# Phenological Mapping of Invasive Insects

Subjects: Entomology

Contributor: Brittany S. Barker, Leonard Coop

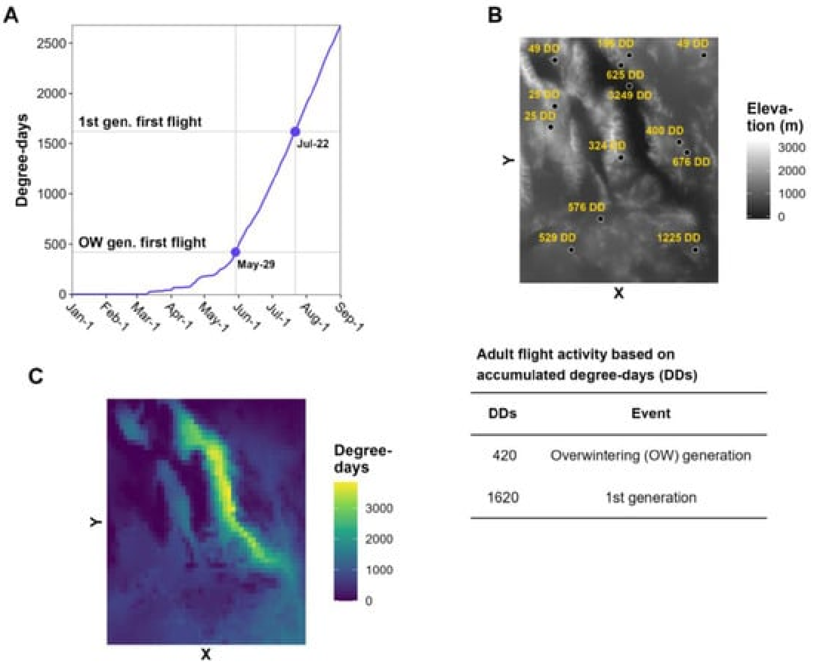
Phenological maps can depict the development and seasonal activities (phenology) of invasive insects at area-wide scales, such as counties, states, or entire nations. When regularly updated using real-time and forecast climate data, these maps may improve the timeliness of early detection and control tactics that target specific life stages. Rapid responses to invasive insects may increase the likelihood that populations are eradicated or controlled before they can spread or increase in size. Phenological maps may also be used to assess pest establishment risk, investigate pest–host interactions, and measure climate-driven changes in pest phenology.

Keywords: degree-day model ; forecast ; pest ; climate

## 1. Introduction

The protection of agricultural and natural resources depends on the precise timing of surveillance, monitoring, and management of invasive insect populations [1][2][3]. Scheduling pest control tactics according to calendar dates and expectations of the "normal" time in which seasonal activities (phenology) of pests have occurred in previous years is often ineffective because rates of insect development often vary annually due to variations in weather [4][5][6][7]. Conversely, modeling the phenology of an insect species using information on their life cycle requirements and climate data for the current year may increase the precision of estimates of dates when important seasonal events occur, such as the first adult emergence and egg hatch [4][7][8]. This information may improve the effectiveness and cost efficiency of early detection and management programs because these programs often target life stages that are more observable (e.g., larvae vs. adults of wood-boring beetles) or more vulnerable to control tactics, such as pesticide treatments [3][9][10][11][12][13].

Degree-day models are widely used in decision support systems that predict the phenology of agricultural insect pests because of their simplicity and ability to accommodate multiple species with varying life histories [8][9][10][14][15][16][17][18][19][20]. The development and phenology of an organism in a degree-day model is driven by heat accumulation above a lower temperature threshold (and oftentimes below an upper temperature threshold) over a daily or weekly time step (**Figure 1**) [4][5][7][21][22][23][24]. The lower developmental temperature is often referred to as the base temperature. Typical examples of degree-day models that have been used for many years include those that predict first egg hatch of the codling moth [*Cydia pomonella* (L.)] in tree fruits [13][25][26][27][28], first emergence of the western cherry fruit fly (*Rhagoletis indifferens* Curran) [29], and adult flight, egg hatch, and larval development of the spongy (formerly "gypsy") moth [*Lymantria dispar* (L.)] [30][31][32][33][34].




Adult flight activity based on accumulated degree-days (DDs)

| DDs | Event |
|---|---|
| 420 | Overwintering (OW) generation |
| 1620 | 1st generation |

**Figure 1.** Degree-day (DD) accumulations for 1 January to 1 September predicted by site-based and spatial phenology models. (**A**) Plot of date vs. DD accumulations depicts dates of adult flight activity at a single site. (**B**) An elevation map with predictions for multiple sites is shown with a key of DD requirements for adult flight activity. (**C**) Phenological map of the same area as (**B**) shows continuous predictions. The X and Y axis in (**B**,**C**) indicate longitude and latitude, respectively.

Most degree-day models for invasive insect species use climate data for a specific site, such as a weather station. Site-based model predictions, such as degree-day accumulations and dates of phenological events (e.g., first adult flight), are typically displayed in tabular and/or graphical formats (**Figure 1**A). This information is useful for decision support for pest surveillance or management in small areas, such as a forest parcel, fruit orchard, or vineyard [3][9][10][13][35]. However, site-based models are less applicable for decision support at area-wide scales, such as large counties or states, because phenology may vary spatially due to geographic factors (e.g., latitude, elevation, and continental effects), anthropogenic disturbances, and biological factors, such as spatial variations in population development and host plant availability.

Model predictions for multiple sites (e.g., in the form of number values, color-coded pins, or other expressions) can be overlayed on a base map to visualize geographic variation in insect phenology [8]. For example, degree accumulations for each site can be shown as text labels on an elevation map, which can be referenced to a key of degree-day requirements for important phenological events (**Figure 1**B). Nonetheless, maps with discontinuous model predictions may be of limited use for decision-makers in areas that lack model predictions, particularly for topographically and climatically complex areas where phenology can vary over short distances.

The continuous mapping of phenology (hereafter phenological mapping) depicts model predictions over an entire geographic area (**Figure 1**C). Phenological mapping of pests became more common beginning in the 1990s with advancements in computers and a growing number of digitized geographic datasets and geographic information systems (GIS) software options [32,39–42]. Digital spatial climate datasets developed over the past ca. 30 years have increased the robustness and timeliness of phenological maps.

## 2. Data Requirements for Degree-Day Models

Detailed reviews on data requirements and methods for degree-day modeling of insects already exist [17][23][24][36][37] and are, therefore, only summarized here. Degree-day models are often developed using experimentally collected data on temperature–development relationships to estimate parameters, such as developmental rates, developmental temperature thresholds, duration of life stages, and stage-specific events [17][38][39][40]. These data are combined with daily temperature data, typically minimum and maximum temperatures ($T_{min}$ and $T_{max}$, respectively), to estimate degree-days using various calculation methods [4][7][14][24][38][41]. A start date or biological event, such as the first flight, is needed to synchronize the insect phenology model to field populations [24][42][43].

## 3. Types of Phenological (Degree-Day) Maps

### 3.1. Generic Degree-Day Map

Generic degree-day maps show the current degree-day accumulations based on one or more standard lower temperature thresholds. For example, degree-day maps at Michigan State University's Enviroweather [https://www.enviroweather.msu.edu (accessed on 19 December 2023)] use a standard lower temperature threshold of 50 °F (10 °C), and those at USPest.org [https://uspest.org/wea/index.html#DDMAPS/ (accessed on 19 December 2023)] use thresholds of 32, 41, or 50 °F (0, 5, or 10 °C, respectively; **Figure 2**). Degree-day maps at the University of Wisconsin's AgWeather Vegetable Disease & Insect Forecasting Network [https://agweather.cals.wisc.edu/vdifn?p=insect (accessed on 19 December 2023)] use several different species-specific thresholds.

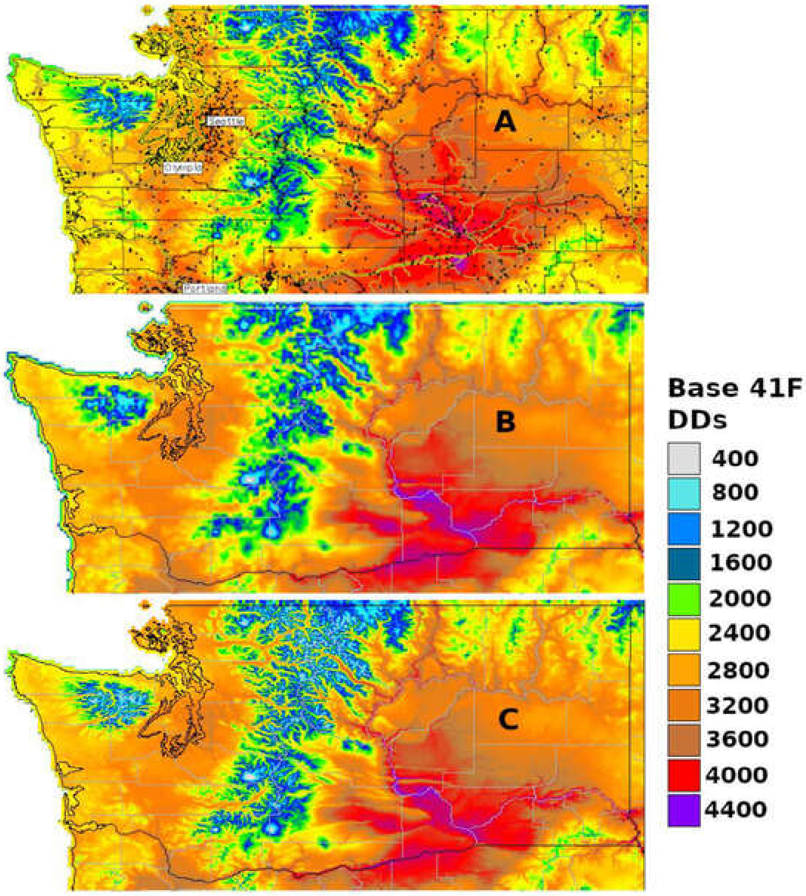



**Figure 2.** Example cumulative degree-day (DD) mapping products for Washington state generated online at USPest.org [https://uspest.org (accessed on 19 December 2023)]. All maps depict DD accumulation [base 41 °F (5 °C)] between 1 January and 31 August of 2020 (calculated using the single triangle method). (**A**) Map generated using an older version of the program [https://uspest.org/cgi-bin/usmapmaker.pl (accessed on 19 December 2023)] Awith a spatial resolution of 800 m. Black dots indicate the locations of weather stations used in the correction of monthly PRISM-based cumulative DDs. (**B**) Map produced by the newer program [https://uspest.org/dd/mapper (accessed on 19 December 2023)] that uses daily PRISM data with a coarser (4 km) spatial resolution (no weather station correction required). (**C**) Downscaled output produced using the newer program (800 m resolution).

Generic degree-day maps provide a good, general reference to show how the season is progressing, especially when compared to averages, such as 30-year normal degree-day maps. However, predictions of current degree-day accumulations are not matched up with insect life stages, so they must be used with experience and care for guiding surveying and management activities.

Enviroweather's degree-day models use 1 March as the start date and includes only Michigan and Wisconsin maps, whereas models at USPest.org at https://uspest.org/ (accessed on 20 December 2023) uses 1 January as the start date and covers all of the contiguous United States (CONUS) with separate mapping of major subregions (e.g., Midwest, Northwest, Southeast) and of states in the Pacific Northwest. Both websites are updated daily to produce maps based on climate data for the current year and historical averages (30-year normals). An additional map depicts the difference between historical and current year degree-day accumulations.

The degree-day mapping program at USPest.org [https://uspest.org/cgi-bin/usmapmaker.pl (accessed on 19 December 2023)] first appeared online in 1998 as a decision support tool for pest management in Oregon. The mapping region was expanded to include the entire Pacific Northwest region by 2002, and then to include CONUS at a higher spatial resolution (800 m) by 2005 [44][45]. Degree-days based on 30-year normals (centered on 1995) are calculated using gridded monthly temperature data from the PRISM database, while daily real-time degree-days are calculated using data from thousands of weather stations in the USPest.org collection of public networks. For the map creation, the degree-day mapping program uses a ‘climatologically aided interpolation’ method (sometimes more generally referred to as ‘delta correction’) that uses a gridded climate dataset, such as PRISM, to improve the interpolation of a site-based dataset, such as recent station observations (**Figure 2**A) [46][47].

Constructed in 2017, a second custom online phenology mapping program at USPest.org [https://uspest.org/dd/mapper (accessed on 19 December 2023)] was developed to offer an alternative and simpler workflow that uses real-time daily PRISM temperature grids and does not require data from multiple weather stations for correction (**Figure 2**B). However, the input data has a lower resolution (4 km), which, although adequate for most state-level maps, would be insufficient for small states or single growing regions that are topographically complex, such as Hood River County, Oregon. To address this issue, this version of the degree-day mapping program includes an option to downscale resulting degree-day maps to 800 m (**Figure 2**C) using a custom distance–elevation weighted regression algorithm.

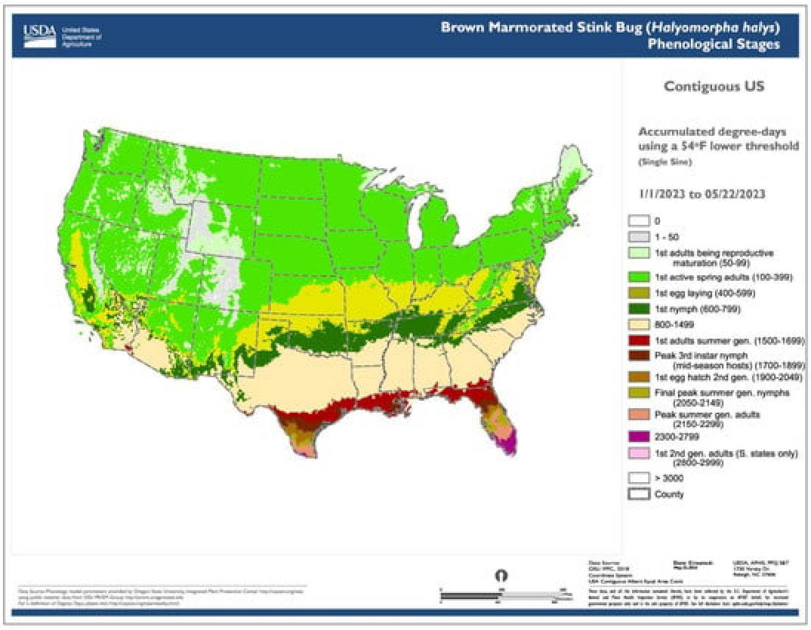



**Figure 3.** Degree-day lookup table map for the brown marmorated stink bug [*Halyomorpha halys* (Stål)] produced as part of the Spatial Analytic Framework for Advanced Risk Information Systems (SAFARIS) Field Operations Weekly map series [48]. The map uses a degree-day lookup table to associate cumulative degree-days with predicted life stages present across the contiguous United States on 22 May 2023. Thus, it provides a “snapshot in time” of phenology model predictions for a specific date. Reproduced with permission from SAFARIS, Brown Marmorated Stink Bug (*Halymorpha halys*) Phenological Stages. Published by SAFARIS, U.S. Department of Agriculture (USDA), and North Carolina State University, 2023. Available online: https://safaris.cipm.info (accessed on 19 December 2023).

### 3.2. Degree-Day Lookup Table Map

Degree-day lookup table maps show the current life stages or phenological events of an organism that correspond to specified values or ranges of accumulated degree-days for a specified date (Figure 3). Thus, degree-day accumulations, which are depicted in generic degree-day maps, are matched to specific points or events during the life cycle. For insects, life cycle points (and events) could typically include the egg stage present, egg hatch, larval stage present, pupal stage present, adult emergence and presence, and egg laying. The simplicity of the approach and its applicability to multiple organisms has sustained its use for several years.

Specific features that make the degree-day lookup table approach so common include:

- A relatively straightforward workflow. The workflow of generating a degree-day lookup table map involves using gridded daily $T_{min}$ and $T_{max}$ data to calculate degree-day accumulations between a start date (usually 1 January, although some models use other start dates, such as 1 March) and a specified end date. Degree-day lookup tables are then used to associate degree-day accumulations with life stages, and output maps depict the results with color tables and legends.

- The use of common base thresholds for multiple species. As degree-day lookup table maps are relatively simple and generic, there is the potential to use the same lower temperature threshold base maps for multiple species. This contrasts with more complex models that would require a separate base map for each case because of the application of different parameter values, including lower and upper thresholds, calculation methods, start dates, or diapause. The use of upper thresholds is relatively rare, at least for degree-day lookup table maps. For example, the SAFARIS FO Weekly maps produced by models for the old world bollworm [*Helicoverpa armigera* (Hübner)] and brown marmorated stink bug [*Halyomorpha halys* (Stål)] are constructed using the same 54 °F base maps, with no upper threshold.

- An ability to provide a “snapshot in time” for a single date. This allows, for example, regular updates that provide a gradually changing view of the current or near-future status of insect phenology. For example, degree-day lookup table maps produced by the Degree-Day, establishment Risk, and Phenological event maps (DDRP) platform [16] every 2−3 days depict the life stage and generation of insects on the map issue date. The USA National Phenology Network’s Pheno Forecast maps take advantage of 7-day National Digital Forecast Database (NDFD) forecasts to provide a 1-week “look ahead” prediction for CONUS [49]. SAFARIS PestCAST maps include a 1-month forecast using a 7-day NDFD forecast followed by three weeks of recent 20-year average PRISM data [15].

- Relatively simple design requirements. Degree-day lookup table maps can be designed as very simple visualization tools, such as by designing legend items to display only the stage or activity of interest (e.g., adult flight or egg hatch). Other stages and activities can then be represented as merged entries. The practice of focusing end users on a single target event represents a clear trade-off in reducing complexity (of multiple life stages) for users who may need clear directions in implementing surveillance or management actions.

### 3.3. Phenological Event Map

In contrast to a degree-day lookup table map, a phenological event map depicts the dates on which accumulating degree-days reach a value (target degree-day total) that corresponds with a selected phenological event [16][32][50][51]. Phenological event maps may offer the following advantages over degree-day lookup table maps to support monitoring and surveillance programs for invasive insects:

- Standardization. Mapping dates of phenological events allows for the standardization of legends and color tables across multiple species and events. For example, the colors assigned to each range of dates in the legend (e.g., 1–8 January = dark blue, 9–16 January = medium blue, etc.) can be applied to several events within a species, as well the same or different events in other species. As an example, **Figure 4** shows a phenological event map produced by DDRP that depicts the average date of egg laying by the overwintering generation of the light brown apple moth [*Epiphyas postvittana* (Walker)] for 2023.

- Operationally ready. Phenological event maps could be considered a more operational (tactical) product than degree-day lookup tables because they predict dates of events for a particular life stage, potentially up to weeks or months into the future.

- Simpler comparisons and expression of error rates. Phenological event maps allow for more direct comparisons of year-to-year variations of events than generic degree-day and degree-day lookup table maps. It is a relatively simple recordkeeping and reporting exercise to express differences in dates in the form of days difference [12][27][28]. This approach can also be used to express errors between predicted and observed events as discussed below (“8. Model validation”).

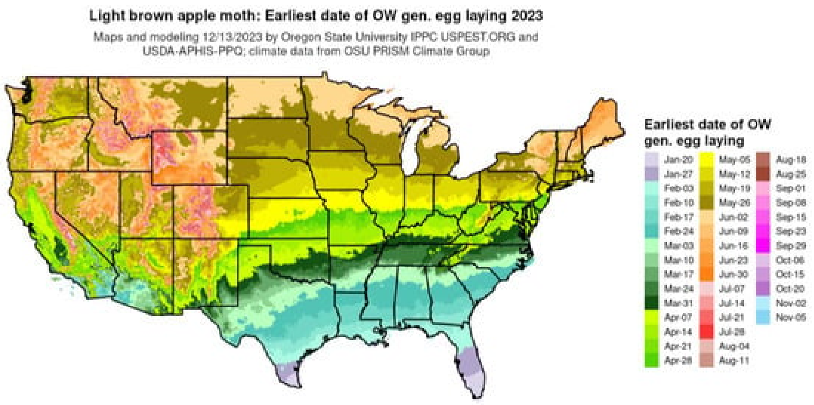


**Figure 4.** Phenological event map depicting the earliest date of egg laying by the overwintered (OW) generation of the light brown apple moth (*Euphyas postvittana*) for 2023 produced by DDRP (map issue date: 13 December 2023).

## 4. Applications of Phenological Maps

Phenological maps produced using real-time and forecast climate data have the potential to support the early detection of invasive pests. For example, regularly updated phenological maps on the SAFARIS platform provide decision support for the Cooperative Agricultural Pest Survey (CAPS) program [15][16], which conducts national and statewide surveys for exotic plant pests in the United States deemed to be of regulatory significance to the United States Department of Agriculture (USDA) Animal and Plant Health Inspection Service's (APHIS) Plant Protection and Quarantine (PPQ) program [52].

Phenological maps can support pest managers in timing treatments or other control tactics that target certain life stages. For example, phenological maps of egg hatch and larval development for the spongy moth were developed to support the timing of insecticidal sprays conducted for "stop the spread" programs in the eastern United States [30][31][32].

Maps that depict a pest's potential number of generations per year (i.e., voltinism) may help identify areas at risk of establishment because persistence in a new area requires a life cycle completion [15][53][54][55]. Additionally, maps of voltinism provide insight into expected levels of pest growth and subsequent damages to host plants for a given year [53][56][57].

Phenological maps may be used to assess the potential impacts of climate change on invasive insect phenology. For example, some studies have modeled the phenology of invasive insects under future climate change scenarios to estimate the impacts of global warming and altered precipitation patterns on important phenological events, potential voltinism, and population growth [58][59][60][61][62][63]. Mapping the extent to which critical time periods of insect life cycles coincide with phenological windows of host plant suitability may provide insight into pest establishment risk and outbreaks dynamics [64][65][66][67][68].

## 5. Gridded Climate Data

Maps used for within-season decision support of invasive insects depend on having access to real-time daily $T_{min}$ and $T_{max}$ data with spatial resolutions that are appropriate for the needs of decision-makers. For example, phenological maps at a 4 km resolution are generally sufficient to support pest surveillance programs for the entire CONUS [15], but are probably not appropriate for smaller scales, such as a county or city. Real-time PRISM data with a spatial resolution of 4 km are freely available, and higher resolution (800 m) data can be purchased from the PRISM group. Real-time DDRP forecasts at USPest.org are produced using PRISM data (4 km resolution) as climatic inputs, whereas monthly updated North America Multi-Model Ensemble (NMME) 7-month forecasts or recent 10-year average PRISM data (calculated on a bimonthly basis) are used to predict pest phenology up to the end of the year [16].

Phenological mapping for within-season decision support in areas outside of the United States is typically hindered by a lack of real-time gridded daily $T_{min}$ and $T_{max}$ data. However, historical datasets may be used for model development and validation, such as those for Europe [69], continental North America and Hawaii [70][71], Brazil [72][73], China [74][75], India [76], and Bangladesh, Nepal, and Pakistan [77].

Some phenological mapping studies overcame an absence of readily available gridded daily climate data by interpolating weather station data over a landscape of interest using custom software [31][50][78][79][80][81][82]. For example, the GEO-BUG platform offered four automated interpolation methods to map the date at which a pest insect species reached a specified life stage in the United Kingdom [78][80]. Interpolation methods commonly applied to $T_{min}$ and $T_{max}$ estimates include those based on distance analyses (e.g., inverse distance weighted and spline interpolation) or geostatistics (e.g., kriging and multiple regression) [33][47][80][81][82][83].

## 6. Potential Sources of Error and Uncertainty

Common sources of error in insect phenology models include natural population variability, microclimatic factors, anthropogenic disturbances (e.g., land use patterns), and biotic factors (e.g., migration, host quality, competition, predation, and disease) [17][23][36][40][50][79][80].

Phenology models should somehow, but seldom do, include estimates of monitoring or sampling errors [84]. The best that can often be accomplished is to rely on observations collected by researchers or that have been verified by multiple people, such as “Research Grade” observations in the iNaturalist database [https://www.inaturalist.org (accessed on 19 December 2023)]. However, there is no guarantee that sampling errors can be minimized even when using published or verified observations [85].

It should be noted, however, that model and sampling errors are often lower than errors resulting from intrinsic population variability. Many species populations, for reasons including selection pressures due to climate variability in time and space, are spread widely phenologically [23][86]. Sometimes, this is referred to as seasonal plasticity [87].

## 7. Increasing Model Realism While Maintaining Simplicity

A common question in phenology modeling discussions is whether to use a simple model that is adaptable to multiple species versus a more complex, single-species model that can potentially deliver greater realism and accuracy [17][37][38][40][43]. Using simple linear degree-day accumulations to display either developmental stages (via lookup table) or dates of phenological events are often adequate in their predictive accuracy, while still simple enough to be readily adapted for dozens, or even hundreds, of species. For example, validation analyses of certain models used by the DDRP, Pheno Forecast, and SAFARIS platforms have revealed evidence of overall good predictive performances [15][16][49][88].

A population-based approach to phenological mapping may improve predictive accuracy because it helps account for developmental variation that naturally occurs within insect populations [89][90][91][92][93][94]. DDRP is a population modeling platform [16] that is most similar to the still relevant and still in use “grandfather” of phenology modeling platforms, Predictive Extension Timing Estimator (PETE) [8][27]. Both platforms use a cohort approach to population modeling that involves tracking the development of population cohorts through all life stages over the year using a daily time step. Cohorts may start development at different times, which produces a distribution of times in which they transition into a new life stage (e.g., egg to larva) or undergo a particular phenological event [90][94].

For many, if not most, insects in temperate climates, the use of single-factor degree-day models (i.e., temperature) have proven adequate as evidenced by their successful implementation for many agricultural pest species [9][10][15][20]. However, multifactor models that include additional driving variables, such as chilling, day length, and water availability, may be appropriate for certain species [36][51][95][96][97][98][99][100][101][102][103].

As an example, the brown marmorated stink bug, an important pest that has recently invaded and spread across the United States, has a reproductive diapause that terminates in mid-spring in response to photoperiod [104]. Modeling of this pest would likely be improved by using a two-phases approach in which photoperiod-cued diapause termination is followed by a degree-day response phase for spring and summer development [100][101].

Models that account for geographic variation in life history traits may be necessary to accurately predict phenology of insects in new environments [23][40][99][105]. For example, Grevstad et al. [99] used different values for the critical day length parameter in spatialized phenology models for the Japanese knotweed psyllid owing to genetically based differences in this species’ critical photoperiod in the native range. However, defining optimal parameter values would create the need for laboratory studies of insects sampled from across the species’ distribution, which may be infeasible. Even if these data were available for the entire known distribution, they may not be useful for newly introduced species that have unknown geographic origins [51]. Therefore, it is most prudent, with this lack of full understanding of the life cycle, to model what is understood and simply state the model’s shortcomings so that they can be considered by managers.

## 8. Model Validation

Errors in predictions of phenology models should be estimated when validation data are available [20][43][82]. Model overprediction, in which events or life stages are predicted later than observed dates, is typically more problematic than underprediction because decision-makers may miss the best opportunity to detect or manage populations. Communicating potential model errors to end users of phenological maps may allow them to adjust the timing of their surveillance and management activities accordingly [43].

Phenology model validation requires a set of observations not used in model development. Observations could be resampled using jackknifing or cross-validation methods, split into separate sets (e.g., 75% for development, 25% for validation), or originate from different years or areas [31][79][82][106][107]. Potential sources of data for model validation include peer-reviewed literature, reports, graduate theses, unpublished monitoring studies, and online databases such as iNaturalist, Nature’s Notebook [https://www.usanpn.org/natures_notebook (accessed on 19 December 2023)], and the

National Agricultural Pest Information System [https://cmr.earthdata.nasa.gov/search/concepts/C1214608223-SCIOPS (accessed on 19 December 2023)] [15][16][49][88].

Validating a spatial phenology involves extracting gridded model predictions for each georeferenced observation using GIS software. Ideally, the geographic precision of a phenological observation should be equal to or greater than the spatial resolution of climatic datasets used for modeling. For CONUS, this would correspond to spatial resolutions of 800 m to 4 km depending on the climatic dataset.

The statistics for phenological model validation, keeping in line with the principle of parsimony, should be done using readily understood terms. Summary statistics may include the mean difference between predicted and observed dates (day of year, DOY), along with variability estimates, such as 95% confidence intervals, to provide an estimate of the overall error including the bias [43][79][82]. The bias may be estimated as the average amount by which predicted DOYs are greater than observed DOYs, whereas the mean absolute error (i.e., the average absolute difference) can estimate the expected number of days a given prediction might be in error. Model performance may also be evaluated using statistical tests, such as confusion matrices or equivalence tests [49][71][77].

## 9. Conclusions

Phenological maps can provide insight into the development and seasonal activities of invasive insects at area-wide scales, such as counties, states, or entire nations. Several web-based platforms offer generic degree-day maps, degree-day lookup table maps, and phenological event maps to support within-season decision-making for the detection and control of invasive insects for CONUS. With the development of real-time gridded climate datasets for more regions of the world, phenological maps could become more commonly used for planning pest surveillance and management activities. Phenological maps may also be used to assess establishment risk and to investigate pest–host interactions and climate-driven changes in pest phenology.

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