

Exploring volatility in crop prices for farmers' benefit

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INTRODUCTION



India ranks second worldwide in farm outputs[Wikipedia, 2023].



As per the Indian economic survey 2018, agriculture employed more than 50 per cent of the Indian workforce and contributed 17–18 per cent to the country's GDP[Wikipedia, 2023].



Farming in India is a risky business. Risk is of many types; rainfall (excess, deficit, bad distribution), pests and diseases, price variation, etc.[Godase et al., 2022]



Our goal is to mainly focus on price variation.



Zhang et al. (2014) stated that accurate price prediction of agricultural products is useful for planning agricultural production and for developing a balance between supply and demand.

MOTIVATION



The majority of farmers, 86 per cent are small and marginal with declining and fragmenting landholdings, these uncertainties make them even more vulnerable and risk-prone to the price volatility of crops.[Business Standard, 2017]



In India, a farmer faces a huge problem due to price fluctuations.



Figure 1: Farmers in Tamil Nadu threw tomatoes on the roadside after the price plummeted to Rs 2 per kilogram.[India Today, 2022]

OBJECTIVE



The goal of our project is to give recommendations to farmers about possible actions to avoid low prices.



Advice includes a window for sowing potatoes and forecasting potato, banana, and spinach prices so that a farmer can avoid losses by taking the produce to the market at the right time.

LITERATURE REVIEW

‘Favorit’: farmers’ volatility risk treatment [Godase et al., 2022]

Introduction: The aim of this paper is not to maximize profit but to reduce losses. The attempt is to use analytics, not to discover any new macroeconomic insight, but to suggest a small change in a farmer’s approach.

FLAP Index: We are trying to combine two dimensions of price (mean and volatility). Let us define a new index to be named the FLAP index. FLAP is the acronym for Fluctuation Adjusted Price. We define it as mean/sd . Note that it is the inverse of the Coefficient of Variation (sd/mean).



LITERATURE REVIEW

Time Series Forecasting of Price of Agricultural Products Using Hybrid Methods [Sourav Kumar Purohit and Beheraa, 2021]

Introduction: Accurate prediction of crop prices assists farmers to decide the best time to sell their products to get maximum benefit and assists Government with post-harvest storage and management of the product so as to stabilize the price volatility throughout the year.

Hence, the prediction of crop prices is a challenging and important problem.

Inspired by this, in this study, they have proposed two additive hybrid methods (Additive-ETS-SVM, Additive-ETS-LSTM) and five multiplicative hybrid methods (Multiplicative-ETS-ANN, Multiplicative-ETS-SVM, Multiplicative-ETS-LSTM, Multiplicative-ARIMA-SVM, Multiplicative-ARIMA-LSTM) to predict the monthly retail and wholesale price of three most commonly used vegetable crops of India, namely, tomato, onion, and potato (TOP).



METADATA

For potatoes, we consider prices from January 3, 2011, to February 13, 2023.

For spinach, we consider prices from July 24, 2016, to February 20, 2023.

For bananas, we consider prices from September 22, 2021, till February 16, 2023.



For potatoes, seven missing values.

For spinach, one missing value.

For bananas, no missing values.

We consider three crops for the analysis: potato, banana, and spinach. And the data we consider is the daily price data of the Pune market. We have also considered the daily potato prices for all the markets of Maharashtra.

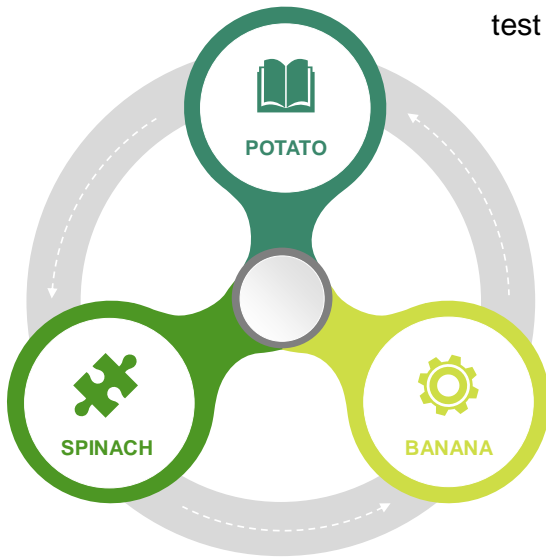
The data is collected from <https://agmarknet.gov.in/PriceAndArrivals/DatewiseCommodityReport.aspx>



METHODOLOGY

METHODOLOGY

We first divide the price data of all three crops into train and test parts. And do the analysis on the train part.



01

The train part for potatoes is from 3rd January 2011 to 30th October 2020. And the test part is from 1st November to 13th February 2023.

02

The train part for spinach is from 24th July 2016 to 21st October 2021. And the test part is from 22nd October 2021 to 20th February 2023.

03

The train part for bananas is from 22nd September 2021 to 8th November 2022. And the test part is from 9th November 2022 to 16th February 2023.

METHODOLOGY



In line with the literature review [Godase et al 2022], we compute a 95 per cent confidence interval of monthly prices for all three commodities i.e. potato, banana, and spinach.

METHODOLOGY

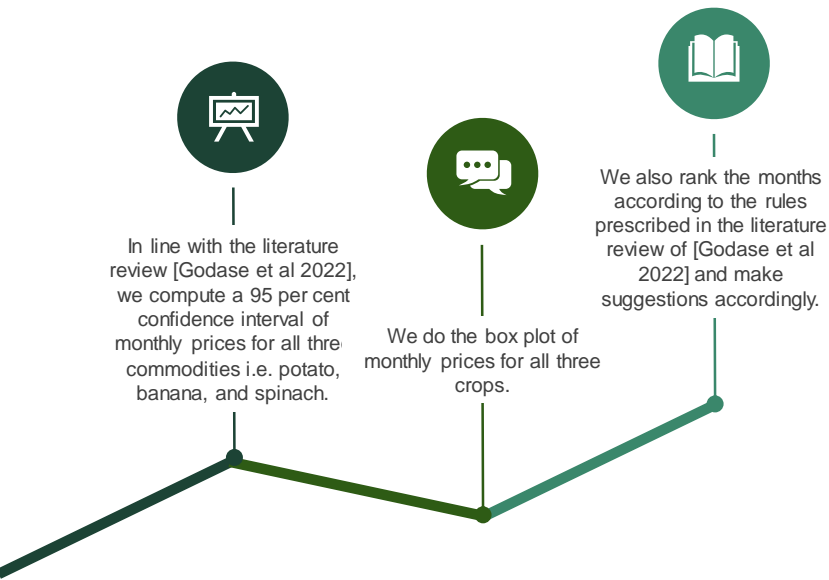


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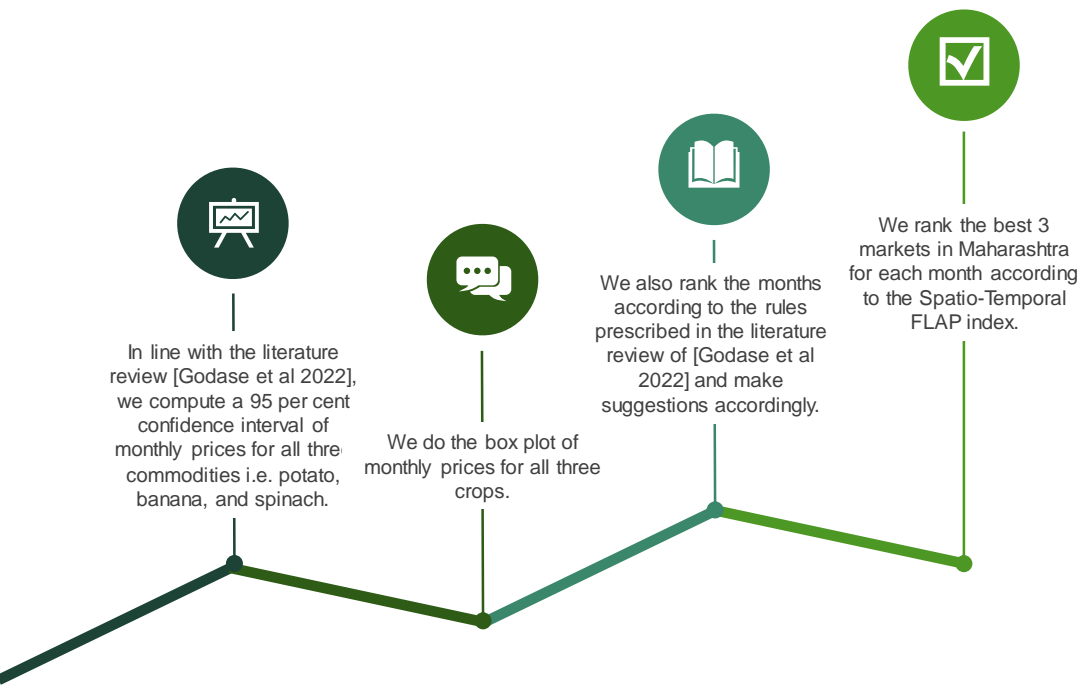


We do the box plot of monthly prices for all three crops.

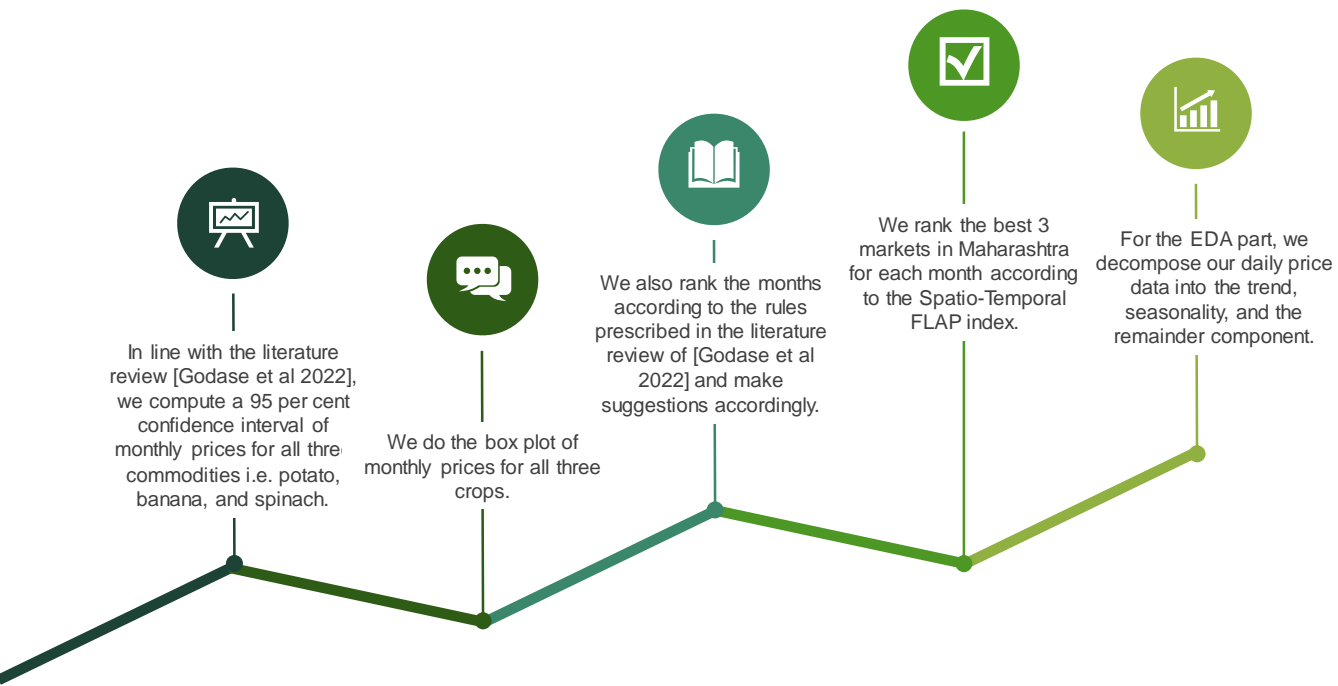
METHODOLOGY



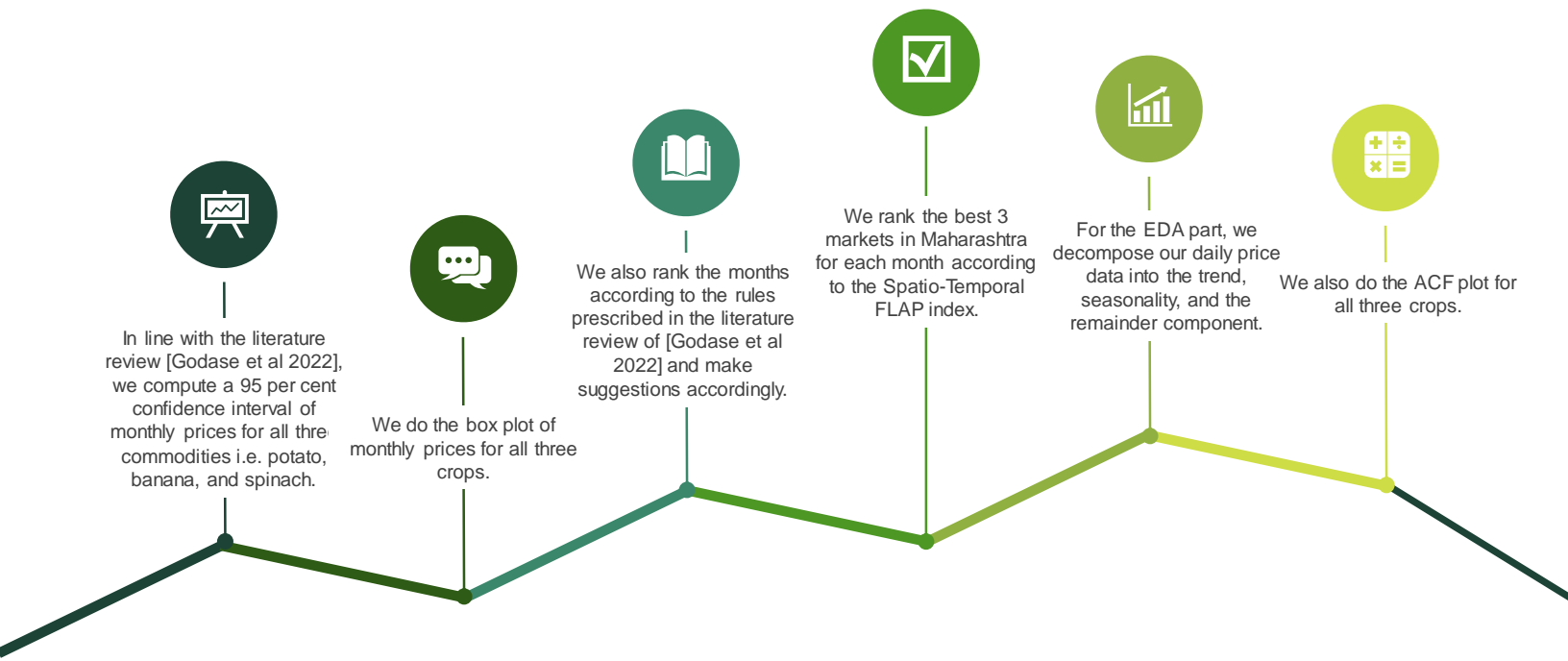
METHODOLOGY



METHODOLOGY



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METHODOLOGY



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For forecasting, we have considered the two most popular statistical forecasting models, namely, ARIMA, exponential smoothing with error, trend, and seasonality (ETS).

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Two popular machine learning models, namely, support vector machine for regression (SVM), and long short-term memory (LSTM) are also considered.

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Two popular machine learning models, namely, support vector machine for regression (SVM), and long short-term memory (LSTM) are also considered.



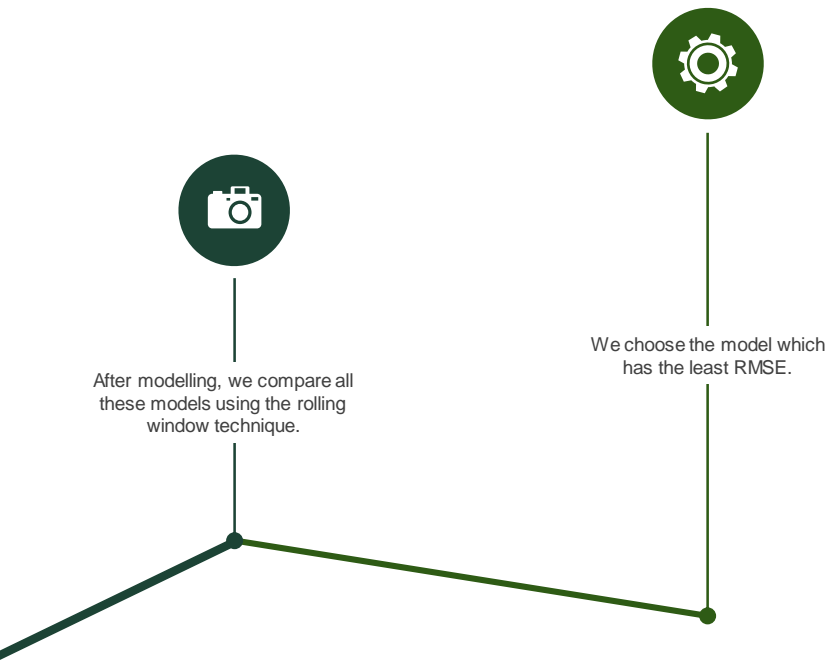
The machine learning models (LSTM and SVM) are considered the additive and multiplicative parts of the hybrid methods along with the aforementioned statistical models.

METHODOLOGY

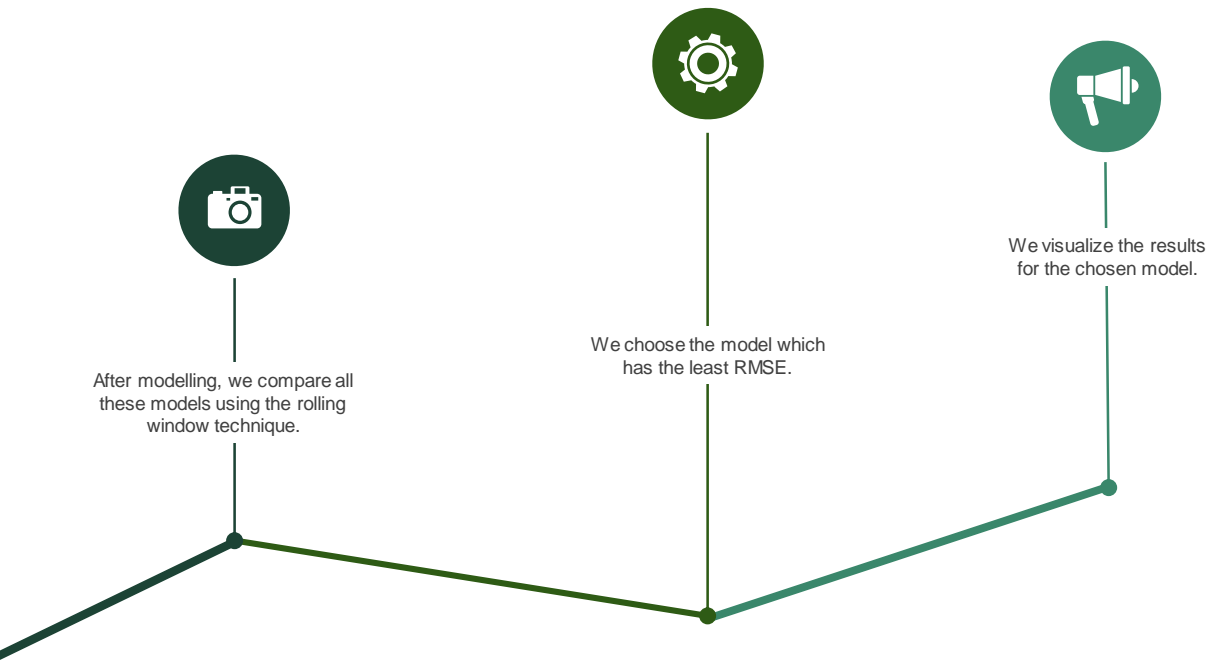


After modelling, we compare all these models using the rolling window technique.

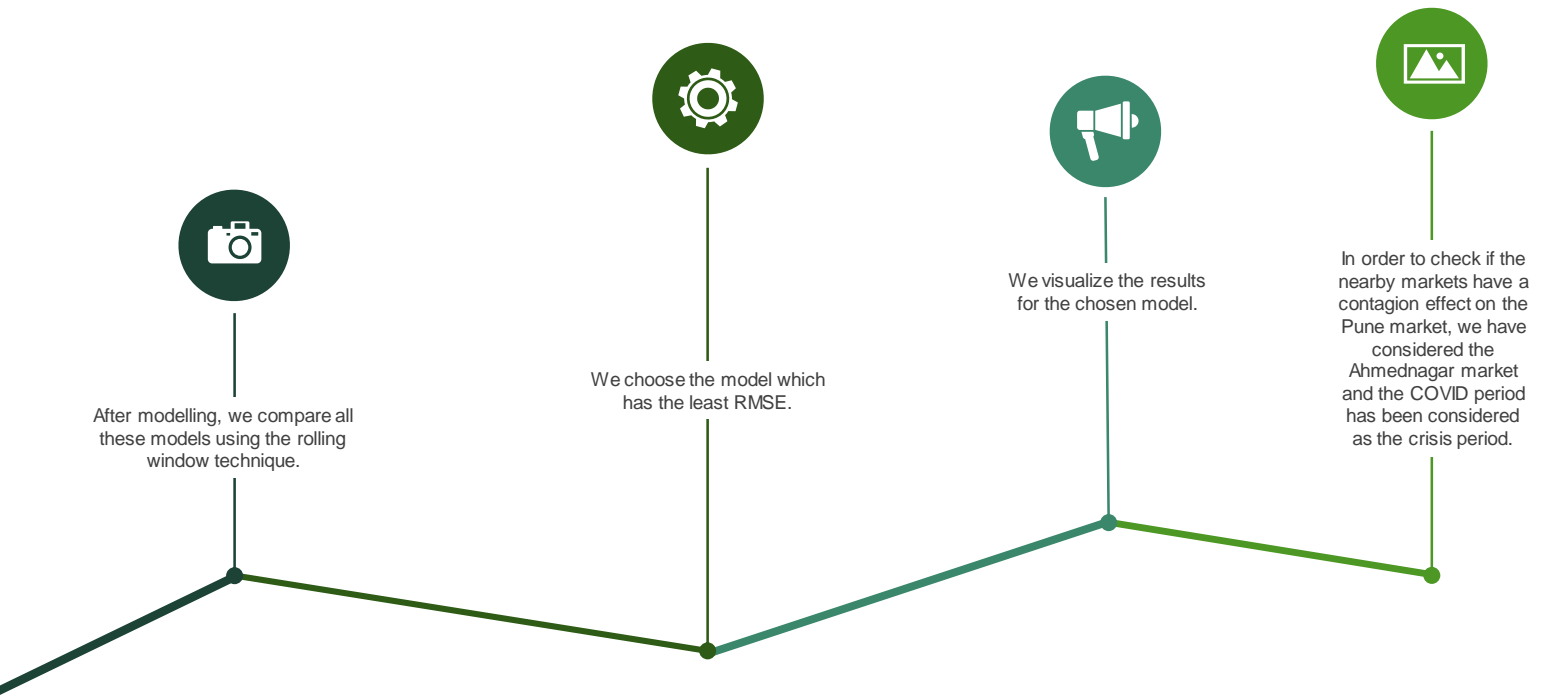
METHODOLOGY



METHODOLOGY



METHODOLOGY



METHODOLOGY

Model Definitions:



ARIMA (Autoregressive Integrated Moving Average) - ARIMA models are typically used for stationary time series data, which means the statistical properties of the data such as mean, variance, and autocorrelation remain constant over time.



ETS (Error-Trend-Seasonality) - ETS models are based on decomposing a time series into its underlying components, such as trend, seasonality, and error. ETS models can be useful for making short-term forecasts.

METHODOLOGY

Model Definitions:



LSTM (Long Short-Term Memory) - LSTM is a type of recurrent neural network (RNN) that is commonly used for time series analysis and forecasting. This allows LSTM models to handle long-term dependencies in the data, making them useful for making long-term forecasts.



SVM (Support Vector Machine) - SVM is a machine learning algorithm that is often used for classification and regression tasks. SVM can also be used for time series forecasting by treating it as a regression problem. In this approach, the SVM algorithm tries to find a hyperplane that maximizes the margin between the predicted values and the actual values. SVM can be useful for making both short-term and long-term forecasts.

METHODOLOGY

For additive hybrid models:

The time series: $y = [y_1, y_2, \dots, y_n]^T$ is considered as an addition of a linear (L) and a nonlinear (N) component as in Equation (1).

$$y = L + N \quad (1)$$

First, a linear model is applied to the time series to obtain the forecasts on the linear component (L).

Then, the residual series(e) is computed by subtracting the forecasts on linear component (L) from the original time series y as in Equation (2).

$$e = y - \hat{L} \quad (2)$$

The residual series is used by a nonlinear model to obtain the forecasts on nonlinear component N.

Then, the final forecasts are obtained by adding the forecasts on the linear component with the forecasts on the nonlinear component as in Equation (3).

$$\hat{y} = \hat{L} + \hat{N} \quad (3)$$

A total of six different combinations, namely, Additive-ARIMA-SVM, Additive-ARIMA-LSTM, Additive-ETS-SVM, and Additive-ETS-LSTM are obtained and used for forecasting.



METHODOLOGY

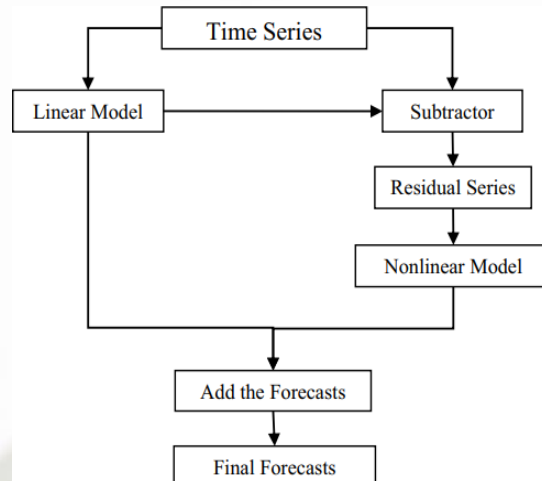


Figure 2: Schematic representation of the additive hybrid method (Sourav Kumar Purohit and Beheraa, 2021, *Applied artificial intelligence*)

METHODOLOGY

For multiplicative hybrid models:

The time series: $y = [y_1, y_2, \dots, y_n]^T$ is considered as a multiplication of a linear (L) and a non-linear linear (N) component as in Equation (4).

$$y = L \times N \quad (4)$$

First, a linear model is applied to the time series to obtain the forecasts on the linear component (L).

Then the residual series (e) is computed by dividing the forecasts on linear component (L) from the original time series y as in Equation (5)

$$e = y \div \hat{L} \quad (5)$$

The residual series is used by a nonlinear model to obtain the forecasts on nonlinear component N.

Then, the final forecasts are computed by multiplying the linear component forecasts with nonlinear component forecasts as in Equation (6)

$$\hat{y} = \hat{L} \times \hat{N} \quad (6)$$

A total of six different combinations namely, Multiplicative-ARIMA-SVM, MultiplicativeARIMA-LSTM, Multiplicative-ETS-SVM, and Multiplicative-ETS-LSTM are obtained and used for forecasting.



METHODOLOGY

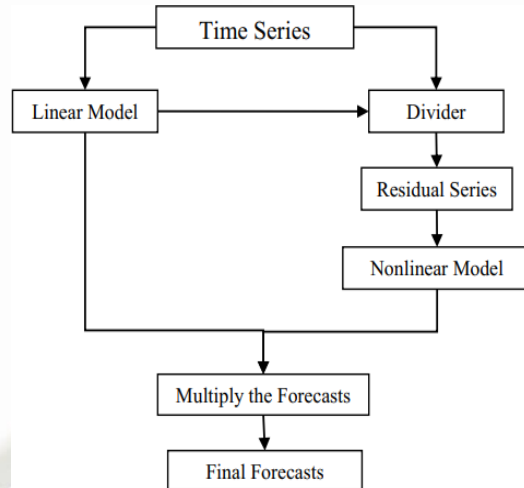


Figure 3: Schematic representation of additive hybrid method (Sourav Kumar Purohit and Beheraa, 2021, *Applied artificial intelligence*)

METHODOLOGY

Rolling Window Technique:

The rolling window technique is a common approach used in time series modelling to generate a series of forecasts based on a sliding window of historical data. The idea is to use a fixed-length window of historical data to fit a model and then use this model to forecast the next value in the time series. The window is then shifted by one time step and the process is repeated to generate a new forecast. This technique is also known as the sliding window approach or the rolling forecast approach.

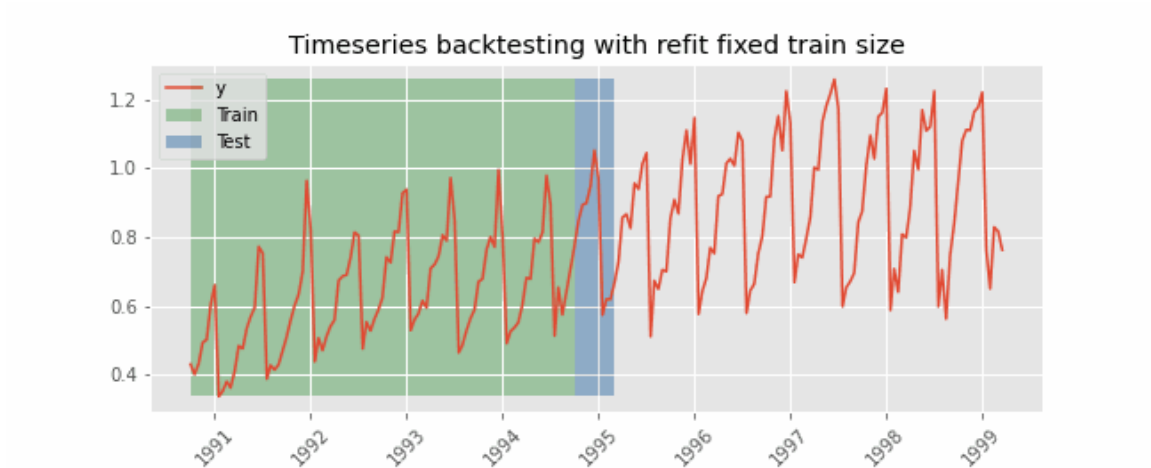
Here, we have defined the window size as 12. We then loop over the time series data starting from the window size and generate forecasts using the chosen model. For each iteration, we select the window of historical data, fit the chosen model to the window, and generate a forecast for the next time step. The forecasts are stored and the test errors are computed.

We perform the Rolling Window technique for each and every model as mentioned earlier. The model with the least RMSE is considered the best model.



METHODOLOGY

Visual Representation of the Rolling Window Technique



GIF Credit: [Rami Krispin](#)



METHODOLOGY

Contagion Effect:

Financial contagion is the spread of financial market disturbances, crises, or shocks from one market to another or from one institution to another, resulting in the amplification of financial stress and instability. The contagion effect can occur in different ways, such as through direct financial linkages, indirect economic linkages, investor behaviour, or psychological factors.

Here, in order to check if the nearby markets have a contagion effect on the Pune market, we have considered the Ahmednagar market and the COVID period has been considered as the crisis period.

Here, we perform the test for financial contagion by means of the local Gaussian correlation developed by Støve, Tjøstheim, and Hufthammer (2013). They test whether the local correlations between two financial time series are different before and during crisis times.



METHODOLOGY

Spatio-Temporal FLAP Index:

The Spatio-Temporal FLAP Index is the FLAP index constructed for the markets across different months. We rank the best 3 markets in Maharashtra for each month and suggest to the farmer where to sell the crop in which month to gain maximum profit with more consistency.

Similar to the FLAP index the Spatio-Temporal FLAP index is defined as, mean/sd . Hence, it prescribes a value for a market for a given month taking both the average and the variation of the prices in the market for that month into consideration at the same time. A higher value of the Spatio-Temporal FLAP index would indicate a market with a higher average price and lesser variation i.e. greater precision.

If Market A has a higher Spatio-Temporal FLAP index than Market B for month X, we rank Market A over Market B for month X.





RESULT & ANALYSIS

RESULT & ANALYSIS

Ranking of months for all three crops based on the FLAP Index

Table 1: Confidence Interval for monthly average price of potato (Rs/Quintal) for Pune Market

Month	Mean	lower_CI	upper_CI	FLAP_Index	Rank
May	1297.47	800	1803.75	4.05645	1
April	1193.89	782.5	1750	3.9766	2
June	1343.41	800	1976.25	3.60652	3
February	1000.54	600	1700	3.43686	4
March	1029.91	641.25	1735	3.4158	5
July	1393.41	700	2250	2.89105	6
August	1466.25	700	2600	2.5809	7
January	1076.23	600	2200	2.55347	8
October	1480.98	811.875	2700	2.54298	9
November	1337.89	700	2496.25	2.51633	10
September	1494.93	713.75	2786.25	2.47528	11
December	1312.84	600	2470	2.29818	12

Table 2: Confidence Interval for Monthly average price of spinach (price/ bunch) for pune market

Month	Mean	lower_CI	upper_CI	FLAP_Index	Rank
February	4.13675	3	5	7.89938	1
January	4.52991	3	5	7.10558	2
March	4.14167	3	6	4.80012	3
April	5.20619	4	8	4.37606	4
May	5.60215	4	9	4.2181	5
July	4.87218	3	8.4	3.87362	6
June	5.84167	4	10.025	3.25199	7
December	4.50394	3	8	3.22502	8
October	8.32824	4	14	2.87762	9
September	6.12587	3.55	10	2.65539	10
August	5.61333	4	10.275	2.62072	11
November	6.71667	4	12.025	2.54268	12

Table 3: Confidence Interval for Monthly average price of banana (price/ quintal) for pune market

Month	Mean	lower_CI	upper_CI	FLAP_Index	Rank
April	1000	1000	1000	Inf	1.5
June	1000	1000	1000	Inf	1.5
May	983.333	912.5	1000	24.0866	3
August	1025	1000	1217.5	11.8357	4
January	937.5	735	1000	8.83883	5
July	1050	1000	1262.5	8.57321	6
March	1025	927.5	1290	8.43322	7
February	960	700	1200	5.20633	8
December	819.048	650	1100	5.02011	9
October	1010.81	700	1500	4.60349	10
September	1138.46	1000	1710	4.49207	11
November	935	700	1405	3.41354	12

In Table 1 we can see the month of May as the preferable month to sell potatoes.

In Tables 2 and 3, we can see even though the months of October and September have a lower value on the FLAP index, it is still a good time to sell spinach and bananas respectively based on the higher value of the lower confidence interval.

Hence, a farmer can plan the sowing in such a way that the profits are maximized.

Note: The FLAP_Index value is Inf for the month of April and June because there is no variation in the banana prices for those months with a lower number of samples.

RESULT & ANALYSIS

Decomposition of the price data into trend, seasonality, and the remainder component

Figure 4: Decomposition of potato price data into a trend, seasonal, and remainder component.

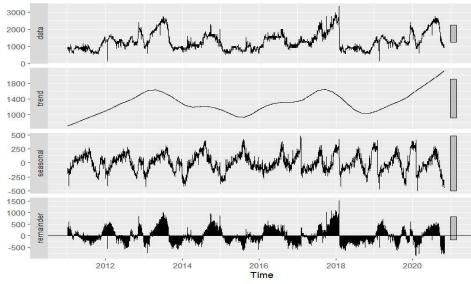


Figure 5: Decomposition of spinach price data into a trend, seasonal, and remainder component.

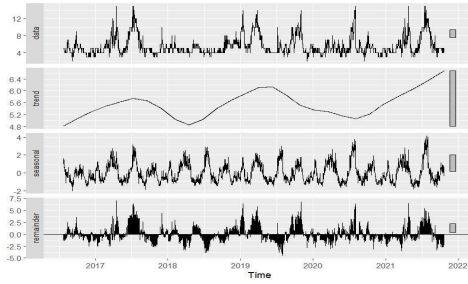
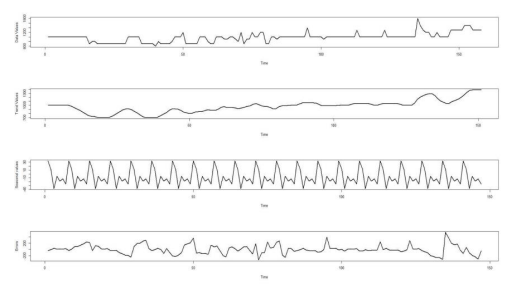
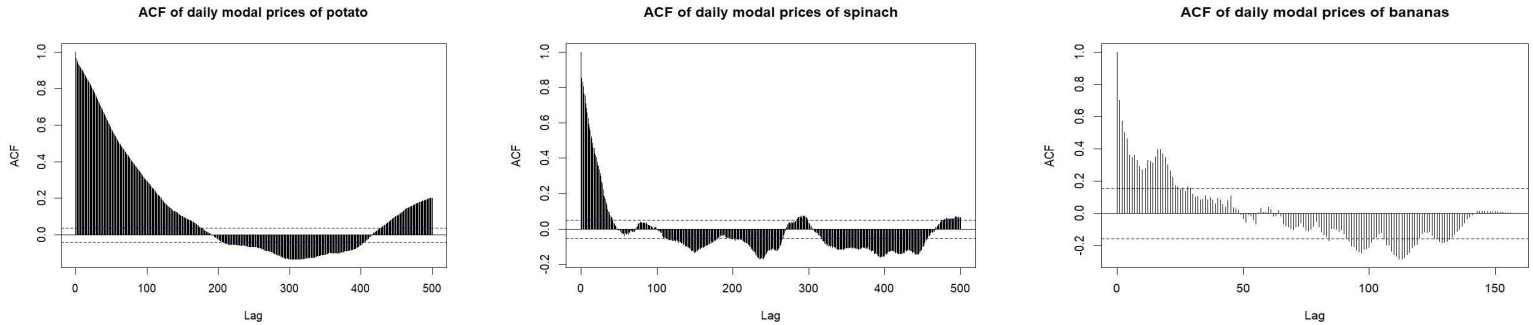


Figure 6: Decomposition of banana price data into a trend, seasonal, and remainder component.



RESULT & ANALYSIS

ACF Plots for all three crops



From the ACF plot of potato prices, we can see that there's a positive dependence on the price of potatoes until around the last 180 days. But the dependency becomes negative when we look after the last 180 days.

From the ACF plot of spinach prices, we can see that there's a significant positive dependence on the price of spinach until around the last 50 days. But the dependency becomes negative when we look after the last 100 days. Interestingly, we also know that spinach is very seasonal, which is also reflected in the ACF plot above. The dependency changes it's in very short intervals throughout the year.

From the ACF plot of banana prices, we can see that there's a significant positive dependence on the price of bananas until around the last 25 days. But the dependency becomes negative when we look after the last 60 days.



RESULT & ANALYSIS

Comparison of different models.

Table 4: Mean RMSE, MAE and other error measures for different methods by considering monthly potato wholesale price time series data.

Models	ME	RMSE	MAE	MPE	MAPE
additive_arima_svm	-3.587655	160.06147	111.77186	29.677753	157.72741
additive_arima_LSTM	4.841429	158.51416	110.40244	-275.333962	437.75647
additive_ETS_SVM	3.099478	153.71833	110.84233	19.449771	173.30553
additive_ETS_LSTM	3.129231	148.92315	106.94896	21.498918	162.4202
multiplicative_ETS_SVM	7.536162	206.68799	126.45176	16.404822	164.36947
multiplicative_ETS_LSTM	-239.649601	442.69333	305.91347	112.839006	161.95554
multiplicative_ARIMA_LSTM	-243.685945	441.38057	305.16839	114.727442	155.4074
multiplicative_ARIMA_SVM	-1.803844	164.05367	114.36722	18.807944	145.23027
ARIMA	-5.444247	158.458	110.63089	34.963484	147.70135
ETS	2.618045	148.85507	107.09062	22.741815	163.10125
SVM	2.681208	156.7514	113.4488	21.54436	168.9744

Table 5: Mean RMSE, MAE and other error measures for different methods by considering monthly spinach wholesale price time series data.

Models	ME	RMSE	MAE	MPE	MAPE
additive_arima_svm	-0.007003269	0.2055419	0.1557875	-2.712849	16.17959
additive_arima_LSTM	0.508757572	0.52882	0.5091569	34.607601	34.64556
additive_ETS_SVM	-0.002939364	0.2049198	0.1534565	-2.089983	15.85964
additive_ETS_LSTM	-0.504595996	0.5266201	0.5056692	-56.194016	56.28236
multiplicative_ETS_SVM	-0.006131052	0.20617	0.1542131	-2.396852	15.93838
multiplicative_ETS_LSTM	0.257613341	0.2881159	0.2596611	26.96386	26.83265
multiplicative_ARIMA_LSTM	0.254765462	0.2889435	0.2578662	25.874192	26.26538
multiplicative_ARIMA_SVM	-0.009276335	0.2064728	0.1561608	-2.982419	16.20012
ARIMA	-0.008451525	0.2053519	0.1552723	-3.189802	16.10508
ETS	-0.005174755	0.2014087	0.1521999	-2.596708	15.7763
SVM	0.00576156	0.2101209	0.1593828	-2.272723	16.41694
LSTM	0.2631166	0.3186313	0.2642644	23.66169	23.89638

Table 6: Mean RMSE, MAE and other error measures for different methods by considering monthly banana wholesale price time series data.

Models	ME	RMSE	MAE	MPE	MAPE
additive_arima_svm	19.518324	192.2893	130.0519	216.05007	325.45785
additive_arima_LSTM	-11.862716	168.2785	109.89956	-1237.36385	3317.1712
additive_ETS_SVM	2.749681	218.5617	154.03328	402.83891	538.14405
additive_ETS_LSTM	-3.245315	196.9014	136.64043	352.71477	449.04052
multiplicative_ETS_SVM	23.936024	239.03	161.00958	489.61753	617.01015
multiplicative_ETS_LSTM	-17.07907	161.8675	114.10793	231.23492	254.55153
multiplicative_ARIMA_LSTM	-3.497777	162.0597	106.77522	146.36164	155.11653
multiplicative_ARIMA_SVM	6.09329	190.8033	126.54003	187.44903	280.17709
ARIMA	11.400195	169.9867	112.49731	161.91365	204.60412
ETS	-3.944912	198.8039	139.08359	358.4874	457.63603
SVM	7.424217	183.5404	130.80513	272.65453	362.88361

From above table 4, we observe that the minimum error (RMSE) is for the ETS model for the potato prices. The additive_ETS_LSTM model is also highlighted since it also has an RMSE closer to ETS one, and the MAE (Mean Absolute Error) lower than the ETS.

From Table 5 above, we observe that the minimum error (RMSE) is for the ETS model for the spinach prices.

From the above table 6, we observe that the minimum error (RMSE) is for Multiplicative_ARIMA_LSTM for the banana prices.



RESULT & ANALYSIS

Forecast Plot for the optimal model

Figure 10: Forecasting on Potato prices using the ETS model

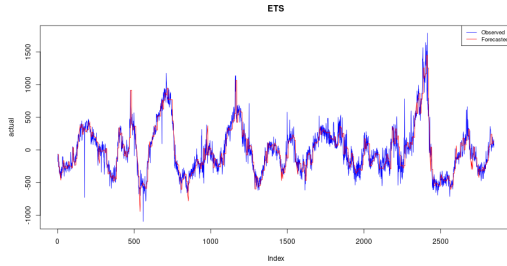


Figure 11: Forecasting on Spinach prices using the ETS model

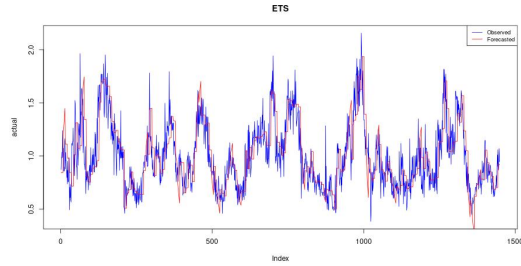
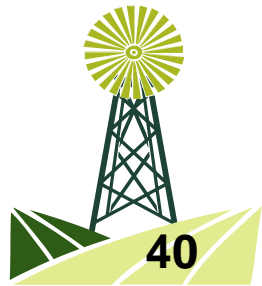
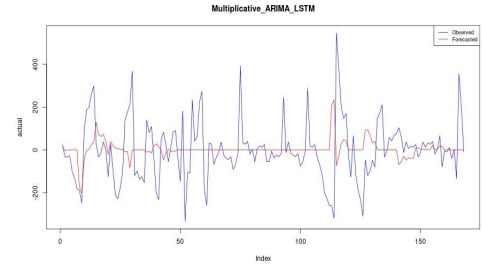
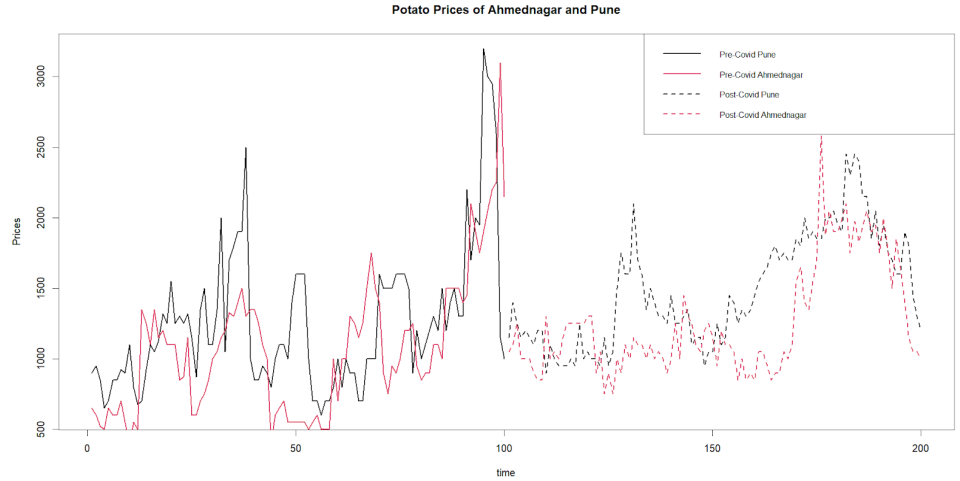


Figure 12: Forecasting on banana prices using the Multiplicative_ARIMA_LSTM model



RESULT & ANALYSIS

Figure 13: Comparison of Potato Prices of Ahmednagar and Pune markets before and during COVID-19.



From the above figure, we can observe that the correlation pattern between the two locations differs from the COVID period to the pre-COVID period.

The confirmatory test fails to reject the null hypothesis that, there is no contagion effect among the two locations.



RESULT & ANALYSIS

Markets	Mean	Lower CI	Upper CI	Spatio FLAP
Ahmednagar	926.0240964	450	2000	1.799125406
Aurangabad	932.300885	450	1868.75	2.560295727
Bhivandi	1518.846154	1061.5	1953.75	5.015043655
Jalgaon	951.9962121	450	1700	2.754457536
Junnar	965.8730159	373.5	2000	2.267769657
Junnar(Otur)	1049.489796	105	2000	2.042275683
Kalyan	843.4782609	527.5	1100	4.761844265
Karad	1195.454545	505	1800	3.718619883
Khed(Chakan)	1042.696629	510	1800	2.814532301
Kolhapur	1000	700	1400	4.188010527
Kolhapur(Malkapur)	755	512.75	997.25	2.093590666
Maanachar	986.2962963	500	2052.5	2.167433878
Mumbai	1093.894737	700	1466.25	4.479085232
Nagpur	1050.148148	375	1925	1.354050151
Nasik	972.4201681	500	1900	2.55480426
Osmanabad	1098.894737	142	1782.5	2.846132374
Palghar	956.5666667	500	1800	2.700504614
Pandharpur	827.7777778	360	1450	1.985475738
Parbhani	975	527.5	1500	2.92466767
Pen	1570.588235	770	3320	1.409531648
Pune	1134.234694	600	2200	2.726822984
Pune(Khadiki)	1003.449198	450	1635	2.734868393
Pune(Pimpri)	1379.204545	550	4000	1.282041917
Satara	1213.590604	550	2180	2.653266154
Shrirampur	1052.140288	546.25	1853.75	2.994368424
Solapur	1044.022388	500	2200	2.448618931
Ulhasnagar	1070.689655	655	1250	5.759672475
Vasai	1402.745098	1000	1875	5.578923887

Markets	Mean	Lower CI	Upper CI	Spatio FLAP
Vashi New Mumbai	1138	600	2070	2.555287937
Koregaon	1070	901.875	1272.125	5.718029303
Chandrapur(Ganjwad)	1177.575758	600	2200	2.288130117
Junnar(Alephata)	550	402.5	782.5	2.523573073
Sangli(Phale, Bhajipura Market)	1161.581921	650	2000	2.345458178
Navapur	1200	622.5	1777.5	2.19089023
Pune(Hadapsar)	916.6666667	562.5	1000	4.490731195
Rahuri	1322.975207	625	2200	2.72970523
Mangal Wedha	1366.666667	1305	1400	23.67136104
Rahata	1196.638655	645	2000	2.981455503
Kamthi	1397.391304	800	2800	2.710980764
Vai	1720	1350	2291.25	5.208082437
Vadgaonpeth	1560	1120	2140	3.750606887
Amarawati	1035.185185	766.25	1517.5	4.323659743
Islampur	1505.666667	800	2480	2.599594858
Akluj	1351.4	700	2000	3.68880649
Ramtek	1036.923077	550	1900	2.502132617
Amrawati(Fru & Veg. Market)	959.9673203	450	1900	2.183294174
Rahuri(Songaon)	2050	2002.5	2097.5	28.99137803
Palthan	743.8596491	700	860	11.3543469
Vita	1000	680	2150	2.745054065
Murbad	1500	1500	1500	Inf
Morshi	1512.4	1072	1870	5.802534722
Pune(Moshi)	938.0597015	700	1367.5	5.309109014
Bhusaval	1624	1045	2000	5.259807304
Pune(Manjri)	1651.515152	1500	1920	8.979637323
Junnar(Narayangaon)	1181.818182	800	1500	5.304576151

Table 7: Table showing the mean, the 95 per cent confidence interval, and the Spatio-Temporal FLAP Index of the prices of Potato for the markets of Maharashtra in the month of January.

RESULT & ANALYSIS

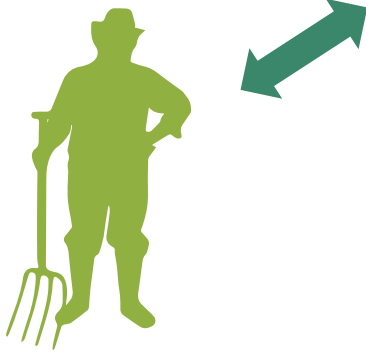
Table 8: Table showing the best 3 markets for Potato in Maharashtra for each month based on the Spatio-Temporal FLAP Index.

Months	Rank 1	Rank 2	Rank 3
January	Murbad	Rahuri(Songaon)	Mangal Wedha
February	Pune(Manjri)	Morshi	Amarawati
March	Aatpadi	Chalisgaon	Pune(Hadapsar)
April	Mangal Wedha	Pen	Vai
May	Koregaon	Aatpadi	Ratnagiri (Nachane)
June	Chalisgaon	Mangal Wedha	Bhusaval
July	Pen	Mangal Wedha	Sangola
August	Rahuri(Songaon)	Junnar(Otur)	Amarawati
September	Pen	Junnar(Narayangaon)	Sangola
October	Barshi	Murbad	Aatpadi
November	Mangal Wedha	Pen	Vasai
December	Aatpadi	Vadgaonpeth	Vasai



RESULT & ANALYSIS

The farmers may develop a monthly contract with the suppliers in the suggested markets for the different months according to the Spatio-Temporal FLAP Index.



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We have provided the top three markets instead of just the best one so that, the farmers can figure out which markets to target in which month considering the expenses for logistics as well.



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Developing a proper supply chain considering the Spatio-Temporal FLAP Index will help the farmers in increasing their sale prices and decrease the uncertainty in their income as well.



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Developing a proper supply chain considering the Spatio-Temporal FLAP Index will help the farmers in increasing their sale prices and decrease the uncertainty in their income as well.

Those markets which consistently show higher ranking like Pen, Vasai, and Mangal Wedha and are close to the farm, a farmer can decide to sell the production to these markets throughout the season if he/she is restricted in the resources.



CONCLUSION



By observing the FLAP Index, the month of May is the preferable month to sell potatoes. We can see the months of October and September are good times to sell spinach and bananas respectively based on the higher value of the lower confidence interval.



For spinach and potato, the optimum model turned out to be ETS. For bananas, the optimal model is Multiplicative_ARIMA_LSTM.



Forecasting lets the farmer select the day on which he/ she can sell the crop. Forecasting is specifically helpful for crops like spinach which is perishable.



There exists no significant contagion effect among the markets of Pune and Ahmednagar for potatoes.



The Spatio-Temporal FLAP Index provides the best three markets for Potato across Maharashtra across different months. The markets of Pen, Vasai, and Mangal Wedha have got featured frequently.



FURTHER STUDY



The Spatio-Temporal FLAP Index work is only based on a single crop. We can construct the Spatio-Temporal FLAP index for different crops which would be helpful for farmers who produce multiple crops.



Construct an index that includes, the FLAP index, the lower confidence interval, and the mean of the prices. And then we can make a more robust suggestion to the farmer.



Repeat contagion effect for different crops for different markets.

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THANK YOU

Exploring volatility in crop prices for farmers' benefit