

Research Article

Integrated Analysis of Climatic, Topographic and Geospatial Factors Affecting Durian Yield in Chanthaburi Province, Thailand

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ABSTRACT

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Durian (*Durio zibethinus*) cultivation in Chanthaburi Province plays a pivotal role in Thailand's fruit economy, yet it faces increasing vulnerability due to climate variability and topographic constraints. This study aimed to investigate the relationships between climatic factors and durian yield through an integrated analytical framework incorporating statistical analysis, time-series forecasting, and geospatial techniques. Climatic variables including temperature, rainfall, humidity, and solar radiation were collected from meteorological stations across the province from 2014 to 2024. Agricultural data were retrieved from the Office of Agricultural Economics, including cultivated area and total yield per district. Pearson correlation and multiple linear regression analyses were employed to quantify the influence of climatic parameters on yield. Results indicated that minimum and maximum temperatures, rainfall, and perennial area were significant predictors. The regression model achieved high explanatory power ($R^2 = 0.935$), while NDVI-based spatial analysis from Sentinel-2 imagery revealed a strong negative correlation ($r = -0.920$) between vegetation health and cultivated area and a weak positive correlation with yield ($r = 0.263$), suggesting ecological limitations to expansion under climate stress. Forecasting results for the period 2025–2030 indicated a gradual decline in durian yield, despite the continued expansion of cultivated areas. These findings underscore the complex interplay between climatic variability and spatial cultivation patterns in determining durian productivity. Furthermore, the results highlight the effectiveness of integrating statistical modeling and geospatial analysis as a robust framework for monitoring, evaluating, and supporting data-driven decision-making in agricultural systems.

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1. Introduction

Climate change has become a critical issue affecting the growth and productivity of crops, both directly and indirectly. At the global scale, climate variability has been widely recognized as a key driver of fluctuations in crop yields, particularly through changes in temperature regimes, rainfall patterns, and the increasing frequency of extreme weather events. The increasing frequency and intensity of climatic events have led to the displacement of agricultural areas and disruption of production systems. These impacts are especially significant in perennial

crop systems, where climatic stress can influence not only current yield but also long-term physiological processes such as flowering, fruit set, and subsequent production cycles. According to Ratree (2018), these changes have become major concerns driving national development, especially in alignment with the United Nations Sustainable Development Goal 13, which addresses climate action (Pakeechay *et al.*, 2020). Thailand's Twelfth National Economic and Social Development Plan emphasizes the need for national resilience to climate change, including natural resource management and disaster preparedness (Wangsayang, 2020). In this context,

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understanding the interactions between climate variability and crop productivity is essential for developing climate-resilient agricultural systems, particularly in high-value perennial crops such as durian. Chanthaburi Province is a key durian-producing region in Thailand, contributing significantly to the national fruit economy. According to the Office of Agricultural Economics (OAE), the productive area increased from 273,648 rai in 2023 to 286,895 rai in 2024 ($\approx 5\%$), whereas total yield declined from 542,115 to 448,692 tons ($\approx -17\%$). This divergence indicates that productivity is increasingly constrained by environmental and climatic factors rather than land expansion alone. In 2025, total production increased to 575,611 tons (+28.3% relative to 2024), reflecting substantial interannual variability. This pattern underscores the influence of climatic variability on durian productivity. However, due to the limited availability of official statistics on cultivated area for 2025, the analysis primarily relies on the most recent complete dataset for 2014-2024.

Environmental factors, particularly rainfall, significantly affect durian production. Heavy rainfall during the flowering or fruit development stages can lead to premature leaf flushes and nutrient competition, resulting in poor fruit quality and yield losses (Pokaekat, 2013). Vorakuldamrongchai *et al.* (2015) noted that shifts in average maximum/minimum temperatures, relative humidity, and rainfall patterns can disrupt flowering cycles and fruit maturation. Consequently, durian trees often flower in multiple batches, increasing labor and input costs. To address this, researchers have applied climatic data and forecasting models to predict crop yield under specific regional and temporal contexts. Notable applications include modeling yield for wheat (Anwar *et al.*, 2007; Özdoğan, 2011) and rice (Masutomi *et al.*, 2009; Babel *et al.*, 2011), which support better planning and adaptation.

Therefore, this study aims to analyze the influence of climatic and topographic factors on durian yield in Chanthaburi Province using an integrated framework that combines statistical modeling, time-series forecasting, and NDVI-based geospatial analysis, in the context of increasing climate variability and extreme climatic events, thereby supporting the application of meteorological and GIS-based data for sustainable agricultural development in Thailand.

2. Materials and Methods

2.1 Data collection

This study focuses on the climate-related factors influencing durian yield in Chanthaburi Province. The climate variables analyzed include atmospheric pressure, rainfall, soil temperature at depths of 10 and 50 centimeters, relative humidity, average temperature, minimum temperature, maximum temperature, sunlight duration, and pan evaporation. The data span 2014 to 2024 and were obtained from the Thai Meteorological Department through two meteorological stations

located in Chanthaburi Province. Monthly climatic data were aggregated into annual values to ensure consistency with agricultural production data. Durian cultivation data, including standing area, productive area, total yield, and yield per productive area, were collected from the Office of Agricultural Economics Region 6. The dataset covers all districts in Chanthaburi Province for the same 10-year period. All datasets were processed and harmonized to ensure temporal alignment and data consistency prior to statistical analysis.

2.2 Statistical analysis

Descriptive statistics, including mean, median, variance, and range, were used to provide an overview and highlight variations across climatic variables and durian production metrics. Correlation analysis was applied to identify the linear relationship between climate variables and durian yield (Cohen *et al.*, 2003). Pearson's correlation coefficient (r) was used, ranging from -1 to +1. As Equation (1).

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \cdot \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (1)$$

Where r represents the correlation coefficient; X_i and Y_i are values of variables X and Y ; $\bar{X}$ and $\bar{Y}$ are the means of X and Y ; and n is the number of observations. The significance of correlation coefficients was tested using a t-test as Equation (2).

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (2)$$

Where r is the Pearson correlation coefficient and n is the number of observations. A p-value < 0.05 indicates a statistically significant correlation at the 95% confidence level (Kutner *et al.*, 2004).

Multiple regression analysis was performed to assess the combined influence of independent climatic variables on durian yield (Draper and Smith, 1998; Cohen *et al.* 2003; Montgomery *et al.*, 2012). The general form of the linear regression as Equation (3).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (3)$$

In this model, Y represents durian yield, X_1 to X_n are climate variables, and ε is the error term. The regression was estimated using the least squares method to minimize the residual sum of squares as Equation (4) (Asmussen and Foss, 2022).

$$Z(k_0, k_1, \dots, k_i) = \sum_{x=1}^j (A_x - k_0 - k_1 a_{x1} - \dots - k_j a_{xi}) \quad (4)$$

Prior to model interpretation, statistical assumptions were evaluated to ensure model validity. Normality was assessed using the Shapiro-Wilk test and graphical inspection of

residuals, while homoscedasticity was examined using residual plots. Multicollinearity among independent variables was evaluated using variance inflation factors (VIF), with values less than 5 considered acceptable.

2.3 Forecasting model

In addition to regression, time-series forecasting was applied using ARIMA (Autoregressive Integrated Moving Average) models (Box *et al.*, 2015; Hyndman and Athanasopoulos, 2018). The general ARIMA as Equation (5).

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_q e_{t-q} + \varepsilon_t \quad (5)$$

Where Y_t is durian yield at time t , ϕ and θ are autoregressive and moving average parameters, and e_t is white noise. Model parameters were determined through autocorrelation and partial autocorrelation functions.

Model identification was performed using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to determine appropriate orders of autoregressive (p), differencing (d), and moving average (q) components. Model selection was based on comparative evaluation of candidate models using performance criteria, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The performance of the forecasting model was evaluated using three commonly adopted statistical metrics. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), as shown in Equations (6), (7), and (8) respectively.

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (8)$$

Where Y_i is the observed value, $\hat{Y}_i$ is the predicted value, and $\bar{Y}$ is the mean of observed values. High R^2 and low MAE/RMSE indicate better model fit.

Durian yield and price forecasts for the period 2025-2030 were generated using regression and ARIMA models to provide analytical insights into future production trends under climate variability. ARIMA model selection was based on the Akaike Information Criterion (AIC) and model adequacy was evaluated using residual diagnostics, including the Ljung-Box test for independence. All analyses were conducted using SPSS version 26.

2.4 Spatial analysis

This study employed a geospatial approach to investigate the relationship between vegetation health and durian cultivation under climatic variability in Chanthaburi Province from 2021 to 2024. Normalized Difference Vegetation Index (NDVI) data were derived from Sentinel-2 imagery and processed using QGIS version 3.34 (QGIS Development Team, 2023). NDVI was calculated using the standard formula, as presented in Equation (9).

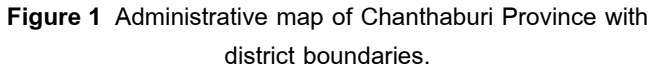
$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (9)$$

Cloud-contaminated pixels were excluded prior to analysis, and annual NDVI composites were generated using the maximum value composite method to minimize atmospheric noise. The processed NDVI data were resampled to a spatial resolution of 10 meters and clipped to the administrative boundaries of the province's ten districts based on official GADM shapefiles. District-level NDVI values were computed using spatial averaging (zonal statistics) rather than visual interpretation to ensure analytical consistency and reproducibility. Simultaneously, statistical data on productive durian cultivation area (rai) and total yield (tons) were obtained from the Office of Agricultural Economics. Yield per unit area was calculated for each year. Pearson correlation analysis was conducted using Microsoft Excel and SPSS version 26 to examine the association between NDVI values and both productive areas and total yield. NDVI was interpreted as a proxy for vegetation condition and not as a direct measure of yield.

3. Results and Discussion

3.1 Geographic scope

Chanthaburi Province, located in eastern Thailand at approximately 12.6110°N and 102.1030°E (Figure 1), is one of the country's major durian-producing regions. The province comprises ten administrative districts: Mueang Chanthaburi, Laem Sing, Na Yai Am, Kaeng Hang Maeo, Soi Dao, Pong Nam Ron, Makham, Khlung, Khao Khitchakut, and Tha Mai. Among these, Mueang Chanthaburi, Khao Khitchakut, and Makham are durian-producing areas. Geographically, the area consists of a mix of coastal lowlands and upland terrain, with elevations ranging from sea level to over 1,000 meters in mountainous zones. This variation in topography influences local microclimatic conditions and water drainage patterns, which are important factors affecting durian growth and yield. The province experiences a tropical monsoon climate with distinct wet (May-October) and dry (November-April) seasons. Annual rainfall ranges from 2,000 to 3,000 mm, and temperatures typically vary between 23°C and 35°C. These climatic and topographic conditions are suitable for durian cultivation but also contribute to variability in production under climate stress.



Meteorological data were obtained from two weather stations in Chanthaburi Province, covering key variables including rainfall, temperature (minimum, maximum, and average), soil temperature, relative humidity, solar radiation, and evaporation over the period 2013-2024. Durian cultivation data, including productive area and total yield, were collected from the Office of Agricultural Economics Region 6 at the district level.

The Pearson correlation analysis revealed that several environmental factors significantly influenced durian yield in Chanthaburi. As shown in Table 1, rainfall, length of sunlight, pressure, and relative humidity exhibited statistically significant correlations with durian yield. Notably, rainfall and fruitful area showed strong positive correlations ($r = 0.737$, $p < 0.01$), while perennial area showed the strongest correlation ($r = 0.962$, $p < 0.01$). Conversely, relative humidity displayed a weak negative correlation ($r = -0.204$, $p < 0.05$), indicating that excess humidity could impair productivity.

These findings align with recent studies such as Matamala *et al.* (2023) and Tharaga (2022), who observed that excessive rainfall during fruit development stages negatively impacts fruit quality due to nutrient competition between young leaves and developing fruits. Similarly, Hu *et al.* (2024) emphasize that even minor fluctuations in environmental conditions such as

Table 1 The relationship between environmental factors and durian yield in Chanthaburi Province.

*Significantly different level ($p < 0.05$), **significantly different level ($p < 0.01$)

Multiple regression analysis was employed to predict durian yield based on significant environmental variables. Table 2 shows the model's coefficients and multicollinearity statistics. The predictors perennial area, minimum temperature, and maximum temperature were statistically significant. All VIF values were below 4 and tolerance values above 0.20, indicating no multicollinearity issues. The regression equation for durian yield (Y) prediction is as follows:

Model validation showed strong performance with $R = 0.967$, $R^2 = 0.935$, and Adjusted $R^2 = 0.933$. The Durbin-Watson statistic (1.045) indicates no autocorrelation, and the overall model was statistically significant ($F = 462.492$, $p < 0.001$).

These findings indicate that perennial area and temperature variables are key determinants of durian yield. However, the strong positive relationship between perennial area and yield ($\beta = 1.420$) should be interpreted with caution, as it may primarily reflect the effect of land expansion rather than improvements in productivity per unit area. This suggests that total yield increases may be driven by increased cultivated area rather than enhanced production efficiency. Furthermore, there is a potential risk of spurious correlation, particularly when variables such as cultivated area and yield are inherently related. Without normalization (e.g., yield per rai) or additional controls, the strength of this relationship may be overestimated. Therefore, the regression results should be interpreted as indicative of association rather than direct causation. The negative coefficient of maximum temperature suggests that heat stress adversely affects durian yield, while minimum temperature shows a positive association. Rather than implying that farmers can

“maintain” temperature conditions, these results should be interpreted in terms of site suitability and climate variability, where optimal temperature ranges support flowering and fruit set. This is consistent with Kozai *et al.* (2014) and Zhao *et al.* (2021), who linked heat stress to reduced flowering and fruit set. Vorakuldamrongchai *et al.* (2015) also observed that climate variability disrupts flowering cycles and increases production

risks. The significance of land use is further supported by Deethong and Boonnam (2022), who noted that appropriate orchard spacing improves nutrient uptake and yield. However, expansion into marginal or suboptimal areas may reduce yield efficiency and increase production risks, reinforcing the need to distinguish between area-driven yield increases and true productivity gains.

Table 2 Variance inflation factor (VIF) and regression coefficients.

Factors	B	Std. error	Beta	T-test	p-value	Tolerance	VIF
Constant	9447.182	29039.255					
Perennial area	1.420	0.038	0.972	37.221	0.000	0.988	1.013
Minimum temperature	3004.513	787.464	0.130	3.815	0.000	0.581	1.722
Maximum temperature	-3033.194	1331.907	-0.077	-2.277	0.025	0.582	1.718

A previous model by Chalernngam and Thumcharoen (2018) explained only 30.9% of the variation in yield based on cultivated area. In contrast, the present study demonstrates a higher predictive capability by incorporating climatic variables, providing a more robust forecasting tool for sustainable durian production.

3.4 Forecasting durian yield and economic implications under climate stress

To assess the applicability of the developed model in forecasting future trends, durian yield from 2025 to 2030 was projected using the regression model and smoothed time series trends. As shown in Figure 2, durian yields are projected to fluctuate over the forecast period, with values ranging from approximately 530,000 to 580,000 tons, rather than exhibiting a consistent decline. This variability reflects the influence of climate-related factors and interannual variability, suggesting that yield responses are not linear but dynamically influenced by environmental conditions. Variability in rainfall and temperature has been shown to directly affect flowering and fruit set in durian production systems (Suwanseree and Yapwattanaphun, 2017). While some years show slight decreases, others indicate recovery or stabilization, highlighting the sensitivity of durian production to climatic fluctuations. Such interannual variability is consistent with broader findings that environmental instability can significantly alter crop physiological responses and yield outcomes (Jittamai *et al.*, 2025). Despite the continued expansion of cultivated areas, the projected yield pattern suggests that increases in production are not consistently sustained, which may indicate diminishing returns in certain years. However, this relationship should be interpreted with caution, as fluctuations may arise from both climatic variability and model limitations.

From a socioeconomic perspective, durian prices are anticipated to exhibit a gradual decline, decreasing from approximately 115–120 Baht/kg in 2026 to below 100 Baht/kg by 2030. Price dynamics are influenced by complex interactions

between supply, demand, and external trade conditions, which may amplify variability under changing environmental and economic contexts (Van den Hurk *et al.*, 2023).

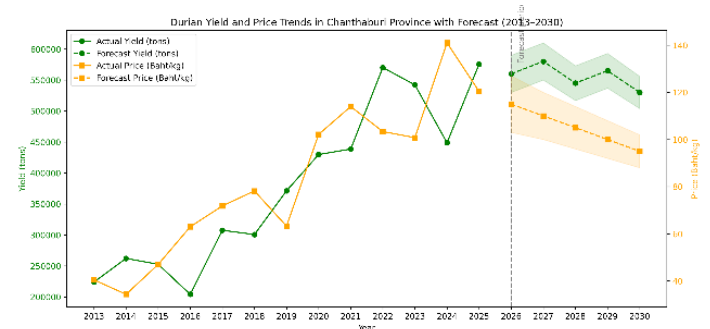


Figure 2 Forecasted durian yields in Chanthaburi Province (2026-2030).

Overall, the results suggest that future yield and price dynamics are characterized by variability rather than monotonic trends. These findings highlight the importance of adaptive management strategies and improved monitoring systems, while acknowledging the inherent uncertainty in model-based forecasts.

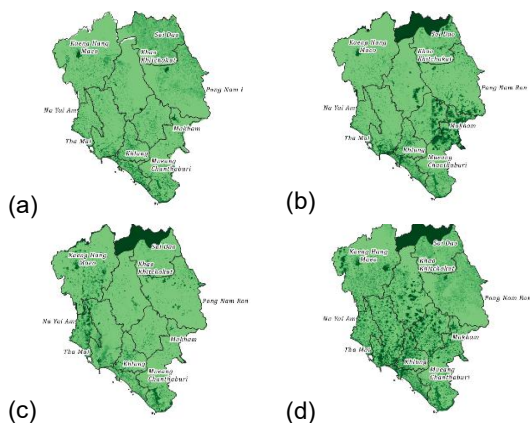
3.5 NDVI-based spatial and economic analysis for 2021–2024

The spatial and temporal analysis of NDVI and durian production data in Chanthaburi Province from 2021 to 2024 revealed significant patterns reflecting the impacts of climatic variability on crop performance. NDVI values, derived from Sentinel-2 imagery during the peak durian growing season (March–June), showed a declining trend from 0.74 in 2021 to 0.60 in 2024, indicating a reduction in overall vegetation health (Table 3). These trends were mapped using choropleth techniques in QGIS and visually interpreted at the district level (Figure 3).

Table 3 NDVI and durian yield metrics in Chanthaburi.

Years	NDVI (Estimate)	Productive area (rai)	Total yields (tons)	Yield per Rai (kg/rai)
2021	0.74	238,034	438,650	1,842
2022	0.72	259,815	570,137	2,194
2023	0.68	273,648	542,115	1,981
2024	0.60	286,895	448,692	1,563

When correlated with agricultural statistics from the Office of Agricultural Economics (OAE), a strong negative correlation ($r = -0.920$) was found between NDVI and productive area, suggesting that increased land use did not result in healthier vegetation and may reflect expansion into marginal or suboptimal areas under ecological stress. Conversely, the relationship between NDVI and total yield was weakly positive ($r = 0.263$), implying that although more land was cultivated, climatic stressors such as prolonged drought, off-season rainfall and intense wind limited the effectiveness of photosynthetic activity and fruit development. It should be noted that NDVI is an indirect proxy of vegetation vigor rather than a direct measure of yield. Therefore, the observed relationships should be interpreted with caution, as NDVI may not fully capture crop productivity, particularly under heterogeneous canopy structures and varying management practices.

**Figure 3** NDVI distribution maps of Chanthaburi Province for the years (a) 2021, (b) 2022, (c) 2023, and (d) 2024.

These observations are consistent with previous studies that demonstrate NDVI's effectiveness as a proxy for vegetation vigor and agricultural yield under environmental stress (Meena *et al.*, 2023). The decreasing NDVI values coincided with reports of physiological disorders in durian trees, including abnormal flowering, immature fruit drop, and increased vulnerability to pests and diseases —factors frequently attributed to erratic climate patterns (Tholkapiyan *et al.*, 2023; Suwanseree and Yapwattanaphun, 2017). In addition, uncertainties associated with remote sensing data should be considered, including potential effects of cloud contamination, atmospheric conditions, sensor resolution, and temporal compositing methods, which may influence NDVI accuracy and spatial interpretation. Beyond

the agronomic implications, economic consequences were also evident. In 2024, durian yield declined sharply in parallel with NDVI deterioration. However, contrary to basic supply-demand expectations, average farm-gate prices also decreased. Field-level surveys and industry interviews indicated that the decline was partly due to a significant reduction in the number of operational durian packing houses (longs), which curtailed buyer competition and weakened price leverage for producers. Consequently, farmers faced both lower output and suppressed pricing, intensifying their financial vulnerability. This pattern aligns with recent findings highlighting that climate-related stress can simultaneously affect crop physiology, product quality, and market dynamics (Jittamai *et al.*, 2025; Eyshi *et al.*, 2023).

Overall, these results underscore the importance of integrated mitigation strategies combining spatial monitoring tools (e.g., NDVI time series), climate-resilient cultivars, improved irrigation management, and strengthened post-harvest and market systems. However, further studies incorporating higher-resolution data and additional biophysical indicators (e.g., NDRE and EVI) are recommended to improve the robustness of remote sensing-based assessments.

4. Conclusion

This study provides an integrated assessment of climatic and topographic influences on durian (*D. zibethinus*) productivity in Chanthaburi Province by combining statistical modeling, time-series forecasting, and NDVI-based geospatial analysis. The results demonstrate that climatic variability, particularly maximum temperature and rainfall patterns, plays a significant role in shaping yield dynamics and production variability. A strong negative correlation between NDVI and productive area ($r = -0.920$) suggests that recent expansion of cultivation may have extended into less suitable areas, while the weak positive relationship between NDVI and yield ($r = 0.263$) indicates that vegetation vigor alone does not necessarily translate into higher productivity under climate-constrained conditions. This study contributes by integrating multi-source data (climate, yield statistics, and satellite-derived NDVI) to provide a comprehensive framework for assessing crop performance under climate variability. It also demonstrates the value of combining statistical and geospatial approaches for understanding yield variability in perennial crop systems. However, several limitations should be acknowledged. The analysis is based on provincial-level data, which may not capture fine-scale variability at the orchard level. In addition, NDVI was used as a proxy for vegetation condition rather than a direct measure of yield, and management practices were not explicitly included in the analysis. These factors may influence the interpretation of the observed relationships.

Overall, the findings suggest that future improvements in durian productivity may depend on better alignment between

environmental suitability and cultivation practices, supported by improved monitoring and data integration approaches.

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