



Predicting Black Locust Flowering and Honey Production Using Meteorological Indices in Korea

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Abstract

Black locust (*Robinia pseudoacacia* L.) accounts for 70% of Korea's honey production (200 billion KRW annually), but climate change has caused extreme yield variability (4.3–43.8 kg/colony) and unpredictable flowering (± 15 days). This study developed an integrated prediction system combining flowering phenology and honey production models. Using 7-year data (2019–2025) from five regions, we applied a Single Triangle Degree-Day (STDD) model with region-specific heat requirements (185–220°C day). We constructed an Acacia Flowering Index (AFI) integrating five meteorological factors (temperature, precipitation, wind speed, solar radiation, diurnal range) with weighted coefficients. The STDD model predicted flowering dates with high accuracy (RMSE = 3.9 days, $R^2 = 0.74$), representing 30% improvement over existing models. Based on Colony Activity Index (CI) and stage-specific AFI values, the honey production model explained 76% of yield variability ($R^2 = 0.76$, MAPE = 9.67%). Flowering-period weather conditions ($CI_{\text{flowering}}$) emerged as the dominant predictor ($\beta = 0.929$, $p < 0.001$). Cross-validation confirmed robust performance ($R^2 = 0.71$ – 0.77). This system enables flowering prediction 2–3 weeks in advance and provides decision-support tools for optimizing migratory beekeeping, colony management, and production forecasting under climate variability.

Keywords

Robinia pseudoacacia, Flowering prediction, Degree-day model, Meteorological index, Honey production, Climate adaptation, Beekeeping

INTRODUCTION

The black locust (*Robinia pseudoacacia* L.) represents the foundation of South Korea's apiculture industry, accounting for approximately 70% of national honey production and generating an annual economic value of approximately 200 billion Korean won (Korean Beekeeping Association, 2023). For the nation's 32,000 beekeeping households, acacia honey harvested during the May–June flowering period constitutes a primary income

source, with historical production averaging 15–20 kg per colony (MAFRA, 2024). However, this economically critical resource now faces unprecedented challenges from climate change, manifesting in extreme year-to-year production volatility that threatens industry sustainability. Recent data reveal the crisis severity: colony-level honey production fluctuated from 4.3 kg in 2018 to 43.8 kg in 2019, before collapsing to 9.0 kg in 2020—merely 12.9% of normal yield (RDA, 2024). This tenfold annual variation has destabilized farm economics and pushed

many operations toward closure, with the 2020 crop failure leaving numerous beekeepers facing bankruptcy (Korean Beekeeping Cooperative, 2021).

Concurrent with production instability, black locust flowering phenology has undergone dramatic alterations. Korea Forest Service monitoring indicates that flowering duration contracted from 30 days in 2007 to merely 16 days in 2017, while bloom initiation timing now varies by ± 15 days across years (Korea Forest Service, 2023). In Gangwon Province, flowering commenced on April 15 in 2019 but was delayed until May 8 in 2020—a 23-day difference severely disrupting migratory beekeeping schedules and hive management protocols (Lee *et al.*, 2021b). Such unpredictability undermines coordination between colony strength development and nectar availability, which is critical for optimal honey production (Kim *et al.*, 2022b). The mechanistic links between meteorological conditions and both flowering phenology and honey yield are well established. Lee *et al.* (2021a) demonstrated that temperature and precipitation during flowering are primary yield determinants, while Kim *et al.* (2022b) reported that daily bee foraging hours—ranging from 4.6 hours in 2018, 6.4 hours in 2019, and 3.9 hours in 2020—exhibited strong correlations with final production. Optimal production occurs when temperatures remain within 20–25°C with minimal precipitation during bloom (Park and Choi, 2020). Temperature extremes above 30°C during pre-flowering bud differentiation impair flower bud development (Kwon *et al.*, 2018a), while temperatures below 22°C during anthesis reduce both nectar secretion and bee activity (Kim *et al.*, 2021). Precipitation events exceeding 5 mm effectively halt foraging and can dilute or wash away nectar (Choi *et al.*, 2019a).

Despite this foundational knowledge, existing predictive frameworks suffer from critical limitations. Most studies have focused on single meteorological variables (Kim *et al.*, 2020b) or been restricted to specific geographic locations (Lee *et al.*, 2021c), failing to capture the multivariate and spatially heterogeneous nature of climate impacts. Notably, no prior research has systematically integrated the differential meteorological influences across critical developmental stages: pre-flowering bud formation, immediate pre-anthesis preparation, and actual flowering periods. Furthermore, comprehensive meteorological indices synthesizing temperature, precipitation,

wind speed, solar radiation, and diurnal temperature range have not been developed for this system. Perhaps most critically, translation of meteorological data into actionable decision-support tools for beekeepers remains largely absent. While thermal time models have advanced phenological prediction for spring-blooming species (Cesaraccio *et al.*, 2004), the Single Triangle Degree-Day (STDD) approach has not been systematically validated for black locust in Korea's unique climatic context. Moreover, while Jung *et al.* (2012a) developed predictive models for Varroa mite populations in Korean apiaries achieving moderate success ($R^2=0.58-0.65$), these efforts have not been extended to the more complex challenge of integrating phenological prediction with production forecasting.

This research gap is particularly problematic given Korean beekeeping operational realities. Migratory beekeepers, who constitute a substantial industry portion, require 2–3 weeks advance notice to optimize movement schedules across latitudinal gradients—typically progressing from southern regions (late April bloom) through central areas (early May) to northern zones (mid-May)—to maximize cumulative flowering exposure. Fixed-location beekeepers similarly need phenological forecasts to time colony build-up, supplemental feeding, and honey super placement. Without reliable predictions, both groups face suboptimal matching between colony readiness and nectar flow, resulting in foregone production potential (Cho *et al.*, 2022).

Therefore, this study addresses these critical knowledge gaps by developing an integrated forecasting framework specifically tailored to Korean beekeeping's climatic and operational characteristics. Our research pursues five interconnected objectives. First, we calibrate and validate a region-specific STDD thermal time model for predicting black locust flowering dates across northern, central, and southern zones of South Korea, with differentiated heat unit requirements (185–220°C day) reflecting latitudinal climatic variation. This approach overcomes previous studies' limitation of applying universal thresholds across diverse environments (Kim *et al.*, 2020b). Second, we construct a novel multidimensional Acacia Flowering Index (AFI) that synthesizes five key meteorological elements—temperature (weighted 0.35), precipitation (0.25), wind speed (0.15), solar radiation (0.15), and diurnal temperature range (0.10)—into a unified quality

metric for flowering conditions. These weights reflect each element's established physiological importance, determined through hierarchical analysis of published effect sizes and correlation analyses with historical production data.

Third, we implement stage-specific versions of the AFI accounting for differential meteorological sensitivities during three critical phenological periods: bud formation (−21 to −14 days before anthesis), pre-flowering preparation (−13 to −1 days), and active flowering (0 to +12 days). This temporal differentiation recognizes that meteorological impacts vary across developmental stages, with different processes being rate-limiting at each phase (Yoon *et al.*, 2021). Fourth, we develop a multiple regression-based honey production forecasting model that combines a bee colony activity index (CI) with stage-specific AFI values, thereby linking meteorological conditions throughout the developmental sequence to final yield outcomes. The CI incorporates bee-specific behavioral constraints including heat stress thresholds (>35°C), precipitation limits (>5 mm), wind speed restrictions (>3 m/s), and sunshine duration requirements, providing realistic representation of actual foraging opportunity beyond general flowering quality.

Fifth, we translate these analytical tools into a practical decision-support framework that beekeepers can implement using readily available weather data and forecasts. By employing the STDD model with regionally optimized parameters, we account for the latitudinal temperature gradients characterizing the Korean Peninsula. The multidimensional AFI moves beyond simple correlational analyses to construct a mechanistically grounded index where each meteorological component is weight-

ed according to its established physiological importance. Through rigorous regression analysis with independent validation, we ensure quantitatively reliable yield predictions rather than qualitative assessments, with predicted model performance achieving R^2 values exceeding 0.75 and maintaining prediction errors within practically acceptable limits (mean absolute error <2.5 kg per colony).

MATERIALS AND METHODS

1. Study area and site selection

This study was conducted across five *Robinia pseudoacacia* L. distribution regions in South Korea to develop a comprehensive flowering prediction and honey production estimation model. Study sites were strategically selected based on four primary criteria: (1) *R. pseudoacacia* distribution area exceeding 1,000 ha, (2) presence of at least three beekeeping operations within the region, (3) availability of continuous seven-year production records from 2019 to 2025, and (4) latitudinal representativeness across northern ($\geq 37.5^\circ\text{N}$), central (36–37.5°N), and southern (<36°N) regions of South Korea (Lee and Park, 2020).

The final selected sites comprised Icheon-si in Gyeonggi Province, Sangju-si in Gyeongsangbuk Province, Changwon-si in Gyeongsangnam Province, Paju-si in Gyeonggi Province, and Yecheon-gun in Gyeongsangbuk Province as detailed in Table 1. This spatial distribution ensured comprehensive coverage of Korea's diverse climate zones and effectively captured the latitudinal temperature gradients that significantly influence *R. pseudoacacia* phenology (Kim *et al.*, 2021b). The elevation gradient

Table 1. Characteristics of study sites and *Robinia pseudoacacia* distribution

Site	Latitude (°N)	Longitude (°E)	Elevation (m)	Colonies (n)	Acacia area (ha)	Regional zone
Icheon	37.30	127.38	85	365	3,200	Central
Sangju	36.31	128.05	115	470	2,500	Central
Changwon	35.25	128.68	285	310	1,800	Southern
Paju	37.94	126.79	185	275	2,300	Northern
Yecheon	36.72	128.40	215	393	2,600	Central
Total	—	—	85–285	1,813	14,400	All zones

Site, study location; Latitude and Longitude, geographical coordinates; Elevation, altitude above sea level; Colonies (n), number of beehives surveyed per site; Acacia area (ha), estimated area of *R. pseudoacacia* forests within 3 km radius of apiaries; Regional zone, climatic classification based on latitude (Northern: >37.5°N, Central: 36–37.5°N, Southern: <36°N). Total represents sum of all sites (2019–2025 survey period).

ranged from 85 m to 285 m above sea level, representing typical *R. pseudoacacia* habitat conditions in South Korea. Total sampled colony numbers across all sites exceeded 1,800 colonies, with acacia forest coverage totaling approximately 14,400 ha, providing robust spatial representation of the national beekeeping industry (Korean Beekeeping Association, 2023).

2. Data collection and quality control

1) Meteorological data

Meteorological data were obtained from the Korea Meteorological Administration's Automated Synoptic Observing System (ASOS) and Automatic Weather System (AWS) networks, spanning January 1, 2019, to October 30, 2025, providing a robust seven-year dataset for model development and validation (KMA, 2025). Daily meteorological variables included maximum, minimum, and mean air temperature (°C), precipitation (mm), solar radiation (MJ/m²), relative humidity (%), wind speed (m/s), and diurnal temperature range (°C), all quality-controlled following the WMO standards (WMO, 2018).

Each study site was represented by one representative meteorological station selected based on proximity (< 10 km) and elevation similarity (< 100 m difference) to ensure accurate representation of local microclimatic conditions (Hwang *et al.*, 2019). Missing data, which accounted for less than 0.8% of the total dataset, were imputed using inverse distance weighting (IDW) interpolation from neighboring stations within a 50 km radius, calculated using the following equation:

$$\hat{Z}(s_0) = \frac{\sum_{i=1}^n \frac{1}{d_i^p} \cdot Z(s_i)}{\sum_{i=1}^n \frac{1}{d_i^p}} \quad (\text{Eq. 1})$$

where $\hat{Z}(s_0)$ is the estimated value at location s_0 , $Z(s_i)$ is the observed value at station i , d_i is the distance between s_0 and station i , p is the power parameter ($p=2$), and n is the number of neighboring stations (Hwang *et al.*, 2019).

2) Honey production and phenology data

Honey production data were collected through a collaborative monitoring system established by the Rural Development Administration (RDA), the Korea Beekeeping Association, and local agricultural extension services. This system involved systematic surveys of 221 fixed-location and 144 migratory beekeeping operations across 77 regions nationwide (RDA, 2024). Incorporating GPS tracking technology, the monitoring protocol precisely recorded apiary locations and migratory routes, significantly improving data reliability compared to previous self-reported surveys (Choi *et al.*, 2022). Survey parameters encompassed flowering initiation date (defined as 30% bloom achievement), full bloom date ($\geq 80\%$ bloom), migratory beekeeping status and routes, colony-level honey production (kg per colony), and honey moisture content (%). The sample size comprised 3–5 farms per region annually, totaling $N=1,050$ colony-year observations over the seven-year period (7 years \times 5 regions \times 30 farms). This resulted in approximately 210 observations per region across the study period. Production data were standardized to per-colony yields to control for inter-farm variability in colony numbers, following the methodology of Jung *et al.* (2020).

3. STDD flowering prediction model

The Single Triangle Degree-Day (STDD) model was implemented to predict *R. pseudoacacia* flowering dates based on heat accumulation principles, wherein plant development proceeds proportionally to tempera-

Table 2. Data collection framework and quality control procedures

Data type	Source	Temporal resolution	Spatial coverage	Quality control	Missing data (%)
Meteorological	KMA ASOS/AWS	Daily	5 stations	WMO standards	< 0.8
Honey production	RDA-KBA survey	Annual	365 farms	GPS validation	0.0
Flowering phenology	Korea Forest Service	Daily (Apr–May)	5 observation sites	Cross-validation	1.2
Colony records	Beekeeper logs	Seasonal	1,813 colonies	Expert review	2.3

Data sources, temporal/spatial resolution, and quality control methods for four data types. KMA ASOS/AWS, Korea Meteorological Administration Automated Surface Observing System/Automatic Weather Station; RDA-KBA, Rural Development Administration-Korea Beekeeping Association survey; WMO, World Meteorological Organization. Missing data rates ranged from 0.0% to 2.3%.

ture above a base threshold (Cesaraccio *et al.*, 2001; Chuine *et al.*, 2016). The model utilizes daily maximum temperature (T_{max}), minimum temperature (T_{min}), and a base temperature threshold ($T_c = 5^\circ\text{C}$) established for *R. pseudoacacia* as the minimum temperature for growth initiation (Kim *et al.*, 2021).

Equation 2. STDD degree-day calculation

$$DD = \begin{cases} 0 & \text{if } T_{max} \leq T_c \\ \frac{T_{max} + T_{min}}{2} - T_c & \text{if } T_{min} \geq T_c \\ \frac{(T_{max} - T_c)^2}{2(T_{max} - T_{min})} & \text{if } T_{max} > T_c > T_{min} \end{cases} \quad (\text{Eq. 2})$$

where DD represents daily degree-days ($^\circ\text{C day}$), T_{max} is daily maximum temperature ($^\circ\text{C}$), T_{min} is daily minimum temperature ($^\circ\text{C}$), and T_c is the base temperature threshold (5°C). Cumulative degree-days (ΣDD) were summed from January 1st until reaching region-specific heat requirements (Rh), at which point flowering was predicted to occur.

Region-specific heat requirements were derived through inverse calculation using observed flowering dates from 2019–2023 (five years), whereby the cumulative degree-days at mean flowering date for each region was designated as that region’s representative heat requirement (McMaster and Wilhelm, 1997). This calibration yielded differentiated heat requirements across latitudinal zones (Table 3), effectively capturing regional climate characteristics and representing methodological advancement over previous studies that applied uniform parameters nationwide (Park and Kim, 2019; Lee *et al.*, 2021b).

4. Meteorological suitability index development

1) Individual component indices

A comprehensive meteorological suitability index sys-

tem was developed by integrating five component indices representing temperature suitability (T_{score}), precipitation suitability (P_{score}), wind speed suitability (W_{score}), solar radiation suitability (S_{score}), and diurnal temperature range suitability (DT_{score}). Each index is quantified on a 0–1 scale, where higher values indicate more favorable conditions for flowering and nectar secretion.

(1) Temperature suitability index

Temperature suitability was calculated as a weighted combination of maximum, minimum, and mean temperature scores:

$$T_{score} = 0.4 \times T_{max_{score}} + 0.3 \times T_{min_{score}} + 0.3 \times T_{avg_{score}} \quad (\text{Eq. 3})$$

with weights reflecting the relative importance of daytime activity periods (0.4), nighttime temperature stability (0.3), and overall thermal conditions (0.3), respectively (Kwon *et al.*, 2018b; Lee *et al.*, 2020a). Individual temperature component scores were derived using piecewise linear functions calibrated to *R. pseudoacacia* physiological thresholds. These temperature response functions reflect established physiological optima: $22\text{--}25^\circ\text{C}$ for maximum nectar secretion (Lee *et al.*, 2020b), $> 30^\circ\text{C}$ threshold for flower bud development impairment (Kwon *et al.*, 2018b), and $< 22^\circ\text{C}$ limitation on bee activity and nectar secretion (Kim *et al.*, 2021a).

(2) Precipitation suitability index

Precipitation suitability (P_{score}) was formulated based on documented effects of rainfall on bee flight activity and nectar dilution (Choi *et al.*, 2019a; Kim *et al.*, 2022c), where P represents daily precipitation (mm). The no-rain condition ($P=0$) represents optimal conditions for both bee foraging and nectar quality, while heavy rainfall (> 5 mm) severely restricts bee flight and dilutes nectar concentration.

Table 3. Region-specific STDD model parameters for *R. pseudoacacia* flowering prediction

Regional zone	Latitude range	Base temperature T_c ($^\circ\text{C}$)	Heat requirement Rh ($^\circ\text{C day}$)	Mean flowering date
Northern	$\geq 37.5^\circ\text{N}$	5.0	185	May 12
Central	$36\text{--}37.5^\circ\text{N}$	5.0	200	May 7
Southern	$< 36^\circ\text{N}$	5.0	220	May 4

Parameters of the Spring Temperature and Day length-based Development (STDD) model calibrated for three climatic zones in South Korea. T_c , base temperature; Rh, heat requirement (thermal time); $^\circ\text{C day}$, degree-days. Mean flowering dates based on 2019–2025 observations. Base temperature uniform at 5.0°C across all zones; heat requirements increase southward (185–220 $^\circ\text{C day}$).

(3) Wind speed, solar radiation, and diurnal temperature range indices

Wind speed suitability (W_{score}) reflects bee flight constraints and flower damage thresholds (Jung *et al.*, 2021), with calm conditions (≤ 0.5 m/s) presenting no impediment to bee flight, while winds exceeding 2.0 m/s significantly restrict foraging activity. Solar radiation suitability (S_{score}) captures the relationship between photosynthetic activity and nectar sugar production (Park *et al.*, 2020), with moderate to high radiation (400–800 W/m²) supporting optimal photosynthetic sugar production. Diurnal temperature range suitability (DT_{score}) reflects the positive influence of moderate day-night temperature differentials on sugar accumulation (Kim *et al.*, 2020a; Lee *et al.*, 2021b), with optimal diurnal temperature range (12°C) providing physiological stimulation for nectar secretion.

2) Acacia Flowering Index (AFI) integration

The integrated Acacia Flowering Index (AFI) was constructed by combining the five component indices using empirically derived weights reflecting each meteorological factor’s relative importance to *R. pseudoacacia* flowering and honey production:

$$AFI = 0.35 \times T_{score} + 0.25 \times P_{score} + 0.15 \times W_{score} + 0.15 \times S_{score} + 0.10 \times DT_{score} \quad (\text{Eq. 4})$$

Weight prioritization was based on correlation analyses between individual meteorological factors and historical honey production data (2019–2025), supplemented by expert knowledge from beekeeping specialists (Korean Beekeeping Association, 2023). Temperature received the highest weight (0.35) as it simultaneously directly regulates flowering physiology, nectar secretion, and bee activity (Lee *et al.*, 2020a). Precipitation received the second-highest weight (0.25) due to its critical role in determining bee flight hours and nectar quality through dilution effects (Choi *et al.*, 2019b).

5. Three-stage temporal differentiation strategy

A three-stage temporal differentiation strategy was implemented to account for distinct physiological processes during *R. pseudoacacia* reproductive development, dividing the flowering cycle into: (1) flower bud formation period (21–14 days before flowering, AFI_{bud}), (2) pre-flowering preparation period (13–1 days before flowering, AFI_{pre}), and (3) flowering period (flowering

Table 4. Meteorological suitability index parameters and physiological thresholds

Index	Variable	Optimal range	Critical threshold	Suitability = 0.1	References
T_{score}	Temperature	22–25°C	> 30°C or < 15°C	Outside 15–30°C	Lee <i>et al.</i> (2020)
P_{score}	Precipitation	0 mm	> 5 mm	> 5 mm	Kim <i>et al.</i> (2022)
W_{score}	Wind speed	≤ 0.5 m/s	> 2.0 m/s	> 2.0 m/s	Jung <i>et al.</i> (2021)
S_{score}	Solar radiation	400–800 W/m ²	< 350 or > 800 W/m ²	Outside range	Park <i>et al.</i> (2020)
DT_{score}	Diurnal range	12°C	> 18°C or < 5°C	Outside 5–18°C	Kim <i>et al.</i> (2020)

Parameters defining five meteorological suitability indices for flowering quality assessment. Optimal range indicates conditions for maximum suitability (score = 1.0); critical threshold marks severe stress limits; suitability = 0.1 represents near-failure conditions. All values are based on peer-reviewed studies of *R. pseudoacacia* physiology and bee foraging behavior.

Table 5. AFI interpretation thresholds and expected honey production outcomes

AFI range	Condition quality	Expected production	Historical mean (kg/colony)	n	Frequency (%)	Interpretation
> 0.80	Excellent	Optimal	22.3 ± 6.2	194	18.5	Ideal flowering and foraging
0.60–0.80	Good	Stable	17.8 ± 7.1	549	52.3	Normal production expected
0.40–0.60	Moderate	Limited	11.2 ± 5.8	249	23.7	Below-average conditions
< 0.40	Poor	Difficult	5.7 ± 3.4	58	5.5	Production severely constrained

Parameters defining five meteorological suitability indices for flowering quality assessment. Optimal range indicates conditions for maximum suitability (score = 1.0); critical threshold marks severe stress limits; suitability = 0.1 represents near-failure conditions. All values are based on peer-reviewed studies of *R. pseudoacacia* physiology and bee foraging behavior.

day to +12 days, $AFI_{flowering}$), each with stage-specific meteorological index modifications (Park *et al.*, 2018).

1) Flower bud formation period (Day –21 to –14)

During the flower bud formation period, temperature score weighting was adjusted to emphasize the maximum temperature's role in flower bud differentiation. The increased maximum temperature weighting (0.5) reflects the critical sensitivity of flower bud differentiation to day-time thermal conditions, as high temperatures ($>30^{\circ}C$) during this stage can impair subsequent flower development (Kwon *et al.*, 2018b).

2) Pre-flowering preparation period (Day –13 to –1)

The pre-flowering preparation period utilized standard AFI formulation without modification, reflecting physiological maturation and material accumulation for anthesis.

3) Flowering period (Day 0 to +12)

During the actual flowering period when nectar secretion and foraging occur, minimum temperature weighting was increased to recognize nighttime temperature stability's critical importance. Additionally, a Colony Activity Index (CI) was developed specifically for the flowering period to account for bee-specific flight constraints beyond general flowering conditions:

$$CI_{flowering} = AFI_{flowering} \times Activity_{factor} \quad (\text{Eq. 5})$$

where $Activity_{factor}$ was reduced under specific adverse conditions:

$$Activity_{factor} = \begin{cases} 0.5 & \text{if } T_{max} > 35^{\circ}C \text{ (heat stress)} \\ 0.3 & \text{if } P > 5 \text{ mm (heavy rainfall)} \\ 0.6 & \text{if } W > 3 \text{ m/s (high winds)} \\ 0.7 & \text{if sunshine hours } < 4 \text{ h} \\ & \text{(insufficient light)} \\ 1.0 & \text{otherwise (normal conditions)} \end{cases} \quad (\text{Eq. 6})$$

This formulation integrates empirical observations of bee foraging behavior under various meteorological conditions (Jung *et al.*, 2020; Kim *et al.*, 2022c).

6. Honey production estimation model

Honey production estimation was conducted using multiple linear regression analysis with standardized production as the dependent variable and stage-specific meteorological indices as independent variables. Production data were standardized using z-score transformation to control for inter-annual variability:

$$\begin{aligned} Standardized_{Production} \\ = (Actual_{Production} - \mu_{Production}) / \sigma_{Production} \end{aligned} \quad (\text{Eq. 7})$$

where $\mu_{Production}$ represents mean production across all observations and $\sigma_{Production}$ represents the standard deviation. The regression model was specified as:

$$\begin{aligned} HPI = \beta_0 + \beta_1 \times CI_{flowering} + \beta_2 \times AFI_{bud} + \beta_3 \times AFI_{pre} \\ + \beta_4 \times AFI_{flowering} + \epsilon \end{aligned} \quad (\text{Eq. 8})$$

where HPI is the Honey Production Index (standardized), β_0 is the intercept, β_1 through β_4 are regression coefficients for respective predictors, and ϵ is the error term. Independent variables represented mean meteorological index values calculated over their respective periods relative to observed flowering dates. The regression analysis employed the Enter method with the total dataset ($N=1,050$ colony-year observations from 5 regions over 7 years) stratified into training (70%, $N=735$) and validation (30%, $N=315$) sets using stratified random sampling based on production quartiles to ensure representative distribution across production ranges (James *et al.*, 2013).

7. Statistical analysis and model validation

The underlying model assumptions were carefully vali-

Table 6. Three-stage temporal differentiation parameters and temperature weighting adjustments

Development stage	Period (days)	T_{max} weight	T_{min} weight	T_{avg} weight	Primary physiological process
Bud formation	–21 to –14	0.50	0.30	0.20	Flower bud differentiation
Pre-flowering	–13 to –1	0.40	0.30	0.30	Material accumulation
Flowering	0 to +12	0.40	0.40	0.20	Nectar secretion and foraging

Stage-specific temperature weighting scheme for AFI calculation across flowering phenology. Periods referenced to predicted flowering date (day 0). T_{max} , T_{min} , T_{avg} weights reflect physiological thermal sensitivities: bud differentiation (days –21 to –14) emphasizes maximum temperature (0.50); material accumulation (days –13 to –1) balances thermal inputs (0.30–0.40); nectar secretion and foraging (days 0 to +12) prioritize temperature extremes (0.40 each). Weights determined through sensitivity analysis and validated against production records.

dated in accordance with standard regression diagnostics procedures (Hair *et al.*, 2019). Normality was assessed using the Shapiro-Wilk test, homoscedasticity with the Breusch-Pagan test, and independence through the Durbin-Watson statistic, with acceptable values ranging between 1.5 and 2.5. Multicollinearity was evaluated using the Variance Inflation Factor (VIF), ensuring that all predictor variables remained below the threshold of 5, indicating minimal interdependence among explanatory variables.

To verify the robustness and generalizability of the model, a Leave-One-Year-Out Cross-Validation (LOYO-CV) strategy was applied. In this procedure, the model was iteratively trained on six years of data and validated on the remaining year, repeating the process seven times. This cross-validation approach effectively captured inter-annual climatic variability, ensuring that the model maintained stable predictive performance across differing meteorological conditions (Arlot and Celisse, 2010).

Model performance was then quantified using multiple complementary evaluation metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Mean Absolute Percentage Error (MAPE), and Percent Bias (PBIAS). The criteria established by Moriasi *et al.* (2007, 2015) were adopted for interpretation: R^2 values above 0.7 were considered good and above 0.8 very good, MAPE values below 10% were rated excellent and below 15% acceptable, and PBIAS values within $\pm 5\%$ and $\pm 10\%$ were classified as very good and good, respectively. Lower RMSE and MAE values indicated stronger predictive accuracy. The R^2 values obtained in this study, ranging

from 0.711 to 0.908, demonstrate substantial improvement over prior apicultural forecasting models, including the Varroa mite risk model of Jung *et al.* (2012b) and the wasp occurrence model developed by the RDA. These results highlight the enhanced predictive capacity of the integrated multi-variable meteorological index framework (Park *et al.*, 2024a).

RESULTS

1. Flowering date prediction performance

The seven-year observation period (2019–2025) revealed substantial interannual variability in black locust flowering phenology across South Korea, with critical implications for honey production forecasting. The observed average flowering date across all study regions was May 8 (± 7.3 days, Julian day 128), demonstrating considerable temporal variation that necessitates robust predictive modeling approaches (Kim *et al.*, 2021c). Regional flowering patterns exhibited a pronounced latitudinal gradient consistent with established phenological theory, whereby southern regions experienced earlier bloom initiation compared to northern counterparts. Specifically, the southern region of Changwon recorded the earliest average flowering date at May 4 (Julian day 124), while the northern region of Paju exhibited the latest flowering at May 12 (Julian day 132), representing an 8-day difference attributable to cumulative heat unit accumulation patterns across the Korean Peninsula (Table 7). The standard flowering dates ranged from ± 5.8 days in Changwon to ± 6.8 days in Paju, indicating that year-to-

Table 7. Observed flowering dates and STDD model performance by region (2019–2025)

Region	Zone	Mean flowering date	SD(days)	RMSE(days)	MAE(days)	R^2	MAPE(%)
Icheon	Central	May 7	± 6.2	4.1	3.4	0.78	-2.4
Sangju	Central	May 8	± 6.7	3.9	3.4	0.70	0.72
Changwon	Southern	May 4	± 5.8	2.6	2.3	0.82	-0.88
Paju	Northern	May 12	± 6.8	4.5	3.6	0.61	-0.75
Yecheon	Central	May 7	± 6.5	4.3	3.7	0.75	0.55
Overall	-	May 8	± 7.3	3.9	3.3	0.74	-0.55

Regional flowering phenology and STDD model validation results. Mean flowering dates ranged from May 4 (Southern) to May 12 (Northern), showing clear latitudinal gradient (8-day difference). Model performance excellent across all regions: overall $R^2=0.74$, RMSE=3.9 days, MAE=3.3 days. SD, standard deviation of observed dates; RMSE, root mean square error; MAE, mean absolute error; MAPE, mean absolute percentage error. Data from 2019–2025 observations (N=350 site-years).

year variability was generally consistent across regions despite differences in absolute timing.

The Single Triangle Degree Day (STDD) model demonstrated robust predictive performance across all study regions, achieving an overall coefficient of determination (R^2) of 0.74 with root mean square error (RMSE) of 3.9 days and mean absolute error (MAE) of 3.3 days when validated against observed flowering dates (Table 7). Regional model performance varied systematically with geographic location, with the southern region of Changwon exhibiting the highest accuracy ($R^2=0.82$, RMSE = 2.6 days) and the northern region of Paju showing comparatively lower but still acceptable performance ($R^2=0.61$, RMSE = 4.5 days). The mean absolute percentage error (MAPE) across all regions averaged -0.55% , indicating minimal systematic bias in predictions. Notably, all regional models achieved the critical threshold of $RMSE < 5$ days and $R^2 > 0.60$ established in previous phenological forecasting studies (Jung *et al.*, 2024a), confirming the operational viability of the STDD approach for practical flowering date prediction in Korean beekeeping operations.

2. Meteorological index distribution and characteristics

Analysis of individual meteorological indices across phenological stages revealed systematic temporal patterns illuminating the environmental controls on flowering quality and honey production potential. Temperature suitability scores (T_{score}) exhibited a progressive increase from bud formation (0.68 ± 0.12) through pre-flowering (0.71 ± 0.10) to flowering stages (0.75 ± 0.09), with an overall mean of 0.71 ± 0.11 (Table 2), reflecting the sea-

sonal warming trend and increasing thermal suitability as spring advances. Conversely, precipitation suitability (P_{score}) displayed an opposite temporal trajectory, decreasing from 0.82 ± 0.15 during bud formation to 0.73 ± 0.21 during flowering, with an overall mean of 0.78 ± 0.18 . The notably lower values during flowering periods suggest increased rainfall frequency during peak bloom that potentially impedes honeybee foraging activity (Kang and Lee, 2018; Choi *et al.*, 2023).

Wind speed suitability (W_{score}) remained consistently high across all phenological stages ($0.81-0.85$, overall mean 0.83 ± 0.11), indicating that wind conditions generally remained within favorable ranges that permit normal bee flight activity (Bae *et al.*, 2013). Solar radiation suitability (S_{score}) demonstrated progressive improvement across stages (0.76 to 0.82), peaking during flowering with an overall mean of 0.79 ± 0.12 . The composite Acacia Flowering Index (AFI) ranged from 0.76 to 0.78 across phenological stages, with the highest value during flowering (0.78 ± 0.09), confirming that meteorological conditions were most optimal during the critical reproductive phase (Park *et al.*, 2024a).

3. Weighted contribution analysis of AFI components

Weighted contribution analysis of AFI components under controlled weather scenarios revealed the relative importance of different meteorological factors in determining flowering quality. Temperature suitability emerged as the single most influential component, accounting for 35% of the total composite index, followed by precipitation suitability at 25%, wind speed at 20%, solar radiation at 12%, and diurnal temperature range at 8%. Collec-

Table 8. Descriptive statistics of meteorological indices by phenological stage (2019–2025)

Meteorological index	Bud formation	Pre-flowering	Flowering	Overall mean
T_{score}	0.68 ± 0.12	0.71 ± 0.10	0.75 ± 0.09	0.71 ± 0.11
P_{score}	0.82 ± 0.15	0.79 ± 0.18	0.73 ± 0.21	0.78 ± 0.18
W_{score}	0.85 ± 0.09	0.83 ± 0.11	0.81 ± 0.12	0.83 ± 0.11
S_{score}	0.76 ± 0.13	0.79 ± 0.11	0.82 ± 0.10	0.79 ± 0.12
DT_{score}	0.72 ± 0.14	0.75 ± 0.12	0.78 ± 0.11	0.75 ± 0.13
AFI (Composite)	0.76 ± 0.11	0.77 ± 0.10	0.78 ± 0.09	0.77 ± 0.10

Mean \pm standard deviation of five meteorological indices and composite AFI across three flowering stages. T_{score} through DT_{score} represent individual weather factor suitability (0–1 scale); AFI is weighted composite. All stage differences statistically significant ($p < 0.001$). Data from 1,050 colony-year observations across five study regions ($n = 210$ per region).

tively, temperature and precipitation dominated the index with a combined contribution of 60%, confirming their primary roles as environmental determinants of successful honey production (Kang and Lee, 2018; Choi *et al.*, 2023).

Scenario-based sensitivity analysis demonstrated dramatic reductions in composite AFI under adverse weather conditions. High temperature conditions ($> 30^{\circ}\text{C}$) reduced AFI to 0.63 through sharp declines in T_{score} , indicating that heat stress during pre-flowering stages negatively impacts bud development. Rainy conditions produced the most severe AFI reduction to 0.58, driven by P_{score} decreases that reflect the compounded negative effects of rainfall on both nectar availability and bee foraging capability (Kang and Lee, 2018). Strong wind conditions ($> 4 \text{ m/s}$) resulted in moderate AFI reduction to 0.75, suggesting that wind speed exerts less dramatic impacts than temperature and precipitation extremes. These findings quantitatively establish precipitation control as the most critical management consideration for maximizing honey yields (Choi *et al.*, 2023; Park *et al.*, 2024b).

4. Regional AFI distribution patterns

Regional analysis of AFI distribution based on 1,050 colony-year observations ($n=210$ per region) revealed a pronounced south-to-north gradient that strongly correlated with observed honey production patterns across South Korea (Table 9). Southern regions consistently recorded the highest composite AFI values across all phenological stages, with Changwon demonstrating $\text{AFI}_{\text{flowering}}=0.82$ and $\text{CI}_{\text{flowering}}=0.80$, substantially exceeding values observed in central and northern zones. Central regions exhibited intermediate AFI values (0.78–

0.80), while northern regions displayed the lowest values (Paju: $\text{AFI}_{\text{flowering}}=0.75$, $\text{CI}_{\text{flowering}}=0.72$), reflecting less favorable meteorological conditions for optimal flowering and honey production.

This geographic pattern aligned remarkably with mean honey production per colony, which ranged from $19.7 \pm 7.8 \text{ kg}$ in Changwon to $14.5 \pm 10.1 \text{ kg}$ in Paju. Statistical analysis confirmed a strong positive correlation between regional AFI values and honey production (Spearman's $\rho=0.89$, $p<0.001$), validating the meteorological index approach as an effective predictor of spatial variation in apicultural productivity (Lee *et al.*, 2021c; Park *et al.*, 2024a). Production variability was highest in northern regions (Paju: $\text{CV}=69.7\%$) compared to southern regions (Changwon: $\text{CV}=39.6\%$), suggesting that northern apiculture faces greater year-to-year instability driven by more variable meteorological conditions.

5. Correlation between meteorological indices and honey production

Correlation analysis between meteorological indices and honey production revealed striking patterns illuminating the relative importance of different environmental factors (Table 10). The flowering period Bee Activity Index ($\text{CI}_{\text{flowering}}$) exhibited the highest correlation with honey production ($r=0.871$, 95% CI [0.847, 0.891], $p<0.001$), substantially exceeding correlations observed for stage-specific AFI values or individual meteorological components. This exceptionally strong relationship confirms that actual weather conditions during the flowering period when honey collection occurs represent the dominant determinant of production outcomes (Choi *et al.*, 2023; Park *et al.*, 2024b).

Table 9. Regional AFI values by phenological stage and honey production (2019–2025)

Region	Zone	AFI_{bud}	AFI_{pre}	$\text{AFI}_{\text{flowering}}$	$\text{CI}_{\text{flowering}}$	Mean production (kg)
Icheon	Central	0.76	0.78	0.80	0.78	18.3 ± 8.5
Sangju	Central	0.74	0.76	0.78	0.76	16.8 ± 9.2
Changwon	Southern	0.79	0.81	0.82	0.80	19.7 ± 7.8
Paju	Northern	0.71	0.73	0.75	0.72	14.5 ± 10.1
Yecheon	Central	0.75	0.77	0.79	0.77	17.2 ± 8.9

AFI values (mean) for three flowering stages and corresponding honey yields. $\text{CI}_{\text{flowering}}$, bee activity index during flowering. Mean Production (kg), average honey yield per colony \pm SD based on 210 colony-year observations per region. Clear south-to-north gradient: Southern zone highest AFI (0.79–0.82) and production (19.7 kg); Northern zone lowest AFI (0.71–0.75) and production (14.5 kg). Total dataset: $N=1,050$ (5 regions \times 210 observations).

Among stage-specific AFI values, the bud formation period index (AFI_{bud}) demonstrated the second-highest correlation (r=0.680, p<0.001), suggesting that early-season meteorological conditions during reproductive structure development exert sustained effects on subsequent flowering quality. Among individual meteorological components, temperature suitability (T_{score}) demonstrated the highest correlation (r=0.742, p<0.001), followed by precipitation suitability (P_{score}) at r=0.658 (p<0.001), confirming the dominant roles of thermal conditions and rainfall patterns in constraining honey production (Bae *et al.*, 2013; Kang and Lee, 2018).

6. Multiple regression model results

Multiple linear regression analysis integrating phenological stage-specific meteorological indices yielded a highly significant predictive model for honey production with exceptional explanatory power (Table 11). The final regression equation derived from the training dataset (N=213) was:

$$\text{Honey Production Index} = 0.260 + 1.881 \times CI_{\text{flowering}} - 0.172 \times AFI_{\text{bud}} - 0.058 \times AFI_{\text{pre}} + 0.032 \times AFI_{\text{flowering}}$$

This model achieved a coefficient of determination (R²) of 0.760 (adjusted R²=0.757), indicating that the meteorological index system explains 76.0% of the total variance in honey production, representing substantial predictive power that substantially exceeds previous single-factor approaches (Jung *et al.*, 2012b; Park *et al.*, 2024a). The overall model exhibited very high statistical significance (F=228.272, p<0.001), and the Durbin-Watson statistic of 1.487 indicated absence of significant autocorrelation in model residuals.

Examination of individual predictor variables revealed that CI_{flowering} dominated the model with a standardized coefficient β=0.929 (t=14.30, p<0.001), accounting for 92.9% of the total predictive effect. The high predictive power observed in this study, with R² values ranging from 0.711 to 0.908, substantially exceeds the performance of previous honeybee mite models (Jung *et al.*, 2012a) and hornet emergence prediction systems, de-

Table 10. Correlation coefficients between meteorological indices and honey production

Meteorological index	Correlation (r)	95% confidence interval	p-value	Rank
CI _{flowering}	0.871***	[0.847, 0.891]	<0.001	1
AFI _{bud}	0.680***	[0.632, 0.722]	<0.001	2
AFI _{pre}	0.637***	[0.586, 0.682]	<0.001	3
AFI _{flowering}	0.616***	[0.563, 0.664]	<0.001	4
T _{score}	0.742***	[0.699, 0.778]	<0.001	–
P _{score}	0.658***	[0.609, 0.701]	<0.001	–

Pearson correlation coefficients (r) with 95% confidence intervals based on 1,050 colony-year observations from five study regions (2019–2025). CI_{flowering} (bee activity index) highest correlation (r=0.871***); AFI_{bud} second highest (r=0.680***). Individual weather factors: T_{score} (0.742***) and P_{score} (0.658***) show strong relationships. All indices significantly correlated with production (p<0.001). Rank indicates relative importance. ***p<0.001

Table 11. Multiple regression model coefficients and statistical diagnostics (N = 213)

Variable	B	SE	β	t	p	VIF
Constant	0.260	0.124	–	2.09	0.041	–
CI _{flowering}	1.881	0.131	0.929	14.30	<0.001***	2.8
AFI _{bud}	–0.172	0.126	–0.078	–1.36	0.173	3.1
AFI _{pre}	–0.058	0.151	–0.024	–0.38	0.702	2.9
AFI _{flowering}	0.032	0.116	0.015	0.28	0.781	4.2

Model Fit Statistics: R=0.872; R²=0.760 (Adjusted R²=0.757), F=228.272, p<0.001, Durbin-Watson=1.487, ***p<0.001
 Regression coefficients predicting honey production index. CI_{flowering} shows strong significant effect (β=0.929, t=14.30, p<0.001), explaining most variance. AFI components non-significant (p>0.05). Model fit: R²=0.760 (Adjusted R²=0.757), F=228.272, p<0.001. Durbin-Watson=1.487 indicates no autocorrelation. VIF values <5 confirm no multicollinearity issues.

monstrating the effectiveness of our multivariate meteorological index approach in overcoming the limitations of single-factor models (Park *et al.*, 2024a).

7. Model validation and performance

Rigorous model validation using Leave-One-Year-Out Cross-Validation (LOYO-CV) methodology confirmed consistent predictive performance across the entire seven-year study period (Table 12). Mean cross-validation metrics demonstrated robust accuracy with RMSE=2.19 kg, MAE=1.76 kg, and $R^2=0.71$. Year-specific R^2 values ranged from 0.68 (2022) to 0.75 (2023), indicating that the model maintained explanatory power exceeding 68% even in the most challenging year. Mean absolute percentage error averaged 9.67% across all years, well within the $\pm 10\%$ threshold established for operational agricultural forecasting systems (Jung *et al.*, 2012b; Park *et al.*, 2024a).

Percent bias (PBIAS) averaged +0.40% across years, demonstrating minimal systematic tendency toward overestimation or underestimation. The 2022 validation year exhibited comparatively lower accuracy ($R^2=0.68$, MAPE=11.3%), likely attributable to unprecedented heat wave conditions that exceeded historical temperature ranges (Kim *et al.*, 2023). Independent validation using a completely withheld dataset (N=89) achieved $R^2=0.77$, RMSE=2.24 kg, and PBIAS=+2.01%, confirming strong generalization capability and absence of overfitting. These validation results substantially exceed

performance benchmarks established in previous agricultural prediction studies and demonstrate operational readiness for deployment in practical beekeeping applications (Rural Development Administration, 2024; Park *et al.*, 2024b).

DISCUSSION

1. STDD flowering prediction model accuracy and significance

The STDD model achieved high predictive accuracy with an average error of 3.8 days (RMSE=3.8, MAE=3.1, $R^2=0.72$, PBIAS=-0.4), representing 30–40% improvement over conventional models that typically exhibit 5–7 day errors (Kim *et al.*, 2020b; Lee *et al.*, 2021c). The model's enhanced accuracy stems from region-specific heat requirement thresholds: 185°C day (northern), 220°C day (central), and 240°C day (southern regions). This geographical stratification reflects thermal accumulation variations across latitudinal gradients, addressing the limitation of uniform threshold application (Cesaraccio *et al.*, 2004).

The triangular method's mathematical formulation captures diurnal temperature variability more accurately than traditional rectangular methods, particularly during transitional seasons. International comparisons demonstrate competitive performance: our RMSE of 3.8 days compares favorably to US cherry blossom models (4.2

Table 12. Leave-One-Year-Out cross-validation performance metrics

Validation year	RMSE (kg)	MAE (kg)	R^2	MAPE (%)	PBIAS (%)	Sample size
2019	2.1	1.7	0.71	9.2	-1.8	150
2020	2.4	1.9	0.69	10.8	+3.2	150
2021	2.0	1.6	0.72	8.9	-1.5	150
2022	2.5	2.1	0.68	11.3	+2.8	150
2023	1.8	1.5	0.75	8.1	-1.2	150
2024	2.3	1.8	0.70	9.9	+1.9	150
2025	2.2	1.7	0.71	9.5	-1.6	150
Mean	2.19	1.76	0.71	9.67	+0.40	1,050

Independent Validation Set (N=89): RMSE=2.24 kg, MAE=1.82 kg, $R^2=0.77$, PBIAS=+2.01%
Annual validation results demonstrating model stability. Mean performance: RMSE 2.19 kg, MAE 1.76 kg, $R^2=0.71$, MAPE=9.67%. Performance ranges: RMSE=1.8–2.5 kg, $R^2=0.68$ –0.75, confirming generalization ability. PBIAS=+0.40% indicates minimal prediction bias. All years maintain $R^2>0.68$, demonstrating consistent predictive accuracy across temporal variations.

days, Cesaraccio *et al.*, 2004) and Japanese plum blossom systems (3.5 days, Omoto and Aono, 2010), suggesting methodological robustness and transferability to other temperate species. This 3.8-day precision provides practical utility for beekeeping operations, enabling strategic hive placement, migration timing, and harvest scheduling. This accuracy becomes critical given the documented flowering duration contraction from 30–40 days (early 2000s) to 16–25 days recently, which has compressed the temporal window for optimal production (NIFoS, 2022). Limitations include the temporal scope (2006–2017 data) potentially missing recent accelerated climate change impacts, 500 m × 500 m grid resolution insufficiently resolving microclimatic heterogeneity in mountainous terrain, and assumptions of stable genetic characteristics across regions. Future iterations should incorporate finer spatial resolution, extend calibration datasets to include recent extreme events, and potentially integrate population-level thermal response diversity.

2. Multidimensional AFI superiority and ecological interpretation

The Aggregated Flowering Index (AFI) integrates five meteorological parameters through weighted composites: temperature (0.35), precipitation (0.25), wind speed (0.15), solar radiation (0.15), and diurnal temperature range (0.10). This multidimensional approach achieved superior predictive performance ($r=0.742$ with honey production) compared to univariate indices: temperature alone ($r=0.521$) or precipitation alone ($r=0.438$) (Lee *et al.*, 2020a; Kim *et al.*, 2021b). The weighting structure reflects physiological processes governing nectar secretion and pollinator activity. Temperature's dominance (0.35) acknowledges its role in enzymatic activity governing nectar synthesis, with optimal ranges of 22–25°C. Precipitation (0.25) captures mechanical flower damage and humidity effects. Wind speed, solar radiation, and diurnal range collectively account for microenvironmental conditions affecting foraging behavior and nectar quality. AFI thresholds provide robust flowering quality categorization based on adequate sample sizes: >0.8 (excellent, 22.3 ± 6.2 kg/colony, $n=194$, 18.5%), $0.6-0.8$ (favorable, 17.8 ± 7.1 kg/colony, $n=549$, 52.3%), $0.4-0.6$ (moderate, 11.2 ± 5.8 kg/colony, $n=249$, 23.7%), and <0.4 (poor, 5.7 ± 3.4 kg/colony, $n=58$, 5.5%). The substantial sample

sizes across all categories, with the majority of observations (52.3%) falling within favorable conditions, demonstrate the practical utility and statistical reliability of these thresholds for beekeeping management decisions. AFI components exhibit nonlinear responses. Precipitation score (P_{score}) achieves maximum (1.0) under zero precipitation, declining to 0.6–0.8 for light rain (1–3 mm) and 0.1 for heavy rainfall (>5 mm), aligning with studies documenting rainfall's mechanical flower damage, nectar dilution, and foraging suppression (Lee *et al.*, 2020b). Diurnal temperature range (DT_{score}) peaks at moderate values ($\sim 12^\circ\text{C}$), reflecting requirements for circadian rhythm maintenance while avoiding thermal stress (Kim *et al.*, 2020a). AFI advances beyond traditional Growing Degree Days (GDD) by incorporating multiple environmental factors. While recent North American Spring Index or European Unified Phenological Models include multiple variables, they employ linear combinations failing to capture nonlinear thresholds (Schwartz *et al.*, 2006). AFI's piecewise-defined scoring functions with empirically calibrated weights provide more flexible, biologically realistic frameworks. AFI addresses critical research gaps. The robustness of the AFI classification system is further supported by the adequate distribution of observations across all condition categories in the five-year dataset (2019–2025, $N=1,050$). Even in extreme conditions, including optimal scenarios ($n=194$) and severely constrained situations ($n=58$), there were sufficient observations to enable reliable statistical estimates. The substantial standard deviations observed across all AFI categories (SD ranging from 3.4 to 7.1 kg/colony) reflect the inherent variability in honey production, which is influenced by meteorological conditions, colony strength, apiary management practices, and local forage availability. Despite this variability, clear production trends emerged across AFI thresholds, demonstrating the dominant role of meteorological conditions as captured by the AFI in determining apicultural productivity. Earlier single-variable or simple combination studies achieved modest explanatory power ($R^2=0.40-0.55$) (Kang and Lee, 2018). AFI's systematic integration and nonlinear transformations substantially elevate predictive capacity ($R^2=0.76$ training, $R^2=0.77$ validation), approaching theoretical maxima given biological variability.

3. Stage-specific differentiation strategies: biological significance

Temporal stratification into three developmental stages—bud formation (−21 to −14 days), pre-flowering (−13 to −1 days), and flowering (0 to +12 days)—represents a conceptual advancement recognizing that meteorological impacts vary across developmental phases. Stage-specific approaches yielded substantially improved performance ($R^2=0.81$) versus aggregated seasonal indices ($R^2=0.62$).

The bud formation period constitutes a critical window when flower primordia undergo rapid cell division. AFI during this phase (AFI_{bud}) correlates strongly ($r=0.68$) with subsequent nectar volume and sugar concentration, suggesting that favorable early conditions establish physiological capacity that cannot be fully compensated later. This aligns with research demonstrating that carbohydrate allocation patterns during floral development exert lasting influences on reproductive investment (Tixier *et al.*, 2013). The pre-flowering period shows diminished importance, reflected in lower regression coefficients for AFI_{pre} ($\beta = -0.058$, $p=0.173$). This counterintuitive negative association, though not significant, may reflect trade-offs where overly favorable conditions stimulate excessive vegetative growth competing with reproductive development, or indicate that moderate stress triggers adaptive nectar production responses. The flowering period emerges as most critical, with $CI_{flowering}$ (bee activity index) dominating production models ($\beta = 0.929$, $p < 0.001$). This paramount importance reflects direct causal linkages between meteorological conditions, pollinator activity, and honey accumulation. Favorable flowering weather enables sustained foraging, efficient nectar collection, and rapid processing. CI 's correlation with production ($r=0.872$) substantially exceeds individual meteorological parameters or comprehensive AFI, highlighting pollinator behavior as the proximate mechanism linking environment to production.

Stage-specific modeling enables identification of vulnerable windows when adverse conditions disproportionately influence outcomes, providing essential tools for climate impact assessment and adaptive planning.

4. Practical applications and policy recommendations

The integrated STDD-AFI framework offers substantial utility across multiple stakeholder groups, from individual beekeeping operations to national agricultural planning and climate adaptation strategy.

For commercial beekeeping, the primary application lies in optimizing migratory strategies through accurate flowering forecasts. The framework's predictive capacity, validated across 1,050 colony-year observations from five regions, provides statistically robust guidance for operational decisions. South Korea's industry relies heavily on migration, with ~70% of operations moving colonies among multiple sites. STDD's 3.8-day accuracy enables precise hive movement timing, ensuring colony arrival before flowering while avoiding premature deployment costs. Regional AFI forecasts provide quantitative route planning guidance, helping prioritize destinations with superior conditions while avoiding poor production areas. Regression-based production forecasting enables data-driven harvest expectations and marketing strategies. Early-season meteorological observations during bud formation and pre-flowering inform preliminary estimates months before harvest, facilitating buyer negotiations and financial planning. Progressive incorporation of flowering-period data allows iterative forecast refinement with increasing precision.

For research institutions and extension services, the framework provides foundations for accessible decision support tools. Web-based or mobile platforms integrating STDD-AFI models with real-time meteorological streams could deliver personalized recommendations based on geographic locations. Alert functions notifying flowering onset, quality ratings for upcoming periods, and comparative regional assessments would enhance operational efficiency. From policy perspectives, the framework addresses critical climate adaptation planning needs. Government agencies can utilize projections to inform targeted support programs, directing resources toward regions with elevated climate-related risks. Subsidized insurance programs could employ AFI-based triggers for eligibility and payouts, providing financial protection against meteorological production failures while incentivizing climate-adaptive practices.

Long-term monitoring programs integrating standardized phenological observations with systematic meteorological collection provide essential foundations for adaptive management. The National Institute of Agricultural Sciences' coordinated survey (77 fixed locations, 144 migratory operations with GPS since 2019) exemplifies necessary data infrastructure. Sustained commitment with periodic model recalibration ensures decision support relevance as conditions evolve. Realizing full potential requires complementary capacity building and technology transfer investments. Many small-scale traditional beekeepers lack internet connectivity or technical literacy for sophisticated tools. Extension programs must employ diverse strategies—printed materials, radio broadcasts, workshops, peer learning—ensuring equitable forecasting access. Demonstration projects showcasing model-guided successes can build trust and encourage broader data-driven adoption.

5. Research limitations and future directions

While representing substantial advancement in integrated meteorological-phenological-production modeling, several limitations warrant acknowledgment and suggest future priorities.

First, temporal scope (2006–2017) may inadequately capture recent acceleration in climate change impacts and extreme event frequency. The past decade witnessed unprecedented warming trends, increased late-spring frosts, and altered precipitation patterns potentially shifting statistical relationships underpinning STDD. Periodic recalibration incorporating recent observations, particularly extreme years, would enhance robustness. Ideally, extending calibration datasets to 20–25 years would adequately represent interannual climate variability including rare high-impact events.

Second, spatial resolution (500 m × 500 m) constrains applicability to individual apiary-scale decisions. South Korea's mountainous terrain generates pronounced microclimatic heterogeneity inadequately resolved at this scale. Downscaling approaches incorporating high-resolution elevation models and land cover could refine predictions, though validation requires expanded monitoring networks including distributed automated sensors.

Third, the framework focuses exclusively on meteorological drivers while neglecting non-meteorological

influences. Despite achieving strong predictive performance ($R^2=0.76$) with adequate sample sizes across all regions ($n=210$ per region), apiary management practices (queen quality, hive strength, disease, supplemental feeding, varroa mite infestation) substantially impact productivity independent of environment and likely contribute to the observed standard deviations in production outcomes ($SD=3.4-10.1$ kg). Landscape factors (alternative forage, pesticide exposure, agricultural proximity) may modulate meteorological responses. Integrating such variables requires interdisciplinary data collection encompassing management surveys, landscape characterization, and veterinary assessments.

Fourth, climate adaptation requires projecting future conditions under evolving regimes. Empirically calibrated models assume stationarity in physiological responses and phenological cue sensitivities, which may not hold as organisms adapt through plasticity or evolution. Mechanistic process-based models grounded in biophysical principles offer greater confidence for extrapolation beyond observed ranges. Hybrid approaches combining mechanistic core processes with empirical calibration, potentially employing machine learning (random forests, gradient boosting, neural networks), could capture complex nonlinear relationships while maintaining interpretability.

Fifth, the framework considers *R. pseudoacacia* in isolation, neglecting interactions with other spring-flowering species competing for pollinators or providing supplementary forage. In mixed forests or agricultural landscapes with diverse phenologies, production depends on synchronization with competitors, sequential forage availability, and landscape-scale resource abundance. Expanding frameworks to incorporate community-level phenological dynamics would enhance applicability.

Future research should focus on several key directions. First, incorporating climate scenario projections (SSP1-2.6, SSP2-4.5, and SSP5-8.5) will enable assessment of long-term viability, accounting for both gradual climatic trends and interannual variability, as well as the frequency of extreme events. Second, developing a mechanistic understanding of key physiological processes through controlled experiments is essential, particularly those examining thermal response curves, precipitation effects on nectar sugar concentration, and wind thresh-

olds that influence foraging cessation. Third, applying machine learning approaches offers potential for integrating diverse datasets and producing probabilistic forecasts with improved precision. Fourth, expanding the model scope to include additional honey flow periods, such as summer chestnut and autumn aster seasons, would allow for more comprehensive annual yield forecasting. Finally, future efforts should investigate how climate factors affect honey quality, including variations in floral composition, color, antioxidant levels, and antimicrobial properties, beyond mere production quantity.

CONCLUSION

This study successfully developed and validated an integrated framework coupling STDD flowering phenology prediction with AFI honey production forecasting for South Korean *R. pseudoacacia* systems. The STDD model achieved high accuracy predicting flowering dates with region-specific thresholds (northern 185°C day, central 220°C day, southern 240°C day), yielding 3.8-day average errors ($R^2=0.72$), representing substantial improvement over previous methodologies and demonstrating practical beekeeping utility.

The multidimensional AFI, integrating five meteorological components through empirically calibrated weights (temperature 0.35, precipitation 0.25, wind 0.15, solar radiation 0.15, diurnal range 0.10), exhibited strong correlations with production ($r=0.742$) and provided biologically interpretable quality thresholds: excellent (>0.8), favorable (0.6–0.8), moderate (0.4–0.6), and poor (<0.4) conditions corresponding to distinct production outcomes.

The stage-specific differentiation strategy, partitioning reproductive cycles into bud formation, pre-flowering, and flowering periods with tailored meteorological assessments, substantially enhanced predictive power. Regression models incorporating stage-differentiated AFI alongside flowering-period bee activity indices achieved high explanatory power ($R^2=0.81$, RMSE=2.19 kg) with robust cross-validation performance ($R^2=0.77$, PBIAS=2.01%). Notably, flowering-period bee activity ($\beta=0.929$, $p<0.001$) overwhelmingly dominated relative to antecedent floral quality indices, highlighting pollinator behavior as the proximate mechanism linking environ-

ment to production.

Practical applications extend across multiple domains: individual apiary optimization through precision phenological forecasts and production projections; regional agricultural planning; national climate adaptation strategy development. For policymakers, quantitative climate sensitivity assessments provide foundations for targeted support programs, risk management instruments, and conservation initiatives addressing pollinator-dependent ecosystem services. The analytical approach offers a template transferable to other phenology-dependent agricultural systems with broader implications for understanding climate change impacts on plant-pollinator synchronization.

Future priorities include extending temporal coverage for recent extremes, refining spatial resolution for micro-environmental heterogeneity, integrating non-meteorological factors, developing mechanistic process-based components, and expanding scope to encompass annual flowering phenologies and quality attributes beyond quantity. Addressing these through interdisciplinary collaboration will advance scientific understanding while enhancing climate-adaptive beekeeping capabilities.

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