Predicting Bloom Progression in Northern Highbush Blueberry With a Weather-driven Phenology Model to Support Pollination Management

Emma Rogers[1], Lisa Wasko DeVetter[1], Clark Kogan[2], David W. Crowder[3], Maxime Eeraerts[4], and Rufus Isaacs[5]

KEYWORDS. *Apis mellifera*, crop pollination, honeybee, phenology models, *Vaccinium corymbosum*

ABSTRACT. Decision-support tools that predict bloom progression based on site-specific weather data can help growers and beekeepers better coordinate pollination management and crop protection activities with crop phenology. A weather-driven bloom phenology model was developed to predict progression of anthesis in northern highbush blueberry (cv. Duke) fields in Washington State. Flower phenology data were collected from commercial fields from 2022 to 2025. At each site, hourly air temperature data were used to calculate growing degree days, and a model was constructed to predict open bloom progression. On average, the model predicted bloom stages within 2.4 days of observed dates at initial 10% bloom, 3.4 days at peak (~50%) bloom, and 3.7 days at remaining 10% bloom (mean absolute prediction error). Results demonstrate that a temperature-based modeling framework can estimate bloom progression and provide guidance to help blueberry growers and beekeepers better align the arrival and departure of managed pollinators with crop phenology.

Introduction

Northern highbush blueberry (*Vaccinium corymbosum*) depends on insect-mediated pollination (MacKenzie 1997; Retamales and Hancock 2018), with managed honeybees (*Apis mellifera*) being the primary pollinator in commercial systems (Eeraerts et al. 2023a). To ensure effective pollination, colonies are introduced at the onset of anthesis (open bloom), which promotes the bees focusing on the crop rather than other flowering plants in the landscape. In addition, growers are advised to introduce bee colonies when the crop reaches 5% to 25% anthesis so that flowers remain receptive to pollination and subsequent fertilization (Isaacs et al. 2016). Near the end of bloom, growers are also eager to have beekeepers remove their colonies once pollination is complete so they can proceed with crop protection activities, such as applying insecticides to manage arthropod pests.

Timing the arrival and departure of bee colonies is logistically challenging and requires coordination between growers and beekeepers, as well as consideration of field-to-field variation in bloom phenology. Advance warning of this growth stage can help growers alert beekeepers who may be bringing hives from long distances. Bloom progression is largely influenced by temperature and cumulative heat units, and most flowers become unsuitable for pollination within days of opening (Kirk and Isaacs 2012). Decision-support tools that predict bloom progression may help both parties align their activities with crop phenology, improving pollination outcomes and facilitating timely crop protection practices. The objective of this study was to develop a weather-driven bloom phenology model designed to predict bloom progression in Washington State with a focus on the anthesis stage.

Received for publication 13 Mar 2026. Accepted for publication 23 May 2026.

Published online 15 Jun 2026.

[1]Department of Horticulture, Washington State University, Mount Vernon, WA 98221, USA

[2]StatsCraft LLC, Spokane, WA, USA

[3]Department of Entomology, Washington State University, Pullman, WA 99164, USA

[4]Estación Biológica de Doñana, CSIC, Seville, Spain

[5]Department of Entomology, Michigan State University, East Lansing, MI 48824, USA

This work was funded by US Department of Agriculture National Institute of Food and Agriculture (NIFA) Specialty Crop Research Institute award #2020-51181-32155 and NIFA Hatch project 1014919. We thank Kayla Brouwer, Salena Helmriech, and Stefano Borghi for their assistance with data collection and modeling.

L.W.D.V. is the corresponding author. E-mail: lisa.devetter@wsu.edu.

https://doi.org/10.21273/HORTTECH05882-26

Materials and methods

PHENOLOGY DATA. Data were collected from mature commercial blueberry fields (cv. Duke) in Whatcom and Skagit counties in western Washington from 2022 to 2025 during pollination. This cultivar is one of the first to bloom and requires bee deliveries before other cultivars. Initially, 12 fields were sampled in 2022 as a sub-component of a larger sampling design (Eeraerts et al. 2023b). Phenology sampling continued in a subset of four and three of these same fields in 2023 and 2024, respectively. In 2025, data were collected from a single field that was part of a separate study. Data collection began at ~10% cumulative bloom, which was determined by visual estimates. Quantitative sampling then occurred one to two times per week and entailed counting the number of closed and open flowers as well as flowers at petal fall during later bloom stages on five representative, randomly selected branches per transect. Individual rows were treated as a transect with four 100-m transects fixed within each field. Transects were located in the field center with systematic spacing of at least 5 m between transects. Sampling concluded when visual estimates of cumulative bloom reached ~90%.

GROWING DEGREE DAY COMPUTATION. For each field, hourly average air temperature data from the nearest AgWeatherNet station were used to calculate growing degree days (GDDs) starting 1 Jan through the last day of phenology sampling for each year of the study. AgWeatherNet is Washington State University's agrometeorological network that collects spatiotemporal weather data from more than 300 stations across the state. The nearest station distance ranged from 0.2 to 15.9 km away from the field sites. Daily maximum and minimum temperatures were derived for all sampling dates and used to calculate GDDs using the single sine method (Zalom et al. 1983), implemented using the function dd_sng_sine of the R package degday (Lyons 2022). The base temperature was set to 7 °C with no upper threshold (Kogan et al. 2023).

STATISTICAL METHODS. A model was constructed using weather data to predict bloom progression. Cumulative percent bloom and cumulative percent petal fall were calculated from field observations. Cumulative bloom and petal fall were defined as the proportion of open flowers plus petal fall, or petal fall alone, respectively, expressed on a 0% to 100% scale. Cumulative bloom and petal fall were modeled with growing-degree–based binomial logistic regression models. GDDs were included as a third-order polynomial function for the former, and as a linear term for the latter. Open bloom was computed as the difference between cumulative bloom and petal fall.

Cluster cross validation, with clusters defined by field-years, was used to compare predictions and estimated actual timing (in calendar days) of initial 10% (during increasing % bloom), peak (~50%), and remaining 10% open bloom (during decreasing % bloom). Validation metrics included mean absolute prediction error, the average absolute difference between predicted and observed values, and root mean squared error (RMSE), the square root of the average squared difference between predicted and observed values. Actual timing for initial 10% and remaining 10% were determined with linear interpolation. For dates in which 10% was not observed in the field data for early or late bloom, the GDD values were estimated by nonlinear least squares fitting of a parametric double logistic curve. Actual timing of peak bloom was estimated as the GDD value corresponding to the maximum of that same fitted curve for each field-year. Model predicted timings in GDDs were converted to field-specific calendar days using a linear interpolation. All statistical analyses were conducted in R (R Core Team, 2025).

Results and discussion

Model accuracy. On average, the model predicted bloom stages within 2.4 d of observed dates at initial 10% open bloom, 3.4 d at peak open bloom, and 3.7 d at remaining 10% open bloom (mean absolute prediction error; RMSE = 2.75, 3.86, and 4.25 d, respectively). Across sampling years, initial 10% bloom occurred between 19 Apr and 3 May, peak bloom fell between 9 and 21 May, and remaining 10% bloom fell between 19 and 30 May. Variability across years was observed (Fig. 1), which may contribute to systematic prediction errors within a given year. The impact of model prediction uncertainty can be offset with closer visual inspection of bloom progression by growers in the days leading up to bloom. In addition, a subset of contracted bee colonies can be deployed for early blooming sections of a farm, with additional colonies delivered as bloom progresses.

Nearest AgWeathernet vs. in-field data. This study and the resulting models relied on weather data from nearby agrometeorological stations, which varied in distance from the field sites. These actively maintained stations provide reliable meteorological data across the season and state. Although in-field data loggers could improve model accuracy by capturing micro- and meso-climatic variation, logger failures have occurred in the past leading to missing data and the necessity for routine logger maintenance. In addition, in-field loggers exhibited higher temperature fluctuations and faster GDD accumulation compared with the agrometeorological stations (data not presented). Given these discrepancies and logistical challenges, the final models used air temperature data from university-maintained stations. This enhances the utility and accessibility of the model when deployed through the DAS online decision-support system for growers across Washington.

Conclusion

This study presents a blueberry phenology timing model that predicts percent cumulative bloom, petal fall, and open bloom across the growing season in Washington State based on historical and forecasted weather information. The model is available online (https://decisionaid.systems/) and provides up to 14-d forecasts of bloom progression, further increasing the tool's practical utility. This model fills an

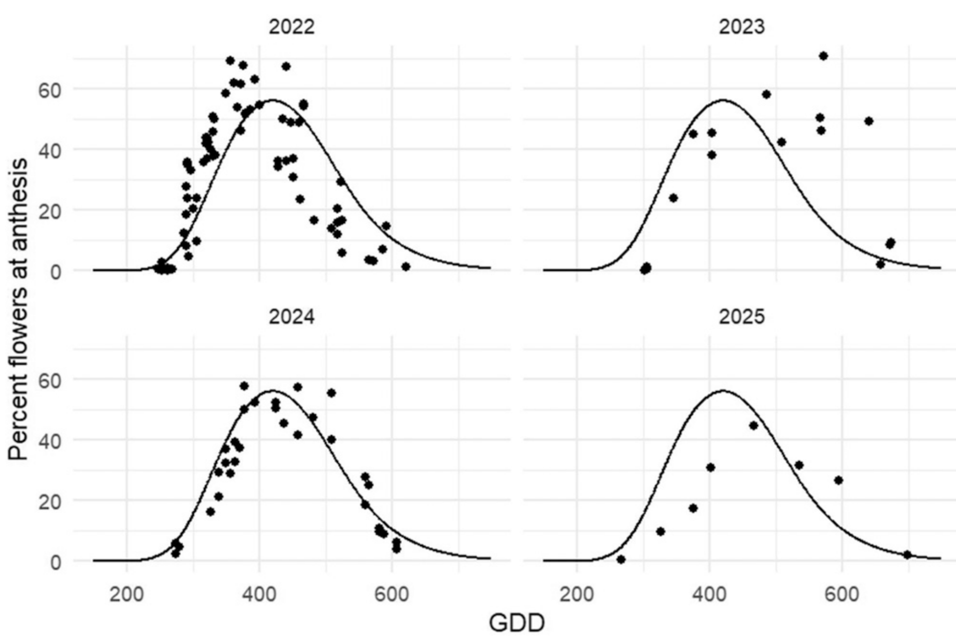

Fig. 1. Observed percent of flowers at anthesis (points) and corresponding modeled predictions (lines) plotted against accumulated growing degree days (GDDs) across blueberry growing seasons in Washington State from 2022 to 2025.

important gap, helping growers and beekeepers predict the timing of key phenological stages to support more effective decisions about when to move bee colonies into and out of fields. The developed modeling framework will be extended to other growth stages, states, and cultivars as supplemental data are collected.

References cited

Eeraerts M, DeVetter LW, Batáry P, Ternest JJ, Mallinger R, Arrington M, Benjamin FE, Blaauw BR, Campbell JW, Cavigliasso P, Daniels JC, Arjen de Groot GA, Ellis JD, Gibbs J, Goldstein L, Hoffman GD, Kleijn D, Melathopoulos A, Miller SZ, Montero-Castaño A, Naranjo SM, Nicholson CC, Perkins JA, Rao S, Raine NE, Reilly JR, Ricketts TH, Rogers E, Isaacs R. 2023a. Synthesis of highbush blueberry pollination research reveals region-specific differences in the contributions of honeybees and wild bees. J Appl Ecol. 60(12):2528–2539. https://doi.org/10.1111/1365-2664.14516.

Eeraerts M, Rogers E, Gillespie B, Best L, Smith OM, DeVetter LW. 2023b. Landscape-level honey bee hive density, instead of field-level hive density, enhances honey bee visitation in blueberry. Landsc Ecol. 38(2):583–595. https://doi.org/10.1007/s10980-022-01562-1.

Isaacs R, Gibbs J, May E, Hanson E, Hancock J. 2016. Invest in pollination for success with highbush blueberries. Michigan State University Extension. https://www.canr.msu.edu/news/invest_in_pollination_for_success_with_highbush_blueberries/.

Kirk AK, Isaacs R. 2012. Predicting flower phenology and viability of highbush blueberry. HortScience. 47(9):1291–1296. https://doi.org/10.21273/HORTSCI.47.9.1291.

Kogan C, DeVetter LW, Hoheisel G-A. 2023. Modeling northern highbush blueberry cold hardiness for the Pacific Northwest. HortScience. 58(11):1314–1320. https://doi.org/10.21273/HORTSCI17320-23.

Lyons A. 2022. *degday: Compute Degree Days*. R package version 0.4.0. https://CRAN.R-project.org/package=degday.

MacKenzie KE. 1997. Pollination requirements of three highbush blueberry (*Vaccinium corymbosum* L.) cultivars. J Am Soc Hortic Sci. 122(6):891–896. https://doi.org/10.21273/JASHS.122.6.891.

R Core Team 2025. A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/.

Retamales JB, Hancock JF. 2018. Blueberries (Vol. 27). CABI, Wallingford, UK.

Zalom FG, Goodell PB, Wilson LT, Barnett WW, Bentley WJ. 1983. Degree-days: The calculation and use of heat units in pest management. UC DANR Leaflet 21373.