DELIVERABLE 5.2
Report and performance evaluation of the Spatial Decision Support System (SDSS) for the Olive fly

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Deliverable 5.2 - Report and performance evaluation of the Spatial Decision Support System (SDSS) for the Olive fly

Revision: **v2**

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Statement of originality:

This deliverable contains original unpublished work except where clearly indicated otherwise. Acknowledgement of previously published material and of the work of others has been made through appropriate citation, quotation or both.

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EXECUTIVE SUMMARY

The Entomatic pest management tool relies on olive fly counts made by a tailored trap that includes a bioacoustic sensor. Much effort was put into energy management and making the sensor and communication module as energy efficient as possible. The low power consumption reduces maintenance requirements, especially because batteries should be replaced a limited number of times. During some months, no olive flies are expected and maintenance can be reduced even further by not powering on the sensors. The SDSS includes an indication when sensors should be switched on again to capture the onset of olive fly counts and to perform the first olive fly control measures of the year. The period in which olive flies are active is strongly correlated with olive growth for which altitude and temperature are important environmental predictor variables. Based on data captured in Italy and Spain, a model was established that provides insight in when to expect olive flies to become active.

The SDSS can be considered in three parts: (i) The *B. oleae* spring onset model (ii) The control decision tree and (iii) Additional analysis on the ENTOMATIC Web app. The *B. oleae* spring onset model serves as an early warning system to notify farmers when to turn on the traps in early spring. It runs from the 1st of January and constantly record the change in daily temperature in each of the orchards. When a critical, threshold temperature (TT) is reached the model calculates the growing degree days (GDD) for the orchard and gives an estimate of when the first peak of *B. oleae* is expected. The model uses the link between spring flowering of the olive trees and the onset of the first generation of *B. oleae* (Ponti et al. 2014) to provide anearly warning to the farmers. Air temperature was used as the main factor for estimating the change in olive phenology because this link has been widely demonstrated (Orlandi et al. 2002; Osborne et al. 2000; Galan et al. 2001).

Once the traps are on and the *B. oleae* population increases, a control decision tree (CDT) model is run in parallel with the wireless sensor network (WSN) of traps that provides data on air temperature (T), relative humidity (RH) and olive fruit fly count. Each branch of the decision tree represents a particular pest management strategy whilst the nodes of each branch indicate the decision points. The leaf node is then the final decision to be taken by the orchard manager. Up till now, olive fruit fly control was done on an expert basis only. Now, the CDT allows to optimise control strategies in an ecological sustainable and cost-efficient manner by taking into account objective criteria and harmonized recommendations for spraying decisions against the olive fruit fly. However, there will always be a certain level of uncertainty as it is rarely possible to fully predict the effects of major interventions.

Finally, the system also allows the user to analyse the raw data and look for additional indicators for the necessity of spraying or other control activities with a descriptive statistics module that is integrated in the web-app.

1 SPRING ONSET MODEL

This model was developed to assess the early spring risk of the emergence of *B. oleae*. The model is based on the relationship between the spring peak in the population density of *B. oleae* and the flowering of the olive tree (Ponti et al. 2014). It is integrated in the web ENTOMATIC app and serves as an early warning system to help the growers make an administrative decision on when to start spraying when there is still no count data from the traps. Once all the traps are turned on, the WSN will be sending data on regular basis to the centralized database. Each node of the WSN will send: device ID, GPS coordinates, temperature, humidity, wind and counts of the olive fruit fly. The model relies on three levels for obtaining the environmental variables: (i) WSN data, (ii) Weather API data, (iii) Climate Normals. The most accurate information would be obtained from the WSN system directly from the orchard. If the traps are not yet turned on, environmental data would be pulled automatically from a weather API (Application Programming Interface) from a reliable meteorological data provider. In case this is not available for the coordinates of the olive orchard, Climate Normals will be used as input variables for that region, and will be taken from a prepared database from Avia-GIS. This constitutes three-decade averages of observed climatological variables.

1.1 GDD AND TT MODEL

In the study by Galan et al. (2004) it was found that TT varied from 5 °C to 12.5 °C depending on bio-geographical characteristics of the orchards. We used the data from Galan et al. (2004) and Bonofiglio et al. (2008) in two linear models to describe the change of TT and GDD with elevation (Figure 1.1). A negative slope coefficient for TT implies that the optimal TT is lower for orchards on higher altitudes. The GDD marking the start of flowering increases with altitude. The significance tests for the models are summarised in Table 1.1 and Table 1.2.

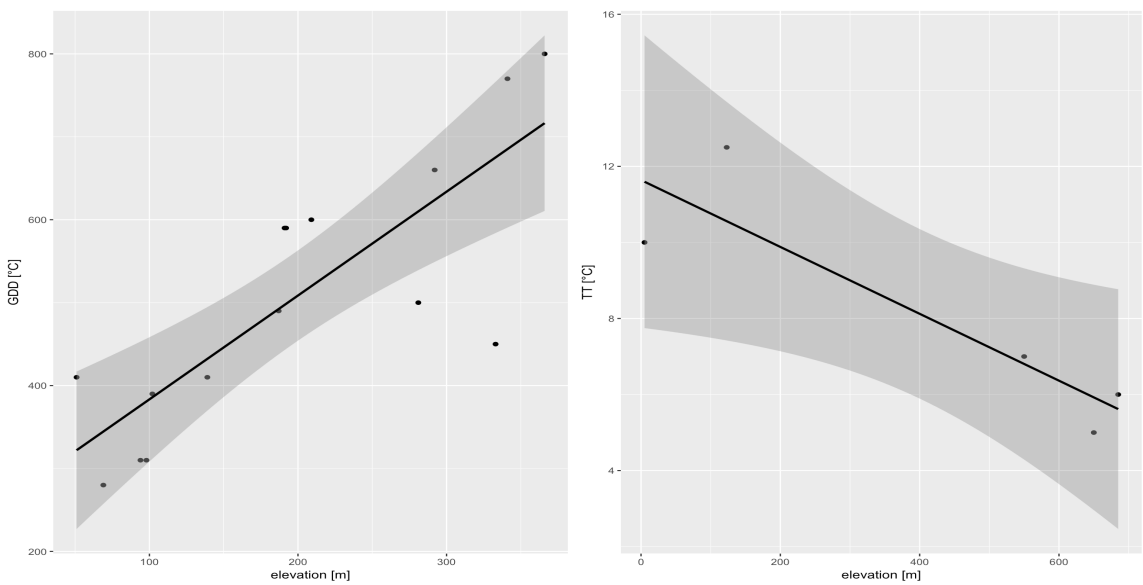


Figure 1.1: Change of GDD (left) and TT (right) with elevation

Table 1.1: Significance test for the GDD model

Formula:	y = 1.2522*x + 258.1507			
Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	258.1507	54.7656	4.714	0.000405
GDD$elev	1.2522	0.2478	5.054	0.000221
Residual standard error:	97.44 on 13 degrees of freedom			
Multiple R-squared:	0.6627			
Adjusted R-squared:	0.6368			
F-statistic:	25.54 on 1 and 13 DF			
p-value:	0.0002209			

Table 1.2: Significance test for the TT model

Formula:	y = -0.008793*x + 11.639936			
Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	11.639936	1.219354	9.546	0.00244
GDD$elev	-0.008793	0.002479	-3.546	0.03819
Residual standard error:	1.566 on 3 degrees of freedom			
Multiple R-squared:	0.8074			
Adjusted R-squared:	0.7432			
F-statistic:	12.58 on 1 and 3 DF			
p-value:	0.03819			

We used the Thermal Time model (TTM) developed by Cannel and Smith (1983). The date of flowering (*y*) expressed as day of the year (DOY) is determined from the equation

$$S_t = \sum_{t_o}^{y} R_f = GDD^* \qquad (2.1)$$

Where S_t is the state of forcing, $R_f(x_t)$ is the forcing rate function and GDD^* is the critical forcing value and T_m is the mean daily temperature. We see that the flower date is reached when the state of forcing is equal to the critical forcing value. The forcing rate function is simply defined as

$$R_f = \begin{cases} 0 & T_m < TT \\ T_m - TT & T_m > TT \end{cases} \qquad (2.2)$$

The following protocol was used for calculating the forcing rate function in the model. Because the model should be able to adapt to different input formats of the temperature data, a different approach is used if the input variables are mean daily temperature values (T_m) and if they are minimum temperature (T_{min}) and maximum temperature (T_{max}). In the first scenario equation (2.2) is used. However, in the second scenario, if we have T_{min} T_{max}, we further distinguish two cases and the forcing rate function is calculated differently. The first case is applied to the situation when the threshold temperature (TT) is below the daily minimum temperature (T_{min}) (Figure 1.2 Right) and the second (Figure 1.2 Left) when the TT is above T_{min} with no upper threshold since maximum spring temperatures are usually not high enough to affect the flowering process.

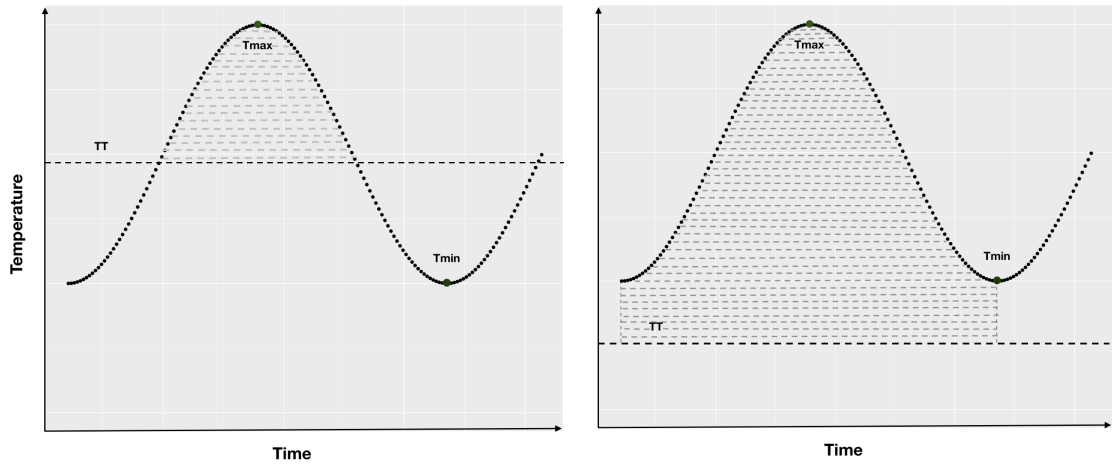


Figure 1.2: Diurnal temperature curve and TT above Tmin (left) and below Tmin (right)

In the second case the degree days are expressed as the area below the diurnal temperature curve, which is approximated using minimum and maximum temperature values and a trigonometric sine curve. The time (t) is represented in radians

$$t = \frac{\pi(h-6)}{12}, \qquad h \in [1,12]$$

$$R_f = \frac{T_{max} + T_{\min}}{2} - TT \qquad T_{min} \geq T_t \qquad (2.3)$$

Where TT is the threshold temperature.
And

$$R_f = \frac{\left[W \int_o^{\frac{\pi}{2}} \sin(t)\, dt - \int_o^{\frac{\pi}{2}} \left(TT - \frac{T_{max} + T_{\min}}{2}\right) dt\right]}{\pi} \qquad T_{min} < TT \qquad (2.4)$$

Where $W = \frac{T_{max} - T_{\min}}{2}$
Or

$$R_f = \frac{\left[\left(\frac{T_{max} + T_{\min}}{2} - TT\right)\left(\frac{\pi}{2} - \theta\right) + W \cos(\theta)\right]}{\pi} \qquad T_{min} < TT \qquad (2.5)$$

Theta (θ) is the time corresponding to the intersection of the diurnal curve and threshold value.

In the following section, we examine the simulated spring onset of *B. oleae* for the Mediterranean region for 2011. An elevation raster (Figure 1.3) was used to calculate the TT (Figure 1.4) and GDD (Figure 1.5) depending on the altitude of each cell. These two values were finally used together with a time series of temperature raster maps to calculate the expected date for the spring onset of the Olive fruit fly (Figure 1.6).

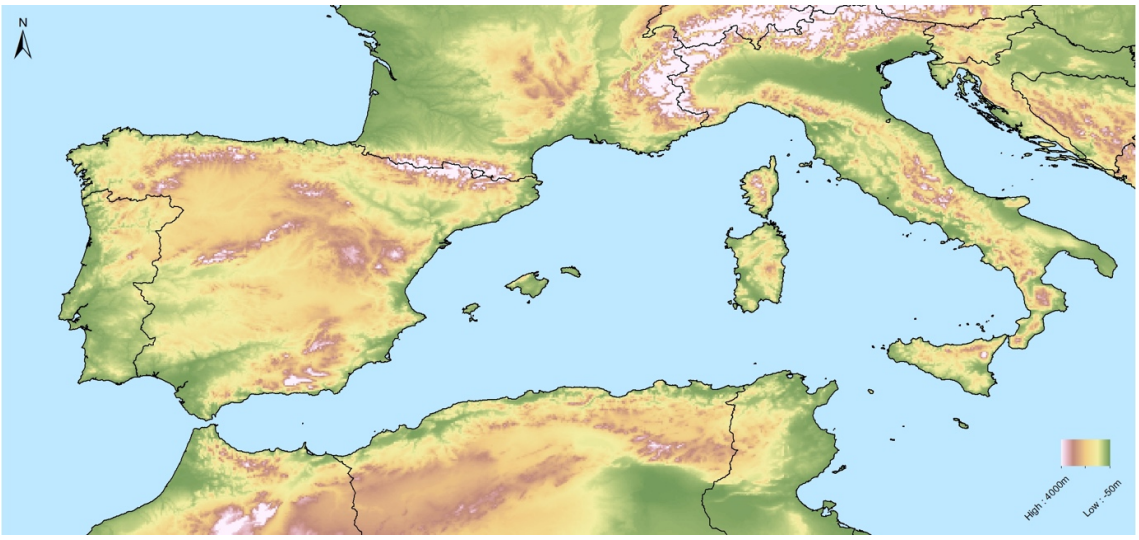


Figure 1.3: Altitude map

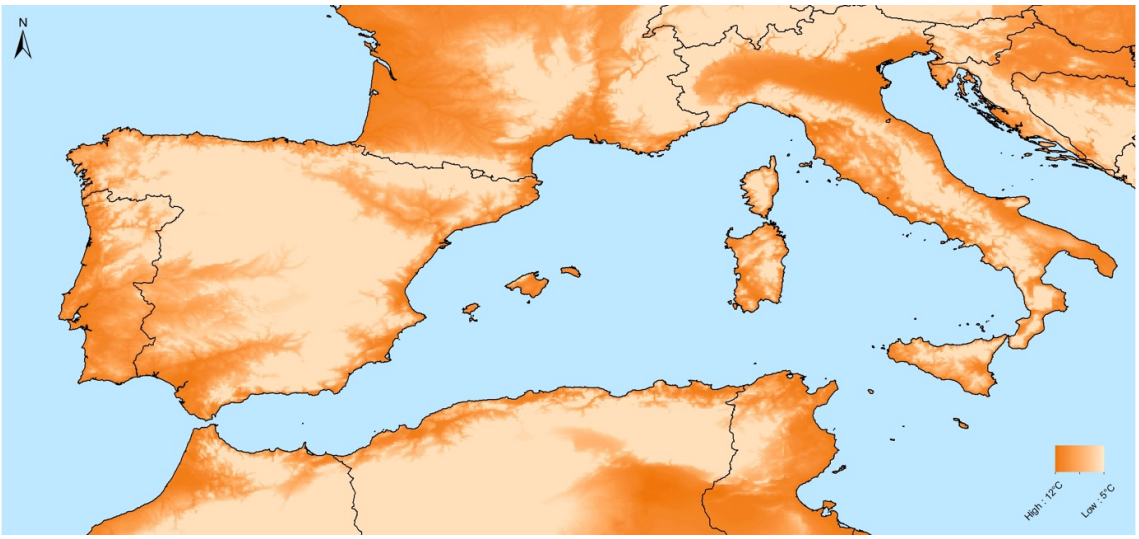


Figure 1.4: TT map

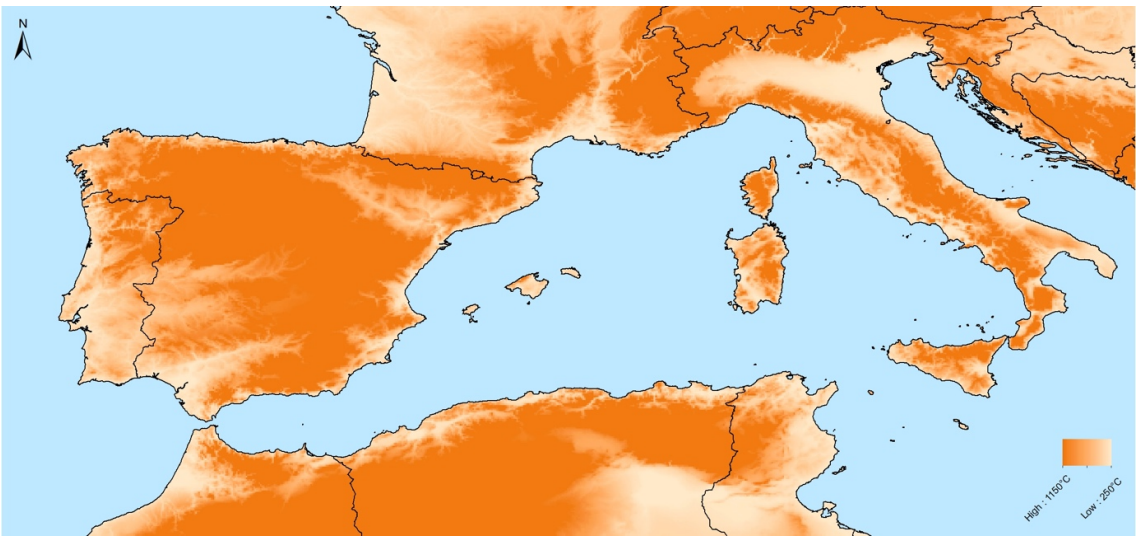


Figure 1.5: GDD map

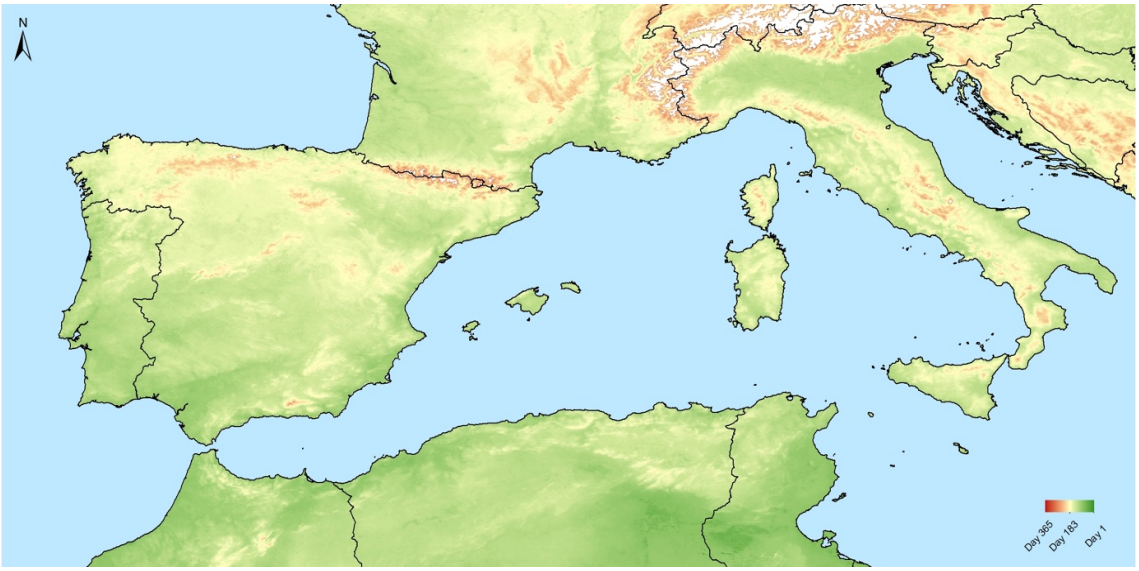


Figure 1.6: Onset map

In (Figure 1.6) the spatial variability in the modelled onset of olive fly activity is shown for 2011. The colour depicts the day number within the year (DOY). Green areas are believed to have an onset early in the year while in yellow or red areas the onset is expected later, assuming of-course that olives are grown in those areas. This entails that the green areas are also more suitable for growing olives, not taking into consideration soil type. Yellow and red areas are not likely to have olive orchards. The later the onset, the shorter the season lasts. White areas indicate where temperature and altitude conditions are unsuitable for olive trees and flies. Besides the spatial variability there is also a temporal variability in the onset of olive fly activity, again linked to temperature. For every location the expected onset can be modelled based on climatological data, weather forecast data and temperature readings from the sensor. The sensor readings are the most accurate to predict the onset of olive fly activity for a specific orchard. However, when this information is not available (e.g. when the sensors are not yet powered on), temperature values are taken from on-line weather services. For future temperature values the model relies on climatological data.

An expected date on which traps have to be powered on and control measures have to be prepared is given from the day the temperature threshold has been reached and updated every time when new temperature data becomes available. New SDSS alerts will be sent by e-mail to the orchard owners so they do not have to sign-in in order to be updated about the latest status.

2 CONTROL DECISION TREE

Once there is information coming from the field a spatial decision support calculates when and where to conduct control using relevant criteria. The relevant criteria for the control decision tree model (CDT) can be divided into three types: continuous, discrete and Boolean. Continuous criteria included (i) the number of flies in the nearest trap; (ii) the population dynamics (especially in between spraying activities); (iii) the history of trapping; and (iv) the condition of the population in the nearby traps. Discrete criteria included the slope and or soil type of the plot. Boolean constraints included (v) the presence of fresh specimens in the nearest trap; (vi) status of the plot—whether it was harvested or not; and (vii) the overall condition of the Olive fly population in predefined regions.

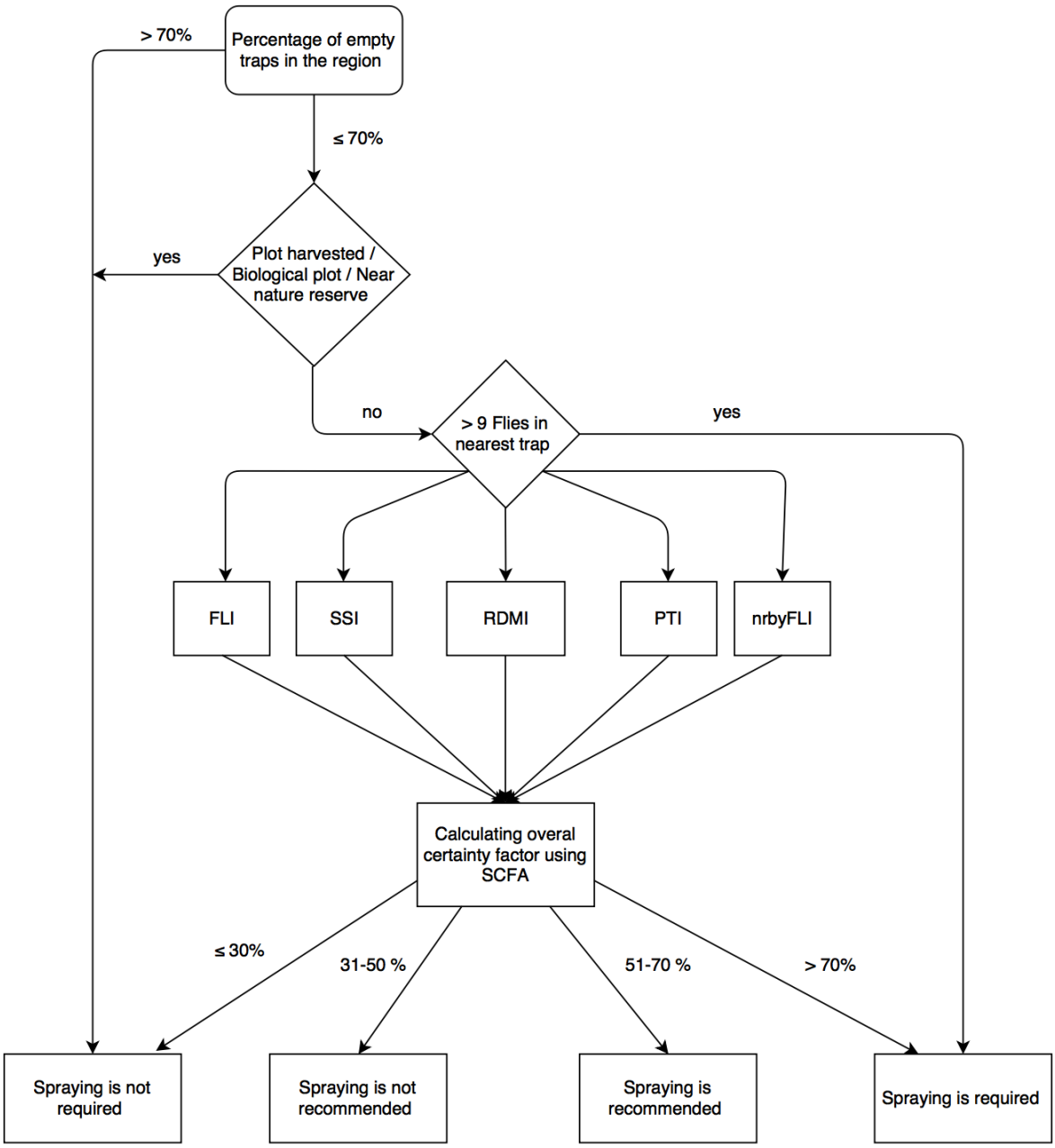


Figure 2.1: Flowchart for the Control Decision Tree model. Abbreviations in the figure are explained in Table 3.1

The outline of the model is given on Figure 2.1. The main part of the CDT is constructing a certainty factor (CF) using SCFA (Stanford Certainty Factor Analysis) from a set of criteria which are described in Table 2.1.

The final output of the CDT model will classify all plots according to different types of recommendations, which will be: (i) 'Spraying is not required' for all plots that gained an overall CF lower than 31%; (ii) 'Spraying is not recommended' for all plots that gained an overall CF between 31% and 50%; (iii) 'Spraying is recommended' for all plots that gained an overall CF between 51% and 70%, (iv) 'Spraying is required' for all plots that gained an overall CF higher than 70%

The CF's in principal express a 'belief' in an event, which can be a fact or hypothesis, and are relative, and thereby not absolute, measures. In general, the CF(x) is a measure of how confident we are in x. This certainty ranges from -1 to +1 with CF = - 1 = very uncertain; CF = 0 = neutral and CF = +1 = very certain. Several rules can be added to the calculation; these can be conjunctive or disjunctive. These

rules have also a certainty factor. The certainty of the rule will be combined with the_initial event certainty to obtain a final certainty factor. The order of adding CFs does not change the overall CF, it's commutative, and they always add up to a value between +1 and -1. Moreover, if one of the CFs equals -1 or +1, providing unambiguous evidence for or against a certain conclusion, the overall CF would be -1 or +1, no matter what the values of the remaining factors are. This means that both soft and robust rules can be integrated by using the same algebra. Adding a CF of 0 will not change the overall CF. Finally, the combined CF value is a monotonically increasing or decreasing function such as one would expect when combining criteria. The Stanford Certainty Theory or Stanford Certainty Factor Analysis uses human expert estimates not based on probabilities but which are heuristically derived from experience in reasoning in a particular domain. This is very relevant in situations for which no previous results are available to derive those probabilities. The spraying decisions for the Olive fly given environmental and biological conditions falls within this category.

Table 2.1: Control Decision Tree Criteria

Factor	Description	Input Variable	CF Equation
CF_{FLI}	Number of flies in nearest trap, corrected for certainty	Number of flies in nearest trap (*FLI*)	$CF_{FLI} = \begin{cases} -0.5 & FLI = 0 \\ \frac{FLI}{10} & 1 \leq \text{FLI} \leq 9 \\ -0.5 & \text{FLI} \geq 10 \end{cases}$
SSI	Ripening of the olive fruit	Time (*t*)	$SSI^* = \begin{cases} 0 & t_{spraying} < t_{start} \\ 0 & \text{t}_{\text{spraying}} > t_{end} \\ \max \times \left(1 - e^{-\frac{t_{spraying} - t_{start}}{p}}\right) & \text{t}_{\text{spraying}} < t_{end} \end{cases}$
RDMI	Olive fruit fly population	Temperature (*T*)	$RDMI^* = a \frac{\sum_{t=0}^{last\ event} \frac{T_{max} - T_{min}}{2} - T_d}{381}$
PTI	Population trend in the nearest trap	$Flies_i$ $Date_i$	$PTI^* = \begin{cases} 0.5 & if\ a \times slope(Flies_{3,2,1}, Date_{3,2,1}) \geq 0.5 \\ -0.5 & if\ \ a \times slope(Flies_{3,2,1}, Date_{3,2,1}) \leq 0.5 \\ a \times slope(Flies_{3,2,1}, Date_{3,2,1}) & otherwise \end{cases}$
nrbyFLI	Number of flies in the nearby traps	FLI_i, n, c	$nrbyFLI = \frac{c \times \sum_{i=0}^{Dist} \frac{FLI_i}{n}}{10}$

*max= 0.3, p = 30 days, a = 0.3, b= 3, c= 1, n= number of traps inside the given distance.

The CF of each piece of evidence ranges between (−1) and (+1). As the CF approaches (+1) or (−1), the

strength of the evidence for or against the conclusion, respectively, increases. A CF around 0 indicates that there is little evidence for or against the conclusion. Combination of the CFs is calculated in a modular mode. An initial CF is taken to be one of the CFs ascribed to the criteria and it is updated x times (depending on the number of criteria included) by adding the CF of each of the other criteria in succession.

The final CDT of the Olive fly SDSS will be made of the Boolean constraints which govern the overall CF calculation based on the SCFA. These constraints will either avoid spraying actions or mandate a spraying action. One of the Boolean constraints is imposed to avoid spraying actions: if a plot is young, harvested, dry or uprooted. Two others are imposed to mandate spraying action: (i) the presence of fresh adults and (ii) more than 3 olive fruit flies (although the latter is different between table olives and olives for oil). Another Boolean constraint to consider is the identification of the plots for which no reliable recommendations can be given: if a plot is too far from a trap and if information from the nearest trap was not correct/unreliable.

3 ADDITIONAL ANALYSIS

Apart from automatic alerts being raised by the SDSS, the system also allows to analyse the raw data and look for additional indicators for the necessity of spraying or other control activities. To this end, the web-app provides both maps and box plots that visualise *B. oleae* counts. Which data is included for visualisation is determined by a spatiotemporal query:

- To select the traps from which data is extracted, the user can select an orchard or a specific trap. The list of orchards and traps to choose from is restricted to orchards and traps owned by the user or by users that are member of the umbrella organisation (when analysis is done by a user with administrator rights for that umbrella organisation) for privacy reasons. In the box plots, the user can compare this data with data from others by specifying a distance to the own traps. Comparison data will be taken from the traps that are within this distance. Also a fixed number of nearest traps can be used to select the comparison data.
- The selected data, including the comparison data, can be restricted in time by setting a start and end date.

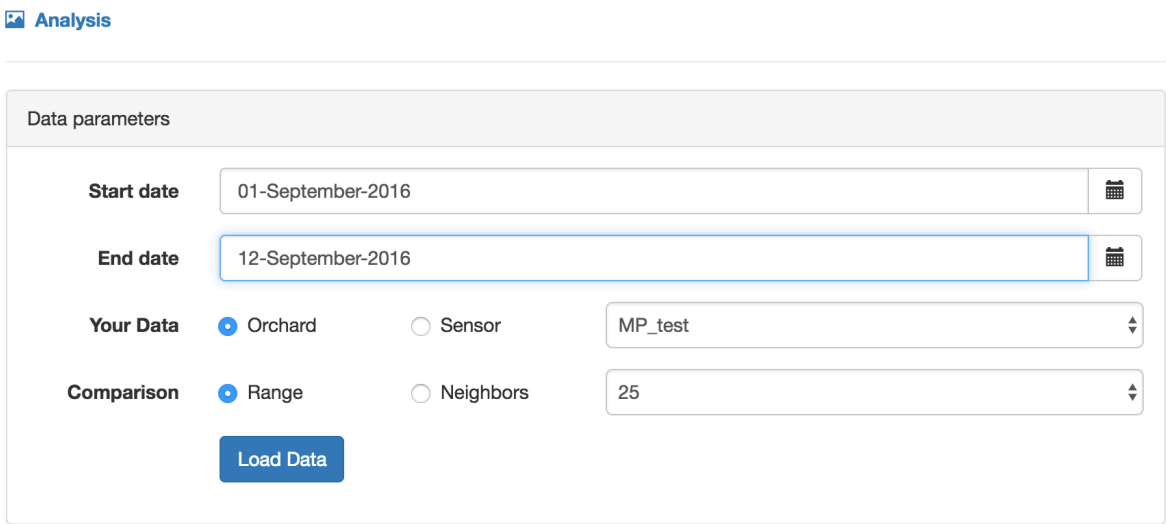


Figure 3.1: The analysis page

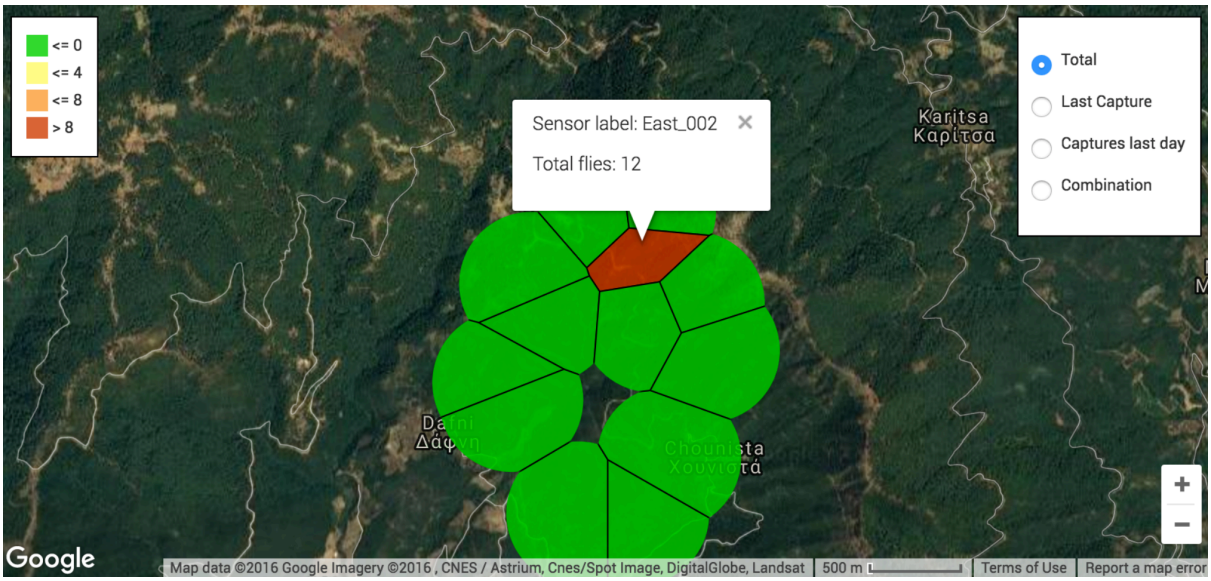


Figure 3.2: WSN count data

Box plots show the distribution of measurements in the own traps giving the quartiles: minimum, Q1, median, Q2 and maximum. The average counts are given as a line. For analysis of data coming from long periods of time, data is aggregated. When moving the mouse pointer over the boxplot, the range of dates for which data is aggregated is shown. In the same box, also the exact values can be found. This way, users can compare *B. oleae* counts over time and between traps of their own and neighbouring traps. While analysis over time reveals a trend of increasing counts one may decide to already start control actions even when decision tree thresholds have not been exceeded yet. The same goes for counts that are higher in traps from neighbouring orchards as compared to the own traps and that may indicate the advance of *B. oleae*.

Figure 3.3: Graphical representation of sensor readings on a timeline. The users' own data are shown using both boxplots as averages. The average of the comparison data is also given.

This does not necessarily mean that spraying activities need to be undertaken but paying more attention in specific areas could be appropriate. This includes checking the web-app more regularly to follow up on the *B. oleae* counts from traps in the own and neighbouring orchards.
Alternatively, analyses may be performed in third party software after extracting the sensor readings as a .csv file.

3.1 SDSS FINAL ANALYSIS

In order to define the optimal actions to be taken, the system uses the Stanford Certainty Factor Analysis, where the decision outcome is reinforced or weakened by adding/subtracting a marginal value for new incoming evidence (Figure 3.4).

```
CF <- c(CFLI, RDMI, CPTI, CNrbyFLI, SSI)
OvCert <- CF[1]
for (cf in (2:length(CF))){
        if (OvCert>0 && CF[cf] >0 ) {OvCert <- 1-((1-OvCert)*(1-CF[cf]))
        } else if (OvCert <0 && CF[cf] <0) {OvCert <- OvCert+CF[cf]+OvCert*CF[cf]
        } else OvCert <- (OvCert+CF[cf])/(1-min(c(abs(OvCert),abs(CF[cf]))))
}
```

Figure 3.4: Stanford Certainty Factor Analysis calculation for the Entomatic SDSS

3.1.1 DATABASE SPECIFICATIONS

Data is necessary to drive the SDSS. Data is collected through the Entomatic smart trap and sensor nodes. A database was built to collect both this data coming from the field as those data needed to feed the GIS engine. The Wireless Sensor Network (WSN) sends data on regular basis to the centralized database. Each device in the WSN will send following information:

- device ID,
- GPS coordinates,
- temperature,
- humidity,
- counts of the olive fruit fly,
- counts of all insects.

This data is being time-stamped. Additional information that are stored are: the gateway details (ID, coordinates, etc.), user information (authentication and password user) and GIS and status information of the plots (coordinates, olive cultivation, ripening olives)

3.1.2 THE APPLICATION

The web application is written using the following technologies:

- Backend, consisting of data models and REST APIs to retrieve, mutate and save data: SailsJS, version 0.11.5
- Frontend, calling the backend to retrieve and update data, visualises and presents data to the user: AngularJS, version 1.5.8
- Database, stores the actual data: Postgresql

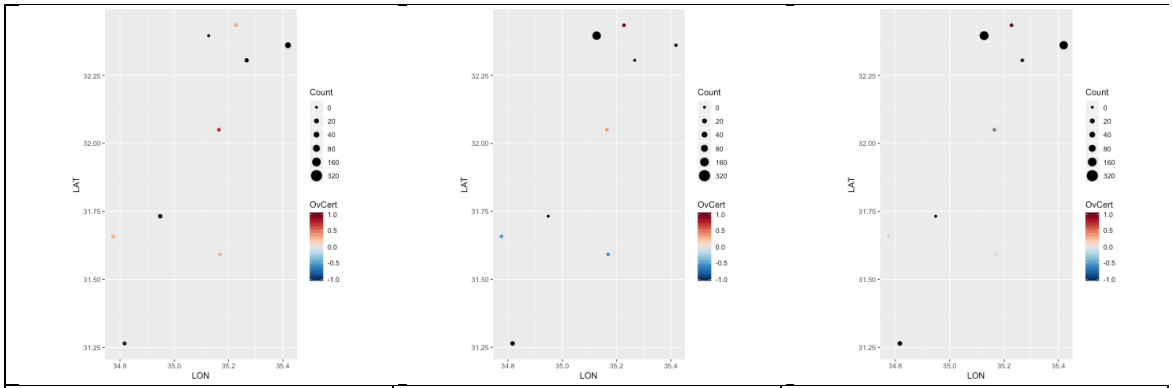
The data sent from sensors can be received in 2 different formats, defined by UPF. One of the formats allows for low energy devices to send their data, using a smaller footprint to preserve energy during the transmission process.
All data are transformed in the backend and stored in the database.
The decision tree is processed using an R-script, which is run every night on the server. This script collates previous data, extracted from the database, and calculates if any control actions are recommended for the fields. The time is set using cron-style configuration.

Some additional libraries were used to improve the application:

- D3.JS: Used for charts and visualisations across the frontend
- Nodemailer: Responsible for sending emails and notifications based on set alarms
- Bootstrap: used for styling of the frontend
- R-script: Used to run the R-script nightly
- PostGIS: Extension for Postgresql, used to store and query GIS data inside the database

3.1.3 RESULTS

In order to externally assess the SDSS response accuracy, the output was compared to field datasets that included both insects count as well as the resulting control actions taken. The time period over which field data from the Entomatic project was available was too short to have a real validation, as at least two years of observations and control actions are required.
Therefore, datasets were obtained from open data sources and field data. This was done so that the decision tree could be validated with a totally unbiased and unused dataset. Validation data from (Ordano et al., 2015) was used to validate the response accuracy. This particular data set had the advantage that it allowed to validate the predicted control actions to the observed control actions which were actually taken into the field by the farmers.
The validation was done by assessing the accuracy of the SDSS as well as visually. Figure 3.5 displays a time series of outputs where both the insect counts, and the Stanford uncertainty index are displayed. The coloured points are the field for which the SDSS predicts, the black dots are the observed insect counts in the traps.



March 1, 2010	June 1, 2010	November 1, 2010

Figure 3.5: Output from Entomatic SDSS for three dates

Additionally, Figure 3.6 shows how the decisions change on a daily basis. A Stanford Certainty Factor Analysis index lower than 0.3 means "spraying not required", between 0.3-0.5 "spraying not recommended", between 0.5 - 0.7: "spraying recommended" and above 0.7 "spraying required".

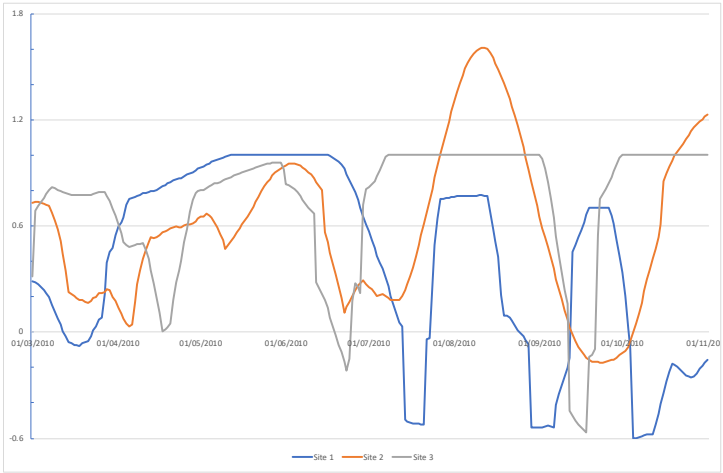


Figure 3.6: Temporal profile of the Stanford Certainty Factor Analysis index over one season. Profile has been run for two consecutive years.

The results visualized at the ENTOMATIC web app are shown in

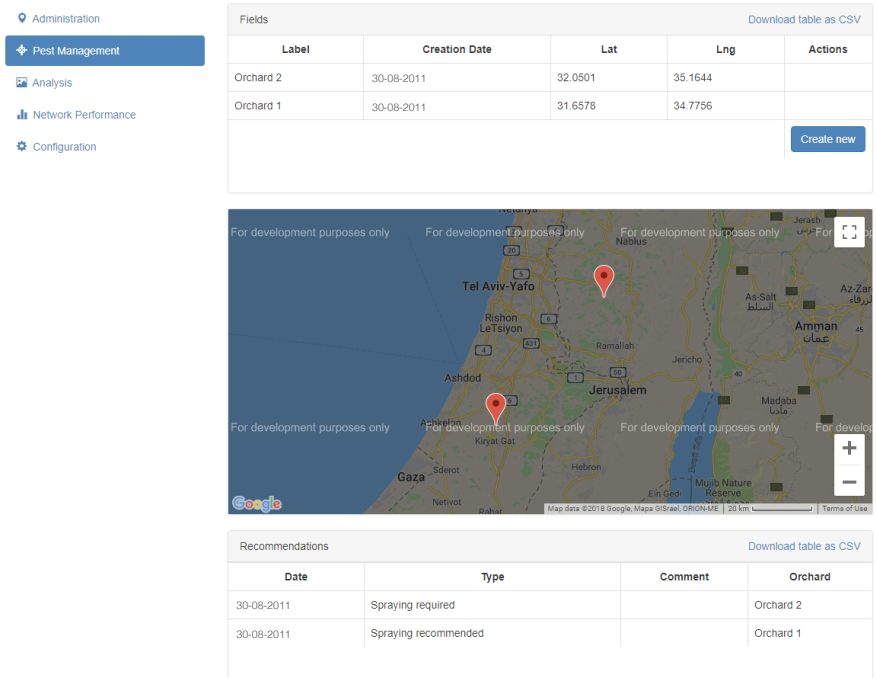


Figure 3.7: Recommendations done by the SDSS at the ENTOMATIC web app

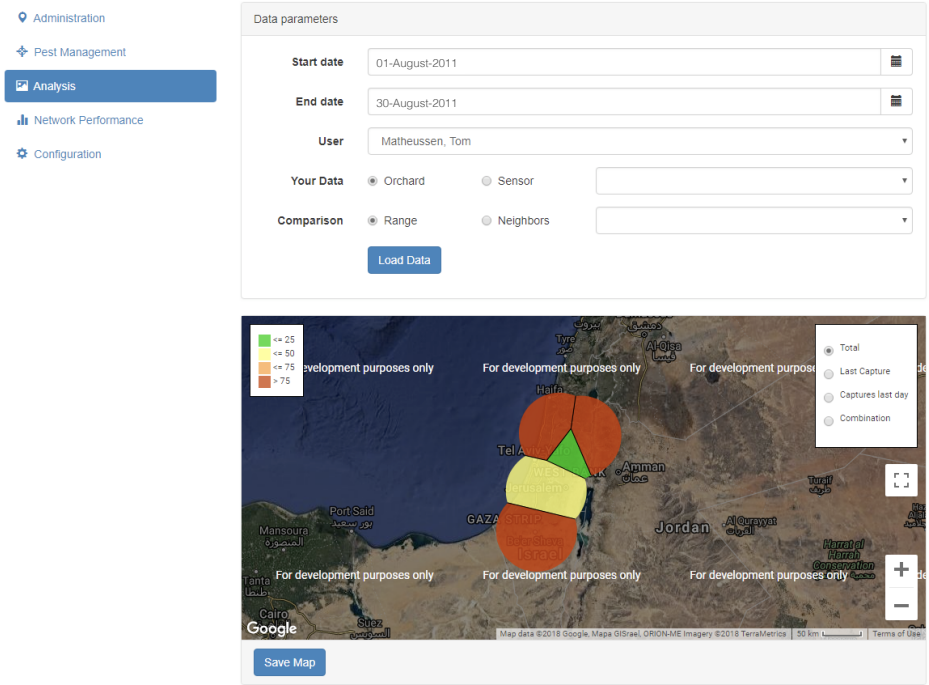


Figure 3.8: Analysis of the data set in Israel at the ENTOMATIC web app

4 CONCLUSIONS

We devised a pest management tool for the olive fly that is based on a tailored trap with a bioacoustic sensor that registers fly counts. The trap's sensor and communication module was made as energy efficient as possible, thereby significantly reducing maintenance requirements. The SDSS consists of three parts: (i) a *B. oleae* spring onset model, (ii) a control decision tree and (iii) the ENTOMATIC Web app to perform additional analyses. The *B. oleae* spring onset model notifies farmers when to turn on the traps in early spring. Once the traps are on and the *B. oleae* population increases, the control decision tree (CDT) is run in parallel with the wireless sensor network (WSN) of traps that provides data on air temperature (T), relative humidity (RH) and olive fruit fly count. Up till now, olive fruit fly control was based on an expert basis only. Now, the CDT will provide objective guidelines and recommendations for spraying of *B. oleae* taking into account olive fly counts and certainty criteria. The Web app allows the user to view and summarize the raw data to provide further support in the decision making around control activities against the olive fruit fly. The system will be operationally tested during the active season of the olive fly in 2017. The validation of the whole system will be reported, as planned, at the WP8 Demonstration of the ENTOMATIC system.

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