Using Earth observation products to predict monthly maize prices in Africa

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Motivation

- Price prediction is important for monitoring of food insecurity.
  - Most rural households are net-buyers of staple grains (Barrett 2008; Stephens & Barrett, 2011; Cardell & Michelson, 2021).
  - Urban households purchase a majority of their staples from the market (Battersby & Watson, 2018)
  - Provide accurate forecasts & spot unusual price movements (Davenport & Funk, 2015)
- Collecting price data in developing countries is costly and often price data is spotty.
- Several papers have verified a relationship between precipitation, temperature, and NDVI and grain prices.
- Earth observation (EO) products are freely available, easily accessible, and available in high resolution and frequencies.

Questions

I. Does the inclusion of EO products in price prediction models statistically improve prediction accuracy?

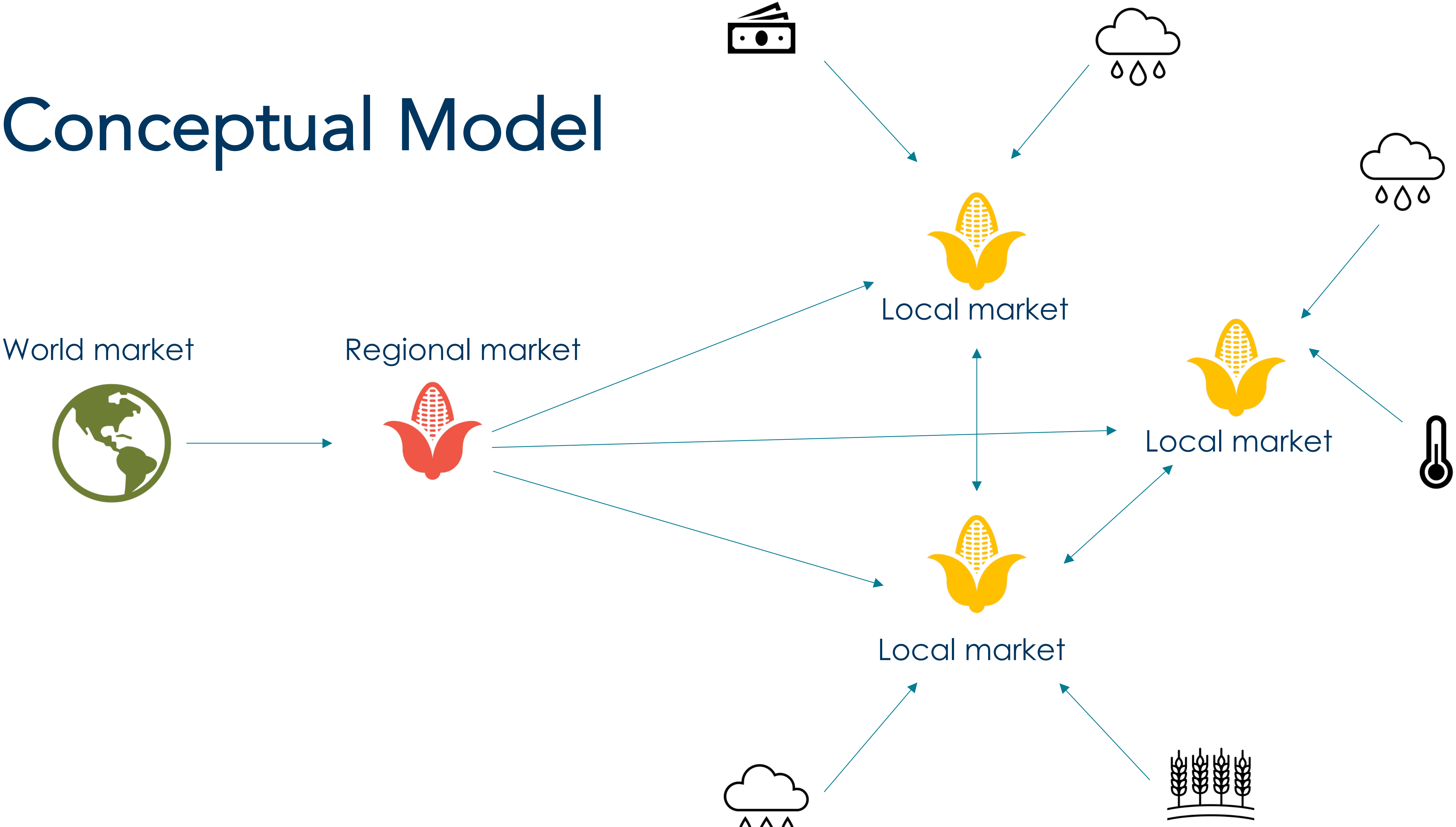
II. Can we accurately predict prices with readily available data?

III. Can we identify a typology of countries/regions in which EO products improve predictive accuracy?

What’s been done

- Several papers have shown drivers of prices to include climate, international prices, regional prices (Baffes et al., 2019; Peri, 2017; Chen & Villoria, 2019; Brown & Kshirsagar, 2015).
- **Brown et al. (2006)** predict millet prices in 445 markets in Burkina Faso, Mali, & Niger using correspondence analysis and Markov chain models. They find If the growing season was characterized by erratic, sparse rainfall it resulted in higher prices and well distributed abundant rainfall resulted in lower prices. Small improvements with the incorporation of NDVI.
- **Higgins, Hitermann, & Brown (2015)** predict millet prices in Burkina Faso, Mali, & Niger using NDVI for 136 markets using Maximum Likelihood estimation. They find the inclusion of NDVI minimally increases the predictive accuracy.
- **Davenport et al. (2021)** Predict maize price averages over 6 & 9 month spans following harvest using univariate ARIMA models and ARIMAX models include start of season variables. Disaggregated results by country, region, market to show improvements in some markets.

Conceptual Model



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Data

Prices

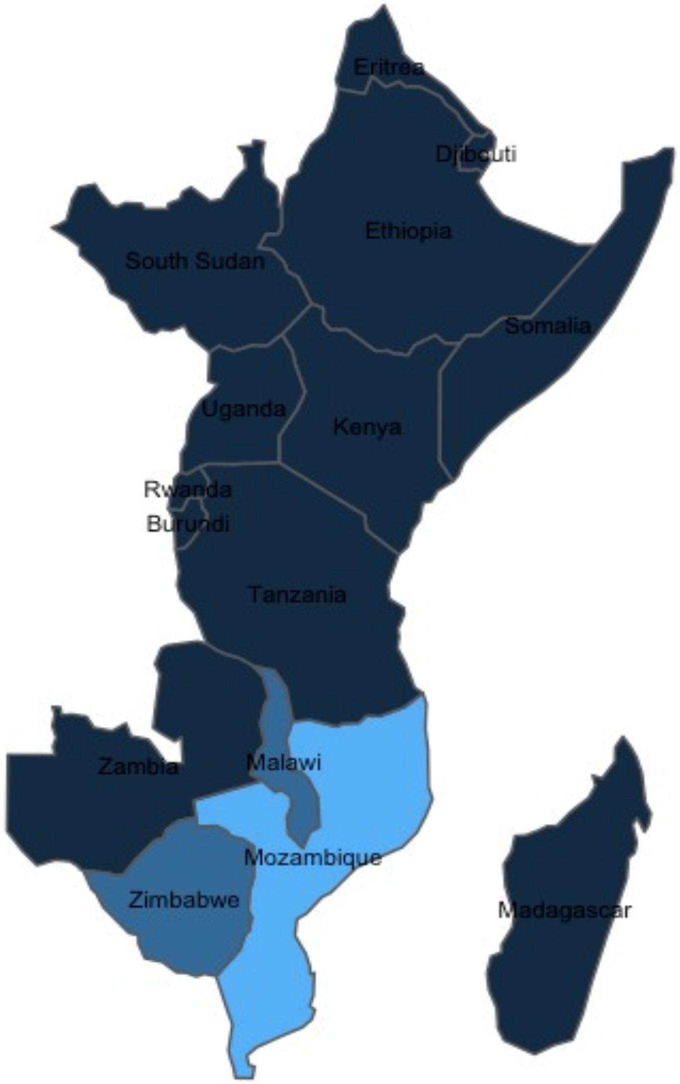
- Monthly prices for countries of interest – FEWSNET

EO products

- Precipitation- Monthly CHIRPS
- Evaporative Demand- Monthly Hobbins
  - We extract all EO products using 100km buffers around each market.

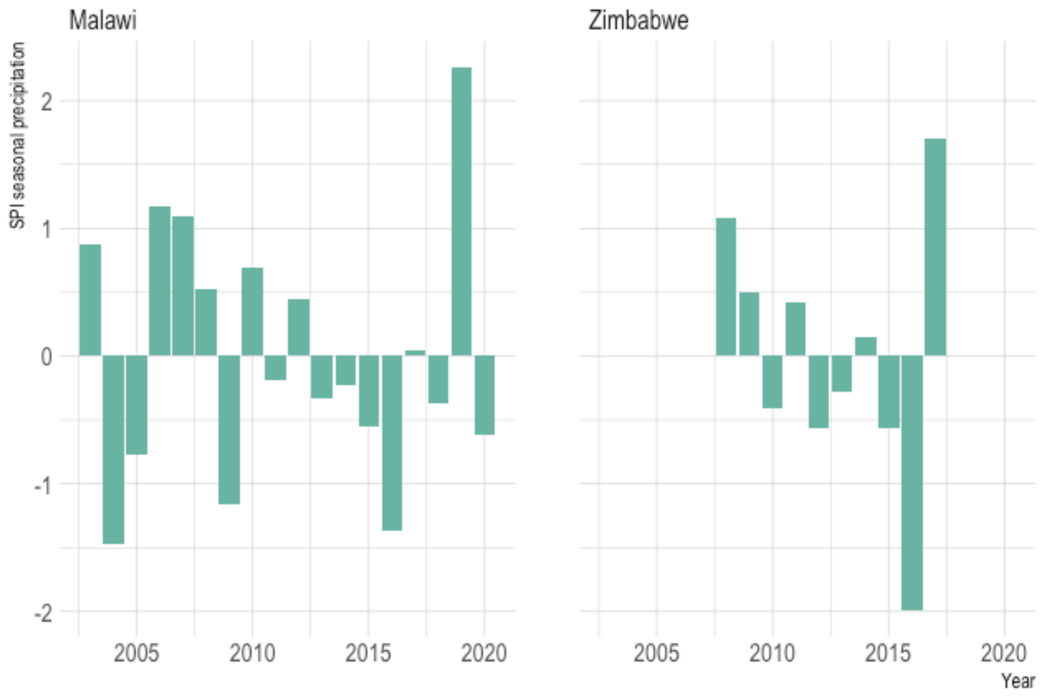
Secondary Data

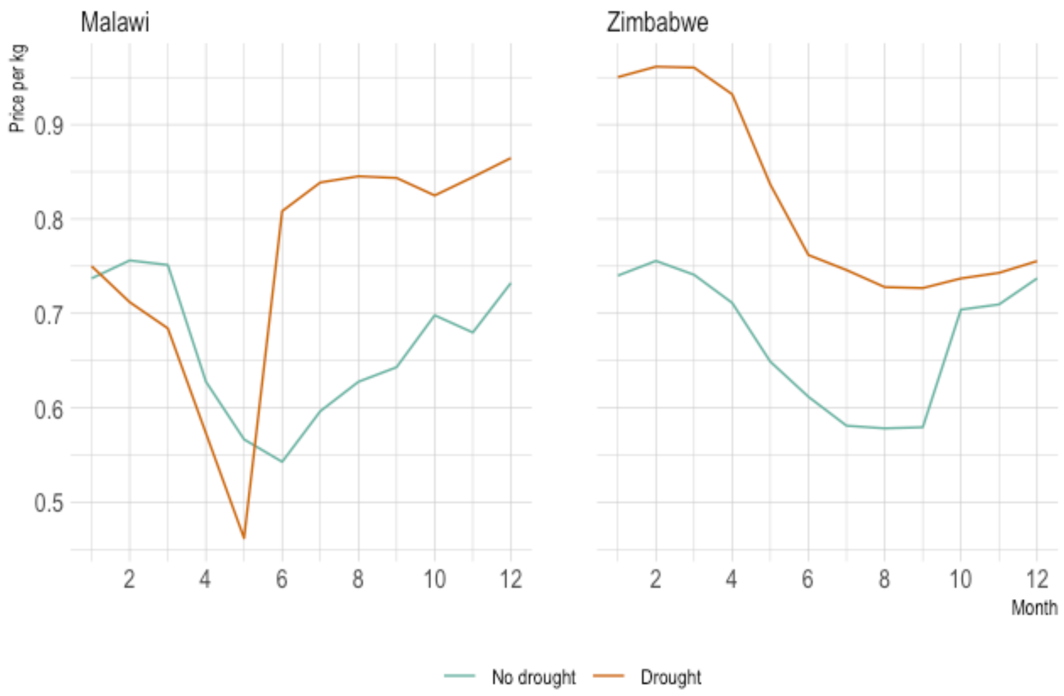
- Purchase Price Parity (PPP) – World Bank
- Food price indices – FAO
- Wholesale maize prices for Randfontein market – FAO GIEWS



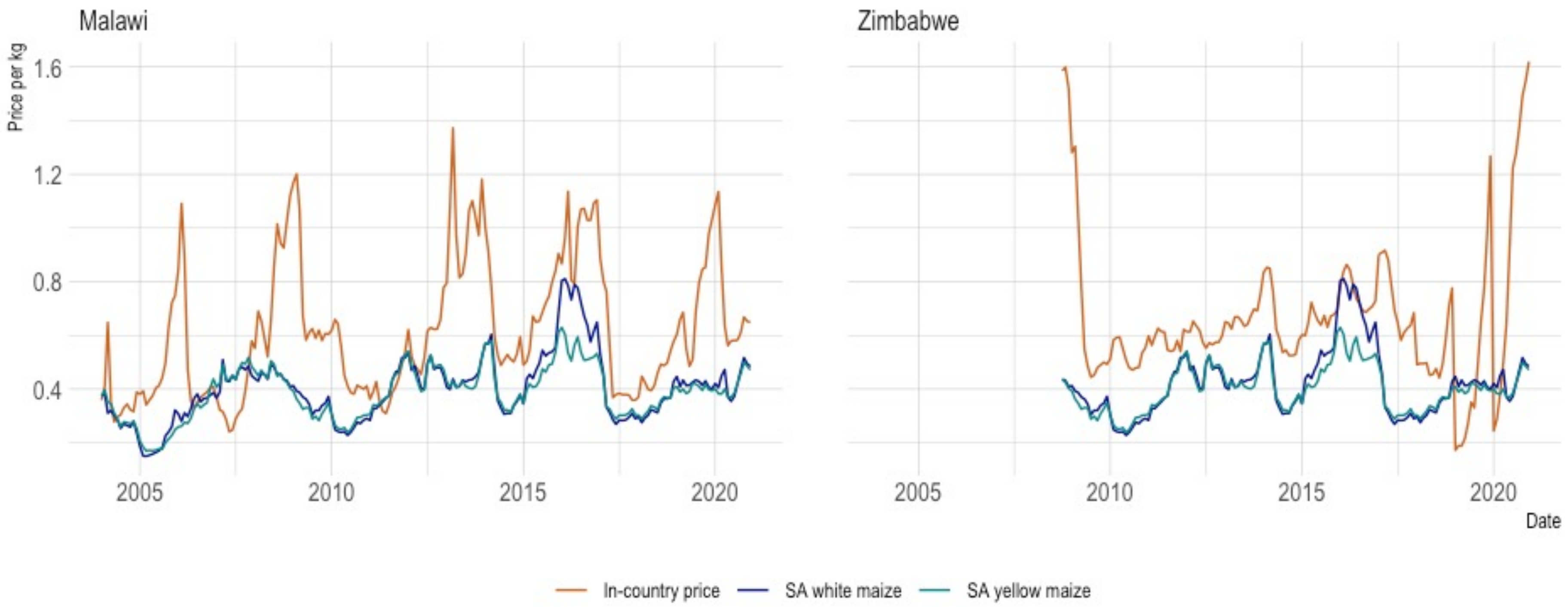
Temporal weather variation

Annual SPI of Rainfall





Temporal price variation
Average price across markets



Prices adjusted using purchase price parity (World Bank)

Methods

1. **Split** the data Train and Test
2. Take training data and use it to **tune** parameters.
3. Use tuned parameters in **LASSO specification** on test data.
4. Analyze **predictive accuracy** at country then market level.
5. **Identify** which markets are improved by EO predictions.
6. **Identify** relevant variables from EO products.

Model Specifications

All specifications include:

- Market indicators
- Month indicators
- Each variable is lagged to 5 time periods

Log price: lagged market logged prices*

Precipitation variables: annual precipitation, annual precipitation squared, SPI, monthly precipitation.

Evaporative demand variables: Total evaporative demand, SPI

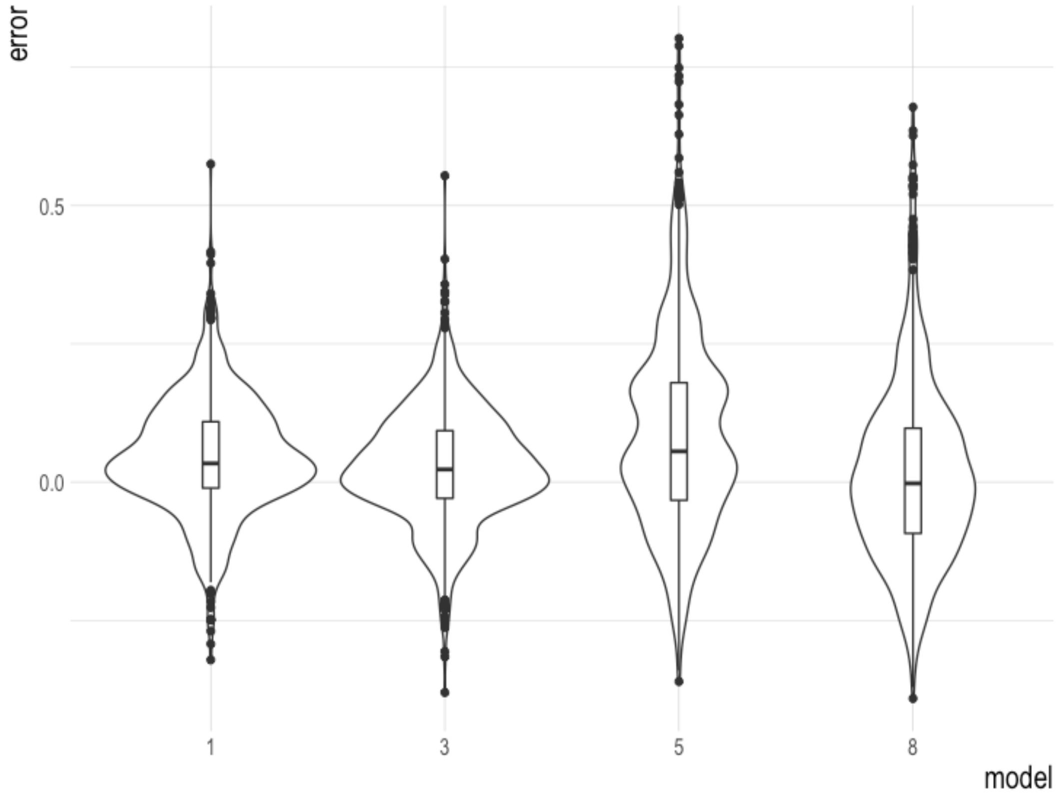
SA maize prices: lagged market logged prices* from Randfontein market in South Africa

Model	Model Name	Log price	Precipitation	Evaporative demand	SA Maize prices
1	MP	X			
2	MP+P	X	X		
3	MP+ED	X		X	
4	MP+P+ED	X	X	X	
5	SA				X
6	SA+ED		X		X
7	SA+P			X	X
8	SA+ED+P		X	X	X

**All prices are adjusted using purchase price parity rates*

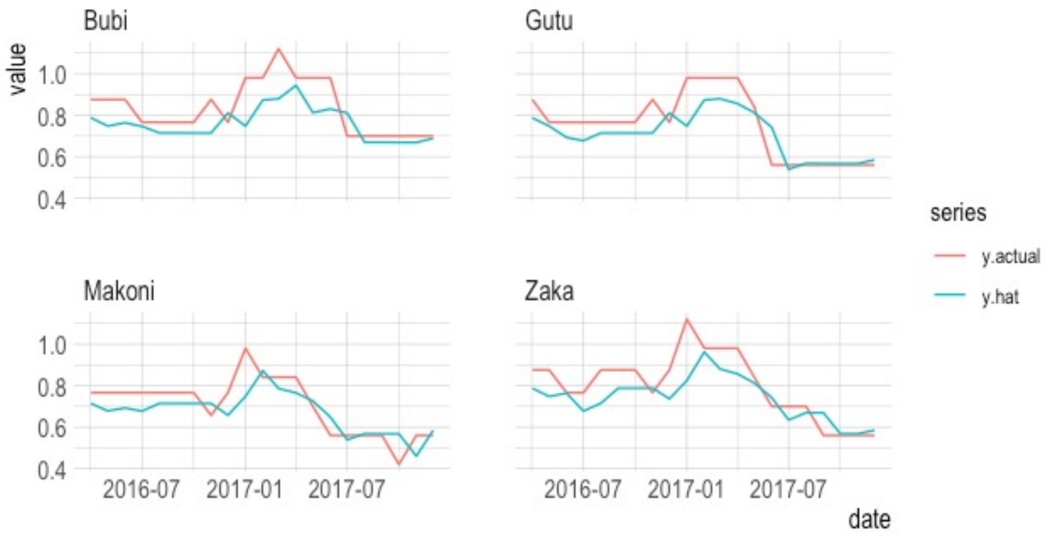
Results: Predictive Accuracy
Country Level

ZIMBABWE				
Model	**Model Name**	**RMSE**	**MAPE**	**MAE**
1	MP	0.1146	11.6488	0.0870
2	MP+P	0.1103	11.9815	0.0845
3	MP+ED	0.1071	11.2117	0.0809
4	MP+P+ED	0.1092	12.0072	0.0838
5	SA	0.1978	19.3416	0.1490
6	SA+ED	0.1735	17.7274	0.1289
7	SA+P	0.1623	17.5607	0.1253
8	SA+ED+P	0.1617	17.2655	0.1217

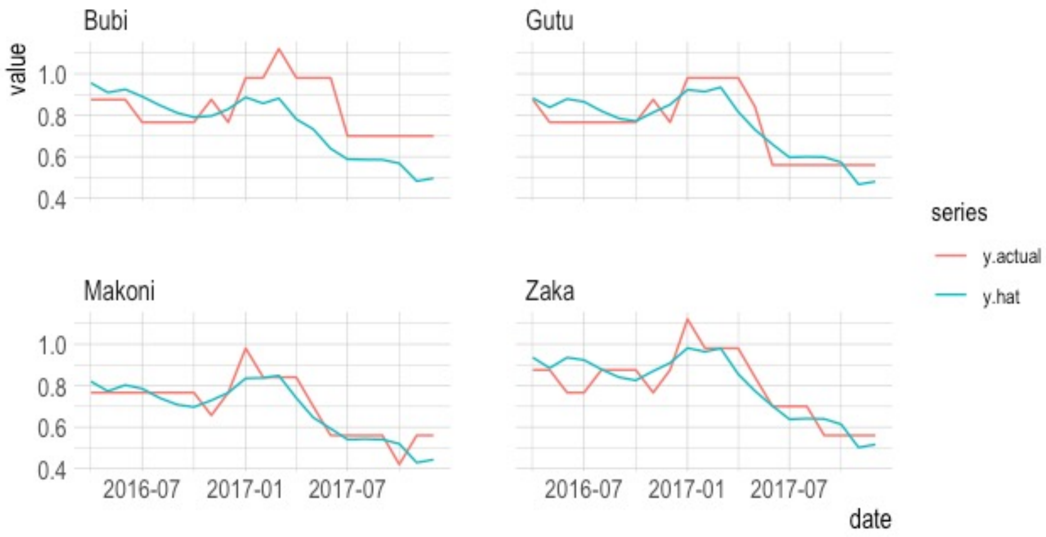


Results: Predictive Accuracy
Zimbabwe

Model 1: MP



Model 8: SA + P + ED



Conclusions

- EO products statistically increase predictive accuracy in maize price predictions

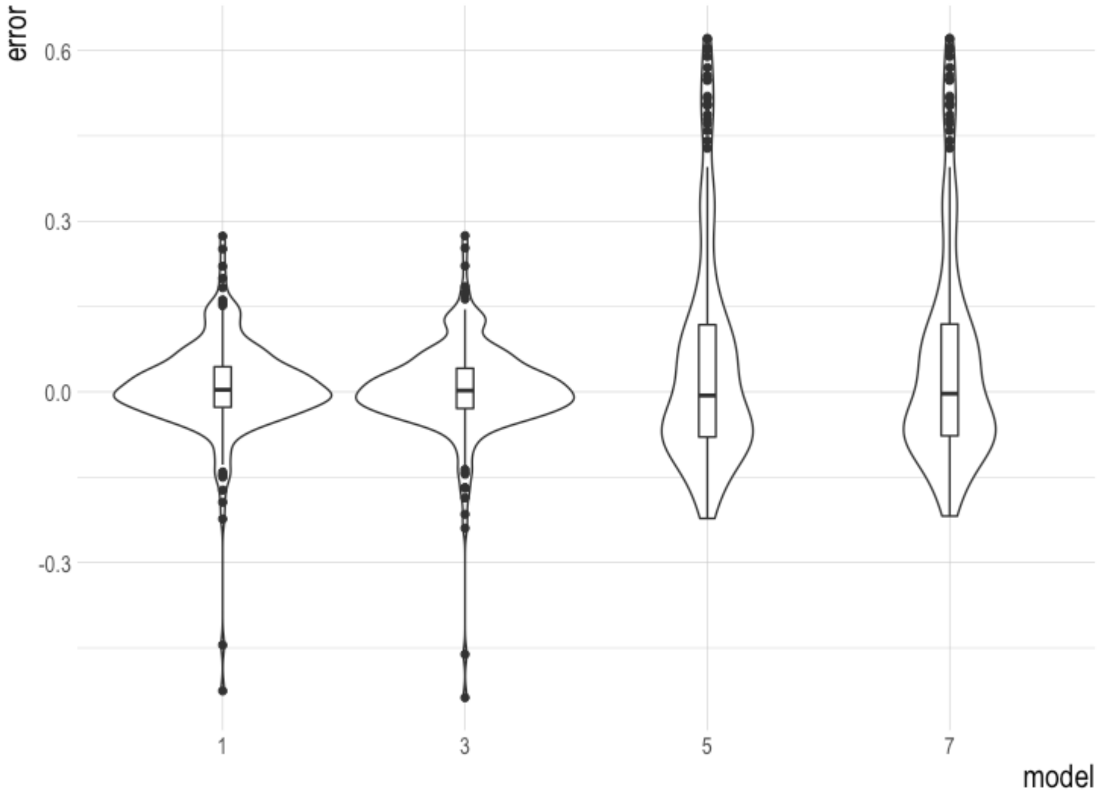
- SA maize prices combined with EO products indicate that in some markets we get better predictive accuracy.

- There is significant heterogeneity across markets. Our next step is to understand what is driving the EO products to work in some places.

Appendix

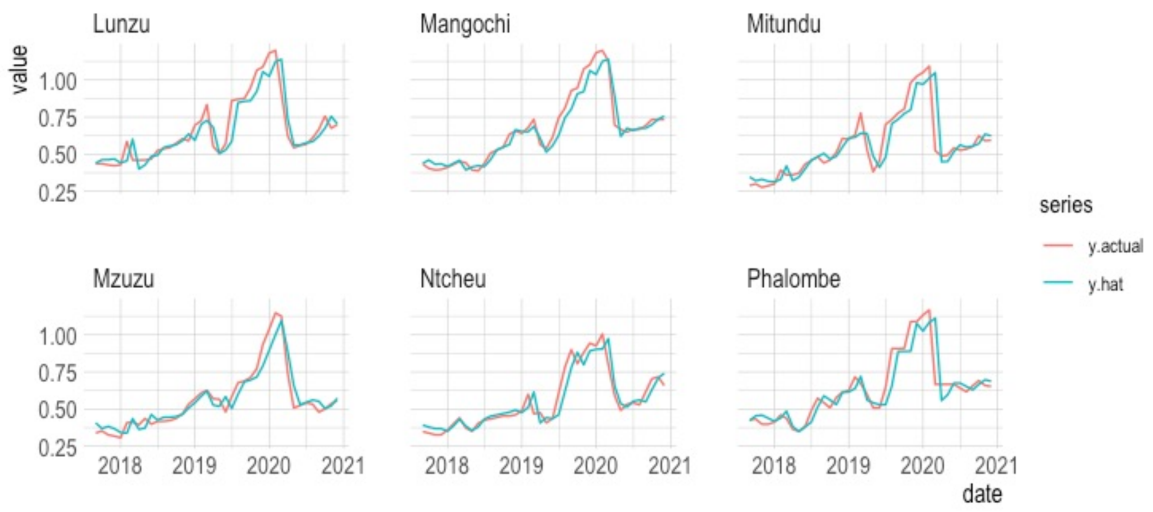
Results: Predictive Accuracy
Country Level

MALAWI				
Model	**Model Name**	**RMSE**	**MAPE**	**MAE**
1	MP	0.0835	8.8866	0.0545
2	MP+P	0.0835	9.1857	0.0567
3	MP+ED	0.0835	8.8740	0.0537
4	MP+P+ED	0.0837	9.2131	0.0569
5	SA	0.2009	22.1890	0.1423
6	SA+ED	0.2026	22.7422	0.1441
7	SA+P	0.2004	21.8985	0.1412
8	SA+ED+P	0.2033	22.6453	0.1439

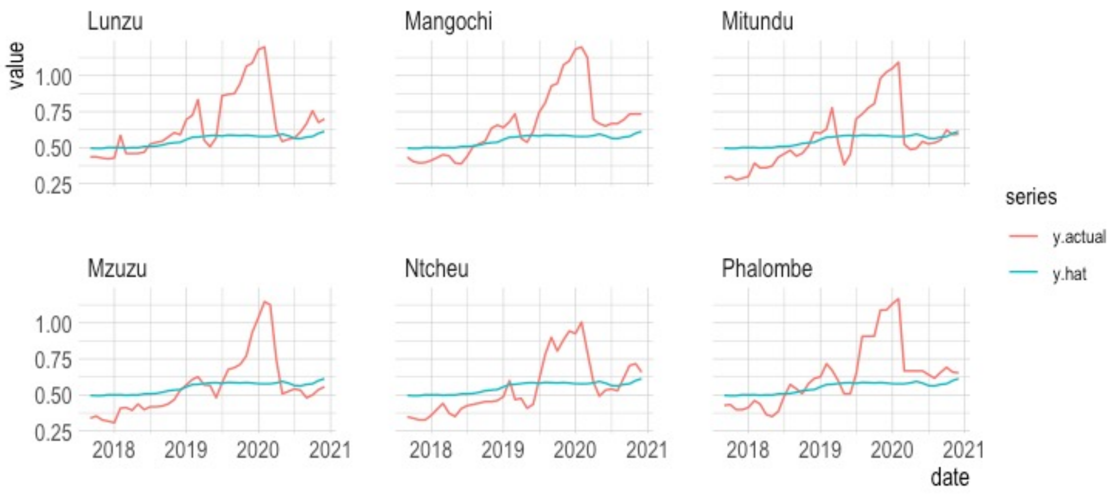


Results: Predictive Accuracy
Malawi

Model 1: P

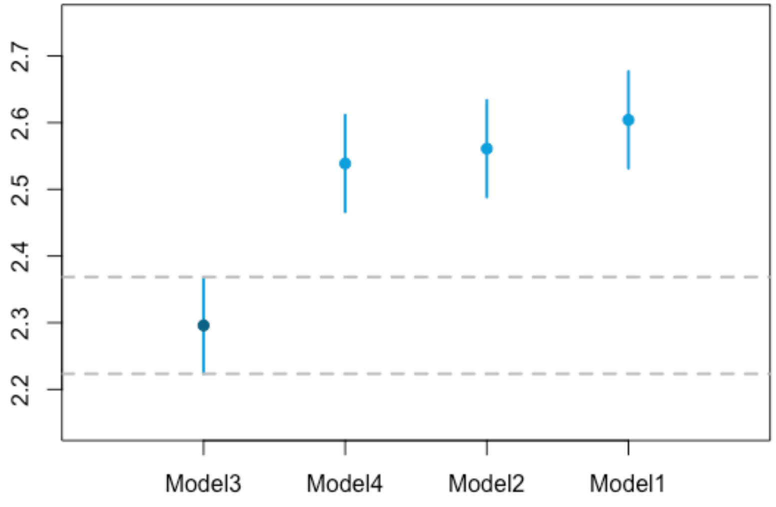


Model 7: SA + ED



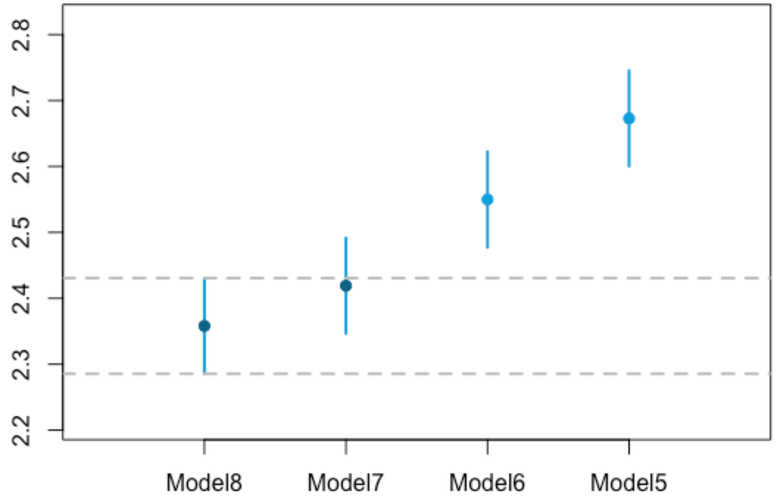
Results: Predictive Accuracy
Nemenyi test
Zimbabwe

Ranks the performance of methods for each time series and then takes the mean of those ranks and produces confidence bounds for those means.



- Model 3 is statistically different from models 1, 2, & 4

- Model 8 is not statistically different from model 7 both have lower ranked errors than models 6 & 5

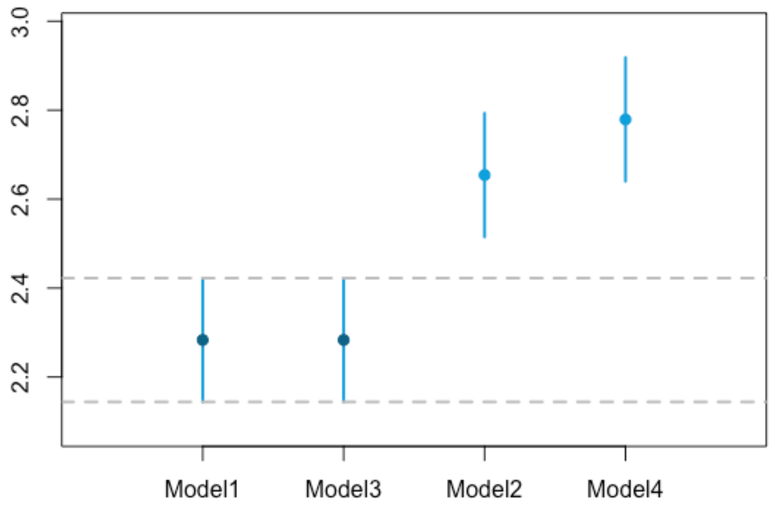


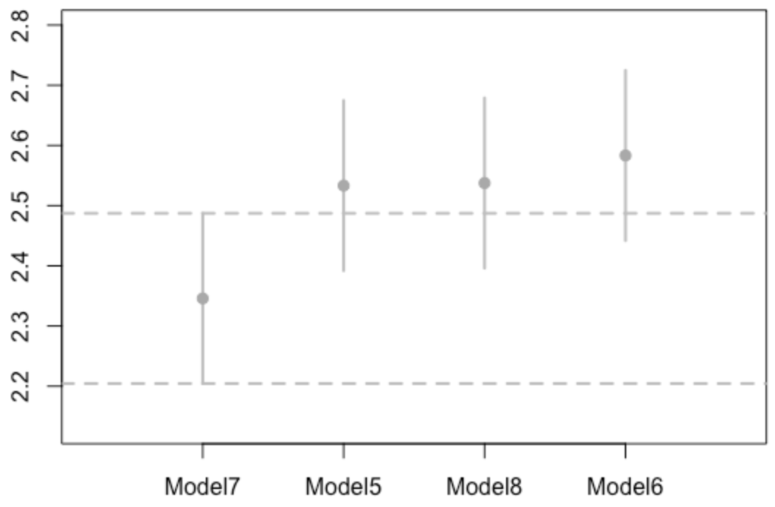
Results: Predictive Accuracy
Nemenyi test
Malawi

Ranks the performance of methods for each time series and then takes the mean of those ranks and produces confidence bounds for those means.

- Model 1 & 3 are statistically different from models 2, & 4 and both have lower ranked errors than models 2 & 4

- The Nemenyi test is not statistically significant, p-value=0.0946





Wilcoxon signed-rank test results

Null hypothesis: the distribution of the time-series are the same

Malawi

- Model 1 & 3: p = 0.8520 do not reject the null
- Model 5 & 7: p = 0.0000 reject the null

Zimbabwe

- Model 1 & 3: p = 0.0890 do not reject the null
- Model 5 & 8: p = 0.0000 reject the null

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