DOI: 10.1111/tgis.12714

RESEARCH ARTICLE

Transactions in GIS WILEY

Combining favorability modeling with collaborative geo-visual analysis to improve agricultural pest management

Gustavo Adolfo García-Chapeton[1] | **Albertus G. Toxopeus**[2] | **Jesús Olivero**[3] | **Frank O. Ostermann**[1] | **Rolf A. de By**[1]

[1]Faculty of Geo-Information Science and Earth Observation, Department of Geo-Information Processing, University of Twente, Enschede, the Netherlands

[2]Faculty of Geo-Information Science and Earth Observation, Department of Natural Resources, University of Twente, Enschede, the Netherlands

[3]Facultad de Ciencias, Departamento de Biología Animal, Universidad de Málaga, Malaga, Spain

Correspondence
Gustavo Adolfo García-Chapeton, Faculty of Geo-Information Science and Earth Observation, Department of Geo-Information Processing, University of Twente, Enschede 7522, the Netherlands.
Email: g.a.garciachapeton@utwente.nl, chape1331@gmail.com

Abstract

In this article, we explore the potential of combining favorability modeling with collaborative geo-visual analysis to determine when and where to apply countermeasures for the olive fruit fly. The favorability function estimates locations and times at which the conditions favor a species exceeding acceptable abundance levels, thus becoming a pest. We built two models based on monitoring data for the olive fruit fly in Andalusia, Spain. The models were used in a geo-visual analytics prototype to produce map series for the seasons 2012 to 2018, and to explore the models' outputs collaboratively with stakeholders. Results showed that the models capture known species' dynamics, but tend to overpredict favorable conditions for pest development. Discussions with stakeholders indicate that the prototype facilitates the communication and discussion of modeling results between researchers, authorities, and field technicians, which also enables a better understanding of the pest dynamics, and the planning and execution of control activities.

1 | INTRODUCTION

A pest is an organism that conflicts with human welfare, because it may affect crops, stored products, animals, or people (Rafikov & Balthazar, 2005). It is important to highlight that an organism is considered a pest only when its abundance reaches a level that seriously affects human welfare (Herzfeld & Sargent, 2017). Such pest outbreaks can threaten local flora and fauna (Tepley, Juan Paritis, & Veblen, 2012), and especially some agricultural pests can cause damages with significant economic impact for producers and the food supply chain, possibly threatening food security (FAO, 2005). Additionally, some pests threaten human health as well when they serve as infection vectors for diseases (Williams, Straw, Townsend, Wilkinson, & Mullins, 2013). Despite such negative effects, these species are part of a natural ecosystem, therefore proper pest management is needed to minimize their negative effects without disrupting that natural ecosystem (Gilioli, Pasquali, & Marchesini, 2016).

Pest management includes three stages. First, the *monitoring stage*, in which the species' presence or abundance is measured at several locations with a set temporal frequency. This aims to represent the pest population dynamics in the area of interest. Second, the *control stage*, in which countermeasures are taken to keep the species within acceptable geographic areas or abundance levels. Third, the *evaluation stage*, in which the effectiveness of the monitoring and control actions is assessed (Herzfeld & Sargent, 2017). The Food and Agriculture Organization of the United Nations (FAO) defines integrated pest management (IPM) as:

> The careful consideration of all available pest control techniques and subsequent integration of appropriate measures that discourage the development of pest populations and keep pesticides and other interventions to levels that are economically justified and reduce or minimize risks to human health and the environment. IPM emphasizes the growth of a healthy crop with the least possible disruption to agro-ecosystems and encourages natural pest control mechanisms. (FAO, 2017)

However, in agronomic production, the use of chemical treatment is significant, and the lack of effective methods to determine when and where to apply the treatment can lead producers to incur unnecessary expenses. Further, overuse can cause problems such as reduced effectiveness of the treatment due to increased resistance of the pest, reduction of biodiversity by affecting also natural enemies of the pest, and accumulation of chemical residues in crops, soil, and water bodies (Herzfeld & Sargent, 2017). For this reason, researchers have developed different methods and tools that aid producers in a better understanding of pest dynamics, and support decision-making in pest management.

Pest monitoring data enables producers to decide when and where to perform control actions. However, its collection is expensive and time-consuming, thus statistical models play a key role in the study of pest populations by providing a means to understand the factors driving the population dynamics, and to estimate pest abundance/presence in non-monitored locations/areas.

The spatiotemporal distribution of pest species is heterogeneous, because of variations in topography, environmental and climatic conditions, and human intervention of ecosystems. Therefore, pest management needs to be addressed as a geographic problem, and spatiotemporal analysis and visualization techniques can enable effective monitoring and control activities (Ivana, Antonela, Renata, & Jasminka Igrc, 2010). Thus, mapping tools are essential for stakeholders such as land managers, conservation biologists, and entomologists in order to understand the distribution and diversity of species in an area of interest, and to make informed decisions on their management and habitats (Janicki, Guo, Conway, Donohue, & Roth, 2014).

Diverse spatiotemporal analysis and visualization techniques have been applied to study and manage pest species. For example, Gutierrez, Ponti, and Cossu (2009) developed a weather-driven physiologically based demographic model to simulate the potential effects of climate change on the distribution and abundance of olive trees and the olive fruit fly (OFF) in the USA (specifically in Arizona and California) and Italy. Pontikakos, Tsiligiridis, and Drougka (2010) developed and validated a location-aware system for precision farming to assist in the planning and execution of chemical treatments for OFF. Voulgaris, Stefanidakis, Floros, and Avlonitis (2013) proposed a real-time online alert information system based on the biological cycle of the OFF, topological configuration, and weather conditions, which predicts OFF outbreaks, aiming to enable timely execution of control activities. Miranda et al. (2019) developed a decision support system based on semi-automatic pest monitoring for managing OFF; the results of a test showed a reduction of one-third in the volume of insecticide used in the control activities. These works mostly focus on the computer processing, modeling, and decision-making parts, but neither enhance stakeholders understanding of the pest dynamics, nor enable collaboration among stakeholders with diverse knowledge and interests regarding pest management. We aim to address this gap.

In this article, our objective is twofold. First, to explore the potential of the *favorability function* (Real, Barbosa, & Vargas, 2006) to build models for the spatiotemporal dynamics of the OFF (*Bactrocera oleae*) using existing data that were collected for applied pest management, which is the result of years of pest management activities following official protocols. The models aim to estimate locations and times at which the combination of human, topographic, environmental, and climatic factors favor a species becoming a pest. Second, to explore the potential of geo-visual analytics (GVA) to enable non-academic stakeholders who are actually doing the pest management to better understand the pest behavior and impact of pest control measures, by building, deploying, and evaluating a prototype. Our focus in this article is on model development and prototype evaluation, at the expense of detailed information about prototype development. In this context, we are convinced that our research offers advances towards promising, scientifically sound solutions to a common real-world problem: improving collaborative decisions based on valuable data that might not be up to the highest scientific standards, obtained by practitioners who might not have scientific training, but years of experience, and who work within a legal and regulatory framework that is not easy to change.

Another innovative aspect of our research is the use of the GVA environment to enable stakeholders with the knowledge to design and develop processing methods (i.e., mostly researchers) to communicate their results to stakeholders who possess valuable domain and local knowledge (i.e., mostly authorities and field technicians), and who can validate the results. Specifically, we show that GVA can help in bridging the gap between scientific modeling and practical pest management.

Based on the stated objective for this article, the following questions guided the research process:

1. How accurate can the favorability function model the OFF spatiotemporal dynamics using existing data collected for practical pest management?
2. How do stakeholders evaluate the utility and usability of the prototype to analyze the pest management data, and the models' outputs?
3. How do stakeholders evaluate the prototype's support for collaborative analysis in general?

2 | BACKGROUND

2.1 | Olive fruit fly

The OFF is considered a major pest in olive-growing regions worldwide. It is currently present in southern Europe, North Africa, the Middle East, and in some areas of the USA and Mexico (Nardi, Carapelli, Dallai, Roderick, & Frati, 2005). It has a high reproductive potential, and depending on the local conditions there can be between three and five generations per year (Pontikakos et al., 2010). Additionally, it has high mobility, with reported flying distances of up to 4 km to find olive tree hosts (Rice, 2000).

The damage caused by the OFF is reflected in the quantity and quality of the produced table olives and olive oil (Nardi et al., 2005). A single female fly can lay up to 500 eggs (in its lifetime), usually one egg per olive fruit (Zalom, Van Steenwyk, Burrack, & Johnson, 2009). The damage is caused by the oviposition stings[1] and the OFF larvae who feed inside the olives, resulting in destroyed pericarp and the entry of secondary infection by bacteria and fungi that rot the fruit (Zalom et al., 2009). The oil from affected olives shows a higher acidity level (Olivero, García, Wong, & Ros, 2004), which reduces its commercial value. Economic losses due to OFF infestations have been reported up to 100% for table olives, and 80% for olive oil (Rice, 2000; Zalom et al., 2009), because the former are not sellable, and the latter can only be used to produce low-quality oils.

The OFF population's development is greatly influenced by the seasonal development of its main host, the cultivated olive (Zalom et al., 2009) and climatic factors, especially temperature and relative humidity (Kalamatianos, Kermanidis, Avlonitis, & Karydis, 2016). In optimum temperature conditions (20–30°C), a complete generation cycle takes about 30–35 days (Rice, 2000; Zalom et al., 2009). Additionally, temperature affects the activity of adult flies—the species is not very active below 15°C and above 35°C (Zalom et al., 2009). Finally, high relative humidity favors ovarian maturation, egg production, and longevity of the OFF (Broufas, Pappas, & Koveos, 2009).

2.2 | Favorability function

The favorability function provides a measurement of the degree to which a set of conditions favors the occurrence of an event, regardless of the event prevalence (Real et al., 2006; Acevedo & Real, 2012). Favorability values range between 0 and 1, and are defined by:

$$F = \frac{e^y}{\frac{n_1}{n_0} + e^y} \tag{1}$$

Here, n_1 and n_0 are the number of positive (i.e., the event occurs) and negative (i.e., the event doesn't occur) samples, respectively, and y is a regression equation of the form:

$$y = \alpha + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_n \cdot x_n \tag{2}$$

where α is a constant and $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients of the n predictor variables $x_1, x_2, \ldots, x_n$. This y can be yielded by logistic regression:

$$P = \frac{e^y}{1 + e^y} \tag{3}$$

Favorability values can, however, also be obtained from any method capable of producing probability estimates (P) using the equation:

$$F = \frac{\frac{P}{1-P}}{\frac{n_1}{n_0} + \frac{P}{1-P}} \tag{4}$$

Because favorability values are leveled to the event prevalence in the dataset, the value 0.5 indicates a combination of conditions that neither increase nor decrease the probability of the event's occurrence with respect to its prevalence, while values under (over) 0.5 represent conditions that are detrimental (favorable) for the occurrence of the event (Acevedo & Real, 2012; Real et al., 2006). Some successful applications of the favorability function are downscaling a species distribution model (Olivero, Toxopeus, Skidmore, & Real, 2016), assessment of a native species' vulnerability due to an invasive species (Romero, Báez, Ferri-Yáñez, Bellido, & Real, 2014), and favorability values as a proxy for species density (Muñoz, Jiménez-Valverde, Márquez, Moleón, & Real, 2015). Additionally, it was also applied successfully in the context of spatiotemporal modeling to assess the effect of deforestation in Ebola virus disease outbreaks (Olivero et al., 2017).

2.3 | Geo-visual analytics

The term "visual analytics" (VA) was used by Wong and Thomas (2004) to describe "the formation of visual abstract metaphors in combination with a human information discourse (interaction) that enables detection of the expected and discovery of the unexpected within massive, dynamically changing information spaces" (p. 20). Later, Thomas and Cook (2005) further discussed visual analytics and defined it as "the science of analytical reasoning assisted by interactive visual interfaces" (p. 4).

GVA can be described as a subfield of VA that deals with the specific issues related to the analysis of geographic phenomena (Andrienko et al., 2007; Ho, 2013). It enables analytical reasoning and decision-making on geographic phenomena by producing a synergy of human analytical skills, with the storage and processing power of computers, coupled through interactive visual interfaces (Andrienko et al., 2007; Tomaszewski, Robinson, Weaver, Stryker, & MacEachren, 2007). GVA integrates knowledge from fields such as information and scientific visualization, GIS, and data mining (Ho, 2013; Tomaszewski et al., 2007). Given that phenomena in geographic space occur or evolve in time, GVA has put special emphasis on the relationship between space and time (Andrienko, Andrienko, Keim, MacEachren, & Wrobel, 2011). GVA deals with applications that usually involve multiple stakeholders with a diversity of interests, knowledge, and skills. For this reason, GVA pays special attention to the issues of collaboration, communication, and flexibility (Andrienko et al., 2007). Recent examples of GVA applications are the analysis of criminal activity (Rodrigo, 2020), human mobility (Zhang et al., 2019), and road accident accumulation zones (Ramos, Silva, Santos, & Pires, 2015).

3 | MODELING THE OFF DYNAMICS

3.1 | Study area

The study area is located in the region of Andalusia, in southern Spain (see Figure 1). It covers an area of approximately 7,000 km^2, with terrain elevation ranging between approximately 0 and 1,400 m above sea level. The area includes a total of 1,210 olive growing parcels with an approximate total area of 40 km^2. The main olive variety in the region is hojiblanca, which can be used for both table olives and oil production. The harvest time defines the olives' destination; while table olives are harvested very soon after summer, between September and October, when the fruits have already achieved their maximum size, and are still green-colored and robust, olives for oil production are harvested later, between November and January, when fruits have naturally turned black and their pulp is becoming soft. The production of olives is an important source of income in the local and regional economy (Extenda, 2017).

3.2 | Data sources and data preparation

The Integrated Production Associations (APIs, by Spanish acronym) "Antequera" and "La Camorra" provided us with a dataset of the monitoring and control of the OFF in the study area for the years 2012 to 2018 (inclusive). This dataset was obtained following the protocol established by the Junta de Andalucía (i.e., the regional administration) for the monitoring of olive crops.[2] This dataset includes information about weekly OFF abundance and fertility, damage to olives, application of chemical treatments, and phenology of the olive trees. Every measurement is georeferenced by a parcel identifier, for which coordinates are available, and time stamped with the date of the field observation.

The dataset was produced for practical pest management, therefore it does not necessarily follow the highest scientific standards for data collection. This is a common scenario in many studies, where data was produced under a legal and regulatory framework. Such datasets might be the result of several years of work and a significant

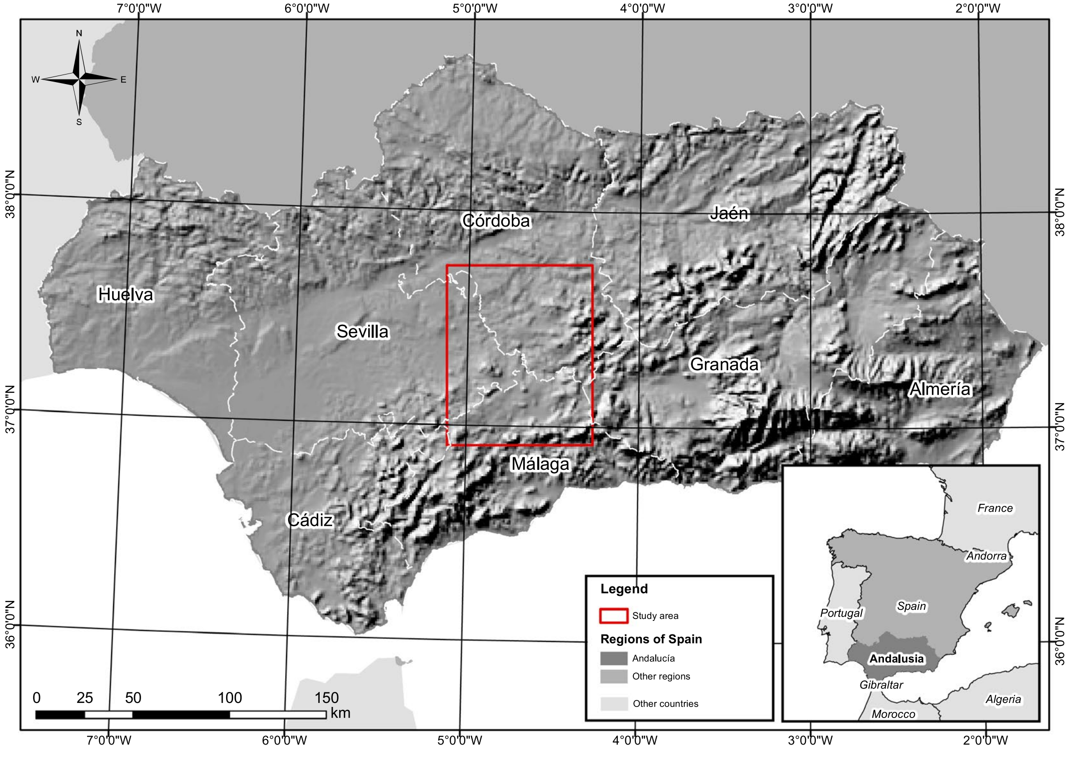

FIGURE 1 Study area in Andalusia, Spain

expenditure, and therefore an asset for their stakeholders. Changing the data collection protocol requires a political and administrative effort, and therefore is out of the researchers' control, moreover, changing it also means that old data will become incomparable. This is the case for pest management in Andalusia, which motivated us to look for a scientifically sound solution to take advantage of the existing data.

The APIs use two types of monitoring device to measure the OFF abundance: plastic McPhail flycatchers and yellow chromotropic sticky traps. The McPhail flycatchers capture flies attracted by the yellow color of the trap and a liquid feeding lure. This device provides information about the general size of the population and attracts in similar proportion males and females (Olivero et al., 2004). The efficacy of this device is conditioned by the weather, because the feeding lure requires evaporation to work. The yellow chromotropic sticky traps capture principally males attracted by the yellow color of the trap and a pheromone. The information provided by this device is directly related to the sexual activity of the OFF population (Olivero et al., 2004). The captured flies are inspected to determine the percentage of female flies and female flies with eggs. Additionally, olives are sampled to determine percentages for: stung olives, olives with alive forms, olives with exit hole, and olives with parasitized flies. This monitoring strategy is described in the Andalusian Integrated Production Regulation for Olives.[3]

The abundance measurements are reported as "flies per trapping device per day," which means that they are the average numbers captured by several devices during several days. The protocol defines that a monitoring point is representative for an area of 300 ha, and should include three devices of each type (i.e., six devices in total per monitoring point), with monitoring visits every 7 days to count the trapped individuals and clean the devices. For example, a measurement of one fly per flycatcher per day means that the field technician found in total 21 flies captured by all three flycatchers over a period of 7 days. The percentage of female flies with eggs is with respect to the total amount of female captures over the monitoring period.

TABLE 1 Treatment thresholds used to define the dependent variables for the statistical models

Name	Description	# Valid observations	Positives	% Positives	Negatives	% Negatives
Threshold 1 (*table olives*)	(flies per flycatcher per day ≥ 1) and (percentage of female flies with eggs ≥ 50%)	1,701	595	35	1,106	65
Threshold 2 (*olives for oil production*)	(flies per flycatcher per day ≥ 1) and (percentage of female flies with eggs ≥ 60%) and (percentage of stung olives> 0%)	1,701	354	21	1,347	79

Note: These thresholds are defined in the Andalusian Integrated Production Regulation for Olives.

The monitoring protocol defines four thresholds for decision-making about the application of chemical treatments: one distinct threshold for each of the first and subsequent applications of a chemical treatment for table olives, and for olives for oil production. We used the provided information to define dependent variables for two favorability models using the thresholds for the first application. Events were defined as "the observation exceeded the threshold." We label as 1 (i.e., positive) the observations with values exceeding the threshold, and 0 otherwise.

To rule out any influence of differing data recording practices between the two APIs, we decided to continue the modeling process only with the data from "Antequera," because it is the largest association and contributes 75% of the data. Table 1 describes the thresholds, the number of observations for each threshold, and the number and percentage of positives and negatives.

Additionally, we selected potential explanatory factors for the occurrence of the previously defined events. These were selected based on literature review and interviews with experts. They are seven expert stakeholders of the OFF management in the study area, and the information was obtained in face-to-face meetings, in which they were asked to describe the behavior of the OFF, and the behavioral drivers. They fall into the following four categories: human intervention and topographic, environmental, and climatic conditions. The data for location (i.e., X, Y coordinates), human intervention (i.e., application of chemical treatment), and phenology of olive tree came from the dataset provided by the APIs. All remaining data were obtained from the publicly available official sources at the Centro Nacional de Información Geográfica (CNIG; www.cnig.es), the Red de Información Ambiental de Andalucía (REDIAM; www.juntadeandalucia.es/medioambiente/site/rediam/), and the Red de Información Agroclimática de Andalucía (RIA; www.juntadeandalucia.es/agriculturaypesca/ifapa/ria/). For a list of the potential explanatory factors and their source, see Table 2.

We used data aggregation and interpolation methods to prepare data layers for the predictors at a spatial resolution of 1 km^2, and, where applicable, at a temporal resolution of 1 week (i.e., some predictors are static in time, see Table 2). In other words, there is one layer for each static predictor such as altitude, slope, and distance to in-land water, and 350 layers for each time-varying predictor such as phenophase, average temperature, and radiation (one for each week of the study period running from 1 January 2012 to 16 September 2018). Later, we used the location and time stamp of the measurements to extract data from those layers and create vectors of the

TABLE 2 Potential predictors for the favorability models for OFF

No.	Category	Predictor	Temporal variation	Source
1	Topographic	X	No	APIs
2	Topographic	Y	No	APIs
3	Topographic	Altitude	No	CNIG
4	Topographic	Altitude average[a]	No	CNIG
5	Topographic	Altitude difference[a]	No	CNIG
6	Topographic	Slope	No	CNIG
7	Topographic	Slope average[a]	No	CNIG
8	Topographic	Slope difference[a]	No	CNIG
9	Topographic	Exposition to south	No	CNIG
10	Topographic	Exposition to west	No	CNIG
11	Environmental	Distance to in-land water	No	REDIAM
12	Environmental	Distance to sea	No	REDIAM
13	Environmental	Distance to wild olives	No	REDIAM
14	Environmental	Distance to roads	No	REDIAM
15	Environmental	Distance to urban centers	No	REDIAM
16	Environmental	Phenophase	Yes	APIs
17	Climatic	Minimum temperature	Yes	RIA
18	Climatic	Average temperature	Yes	RIA
19	Climatic	Maximum temperature	Yes	RIA
20	Climatic	Precipitation	Yes	RIA
21	Climatic	Accumulated precipitation[b]	Yes	RIA
22	Climatic	Minimum humidity	Yes	RIA
23	Climatic	Average humidity	Yes	RIA
24	Climatic	Maximum humidity	Yes	RIA
25	Climatic	Radiation	Yes	RIA
26	Climatic	Evapotranspiration	Yes	RIA
27	Climatic	Accumulated evapotranspiration[b]	Yes	RIA
28	Climatic	Wind direction	Yes	RIA
29	Climatic	Wind speed	Yes	RIA
30	Human intervention	Chemical treatment	Yes	APIs

Abbreviations: APIs, Asociaciones de Producción Integrada; CNIG, Centro Nacional de Información Geográfica; REDIAM, Red Ambiental de Andalucía; RIA, Red de Información Agroclimática de Andalucía.

[a]Variables were interpolated over a grid with cells of 1 km^2; the values of these variables were calculated from the eight neighboring cells of the corresponding predictor.

[b]Accumulated precipitation/evapotranspiration from the last 1 September (start of hydrological year for the region).

predictors for each field measurement. In this step, we also created variables that represent the conditions of the *n* previous weeks (i.e., time-lagged predictors). This procedure is illustrated in Figure 2. For the modeling process, we decided to use a time lag of 5 weeks, because under optimal conditions, a complete OFF generation cycle takes about 30–35 days (Rice, 2000; Zalom et al., 2009).

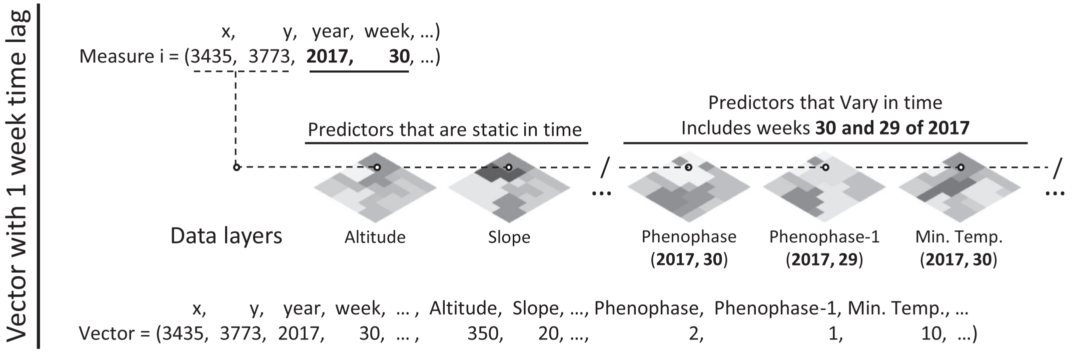

FIGURE 2 Using location and time stamp to prepare vectors with 1-week time lag of the predictors for each measurement. Min. Temp, minimum temperature; Phenophase-1, phenophase of 1 week before the measurement

Additionally, during this step we also created 24 derived variables as defined in Table 3. The procedure to create these variables is illustrated in Figure 3.

3.3 | Modeling process and validation

We started the modeling process with 129 candidate variables: 15 static independent variables and 15 dynamic independent variables for which we use the week of the measurement and the previous 5 weeks (i.e., 90 variables in total, see Table 2), and 24 derived variables as defined in Table 3. After removing any predictor with a constant value, we identified and removed predictors with high multi-collinearity. For the latter, we iteratively removed variables until the remaining ones had a variance inflation factor (VIF) of less than 10 (Marquaridt, 1970; Montgomery & Peck, 1982). The VIF measures the correlation between variables, which can be used to detect and remove redundant predictors. This is important because adding highly correlated variables increases the model's complexity but contributes little to its accuracy. The high number of predictor variables might cause type I errors. To reduce the false discovery rate (FDR), we used the procedure proposed by Benjamini and Hochberg (1995), keeping only predictors that are significant when tested on $q = 0.05$. This is crucial because as the number of performed hypothesis tests increases, the probability of obtaining false positives also increases; the FDR is the ratio of false positives to total positives, therefore the controlling procedures aim to limit the tolerance for that ratio. Finally, we used forward–backward stepwise logistic regression based on statistical significance to select a linear combination of variables. The importance of each variable within the model was assessed using the Wald test. This test measures whether there is a significant difference in the model's accuracy with and without a predictor, therefore it provides evidence to decide if a predictor should be included or not.

To assess whether the modeling process results in overfitting of the models, we performed a cross-validation test. We used the repeated hold-out method on each dependent variable, and generated boxplots (for sensitivity, specificity, and correct classification rate—based on a favorability threshold of 0.5) to compare the models' classification performance. We ran a total of 100 tests for each dependent variable. For each test, we split the dataset into training and testing datasets, using a random sample with substitution of 20% of the observations as testing dataset, and the remaining 80% of the observations as training dataset.

Once we tested that the modeling procedure was not generating overfitted models, we produced models using all the observations. We assessed the models' quality based on classification and discrimination capacity. For the classification capacity, we used sensitivity (i.e., proportion of correctly classified positives with respect to total positives), specificity (i.e., proportion of correctly classified negatives with respect to total negatives),

TABLE 3 List of derived variables

Derived variable	# Variables	Base variable
Consecutive weeks with [low, optimum, high] minimum temperature	3	Minimum temperature
Consecutive weeks with [low, optimum, high] average temperature	3	Average temperature
Consecutive weeks with [low, optimum, high] maximum temperature	3	Maximum temperature
Consecutive weeks with [low, medium, high] minimum humidity	3	Minimum humidity
Consecutive weeks with [low, medium, high] average humidity	3	Average humidity
Consecutive weeks with [low, medium, high] maximum humidity	3	Maximum humidity
Consecutive weeks [with, without] precipitation	2	Precipitation
Amount of precipitation in weeks	1	Precipitation
Amount of evapotranspiration in weeks	1	Evapotranspiration
Consecutive weeks [with, without] chemical treatment	2	Chemical treatment

Note: Variables of the type "consecutive weeks with/without" are computed starting from the week of the measurement and moving backwards to a maximum of five previous weeks.

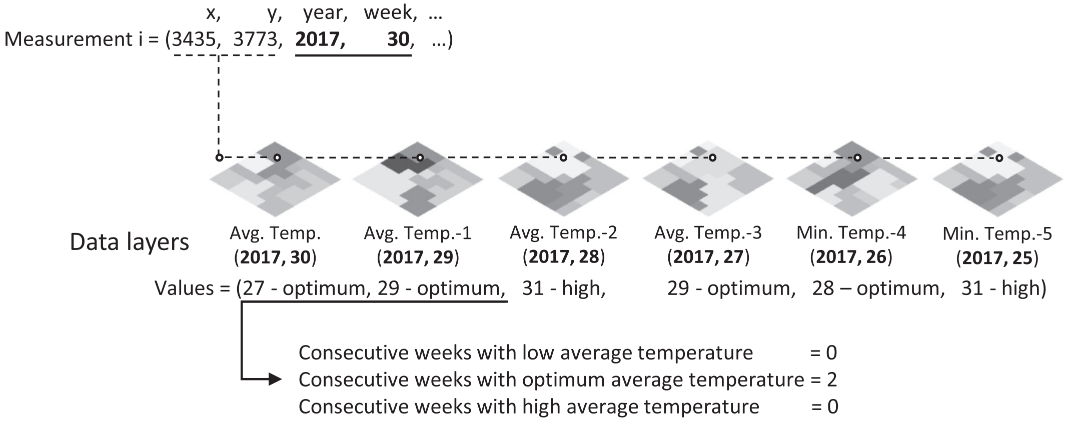

FIGURE 3 Creation of derived variables for average temperature. Avg. Temp, Average temperature; Avg. Temp.-*N*, average temperature of *N* weeks before

correct classification rate (i.e., proportion of correctly classified observations with respect to total observations), and Cohen's kappa (which measures the reliability of the classifier while accounting for the probability of correct results obtained by chance); all of them based on a favorability threshold of 0.5. For the discrimination capacity (i.e., capacity to separate positive and negative instances), we used the area under the ROC curve (AUC). The ROC curve is a graphical summary of the sensitivity and specificity values for different thresholds, ranging between 0 and 1, and the AUC is the value of a given threshold, in our case 0.5.

4 | COLLABORATIVE GEO-VISUAL ANALYTICS PROTOTYPE

4.1 | System overview

As part of the wider objective to improve pest control, we developed a GVA prototype to enable stakeholders such as field technicians, authorities, researchers, and landowners to analyze the dynamics of a pest, and to support decision-making regarding the monitoring and control of it. Figure 4 shows a simplified overview of the components of the system. In the system, field technicians provide monitoring data which are combined with other relevant datasets and processed using application-specific processing functionality (i.e., the favorability models). The monitoring data and processing outputs are available through a web-based visual interface that enables collaborative analysis among the stakeholders.

The prototype supports collaborative analysis by implementing a novel approach called spatial-temporal analysis spaces (STAS), designed by us. It is an approach for long-term distributed asynchronous collaborative analysis in GVA environments. The main assumption of its design is that in data spaces with large spatial and temporal extents, features of interest such as patterns (e.g., pest population outbreak) and outliers (e.g., unrealistic high pest population abundance) occur in different locations and times. Therefore, enabling the analysts to create analysis spaces with a well-defined context, which includes a description of the feature of interest (i.e., thematic context) and spatial and temporal boundaries for it (i.e., spatial and temporal context), helps to focus the attention of the analysts on the feature of interest, eliciting sensible contributions and leading to the generation of meaningful knowledge. Inside the analysis spaces, the bounded data are highlighted, and analysts can use collaborative techniques such as discussion forums and storytelling to analyze the feature of interest. In our prototype, the implemented collaborative technique allows analysts to post and answer questions regarding the feature of interest. Additionally, STAS allows us to create links between related analysis spaces, so that knowledge can be generated from previous contributions, therefore STAS supports a long-term incremental knowledge-building process. Figure 5 shows the STAS interface integrated in the GVA environment.

While the system aims to provide general support for pest management efforts, this article focuses on the potential of the system to enable modelers (e.g., researchers) to communicate their results to other stakeholders with valuable domain and local knowledge (e.g., authorities and technicians), so that the latter can help to validate such processing methods. Once validated, the developed models and methods could become part of the stakeholders' analytics toolbox for daily use.

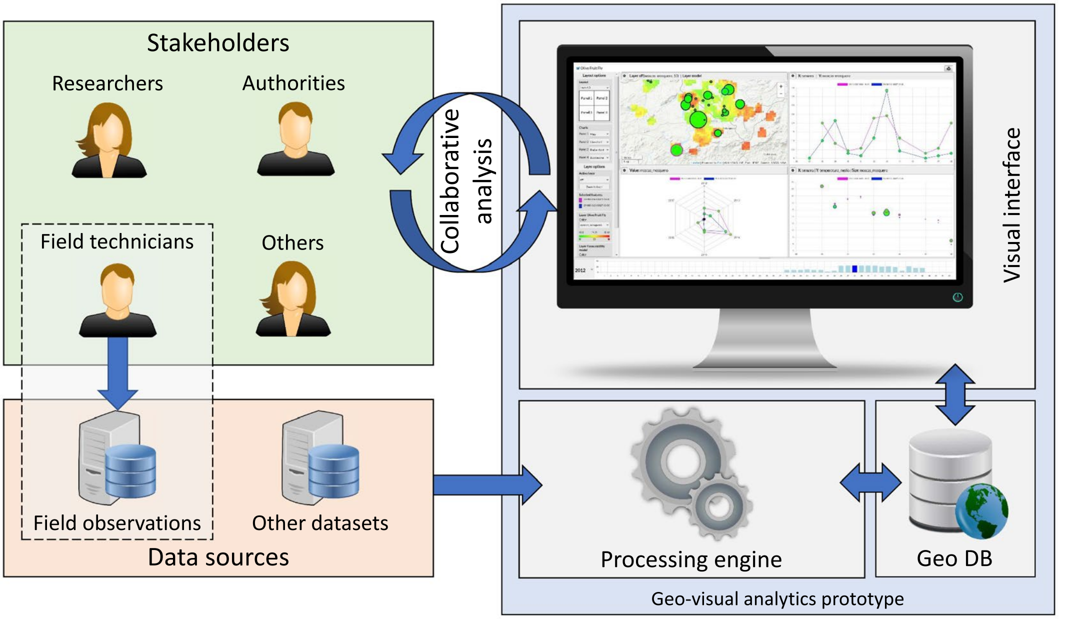

FIGURE 4 The GVA system aims to support stakeholders to understand the development of a pest, and support decision-making regarding control measurement and assess their effectiveness

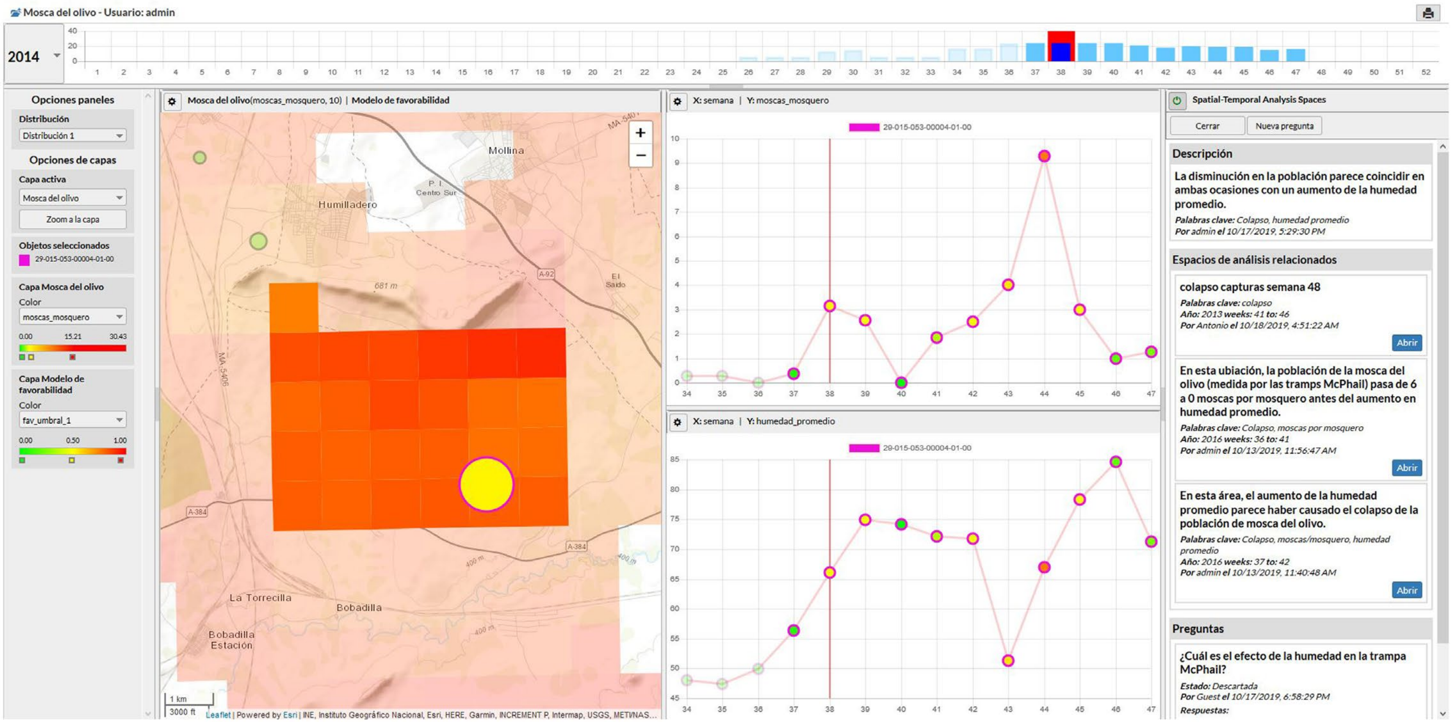

FIGURE 5 The data inside the analysis spaces are highlighted in the visual components to focus analysts' attention. The panel on the right displays the analysis space description, the linked analysis spaces, and the questions and answers about the feature of interest

4.2 | Integration of the prototype and models

The integration of the prototype and the favorability models was implemented through a shared database. To this end, we used the models to produce favorability maps for the monitoring seasons 2012 to 2018 at a spatial resolution of 1 km^2 for the study area, specifically for 1,162 grid cells where the olive crops are located, and a temporal resolution of 1 week. Those maps were stored according to the prototype's database structure, which enables it to expose the maps through the web interface. To create the maps, we prepared one file for each week of the study period, which contains 1,162 rows with the locations of interest and time stamps (which are constant within each file, because each file corresponds to a specific week). Then, for each file, we used the coordinates and time stamps to produce vectors of the predictors following the same procedure as with the field measurements. Later, we used the models to produce the favorability weekly maps. These maps show how favorable or detrimental the conditions were at locations and in times of interest for OFF development.

4.3 | Evaluation by stakeholders

The prototype was tested by seven stakeholders: one authority representative, one researcher, and five field technicians. Their expertise regarding spatiotemporal analysis and GIS varies from one very skilled user (i.e., the researcher) to others with no expertise at all. They all have domain and local knowledge about OFF, and were involved in some degree throughout the prototype's development. They all use computers and mobile devices on a daily basis, therefore they can be considered technology literate at an operational level. All participants were trained to use the prototype, and then were asked to use the prototype to explore the monitoring data and the models' outputs, and to perform activities that require the use of exploration and collaboration tools.

The test consisted of an evaluation form[4] divided into four sections. The first section aimed to train the participants to use the prototype; it asked them to watch a series of videos explaining how to use the prototype's features, try each of them, and rate several statements about those features on a five-step scale ranging from "strongly disagree" to "strongly agree." The reason for using this scale is consistency throughout the four sections, because the third section uses the system usability scale (SUS) (Brooke, 1986), and this approach uses the aforementioned five-step scale. The second section aims to assess the ease of performing tasks with the prototype for a trained user and asks participants to perform four tasks with the individual and collaborative tools. Once each task has been completed, the user is asked to assess how easy it was to perform it. The third section uses the SUS, which is a 10-statement questionnaire to evaluate the general usability of the prototype. The responses can be converted to a numerical scale and aggregated to produce a per-test user score on a 100-point scale (Brooke, 1986); those results can then be aggregated by simple averaging. Finally, the fourth section aims to assess the prototype's usefulness for the monitoring and control of pests.

5 | RESULTS

5.1 | Model performance

The cross-validation test shows that the modeling process is not producing overfitted models. Figure 6 shows that on average the performance of the models drops by about 2% for the test datasets. This means that the accuracy of the models on new observations is close to the accuracy achieved during calibration. A large drop in performance would indicate that a model is overfitted and hence generalizes poorly.

The modeling process resulted in the selection of 21 variables for the model based on threshold 1 (hereafter referred to as Model 1), and 10 variables for the model based on threshold 2 (hereafter referred to as Model 2). Tables 4 and 5 show the selected variables, coefficients (β), standard error (SE), Wald test value (Wald), significance (*P*), and VIF for Models 1 and 2, respectively.

Model 1 succeeds in classifying correctly 85% of the cases in which the threshold is exceeded (sensitivity), and 72% of the cases in which it is not (specificity), for a correct classification rate of 77%. In comparison, Model 2 also achieves a sensitivity of 85%, but only a specificity of 67%, for a correct classification rate of 71%. The Cohen's kappa for Model 1 is 0.53 and for Model 2 it is 0.37. According to Landis and Koch (1977), this is moderately good ($0.41 < \kappa < 0.6$) for Model 1, and fair ($0.21 < \kappa < 0.40$) for Model 2. Finally, the discrimination capacity (AUC) for Model 1 is 0.84, while for Model 2 it is 0.81. According to Hosmer and Lemeshow (2000), this is excellent ($0.8 \le$ AUC < 0.9) for both models.

5.2 | Integration of the prototype and models

Figures 7 and 8 show examples of the generated maps together with spatial and temporal summaries of the results. The former shows the spatial distribution of the monitoring points and the percentages of correctly classified observations for each, and the latter shows the number of correctly classified observations per week. The gap between weeks 28 and 34 is due to the absence of field observations, usually because no OFF activity was observed in previous weeks. The visual comparison of those summaries shows that the models' accuracy is not uniform either in space or time, and that in general Model 1 performs better than Model 2. An interesting observation is the accuracy drop around week 37, which we cannot yet explain.

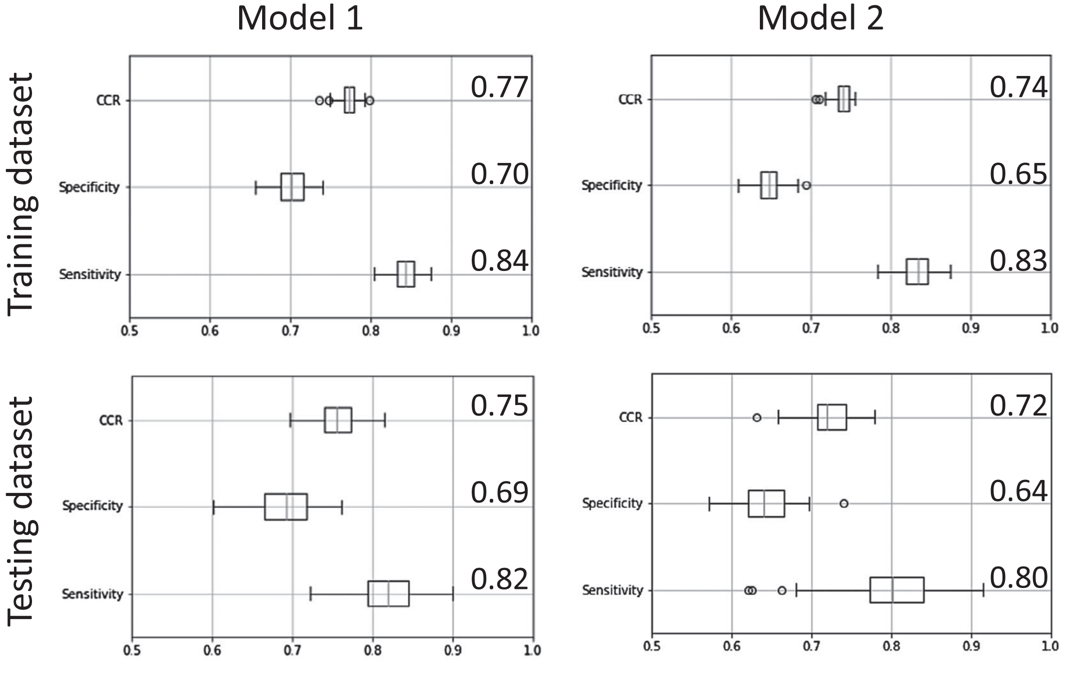

FIGURE 6 Results of the cross-validation test. CCR, correct classification rate; number beside CCR, specificity and sensitivity is the average for that specific boxplot

TABLE 4 Variables included in Model 1. Number in parentheses in a variable name indicates the number of weeks before the measurement

No.	Variable	*B*	*SE*	Wald	*p*	VIF
0	Const.	−1.084	0.079	−13.665	<.001	–
1	Accumulated precipitation (1)	−0.809	0.116	−6.978	<0.001	3.324
2	Minimum temperature (2)	0.897	0.155	5.804	<0.001	5.404
3	Wind speed (3)	−0.620	0.103	−6.034	<0.001	1.892
4	Accumulated evapotranspiration	−0.407	0.123	−3.303	0.001	2.804
5	Accumulated evapotranspiration (2)	−0.235	0.120	−1.973	0.049	4.663
6	Consecutive weeks with medium maximum humidity	0.661	0.099	6.678	<0.001	3.015
7	Maximum humidity (3)	0.384	0.098	3.904	<0.001	2.525
8	Distance to wild olives	−0.334	0.079	−4.231	<0.001	1.280
9	Wind speed (4)	−0.222	0.094	−2.364	0.018	1.834
10	Maximum humidity (1)	0.244	0.115	2.135	0.033	3.072
11	Altitude difference	0.501	0.111	4.517	<0.001	3.097
12	Consecutive weeks with medium minimum humidity	−0.446	0.105	−4.271	<0.001	3.091
13	Distance to in-land water	−0.286	0.069	−4.178	<0.001	1.170
14	Slope difference	−0.275	0.105	−2.632	0.009	2.809
15	Accumulated evapotranspiration (3)	−0.523	0.129	−4.054	<0.001	4.791
16	Consecutive weeks with low maximum temperature	0.546	0.119	4.574	<0.001	2.650
17	Minimum temperature (4)	0.634	0.135	4.689	<0.001	3.375
18	Consecutive weeks with precipitation	0.318	0.082	3.903	<0.001	1.788
19	Maximum humidity (5)	0.291	0.099	2.945	0.003	2.716
20	Consecutive weeks with low minimum humidity	−0.346	0.105	−3.308	0.001	2.787
21	Phenophase (1)	−0.216	0.096	−2.263	0.024	2.390

Abbreviations: β, coefficients' value; *p*, statistical significance; *SE*, standard error; Wald, Wald test value; VIF, variance inflation factor.

Figure 9 shows the interface of the prototype displaying the favorability map for week 36 of 2017, produced by Model 1. The user can choose a specific week from the timeline, located in the upper part of the interface. The timeline displays the distribution of the available data through the (selected) year, thus for the models there are always 1,162 locations with data. However, for the field observations layer it changes from week to week (see Figure 5). The user can select locations of interest and assess their evolution through the year (using the line chart), and compare the values of the locations for the same week across different years (using the radar chart). Additionally, selecting multiple locations allows us to compare between those locations. All the charts (five in total: map, line, radar, bar, and bubble) include several settings to select the variables to be displayed and the visual schema. Using these tools, we visually analyzed the models' outputs during one-on-one sessions with the stakeholders.

TABLE 5 Variables included in Model 2. Number in parentheses in a variable name indicates the number of weeks before the measurement

No.	Variable	β	*SE*	Wald	*p*	VIF
0	Const.	−1.993	0.110	−18.073	<0.001	–
1	Accumulated precipitation (1)	−0.546	0.135	−4.040	<0.001	2.586
2	Altitude difference	0.307	0.069	4.450	<0.001	1.180
3	Accumulated evapotranspiration	−0.665	0.170	−3.914	<0.001	2.499
4	Y	−0.361	0.086	−4.204	<0.001	1.212
5	Accumulated evapotranspiration (2)	−0.573	0.107	−5.331	<0.001	3.013
6	Minimum temperature (2)	0.690	0.117	5.894	<0.001	2.666
7	Wind speed (4)	−0.333	0.097	−3.434	0.001	1.320
8	Consecutive weeks with precipitation	0.202	0.066	3.062	0.002	1.241
9	Maximum humidity (4)	−0.190	0.082	−2.329	0.020	1.584
10	Consecutive weeks with high maximum temperature	−0.309	0.136	−2.274	0.023	2.309

Abbreviations: β, coefficients' value; *p*, statistical significance; *SE*, standard error; VIF, variance inflation factor; Wald, Wald test value.

5.3 | System evaluation[5]

The first section is almost entirely composed of statements with the form “it is easy to…” (i.e., there is one exception), therefore a good result would be a tendency to the “strongly agree” side of the scale. In this section, “strongly agree” alone accounts for 63% of the total answers, and combined with “agree” they account for 98%. The comparison between the responses to the statements regarding the individual tools (i.e., statements 1–12) and the collaborative tool (i.e., statements 13–23) shows a slightly different tendency. While both are mostly within “agree” and “strongly agree,” the statements for the individual tools were rated as “strongly agree” in 73% of the responses, and for the collaborative workspace it was 52%. Post-evaluation discussions with stakeholders suggested two reasons: first, it isn’t straightforward to decide the spatial and temporal boundaries for an analysis space, because the features of interest don’t necessarily have well-defined boundaries; and second, the sections for related analysis spaces and questions don’t have a prominent separation, which results in confusion.

Once the users were trained, they were asked to perform four tasks (Section 2). While the users didn’t have any serious difficulty completing the tasks, it was clear that using the system on their own was harder than following the training videos. In this section, all the statements are “it was easy to complete the task,” therefore, as with Section 1, a good result would be a tendency to the “strongly agree” side of the scale. The majority of responses were for “agree,” which represents 68% of the total responses, and together with “strongly agree” they represent 89%, while the remainder (i.e., 11%) of the responses were “neutral.”

Section 3 is the SUS, which aims to assess the general usability of the prototype. It is important to mention that the statements in this section alternate between positive and negative, therefore a good result would be a tendency to “strongly agree” with positive statements, and “strongly disagree” with negative ones. In total, two users rated the prototype as “okay/fair,” with scores of 67.5 and 70; three rated it as “good,” with scores of 72.5, 75, and 80; and two rated it as “excellent,” with scores of 85 and 90. The total average score is 77.14, which corresponds to the rating of “good” (Bangor, Kortum, & Miller, 2009). This score means that while the prototype is certainly usable, there is room for improvement.

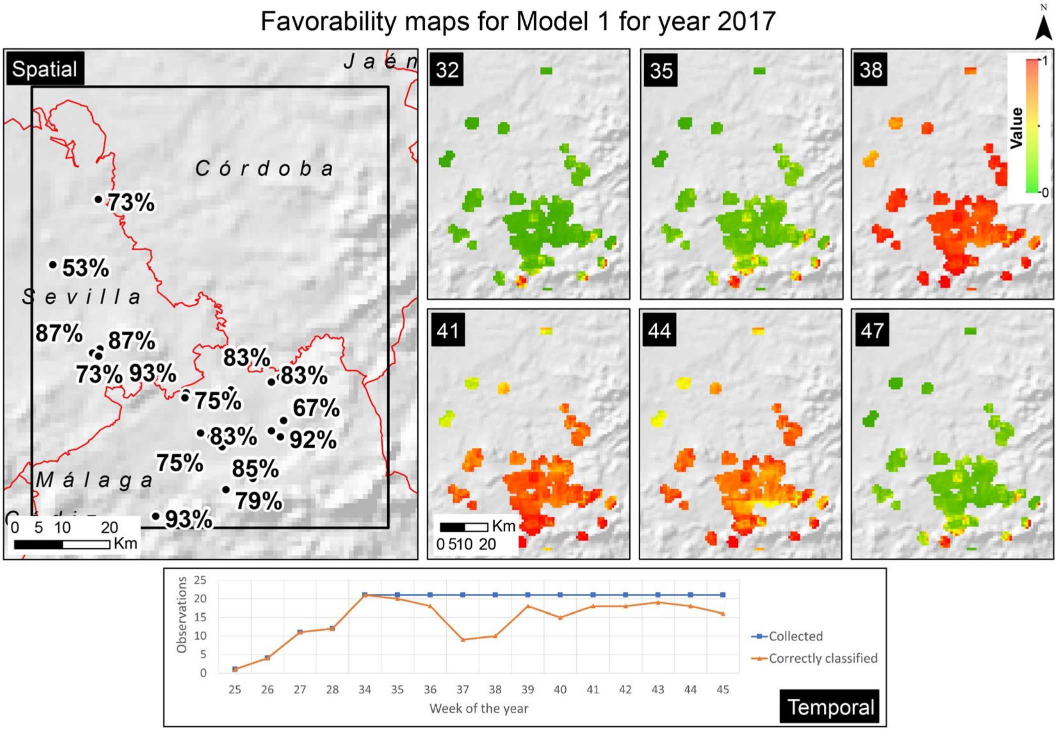

FIGURE 7 (Spatial) The spatial distribution of the monitoring points and the percentage of correctly classified observations. (Temporal) The temporal distribution of the field observations and correctly classified ones. (32–47) The spatial and temporal variation of the favorability for the OFF population to exceed threshold 1 for weeks 32 to 47 (with steps of 3 weeks), in 2017

Section 4 focuses on the prototype's potential usefulness for the monitoring and control of pests. All the statements in this section are positive, therefore a good result would be a tendency to the "strongly agree" side of the scale. The responses were 43% for "strongly agree," 48% for "agree," and 9% for "neutral," which indicates that users considered the prototype to be a useful tool for the monitoring and control of pests. In the post-evaluation discussions, all the users mentioned that they would like the prototype to become a production system, and that it could be of general application for agronomic pests and diseases. Additionally, they suggested potential extensions such as an option to highlight locations and times where a treatment threshold is reached, and producing predictions based on historical data.

6 | DISCUSSION

The existing data is appropriate for practical pest management, but it has deficits that limit its potential use for statistical modeling at high spatial and temporal resolutions. Specifically, the monitoring points change from year to year (i.e., heterogeneous spatial sampling), and data collection in a monitoring point only starts when OFF activity has been observed (i.e., heterogeneous temporal sampling). Therefore, the dataset does not allow us to build robust models. This led to models with excellent discrimination capacity, but low classification capacity, which limits their practical use. Another potential cause for those results is that the OFF population dynamics might be influenced by agricultural practices aimed at controlling other species in the study area, and this potential influence was not accounted for.

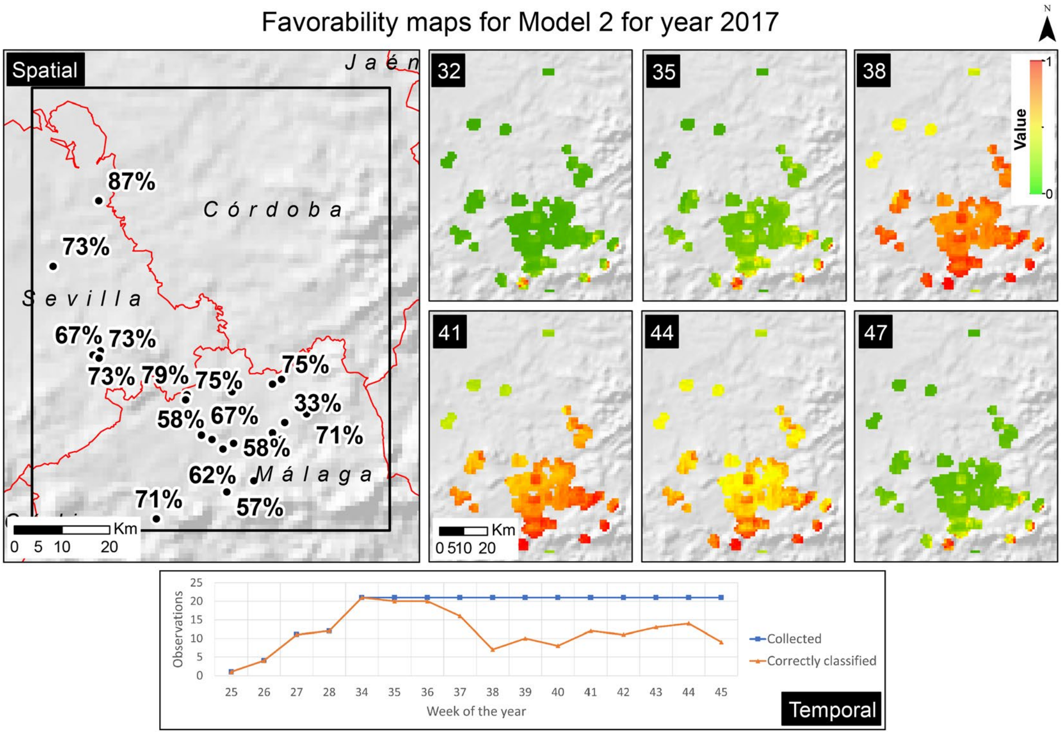

FIGURE 8 (Spatial) The spatial distribution of the monitoring points and the percentage of correctly classified observations. (Temporal) The temporal distribution of the field observations and correctly classified ones. (32–47) The spatial and temporal variation of the favorability for the OFF population to exceed threshold 2 for weeks 32 to 47 (with steps of 3 weeks), in 2017

The weekly maps provide information to aid in the monitoring and control of OFF. For monitoring, they provide context for the field measurements, enabling analysts to quickly assess how favorable or detrimental the conditions were at locations and times of interest, which helps to understand the development and current status of the OFF population. For control, the maps could help to understand better how the chemical treatments change the conditions (in space and time) that influence population development, and how they can be used to design strategies to determine the best locations and times for chemical treatment application.

We analyzed the produced maps with stakeholders in one-on-one sessions and supervised analysis using the GVA prototype. In their opinion, the maps are coherent with known OFF dynamics, for example, areas near the mountains offer more favorable conditions for species development. For this reason, they agree that these maps are a valuable tool for monitoring and control activities. However, it was also noticed that the models tend to overpredict favorable conditions for pest development, which means that they still require fine-tuning.

The stakeholders were able to work independently with the prototype very soon after training, showing that there is a gentle learning curve. We observed the stakeholders experimenting with the tools of the prototype to visualize known dynamics on the monitoring data, and using the resulting visualizations to explain the pest dynamics. A visualization that was produced by all the stakeholders (five on their own, and two with some assistance) was to observe the locations and times at which threshold 1 occurred. In Figure 10, the interface is configured to display this information, and a location is selected to assess how the two variables involved change through the year.

We also observed the stakeholders selecting diverse locations and comparing the favorability values against different predictors, especially temperature, precipitation, and humidity. For example, Figure 11 shows that

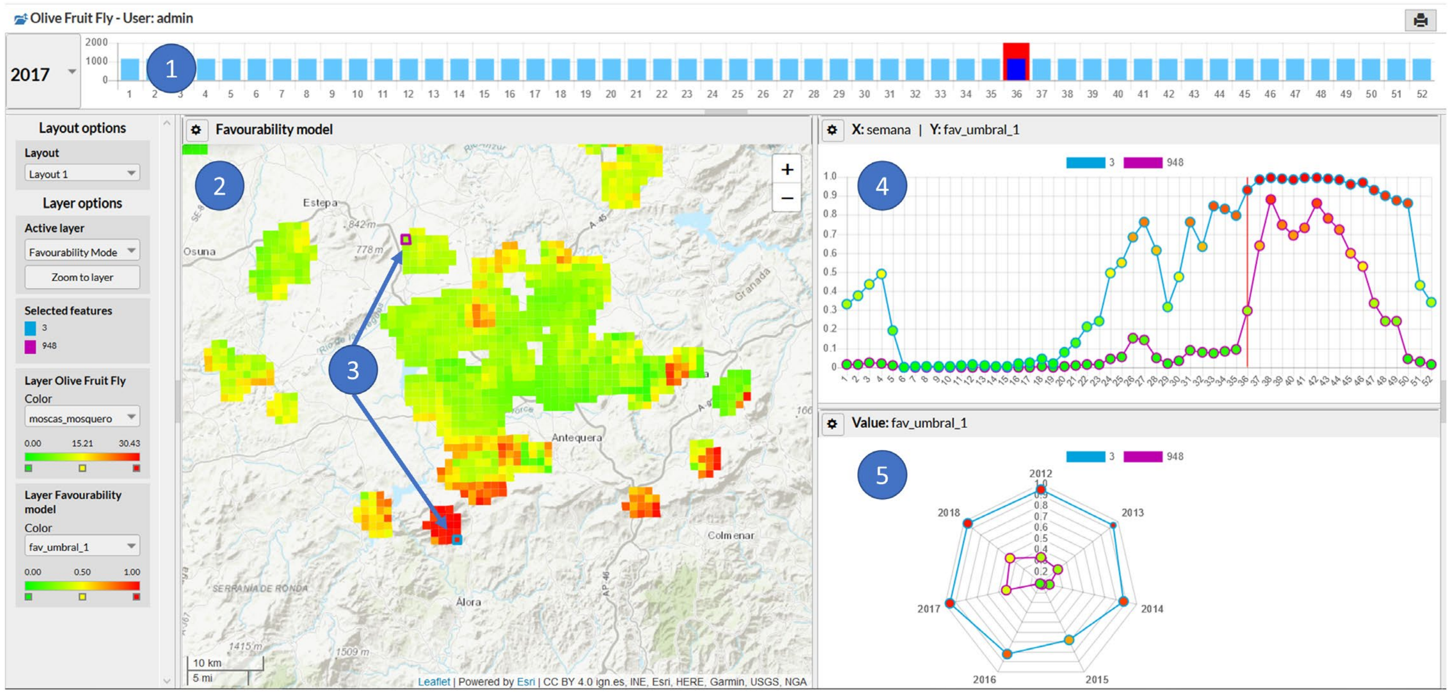

FIGURE 9 GVA prototype interface. (1) The timeline displays the distribution of available data over the selected year, in this case 2017. (2) The map view displays the spatial distribution of favorability for a given week of the year, in this case week 36 of 2017. (3) Two locations of interest are selected, and detailed information is shown in 4 and 5. (4) The line chart shows the evolution of a variable for locations of interest through the year. (5) The radar chart shows the values of a variable for the same week in different years

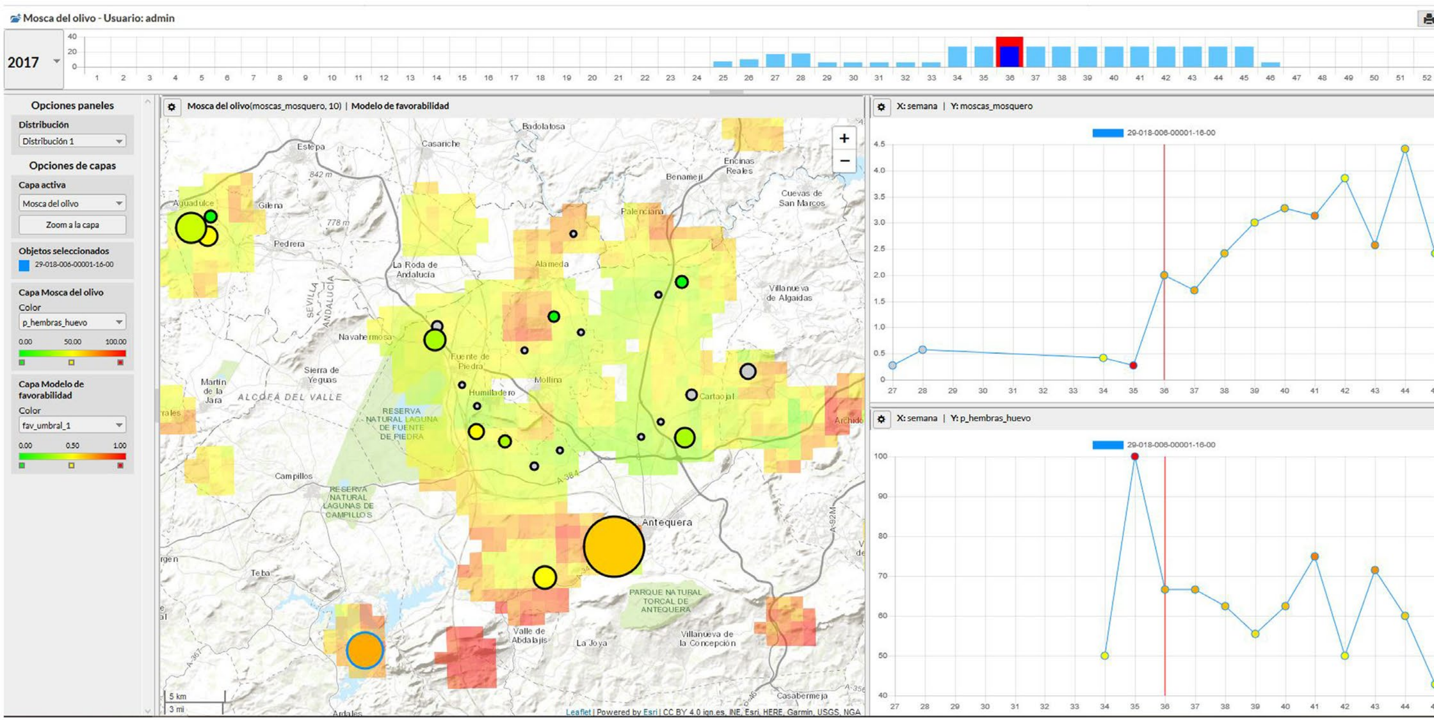

FIGURE 10 Stakeholders used the prototype to visualize the locations and times at which threshold 1 occurred. With this aim, they configured the map to show the number of flies per flycatcher per day as the size of the circles, and the color ramp represents the percentage of female flies with eggs. Additionally, two line charts were configured to show the evolution of the two variables along the year; the upper one shows the number of flies per flycatcher per day, and the lower one the percentage of female flies with eggs

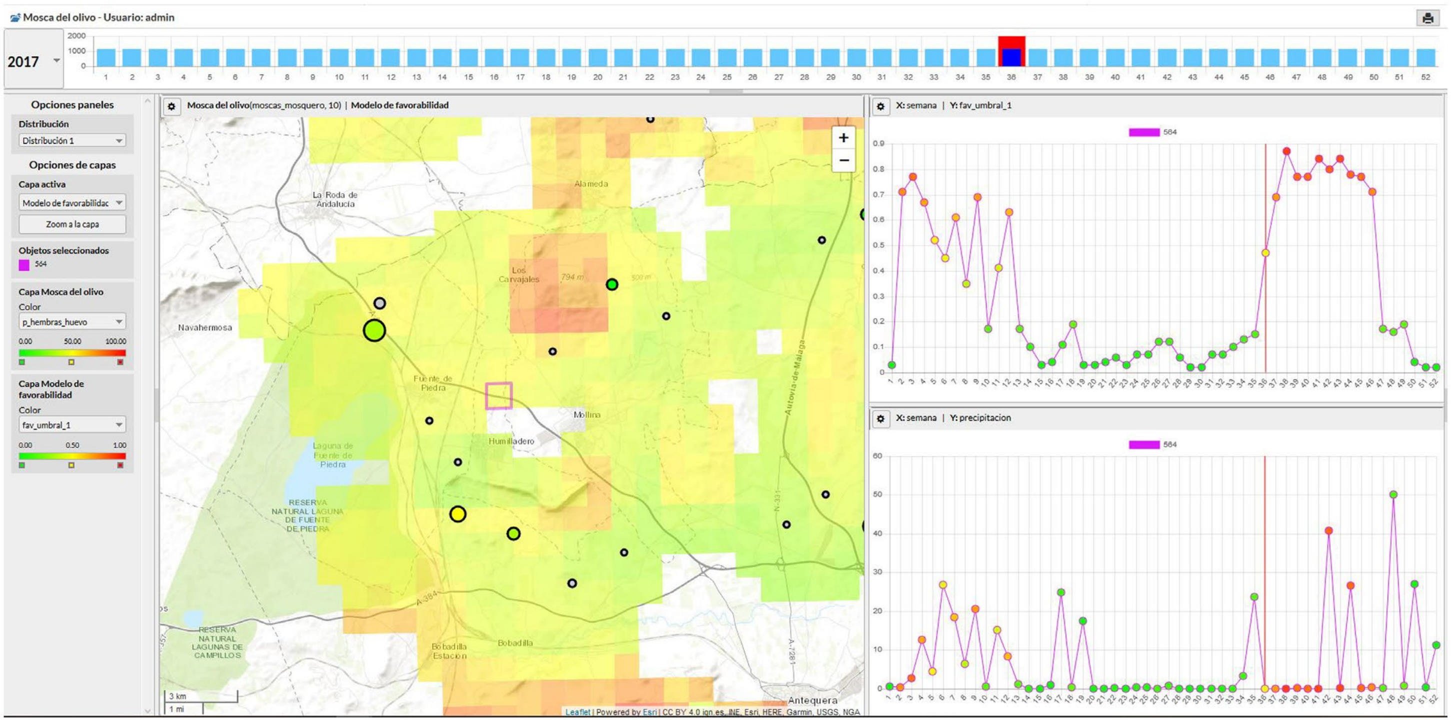

FIGURE 11 Stakeholders used two line charts to visualize the effect of the various predictors on the favorability values. In this example, the favorability values are shown in the upper chart and weekly precipitation is shown in the lower one

favorability values are clearly influenced by precipitation. It was from this exercise that they pointed out that while the selected predictors for the models are correct, and the general patterns fit with the known OFF dynamics, the models tend to overestimate favorable conditions for pest development.

The results show that the general stakeholders' opinion is that the models and prototype are valuable tools for OFF management. This is supported by the responses to the evaluation form, and by the direct claims from the stakeholders to be willing to see it becoming a production system to support their work. Some characteristics of GVA that were deemed relevant are: it enables a stakeholder without knowledge of GIS to work with complex geodata sets, which has the potential to improve their understanding of the spatiotemporal dynamics of a pest; it enables asynchronous collaborative analysis among geographically distant stakeholders, which removes the constraints of time and location on participation in the analysis effort; and it has the potential to effectively support the design of eco-friendly and cost-effective control strategies. Additionally, this case study showed that GVA can enable stakeholders to work with the outputs of advanced processing methods, and use their domain and local knowledge to provide feedback to improve and validate such methods.

Finally, the models and prototype can be used to simulate and perform visual analysis of different scenarios such as early/late spring, years with low/high precipitation, and different strategies to apply chemical treatment. With this aim, the values of the predictors can be adjusted to represent the simulated conditions, using the model to assess how the pest dynamics are influenced. This has the potential to improve stakeholders' understanding of how different conditions may affect the development of the species, and how they favor or prevent it becoming a pest. This knowledge can become an important input in the development of IPM programs.

7 | CONCLUSIONS

The results of the models' calibration show that the models created from existing data produced for practical pest management have excellent discrimination capacity, but low classification capacity, thus with potentially limited application in practice. Additionally, the analysis of the weekly favorability maps show that the models capture known OFF dynamics, but tend to overpredict favorable conditions. Therefore, the produced models are not very accurate in terms of capturing the spatiotemporal dynamics of the OFF population. We currently see two options to improve the presented results: first, by looking for potential predictors that were not identified during this attempt to build the models; second, by exploring the potential of using a spatiotemporally explicit model to yield the probabilities that will later be transformed into favorability values. On the positive side, the combination of modeling and GVA prototype gives clear indications and guidelines how to improve the spatial and temporal sampling. This will not require any change in the monitoring protocol, and has the potential to greatly improve the quality of the dataset.

The results of the prototype's testing provided evidence that stakeholders find the prototype useful to analyze the pest monitoring data and models' outputs. Of special relevance is that all stakeholders claim to be willing to see the prototype becoming a production system. Additionally, it was evident that the prototype has a smooth learning curve and provided an effective mechanism to analyze the pest's spatiotemporal dynamics. Regarding the support for collaborative analysis, the prototype also received a positive evaluation, although it was slightly harder for the stakeholders to grasp how it works. The stakeholders especially appreciated the possibility of contributing regardless of location or time, and building upon previous contributions. Finally, our experience during this exercise suggests that GVA has the potential to help bridge the gap between data science and practical pest management.

ACKNOWLEDGMENTS

The authors appreciate the knowledge and data provided by Emilio García (Departamento de Sanidad Vegetal, Malaga, Spain), Antonio Sánchez (Asociación de Producción Integrada "Antequera," Malaga, Spain), and Gonzalo Reina (Asociación de Producción Integrada "La Camorra," Malaga, Spain).

ORCID

Gustavo Adolfo García-Chapeton https://orcid.org/0000-0001-6709-4783
Frank O. Ostermann https://orcid.org/0000-0002-9317-8291

ENDNOTES

[1] Hole in the olive fruit where the OFF egg was laid.

[2] Available in Spanish at https://www.juntadeandalucia.es/agriculturaypesca/portal/export/sites/default/comun/galerias/galeriaDescargas/minisites/raif/manuales_de_campo/ProtocolosCampos_Olivar.pdf

[3] Available in Spanish at http://www.juntadeandalucia.es/boja/2008/83/d2.pdf

[4] It was applied in Spanish, because all the stakeholders are native Spanish speakers. For the interested reader, the form is available as Supporting Information.

[5] The responses to the evaluation form are available in a tabular format as Supporting Information.

REFERENCES

Acevedo, P., & Real, R. (2012). Favourability: Concept, distinctive characteristics and potential usefulness. *Naturwissenschaften*, *99*(7), 515–522.

Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M. J., MacEachren, A., & Wrobel, S. (2007). Geovisual analytics for spatial decision support: Setting the research agenda. *International Journal of Geographical Information Science*, *21*(8), 839–857.

Andrienko, G., Andrienko, N., Keim, D., MacEachren, A. M., & Wrobel, S. (2011). Challenging problems of geospatial visual analytics. *Journal of Visual Languages & Computing*, *22*(4), 251–256.

Bangor, A., Kortum, P., & Miller, J. (2009). Determining what individual SUS scores mean: Adding an adjective rating scale. *Journal of Usability Studies*, *4*(3), 114–123.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, Series B (Methodological)*, *57*(1), 289–300.

Brooke, J. (1986). SUS: A quick and dirty usability scale. In P. Jordan, B. Thomas, I. McClelland, & B. Weerdmeester (Eds.), *Usability evaluation in industry* (pp. 189–194). London, UK: CRC Press.

Broufas, G., Pappas, M., & Koveos, D. (2009). Effect of relative humidity on longevity, ovarian maturation, and egg production in the olive fruit fly (Diptera: Tephritidae). *Annals of the Entomological Society of America*, *102*(1), 70–75.

Extenda. (2017). *Estudio del sector del aceite de oliva de Andalucía*. Retrieved from https://www.extenda.es/wp-content/uploads/2018/01/ESTUDIO-DEL-ACEITE-DE-OLIVA-EN-ANDALUCIA-2017.pdf

FAO. (2005). *Impact of climate change, pests and diseases on food security and poverty reduction*. Retrieved from http://www.fao.org/unfao/bodies/cfs/cfs31/cfs2005_events_en.htm

FAO. (2017). *AGP-integrated pest management*. Retrieved from http://www.fao.org/agriculture/crops/core-themes/theme/pests/ipm/en/

Gilioli, G., Pasquali, S., & Marchesini, E. (2016). A modelling framework for pest population dynamics and management: An application to the grape berry moth. *Ecological Modelling*, *320*, 348–357.

Gutierrez, A. P., Ponti, L., & Cossu, Q. A. (2009). Effects of climate warming on olive and olive fly (*Bactrocera oleae* (Gmelin)) in California and Italy. *Climatic Change*, *95*(1), 195–217.

Herzfeld, D., & Sargent, K. (2017). Integrated pest management. In N. Goodman (Ed.), *Private pesticide applicator safety education manual* (19th ed., pp. 1–34). St. Paul, MN: University of Minnesota Extension.

Ho, Q. (2013). *Architecture and applications of a geovisual analytics framework* (Unpublished PhD dissertation). Linköping, Sweden: Linköping University.

Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression* (2nd ed.). New York, NY: John Wiley & Sons.

Ivana, D., Antonela, K., Renata, B., & Jasminka Igrc, B. (2010). Geographic information systems (GIS) and entomological research: A review. *Journal of Food, Agriculture & Environment*, *8*(2), 1193–1198.

Janicki, J., Guo, C., Conway, M., Donohue, R., & Roth, R. E. (2014). Weevil Viewer: An interactive mapping application for geographic and phenological exploration of Wisconsin's primitive weevils. *Journal of Maps*, *10*(2), 289–296.

Kalamatianos, R., Kermanidis, K., Avlonitis, M., & Karydis, I. (2016). Environmental impact on predicting olive fruit fly population using trap measurements. In L. Iliadis & I. Maglogiannis (Eds.), *Artificial intelligence applications and innovations: AIAI 2016* (IFIP Advances in Information and Communication Technology, Vol. *475*, pp. 180–190). Cham, Switzerland: Springer.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174.

Marquaridt, D. W. (1970). Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. *Technometrics*, *12*(3), 591–612.

Miranda, M. Á., Barceló, C., Valdés, F., Feliu, J. F., Nestel, D., Papadopoulos, N., ... Alorda, B. (2019). Developing and implementation of Decision Support System (DSS) for the control of olive fruit fly, *Bactrocera Oleae*, in Mediterranean olive orchards. *Agronomy*, *9*(10), 620.

Montgomery, D. C., & Peck, E. A. (1982). *Introduction to linear regression analysis*. New York, NY: John Wiley & Sons.

Muñoz, A.-R., Jiménez-Valverde, A., Márquez, A. L., Moleón, M., & Real, R. (2015). Environmental favourability as a cost-efficient tool to estimate carrying capacity. *Diversity & Distributions*, *21*(12), 1388–1400.

Nardi, F., Carapelli, A., Dallai, R., Roderick, G. K., & Frati, F. (2005). Population structure and colonization history of the olive fly, *Bactrocera oleae* (Diptera, Tephritidae). *Molecular Ecology*, *14*(9), 2729–2738.

Olivero, J., Fa, J. E., Real, R., Márquez, A. L., Farfán, M. A., Vargas, J. M., ... Nasi, R. (2017). Recent loss of closed forests is associated with Ebola virus disease outbreaks. *Scientific Reports*, *7*(1), 14291.

Olivero, J., García, E. J., Wong, M. E., & Ros, J. P. (2004). Ensayo de eficacia de diferentes combinaciones soporte-atrayente para el trampeo de "Bactrocera oleae" (Gmel.). *Mosca del Olivo. Boletín de Sanidad Vegetal – Plagas*, *30*(2), 439–450.

Olivero, J., Toxopeus, A. G., Skidmore, A. K., & Real, R. (2016). Testing the efficacy of downscaling in species distribution modelling: A comparison between MaxEnt and favourability function models. *Animal Biodiversity & Conservation*, *39*(1), 99–114.

Pontikakos, C. M., Tsiligiridis, T. A., & Drougka, M. E. (2010). Location-aware system for olive fruit fly spray control. *Computers & Electronics in Agriculture*, *70*(2), 355–368.

Rafikov, M., & Balthazar, J. M. (2005). Optimal pest control problem in population dynamics. *Computational & Applied Mathematics*, *24*, 65–81.

Ramos, L., Silva, L., Santos, M. Y., & Pires, J. M. (2015). Detection of road accident accumulation zones with a visual analytics approach. *Procedia Computer Science*, *64*, 969–976.

Real, R., Barbosa, A. M., & Vargas, J. M. (2006). Obtaining environmental favourability functions from logistic regression. *Environmental & Ecological Statistics*, *13*(2), 237–245.

Rice, R. E. (2000). Bionomics of the olive fruit fly Bactrocera (Dacus) oleae. *Plant Protection Quarterly*, *10*, 1–5.

Rodrigo, T.-M. (2020). Exploring the use of a spatio-temporal city dashboard to study criminal incidence: A case study for the Mexican State of Aguascalientes. *Sustainability*, *12*(6), 2199.

Romero, D., Báez, J. C., Ferri-Yáñez, F., Bellido, J. J., & Real, R. (2014). Modelling favourability for invasive species encroachment to identify areas of native species vulnerability. *Scientific World Journal*, *2014*, 519710.

Tepley, A. J., Juan Paritis, J., & Veblen, T. T. (2012). Outbreak species. In R. K. Craig, J. C. Nagle, B. Pardy, O. Schmitz, & W. Smith (Eds.), *The Berkshire encyclopedia of sustainability* (Ecosystem Management and Sustainability, Vol. *5*, pp. 98–102). Great Barrington, MA: Berkshire Publishing.

Thomas, J., & Cook, K. (2005). *Illuminating the path: The research and development agenda for visual analytics*. Richland, WA: Pacific Northwest National Laboratory, National Visualization and Analytics Center.

Tomaszewski, B. M., Robinson, A. C., Weaver, C., Stryker, M., & MacEachren, A. M. (2007). Geovisual analytics and crisis management. In *Proceedings of the Fourth International Conference on Information Systems for Crisis Response and Management*, Delft, the Netherlands (pp. 173–179).

Voulgaris, S., Stefanidakis, M., Floros, A., & Avlonitis, M. (2013). Stochastic modeling and simulation of olive fruit fly outbreaks. *Procedia Technology*, *8*, 580–586.

Williams, D. T., Straw, N., Townsend, M., Wilkinson, A. S., & Mullins, A. (2013). Monitoring oak processionary moth *Thaumetopoea processionea* L. using pheromone traps: The influence of pheromone lure source, trap design and height above the ground on capture rates. *Agricultural & Forest Entomology*, *15*(2), 126–134.

Wong, P. C., & Thomas, J. (2004). Visual analytics. *IEEE Computer Graphics & Applications*, *24*(5), 20–21.

Zalom, F. G., Van Steenwyk, R. A., Burrack, H. J., & Johnson, M. W. (2009). *Pest notes: Olive fruit fly*. Retrieved from http://www.ipm.ucdavis.edu/PMG/PESTNOTES/pn74112.html

Zhang, T., Wang, J., Cui, C., Li, Y., He, W., Lu, Y., & Qiao, Q. (2019). Integrating geovisual analytics with machine learning for human mobility pattern discovery. *ISPRS International Journal of Geo-Information*, *8*(10), 434.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the Supporting Information section.

How to cite this article: García-Chapeton GA, Toxopeus AG, Olivero J, Ostermann FO, de By RA. Combining favorability modeling with collaborative geo-visual analysis to improve agricultural pest management. *Transactions in GIS*. 2020;00:1–24. https://doi.org/10.1111/tgis.12714