Early detection and recommendation of higher precision in treatment of late blight in potato crops by using drone photos

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Abstract
In this thesis an evaluation was performed for the potential use of drone photos in Decision Support System (DSS) to detect outbreak of late blight and provide recommend treatment with fungicides. Late blight is a common crop infection on potato in Sweden. A DSS with and without information from drones were developed in three steps. Firstly, risk classification model for late blight was specified based on weather data, output from a blight forecasting models (SIMCAST) and drone photos. Secondly, this risk model was calibrated and evaluated with data from a late blight field trial and drone images taken during the time of the trial. Thirdly, a decision model specified as a probabilistic (Bayesian) network was built integrating the risk model with management costs and the decisions to spray with fungicides and/or to collect more information by drones to improve the accuracy of the risk classification. The decision model was used to evaluate the cost-benefit of using drone photos in potato late blight management under scenarios of blight incidence and management costs. The findings showed that drone photos may reduce the expected cost under certain conditions such as low blight incidence and low costs. If costs for drones can be held back, there are several opportunities to combine the technology of unmanned vehicles with DSS in order to manage late blight in potato crops. However, a number of limitations exist and further research is needed to achieve a more accurate model and a decision analysis considering multiple decisions before the method can be applied in practice.

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Eventually, I got the opportunity to combine knowledge from my various courses at the Faculty of Engineering at Lund University into my thesis. Therefore, I was able to use my knowledge in a wider perspective, which has been invaluable to me. Moreover, I have learnt new methods and theories which were not taught at my educational program before.

Background

Late blight is considered to be one of the world's worst crop diseases (1). The Irish potato famine which started in the mid-1840s is probably the most famous catastrophe associated with late blight. Since then, late blight has been considered a substantial problem in agroecosystems (2). The disease implies different types of risks in different fields, for instance late blight is associated with economic and environmental damage (3-6).

Large amounts of pesticides, more specified fungicides, are sprayed in preventive purpose on the potato crops. This is to prevent the harvest from being damaged by the disease, which leads to economic loss (5, 6). The possible economic loss is much greater than the cost of the used fungicides, hence the large amounts of spray application. However, excessive application of fungicides can also cause unnecessary costs (4). After the application on the potato crops large amounts of fungicides are spread further in the environment. The water within the agriculture landscapes primarily possesses the risk to be contaminated by the fungicides. Furthermore, the fungicides can also be spread to other areas through the wind and through the water, either running away from the field or running down to the groundwater (3).

Physiology and impact

Late blight is caused by the oomycete *Phytophthora infestans* and infects potato and tomato plants (1, 2, 4-6). When *P. infestans* infects the leaves on the potato plant, it is called late blight. Late blight can lead to tuber blight, which means that the infection can be spread to the potato tubers of the plant (4, 6). Weather conditions have a very important impact on the infection outbreak and the development of late blight (2, 5, 7-9). Important variables are temperature, humidity and leaf moisture (9). The risk for infection of late blight increases at high humidity (5, 6, 10, 11). The economic loss in the potato crop due to late blight is both qualitatively and quantitatively dependent on the severity of the infection and weather conditions (4).

Control of late blight

Control of late blight is usually preventive. This is due to the fact that it is difficult to control an ongoing outbreak and due to the high risk of development of tuber blight even at small outbreaks. There exist different types of fungicides which can be applied by using various recommendations (12).

Weather conditions have an important impact on the outbreak and development of late blight, and therefore weather data is used to forecast outbreaks. Other factors are the potato crop's level of susceptibility to the disease. So-called Decision support systems (DSS) have been built to help potato growers to forecast outbreaks of late blight, and in some cases to give recommendations on the application of fungicides (2, 5, 7, 8).

There exists an associated risk to tuber blight due to reduced fungicide doses (6). However, it has been shown that reduced doses (halved doses) do not contribute to a more aggressive late blight. This finding is highlighted in the thesis *Reducerade funguiciddoser vid bekämpning av potatismögel* from 2015 by Jönsson & Olsson. Furthermore, it is argued that the achieved control effect is more important than the amount of fungicides. This control effect can be achieved by using a DSS to control late blight. If successful, DSSs can then reduce the amount of fungicides compared to preventive application schemes. A higher precision in the use of fungicides would be profitable in both economic and environmental perspectives.

Due to the fact that large amounts of fungicides are sprayed in preventive purpose to control late blight it would be valuable to be able to detect late blight in an early stage with a higher precision than field level. If late blight could be detected in an early stage unnecessary excessive spray could be avoidable with positive effects on economy, environment and health.

Decision Support Systems for Late Blight

There are several Decision Support System (DSS) in for forecasting and treatment of late blight. Potato growers in the Nordic region have access to the Norwegian VIPS, the Danish Skimmelstyrning and the Dutch Dacom (former Plant Plus) (12). The first two are available at the website of the Swedish Board of Agriculture (13). Another example of a DSS is the prediction model SIMCAST (5, 10). This late blight infection model is developed by William E. Fry and the model can be adjusted for different susceptibility levels (susceptible cultivars, moderate susceptible cultivars and moderate resistant cultivars) at different durations of moist periods. In addition to predict the outbreak of infection, the model can be used to estimate if a new spray application is needed by using a threshold. The output from the model can be cumulatively summed up and when the sum exceeds the threshold then spray should be applied (14).

Experiments in potato fields are used to investigate the effect of different control programs to control late blight. A field trial can test the effect of a forecasting model in combination with reduced fungicides doses (6) and compare it to new alternatives to fungicides (8).

The recommendation is to regard DSS as a support and combine it with one's own experience and common sense. Field trials have shown that technical problems may occur with weather data and that there are limitations of forecasting models and DSS (8). An alternative is to base forecasting models with complementary information, for example obtained by remote sensing.

Precision agriculture using drones

Precision agriculture is emerging as a revolutionary technology, which open up to processes data from fields to refine decision-making in agriculture (7). Information with a high detail of variation within an agricultural field can for example come from data measured by the machines or by images taken above the field. This thesis focuses on the possibility to use aerial photographs to detect and map outbreak of late blight in potato crops. The idea is to identify less healthy plants from images of Normalized Difference Vegetation Index (NDVI) of potato crop fields. Such can be derived from multispectral images using drone-based remote sensing (15).

Drones, or more technically, Unmanned Aerial Systems (UAS), have a military background, but today is UAS used in many different contexts where remote sensing, among other applications, is a growing industry (16).

Regarding today's photogrammetry and remote sensing (PaRS), the possibilities for images obtained from UAS were already identified for more than thirty years ago. Since the last decade, technology in PaRS has developed which has resulted in a greater range of products which enable high resolution and accuracy. These products have also begun to have a greater availability in terms of cost due to the emergence of technology. Especially in agriculture, the market for UAS PaRS has quickly been developing within UAS (16). An article by S. Nebiker et al, *Light-weight multispectral UAV sensors and their capabilities for predicting grain yield and detecting plant diseases*, 2016, presents the opportunities concerning the use of PaRS in UAS in the context of agriculture. The authors highlight the performance and application of light-weight multispectral sensors for micro UAV in an agricultural context (15).

Aim and limitations

The aim of the thesis was to evaluate the potential of using drone photos from UAS to improve decision support systems for potato blight. In order to achieve this aim we

1) specified a risk model for late blight in potatoes by using forecasts of potato late blight at field level based on weather data and the SIMCAST model (Appendix A) and drone photos,
2) calibrated and evaluated the risk model on field data, and
3) integrated the risk model into a Bayesian Network to evaluate the cost-benefit of using drone photos in potato late blight management.

The risk model was calibrated from field data. The decision analysis used the risk model and cost scenario, and not realistic cost estimates. This thesis developed a model and analysis which can be used to evaluate the cost-benefit of drone photos under more realistic settings. In order to use this in a more realistic context the risk model and the decision analysis need to be improved before the use of realistic values becomes more relevant. Furthermore, this thesis was limited to a version of the forecasting model SIMCAST, even though there are other models doing the same thing. SIMCAST was chosen mainly because it was more approachable and available than the others.

Method

Overview

The use of drone photos to support late blight risk assessment and management was evaluated through a decision analysis of expected cost under different risk and management scenarios. The decision problem was set up as an influence diagram, which links decisions and costs to stochastic variables. The influence diagram was specified as a probabilistic (Bayesian) network. A Bayesian network express variability using probability and it is possible to update the probabilities using Bayes rule for any given configuration of the network. Thus it is possible to set the values on decisions and states of stochastic variables, and thereby evaluate the impact of a decision on the values important for the decision maker (here cost).

The parameters in a Bayesian network are probabilities expressing the conditional dependence of stochastic variables. These parameters were estimated by a separate data analysis using a risk classification model. Values on cost for different management actions and blight outcomes were set in different cost scenarios. The general risk for an infestation (incidence) was defined as the probability of new infection outbreak of late blight a given day without any knowledge of SIMCAST nor drones. These different concepts regarding the decision model will be explained in more detail in the decision modeling section, but first the risk classification model will be presented.

Risk classification model

The risk classification model was created to assess the risk of late blight through analyses of field data. In order to create the risk model, different types of data were obtained and analyzed (Figure 1). The data consisted of drone photos and weather data. An expert and data driven prediction model for late blight called SIMCAST (Appendix A) was used to obtain predictions of possible occurrence of late blight. The data analyses provided information of predicted occurrence of late blight. Information in terms of: probabilities to detect late blight if late blight occurred and probabilities of believed occurrence of late blight if late blight did not occur.

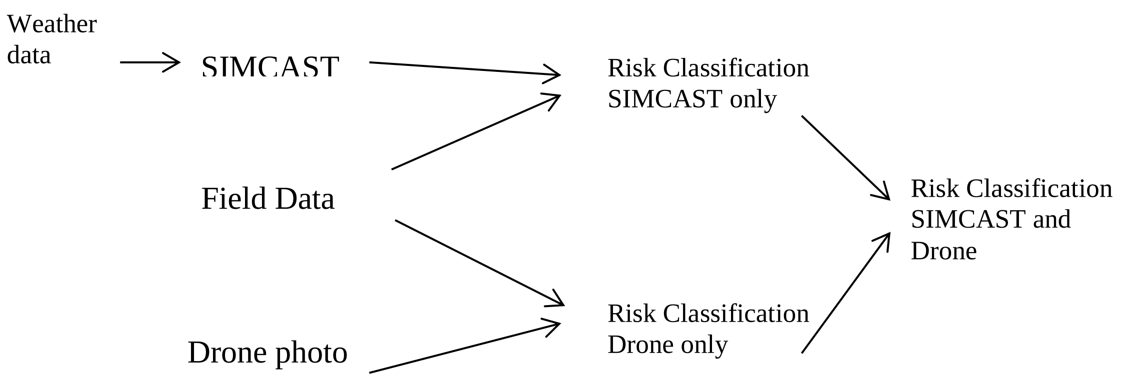

Figure 1: Overview of input and output of the data analysis and risk modelling.

Two programs were mainly used to process the data; R and GeNIe (Data fusion). R is a program language and an open source program for data analysis (17). GeNIe is an open source program for building and learning of Bayesian Networks (18). R was used for the data analyses (the risk model) and GeNIe was used to specify and run the decision model.

Field data

This thesis includes data from a trial field in Mosslunda, which is located near Kristianstad. The field contains different areas which have different control programs concerning late blight for different orders. In this thesis one area in the trial field is included. The field trial in this area is ordered by the Swedish University of Agricultural Sciences. This area was divided into 32 parcels and contained four types of treatments (A, B, C and D) for each potato sort, which was repeated in four different blocks. Three of the treatments were including spray application at certain dates; B, C and D. Moreover, two kinds of potatoes were included in the trial field; King Edward and Melody (19). The two potato sorts possess different susceptibility to late blight and it has been suggested that Melody, in general, is more resistant in comparison to King Edward. King Edward has been reported to be quite susceptibility to late blight (20).

The occurrence of late blight (Figure 2) in field was measured by Hushållningssällskapet (Lars Wiik) in percentage of late blight (and withering) for each parcel. The gradation took place at once a week from the 4th of July to the 28th of August 2017.

Figure 2: Photography by Anna Lindéus of late blight infection on a potato plant, 2017-09-10, Mosslunda.

Forecast of late blight at field level

Predictions and spray recommendations of late blight at field level were obtained by the SIMCAST model. The SIMCAST model has two input variables: daily hours of relative humidity (≥90%) and the daily mean temperature. The output from SIMCAST is something called blight units which indicate if a day has good conditions for late blight. Spray with fungicides is recommended when the cumulative sum of blight units is high (exceeds a threshold) (5, 10). The threshold can be adjusted to consider differences in susceptibility in potato varieties (11, 14). Here, the SIMCAST model for a high susceptible potato sort was used for both potato varieties (Appendix A). Initially, King Edward was set to a lower threshold than Melody, 30 blight units respectively 35 blight units. These thresholds were set due to already existed threshold (14), but how they are applied in this thesis is an assumption regarding the fact of the two potato sorts which are included in this thesis. Predictions were calculated for each day in SIMCAST. If spray were applied at a certain date then the summed up prediction were reset to 0. Furthermore, the different types of treatments which were including spray application were not separated.

The weather data were obtained from the database LantMet at Swedish University of Agricultural Sciences' website. The chosen weather station where Mosslunda grid, number 10435, and the extracted data is covering the time period from the 22nd of June to the 28th of August (21).

Drone photos

Drones were sent up at three occasions over the potato trial field in Mosslunda during the field trial in the summer of 2017 (Appendix B). The drone photos and after processing of the images were done by the company Vultus (Appendix B). The spatial resolution of the drone photos is 4cmx4cm and the reference system is WGS 84 with the projection zone 33N in UTM (Universal Transverse Mercator). Every cell contains a NDVI value and, as previously mentioned, a higher NDVI value indicates a healthier plant.

Shape files for the different parcels were created in the program ArcMap (Figure5). ArcMap is a program within ArcGIS, which is developed by Erisi, and the program can be used to create, analyze and edit geographical data (22).

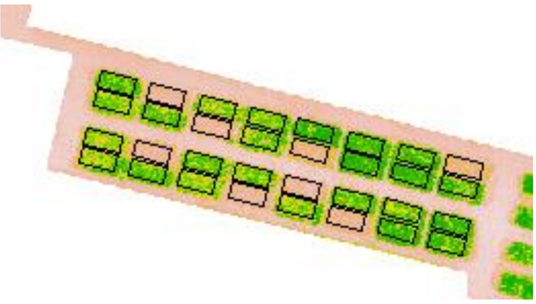

Figure 3: An example of an image derived from drone photos of the field trial area in Mosslunda. This drone photo is overlaid with shapefiles for each parcel with alternative treatments. Each parcel is of the size 3.2x7 m = 22.4 m^2.

In order to be able to extract the NDVI values from specific parcels, the shapefiles were transformed to raster objects and then trimmed to only containing values which were included within the area of the specific shapefile (Figure 6). Spatial autocorrelation were then taken into account by calculating moving averages using a window of nine parcels around every point. Through this operation, a cell with low NDVI value and its neighbors got a lower value compared to a cell with a low NDVI surrounded by high NDVI. This is a way to highlight the pattern and reduce impact from the edges (Figure 7).

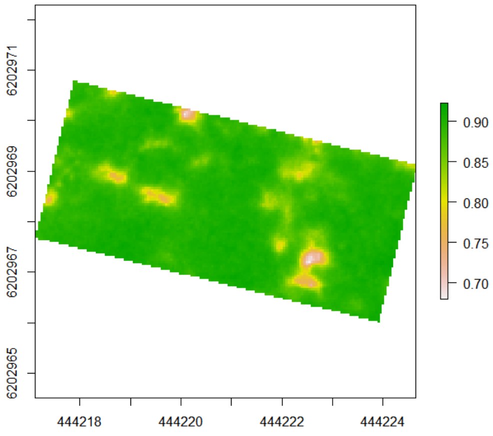

Figure 4: NDVI values for a trimmed raster object for a parcel.

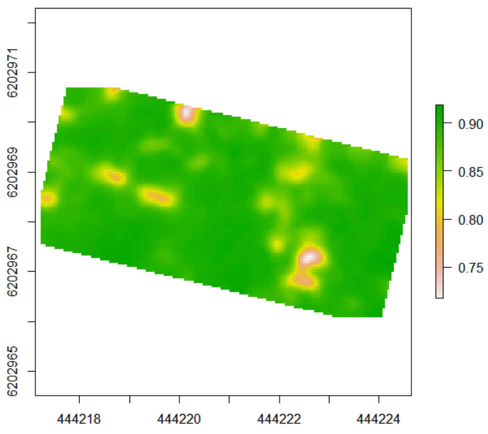

Figure 5: Smoothed NDVI values calculated by spatial moving averages for a parcel.

Afterwards, every raster object was containing new NDVI values and these values were then stored in separate histogram objects for each parcel.

The percentage of blight was calculated as the relative frequency of cells with NDVI values below a specific threshold. The threshold was set from the lower NDVI values in parcels with low observed late blight from the field study.

Drone photos have been taken at three occasions, one in an early stage and two at a later stage of the infection of late blight. In order to compare drone photos with SIMCAST predictions and field data, the information from drone photos were interpolated assuming a monotone sigmoidal growth from 0 to 100 in percentage of blight over the season (Figure 8). The percentages included observed withering, since the upper bound is 100%. Every parcel got one curve which was fitted by assuming a zero percentage a week before the first photo and finding the two parameters for the sigmoidal curve which minimized the maximum absolute distance to the line. The curves were used to extract relative frequencies of late blight from possible drone photos at any date.

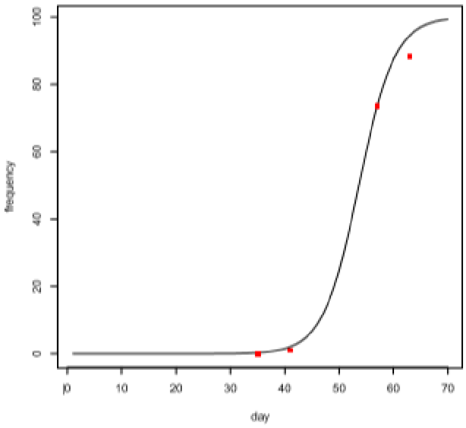

Figure 6: A sigmoid curve fitted to relative frequencies of brown leaves within a parcel as extracted from images taken by drones (red dots).

Risk classification
In order to inform the decision analysis, the risk model classified a field as infected by late blight or not. There are two types of errors in the risk classification model; to classify a non-infected area as having late blight and to miss an infected area. Here, the risk classification model was defined by a continuous score variable (classifier) for which a cut-off is chosen. The cut-off is chosen by finding a desirable balance between two types of errors.

Receiver Operating Characteristic (ROC) curves offer a methodology to select a cut-off but also to compare classifiers without choosing a cut-off. The ROC curve visualizes the tradeoff between the true-positive and false-positive rate of the two involved data sets in a test. Initially the conditional probability is calculated of the test. Then, when plotting a ROC curve, the purpose is to investigate how the curve is positioned relative a 45 degree line between the axes. Each point is located either on the line, above or below the line. If the points are located on the line the probability of the event was not affected by the test result. The likelihood ratio for the points is then 1.0, due to Bayes' theorem: when the post-test odds equal the pre-test odds. If the points instead are located above or below the 45 degree line then the likelihood ratio for the results is greater than 1.0 respectively less than 1.0. In other words, this means the test result increases the probability of the event when the points are located above the line and the probability for the event decreases when the points are located below the line (23).

The ROC curves were created by testing the field data of the occurrence of late blight against predictions from SIMCAST and the drone photos. Two ROC curves were calculated: one for the predictions from SIMCAST and one for the predictions from the drone photos. The true-positive and false-positive rates were estimated from the ROC curves in order to select cut-off values. These were used to inform the decision model.

Evaluate SIMCAST versus Drone photo
ROC curves are used to compare alternative classifiers. Here, the classification is based on predictions from SIMCAST were compared to classification based on drone photos alone. Moreover, situations which were interesting to study were situations when drone photos detect late blight earlier than SIMCAST and situations when SIMCAST is exaggerating the risk of blight while the drone photos did not.

Decision modelling
A Bayesian network is a graphical model which represents linked conditional probabilities. The concept of Bayesian networks was introduced by Judea Pearl in 1988 and it is based on statistic theory of probabilistic independence (24). In this thesis, two Influence Diagrams were built to facilitate the analysis of the impact of the drone photos. These Bayesian networks with chance nodes (i.e. variables with a few set of states and a probability assigned for each state), decision nodes and value nodes (i.e. a variable taking different values depending on the state of other nodes). The chance nodes are illustrated as ovals, decision nodes as rectangles, value nodes as hexagons. The networks also included input nodes representing alternative values on incidence and cost values, illustrated as ovals with a red border.

The first influence diagram used SIMCAST predictions only (Figure 7). In this network there are two input nodes; one for incidence and one for cost regarding loss of harvest. The incidence is expressed in percent and can be derived from experience of blight in the area or by expert judgement.

The second influence diagram integrated SIMCAST predictions and drone photos to decide if drones shall be sent up to collect more information and when to spray for potato blight or not (Figure 8). This network includes more nodes. Besides the decision to spray, there is a decision to take a photo or not. The influence diagram is constructed such that the decision to take a drone photo is triggered when the SIMCAST prediction is at an intermediate value. A risk classification model for SIMCAST only is combined with the risk classification based on drones according to the scheme in Figure 1. The second influence diagram has four input nodes: incidence, the cost due to loss of harvest if a non-treated outbreak, the cost for getting information from drones and the cost for spraying, which is assumed to be reduced when using the more detailed information from drones. The values on the input nodes (cost for spray, cost for loss of harvest, cost for drone photo and incidence) in the networks were selected to create scenarios for the decision analysis (Table 1 and Table 2).

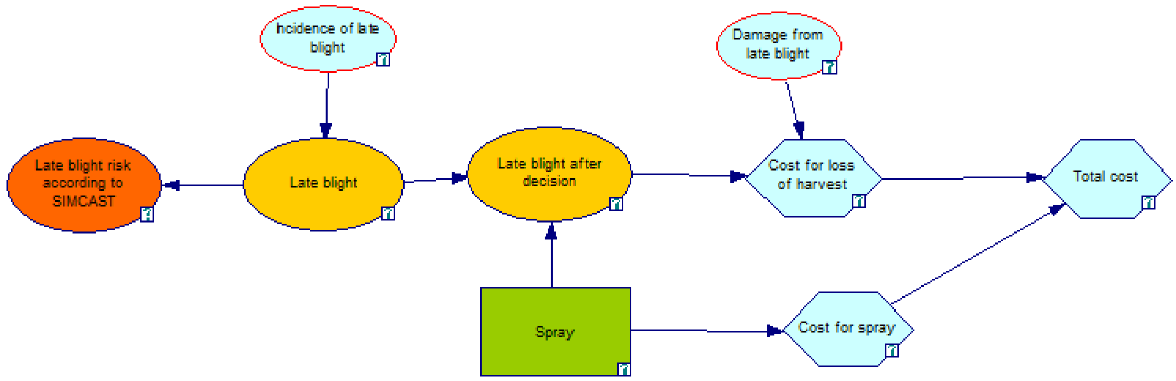

Figure 7: Influence diagram which relies on SIMCAST predictions only.

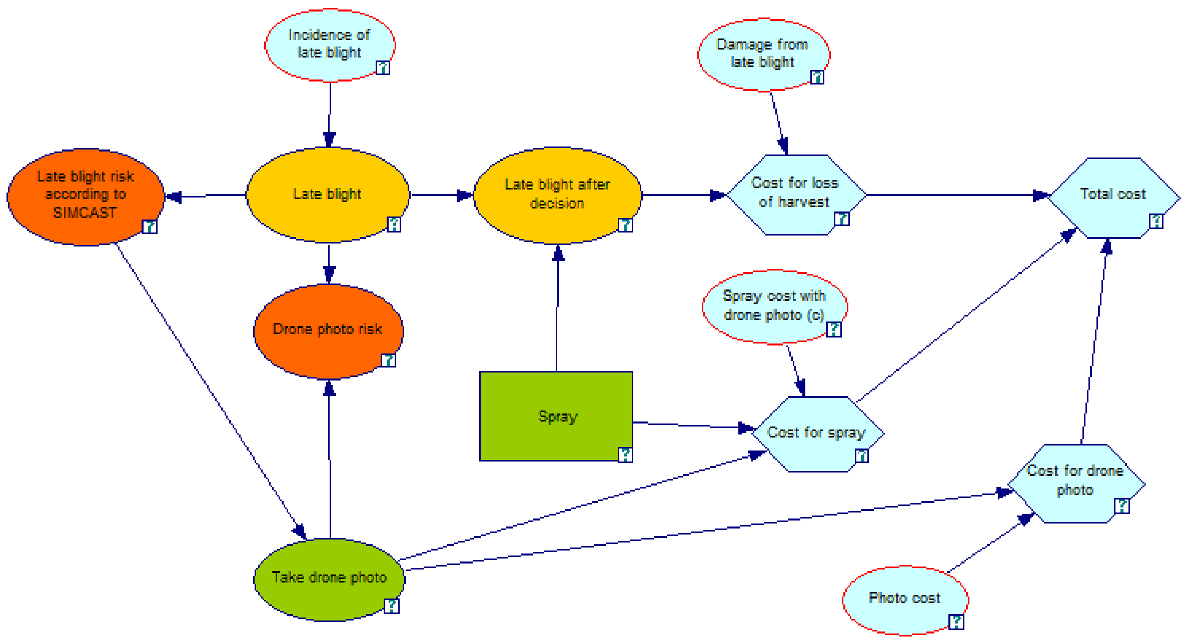

Figure 8: Influence diagram which relies on SIMCAST integrated with drone photo. SIMCAST within an interval trigger taking a drone photo.

Table 1: The assumptions for the relations between different types of costs.

Type of cost	**Relation**
Cost for spray (C_{spray})	Is set to be a constant
Cost for loss of harvest (C_{loss})	$C_{loss} > C_{spray}$
Cost for drone photo (C_{drone})	$C_{drone} < C_{spray}$
Cost for prevention (C_{prev})	= 0, if no action = C_{spray}, if spraying only = C_{drone}, if drone photo and no spraying = $c*C_{spray}+C_{drone}$, if drone photo and spraying c: spray cost reduction, if drone photo
Total cost (C_{total})	= $C_{prev} + C_{loss}$, if late blight = C_{prev}, if no late blight

The test values for the costs for management and the incidence of late blight is presented in Table 2. The test values for cost were set to values due to the assumptions in Table 1. The different states in Table 2 show how the cost values and the incidence can be changed for different updates in the networks, for example if a parameter has two states then it has two possible values.

Table 2: Test values for cost and incidence of late blight which were evaluated by the Networks.

Type of node	**State 1**	**State 2**	**State 3**	**State 4**
Cost for spray (C_{spray})	1	-	-	-
Reduced cost for spray (C_{spray}) if drone photo has been taken ← Spray cost with drone photo (c)	1	1/4	1/10	-
Cost for drone photo (C_{drone})	1	1/2	1/4	1/10
Cost for loss of harvest (C_{loss}) ← Damage from late blight	100	-	-	-
Incidence of late blight	10%	50%	90%	-

Sensitivity analysis

A sensitivity analysis was performed by using the outputs from the decision analysis to compare the total cost when changing different cost values and different incidence of late blight (Table 2). In order to compare the outputs, different scenarios were visualized to evaluate the cost-benefit for when drone photos were used and when they were not used.

Results

Data and risk analysis

Two ROC curves were created, when the observed occurrence of late blight were above 2.5 percentage of late blight (Figure 9). In the subplot A the ROC curve for the predictions from SIMCAST is viewed and in the subplot B the ROC curve for the predictions from the interpolated drone photos is viewed. The cut-off values from the ROC curves in A and B are visualized as dots on the curves and as lines in the subplots C respectively D. The cut-off values were chosen, as previously mentioned, by estimating a tradeoff between the true-positive and false-positive rate. It is preferable to have a high true-positive rate when the false-positive rate is low.

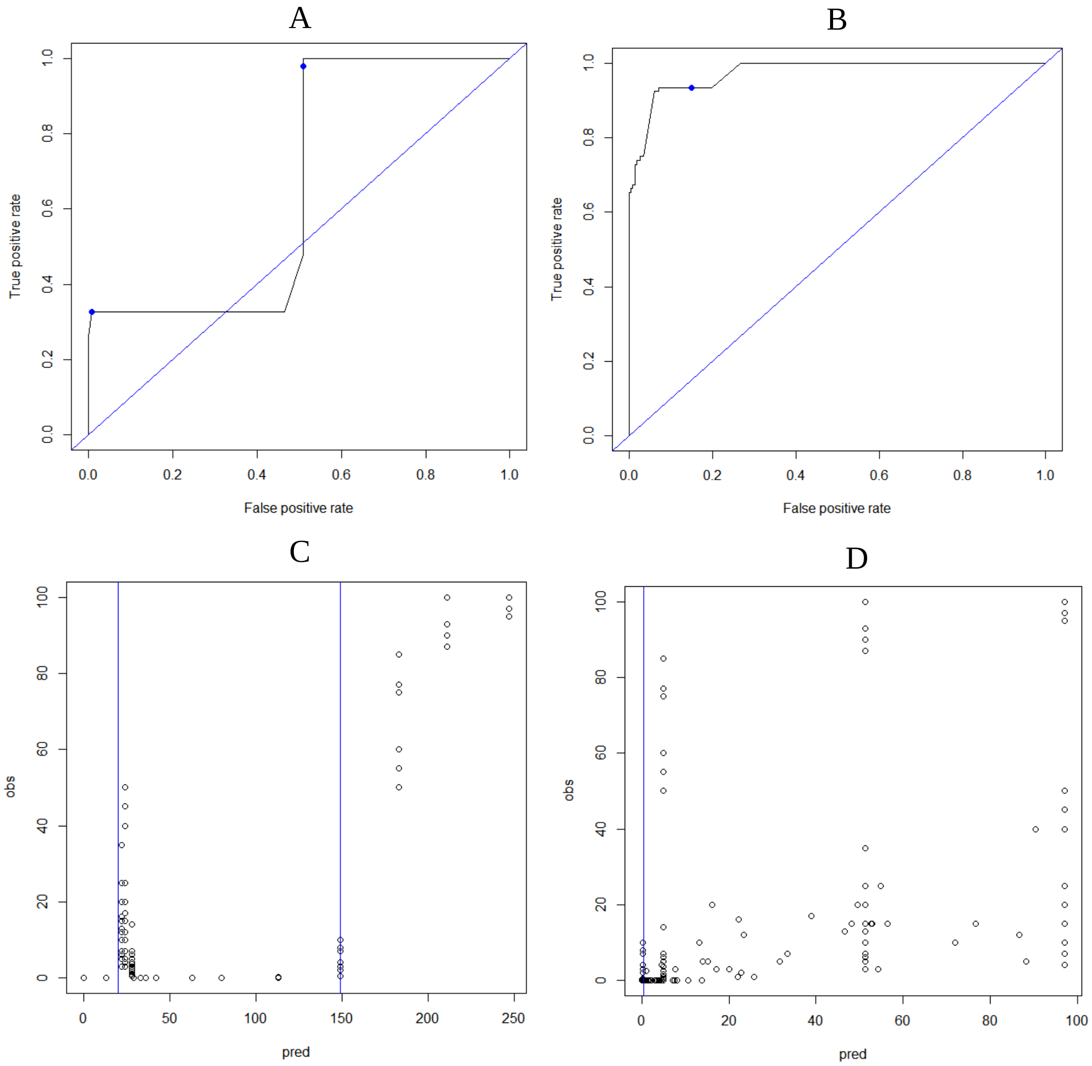

Figure 9: Results from the ROC analysis (A-D). Subplot A shows the ROC for the SIMCAST predictions and subplot B shows the ROC for the drone photos. The cut-off values are shown as dots on the ROC curves in A and B. In C and D, the cut-off values are shown as lines for the SIMCAST predictions respectively for the drone photo predictions. The blue lines have the cut-off values 20 and 149. Regarding the cut-off in D, the blue line has the cut-off value 0.48.

Table 3: Cut-off values for SIMCAST.

Cut-off (blight units)	False-positive rate	True-positive rate
20	0.506	0.979
149	0.009	0.326

One cut-off value, 20 blight units (Table 3), was chosen for the SIMCAST node in the network for only predictions from SIMCAST. Thus, two classifications of risk were set for this node: low and high. Regarding the SIMCAST node in the combined network, two cut-off values were chosen instead of one, 20 and 149 blight units (Table 3). Therefore, three classifications were set for this node which represents low, medium and high risk.

Table 4: Cut-off value for interpolated drone photos.

Cut-off (%)	False-positive rate	True-positive rate
0.48	0.158	0.935

For the drone photo node one cut-off value was chosen, 0.48 percent (Table 4), and thus two thresholds were set in the current Network which are representing low and high risk.

Regarding how to evaluate the ROC curves, they can be compared visually in Figure 9 (A versus B). The ROC curve for the interpolated drone photos (B) has a higher true-positive rate, when the false positive rate is lower than the ROC curve for the predictions from SIMCAST (A). This implies that the ROC curve for the drone photos is a better classifier than SIMCAST to predict the risk of late blight.

Decision and sensitivity analysis

The two networks were updated with different possible cases and different values (Table 2). In Figure 10-12 three different updates are visualized in order to show how these networks are built: one for the network which is only relied on predictions from SIMCAST and two for the other network for both SIMCAST (Figure 10) and drone photo (Figure 11 and Figure 12). In these figures are the nodes viewed as bar charts where the properties for every node are visible. The node for total cost has two values; one value for “Yes” and one for “No”. These values are related to the spray application. If “Yes” has a lower value than “No” spray should be applied because the total cost is higher for no spray application and conversely, if “No” has the lowest value. Moreover, if a selection of property has been made, then the selected property is viewed in bold letters.

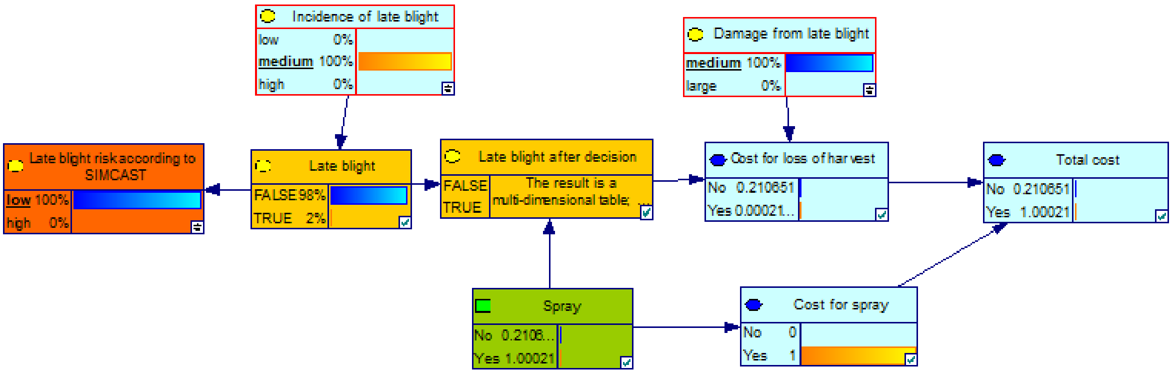

Figure 10: An update for the network which relies only on SIMCAST. The total value indicates that it is more cost-beneficial to not spray than to spray under the selected circumstances.

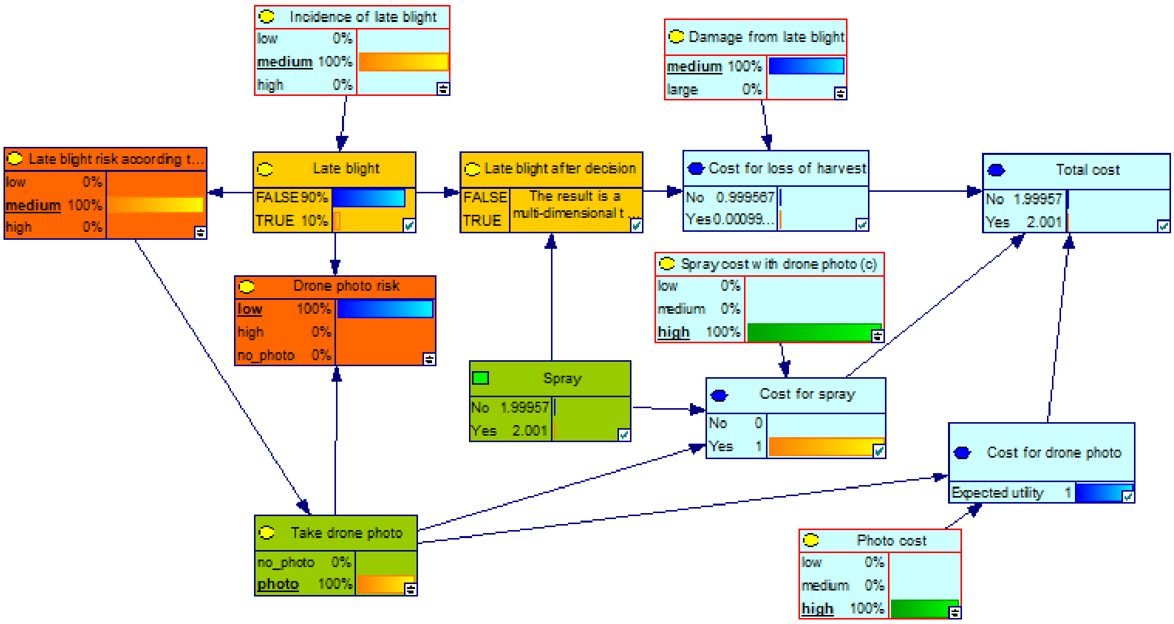

Figure 11: An update for the network which relies on SIMCAST and drone photo when the nodes are viewed as bar charts. This update visualizes the total costs for to spray or not to spray when a drone photo is taken under selected circumstances. In this case it is more cost-beneficial to not spray than to spray.

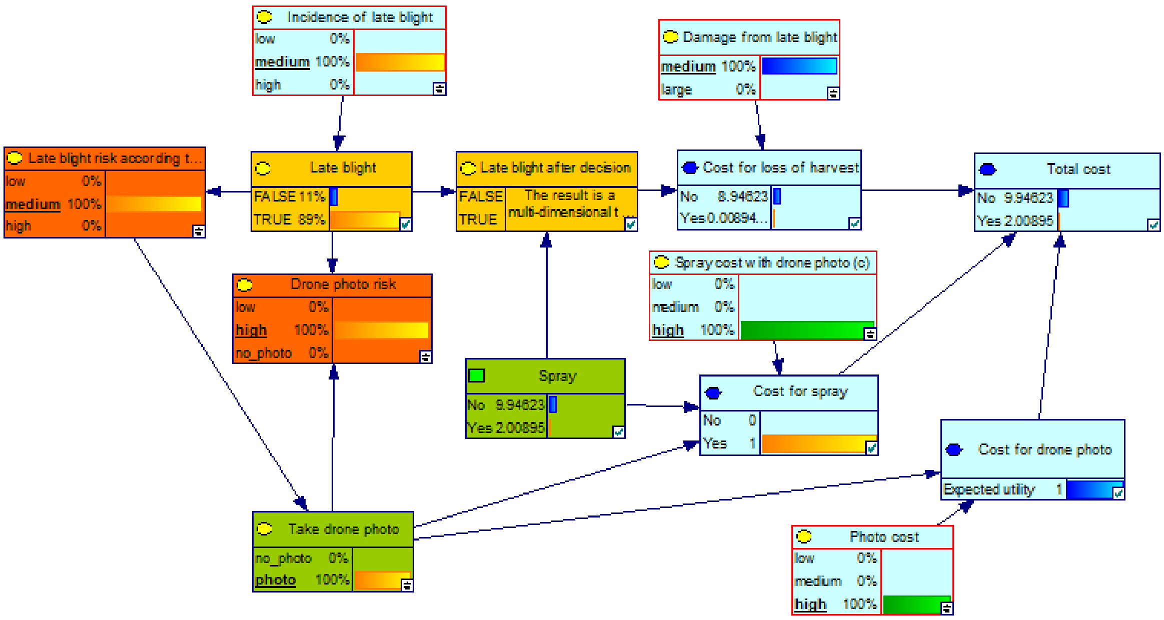

Figure 12: An update for the Network which relies on SIMCAST and drone photo when the nodes are viewed as bar charts. This update visualizes the total costs for to spray or not to spray when a drone photo is taken under selected circumstances. In this case it is more cost-beneficial to spray than not to spray.

The output from the decision analysis was extracted and later on evaluated through a sensitivity analysis. Different scenarios from the sensitivity analysis are presented in Table 5. The expected cost for these scenarios are visualized in three diagrams for each scenario in Figure 13-18, one diagram for each incidence. The incidence is set to 10% (subplot A), 50% (subplot B) and 90% (subplot C) from Table 2. When only SIMCAST is used, it is shown as a solid line and when the drone photos are included it is shown as a dashed line. Furthermore, the diagrams are showing the expected total cost on the y-axis and the risk thresholds in blight units (low and high for only SIMCAST: low, medium and high when including drone photo) on the x-axis. These thresholds are viewed in a logarithmic scale in order to visualize the variation of total cost, in an easier way, due to different parameters values. The main purpose of these diagrams is to visually compare the two lines. The line which is above the other is the line which has a higher cost and thereby an evaluation of the impact of the drone photos in the decision system can be done.

Table 5: Overview of the test values for different scenarios. The assumptions for the parameters (C_{spray}, C_{drone}, c and C_{loss}) are presented in Table 1 and the values for the parameters are initially presented in Table 2.

Scenario	Name	C_{spray}	C_{drone}	c (reduced C_{spray})	C_{loss}	Result
1	Ref. high damage cost	1	1	1	100	SIMCAST best
2	Ref. low damage cost	1	1	1	10	SIMCAST best
3	50% photo 75% reduction spray cost	1	0.5	0.25	10	Drone best for low and medium incidence
4	25% photo 75% reduction spray cost	1	0.25	0.25	10	Drone best for low and medium incidence and equal for high incidence
5	10% photo 75% reduction spray cost	1	0.1	0.25	10	Drone best
6	25% photo 90% reduction spray cost	1	0.25	0.1	10	Drone best

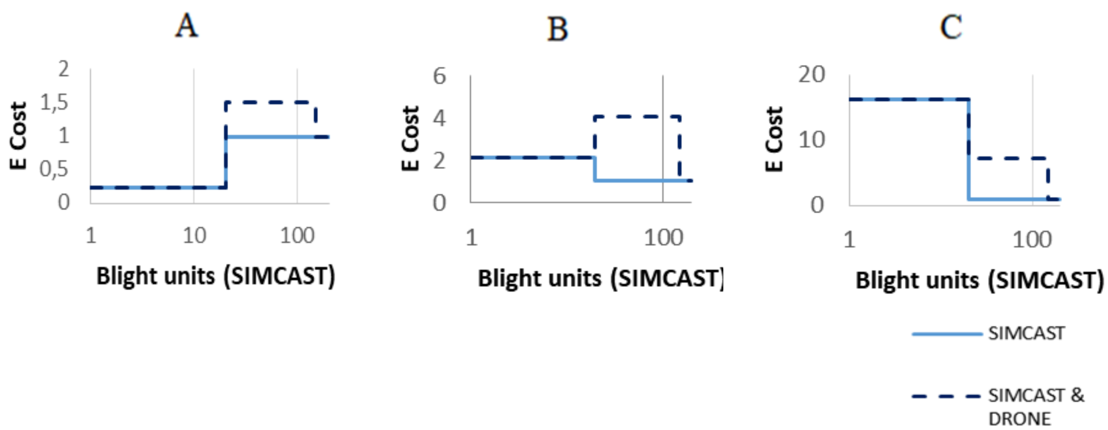

Figure 13: Scenario 1. This scenario is used as a reference scenario for when the damage cost is high. SIMCAST has a lower cost than the combined SIMCAST and drone photo management for the three types of incidence (A-C).

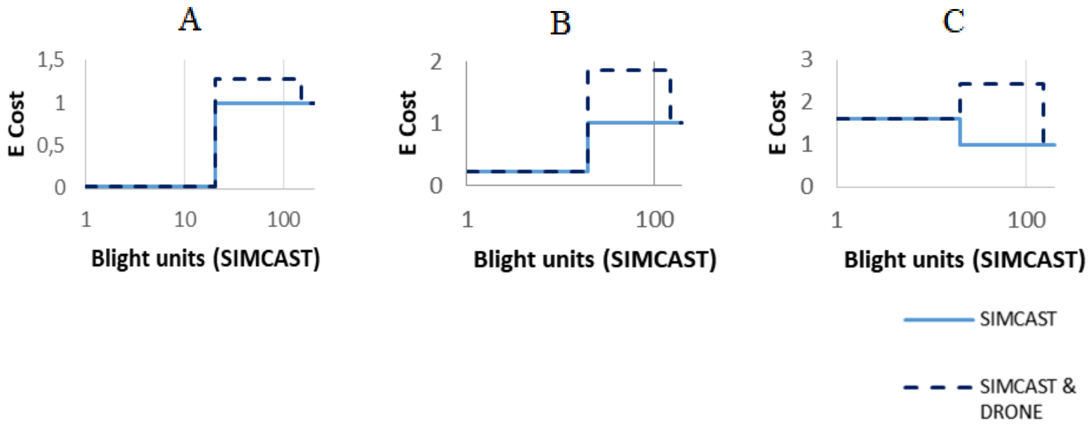

Figure 14: Scenario 2. This scenario is used as a reference scenario for when the damage cost is low. SIMCAST has a lower cost than the combined SIMCAST and drone photo management for the three types of incidence (A-C).

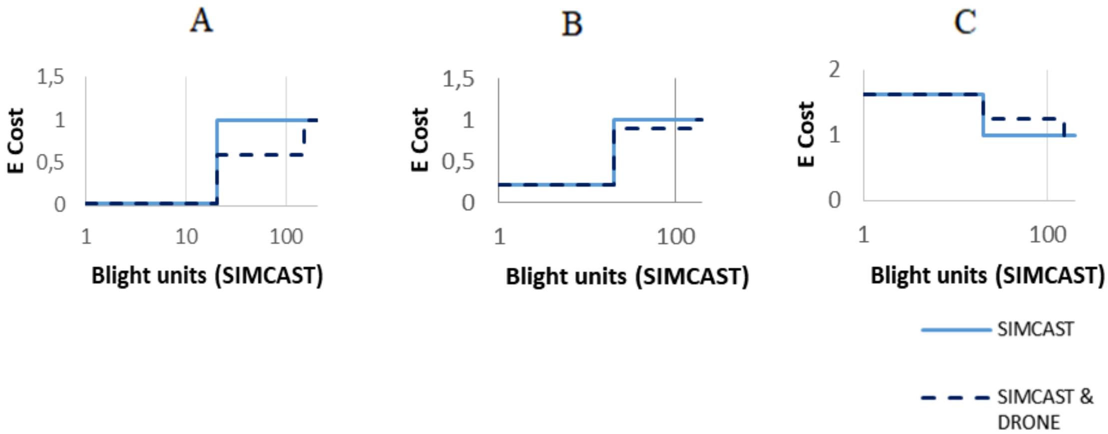

Figure 15: Scenario 3. In this scenario the cost for drone photo is reduced to 50% and the cost for spray is reduced to 75%. The combined SIMCAST and drone photo is the best for low and medium incidence (A and B).

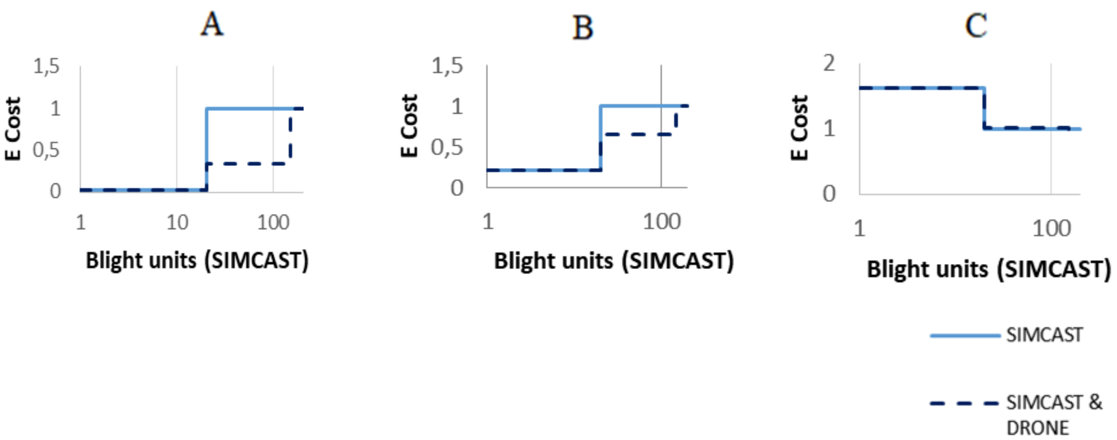

Figure 16: Scenario 4. In this scenario the cost for drone photo is 25% of the reference cost and the cost for spray is reduced to 75%. The combined SIMCAST and drone photo is the best for low and medium incidence (A and B). Regarding high incidence, SIMCAST and the combined SIMCAST and drone photo is nearly equal.

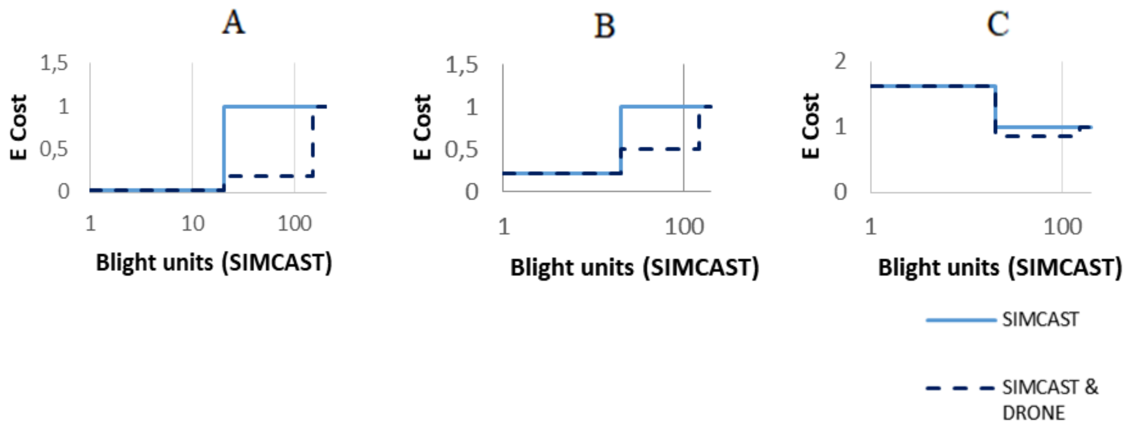

Figure 17: Scenario 5. In this scenario the cost for drone photo is 10% of the reference cost and the cost for spray is reduced to 75%. The combined SIMCAST and drone photo is the best for all three types of incidence (A-C).

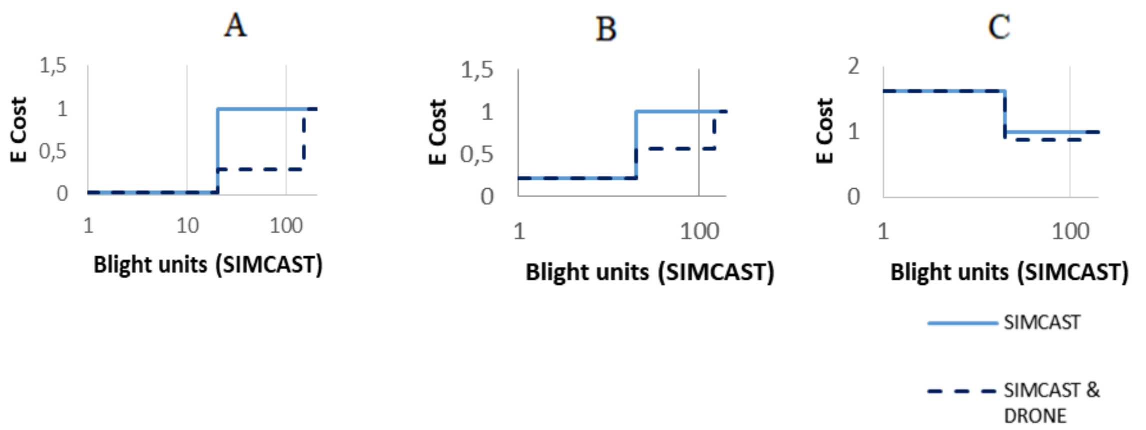

Figure 18: Scenario 6. In this scenario the cost for drone photo is 25% of the reference cost and the cost for spray is reduced to 90%. The combined SIMCAST and drone photo is the best for all three types of incidence (A-C).

Discussion

The impact of drone images on risk assessment and late blight management

When comparing ROC curves, for the predictions from the drone photos and for the predictions from SIMCAST, the ROC curve for the drone photos was a better classifier than the ROC curve for SIMCAST to predict the risk of late blight. Thus, the drone photos seem to be better than the prediction model SIMCAST regarding predicting the risk of late blight. However, whereas daily SIMCAST predictions are easy to obtain, it is a large question if the cost to use drones is comparable to the improved accuracy from using information from drones. Our results show that cost-effectiveness in using drones decreases with the risk for potato blight damage. This is because SIMCAST is providing conservative forecasts (i.e. error on the safe side) while using drones increases the cases of blight outbreaks.

Regarding the results from the sensitivity analysis, i.e. the evaluation of the cost, they were indicating that SIMCAST alone was better than the combined decision model with both SIMCAST and drone photo for the reference scenarios. SIMCAST and the drone photo were the best, generally, when the costs for photo and spray had been reduced. Regarding the incidence, it seemed like the combined SIMCAST and drone photo was less efficient than only SIMCAST when the incidence of late blight was high. This can be due to choose of cut-offs in the ROC curves, because SIMCAST had two cut-off values and the drone photo had only one cut-off. The higher cut-off value for SIMCAST contributes to better predictions when the incidence is higher.

Furthermore, when the decision model was informed with thresholds from the ROC curve for the predictions from SIMCAST, a lower threshold was used (20 blight units) compared to the initially set thresholds (30 and 35 blight units) which were used when the predictions from SIMCAST were calculated. If a higher threshold was used then many events of late blight had been ignored. This would have a negative effect on the decision model which used both SIMCAST and drone photo, due to the fact that a medium risk according to SIMCAST was set to trigger to take a drone photo. Moreover, this calibration also improved the SIMCAST model (when alone) in the decision model, but it might also highlight the impact of the drone photo in a less favorably way.

Although, an aspect which was not taken into account in this thesis is regarding excessive spray cost. This might also have an impact of the result from the sensitivity analysis. SIMCAST is good to predict late blight if it occurs in this decision model, but SIMCAST will also result in unnecessary spray applications. Consequently, recommendations for spray applications will be more frequent in the use of SIMCAST than in the use of the combined SIMCAST and drone photo, due to the fact that SIMCAST might exaggerate the risk for late blight sometimes.

Moreover, an interesting finding in this thesis was regarding the versatility of the created decision model. Though, this study aimed to evaluate the potential of using drone photo to improve a decision support system for management of late blight, it can also be used as a support to decide if one should spray or not spray.

Weakness and improvements
There are several opportunities to improve and develop the decision model and the data analysis more precise and accurate. Furthermore, to be able to use these models in more than a theoretical level, the decision model should be put in a more realistic context where real values should be used instead of fictional values.

It is possible that another prediction model than SIMCAST can be used as well to predict the risk of late blight. There exist different types of DSS in this field, but SIMCAST were considered to be used in this thesis due to the availability and access to input data.

Regarding the quantity of the data, larger data sets would be more preferable. If more field data were included in the analyses that would have improved the risk model and thus the decision model. Continued expansion of data can be done, though the extent is limited to the access to relevant data. Furthermore, there were difficulties to create the interpolated curves for the drone photos due to the fact that there were only three drone photos which were related observation data.

The quality of the data can be improved and thus improving the output of the data analyses. An example of improvement of the quality of the data is regarding precision of the location of the shapefiles. These shapefiles were manually placed in ArcMap and there were difficulties to decide the center of the shapefile. Due to the fact that the shapefiles were exactly the same size and shape, but the parcels in reality did not have those properties. Thus, some unwanted information could be included or wanted information could be loss. The parcels were also tilted in the coordinate system. To improve this aspect an algorithm could be used to calculate and determine the positions of the shapefiles direct in R instead of using manually creating these shape files. Though, in this thesis, it was considered that it was more advantageous to create the files manually instead. This was due to lack of time when trying to create the algorithm, but an algorithm would also have been advantageous according time.

Several assumptions were made in order to simplify the data analyses and the modelling. These assumptions can be adjusted, developed and more detailed to represent the reality in a more realistic way. Firstly, the assumptions related to the risk model will be discussed. Then the assumption related to the decision model will be discussed later on.

Different types of amounts of fungicides were applied due to the different treatments, but in the data analyses the treatments were not separated from each other. The only separation which was made, regarding the treatments, was if the parcels were sprayed or not. This assumption, may affect the classification of the predictions from SIMCAST. Due to the fact, that different amounts of fungicides might not have the same effect on late blight. In other words, it is a simple assumption to set all the cumulatively summed up predictions from SIMCAST to the value zero when spray has been applied.

Regarding decision model, it is a simplification of reality and consists of different types of nodes. These nodes are connected to each other and affect each other. Assumptions are necessary to create the networks, because the networks are only models of the reality. The detail level could be higher in the decision model in order to describe the reality in a more realistic way. This aspect could be improved. For example the percentage of late blight is not equal to cost of loss of harvest in reality (4). The loss of harvest is due to the percentage of damage caused by the late blight.

Another aspect regarding the assumptions of the decision model is how time aspect is handled in the networks. The decision model is based on assumptions for only one decision. The possibility of using the model is limited to one occasion and the result is only one outcome at that precise occasion. In order to improve this limitation, it would be desirable to be able to handle time series including both previous and predicted future occasions. To achieve that, a Markov Decision Process could be used to create decision series (25, 26).

Outlook and opportunities

Regarding the cost of spray, the cost can be decreased if the amount of spray is decreased. If late blight is detected only in a certain area, there is an option to concentrate the application of the spray at the infected area and apply less amount of spray on the rest of the uninfected field. However, the amount of the spray which actually can be reduced in practice has not been taken into account into this thesis. This aspect can be investigated further on.

Another advantage regarding the usage of drone photos concerns the layer change in camera surveillance which came into force on the first of August in 2017. This layer change made it possible for private individuals and companies to take photos from a drone without permission from the County Administrative Broad. Though, there are still other rules and permissions from different authorities which need to be taken in consideration (26).

Due to the cost of taking and processing images from drones, it may be not profitable to use drone photos to improve the management of late blight. Considering the advancement of technology there seem to be great opportunities for this kind of applications.

Conclusion

The findings of this thesis showed that drone photos can be used, in theory, in order to decrease the total cost for late blight management, but only under certain circumstances. It is difficult to provide a solid statement for using drone photos due to the cost. Although, due to the fast emergence of technology and despite this study's limitations, there seems to be a potential future to combine this kind of technology with Decision Support Systems in order to manage late blight in potato crops.

This study can be used for further research in order to create a risk model which can be applied in practice, and though contribute to a more efficient and environmental friendly cultivation of potato crops.

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Appendix A

SIMCAST function
The structure and values of the function for the used SIMCAST model in this thesis is retrieve from Lukas Bengtsson's Master thesis: Late Blight, Prediction and Analysis, 2017 (10).

```
# SIMCAST function
# time.int: the number of hours when the relative humidity is above 90%
# temp: daily mean temperature.
# Output: in blight units, which may be used cumulatively for prediction of late blight appearance.
# use for a highly susceptible potato sort

SIMCAST_function = function(time.int , temp)

{

  if (temp<=27 & temp>=23){

    if (time.int>=7 & time.int <=9){return (1)}

    if (time.int >=10 & time.int <=12){return (2)}

    if (time.int >=13 & time.int <=15){return (3)}

    if (time.int >=16 & time.int <=18){return (4)}

    if (time.int >=19 & time.int <=24){return (5)}

  }

  if (temp<=22 & temp>=13){

    if (time.int>=7 & time.int <=9){return (5)}

    if (time.int >=10 & time.int <=12){return (6)}

    if (time.int >=13 & time.int <=24){return (7)}

  }

  if (temp<=12 & temp>=8){

    if (time.int==7){return (1)}

    if (time.int>=8 & time.int <=9){return (2)}

    if (time.int==10){return (3)}

    if (time.int >=11 & time.int <=12){return (4)}

    if (time.int >=13 & time.int <=15){return (5)}

    if (time.int >=16 & time.int <=24){return (6)}

  }

  if (temp<=7 & temp>=3){

    if (time.int >=10 & time.int <=12){return (1)}
```

```
    if (time.int >=13 & time.int <=15){return (2)}
    if (time.int >=16 & time.int <=18){return (3)}
    if (time.int >=19 & time.int <=24){return (4)}
  }
  return(0)
}
```

Appendix B

The drone photos were obtained from Vultus. Vultus is a small company in Lund which is focusing on precision farming by using satellites, machine learning (and drones) (27).

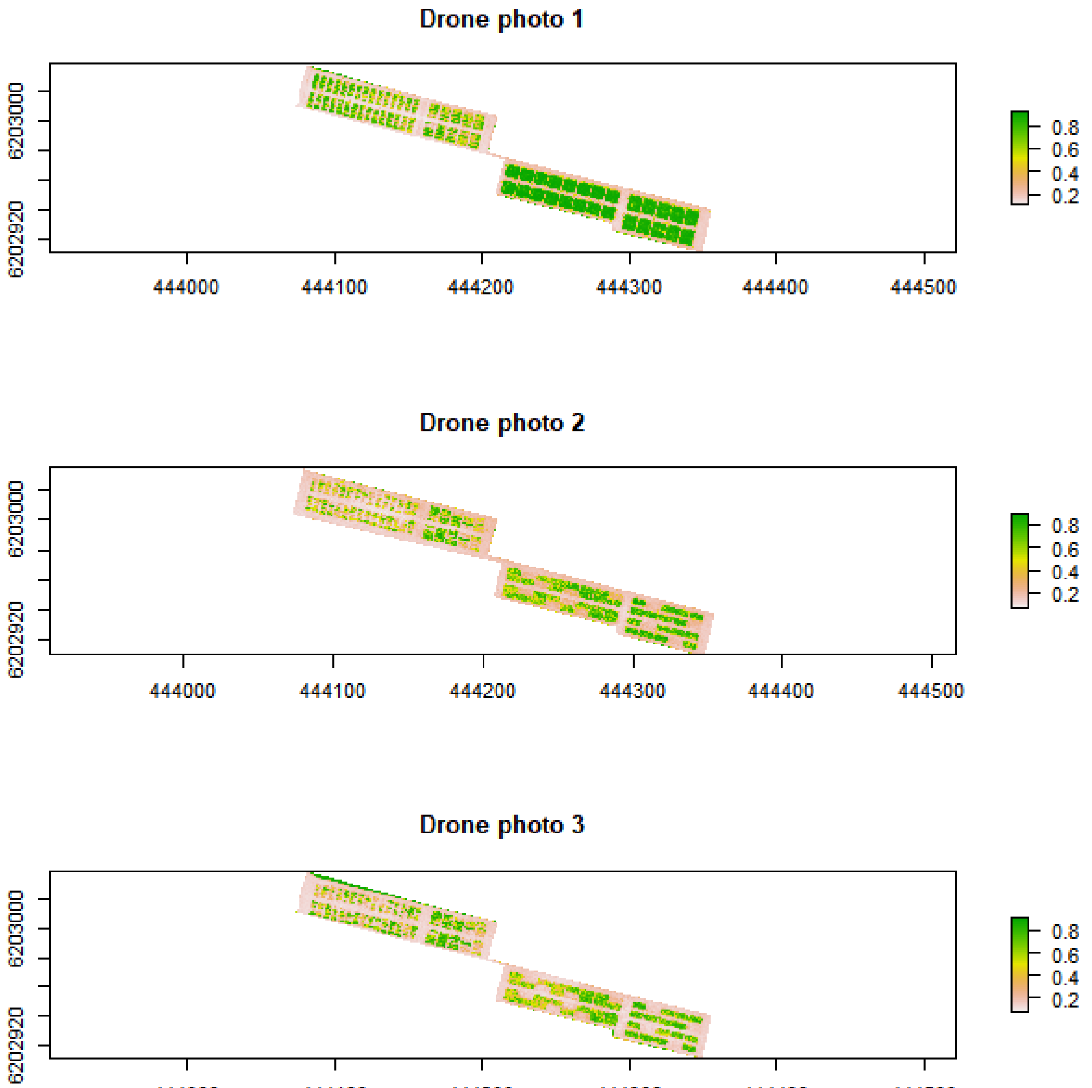

Figure 19: The image displays three drone photos of the trial field in Mosslunda. The photos are taken in the summer of 2017.