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# Importance of vegetation index in codling moth *Cydia pomonella* distribution modeling

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**Abstract**

Codling moth, *Cydia pomonella* L. (Lepidoptera: Tortricidae) is the key insect pest of apple orchards in Iran. This study was conducted in the main apple-growing regions of East Azarbaijan Province to generate potential habitat suitability maps of *C. pomonella* using MaxEnt modeling and to determine the importance of vegetation index in improving the accuracy of these models. Field surveys for collecting the occurrence data of codling moth were conducted during three growing seasons, 2017 - 2019. The activity of codling moth adult males was monitored using delta-shaped traps baited with female sex pheromone. Fifteen environmental variables were considered as potential predictors for estimating codling moth distribution. These variables were categorized into topographic, climatic, and remote sensing variables. A MaxEnt modeling algorithm was used to predict the distribution of codling moth. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC). By using the topographic, climatic, and topographic+climatic variables, the AUC values were 0.840, 0.951, and 0.938, respectively. The model including normalized difference vegetation index (NDVI) had the highest AUC value (0.99), which strongly supports model predictive power and indicates the importance of vegetation index in codling moth distribution modeling. NDVI was the most contributed variable in the model followed by precipitation of September, slope, minimum temperature of May, and mean temperature of April. The distribution map obtained in MaxEnt provides an important tool for identifying potential risk zones of codling moth. This map can assist managers in forecasting and planning control measures and therefore, effective management of current infestations of codling moth.

**Keywords**: Species distribution, niche modeling, risk map, pest management, forecasting

# اهمیت شاخص پوشش گیاهی در مدل‌سازی پراکنش کرم سیب *Cydia pomonella*

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**چکیده**

کرم سیب آفت کلیدی باغ‌های سیب در ایران می‌باشد. این مطالعه در مناطق اصلی سیب‌کاری استان آذربایجان شرقی، با هدف تهیه نقشه زیستگاه‌های بالقوه این آفت با استفاده از مدل‌سازی مکس‌انت و تعیین نقش شاخص پوشش گیاهی در بهبود دقت این مدل‌ها انجام شد. داده‌های حضور آفت طی سه فصل رشدی، ۹۸-۹۶ از مناطق مورد مطالعه جمع‌آوری شدند. از تله های فرمونی برای پایش فعالیت حشرات کامل نر کرم سیب استفاده شد. اثر ۱۵ متغیر محیطی شامل متغیرهای اقلیمی، توپوگرافیک و سنجش از دور با استفاده از الگوریتم مکس‌انت روی پراکنش کرم سیب بررسی شد. عملکرد مدل‌ها و بررسی صحت و دقت آنها با استفاده از شاخص سطح زیر منحنی مشخصه عملکرد گیرنده (ROC) ارزیابی شد. در مدل‌های اجرا شده با استفاده از متغیرهای اقلیمی و توپوگرافیک مقدار AUC به ترتیب ۰/۸۴۰ و ۰/۹۵۱ بود، با تلفیق این دو گروه متغیر مقدار AUC مدل به ۰/۹۳۸ رسید. مدلی که دربرگیرنده هر سه گروه متغیرهای اقلیمی، توپوگرافیک و شاخص پوشش گیاهی تفاضلی نرمال شده (NDVI) بود بیشترین مقدار AUC را داشت ( که نشان دهنده نقش مهم این شاخص در پیش‌بینی پراکنش بالقوه کرم سیب است. NDVI، بارندگی ماه سپتامبر، شیب، حداقل دمای می و میانگین دمای آوریل به ترتیب بیشترین سهم را در مدل نهایی و بیشترین ارتباط را با پراکنش کرم سیب داشتند. نقشه پراکنش به دست آمده در این مطالعه ابزار مفیدی برای تشخیص مناطق خطر بالقوه کرم سیب می‌باشد که می‌تواند در پیش‌آگاهی و برنامه‌های مدیریت این آفت مهم مورد استفاده قرار گیرد.

**کلمات کلیدی:** پراکنش گونه، مدل‌سازی نیچ، نقشه خطر، مدیریت آفت، پیش آگاهی

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**Introduction**

Codling moth, *Cydia pomonella* L. (Lepidoptera: Tortricidae) is the key insect pest of apple orchards in Iran. It has the potential to cause 100% infestation in untreated apple orchards (Beers *et al.* 2003). Implementation of effective codling moth management programs requires sufficient information about its biology and ecology, geographic distribution, and influencing factors (Dminić *et al.* 2010). Before any attempt is made in the management of a pest, understanding the effect of each factor on the pest population distribution should be known.

In recent years, methods have been developed to estimate distributional areas based on the correlations of known occurrences with environmental variables (Peterson & Soberón 2012). Also, improved geographical information systems (GIS) and increased availability of digital environmental layers permit the development of new modeling techniques that create multivariate species niche models encompassing large geographic areas (Rotenberry *et al.* 2006).

Ecological niche models (ENMs) use occurrence data of a species in relation to environmental variables to make a correlative model of the environmental conditions that meet a species' ecological requirements and predict the relative suitability of habitat (Warren & Seifert 2011). So ecological niche modeling (EN) has become an important tool in biological, ecological, and entomological studies (Villordon *et al.* 2006). Generally, there are two types of ecological niche models: mechanistic models e.g. CLIMEX and correlative models e.g. MaxEnt, GARP and ENFA (Jiang *et al.* 2018).

The mechanistic ENMs are built using physiological information obtained from laboratory or field studies, whereas the correlative ENMs integrate species occurrence data (presence, presence-absence or abundance) with spatial environmental variables of the study area (Kumar *et al.* 2015). Both types of models have advantages and disadvantages. Studies have compared the performance of several EN modeling algorithms to predict the distribution of different species and found that MaxEnt was the best-performing model using presence-only data (Richard *et al.* 2018).

MaxEnt has great potential for use in entomological studies and can be used for several purposes such as determining the potential geographic distribution of invasive species (West *et al.* 2016), predicting the distribution of endemic insects in response to climate change (Urbani *et al.* 2017) and managing insect vectors of pathogens (Sallam *et al.* 2016). This model integrates presence-only data of a species with a set of environmental variables and generates the probability of species presence or predicts local abundance. MaxEnt identifies areas with conditions that are the most similar to the current known occurrences of the species and ranks them from 0 (unsuitable) to 1 (most suitable) (Phillips 2005).

The choice of environmental predictors is fundamental for MaxEnt niche modeling. Predictors should measure the processes that link environmental conditions to species occurrence, and match the spatial and temporal scales at which such processes occur. Climatic and topographic data are commonly used with this modeling approach (Lestina *et al.* 2016) because this data can provide continuous spatial coverage, usually through interpolation methods (Miller & Rogan 2007). However, some studies indicated that an accurate and realistic geographic distribution of pest species is attained by integrating vegetation variables, derived from remote sensing data, with climatic and topographic variables (Lestina *et al.* 2016; Makori *et al.* 2017; Richard *et al.* 2018). These predictors could be more informative because they may explain the availability of resources, shelter, etc. (Leitão & Santos 2019). Also, the remote sensing vegetation pattern variables are useful additional predictors for the spatial distribution of species since EN models rely on the correlation between a habitat's characteristics and the biophysical properties of the studied species (Richard *et al.* 2018).

Identifying variables associated with the geographic distribution of *C. pomonella* is useful for the suitable management of this pest to reduce ecological destruction and economic losses. The ENMs have been used to reveal the effects of environmental variables on the distribution of codling moth and estimate its potential risk on a global and national scale. Jiang *et al.* (2018) used MaxEnt to predict the potential global distribution of codling moth. Global accessibility data, apple yield data, elevation data, and 19 bioclimatic variables were used as predictors. The results showed that suitable habitats of codling moth are mainly distributed in Europe, Asia, and North America; and global accessibility, mean temperature of the coldest quarter, precipitation of the driest month, annual mean temperature, and apple yield were the most important variables associated with the global distribution of codling moths.

In another study, MaxEnt was used to identify areas with the highest potential risk of codling moth establishment and spread in China (Zhu *et al.* 2017). A total of 26 climatic, topographic, and anthropogenic variables were considered in the modeling. Human footprint, annual temperature range, precipitation of the wettest quarter, and degree days 10 C were the most important predictors associated with codling moth distribution.

Svobodová *et al.* (2014) used the mechanistic model, CLIMEX to identify climatically favorable areas for European corn borer *Ostrinia nubilalis* (Hubner), European grapevine moth *Lobesia botrana* (Denis & Schiffermüller), and codling moth *C. pomonella* development and long-term survival in the area of southern Moravia and northern part of Austria during the 1803–2008 period. The climatic parameters especially daily air temperature was used as a determining factor in the model. Besides the estimation of climatic suitability for the pests' persistence in the past, they specified the core of the climatic niche with the continuing presence of the pest and concluded that in the case of widespread species (*C. pomonella*) the climatic core could be detected only if the study covers large enough area. Kamangar and Ranjbar Aghdam (2020) prepared a predictive model of codling moth phenology based on total efficient temperature, in Kamyaran and Saqez located in the Kudistan province of Iran and showed that the peak population of the first-generation larvae of the winter generations is 6634±430 GDH (Growing Degree Hours), and in the summer generation is 23700± 846 GDH.

To the best of our knowledge, there is no study about the effect of climatic, topographic, and remote sensing variables, and their interactions on codling moth distribution and abundance at a landscape scale. Therefore, the objectives of this study were to: 1) develop potential habitat suitability maps of *C. pomonella* in East Azerbaijan province using MaxEnt, and 2) determine if remote sensing variables improve the accuracy of these models compared to those using only climatic or topographic variables.

## Materials and methods

*Study area*

This study was conducted in seven apple-growing counties of East Azarbaijan Province including Ahar, Maragheh, Marand, Horand, Shabestar, Miyaneh, and Tabriz (Fig. 1). East Azarbaijan Province extends from 36˚ 45´ to 39˚ 26´ N and from 45˚ 05´ to 48˚ 22´ E. Local climates vary across the province due to the differences in elevation.

*Species occurrence data*

Field surveys for collecting the occurrence data of codling moth were conducted during three growing seasons, 2017 - 2019. The activity of codling moth adult males was monitored using delta-shaped traps baited with female sex pheromone (PH-227-1RR, Russell IPM, UK). One trap was placed in the tree canopy at a height of 1.5 - 1.7 m in each orchard. Spatial locations of the trees were saved in a hand-held GPS receiver (Model GPS-map 76CSx; Garmin, Olathe, Kansas) in the Universal Transverse Mercator (UTM) coordinate system with a positional accuracy of ± 3 m. A minimum 1 km radius was established between neighboring sites. During the three years surveys, 59 occurrence points of codling moth were identified and used to create the models.

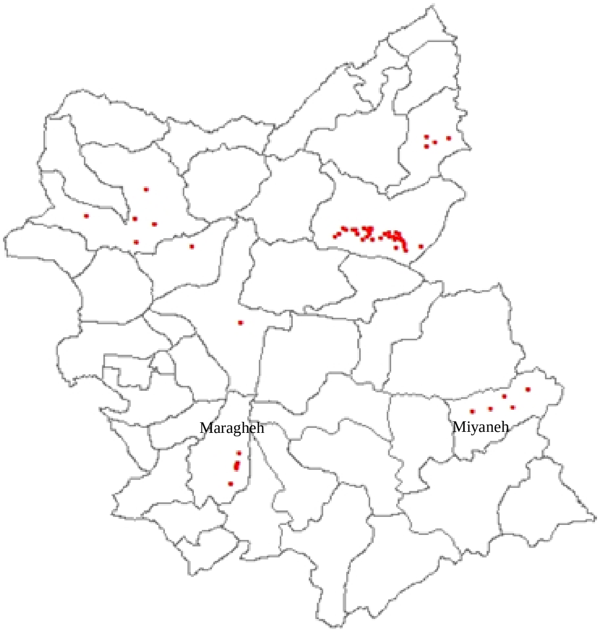


**Figure 1.** Location map of counties studied and sampling points.

*Environmental variables*

Fifteen environmental variables were considered as potential predictors for estimating codling moth distribution. These variables were categorized into topographic, climatic, and remote sensing variables (Table 1).

Topographic layers were derived from a 30-m digital elevation map (DEM) of East Azarbaijan (produced by Azarpeymayesh Consulting Engineers). These data were analyzed in ArcGIS 10.3.1 to create layers of the slope, aspect, landshape, northness, eastness, and sun index. Slope and aspect layers (both in degrees) were obtained from DEM using ArcGIS slope and aspect tools. Landshape layer was created by taking the mean elevation value (i.e., from the DEM) in a circle with a three-cell (90-m) radius around the sample point, and subtracting that value from the sample point elevation using ArcGIS 10.3.1 “Raster Calculator” (Merrill *et al.* 2009). Northness and eastness were generated using Raster Calculator by taking the cosine and sine of the aspect layer, respectively (Lestina *et al.* 2016). The sun index was calculated using slope and aspect values as follows (Karimzadeh *et al.* 2014):

$$\text{Sun index} = -\cos(\text{aspect}) \times \cot(\text{slope}), \text{ when } 0^\circ \leq \text{aspect} \leq 90^\circ \text{ or } \geq 270^\circ$$

and

$$\text{Sun index} = -\cos(\text{aspect}) \times \tan(\text{slope}), \text{ when } 90^\circ < \text{aspect} < 270^\circ$$

Then, these point datasets are interpolated using the IDW algorithm in ArcGIS 10.3.1 to create raster datasets.

Meteorological data were obtained from East Azarbaijan Applied Meteorological Research Center. These data were used to calculate the mean, minimum and maximum absolute temperatures and relative humidity (Rh), and total precipitation per month (April, May, June, July, August and September) for three years of the study. Then, these point datasets are interpolated using the inverse distance weighting (IDW) algorithm in ArcGIS 10.3.1 to create raster layers. Finally, the average of each variable was taken from three layers using the cell statistics tool in ArcGIS 10.3.1.

Normalized difference vegetation index (NDVI) was the remote sensing variable studied. Multispectral Landsat-8 (OLI / TIRS-2018) with 30-m accuracy was used to produce this index. For this purpose, after applying radiometric and atmospheric corrections, a mosaic image was prepared for the study area. Then NDVI was calculated using the following formula 1 and by spectral indices tool of ENVI 5.3 software.

1) NDVI= (Near Infrared - Red)/ (Near Infrared + Red)

**Table 1.** Environmental variables used for modeling the suitable habitat of codling moth in East Azarbaijan province.

| Data Source | Category | Variables Description | Unit | Abbreviations |
|---|---|---|---|---|
| meteorological stations | Climatic | Mean temperature per month | Degree Celsius | tmean |
| | | Maximum absolute temperature per month | Degree Celsius | tmax |
| | | Minimum absolute temperature per month | Degree Celsius | tmin |
| | | Mean relative humidity per month | Percentage | rhmean |
| | | Maximum absolute relative humidity per month | Percentage | rhmax |
| | | Minimum absolute relative humidity per month | Percentage | rhmin |
| | | Total precipitation per month | Millimeter | Precipitation |
| SRTM | Topographic | The elevation of each cell | Meter | Elevation |
| | | The degree slope of each cell | Degree | Slope |
| | | The compass direction that the slope faces in each cell | Degree | Aspect |
| | | The relative elevation of the georeferenced plot to its surroundings | Meter | Landshape |
| | | North-south linear variable of direction in each cell | Degree | Northness |
| | | East-west linear variable of direction in each cell | Degree | Eastness |
| | | Amount of solar energy received at each point based on its slope and aspect | - | Sun index |
| Landsat | Remote sensing | Difference between near-infrared (which vegetation strongly reflects) and red bands (which vegetation absorbs) | - | NDVI |

*MaxEnt modeling*

A MaxEnt modeling algorithm was used to predict the distribution of codling moth because it is a presence-only model which is suitable for occurrence data in this study. To determine which variables are significantly related to the distribution of codling moth, initial models were run using environmental variables of climatic and topographic separately. The jackknife test in the MaxEnt was used to evaluate the influence of each environmental variable on the potential distribution of codling moth. Cross-correlation between variables was also performed and only one variable from each set of highly correlated variables (Pearson correlation coefficient $|r| \geq 0.75$) was included in the models. The predictive power of each variable in the Jackknife test as well as their relationship with codling moth biology was considered to remove or include variables in the final model. After specifying the most significant variables in climatic and topographic categories, the subsequent model was run to combine variables of these two categories and determine those that would be included in the final model. The NDVI index was integrated at the end to evaluate its importance in improving the prediction capability of the executed model with climatic and topographic variables.

One of the limitations of presence-only data is sampling bias, which can lead to inaccurate predictions. Since the data collection in this study was not random, the Gaussian Kernel Density tool in the SDMToolbox of ArcGIS 10.3.1 was used to generate a bias layer to account for potential sampling bias (Lestina *et al.* 2016). Models were averaged across 10 replicates using the bootstrap procedure. In this method, 75 % of the presence points were randomly used to construct the model and the remaining 25 % were used to evaluate the results of the model.

Model performance was evaluated using the area under the ROC curve (AUC). ROC is an abbreviation of "receiver operating characteristic". AUC measures the probability that a random presence site is ranked above background (or pseudo-absence) points. Models with random predictions have an AUC value of 0.5. High-performance models have an AUC value greater than 0.8 and are ideal for interpreting species-environment relationships.

## Results

*MaxEnt models*

Figures 2 and 3 show the results of the jackknife test for the models with topographic and climatic variables, respectively. Blue shades show the individual importance of each variable when used in isolation, while green shades show the model performance when each variable is excluded from the model. Red shades also indicate the performance of the model created using all variables. According to the results of the jackknife test, cross-correlations (Tables 2 and 3) and the importance of variables in codling moth biology, two topographic variables including elevation and slope, 10 climatic variables including precipitation of September, mean relative humidity of August, the maximum temperature of May, June and July, minimum temperature of April, May, August, September and mean temperature of April were selected to include in the model.

**Table 2.** Correlation matrix among topographic variables. Variables showing $|r| \geq \pm 0.75$ were eliminated from the analyses.

| Variable | Elevation | Slope | Aspect | Landshape | Northness | Eastness | Sun index |
|---|---|---|---|---|---|---|---|
| Elevation | 1 | | | | | | |
| Slope | 0.369 | 1 | | | | | |
| Aspect | 0.012 | 0.115 | 1 | | | | |
| Landshape | -0.034 | -0.014 | 0.005 | 1 | | | |
| Northness | 0.021 | -0.050 | -0.139 | 0.002 | 1 | | |
| Eastness | 0.015 | 0.014 | -0.009 | -0.002 | 0.020 | 1 | |
| Sun index | -0.078 | 0.018 | 0.015 | 0.000 | 0.024 | 0.013 | 1 |

*Accuracy analysis*

The AUC values of implemented models are presented in Table 4. By using the topographic, climatic, and topographic+climatic variables, the AUC values were 0.840, 0.951 and 0.938, respectively. The model including NDVI had the highest AUC value (0.99), which strongly supports model predictive power and indicates the importance of vegetation index in codling moth distribution modeling.

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**Table 3.** Correlation matrix among climatic variables. Variables showing |r| ≥ ±0.75 were eliminated from the analyses.

| Month | | T_min | T_mean | T_max | Rh_mean | Precipitation |
|---|---|---|---|---|---|---|
| April | T_min | 1 | | | | |
| | T_mean | 0.659 | 1 | | | |
| | T_max | 0.541 | 0.475 | 1 | | |
| | Rh_mean | -0.742 | -0.579 | -0.024 | 1 | |
| | Precipitation | 0.118 | 0.177 | -0.165 | -0.261 | 1 |
| May | T_min | 1 | | | | |
| | T_mean | 0.865 | 1 | | | |
| | T_max | 0.690 | 0.705 | 1 | | |
| | Rh_mean | -0.035 | -0.164 | -0.320 | 1 | |
| | Precipitation | 0.079 | 0.183 | 0.285 | -0.631 | 1 |
| June | T_min | 1 | | | | |
| | T_mean | 0.773 | 1 | | | |
| | T_max | 0.488 | 0.797 | 1 | | |
| | Rh_mean | -0.711 | -0.860 | -0.771 | 1 | |
| | Precipitation | -0.638 | -0.596 | -0.617 | 0.669 | 1 |
| July | T_min | 1 | | | | |
| | T_mean | 0.913 | 1 | | | |
| | T_max | 0.821 | 0.901 | 1 | | |
| | Rh_mean | -0.684 | -0.754 | -0.554 | 1 | |
| | Precipitation | 0.876 | -0.838 | -0.799 | 0.718 | 1 |
| August | T_min | 1 | | | | |
| | T_mean | 0.899 | 1 | | | |
| | T_max | 0.740 | 0.879 | 1 | | |
| | Rh_mean | -0.648 | -0.834 | -0.835 | 1 | |
| | Precipitation | -0.362 | -0.627 | -0.725 | 0.880 | 1 |
| September | T_min | 1 | | | | |
| | T_mean | 0.913 | 1 | | | |
| | T_max | 0.638 | 0.736 | 1 | | |
| | Rh_mean | -0.669 | -0.824 | -0.532 | 1 | |
| | Precipitation | -0.255 | -0.484 | -0.435 | 0.828 | 1 |

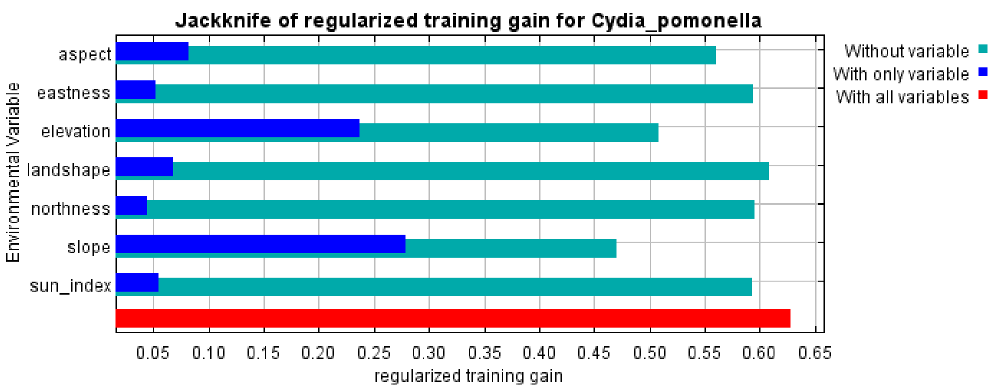


**Figure 2.** Jackknife variable importance test of regulated gains for the model with topographic variables.

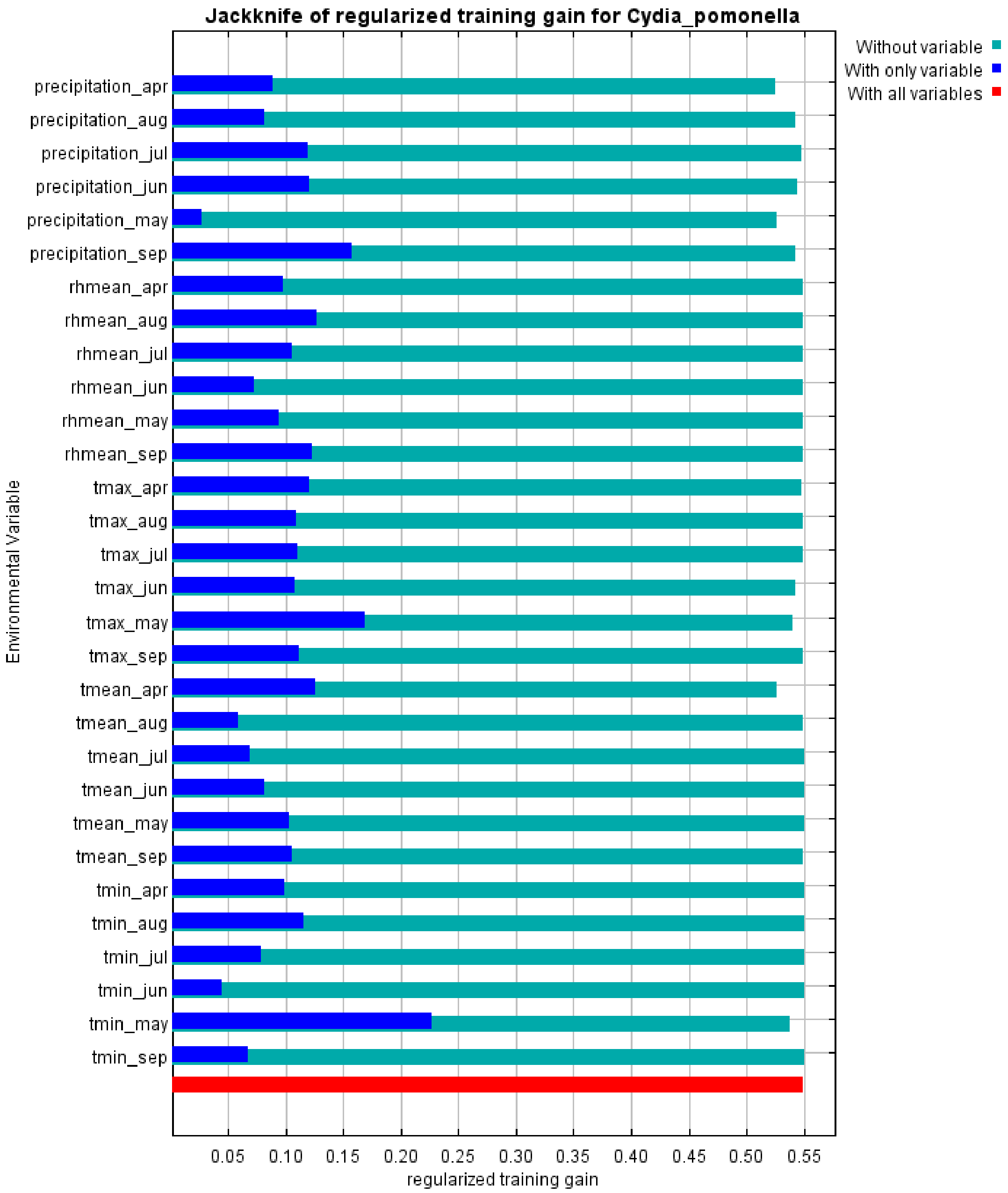


**Figure 3.** Jackknife variable importance test of regulated gains for the model with climatic variables.

**Table 4.** The AUC values of models implemented in MaxEnt.

| Model No. | Variables | AUC value |
|---|---|---|
| 1 | Topographic variables | 0.840 |
| 2 | Climatic variables | 0.951 |
| 3 | Topographic and climatic variables | 0.938 |
| 4 | Topographic, climatic and remote sensing variables | 0.990 |

*The importance of variables*

Determining the most important environmental variables affecting codling moth distribution was one of the objectives of this study. Figures 4 and 5 show the Jackknife variable importance test of regulated gains for the models without and with the NDVI index, respectively. In the model without NDVI index, elevation, slope and minimum temperature of May, and the models with NDVI index, NDVI, elevation, and slope were the most important variables affecting codling moth distribution.

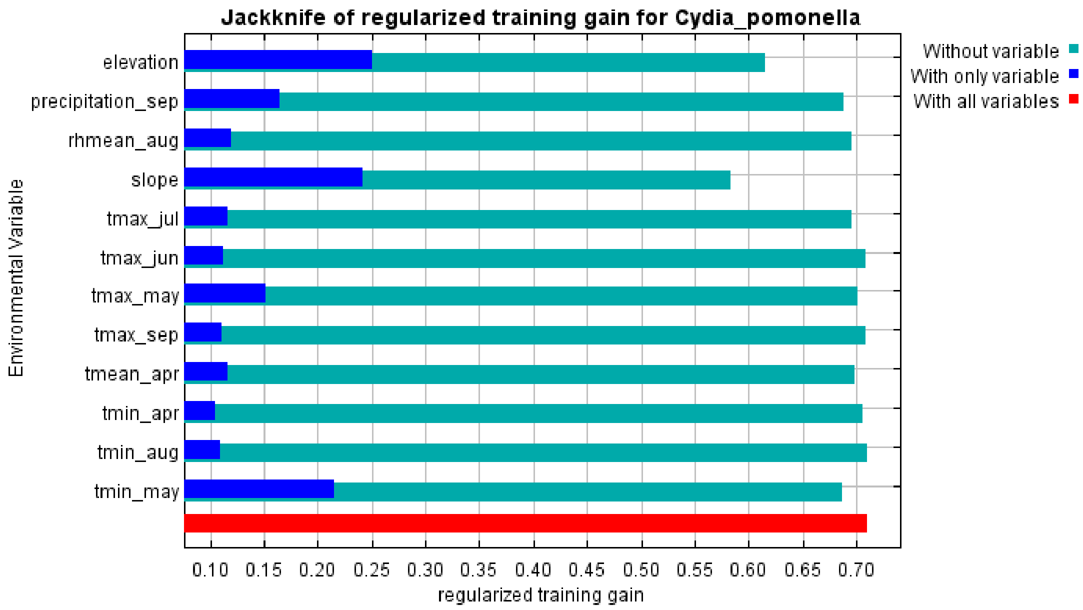


**Figure 4.** Jackknife variable importance test of regulated gains for the model with topographic+climatic variables.

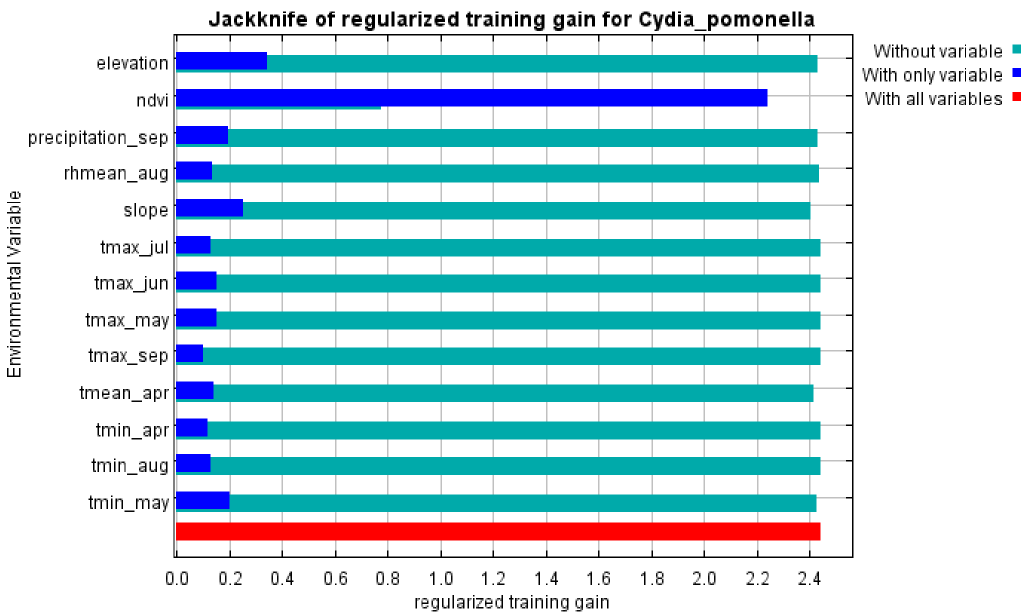


**Figure 5.** Jackknife variable importance test of regulated gains for the model with topographic+climatic+remote sensing variables.

Table 5 presents the percentage contribution of each variable and its permutation importance in the models without and with NDVI. In the model without NDVI, the slope was the variable with the most contribution (31%) followed by precipitation of September (17.4%), mean temperature of May (16.4%) and elevation (16.3%). In the model with the RS variable, NDVI was the most contributed variable with 92.3% contribution followed by precipitation of September (2%), slope (1.8%), minimum temperature of May (1.3%) and mean temperature of April (1.1%). The Jackknife variable importance test also showed that these variables had higher predictive importance than other variables (Figures 4 and 5).

**Table 5.** Permutation importance (percentage) of each variable in the models without and with RS variable, NDVI.

| Model | Variable | Percent contribution |
|---|---|---|
| Model without NDVI | Slope | 31.0 |
| | Precipitation of September | 17.4 |
| | Minimum temperature of May | 16.4 |
| | Elevation | 16.3 |
| | Maximum temperature of May | 5.5 |
| | Mean RH of August | 3.9 |
| | Maximum temperature of September | 3.1 |
| | Maximum temperature of July | 2.7 |
| | Mean temperature of April | 2.2 |
| | Maximum temperature of June | 0.9 |
| | Minimum temperature of April | 0.6 |
| | Minimum temperature of August | 0.0 |
| Model with NDVI | NDVI | 92.3 |
| | Precipitation of September | 2.0 |
| | Slope | 1.8 |
| | Minimum temperature of May | 1.3 |
| | Mean temperature of April | 1.1 |
| | Elevation | 0.6 |
| | Maximum temperature of September | 0.3 |
| | Mean RH of August | 0.1 |
| | Minimum temperature of August | 0.1 |
| | Maximum temperature of June | 0.1 |
| | Maximum temperature of July | 0.1 |
| | Maximum temperature of May | 0.1 |
| | Minimum temperature of April | 0.0 |

Figures 6 and 7 show the response curves of the variables with more percentage contribution in the models without and with NDVI, respectively. The response curves indicated that the frequency of codling moth increased in the ranges of 0 - 7 mm precipitation in September, -1 – 2 degrees of slope, 3 – 6.1 ˚C of the minimum temperature of May, 200 – 1300 m of elevation, 5 – 7.9 ˚C of the mean temperature of April and 0.2 – 0.62 NDVI.

*Predicted distribution map*

Figures 6 and 7 show the predicted distribution maps of codling moth using models without and with NDVI. Warmers colors (red) and cooler colors (blue) on the maps indicate the more suitable and less suitable areas, respectively. High environmental suitability was predicted for areas within the northern portions of East Azarbaijan province in the model created without NDVI (Fig. 8). The predicted suitable area was significantly restricted with the addition of the RS variable (Fig. 9).

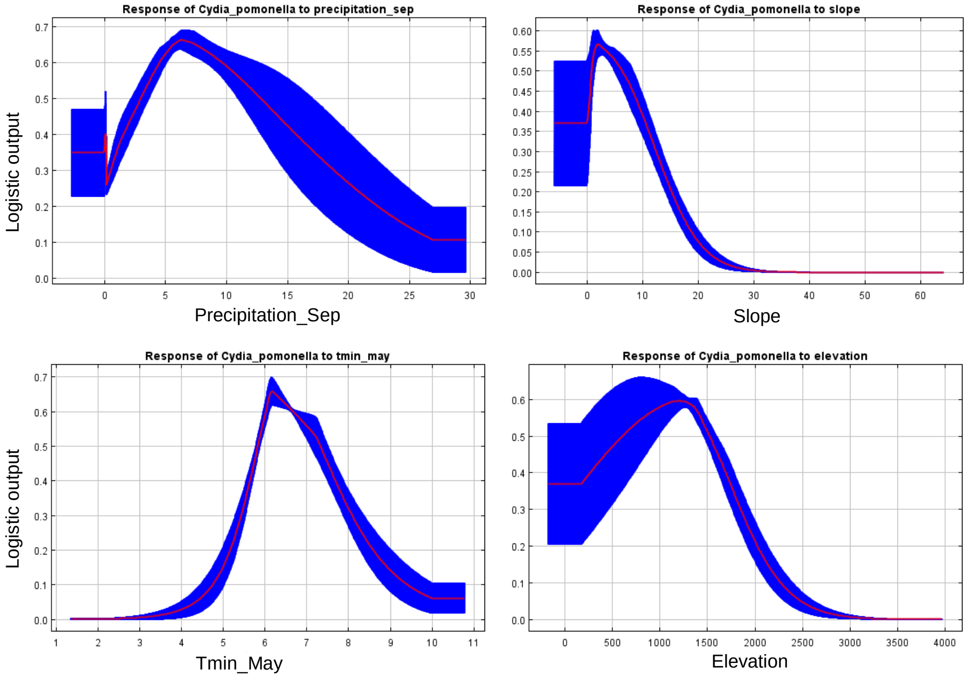


**Figure 6.** Codling moth response curves from the top contributing variables in the MaxEnt model with topographic and climatic variables.

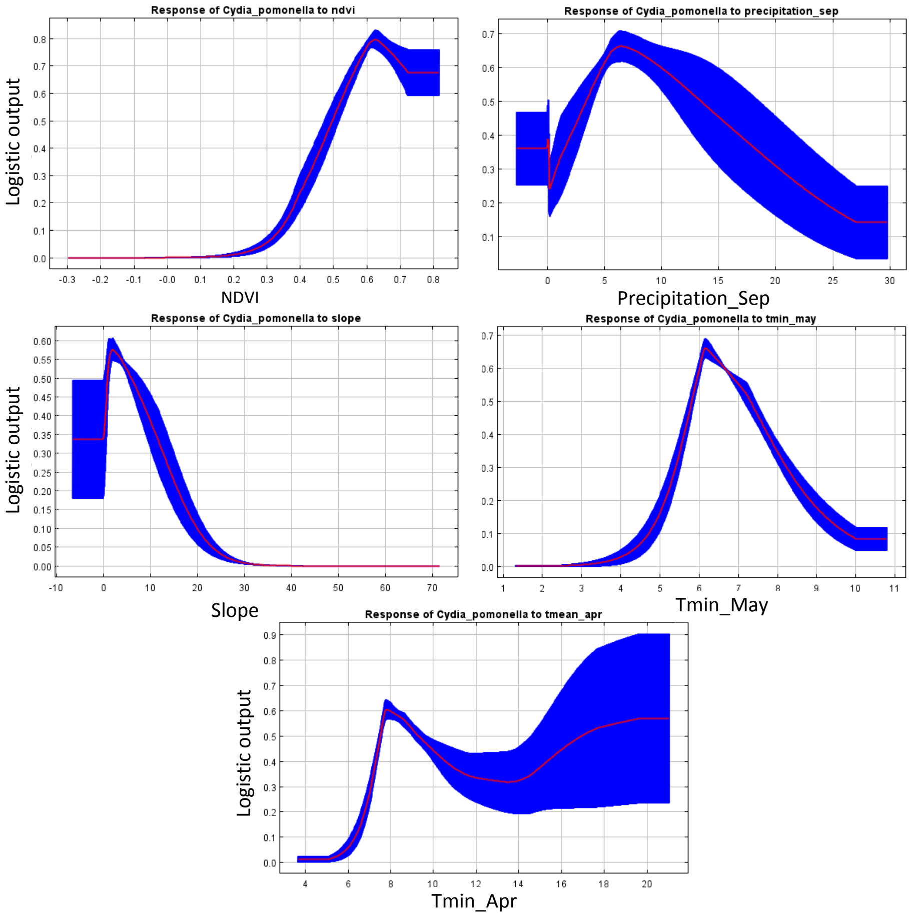


**Figure 7.** Codling moth response curves from the top contributing variables in the MaxEnt model with topographic, climatic and remote sensing variables.

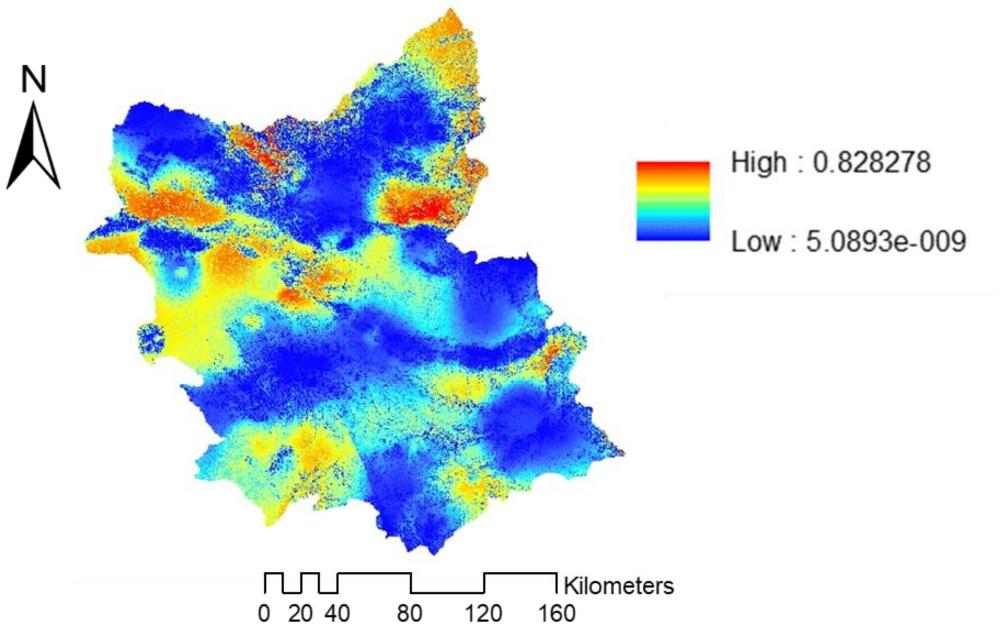


**Figure 8.** Predicted distribution map for codling moth using bioclimatic and topographic variables. Blue color indicates less suitable sites, while red color indicates more suitable sites.

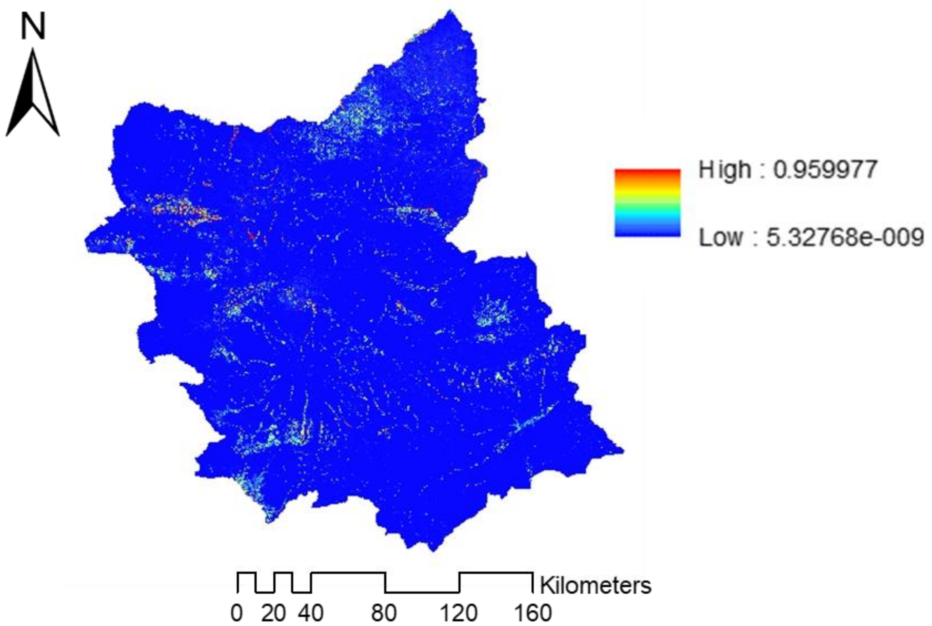


**Figure 9.** Predicted distribution map for codling moth using bioclimatic, topographic, and remote sensing variables. Blue color indicates less suitable sites, while red color indicates more suitable sites.

**Discussion**

In this study, we used the MaxEnt machine learning method for codling moth niche modeling and assessing the effect of environmental variables on codling moth distribution patterns. Codling moth occurrence data were collected from apple-growing regions over three years. In addition to climatic variables, the topographic and remote sensing variables were also taken into account. The high AUC value (0.99) indicated that the model performed well and accurately. Predicted distribution areas for codling moth using bioclimatic and topographic variables confirmed with the currently known occurrence regions.

To facilitate pest management programs, accurate models are needed to determine the potential distribution of economically important pests. Other studies present the global potential risk of distribution of codling moth using correlative and mechanistic niche models (Kumar *et al.* 2015; Zhu *et al.* 2017; Jiang *et al.* 2018). But, our study is the first on a local scale that used topographic and remote sensing variables along with climatic variables which are commonly used in studies. However, there are some other factors such as host availability that affect the potential distribution of codling moth which have not been considered in this study and should be taken into account in future models.

All four models generated in our study accurately predicted codling moth habitat suitability (AUC > 0.8), but the model including NDVI, had the highest AUC value. Models did not predict suitable habitat in regions located in high elevations primarily because of the shorter photoperiod in these areas and lack of chilling requirement (<60 d at ≤10°C) in these areas for the codling moth to break diapause (Kumar *et al.* 2015).

NDVI, slope, precipitation of September, mean temperature of May and elevation were the top environmental variables associated with codling moth distribution. Kumar *et al.* (2015) and Jones *et al.* (2013) also showed a strong influence of elevation on the biology and distribution of codling moth. While Zhu *et al.* (2017) in studying codling moth establishment in China, introduced human footprint, annual temperature range, precipitation of wettest quarter, and degree days ≥10 °C as the most important predictors associated with codling moth distribution.

In the studies, the potential global distribution of codling moth was studied, and different variables were detected as the most important predictors. Jiang *et al.* (2018) used MaxEnt to predict the potential global using global accessibility data, apple yield data, elevation data and 19 bioclimatic variables. Their results indicated that global accessibility, mean temperature of the coldest quarter, precipitation of the driest month, annual mean temperature and apple yield were the most important environmental predictors associated with the global distribution of codling moths. Average annual temperature and latitude were the main environmental variables associated with codling moth distribution at the global level in another study (Kumar *et al.* 2015). Comparing these results with the results of the present study indicated that different variables may affect the spatial distribution of codling moth on the local and global scales.

Kumar *et al.* (2015) recommended that the results of niche modeling studies should be interpreted cautiously because niche model predictions may be affected by the quality of occurrence data, sampling bias, resolution of spatial data layers, species characteristics, and spatial autocorrelation. Phillips *et al.* (2004) showed that MaxEnt is substantially superior to the standard methods, performing well with fairly few presence data, particularly when regularization is employed. They also showed that the models generated by MaxEnt can be easily interpreted by human experts, a property of great practical importance.

Apple is an economically important crop in East Azarbaijan Province and codling moth is the most destructive and economically important insect pest of apple. Understanding the impact of spatially heterogeneous environmental factors on the codling moth distribution is fundamental for the management of this pest. The results of this study indicated that along with the climatic and topographic variables like temperature, precipitation, and elevation, the vegetation patterns at a landscape level play a key role in codling moth distribution. So that NDVI was identified as the most important contributor to the MaxEnt model and improved model performance. This method can also be used for other important agricultural pests of Iran. The distribution map obtained in MaxEnt provided an important tool for identifying potential risk zones of codling moth. This map can assist managers in forecasting and planning control measures and therefore, effective management of current infestations of codling moth. In other words, these distribution maps can provide baseline information for the development and implementation of effective IPM strategies. Since changes in climatic variables may influence codling moth distribution patterns, further studies are needed to investigate the effects of climate changes on codling moth distribution and biology.

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