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Time series analysis and forecasting of kinnow (*Citrus reticulata*) arrivals and prices in Himachal Pradesh

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ABSTRACT

Kinnow (*Citrus reticulata* Blanco) plays a significant role in the economic and agricultural sustainability of farmers in Himachal Pradesh, contributing approximately 47.31% to the state's total citrus production. The present study investigated long-term trends, seasonal variations, instability, and forecasting of kinnow prices and market arrivals in two major markets, Dhanotu and Kangra, Himachal Pradesh during the period 2005–23. Trend analysis based on regression models indicated that market arrivals followed quadratic and power functional forms, whereas prices exhibited a cubic trend across the selected markets. The Compound Annual Growth Rate (CAGR) indicated a positive growth in both arrivals and prices over the study period. Seasonal indices highlighted clear monthly variations, reflecting distinct seasonal patterns in market arrivals and prices fluctuations. The Cuddy-Della Valle Instability Index (CDVI) showed significant instability in arrivals, whereas prices instability remained relatively low across both markets. For forecasting, SARIMA models were employed, which projected a steady increase in kinnow prices in the coming years, while arrivals are expected to stabilise and follow a relatively constant trend beyond 2025. The forecasting results indicated potential for better price realisation for farmers if market arrivals are managed efficiently. The findings may provide useful insights for farmers to optimise harvesting and marketing decisions, and for policymakers to design effective price stabilisation measures, improve market infrastructure, and enhance supply chain efficiency. Overall, the study contributes to informed decision-making and sustainable development in the kinnow sector.

Keywords: AIC, RMSE, SARIMA, Time series, Trend

Citrus (*Citrus* spp.) belonging to family Rutaceae is one of the most significant crops produced for human consumption in the world and is grown in many countries with tropical and subtropical climates. India is the 6th largest producer of citrus in the world where most appreciated citrus variety introduced to India was kinnow, mandarin. Kinnow (*Citrus reticulata* Blanco), a hybrid citrus fruit originating from the Punjab region of India and Pakistan, is known for its sweet-tangy taste and high vitamin C content.

In India, citrus crops occupy a 13.42% (14,870.25 Mt) of the total fruits production while in Himachal Pradesh, citrus crops occupy a 4.77% (30.94 Mt) of the total fruits production. Within citrus crops, kinnow's share is 45.25% in India and for Himachal Pradesh, it is 47.31% (APEDA 2025). The total area and production of kinnow in India for the year 2024–25 are 4,74,100 ha and 6,729.17 Mt, respectively, while in Himachal Pradesh, the area and production are 8,850 ha and 18.38 mt, respectively (MoA&FFW 2025). Prathima *et al.* (2024) forecasted the monthly arrivals and price of tender coconut in Maddur market, Karnataka using seasonal times series models, in which SARIMA (1,1,1) (2,1,1) and ARIMA (1,1,3) models were selected as best-fitted models for forecasting the arrivals and prices of coconut. Areef *et al.* (2020) studied the market arrivals and prices behaviour of potato in Bengaluru market, and found SARIMA (0,1,1) (0,1,1) model as best model to forecast arrivals and prices of potato. Kumar *et al.* (2024) forecasted cotton prices in major markets of Haryana using ARIMA models. Considering the above facts, the current research aimed to study trend analysis and forecast of arrivals and prices of kinnow crop in Himachal Pradesh wing different models.

MATERIALS AND METHODS

The time series data on monthly arrivals and prices of kinnow crop were sourced from AGMARKET portal, for the last 19 years (2005–23) for Dhanotu and Kangra markets of Himachal Pradesh in 2024 (DMI 2023). The time series data were used to compute the trends model and forecasting models of the kinnow crop. The softwares like Python in Jupyter notebook, R, SPSS and Excel were employed for statistical analysis.

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Trend detection using regression models: To examine the trend component in market arrivals and prices, following regression models have been utilised:

$$\text{Linear model: } Y = a + bt + \varepsilon_t \quad (1)$$

$$\text{Quadratic model: } Y = a + bt + ct^2 + \varepsilon_t \quad (2)$$

$$\text{Cubic model: } Y = a + bt + ct^2 + dt^3 + \varepsilon_t \quad (3)$$

$$\text{Compound model: } Y = ab^t + \varepsilon_t \quad (4)$$

$$\text{Exponential model: } Y = ae^{bt} + \varepsilon_t \quad (5)$$

$$\text{Power model: } Y = at^b + \varepsilon_t \quad (6)$$

Where Y, Market arrivals/prices of kinnow crop under study; a, Intercept; b, Regression coefficient of t; c, Regression coefficient of t^2, d, Regression coefficient of t^3; t, Time variable; εt, error.

Seasonal indices: The seasonal patterns in market arrivals and prices of the kinnow crop were analysed using a multiplicative model.

$$Y_t = T_t \times S_t \times C_t \times I_t$$

Where Y_t, Market arrivals/prices of kinnow crop; T_t, Trend value at time t; S_t, Seasonal fluctuation at time t; C_t, Cyclic fluctuation at time t; I_t, Irregular fluctuation at time t.

Coefficient of variation: To analyse the fluctuations in arrivals and prices indices both within and across years, the coefficient of variation (CV) was calculated using the index numbers from different months and years as follows:

$$CV = \frac{\text{Standard deviation}}{\text{Overall mean}} \times 100$$

Cuddy-Della Valle Index: Due to the presence of long-term trends in time series data, the coefficient of variation (CV) often overestimates instability. To address this limitation, the Cuddy-Della Valle Index (CDVI) was developed. It helps identify periods of volatility and stability, offering valuable insights into data behaviour over time (Cuddy and Valle 1978).

$$CDVI = CV\sqrt{1 - \overline{R}^2}$$

Where CV, Coefficient of variation; $\overline{R^2}$, Adjusted estimated coefficient of determination.

Compound growth rate: This study applied Compound Growth Rates (CGR) to analyse the monthly trends in kinnow crop arrivals and prices over the years. The CGR was calculated using the following growth model:

$$Y = ae^{bt} + \varepsilon_t$$
$$\text{Then, } CGR = b \times 100$$

Seasonal ARIMA: The Seasonal ARIMA (SARIMA) model is a specialised extension of the ARIMA model designed to accommodate seasonal data patterns. In time series analysis, seasonality refers to recurring fluctuations that occur at regular intervals. The SARIMA model follows a multiplicative structure, integrating both non-seasonal and seasonal components of the data. This makes it a robust and effective tool for forecasting seasonal time series. The fundamental form of the SARIMA model is expressed as:

$$\text{ARIMA}(p,d,q) \times (P,D,Q)s,$$

Where p, Non-seasonal AR order; d, Non-seasonal differencing; q, Non-seasonal MA order; P, Seasonal AR order; D, Seasonal differencing; Q, Seasonal MA order; S, Time span of repeating seasonal pattern.

The mathematical form of general SARIMA model is:

$$(1-\phi_p B)(1-\phi_p\, B^S)(1-B)(1-B^S)\, y_t = (1-\theta_q B)(1-\theta_q\, B^S)$$

Identification of models: The goal is to select a specific SARIMA model from the broad class of ARIMA (p,d,q)(P,D,Q). This involves analysing the data to determine the best-fitting model by examining sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of differenced series Y_t. ACF and PACF are typically calculated up to 36 lags for seasonal data. The non-seasonal autoregressive (AR) order (p) corresponds to number of significant partial autocorrelations at the initial lags, while the seasonal AR order (P) is based on significant partial autocorrelations at seasonal lags. The moving average (MA) order is determined using the ACF. The non-seasonal MA order (q) is identified by the number of significant autocorrelations at initial lags, whereas seasonal MA order (Q) is based on significant autocorrelations at seasonal lags.

Criterion of model selection: Model adequacy checking assesses the fit of a regression model to the available data. Different indices that have been used to examine the goodness of fit and to make comparison of forecasting ability among different regression and time series models are being discussed as below:

Adjusted coefficient of determination ($\overline{R^2}$): The adjusted R-squared modifies the R-squared value by accounting for the number of predictors in the model, offering a metric that penalises excessive complexity.

$$\overline{R^2} = 1 - \frac{(1 - R^2)(n-1)}{n-p-1}$$

Where R^2, Coefficient of determination; n, Sample size; p, Number of predictors in the model.

Root mean square error: The root mean square error (RMSE) is a widely used metric for assessing the discrepancy between predicted values from a fitted model and the actual values.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}}$$

Where y_t, Actual value, $\hat{y}_t$, Predicted value.

Theil's Inequality: Theil's index (TI) is an effective measure of inequality when analysing multiple groups (Theil *et al.* 1966).

$$TI = \frac{\sqrt{\sum(y_i - \widehat{y_1})^2}}{\sqrt{\frac{y_i^2}{n}} + \sqrt{\frac{\widehat{y_1}^2}{n}}}$$

t-test: t-statistic is a measure used for testing the significance of regression coefficients of a model.

$$t = \frac{\widehat{\beta}}{SE(\widehat{\beta})}$$

Where $\widehat{\beta}$, Estimate of the regression coefficient; SE $(\widehat{\beta}) = \sqrt{var.(\widehat{\beta})}$ is the standard error of estimate of the regression coefficient.

Mean Absolute Error (MAE): It is the difference between the predicted and actual observations, with each individual difference given equal importance and calculated using:

$$MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{y_t}$$

Mean absolute percentage error: The Mean Absolute Percentage Error (MAPE) is a statistical metric used to assess the accuracy of a forecasting method.

$$MAPE = \frac{1}{n} \sum \left| \frac{e_t}{y_t} \right| \times 100 = \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

Akaike information criterion: The AIC is a widely used measure for model selection in statistics. The AIC is calculated using the following equation (Akaike 1969):

$$AIC = 2k - 2 \ln(\widehat{L})$$

Where $\widehat{L}$, Likelihood function of the model; n, Sample size; k, Number of model parameters.

Comparison of average prices and arrivals for different years: The Analysis of Variance (ANOVA) technique was employed to compare the arrivals and prices. ANOVA is a method for partitioning the total variation into two components: Assignable and non-assignable factors. A one-way classification was applied to compare the means at a 5% significance level, with the critical difference ($CD_{0.05}$) value was employed to check the statistical significance of arrivals and prices of different years.

SARIMA for forecasting kinnow arrivals and prices in Dhanotu and Kangra: The time series data on kinnow arrivals and prices in the Dhanotu and Kangra markets were divided into training (80%) and testing (20%) sets. Stationarity was assessed using the ADF test, and appropriate differencing was applied where necessary. Autocorrelation patterns were examined through ACF and PACF plots. Given the seasonal nature of kinnow arrivals (November to April), SARIMA models were employed. The models were selected based on goodness-of-fit and accuracy criteria, including AIC, RMSE, MAE, and MAPE. Similar use of SARIMA models for seasonal agricultural data has been reported by Reddy (2018).

RESULTS AND DISCUSSION

Trend analysis of arrivals and prices of kinnow: To illustrate the overall trend of kinnow arrivals and prices in the markets, monthly time series data were subjected to regression analysis.

For the arrivals in Dhanotu, power model were used with coefficients a and b were significant, adjusted R^2 was 0.71, explaining 71% of the variance; RMSE of 48.16 and Theil's inequality coefficients of 0.18 indicating moderate accuracy of prediction while the equation of power model was $\widehat{Y}_t = 16.08t^{0.08}$ (Table 1). For arrivals in Kangra, Quadratic model were used with none of the coefficients a, b, c being significant, while the adjusted R^2 was lower (0.53) concluding less explanatory power; RMSE of 27.88 and Theil's inequality of 0.12 indicating better accuracy than that of Dhanotu arrivals and the equation of quadratic model was $\widehat{Y}_t = 8.85 + 25.80\,(t) - 1.18\,(t^2)$. Similarly, Roccetti (2025) studied time series data on COVID-19 deaths using linear regression models.

In case of prices for the Dhanotu market, the cubic model provided the best representation of price trends. All coefficients (a, b, c, and d) were statistically significant, indicating that the model effectively captured the underlying price dynamics over time. The model achieved a high adjusted R^2 value of 0.85, suggesting that approximately 85% of the variation in prices is explained. In addition, the relatively low RMSE (259.04) and Theil's inequality coefficient (0.05) reflected strong predictive performance and a high level of accuracy and the equation of cubic model is $\widehat{Y}_t = 1322.44 + 289.29\,(t) - 38.50\,(t^2) + 1.66(t^3)$. These results indicate that price movements in the Dhanotu market followed a well-defined pattern, making the model reliable for forecasting future price behaviour.

In contrast, for the Kangra market prices, the cubic model was also selected; however, only the intercept (a) was statistically significant, while the remaining coefficients were not. Although the adjusted R^2 value was slightly higher at 0.87, the RMSE (344.09) and Theil's inequality coefficient (0.06) were comparatively larger than those of Dhanotu, indicating relatively lower predictive precision. The cubic model equation was $\widehat{Y}_t = 922.33 + 245.69(t) - 25.09(t^2) + 1.20(t^3)$. This suggests that price variations in the Kangra market are less consistently explained by the model and may be influenced by additional external factors. Similar applications of non-linear trend models in agricultural studies have also been reported by Sharma *et al.* (2025) in the analysis of pomegranate production.

Thus, the findings provide actionable insights for both farmers and policymakers. Farmers can benefit by aligning their harvesting and marketing decisions with observed price trends, particularly by targeting periods of lower arrivals to achieve better returns. The relatively stable nature of the Dhanotu market offers more predictable opportunities, while the variability in Kangra calls for cautious planning and diversification strategies. For policymakers, the results underline the importance of strengthening market infrastructure, improving storage and transportation facilities, and ensuring timely dissemination of market information. Additionally, implementing effective price stabilisation measures in more volatile markets can help reduce uncertainty and protect farmers' incomes. Collectively, these interventions can enhance market efficiency and promote sustainable growth in the kinnow sector.

Instability analysis and seasonality pattern of arrivals of kinnow: To gain a comprehensive understanding of the

Table 1 Trend analysis of arrivals and prices of kinnow

Commodity	Market	Statistical model	Regression coefficient		$\hat{Y}$	t-statistic	$\overline{R^2}$	RMSE	Theil's inequality coefficient
Arrivals	Dhanotu	Power	a	16.08*	5.81	2.76	0.71	48.16	0.18
			b	0.08*	0.16	5.1			
	Kangra	Quadratic	a	8.85	23.75	0.37	0.53	27.88	0.12
			b	25.80*	5.46	4.71			
			c	-1.18*	0.27	-4.47			
Prices	Dhanotu	Cubic	a	1322.44*	330.42	4.00	0.85	259.04	0.05
			b	289.29*	139.42	2.08			
			c	-38.50*	15.98	-2.40			
			d	1.66*	0.52	3.15			
	Kangra	Cubic	a	922.33*	438.92	2.10	0.87	344.09	0.06
			b	245.69	185.19	1.32			
			c	-25.09	21.23	-1.18			
			d	1.20	0.69	1.72			

*, significance at 5% level of significance. RMSE, Root mean square error; ŷ, Predicted value; $\overline{R^2}$, Adjusted coefficient of determination.

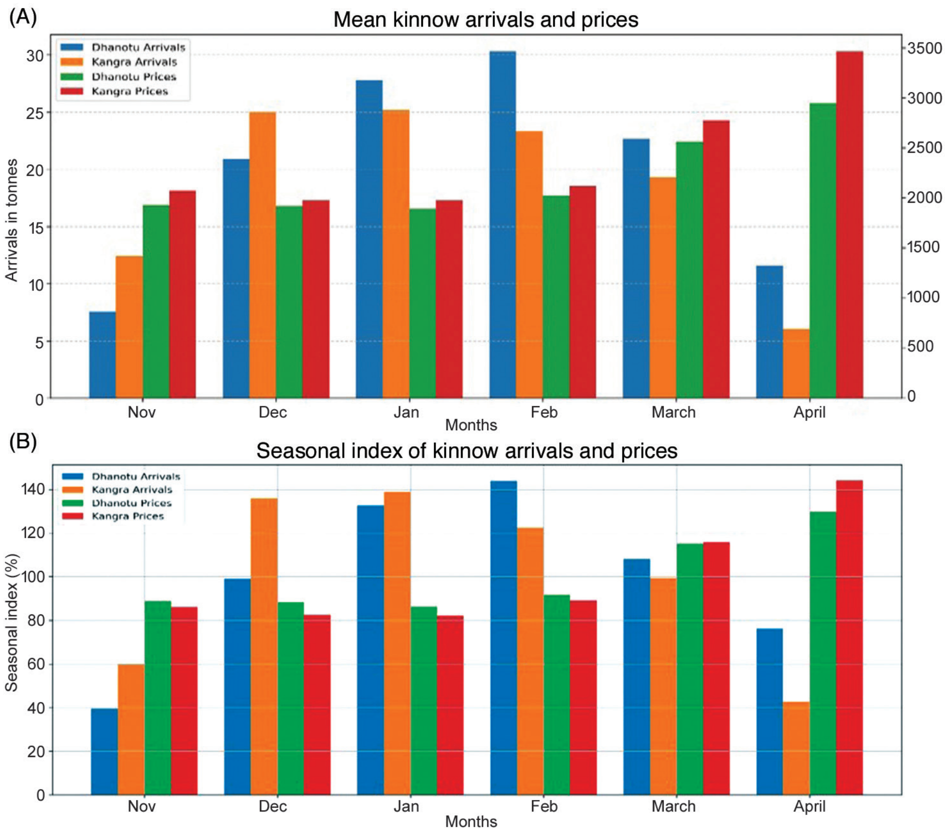

Fig. 1 (A) Mean and (B) Seasonal index of prices and arrivals of kinnow markets.

data and to capture seasonal fluctuations in crop quantities, a seasonal instability analysis was conducted for the peak marketing period (November–April).

Fig. 1(A) shows clear seasonal fluctuations in kinnow arrivals across both Dhanotu and Kangra markets, reflecting the crop's harvest cycle. In Dhanotu, mean arrivals ranged from 7.52–30.30 t, while in Kangra, they varied between 6.05 and 25.20 t. Statistical analysis using ANOVA confirmed that these monthly variations are significant (Tamilselvi *et al.* 2020). Peak arrivals were observed in February for Dhanotu and January for Kangra, with nearby months also showing similar levels, indicating that most harvesting and marketing activity is concentrated during the winter season.

A similar seasonal pattern is evident in prices. In Dhanotu, mean prices ranged from ₹1,894–₹2,944/q, while in Kangra, they varied from ₹1,977–₹3,462. The highest prices were recorded in April in both markets, closely followed by March, suggesting that prices improve once arrivals decline. Overall, the results highlight an inverse relationship between arrivals

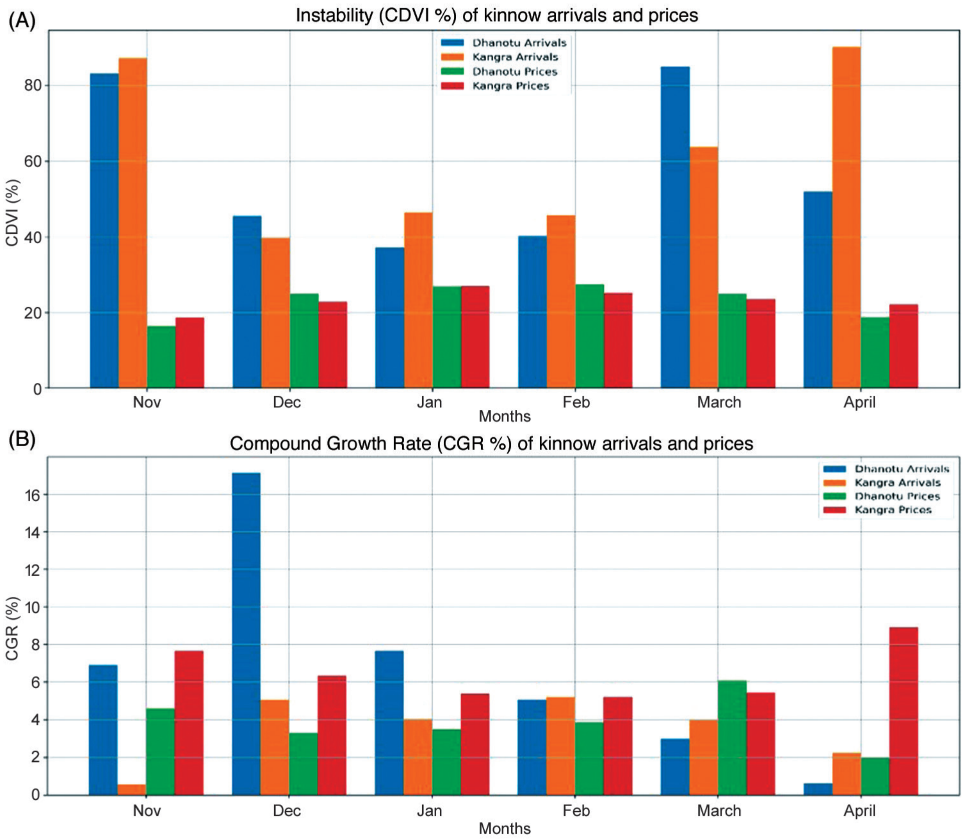

Fig. 2 (a) Cuddy-Della Valle Index (CDVI) and (b) Compound Growth Rate (CGR) of prices and arrivals of kinnow markets.

and prices. Fig. 1(B) highlights the seasonal patterns in kinnow arrivals and prices through seasonal index (SI%) values. In the Dhanotu market, the SI for arrivals ranged from 39.58–143.97%, while in Kangra, it varied from 42.79–139.02%. These indices clearly showed recurring patterns in market arrivals over time. Peak arrivals were observed in February for Dhanotu and January for Kangra, whereas the lowest arrivals occurred in November and April, respectively. This pattern reflects the natural harvesting cycle of kinnow and the resulting fluctuations in market supply (Sarkar and Bera 2022).

In the case of prices, the SI values for Dhanotu ranged from 86.34–129.70%, while for Kangra, they varied from 82.23–144.15%. Both markets recorded peak prices in April and the lowest prices in January. This inverse relationship between arrivals and prices suggests that higher supply during peak arrival months tends to reduce prices, while lower arrivals contribute to price increases. These consistent seasonal patterns are highly useful for farmers, as they can plan harvesting, storage, and marketing strategies to sell produce during higher price periods. For policymakers, the findings highlight the need for improved storage, transport, and price stabilisation measures to manage seasonal fluctuations. Similar trends have also been observed in other agricultural markets by Nitharwal *et al.* (2024).

Fig. 2(a) presents the Cuddy-Della Valle Instability Index (CDVI), which shows a high level of variability in kinnow arrivals across both markets. In Dhanotu, the CDVI for arrivals ranged from 37.10–85.00%, while in Kangra, it varied from 39.70–90.20%. These high values indicate that arrivals fluctuate considerably over time, mainly due to seasonal production patterns, weather conditions, and changing market demand. Similar patterns of high variability have been reported in other agricultural markets, such as potato markets in India by Saha *et al.* (2020).

In contrast, price variability was relatively moderate. The CDVI for prices ranged from 16.40–27.50% in Dhanotu and from 18.70–27.00% in Kangra, suggesting that prices remain more stable despite fluctuations in arrivals, possibly due to market adjustments.

These findings are important for both farmers and policymakers. Farmers can use this information to plan harvesting, storage, and marketing more effectively to avoid selling during periods of excess supply. For policymakers, the results highlight the need to strengthen infrastructure, improve storage and transport systems, and enhance market information services to stabilise markets and support farmers' incomes.

Fig. 2(b) presents the compound growth rate (CGR) analysis which shows a generally positive growth trend in kinnow arrivals across both markets. In Dhanotu, arrivals increased between 0.61–17.13%, while in Kangra, the growth ranged from 0.57–5.22%. This indicated a steady expansion in market supply over time. The comparatively higher growth observed in Dhanotu suggested better market performance, possibly due to improved infrastructure or market access. Similar trends have been reported in other agricultural markets, by Sudeepthi *et al.* (2025) on chilli markets.

Price growth also showed a positive trend in both markets. In Dhanotu, prices increased between 1.96–6.08%, whereas Kangra recorded a higher range of 5.23–8.91%. This reflects improving demand and favourable market conditions, which can enhance farmers' income potential. Comparable results were observed by Saha *et al.* (2020) in their study on potato markets in India, where positive price growth trends were also identified.

Overall, the consistent growth in both arrivals and prices indicated a strengthening kinnow market. For farmers, this provides confidence in the profitability of cultivation

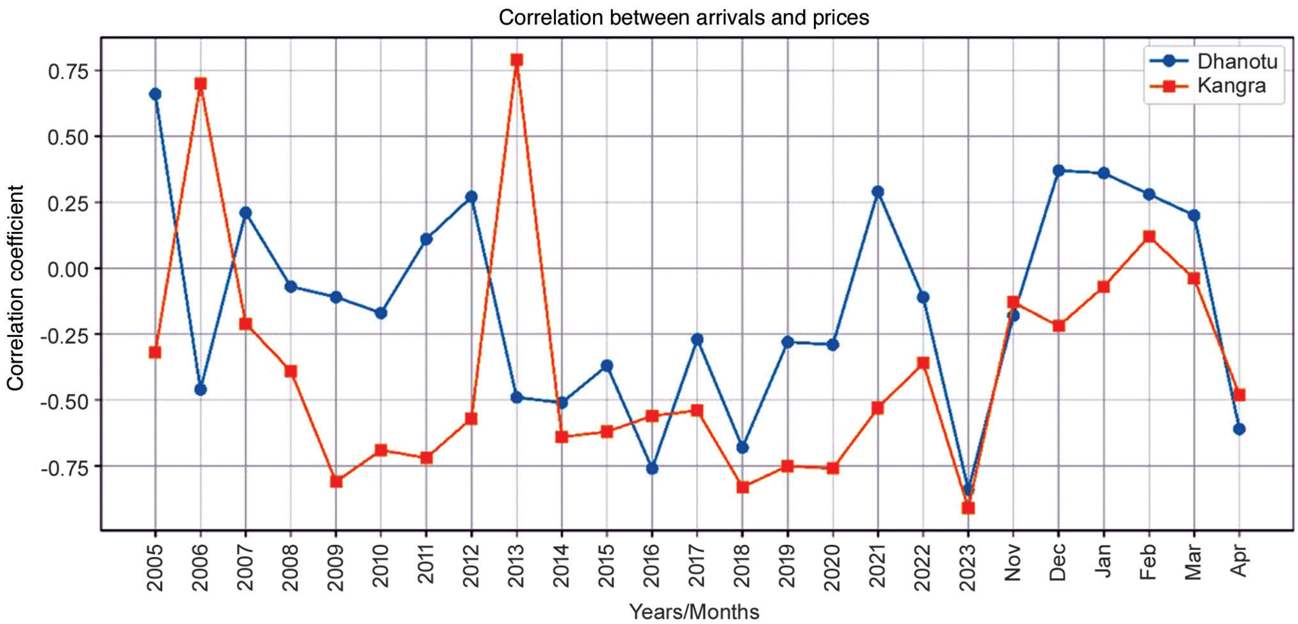

Fig. 3 Association between arrivals and prices of kinnow markets.

and supports better planning of production and sales. For policymakers, the findings highlight the importance of strengthening infrastructure, improving market information systems, and ensuring efficient supply chains to sustain growth and maintain market stability.

Association between market arrivals and prices of kinnow: The relationship between kinnow arrivals and prices in the Dhanotu and Kangra markets was examined for the period 2005–23 using correlation analysis (Fig. 3). Correlation helps in understanding how two variables move together. A negative (inverse) correlation means that when arrivals increase, prices tend to decrease while a positive correlation implies that both arrivals and prices move in the same direction. The results show that the relationship is mostly negative, indicating that higher market arrivals generally lead to lower prices, which is consistent with basic demand-supply principles. However, this pattern is not uniform across all years. In Dhanotu, the negative relationship was mostly weak to moderate, becoming statistically significant only in 2023. In contrast, Kangra showed relatively stronger and more consistent negative correlations in several years. Occasional positive relationships were also observed, but these were mostly weak and not statistically significant, suggesting that other market factors may influence prices at times.

The monthly analysis further highlighted this pattern, with a significant negative relationship observed in April in both markets. This indicated that during peak arrival periods, increased supply tends to reduce prices. The observed inverse relationship is in line with earlier findings, such as those reported by Kumar *et al.* (2005), who also identified a negative association between arrivals and prices in agricultural markets.

SARIMA for forecasting kinnow arrivals and prices in Dhanotu and Kangra: The time series analysis of kinnow arrivals and prices in the Dhanotu and Kangra markets demonstrated that the selected SARIMA models effectively captured the underlying trends and seasonal patterns. The graphical results (Fig. 4) showed a close alignment between observed and fitted values, confirming that the models

Table 2 Identification of best forecasting models for kinnow arrivals and prices in Dhanotu and Kangra market

Commodity		Arrivals		Prices	
Market		Dhanotu	Kangra	Dhanotu	Kangra
Model		(0,1,3)(1,0,1)6	(1, 0, 1)(0, 1, 1)6	(1,0,0)(2,1,2)6 with drift	(1,0,0)(0,1,1)6 with drift
AIC		792.49	706.72	1423.82	1442.07
RMSE		11.22	8.73	339.771	395.67
MAE		8.42	6.73	235.043	280
MAPE		275.84	279.25	10.9134	13.06
Ljung-box test	Statistic	0.16	0.15	0.69	0.015
	p-value	0.68	0.89	0.4	0.89

AIC, Akaike information criterion; RMSE, Root mean square error; MAE, Mean absolute error; MAPE, Mean absolute percentage error.

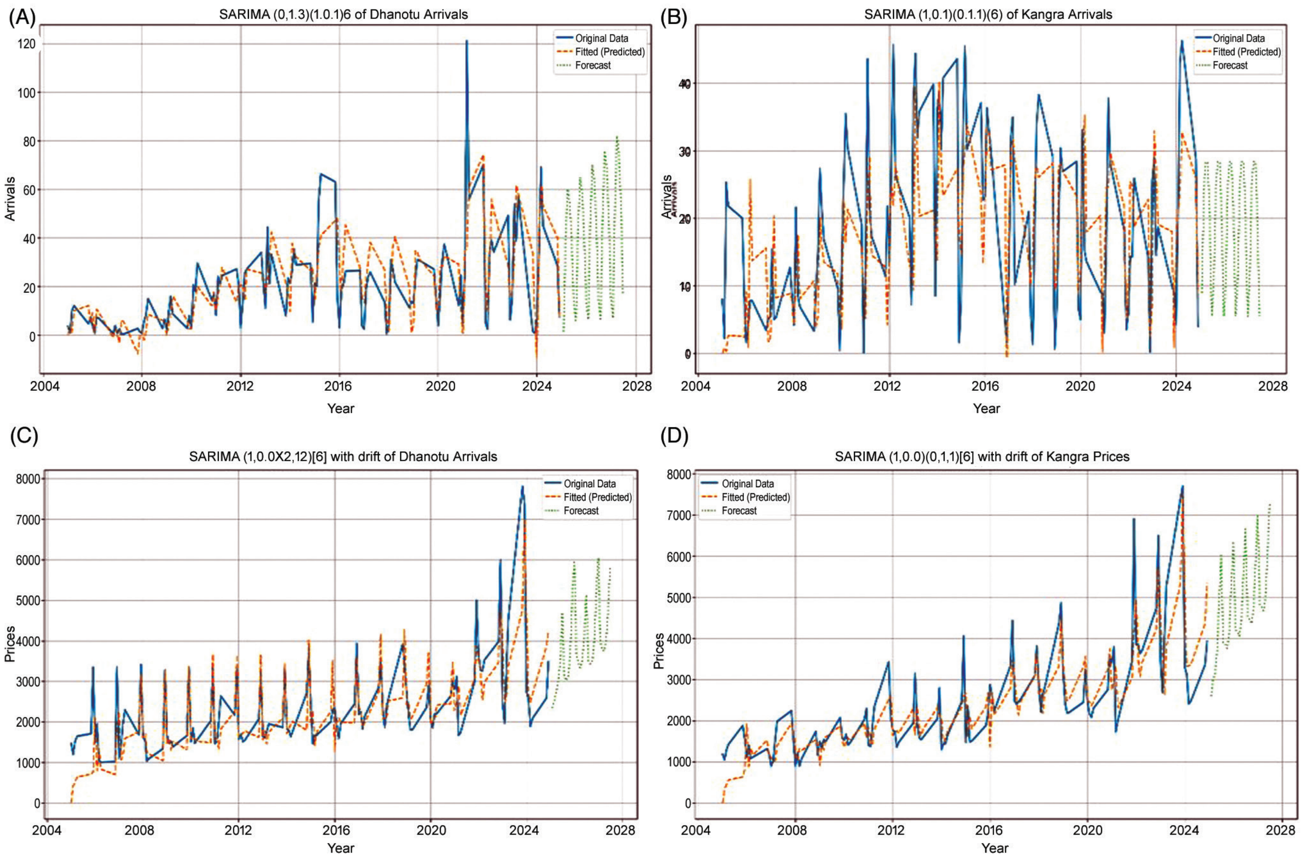

Fig. 4　SARIMA-based trends of kinnow arrivals and prices in Dhanotu and Kangra.

adequately represent the data structure.

Model performance was satisfactory across all series. The relatively low AIC values indicated a good model fit, while RMSE and MAE values suggested acceptable predictive accuracy (Table 2). Although the MAPE values for arrivals appear high, this is primarily due to the presence of small or near-zero observations, which tend to inflate percentage-based error measures. The Ljung-box test results showed non-significant p-values (p>0.05) for all models (Table 2), confirming the absence of residual autocorrelation and validating model adequacy.

Arrivals in both markets exhibited clear seasonal behaviour with peaks during the harvest period. As shown in Table 2, the Dhanotu SARIMA (0,1,3)(1,0,1)6 model indicated relatively stable and consistent arrival patterns, whereas the Kangra SARIMA (1,0,1)$(0,1,1)_6$ model demonstrated higher variability. Fig. 4(A) and 4(B) show that the forecasts suggest arrivals will continue to follow a stable trajectory with moderate fluctuations, indicating predictable supply conditions. Comparable findings were reported by Prathima *et al.* (2024) in their study on coconut arrivals in Karnataka.

The price models presented in Table 2, SARIMA (1,0,0)(2,1,2)6 with drift for Dhanotu and SARIMA (1,0,0) $(0,1,1)_6$ with drift for Kangra, revealed a gradual upward trend with seasonal variation in both markets. Fig. 4(C) and 4(D) indicate that prices are expected to continously increase, reflecting favourable market prospects. Similar results were reported by Mutwiri (2019) in their analysis of wholesale tomato prices in Nairobi, Kenya. Likewise, Kumar *et al.* (2021) identified an ARIMA (0,1,2)$(1,0,0)_{52}$ model as the best fit for onion price forecasting in Varanasi, Uttar Pradesh, while Giri and Giri (2024) reported comparable findings for cauliflower prices in Nepal. Higher prices during lean supply periods highlight the potential for farmers to improve returns through better timing of market participation and storage practices. From a policy perspective, these trends emphasise the need for effective price stabilisation measures and efficient market regulation to ensure balanced growth.

Overall, the results suggest that the kinnow market is likely to experience stable arrivals and increasing prices in coming years. The findings provide valuable insights for both farmers and policymakers, supporting informed decision-making, reducing uncertainty, and contributing to improved market efficiency and income stability.

This study provided practical insights into the behaviour of kinnow arrivals and prices in the Dhanotu and Kangra markets, with a clear focus on supporting farmers and policymakers. The results highlighted strong seasonality, where arrivals peak during harvest months while prices tend to rise during lean periods, reflecting a typical inverse relationship between supply and price. For farmers, these findings are especially useful. Understanding that prices improve when arrivals decline allows them to make better decisions about when to sell their produce. By adjusting harvesting time or using storage where possible, farmers can avoid periods of excess supply and low prices, thereby improving their income. The relatively stable and predictable price patterns in the Dhanotu market further provide confidence for planning production and marketing strategies. For policymakers, the study emphasises the importance of strengthening market systems. The observed variability in arrivals, particularly in Kangra, points to the need for better storage facilities, transportation, and market infrastructure. Reliable forecasts from SARIMA models also offer a valuable tool for planning interventions, such as price stabilisation measures and improved market information systems.

However, the study had some limitations. It was based on historical time series data and did not incorporate external factors such as weather conditions, input costs, or policy changes, which may also influence market behaviour. Future research can focus on integrating such variables and applying advanced or hybrid models to improve forecasting accuracy. Expanding the analysis to more markets would also provide a broader understanding of regional market dynamics. Overall, the study supports more informed decision-making, helping farmers maximise returns while enabling policymakers to create more stable and efficient market conditions in the kinnow sector.

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