Optimization of Fire blight Scouting with a Decision Support System based on Infection Risk

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Abstract

This paper presents FireFight, which is a model-driven decision support system designed to help optimization of scouting efforts for Fire blight disease symptoms in an area where the disease is not yet established. Fire blight is the most destructive bacterial disease of apple and pear. The most effective method to prevent disease spreading inside a new area is the accurate monitoring of orchards to identify symptoms and destroy the infected material. Infections occur only if the pathogen is present during favorable environmental and plant conditions. Scouting for the disease is expensive and time-consuming, due to the vast areas to be monitored in a very short period of time (immediately after the end of the disease incubation period). In some areas, as in the Trentino region (northern Italy), exhaustive monitoring is almost impossible due to the large number of trees, and therefore only a random sample is examined after the infection risk period. This approach is problematic, since it may fail to identify infected plants. Fire blight warning systems are widely used to forecast disease outbreak and support treatment planning. However, these systems are known to suit the specific regional conditions for which they were developed. In order to overcome the uncertainty due to the local nature of disease prediction models, several algorithms were applied in parallel, so that a wide range of different environmental conditions could be covered. FireFight is based on three of the most widely used Fire blight forecasting models (MARYBLIGHT, BIS95, and Fire blight Control Advisory). Disease incubation period was also included to advice scouting efforts when visible infection symptoms are timed to appear. Historical weather data analysis of the 57 subareas of Trentino revealed that there is relatively little risk (average of 1.13 risky days per subarea per year) during bloom. In 2003, 2004 and 2005 there were risky conditions in 37%, 51% and 67% of the subareas, respectively. By comparing the current sample-based scouting (where no symptoms were found even if they were present in the orchards) and the positive FireFight risk prediction in the areas where disease symptoms were actually found, we can conclude that FireFight can assist in the optimization of scouting efforts. It seems that the FireFight DSS approach can be applied in general to others plant diseases where accurate monitoring is needed in areas where disease is not yet present.

Keywords: Optimization of resource allocation, Model based agricultural decision support system

1. Introduction

Fire blight, caused by the bacterium *Erwinia amylovora,* is one of the most destructive diseases of apple, pear and other species of the subfamily *Pomoideae* in the family *Rosaceae*. The bacterium is native to North America and was first introduced into northern Europe in the 1950s. At present the disease is spread over several countries in the world, but is still considered a quarantine pest by the European and Mediterranean Plant Protection Organization (EPPO, http://www.eppo.org/QUARANTINE/quarantine.htm). Fire blight attacks and kills all the tissues of the tree: blossoms, leaves, shoots, branches, fruits, and roots. Cankers are usually formed on main branches or the trunk (Agrios, 1978; Beer, 1990). *E. amylovora* survives the winter quiescently in blighted branches and cankers, and becomes active in the spring during warm, humid weather. It can then be spread to nearby plants by wind, rain, birds, and insects or simply by contaminated pruning tools. It penetrates the plant through its flowers or wounds. About one to two weeks after the infection (depending upon the temperature, which affects the incubation period), the symptoms become evident. Weather conditions delimit disease development: conditions favourable to the bacteria during blossom or after hail injuries characterize the periods of high infection risk.

The need to remove Fire blight-infected parts from the plant forces the grower to prune away large portions of the tree, which has a long-term severe impact on the plant itself (Shtienberg *et al.*, 2003). Under conditions of heavy infection during bloom, yield can be considerably reduced or even destroyed, because of blighted blossoms.

The difficulty, cost and pollution involved in chemical treatments applied against the disease have lead to the development of a large number of warning systems, based mainly on weather data, to predict infection events and help growers optimize the use of pesticides (Lightner and Steiner, 1990; Thomson *et al.*, 1982). Their underlying models were derived from correlations between local weather conditions and disease occurrence and are consequently developed for specific areas. Currently, the most widely used disease forecasting models are: Mean temperature line and Cougarblight (Smith, 2002), developed and used in the Northern American pacific coast; MARYBLYT (Steiner and Lightner, 1996), used in the USA and, with some adaptation, in other countries in the world (for example Switzerland and South Africa.); BIS95 (Billing, 1996) developed in England and considered accurate for northern Europe conditions; and Fire blight Control Advisory or FBCA (Shtienberg *et al.*, 1998), developed in Israel and suitable for the Mediterranean climate of this country. When these models are transferred to a new region, different from the one for which they were developed, an adaptation is usually required. Sometimes the modifications are not sufficient and new algorithms have to be set up (Shtienberg *et al*., 1998).

The most effective method for preventing or slowing the spread of *E. amylovora* into uninfected areas is to impose strict phytosanitary measures (procedures, requirements, or regulations taken by governments to protect plant life from the risks arising from the spread of pests, diseases and disease-causing organisms on imported host plant material) and to maintain vigilance in orchards and nurseries. To detect the disease in a previously uninfected area, it is necessary to make inspections in the apple orchards or on other susceptible host plants during the growing season, when the symptoms can be visible. Timing is an important factor in this process. It is preferable to inspect after bloom until late summer, when the symptoms are more evident; symptoms must be recorded and removed as soon as possible, in order to avoid a subsequent spread of the disease. Scouting should take into account the incubation period (plants must be monitored only after the symptoms become visible) and be conducted after the last possible infection date during bloom or after a hail event. Only an exhaustive control of all plants can theoretically detect infections when the pathogen is sporadically occurring during the first stages of disease development in a previously disease-free area. However, even though scouting for the disease with accurate monitoring of the orchards is a required measure in such cases, it is highly time consuming and expensive.

Trentino is a region in Northern Italy, which is still considered free of the disease, even though in the surrounding countries and regions (Switzerland, Austria and nearby Italian regions of Alto Adige, Lombardia and Veneto) Fire blight is already present. Apple is the most important crop in the region, accounting for about 12,000 hectares of cropped area, with about 24,000,000 trees and an annual yield of 42,500 tons of fruit (Provincia Autonoma di Trento, 2004). Therefore early eradication of any Fire blight is the best action to delay disease spread and avoid losses. As the site of the first appearance of the disease cannot be determined *a priori*, scouting for the disease must theoretically cover the whole apple area.

Assuming that a trained person can examine a tree in 15 seconds (=240 trees per hour) it would take 100,000 hours to examine exhaustively all 24,000,000 trees in Trentino once. This is almost impossible (this task may require about 700 man-months, based on 150 hours/month). As a result, scouting is currently done by randomly inspecting about 0.5% of the trees during growing season. This task requires about 500 hours (based on the above calculation) and it can be accomplished by 10-20 people in a period of a few days.

In autumn 2003, symptoms of Fire blight were found on two plants that were promptly removed. During 2004, a random sample of 488 orchards - 56 sites of the susceptible host monitoring network (number of susceptible host plants randomly selected in the region and yearly monitored), 365 young plantations, and 67 pear orchards - was randomly selected for monitoring. Scouting in 2004 was done twice, at the end of bloom and at the end of the summer, but no infections were found during sample scouting. In 2005, the 56 sites of the susceptible host monitoring network, 177 pear orchards and 1160 young plantations were randomly examined once. During 2005, 21 cases of infection were found in six different areas, none of them was found as the result of the scouting efforts based on the random sampling approach.

One should note that even in the presence of the bacterium in the orchards, if the conditions are not conducive to disease development, the whole scouting effort becomes simply a waste of time. As an example, if scouting is done only once in a season when infection conditions and incubation period are not yet fulfilled, symptoms can not be detected and the disease develops unnoticed.

The period of high disease risk, when scouting has to be performed periodically, is during and after bloom. Increased risk also exists after a hail event with appropriate meteorological conditions and during secondary bloom, which is relatively rare. These aspects will not be discussed here, since they cannot be predicted. The blooming period in Trentino varies between eight and 20 days, depending on the temperature. It is ten days on average at high altitudes (> 600 meters above sea level) and 20 days on average at medium and low altitudes (< 600 meters above sea level). Since Fire blight infection is highly dependent on favorable meteorological conditions (rainfall, temperature) scouting efforts can be optimized by taking these parameters into account. Given the 2005 data of 21 Fire blight symptomatic trees (out of 24,000,000) found in six different subareas (none of them by the scouts), it seems that a better planning of scouting based on the predicted risk of infection may dramatically improve scouting effectiveness, at no additional cost.

A decision support system seems a good way to achieve scouting optimization, especially when risk prediction algorithms already exist, so a model-driven decision support system based on these models seemed the right way to proceed. A model-driven DSS is "A category or type of DSS that emphasizes access to and manipulation of a model" (Power, 2007). "*Two characteristics differentiate a model-driven DSS from the computer support used for a decision analytic or operations research special decision study: (1) a model in a model-driven DSS is made accessible to a non-technical specialist such as a manager through an easy to use interface, and (2) a specific DSS is intended for some repeated use in the same or a similar decision situation*" (Power and Sharda, 2007). Generally, model-driven DSSs are quite common in agriculture; they are developed to help growers in planning and applying treatments to their crops, such as the individual Fire blight risk prediction algorithms mentioned earlier. A few more examples are: 'PC-Plant Protection' (PCPP) developed in Denmark to help growers control weeds, pests and diseases in cereals (Muraly *et al.*, 1999); Habitat creation model which is a decision support system designed to assess the viability of converting set-aside land into semi-natural habitat (Gilbert *et al.*, 2000); AgClimate, a DSS for evaluating crop production risk under alternative climate forecasts (Fraisse *et al.*, 2006).

The system model is based on infection risk prediction extended to include the disease incubation period, so it predicts when Fire blight symptoms may be visible, assuming an infection occurred. Another challenge was dealing with uncertainty: the disease is not present in Trentino and the individual risk prediction algorithms are known to be highly specific. Hence three different prediction models were integrated, an approach well known in other areas of DSS application (Kuncheva, 2002).

Combining the output of several different algorithms that perform the same task individually is common practice when dealing with uncertainty and attempting to increase confidence in a recommendation for action. This approach is common in various areas such as classification or categorization tasks, where a level of uncertainty exists, and where no single approach provides a correct solution in every case. Applications examples can be found in: graphology (Cao *et al.*, 1995), text categorization (Sebastiani, 2002), robot positioning (Bison *et al*., 1997a; Bison *et al*., 1997b), mission critical systems (Leveson, 1995), medical diagnosis decision support systems (Mangiameli *et al*., 2004), pattern recognition (Kuncheva., 2002), and more. Various mechanisms are applied to achieve data fusion of the results of such ensembles of classifiers or systems, depending on the nature of the problem and the data, for example, minimum, average, weighted average, maximum, median, and majority voting (Kuncheva, 2002; Mangiameli *et al*., 2004). In other cases, probabilistic approaches can be found (Bison *et al.*, 1997a), as well as logic-based approaches (Bison *et al.*, 1997b), and also machine learning techniques such as fuzzy logic (Bison *et al.*, 1997b) or Neural networks (Bison *et al.*, 1997b) trained to perform data fusion when there are several competing sources of information.

The novelty of our DSS is in the use of a pool of algorithms predicting infection risk, commonly used for planning chemical treatments in areas where the disease already exists, for the optimization of scouting to prevent disease spread in a new area where, due to lack of historical data on the disease, a specific prediction model has not yet been developed or validated.

2. Methods

The predicting algorithms

The system integrates three infection risk prediction algorithms (MARYBLYGHT, BIS95, and FBCA) selected to cover the widest environmental conditions, but limited to risk estimation during bloom only.

The algorithms use the following parameters: the minimal temperature in a specific day in Celsius degrees (T_Min); the average temperature in a specific day in Celsius degrees (T_Ave); the maximal temperature in a specific day in Celsius degrees (T_Max); “Degree-hours", the number of hours in a specific day (d), when the temperature was above temperature (x), multiplied by the difference between the temperature (T) during these hours and the threshold temperature (x) (T-x = dt) ((>x,d)*dt) and "Wetness" - the amount of rain that fell on a specific day (d) (if measured by mm than it is denoted by Wetness and if by a period of time in hours it is denoted by Wet_Int).

The algorithms categorize the risk to four levels. Negative, in which there is no risk at all; Low, in which there is a low level of risk; High, in which there is a high level of risk; and Positive, in which an infection may occur, as all the conditions were met.

MARYBLIGHT was developed at Maryland, USA (Steiner & Lisinger, 1996). Four conditions must be met in order for infection to be possible: open flowers; at least 110 degree-hours where the average temperature above 18.3^{o}C; existence of wetness event above 0.25 mm during the current day or 2.5 mm during the previous day; average temperature above 15.6^{o}C. The input to this model is: minimal temperature, maximal temperature, average temperature, degree-hours and wetness (mm) (Figure 1).

The SdT represents the sum of accumulated degree hours (dT) on several days. However, for days, during which the minimal temperature is below 0, it is zeroed. Alternatively, if the maximal temperature is below 18.3^{o}C, then in addition it is checked whether the maximal temperature on the previous day was below 18.3°C. If "yes," the SdT value is decreased by half, and if "no," it is decreased by two thirds of its value.

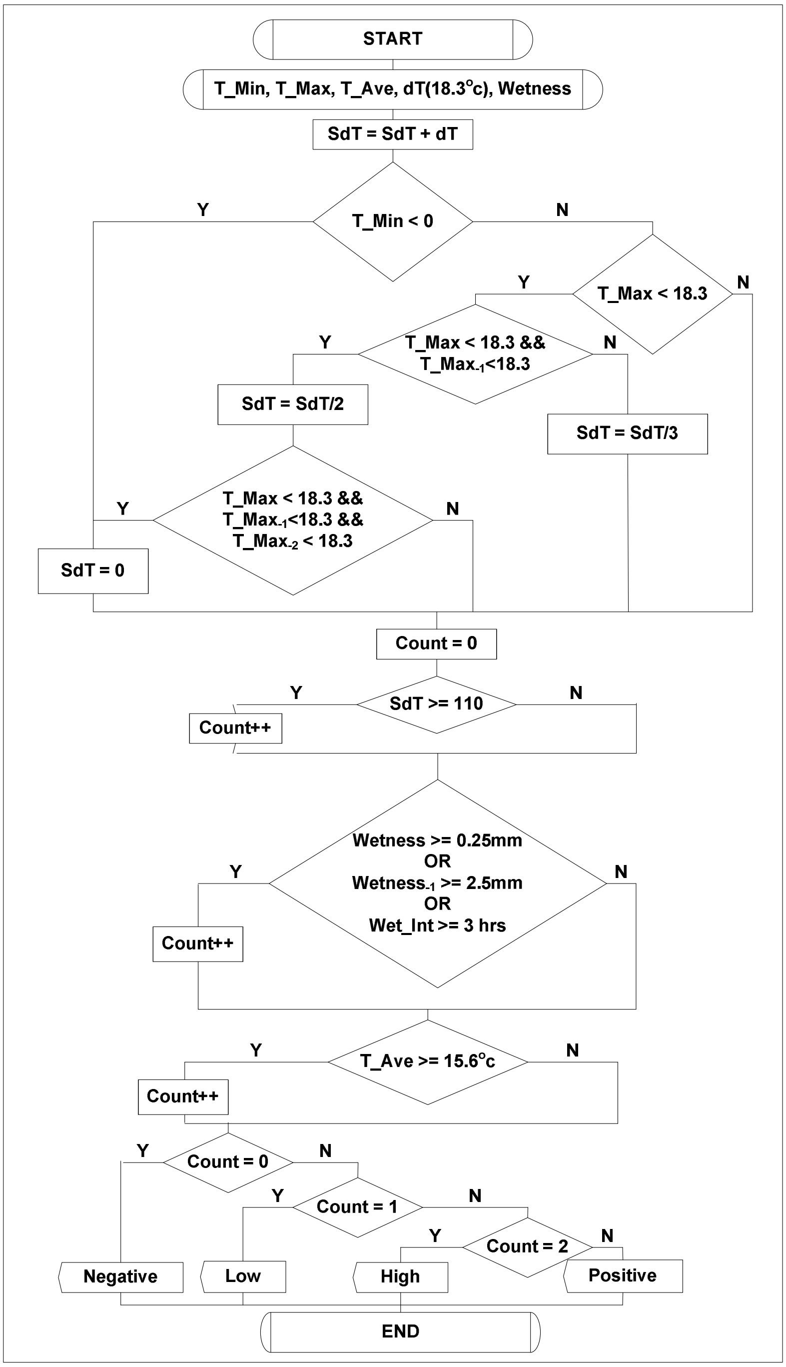

Figure 1 – Flowchart of the implementation of MARYBLIGHT algorithm used to calculate the risk of infection by *Erwinia amylovora* (after Steiner & Lisinger, 1996). The algorithm categorizes the level of risk based on the input parameters of temperature, accumulated degrees, and wetness level.

Later the count variable counts how many conditions were met: whether (1) the SdT is above 110, (2) the wetness level is above 0.25 mm, or 2.5mm on the previous day, or it was raining for more than 3 hours, (3) the average temperature is above 15.6°C. The value of the count determines the level of the risk.

BIS95 was developed in England (Billing, 1996).

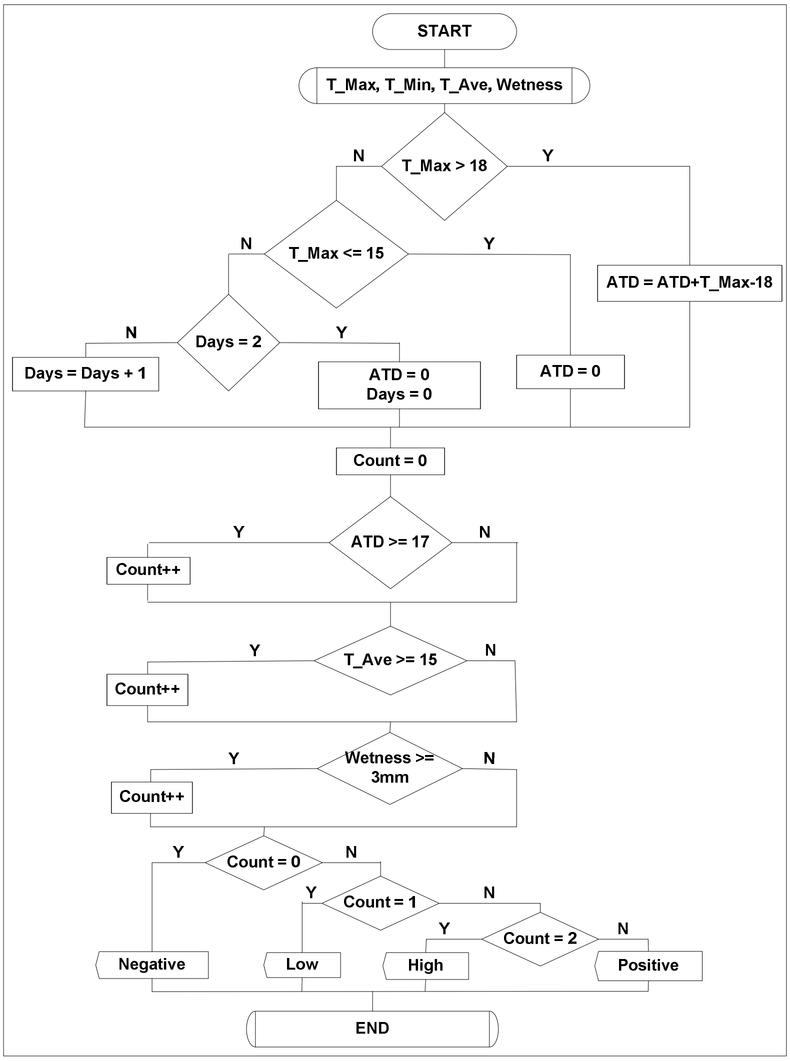

Figure 2 – Flowchart of the implementation of BIS95 algorithm used to calculate the risk of infection by *Erwinia amylovora* (after Billing, 1996). The algorithm categorizes the level of risk based on the input parameters of temperature, accumulated degrees, and wetness level.

It predicts risk for two possible infection mechanisms: Direct and Dry. The Direct spreading happens when three conditions are met: at least 17 days accumulated (degree days) where the maximal temperature was above 18°C; average temperature above or equal to 15°C; existence of wetness above 3 mm. (Figure 2).

Dry spreading happens when two conditions are met: at least 17 days accumulated where the maximal temperature was above 18°C (like the Direct) and maximal temperature above or equal to 27°C or average temperature above or equal to 20°C. The input data to this model are: minimal temperature, maximal temperature, average temperature, degree days (T_Max>18°C), wetness (mm).

The ATD represents the accumulated degree hours in which the maximal temperature was above 18°C. A sequence of two days, in which the maximal temperature was between 15°C and 18°C will zero the value of the ATD. The same happens whenever in a single day the maximal temperature is below 15°C. Eventually, the count increases as more conditions were met, which is the estimated risk.

FBCA was developed in Israel (Shtienberg *et al.*, 1998). This algorithm has a variety of heuristics and suggests quite a few combinations of conditions, in which the disease can be spread, unlike the previous models (Figure 3). Please note that circles containing “A” or "B" on the top left part of the flowchart should be connected to the “A” or “B“ circles in the lower right part of the flowchart, meaning “Low” (follow the connector marked with “A”) and “High” (follow the connector marked with “B”). Please note that here there are only three levels of risk defined in FBCA, unlike the previously described algorithms and negative risk is included in the “Low” level.

The input data are: minimal temperature, maximal temperature, average temperature and wetness interval (in hours). The output here is termed in levels: Low Risk, High Risk, and Positive Risk, respectively. Wet_int represents wetness conditions in hours during that day.

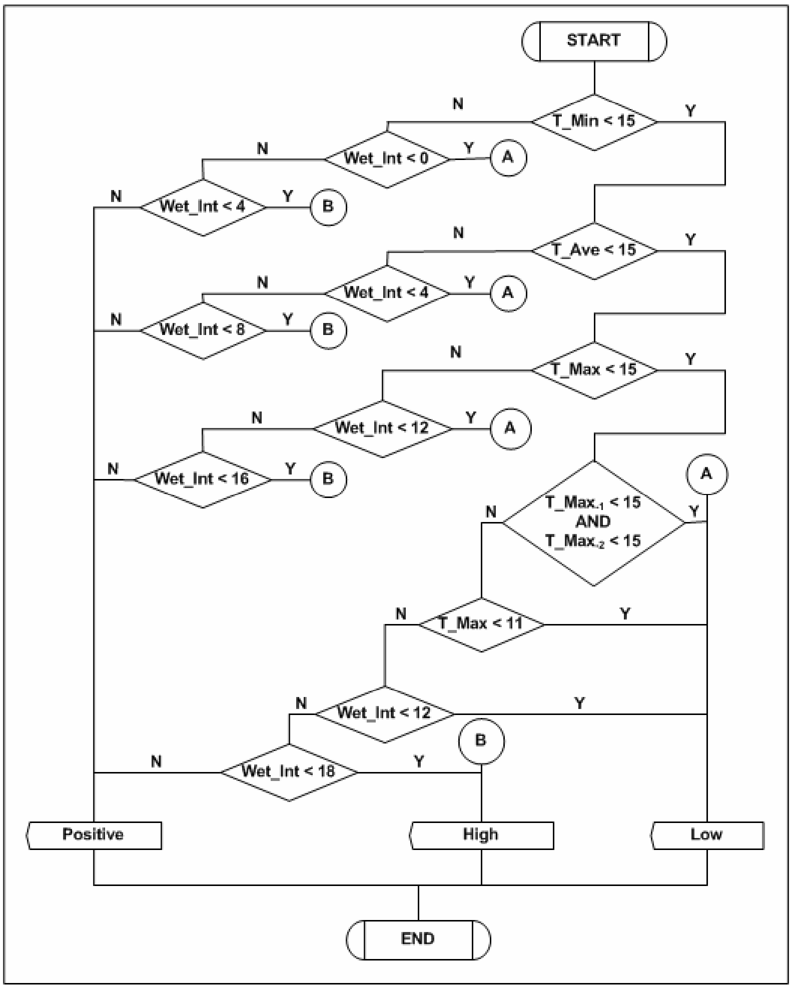

Figure 3 – Flowchart of the implementation of Fire Blight Control Advisory algorithm used to calculate the risk of infection by *Erwinia amylovora* (Shtienberg et al., 1998). The algorithm categorizes the level of risk based on the temperature levels and the wetness level.

Disease incubation period as calculated in MARYBLIGHT was included. In order to overcome the uncertainty of the individual predicting algorithms, a weighted average of the three algorithms output is calculated to give an integrated prediction (and to allow adaptation based on future performance).

System Architecture of "FireFight DSS" – Decision Support System for Optimizing Scouting Efforts System

The system architecture of "FireFight" DSS is depicted in Figure 4.

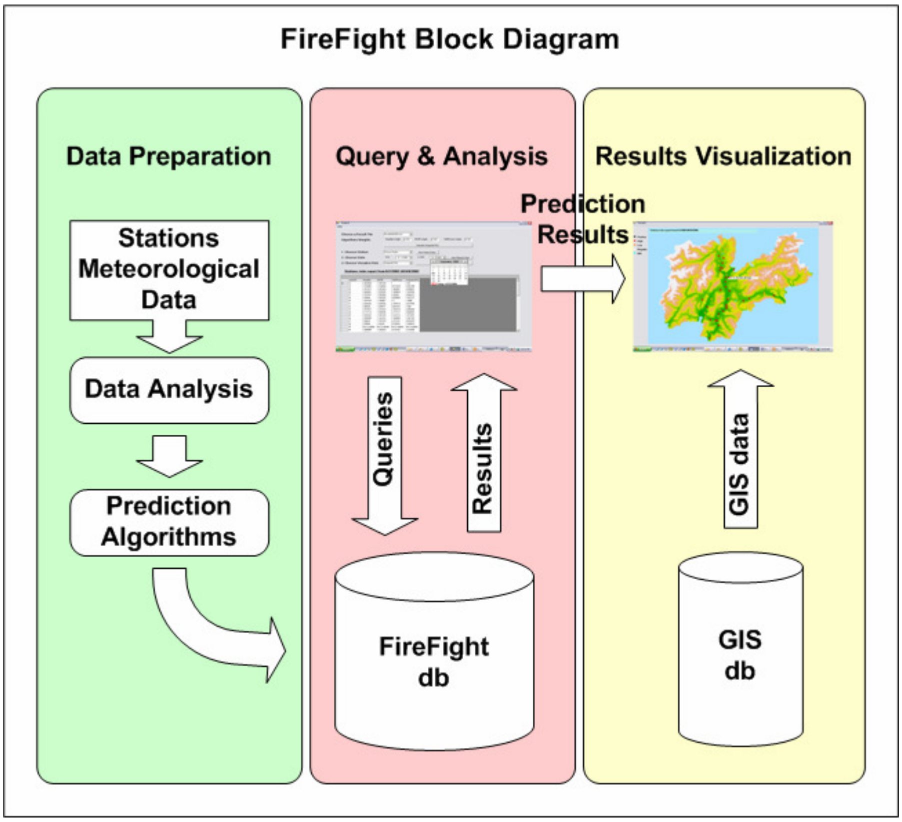

Figure 4 - FireFight block diagram. The first block (from left) presents the data analysis, starts by receiving the meteorological data, preprocessing, applying the three prediction models and indexing in the database. The second block presents to the user a query interface, to query for periods of time and geographical regions. The last block presents a visualization of the results, combined with geographical data, which presents the results on Trentino map.

Meteorological data are received in textual form from the meteorological stations. Data are preprocessed and analyzed independently by the three prediction algorithms. The results are indexed in the XML database. The system user can view analysis results in tabular form, in response to a specific query. The results can be visualized also over a regional map of Trentino, to provide a general view of the risk in the province.

Querying options

The system has two modes of operation: daily prediction (where, based on today's forecast and previous days' measurements, it estimates the risk) and historical risk analysis (based on past data, it can provide a risk analysis for a requested period of time in the past for a specified subarea).

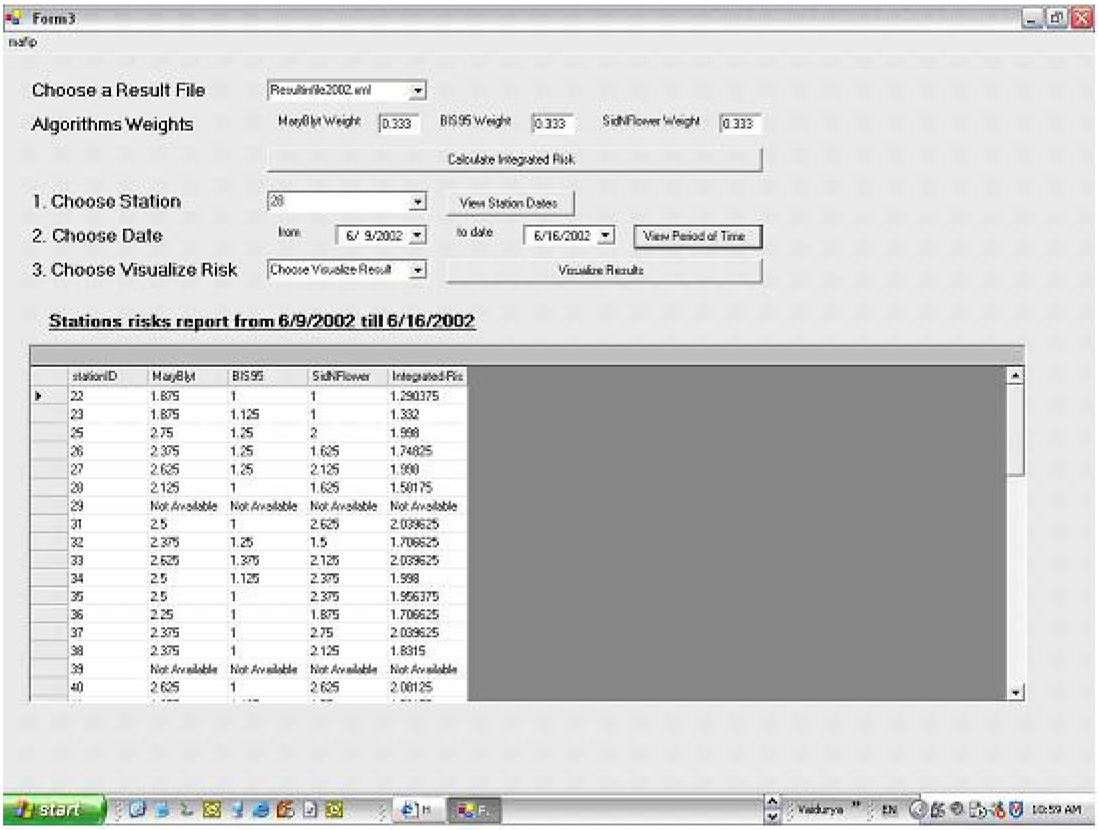

Figure 5 - Tabular form of results in FireFight DSS: the averaged risk along the period of time for each model and station, for the week between June 9th and June 16th, 2002.

The historical data analysis serves two purposes: to assess past infection conditions met according the disease forecasting models used, in order to identify the degree of risk in the area, and to validate the prediction algorithms accuracy, if the disease is present.

Figure 5 presents the results in tabular form; the average risk estimation along a queried period of time, where the same weight was given to each forecasting model. The second to the fourth columns (from left to right) in Figure 5 present the risk assessment for the individual algorithms (0, 1, 2, 3 respectively negative, low, high, positive, averaged over one week period) and the fifth presents the integrated risk, which can be set in the system as a weighted average among algorithms.

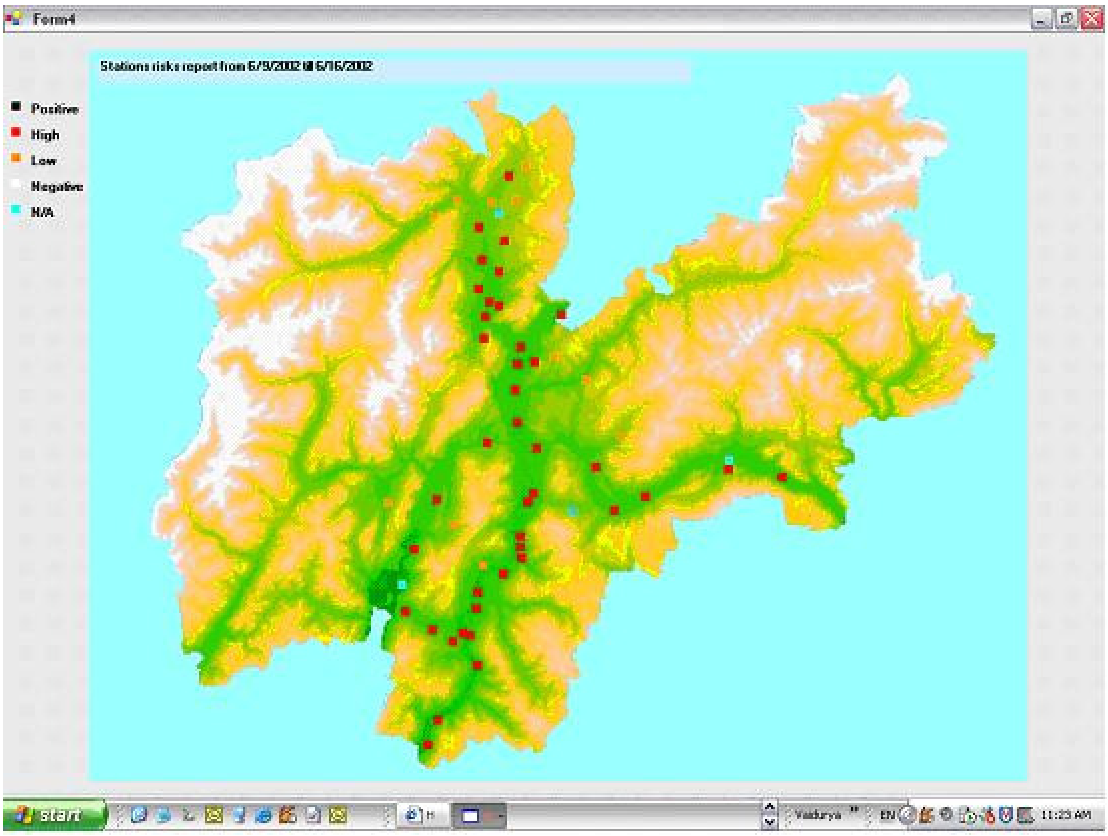

Figure 6 - Example of graphical visualization of the risks ranks for each weather station (subarea) on a map of the Trentino region. Each colored rectangle represents a meteorological station. Its color represents the risk level: Negative (white), Low (orange), High (red), Positive (black), and N/A (turquoise) for a station for which the data were unavailable.

In graphical form, as presented in Figure 6, different colors present the results of the individual algorithms or the integrated risk over the Trentino map (colored aerial map of the region, where green represents the valleys while brown represents the mountains and white represents the highest peaks).

3. Results and discussion

Offline historical data analysis was performed for the period from 2003 until 2005, using data collected from 57 local weather stations (representing the 57 different subareas of

Trentino). The stations were grouped according to their location in Trentino Region (low altitude, central area corresponding to the geographical region of Adige Valley, medium altitude, southern area corresponding to the Valsugana Valley, and high altitude, northern area corresponding to Non Valley). MARYBLIGHT and BIS95 found no positive risk (infection conditions fulfilled) during the blooming period of these years. FBCA found on average 1.13 positive risky days per subarea (corresponding to a weather station) per year during blooming period for these years (standard deviation of 0.86 days and values vary between 0 and 4.6 risky days). This historical analysis therefore revealed that the risk in Trentino (as found by the system) is generally low and that the differences between the three subareas were not statistically significant (T-test, $p>0.05$).

Table 1 – Number of sub-areas of Trentino region with at least one day during bloom with at least one algorithm giving “positive” risk.

Area / **Year**	**2003**	**2004**	**2005**
Low altitude area : **31** sub areas	7	10	13
Medium altitude area: **7** sub areas	1	3	7
High altitude area: **19** sub areas	13	16	17
Total: **57** sub areas	**21**	**29**	**37**

Risk (defined as at least one model giving “positive” risk) exists in different areas and differs between the years (Table 1). Moreover, it was found that risky conditions existed in different subareas on different dates in the different years (data not shown). Based on FireFight risk assessment (Table 1), in 2003 there was a need to visit 21 out of the 57 sub areas (37%). If the exhaustive scouting is estimated as about 100,000 man hours, this can be reduced to 37000 working hours (about 250 man-months) in 2003, a task that can be carried out by about 200 scouts within a little more than a month by applying FireFight. In 2004, based on risk prediction, there was a need to visit 29 out of the 57 areas (51%), entailing 51000 work hours (about 340 man-months), a task that can be carried out by about 300 scouts, within a month. In 2005 risk days were identified in 37 out of the 57 sub areas of Trentino (65% of the subareas). Exhaustive scouting would have required 65000 working hours to cover all suspected areas.

While the exhaustive scouting of the risky subareas based on historical data is not yet a reasonable effort, the analysis demonstrates the potential of optimization of scouting efforts. Even though, because of the large number of subareas to be scouted, the sampling approach must be selected, if scouting is done only in these specific areas, and after incubation period (instead of randomly, as is done nowadays), it will dramatically increase the chance of finding symptoms, unlike the random sampling currently applied.

In 2005, all areas where symptoms (infected samples) were identified after bloom by growers during agronomical procedures in the orchards were also predicted by the system to be areas at risk of infection during blooming period. Given the number of infected samples (21) compared to the number of trees (24,000,000), less than 0.001% of the trees are infected, about one in a million in 2005 (and one in six million in 2003), and there is very little chance of finding all infected trees by random scouting. Therefore, exhaustive scouting limited to these areas after the end of the incubation period of the last infection date, would have found those symptoms that were not found by random sampling.

The obvious conclusion is that optimization of scouting efforts may greatly increase scouting efficiency while reducing scouting costs. Since finding all infected trees in a disease-free area is crucial, the FireFight approach is very helpful.

The analysis of 2003-2005 data shows that FireFight is highly cautious. It recommends relatively high scouting efforts compared to actual symptomatic plants observed. Infections occur when both climatic conditions and the presence of the bacterium are met. The overestimation of risk can therefore be due simply to the absence of the bacterium in some areas or it may indicate that there is a need to adapt the system to Trentino characteristics. This can be done only after several years of disease presence in the region. However, even in its current state, the system increases the probability of identifying infection symptoms at a reduced cost compared to exhaustive scouting (and much more effectively than the current random scouting), and it is able to highlight the risk in all areas where the disease was actually found.

4. Conclusions

Scouting for the disease cannot be avoided in a territory like Trentino, where Fire blight is not yet established and the main crop is susceptible to the disease. The right timing of scouting is crucial for the detection of new infection symptoms. Risk evaluation, as performed by the "FireFight" system, enables scheduling optimization and better allocation of resources for scouting as compared to random sampling.

The DSS is a simple aid for finding and eradicating the disease and could be used directly by growers acting as scouts. If the disease appears, FireFight will then enable the rapid identification of the best prediction algorithm among those tested or its adaptation to the local conditions.

Based on initial results, the system may be developed further, to include risk calculation in individual orchards rather than in an area, to use local logged data instead of the local weather station data, or to include other additional prediction algorithms. The system can also be extended to other regions where the disease is not yet present or for an easy comparison of existing Fire blight forecasting models in an infected area.

The FireFight DSS approach can be applied in general to others plant diseases where there is a need for accurate monitoring in areas where disease is not yet present.

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6. References

Agrios, G.N. 1978. Plant Pathology, Academic Press Inc., Orlando, FL.

Beer, S.V. 1990. Fire blight. In: Compendium of Apple and Pear Diseases, The American Phytopathological Society, St. Paul, MN.

Billing, E., 1996. BIS95, an improved approach to Fire blight Risk assessment, Acta Hort. (ISHS) 411:121-126

Bison, P., Chemello, G., Sossai, C. and Trainito, G. 1997a. A possibilistic approach to sensor fusion in mobile robotics. Proceedings of the Second Euromicro Workshop on Advanced Mobile Robots (EUROBOT '97), p. 73-79.

Bison, P., Chemello, G., Sossai, C. and Trainito, G. 1997b. Logic-based sensor fusion for localization. Proceedings of the 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA'97), pp 254.

Cao, J., Shridhar, M., Ahmadi, M. 1995. Fusion of classifiers with fuzzy integrals. Proceedings of the Third International Conference on Document Analysis and Recognition (ICDAR '95), p. 108-111.

EPPO, http://www.eppo.org/QUARANTINE/quarantine.htm. Accessed June 2007.

Fraisse, C.W., Breuer, N., Zierden, D., Bellow, J.G., Paz, J.O., Cabrera, V., Ingram, K., O'Brien, J., Jones, J.W., Hoogenboom, G., Hatch, L.U., 2006. AgClimate: a climate forecast information system for agricultural risk management in the southeastern USA. Comput. Electron. Agric., 53 (1), 13–27.

Gilbert, J.C., Gowing, D.J.G., Higginbottom, P.R.G., Godwin, R.J. 2000. The habitat creation model: a decision support system to assess the viability of converting arable land into semi-natural habitat. Comput. Electron. Agric., 28, p. 67–85

Kuncheva, L.I. 2002. A theoretical study on six classifier fusion strategies. IEEE Transactions on pattern analysis and machine intelligence, 24(2), p. 281-286.

Leveson, N.G. 1995. Safeware – System Safety and Computers, Addison-Wesley, Reading, Mass. USA.

Lightner, G.W. and Steiner, P.W. 1990. Computerization of blossom blight prediction model, Acta Hort. (ISHS) 273 pp. 159-162

Mangiameli, P., West, D. and Rampal, R. 2004. Model selection for medical diagnosis decision support systems. Decision Support Systems 36, 247-259.

Murali, N.S.,. Secher B.J.M, Rydahl P., Andreasen F.M. 1999. Application of information technology in plant protection in Denmark: from vision to reality Computers and Electronics in Agriculture, 22, pp 109–115

Paz, J.O., Fraisse, C.W., Hatch, L.U., Garcia y Garcia, A., Guerra, L.C., Uryasev, O., Bellow, J.G., Jones, J.W., Hoogenboom, G. 2007. Development of an ENSO-based irrigation decision support tool for peanut production in the southeastern US Comput. Electron. Agric., 55(1), pp. 28-35.

Power, D.J., 2007. Free Decision Support Systems Glossary, http://dssresources.com/glossary/. Accessed June 2007.

Power, D.J., R. Sharda. 2007. "Model-Driven DSS: Concepts and Research Directions", Decision Support Systems, 43, p. 1044-1061.

Provincia Autonoma di Trento, 2004. Rapporto agricoltura 2002. Servizio agricoltura, PAT, Italy, p 6.

Sebastiani, F. 2002. Machine learning in automated text categorization. ACM Computing Surveys, 34(1), pp 1-47.

Shtienberg, D., Kritzman, GT., Herzog, Z., Openhaim, D., Zillberstein, M. and Blatchinsky, D. 1998. Development and evaluation of support system for management of Fire blight in pears, Acta Hort. (ISHS) 489, pp. 385-392.

Shtienberg, D., Zilberstaine, M., Oppenheim, D., Levi, S., Shwartz, H. and Kritzman, G. 2003. New considerations for pruning in management of Fire blight in pears, Plant Dis. 87 (Sept. 2003) pp. 1083-1088.

Smith, T.J., Cougarblight. 2002. Fire blight Risk Assessment Model. WSU Cooperative Extension, 303 Palouse, Wenatchee, WA 98801.

Steiner, P.W. and Lightner, G.W. 1996. MARYBLYT™ 4.3, A predictive program for forecasting Fire blight disease in apples and pears. Gempler, Inc. PO Box 270, Mt. Hebron, WI 53572.

Thomson, S.V., Schroth, M.N., Moller, W.J. and Reil, W.O. 1982. A forecasting model for Fire blight of pear, Plant Disease 66, pp. 576-579.