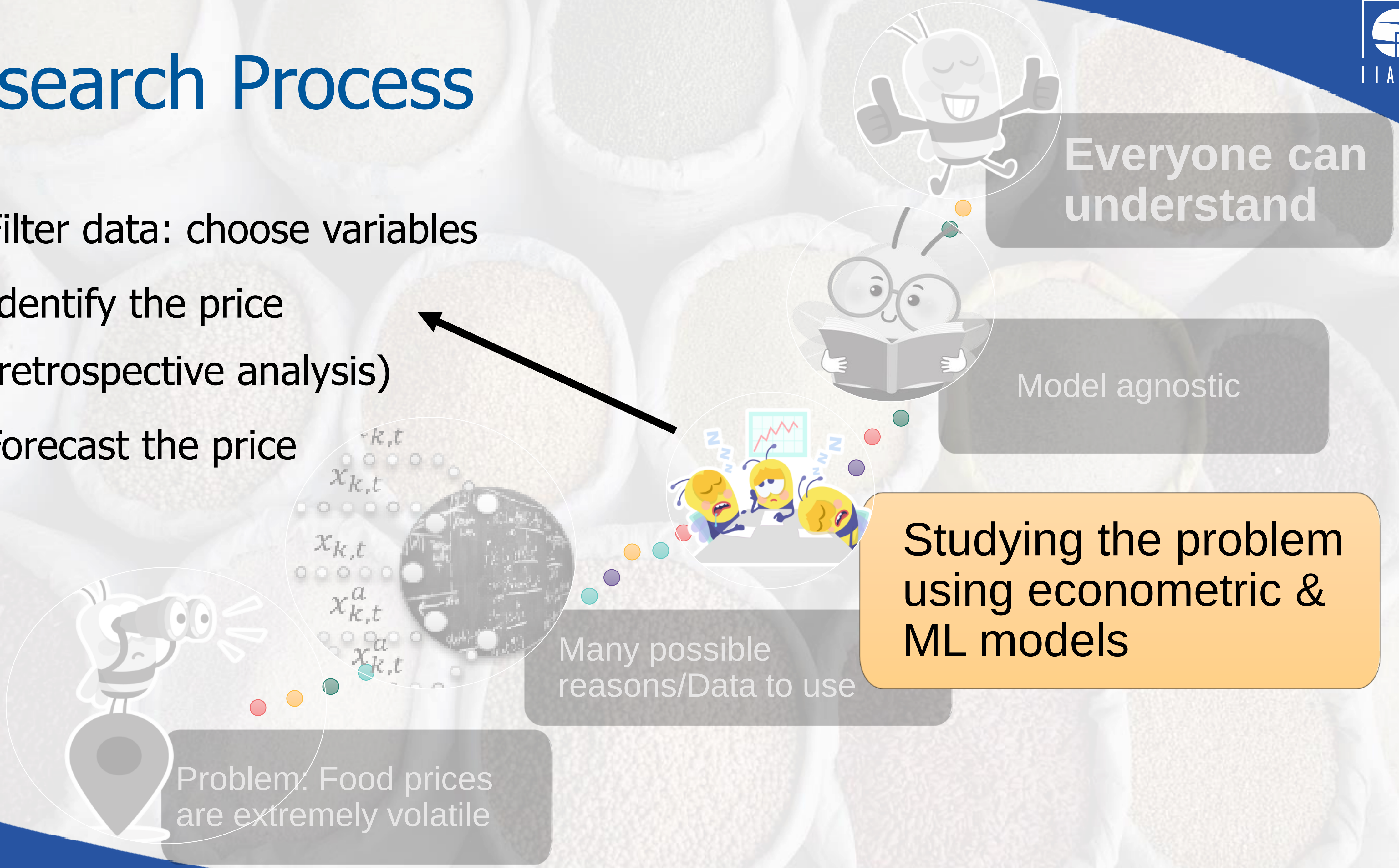


Research Process

I. Filter data: choose variables

II. Identify the price (retrospective analysis)

III. Forecast the price



Model specification & application

- Two types of $p_{m,Y}$ **An**alysis & **For**ecasting
  - **Reg**ression → Relative change
  - **Clas**sification → Increase/decrease
- Approach: **Eco**nometric/**M**achine **L**earning
- Model accuracy assessment**:
  - Regression: $RMSE$ 
  - Classification: Area under curve (AUC)

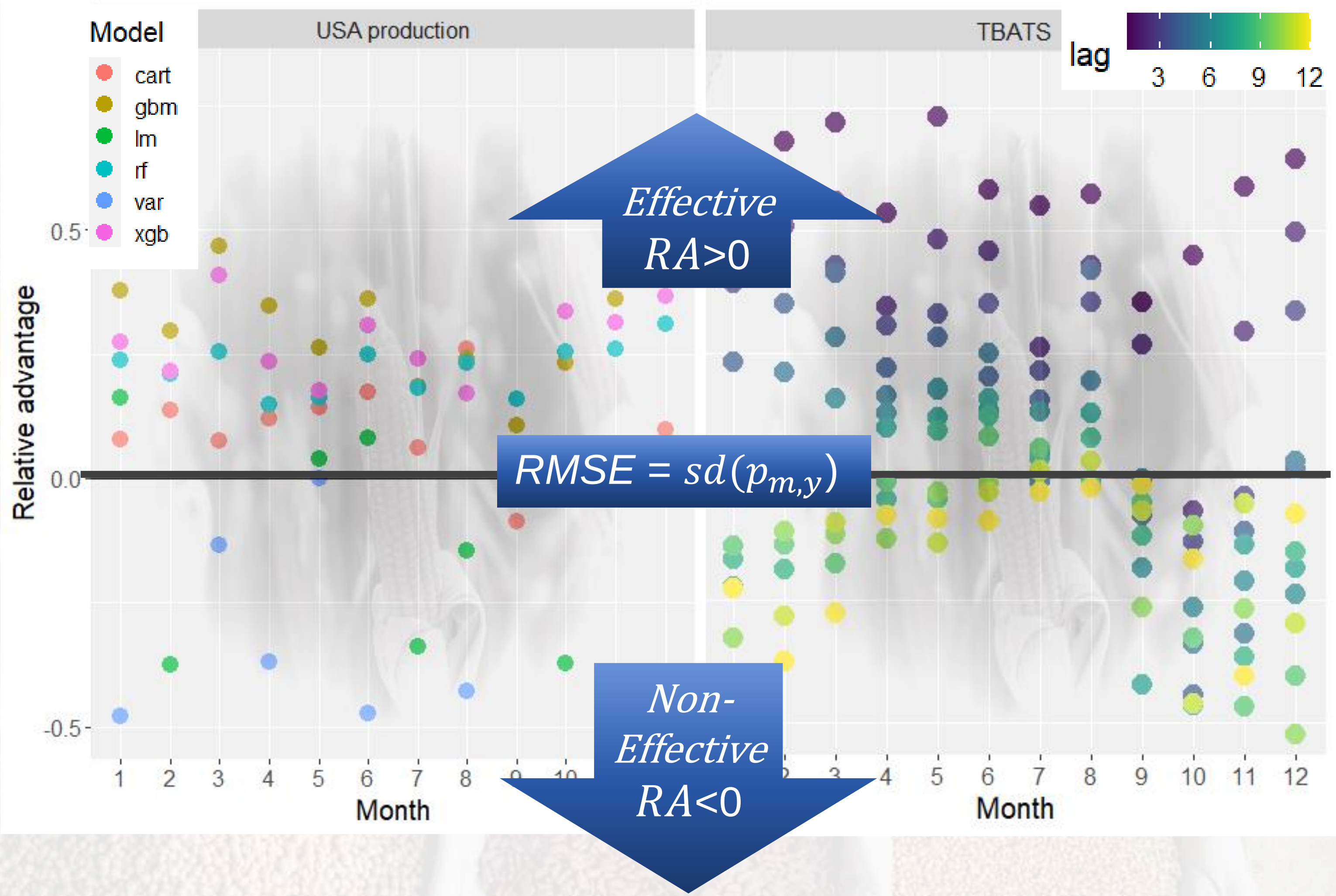
#	Algorithm	An	For	Reg	Clas	Model Type
1	LM, GLM		✓	✓	✓	Eco
2	VAR		✓	✓		Eco
3	CART	✓	✓	✓	✓	ML
4	RF	✓	✓	✓	✓	ML
5	GBM	✓	✓	✓	✓	ML
6	XGBoost	✓	✓	✓	✓	ML
7	KNN				✓	ML
8	TBATS		✓	✓		ML

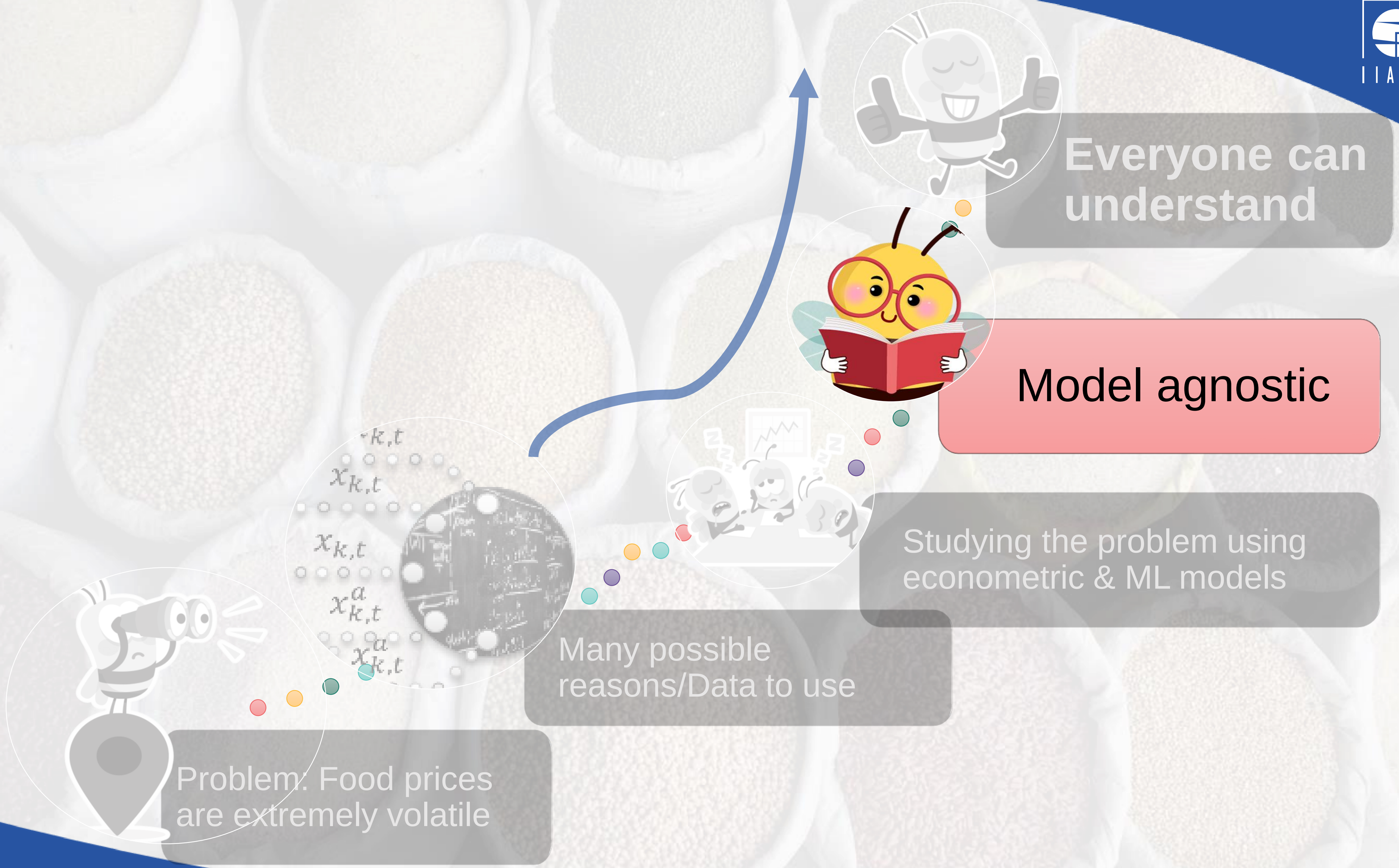
Relative advantage

$$\mathrm{RA} = 1 - \frac{RMSE}{sd(p_{m,y})}$$

Higher = Better performance

Lower = Worse performance





Everyone can understand
Model agnostic
Studying the problem using econometric & ML models
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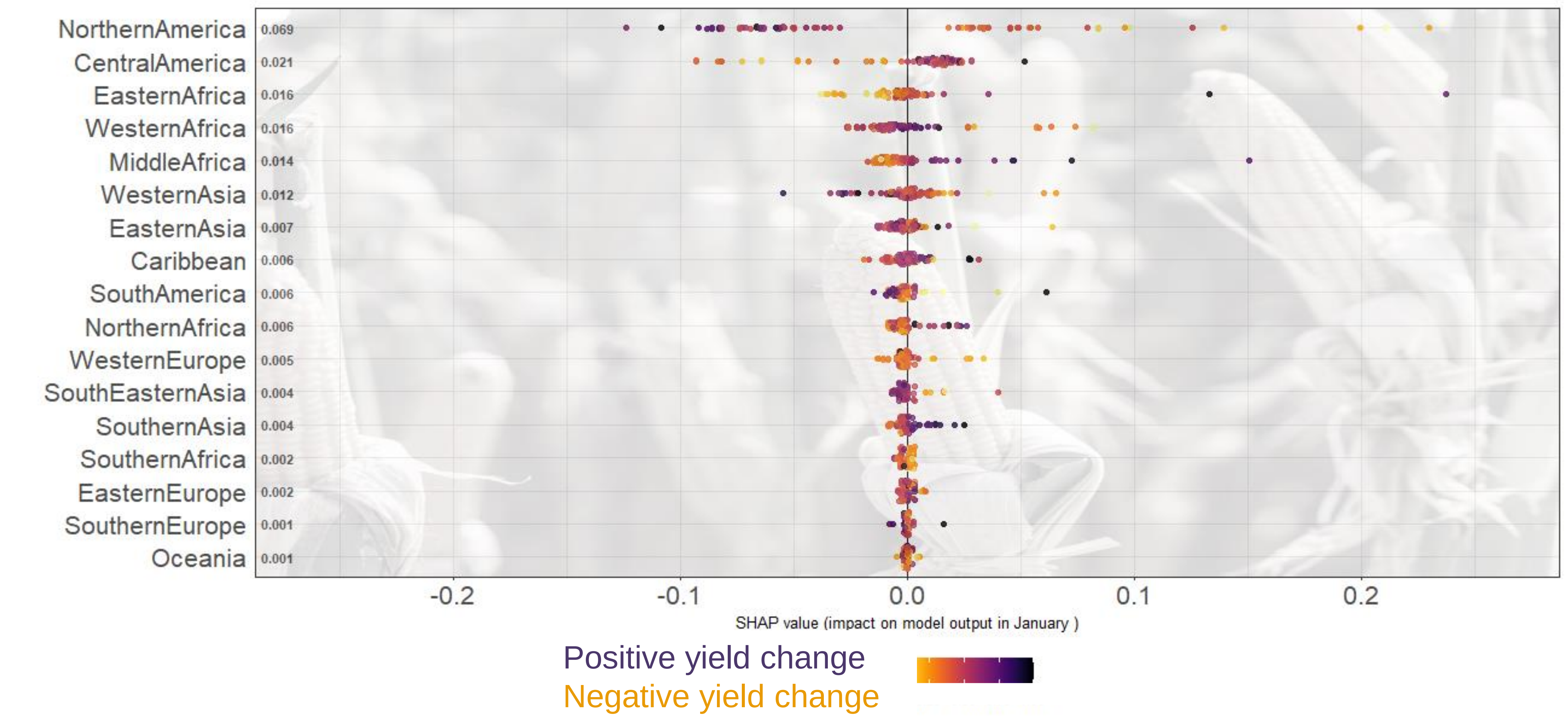
Problem: Food prices are extremely volatile

Explore Relative Importance (SHAP)

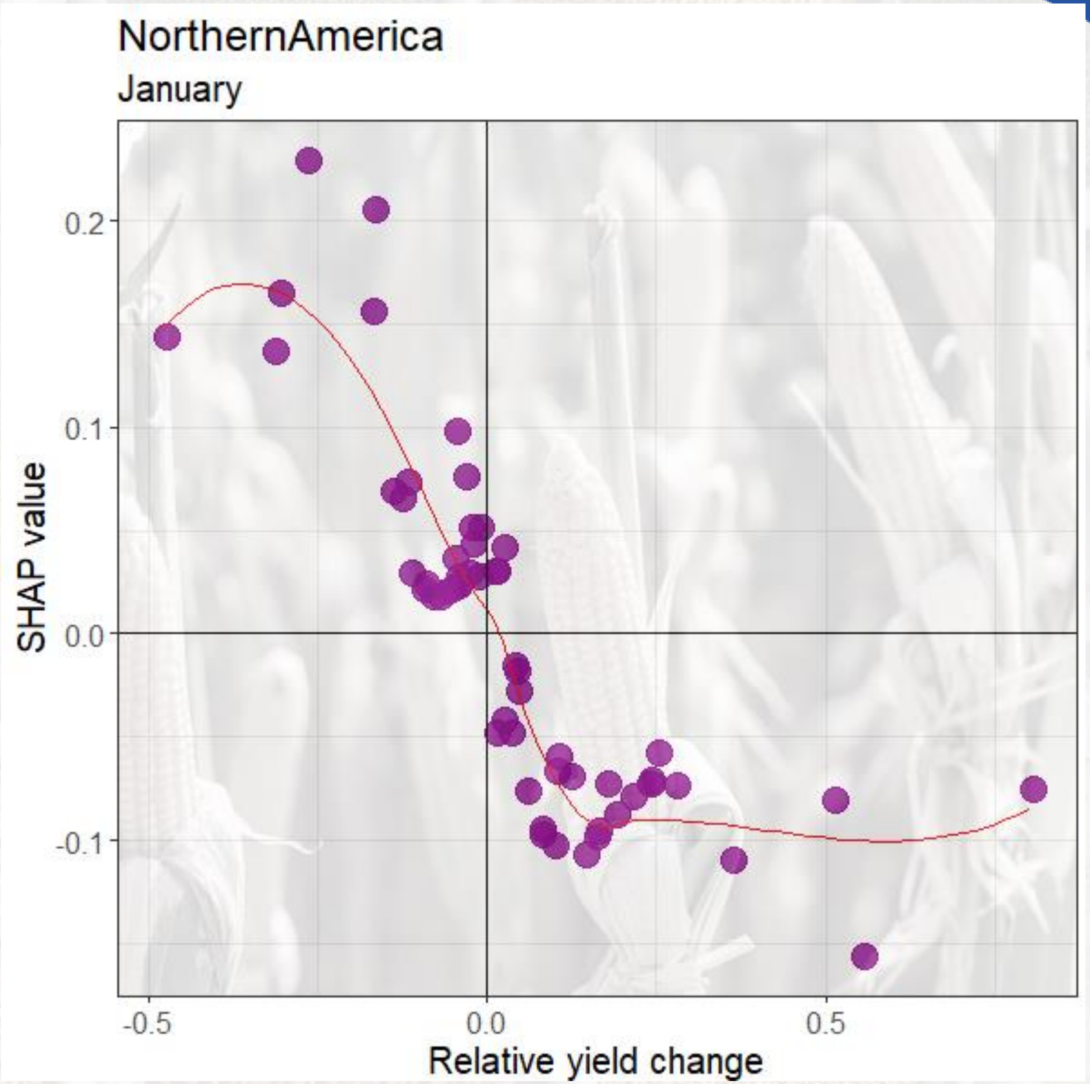


Explore Partial Dependence

- Average response of $p_{m,y}$ to variations of maize yield Northern America
- PDPs show negative correlation

$$x_{k,y} \downarrow \; \Rightarrow \; p_{m,y} \uparrow$$

- Strong negative influence of Northern America yield over global maize price
- $x_{k,y} < 0$ affects more than $x_{k,y} > 0$



Where does this project head to?

Make price forecasting and analysing a **Social Good**

- The first tool to provide medium-term price analysis and forecasting of AC in a way that would be useful for all humans.
- Promote understanding of the global food trade to enhance food security and social equity
- Publicly available as an open online platform

Everyone can understand

My research

Statistical modelling & Applied research

Using statistical and machine learning methods

Agriculture	Food security	Environment and ecology	Trade	And more

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THANK YOU

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Appendix

Data sources

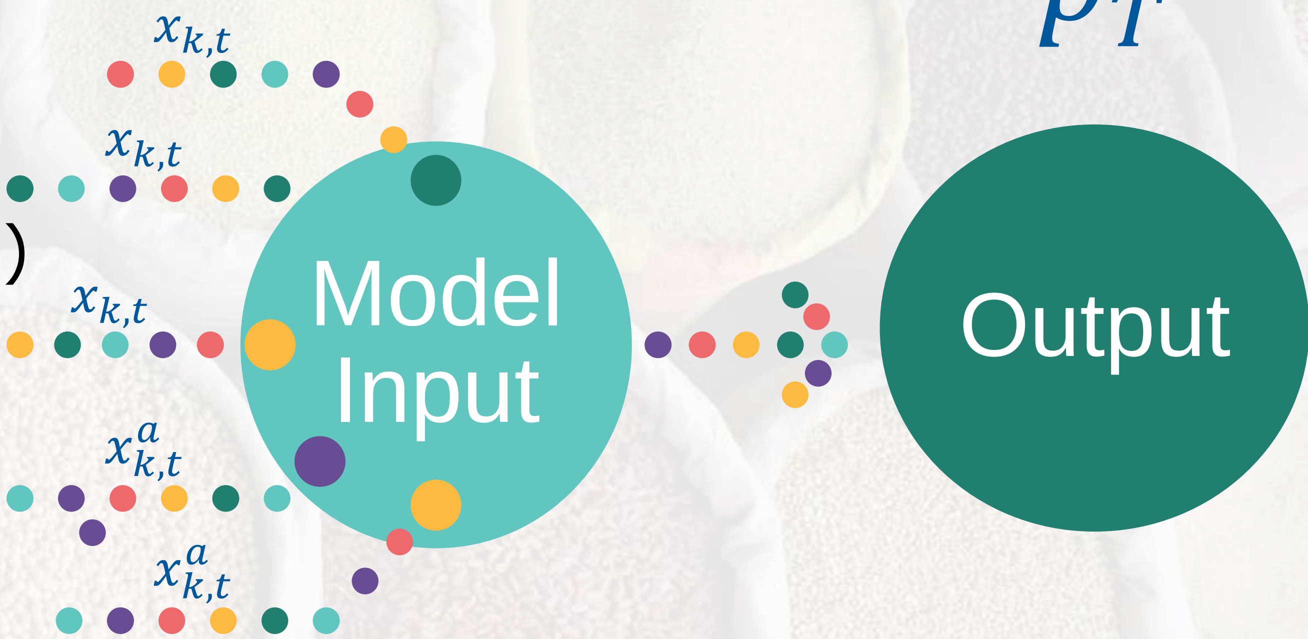
- Production, yield, stocks ($x_{k,t}^{d}$)
  - Four geographic scales (k)
  - Observed annually or monthly
  - Source: FAO-STAT, USDA*
- Additional & Case specific variables ($x_{k,t}^{a}$)
- Global prices, 1960-2022 (p_t)
  - Source: World Bank*
- Units: relative annual change

Observed data

$p_t, x_{k,t}$
$(t \neq T)$

Price to produce

p_T



Practical Motivation:
Forecasting global prices for stabilising local prices

If the decision-maker can:

- Spot unusual price shifts
- Foresee them
- Long enough for adaptation

Research Goals (II)

Enhance social equality

Promote understanding and equality in the global AC trade markets

- Data and knowledge are no longer resource-dependent

Assist low-income decision-makers

- Market analysis and price forecasting
- Recognise threats and opportunities
- Strategic design – sell/buy, consume/stock, substitutions

Random Forests (RF, Bagging)

- Random K sub-samples of the training set
  - Many trees $\rightarrow$ multiple independent training-data
- Result: Many trees lead to a preferable final result
  - Reduced correlation effect
  - Each prediction = average of K (up to 500) “weaker” trees

Boosting algorithm – GBM

- Creates multiple trees
- Each training set learns from the tree before
- High performance → Frequent appearance
- The result: Powerful final decision tree

Part I – Choose variables

Adding new variables

Are they potential regressors?

- Test for stationarity
- Correlation with price
- Lagged effects

How do they behave together?

- Correlation between features
- Regression Price ~ remained variables
  - Random Forests, GBM, XGB, CART
- Importance ranking
- Remove variables with negative impact on accuracy

New dataset

Part II – Retrospective analysis

1. **Split** data: Train (i years), Test (1 year) sets
2. **Train** an algorithm using the training set
   - Test different hyperparameters (in ML)
3. Use the Train set to **Identify**

$$p_{m,Y} = f\left(x^d_{1,y}, \dots, x^d_{k,y}, x^a_{k,m,y}\right)$$

4. **Test** of the algorithms based on test dataset
5. **Assess** detection accuracy using LOOCV
6. **Rank** features by their contribution level
7. **Filter** data - leave only those improving accuracy

	y=1	y=2	…	…	y=Y-1	$y = \mathrm{Y}$
y=1	Test	Train				
y=2	Train	Test	Train			
…	Train		Test	Train		
…	Train			Test	Train	
y=Y-1	Train				Test	Train
$y = \mathrm{Y}$	Train					Test

Part III – Price forecast

1. **Split** data: Train (45≤ i years), Test (1 year) sets
2. **Train** an algorithm using the training set
   - Tune ML algorithms
3. Use the Train set to **Forecast**

$$p_{m,Y} = f\left(x^{d}_{1,y}, \dots, x^{d}_{k,y}, x^{a}_{k,m,y}\right); Y = y_{max} + 1$$

4. **Test** of the algorithms based on test dataset
5. **Assess** forecasting accuracy using Rolling CV
6. **Rank** features by their contribution level

<table>
<tr><th></th><th>y<44</th><th>…</th><th>y=44</th><th>…</th><th>y=Y-1</th><th>y = Y</th></tr>
<tr><td>y<44</td><td colspan="6"></td></tr>
<tr><td>…</td><td colspan="6"></td></tr>
<tr><td>y=44</td><td colspan="2">Train</td><td>Test</td><td colspan="3"></td></tr>
<tr><td>…</td><td colspan="3">Train</td><td>Test</td><td colspan="2"></td></tr>
<tr><td>y=Y-1</td><td colspan="4">Train</td><td>Test</td><td></td></tr>
<tr><td>y = Y</td><td colspan="5">Train</td><td>Test</td></tr>
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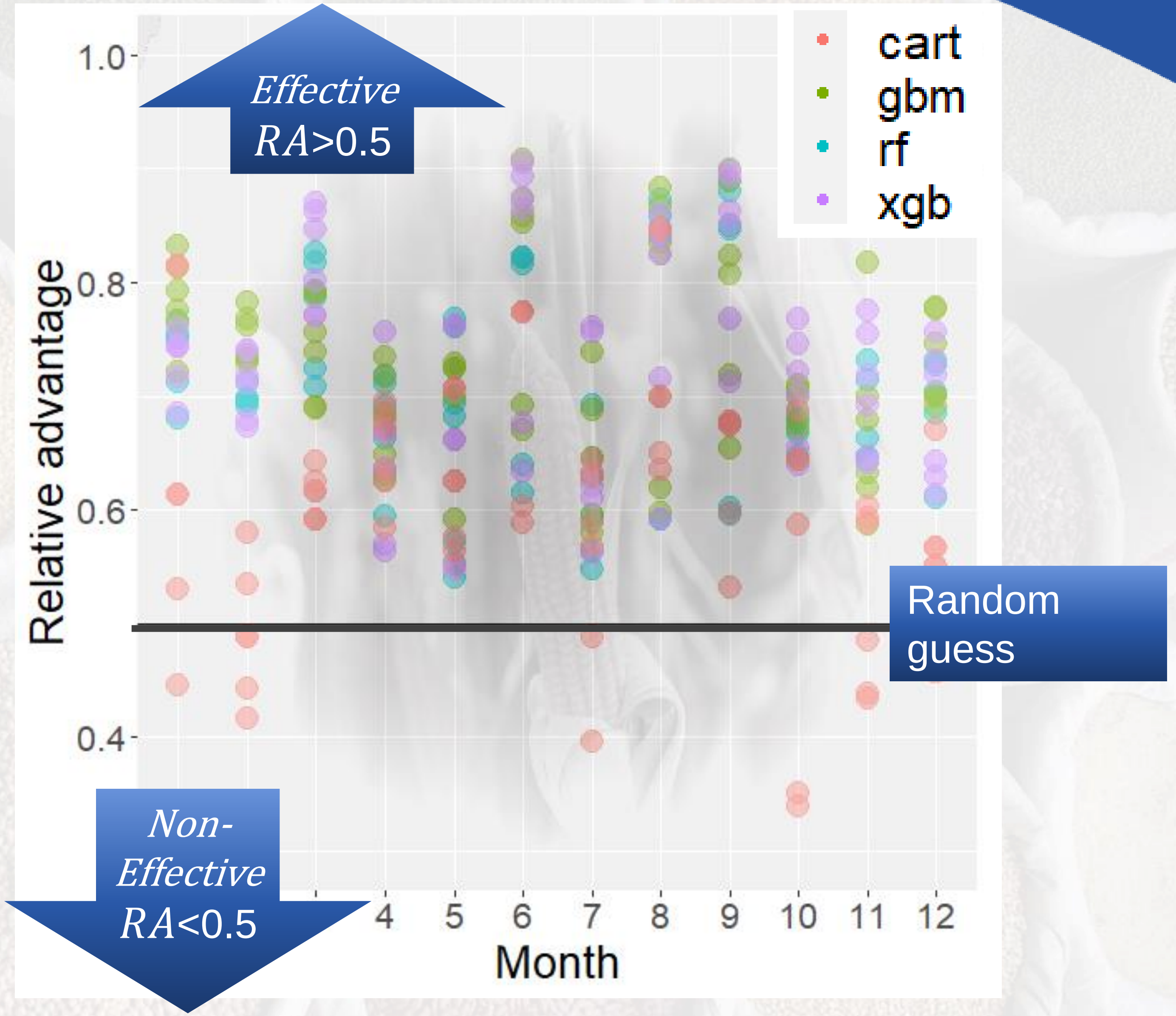
Area Under ROC Curve (AUC)

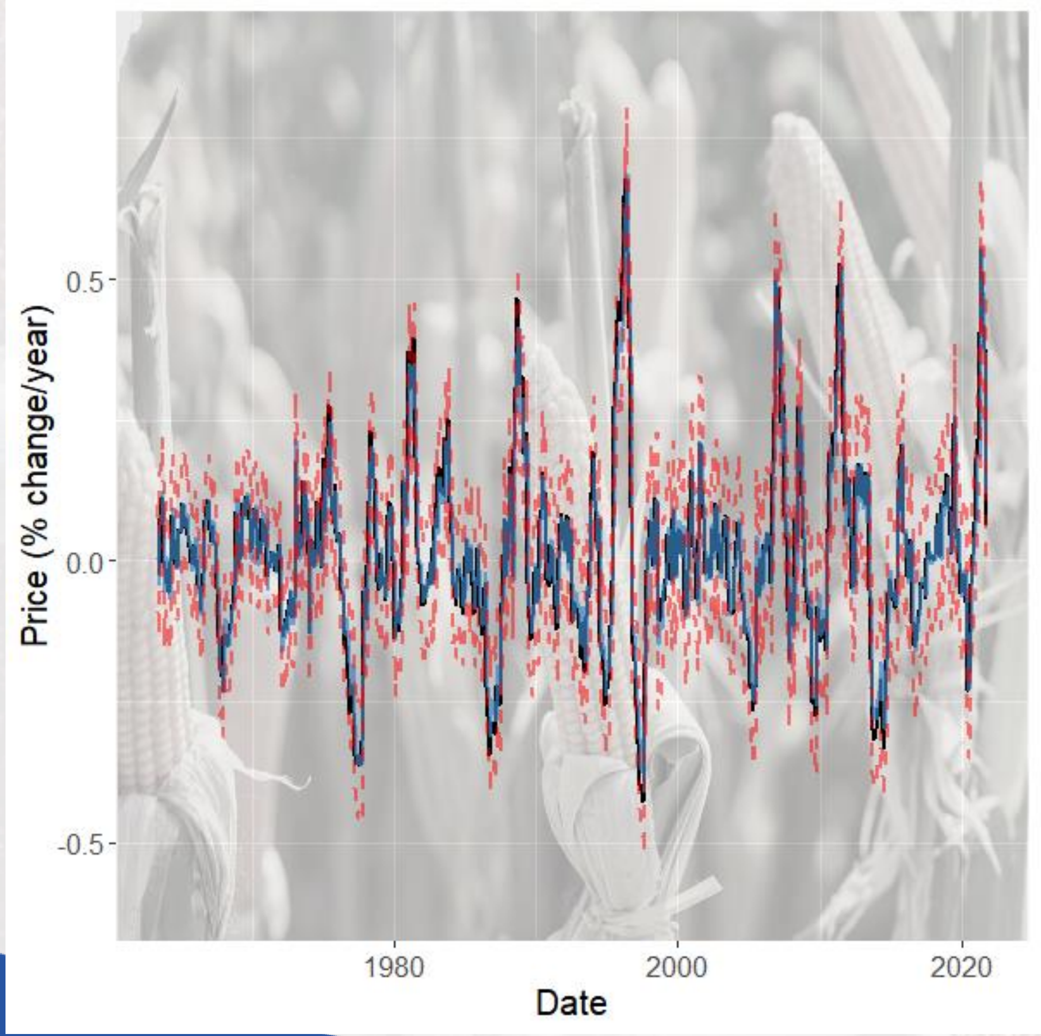
Higher = Better performance

Lower = Worse performance

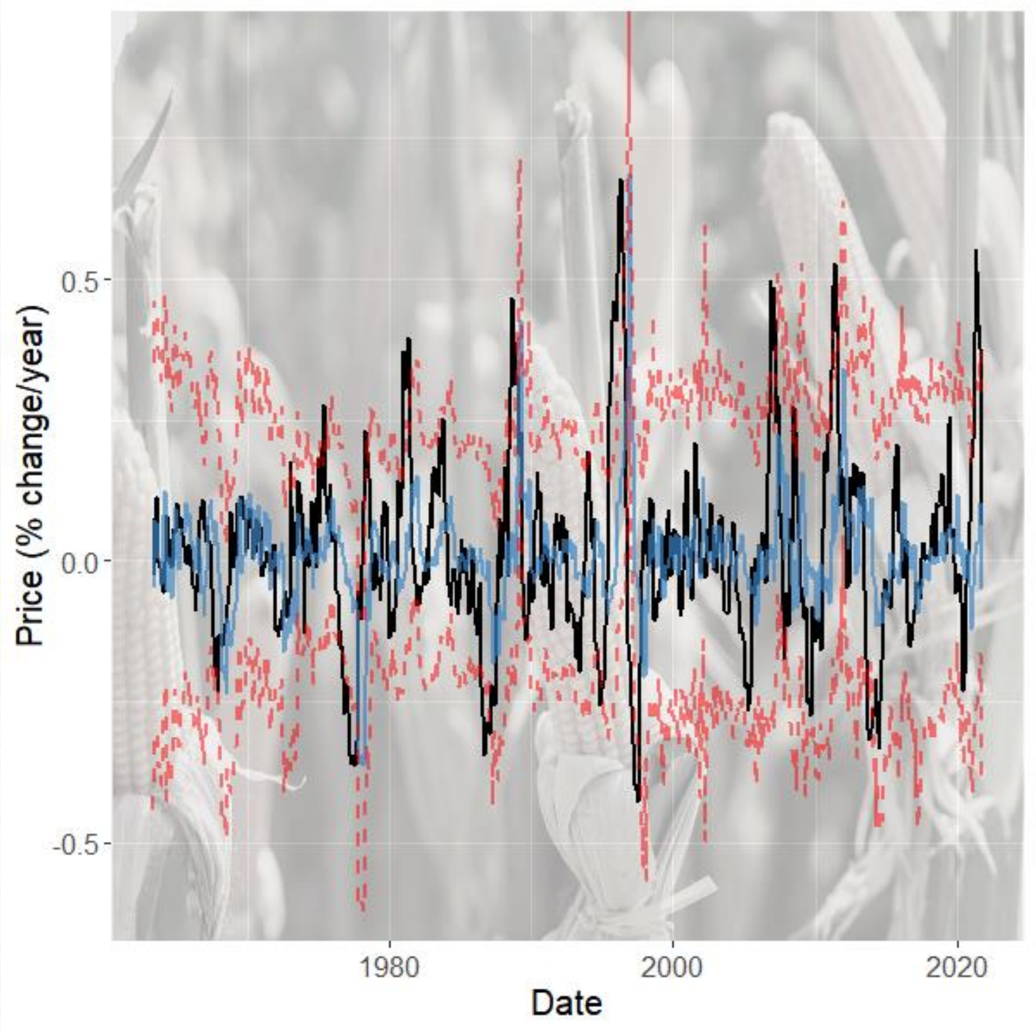


Time-Series Model - TBATS

Lag = 1 month



Lag = 12 months

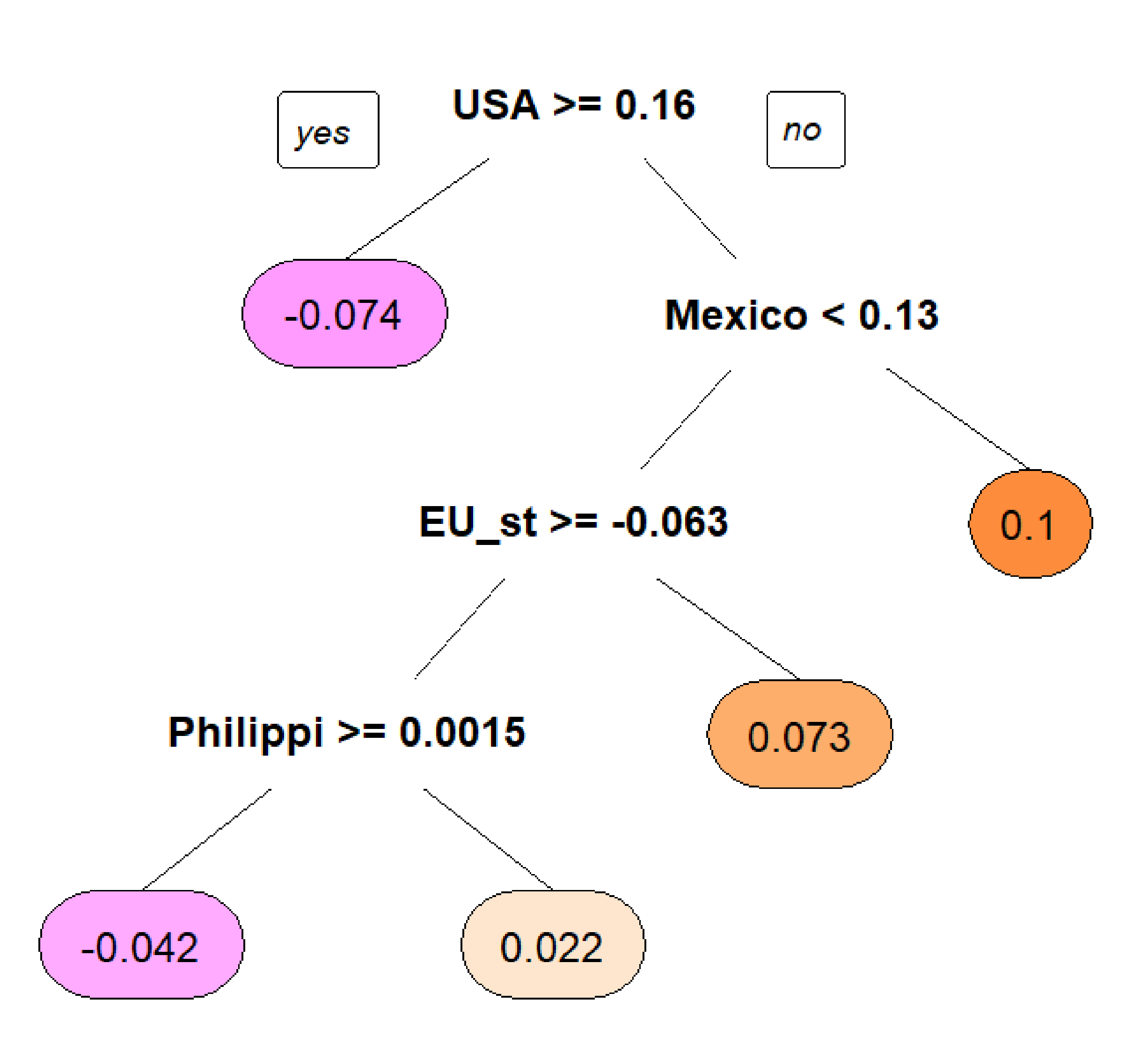


What drove the model's decision?

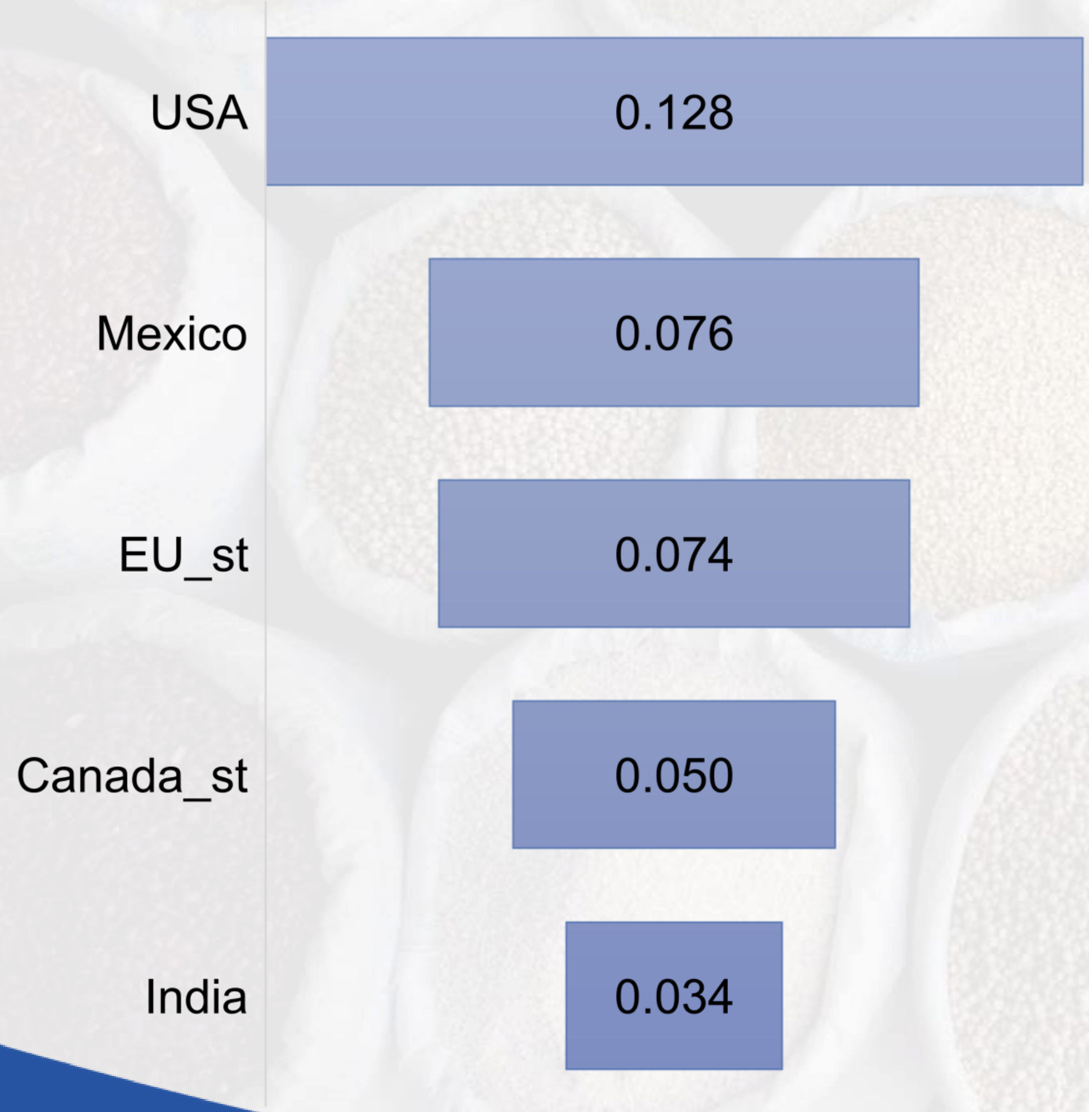
CART

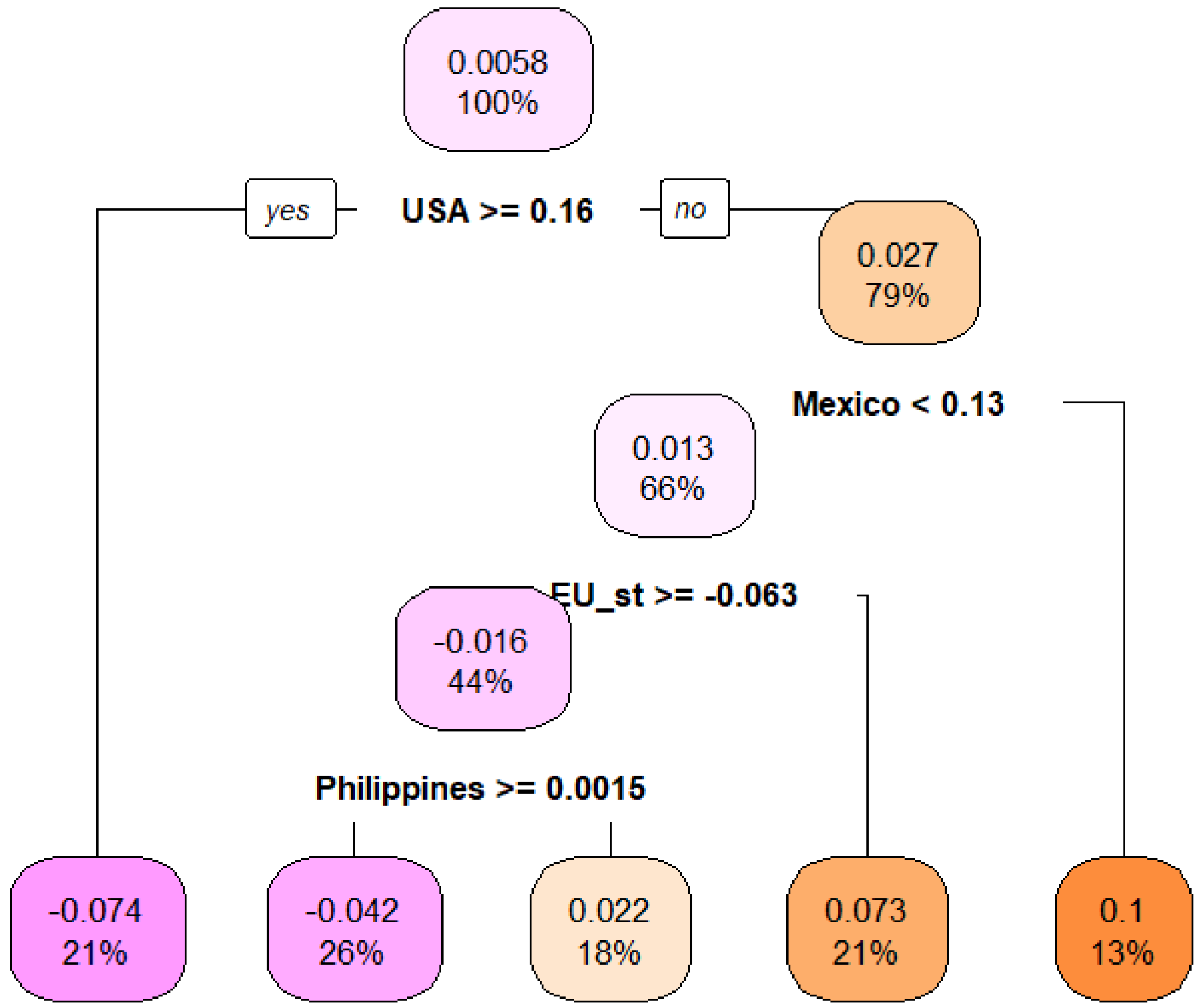
Classification **A**nd **R**egression **T**ree

- Split = partition into 2 subsets
- Simply visualised
- Easy to interpret
- Applied on black-box models

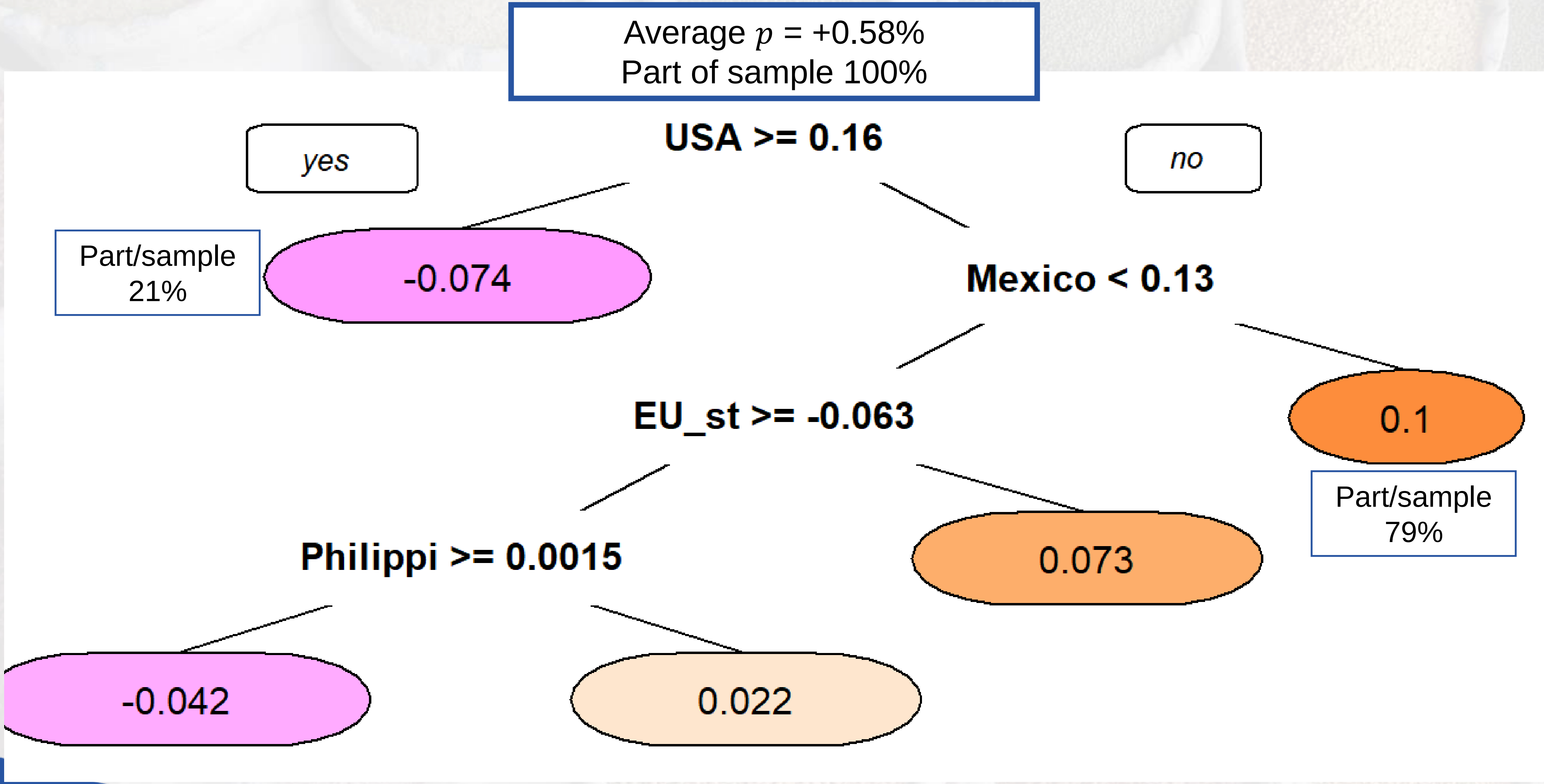


Variable Importance (October price)

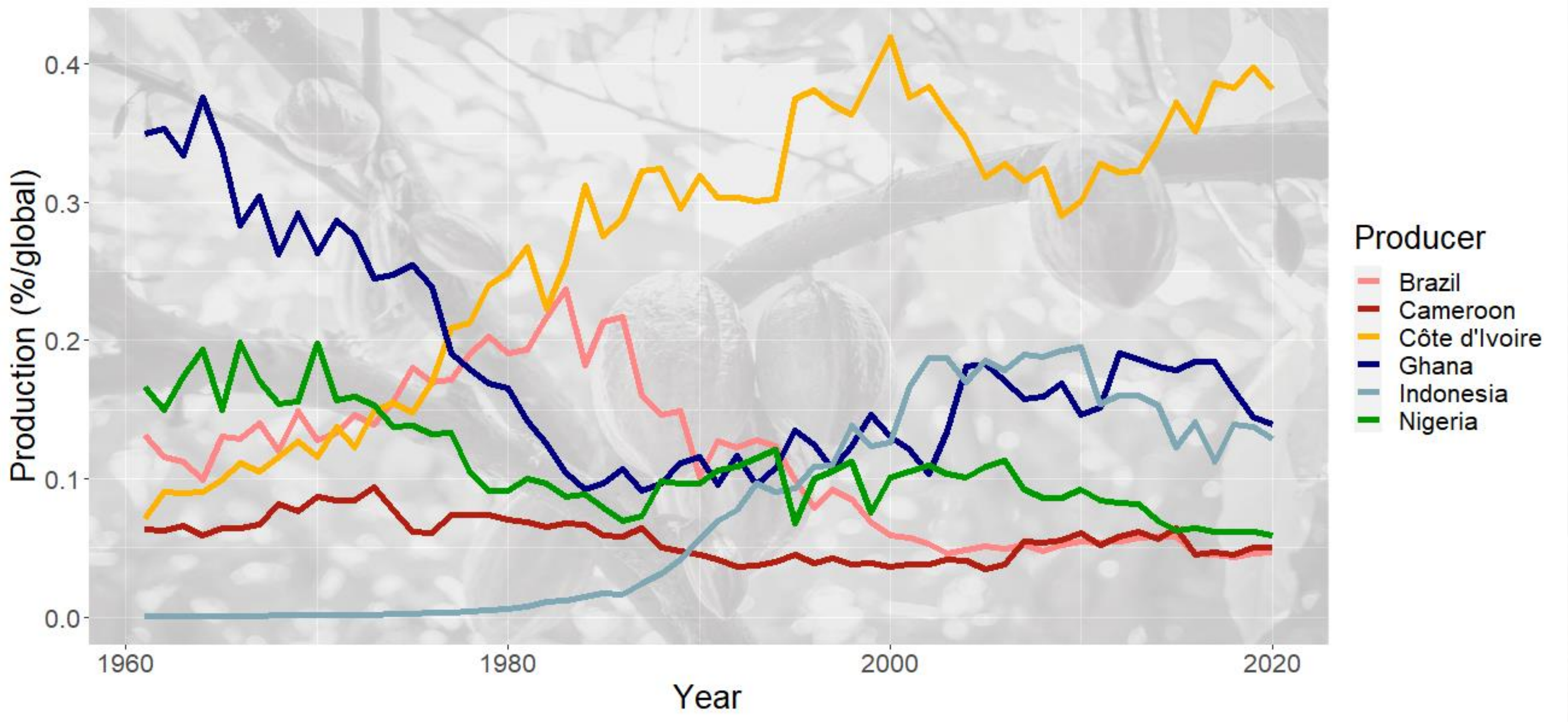




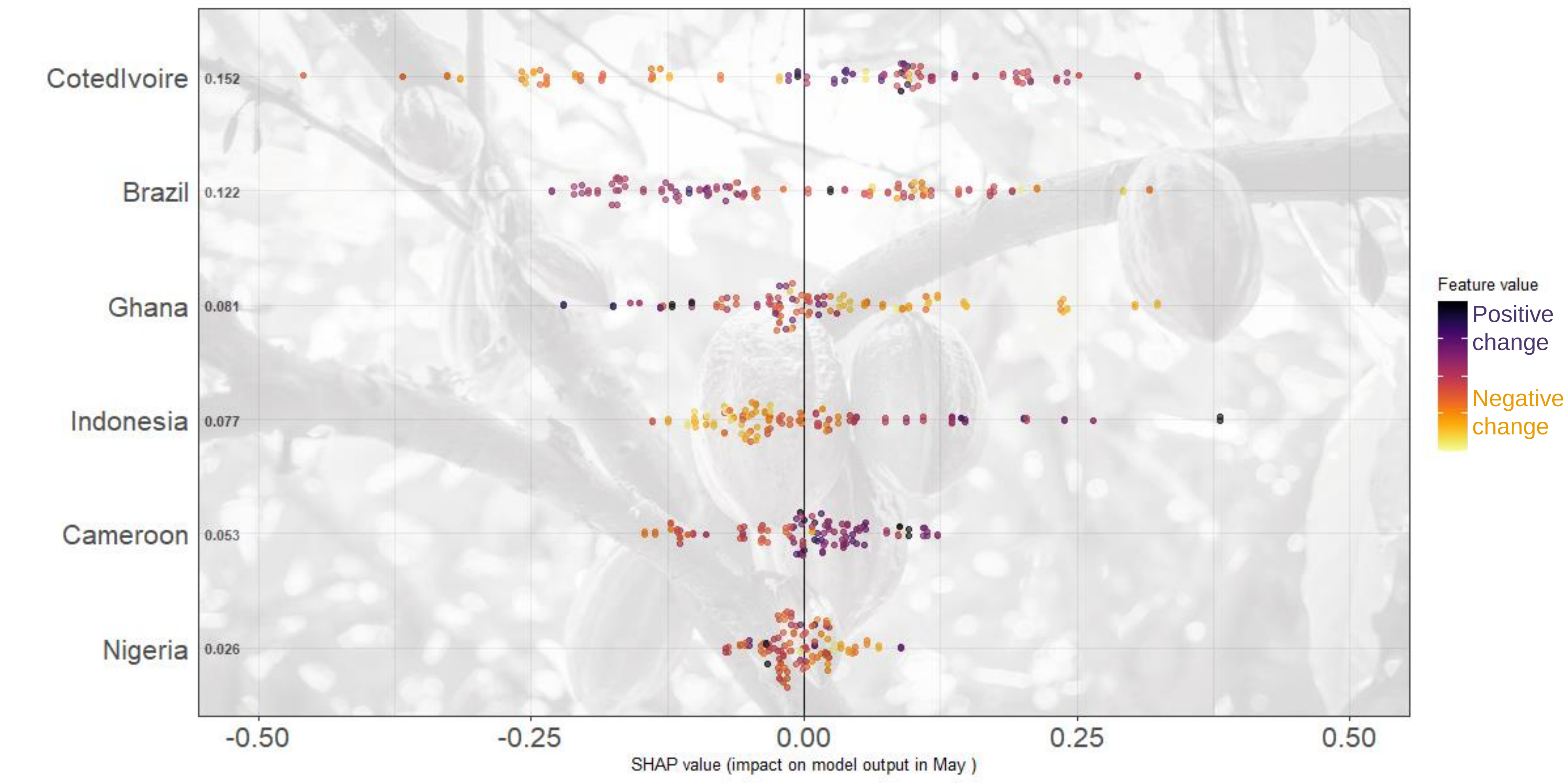
What happened in the model (October price)



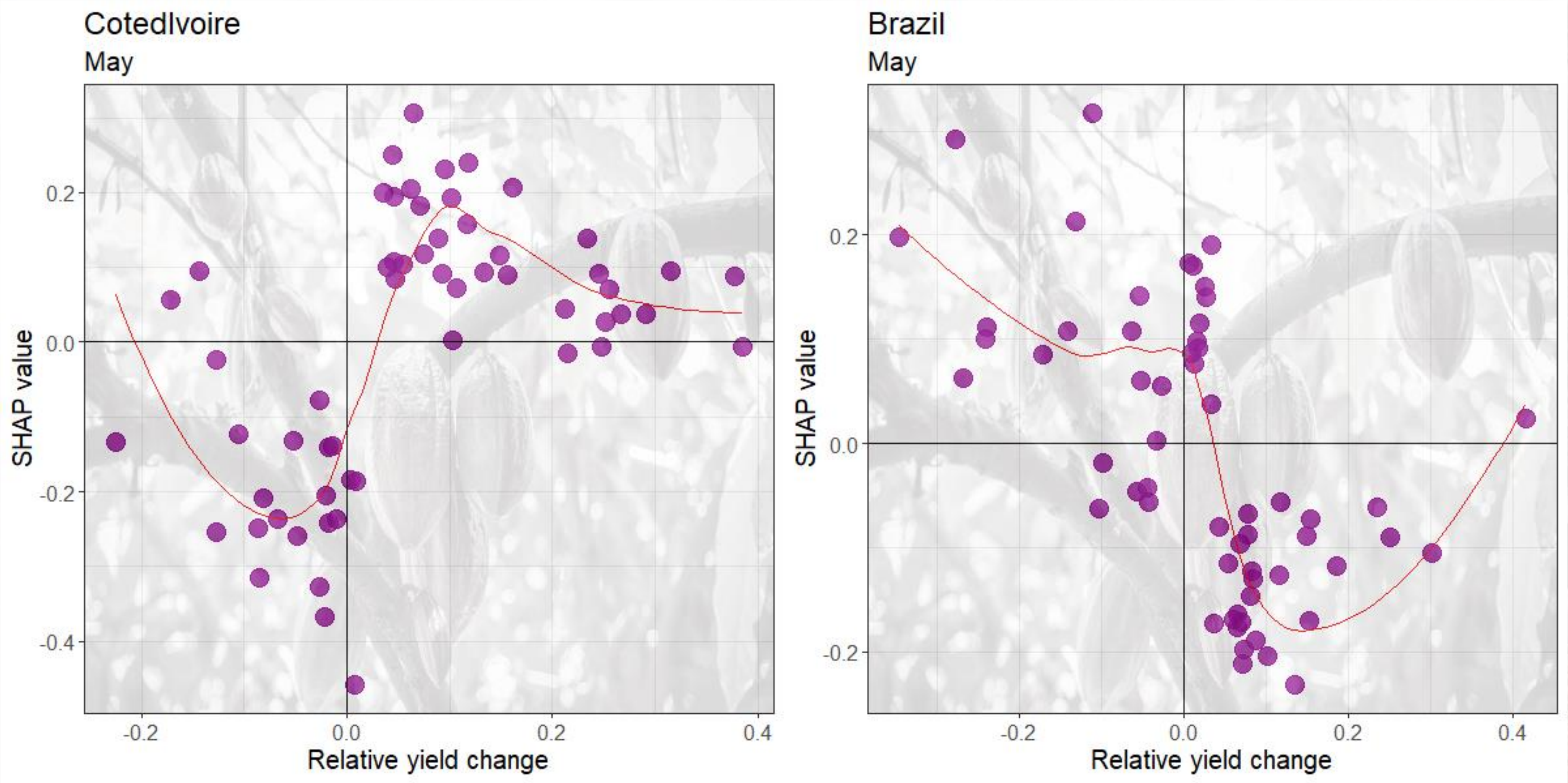
Cocoa top producing markets – Radical market chages



Relative Importance (SHAP) Cocoa



Partial Dependence - Cocoa



What did we achieve?

1. Understand how changes in local features affect AC global prices ✓
2. Forecast AC world prices from local production ✓
   - Applying comprehensive ML methods
   - Use public, regularly updated data
   - Achieve accurate forecasting results
   - In optimal time frame for adaptation (up to a year ahead)
3. Provide policy makers a transparent, ready-to-use model ✗