DECISION MAKING AND OPERATIONAL PLANNING IN AUTOMATIC CROP FARMING

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ABSTRACT

In order to automatize crop farming and its processes, a number of technological and other problems have to be solved. Agricultural field robots are in our vision to fulfill operations in fields. Robots involve number of technological challenges in order to be functional and reliable, but also systems controlling these robots are to be developed. In this paper automatic crop farming is the vision, and decision making models and operational planning is discussed. Study is carried out with simulation environment capable of simulating crop growth, weather, automatic crop farm storages and sheds, robots and stationary systems, and systems controlling the robots. The driving force for simulation is spatial variation of soil, crop growth potential and variable solar radiation; and this sets challenges for automatic decision making. This study concentrates on fictional barley crop farm in Southern Finland. The operations to be done are conventional: harrowing and seeding together with local fertilizing, weed control, supplementary fertilizing, crop disease control and harvesting. Automatic decision making models are studied, and developed for each operation. Operational planning involves question that in which order fields are operated. Decision making for seeding including harrowing and fertilizing is considered as one operation, and the developed model relies on stationary online moisture and temperature measurements from field; and decision for seeding is done when a certain threshold is exceeded. For weed and crop disease control operations a fuzzy logic is utilized and it works using normalized measurements. The most challenging operations from a point of decision making are supplementary fertilizing and harvesting, as they have a strong influence over incoming weather, and therefore the decision making model requires probabilistic and prediction based approaches. The developed decision making model for supplementary is based on simulated crop growth model over the rest of farming season and varying weather scenarios.

Keywords: crop farming, crop growth models, planning, simulation, robots

INTRODUCTION

Automation is nowadays utilized in many fields of industry. Manufacturing factories automatically produce parts and the others assemble them to functional products. At processing factories raw material is supplied to a process that is automatically controlled, to produce paper or gasoline for instance. “Robotic workers” in automobile assembly line are well known application where more precision and efficiency is found.

Automation is used also in agriculture. Modern tractors and other mobile machinery contain many kinds of embedded automation, which benefits driver’s work, time efficiency, fuel efficiency, or all of them. Also in dairy farming, automatic milking systems made a revolution some years ago.

In crop farming, the recent developments have made mobile machines semi-autonomous, by utilizing GPS positioning with some correction, to enable automatic steering while the driver may concentrate on other things than keeping a machine on lane. Also the process control of machines has improved when cruise control, automatic load controls among other have become usual.

The next predicted step is to make field machines fully autonomous. In other words human would no more sit on a tractor, but the machine makes operations autonomously.

BACKGROUND

Agricultural field robots have been actively studied at least during last 20 years worldwide. To build a robot, several technologies are required, e.g. mechatronics, embedded systems, sensors, computing sciences, artificial intelligence, machine vision, information and communication sciences, automation and control, positioning just to mention a few. The result is easily a complex system, or robot. Today, all the required technology is available to build small robots. For larger robots, safety aspects have to be solved before commercial robots can be sold.

However, agricultural field robots are just one piece of big vision, where field work is going to be automatized. Field robots are special type of unmanned autonomous vehicles (UAV), and do operations on agricultural fields, like sowing, planting, spraying, weeding, or harvesting. Field robots in the future may also do new kind of operations which are not sensible with current machinery, like pruning.

In the vision, all operations on a single farm are automatized and human beings are only supervising the operation. Technologically robots are just autonomous machines that work on fields like current machines, but no human is needed onboard. Still, a question remains that when, where and how much operation has to be done. For a human driven system, the driver has had responsibility to do sensible things in the field, and farmer or manager has decided when operation is needed in a certain field and e.g. how much fertilizer is to be dosed.

In case of robots, and an autonomous farm, also the decision making and operation planning is to be automatized. There are two reasons for this: a) the operator is no more supervising the work onboard → human errors have to be eliminated and b) robots enable a new era of precision farming, where robots and stationary sensor systems monitor the fields by position and time, and for robots it is no problem of doing VRA.

Crop farming simulation has been studied in the past. The first crop growth models were developed in 1970's for research purposes, and in 1980's the first models which could be utilized in farm planning were developed (Rotz 2008, Yin and Laar 2005; Stöckle et al. 2003). The first simulation models concentrated on specific sub process of crop farming, and were not complete simulators. Now some advanced simulators exists, which predict yield and try to optimize fertilizer usage. The common structure in the simulators includes similar low-level models (Eckersten et al. 2004; Eckersten et al. 2006; Eriksson et al. 2005; Hill 2006; Jones et al. 2003; Larsbo and Jarvis 2003; Stöckle et al. 2003; Yin and Laar 2005; Wang et al. 2002). The most advanced simulators have specific models for pests, diseases and microclimate. (Stöckle et al. 2003; Eriksson et al. 2005; Jones et al. 2003).

This paper discusses automatic decision making models to be applicable to autonomous robots in an autonomous farm. The objective has been far in the future, but these methods should be also applicable in the near future, for human driven systems. The methods are tested using an autonomous farm simulator.

The objective of this research was to develop automatic decision making algorithms relying online measurement data from the field in Finnish farming context.

THE PROJECT "AUTOCROP"

This research is related to a research project names "Fully Automatic Crop Farming in Finland", financed by Academy of Finland. The project tries to clarify the requirements for technology, methods and models needed to make automatized crop production possible. The research methods are modeling, simulation and simulation based analysis. An automatic farm simulator was developed in this project. Models in scientific agricultural and agricultural engineering literature were to be utilized and supplementary models were to be developed – in supplementary models the structure is more important than the parameters. The approach in the project was top-to-bottom. The analysis was based on simulation of imaginable scenarios, differing resource sets, like machine repertoire.

During the AutoCrop project, the focus of simulations and modeling was set to cover a single cultivating season of spring cereal crops in Finland, in a fictive farm that corresponds Finnish farm structure. The operations carried in the field were corresponding to operations done in precision farming nowadays: sowing with local fertilizing, spraying herbicides, spraying fungicides, spreading additional fertilizer during the season and harvesting.

The simulator

The framework of research was a simulator developed in the project. The simulator incorporates a crop model, a soil water model and a plant model for three weeds. In the environment, the solar radiation is computed by taking shadows on account; and the weather is simulated based on statistics from Finland. The simulator supports the farm structure of several fields and other resources like shelves, storage buildings, and roads. All fields are split on the raster grid; the cell size of raster is tunable. The cell size of 5x5 meters was used in all simulations. This size is a good compromise between the natural variation within the fields and computational speed of simulator. (Maksimow, 2007).

The simulator is realized using multi software integration. The good properties of several softwares were combined: Matlab/Simulink, ArcGIS, SQL Server database and Visual Studio programming environment. (Maksimow, 2007).

The homogenous area crop model was modeled and developed using Matlab/Simulink, which is a powerful tool for developing dynamic models. The underlying base time step was selected to be one hour. The simulink model has takes in environment values, like rainfall (during an hour), the temperature, humidity and solar radiation; and state information of underlying soil. The model output is the state vector, which contains e.g. the growth stage, crop biomass, grain mass, moisture content, nutrient content. Only nitrogen and phosphorus are considered in the model. The soil model is a multilayered model where rainfall slowly infiltrates to bottom layers, and on the other hand capillary action is considered.

Visual Studio was used to run the simulation. Simulink model of a crop, soil and weeds for a small homogenous area was compiled to C++ code. In Visual Studio this C++ code is wrapped in .NET component for easier usage. The .NET component contains methods to set the inputs, to read the outputs, to set the parameters and to run the simulation one hour further. In runtime environment, which is programmed with C# language, the environment computes the spatial model, which contains only a water flow model on surface and in ground layers. The weather generation model was implemented using Matlab, and this model can be utilized in Visual Studio environment by compiling Matlab functions to .NET component. All simulation data is stored in SQL Server database and the visualization of the results is done using ArcGIS/ArcMap. Also the scenario is designed using ArcMap.

The solar radiation for each cell is computed using ArcGIS Solar Analyst and this computation is done prior simulation, as the sun runs constant route. During the simulation, the weather generator produces cloudiness which decreases the amount of solar radiation to a cell.

The structure of the simulator is presented in Fig. 1. The simulator is divided into two parts, on the left is infrastructure and decision making and on the right is the environment. The detector generates measurements corresponding to real life use from the environment state information. The measurements are based on estimation and contain realistic noises and biases.

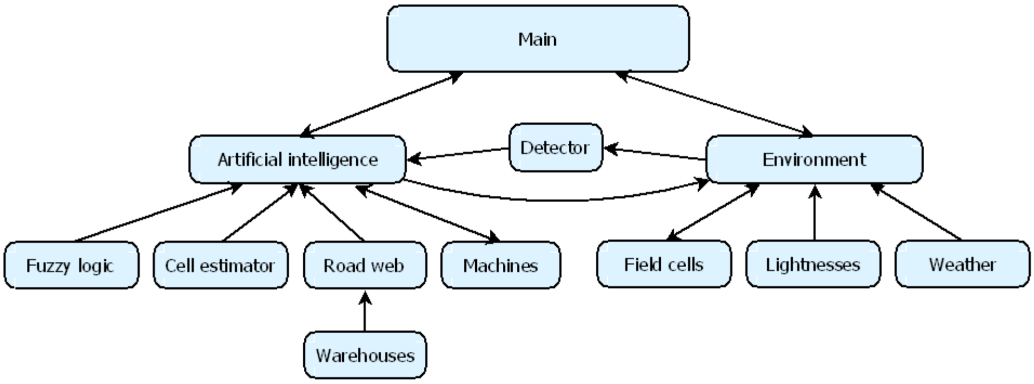

Fig. 1. Simulator structure (Aspiala 2010).

Simulation parameters

The simulation starts at the beginning of April and all the cells in the field are wet. This corresponds to Finnish weather, when the snow melts. Typically, the sowing time is in the first week of May, so at the beginning of simulation it takes about four weeks to dry before sowing can act. During this period, the randomized parameters of the field start to act and the field drying is not happening at the same rate all over the fields. As simulation is started that early, the initial moisture value in cells may be equal, as during the initial phase of simulation the variation takes place.

The weather generation is based on statistics. The weather dynamics follows both yearly trends and short time trends. The rainfall model was the most challenging model as the rain has binary appearance and there is strong time correlation. The model follows idea of Sorensen (1999): the model gives probabilities for the rain in next hour based on the current state of rain. The model was derived from Finnish hourly data. The probability of rain follows Poisson distribution (Tattelman and Knight, 1988).

MATERIALS AND METHODS

The decision making is based on three methods: *logic*, *fuzzy logic* and *expectation value* based logic. The logic is the simplest form of decision making and works like “if a value exceeds the certain threshold then do the action”, and the only tunable parameter is the threshold. In the logic multiple clauses can be combined by using *and*, *or* and *not* operations. By contrast to fuzzy logic, the simple logic is known as *binary logic* or *boolean logic*.

Fuzzy logic

In fuzzy logic, the truthness is not only true or false, but all the *truth values* between 0 and 1 are possible. The first step is *fuzzification*, where a real value is converted to a truth value by using *membership functions* to *degree of membership*. In fuzzy space the logic operations are applied and the result is converted back to real values with *defuzzification*.

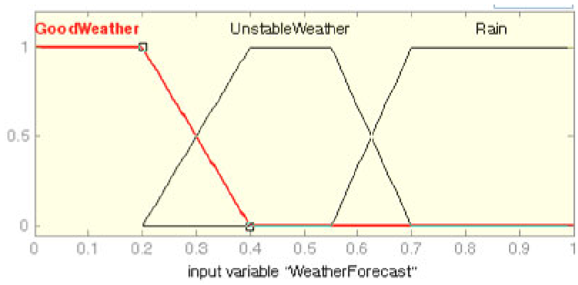

Fig. 2. Membership functions for short time weather forecast (Aspiala 2010).

In this paper, a *Mamdani type* inference was used to combine rules and do the defuzzification. In Fig. 2 are presented three membership functions for the weather forecast used in herbicide and fungicide application decision making.

Expectation value

A common way to evaluate risks and make decisions is through expectation values. Several methods exist to compute expectation values, like Bayes network, probability tree, and analytic hierarchy process. (Hardaker 2004, Malczewski et al. 1999, Sørensen 1999).

In this paper, the expectation value is computed by using the simulation model to predict the state of the crop over the time horizon; and the expectation values are used to make decisions. This is required for operations, the effect of which are not immediate. The predicted expectation values are used to make decisions for additional fertilizing and harvesting.

DECISION MAKING MODELS

In the project, the objective was to develop decision making models for five operations (sowing, additional fertilizing, herbicide & fungicide application and harvesting) and the focus is in *cereal crop* farming in *Finland*. All the decision making algorithms are run once a day in the simulation.

Both additional fertilizing, chemical application and harvesting produce normalized index for a *need* of operation. Zero corresponds to not needed operation for a cell or for a field plot and one corresponds to an immediate need. Values between zero and one are used to set the priority of operations on later stages.

Sowing

In Finland, the strategy in sowing is to do it as early as possible, as the farming season is short in the North. The challenge in decision making relates to situation when the whole field is not drying evenly.

For sowing the implemented decision making algorithm relies on online moisture measurements from the field and the sowing is done as soon as the soil moisture has decreased below the load capacity threshold for a machine. The implementation assumes that the measurements can be gathered online, and in real life this would require either subsoil stationary wireless network or lightweight robots scouting the moisture.

The threshold for moisture content was calculated as in units of field capacity. The soil type is taken account while computing the field capacity. For clay, the set threshold in the simulation was 94% of field capacity. This threshold was used also as a constraint for all the other operations.

Additional fertilizing

It is not usual operation in Finland to do additional fertilizing for spring cereal crops. One of the reasons is that in Finland the season is short, but also the machine cost for operation is high due human made operation and furthermore the lack of measurements limits usage of improved precision fertilizing. For operations made by robot additional fertilizing is assumed to be economical enough to do.

In Finland fertilizing is required as the soil contains insufficient amount of nutrients for a good yield. The nitrogen is the most crucial nutrient. The grain yield function of nitrogen fertilizing follows roughly a parable curve (Cooke, 1972). More accurate nitrogen response curves have been identified later on.

The benefit of the additional fertilizer is seen in harvest, in amount and quality of yield. In this decision making process, the time horizon of effect is long, so expectation values are to be used.

This prediction is done for one field in time, so “an average cell” is calculated from all the cells (available measurements). The simulation is done without additional fertilizing to get a reference, and then by making additional fertilizing at that time step and these two predicted states are compared. The time horizon for prediction is tunable, and in the following results time horizon of two weeks was used. If the predicted expectation value for the yield is more than the operational cost (robotic operation + fertilizer inputs), the need for operation is positive.

The crucial part of prediction is the weather forecast. The future weather is known in the simulator and the forecast is computed from the simulated weather. The forecast is assumed to be an expectation function for weather variables. For better accuracy, Monte Carlo methods should be used to handle the uncertainty of future weather and simulation. However, in the case of this simulator this was not possible as the computation time for one season simulation may not be longer than some hours. For real-time usage, more computationally heavy prediction methods may be used.

As it is not possible to forecast the weather more than 7-10 days further with current methods, for the remaining period of season to the harvest is simulated over “minimum rainfall weather”. The reason to use minimum rain case is based on the objective to minimize fertilizer usage and the minimum usage by a crop is happening when the rainfall is small. In case of Finland, from the statistics 1971-2000, the least rainfall was reported being 14.1 mm per month during summer, and this is used as in the simulation for the period beyond the weather forecast to the harvest time.

In the decision making process both the increase in the yield and rate of increase are counted. If the positive need for additional fertilizing exceeds the threshold, the next step is to check which cells of the field are to be operated, and the operation is only applied to those cells.

Herbicide and fungicide application

Both for herbicide application and fungicide application, a fuzzy logic model was developed. In both models four inputs were used and the only difference is that in herbicide decision making the number of weeds is used and in fungicide the amount of disease. The other three inputs to both models are: the development stage of the crop, soil moisture and short time weather forecast. The time horizon for the weather forecast should be equal to the impact time for an effective agent of herbicide/fungicide. Time horizon of 24 hours was used in the following tests.

The rules for fuzzy logic are based on expert interview, and therefore mimicking current decision making culture – but here the decision making relies on online data. The response curves in herbicide application are shown in Fig. 3. On the left is presented the need in space of the weed amount and the development stage and on the right soil moisture effect. The two figures (left and right) visualize the same four-degree space in two dimensions at a time.

Harvesting

The decision making for cereal crop harvesting is done using the expectation value method. The time horizon is two weeks. Also in this decision making "an average cell" is formed corresponding each field plot to speed up simulation remarkably. The weather forecast is used in the prediction with simulation. The prediction gives an estimate when the yield is ripened and what is the grain moisture. In the weather forecast, the worst case scenario is used: if the weather forecast predicts rain in a certain time in the future over 10% probability, in the simulation the rain happens.

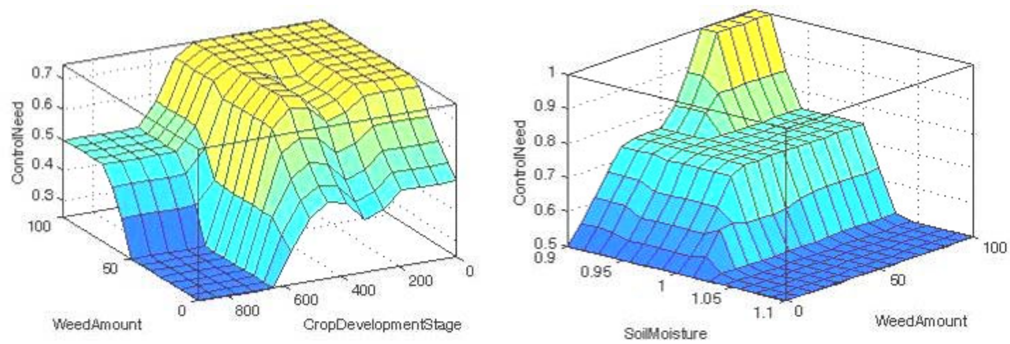

Fig. 3. Fuzzy model for weed control need computation (Aspiala 2010).

RESULTS

To test the developed decision making algorithms, a fictive farm was set to as a scenario. The field area is taken from the real world, from southern Finland, but there was no information whether these fields belong to one farm today – and for this simulation it is not relevant. The elevation of field plots, soil type and nutrient contents in the soil were randomized. Soil type is characterized by six parameters (Karvonen and Varis, 1992). Randomization was made by randomizing a set of points to field area, by randomizing value (height, soil type parameters, N/P/K content and weed seed banks) corresponding to each point. Finally, a surface was fit to points to form a smooth variation. The field area is shown in Fig. 4, on the left and the generated elevation map on the right.

Weed germination is based on the initially randomized seed bank. Three weeds were used in the simulation: bedstraw, fat hen and *Galeopsis bifida*. Each of common weeds represents a different type and three different herbicides are used to control the weeds, in respect. In the simulated operation, the weed is killed and not appearing again that season – this was considered realistic enough as a better simulation model for weed crops was not available.

Solar radiation for fields is computed using ArcGIS Solar Analyst. The forests cause shadows for the fields and the elevation variation within the field area also causes uneven solar radiation for cells. In Fig. 5 is shown a cumulative solar radiation during a week. In dark areas, the solar radiation is limited as the forest shadows the area. The purpose of adding forests was to increase variation within the fields, to test the decision making process better.

A single season was simulated in different parameters. In Fig. 6 is presented a nominal season, where the accumulation of the yield as well as operations are shown. The simulation begins April 1st, and the field dries so that the sowing is done May 1st with generated weather. Herbicide operations start May 17th and the last operation is done June 19th. For fungicide application, the need for operation appears at the same time for all the fields June 7th. Additional fertilizing is done during June. Harvesting time is computed per field and the timing is seen last phases.

The effect of additional fertilizer usage per operation was studied. It was found out that in the simulation the smaller increment will give the best profit, the peak appearing in +10 N kg/ha per operation. In Fig. 7 is shown an example of additional fertilizing with small increments. As it can be seen, a part of the field is operated once and some areas twice. The cost of operation was based on current market prices: fertilizer 0.25 €/kg, operational cost 13.2 €/ha and grain price 0.118 €/kg.

Fig. 4. On left: field area used in scenario (Google - Geocentre Consulting, Tele Atlas, 2009). On right: randomly generated elevation for fields in scenario (the lighter - the higher). The forests are plotted with green. (Aspiala 2010).

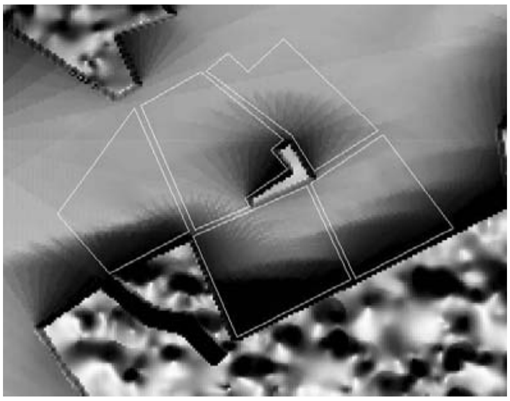

Fig. 5. Solar radiation for fields. Fields shown with white lines. The lighter – the more solar radiation (Aspiala 2010).

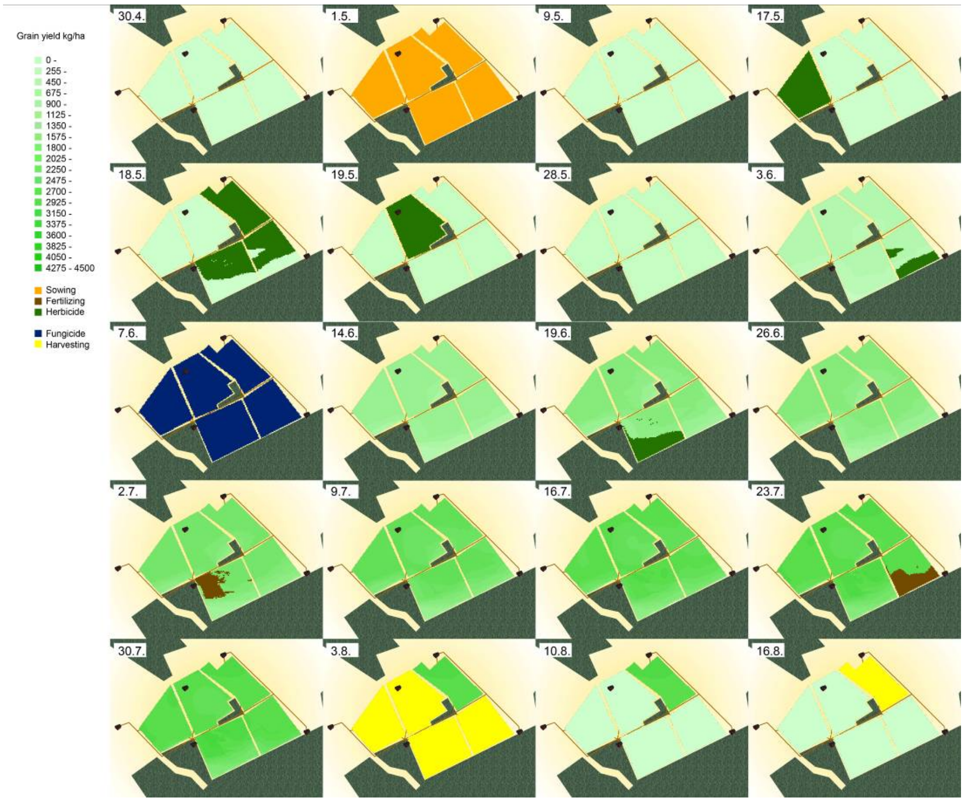

Fig. 6. Simulation over one season (Aspiala 2010).

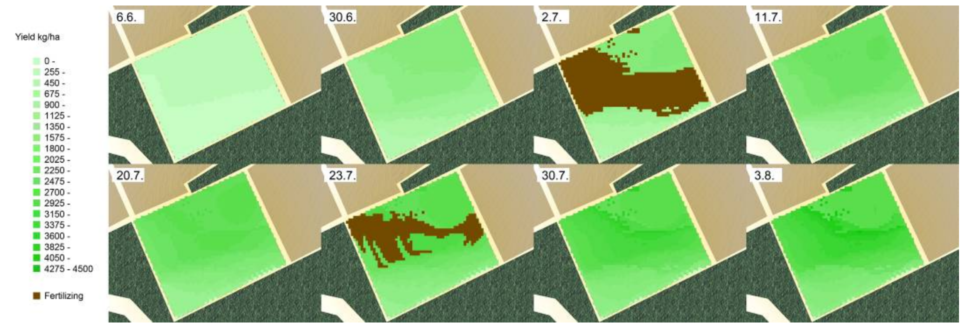

Fig. 7. Additional fertilizing in small increments (Aspiala 2010).

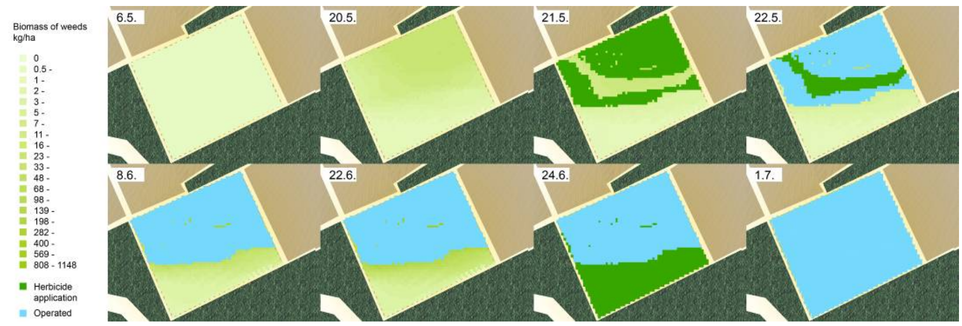

Fig. 8. Herbicide operation in four stages (Aspiala 2010).

DISCUSSION AND CONCLUSIONS

The developed decision making models work well when they are used to control a simulated farm.

All the models rely on online information from the field and real life application requires more online measurements than are used in farms today. Also the expectation value methods are optimizing the simulation model and real life application would require a calibration of this crop model.

Methods relying on fuzzy logic (herbicide & fungicide application) were working very well, and the development of the models was rapid. The fuzzy models are quick to compute and therefore good for a simulator running the whole season 5x5 meters grid hour to hour.

Expectation value methods (additional fertilizing and harvesting) are computationally so heavy that in simulator it was not possible to compute these methods for all the field cells in every hour. The selected solution was to calculate "an average cell" from all cells in a single field plot and compute the expectation values over the horizon for this representative sample "cell". This worked pretty well in the fields where properties did not vary much. However, if the variation is large and as the models are nonlinear, "the average cell" by using mean values is not representing well enough the whole field.

In the decision making for additional fertilizing, the best result would be get if position specific demand for fertilized was known beforehand; and dosed as demand at sowing time. However, in real life this is not possible as the weather forecast for ~100 days cannot be done; and it was found with the simulator that for the scenario used, the best strategy was to use 10 (N)kg/ha additional fertilizer per time.

The decision making model for harvesting seems to work satisfactorily, as the estimated grain moisture content follows the averaged moisture well in the field during the simulation.

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