NEW DEVELOPMENTS AND INTEGRATION FOR PRECISION AGRICULTURE

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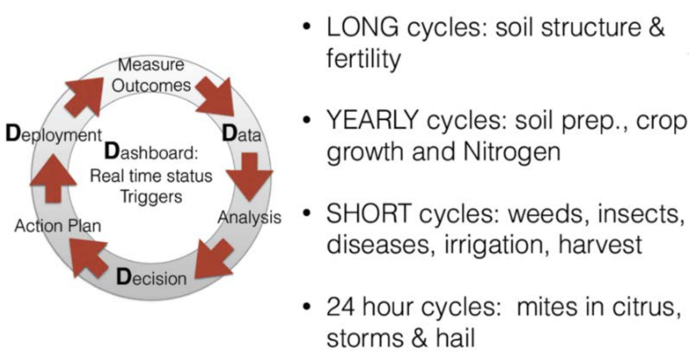
1 INTRODUCTION: MANAGEMENT CYCLES IN PRECISION AGRICULTURE

The agricultural production systems involve processes and process conditions are that *very variable* (natural variability of biological processes, soils, climate). The level of production, and therefor also the potential profit for a farmer is the result of the interaction between crop genetics, the environment, the available technology and the management and decision making skills of the farmer. It can be expected that a combination of these 4 components can be optimized with respect to income in one growing season or for a long term sustainable production and profit. This optimization is then based on the following:

• Correct observation • Correct analysis • Correct information (soil, previous crops and treatment…) • Correct genotype • Correct dose • Correct chemical/biological compound • Correct place • Correct time • Correct (climatic) conditions • Correct (use of) equipment	
Doing the right things	*Management cycles in precision agriculture (Vanacht, 2014)*

In these management cycles, the activities in precision agriculture must take into account the variability in time as well as in space time variable. They depend on::

- Data availability: these can be stored data (soil maps, etc.), human observation or sensor systems that relate to the condition of the soil, the crop, the environment or other parameters.
- Analysis of the available data to extract information on the actual state or possible evolution of the crop production processes.
- Decisions to be made on the management of the fields or crops based on the available information and ‘expert knowledge’ about the expected effect of actions. Different options can be considered. Use is also made of market expectations. Production and market models are used.
- Equipment with the capability to execute the decisions with the required accuracy in terms of type and dose of treatment as well as a suitable spatial resolution.

There are more books being published on precision agriculture that deal with some or all of these components. Also new insights and tools are presented in conferences on precision agriculture and smart farming. Smart farming also relates to the digitization of agriculture. Indeed, starting with the use of smart phones, the society has embraced a digitization evolution and is now becoming familiar with the Internet of Things (IoT). Agriculture is moving very rapidly towards the introduction of the IoF (Internet of Food and Farming,, see also IOF2020) that will help improve yields and meet the growing demand.

2 SENSING AND DATA AVAILABILITY IN PRECISION AGRICULTURE

Soils sensing.

The spatial and temporal variation in soil physical and chemical and biological properties include clay content, water content, and salt content (i.e. salinity), NPK mineral content, micro-biome. Besides laboratory analysis on soil samples, in the field sensing research is based on electrical and electromagnetic, optical and radiometric, mechanical, acoustic, pneumatic, and electrochemical measurement concepts (Adamchuk, 2011). Sudduth et al., (2017) used a model inversion approach to calculate soil layer texture fractions on the basis of mobile measurements of apparent soil electrical conductivity (ECa) rather than using an averaged value over a given soil profile depth. The approach has yet to be refined, but may give information related to planting depth or water management.

At a recent International Conference on Intelligent Agriculture (ICIA) in , China NERCITA (National Engineering Research Center for Information Technology in Agriculture, PR China) claimed the development of a portable LIBS (laser induced breakdown spectroscopy) system capable of measuring soil available N and perhaps also other minerals like K and P on a small soil sample in the field within 2 seconds (Liping Chen, 2017). Even at a slightly reduced accuracy, this can be a major tool for estimating temporal and spatial variability in nutrient availability based on connecting dynamic crop models (and nutrient uptake) with sensor observations (Wallor et al., 2017). Using actual values of nutrient availability will refine fertilizer recommendations and make crop growth and yield predictions more reliable.

An important component of soil fertility and nutrient availability is the soil microbial activity. Bender et al., (2016) compiled promising approaches to enhance agricultural sustainability through the promotion of soil biodiversity and targeted management of the soil microbioom. Spatial variability n available substrate and environment affects soil microbial activity. The spatial heterogeneity of microbial activity has received less attention to improve local soil (and crop) management. Adamchuck et al., (2017) discussed techniques that may lead to portable instruments for detailed mapping of indices of soil biological health at any specific point in time. Soil respiration using either extracted soil air or a substrate induced approach appear promising.

Crop inspection and nutrition status

Use of N-fertilizer must be with regard to an optimal N-use efficiency by crops to assure that N that is efficiently conserved and taken away in crop harvest where it eventually makes its way back to the environment. A number of technologies are available today to estimate crop N-status. Developments in photonics are the basis for measurement systems to observe plant nutritional status and potential stress at different spatial and temporal scales. These systems can be based on light transmittance of leaves, on leaf and canopy reflectance or also on leaf or canopy fluorescence (Muñoz-Huerta, 2013). In many cases canopy or leaf reflectance of natural or sunlight is measured in different wavebands of light and related to the incoming light that is also measured. It implies that measurements are done during the day. Recently active reflectance and also fluorescence measurements have been introduced, making use off an artificial light source operating at specific wavebands. (Tremblay et al., 2012). These can also be used during night time. measurements make use of active light source.

The equipment in which these sensors are incorporated can be handheld, on board tractors or other mobile equipment. Airborne systems in satellites, aircraft and more recently in UAV's tend to use lightweight but versatile hyperspectral imaging systems (Thorsten et al., 2011). These can make images at different wavebands such that for the whole field detailed crop indices are thereby giving information about of nutritional status and its spatial variability.

Crop density

The amount of biomass of a growing field crop has an effect on the micro-climate within the canopy and as such on the risks of disease development and spreading. In the case of combinable crops then the amount of crop mass to be processed affects the efficiency of the combines. Saeys et al. (2009) looked at Light Detection And Ranging (LiDAR) sensors and different methods of online data-processing for estimating crop density in front of a combine harvester. A method for the estimation of crop volume was based on calculating the volume between the ground profile and the crop profile. It also has the potential for a 3-D crop reconstruction. Recently, a coherent, frequency-modulated LiDAR was introduced that produces both range and velocity data for each point in its field of view. It is solid-state, with no mechanics at any scale and has auto-grade durability (Oryx, 2017). The use in agriculture will be facilitated as it can profit from the large automotive market.

Weed detection

The developments of automated mechanical weed control requires that reliable technologies for the detection of weeds and discrimination between weeds and crops are available. Various methods have been developed to discriminate between weeds and the crop based on spectral characteristics and/or image based shape recognition (Vrindts et al., 2002; Slaughter et al., 2008). Christensen et al. (2009) conclude that given a wide range of weed sensing techniques studied over the last 10 years, so far none has been developed into a commercial product. It seems that the robustness of the sensing systems, i.e. their ability to cope with the natural variations of spectral or morphological characteristics and mutual shading among weed species in a field requires the application of combinations of high-speed spectral cameras, image processing and embedded algorithms in the weed management model. There are new approaches. Hadoux et al., (2012) showed the potential of detailed hyperspectral information to discriminate vegetation species, provided the influence of lighting variability can be overcome. The detection systems can be on board of applications of tractors or specialized (mechanical or chemical) weeding robots. Drone technology using on board hyperspectral or multispectral cameras can discriminate between crops and weeds making use of information on rows. This may then be a rapid and reliable tool for detecting weed patches in fields. PrecisionHawk (2017) introduced automated Weed Pressure software for an accurate analysis of weed pressure in the fields.

Pest and disease observation

Reliable techniques have been under investigation for detecting the outbreaks or onset of pests and diseases based on frequent measurements in time and at a sufficient spatial resolution. Sankaran et al. (2010) concluded that the challenges in these techniques are: (i) the effect of background data in the resulting profile or data, (ii) optimization of the technique for a specific plant/tree and disease, and (iii) automation of the technique for continuous automated monitoring of plant diseases under real world field conditions. In a review on plant disease detection by optical sensors (Mahlein (2016) finds that sensors that can be used to specifically detect plant diseases are still not available on the market. Instruments and technological solutions for field, greenhouse, and for phenotyping are available. However, these are highly specific and tailored prototypes and cannot be used on a broad scale (Mahlein, 2016).

Volatile organic compounds (VOCs) are important signaling molecules, and the deciphering of this chemical information will be of relevance for the early detection of plant responses to biotic and abiotic stress, in search for new sustainable methods for pest and environmental control (Maffei et al., 2011). There is a need for affordable field usable detection systems (artificial nose?) combined with localization tools.

3 INFORMATION MANAGEMENT AND DECISION MAKING FOR IMPROVING THE EFFICIENCY OF FERTILIZER AND CROP PROTECTION USE IN AGRICULTURE

Fertilizer use

Diacono et al., (2013), give a review of Precision nitrogen management of wheat.

If the crop index (like NDVI) can be attributed to fertilizer needs rather that other stress factors like water availability, pest or diseases then decisions can be made for be optimal level of fertilizer to be applied at each point in time. Knowledge of soil water conditions as well as expected weather conditions provide additional information for decision making. Using crop growth models enhances the estimation of nutrient requirements within a future time span and help to forecast yield under given nutrient management. Crop models use the existing knowledge of the physics, physiology and ecology of crop responses to the environment end nutrient availability. Most of the time the spatial variability of soils is not incorporated, but it should be possible at the cost of simulation time. Indeed, few studies are available in the literature on how to account for the effects of spatial variability of measured soil properties and local micro-climatic conditions on simulated crop growth and (growth limiting factors affecting) yield variability. Ma et al., (2016) concluded that the variability in yield and biomass as simulated by their model due to spatial distribution in soil water field capacity (FC) was less than observed variability in the field. Other soil properties, such as bulk density, nutrient level, and uneven distribution of irrigation water, might have contributed to the larger variation in measured yield and biomass. There is a need to include in the models of the soil processes involving nutrient availability.

Crop growth models and weather forecast for decision making on fertilizer application can be enhanced by recalibration with measured estimates of crop biomass. A number of commercial companies offer farmers help with daily decision making using detailed field-level current and future weather, soil data and management zones, and crop growth stage information. Recommendations can include variety selection and planting date that will optimize yield, variable rate nitrogen application, integrated pest management strategies and harvest dates to optimize yields and minimizer drying costs .

It is clear that optimal fertilizer use (and best N-use efficiency) will require a portfolio approach in which different technologies are used in different combinations to address site-specific challenges. This approach may be different for the different crops that a farmer grows. Grains crops have been mostly studied in this respect, while pulse crops or root crops seem to require more complex strategies. Also, Calcium, Potassium and Phosphor are other minerals that must be incorporated in an efficient fertilizer management strategy.

Weed management

Weed control remains an important management activity to avoid crop growth and yield reduction. Some management issues are the following:

- There exist a number of mechanized weeding tools in the market or close to the market that have the precision needed to effectively and safely control weeds without harmful side effects (see

Young and Pierce, 2014). In robotic weeding there are concepts developed in agricultural engineering research as well those of large industrial automation companies like the Bosch Start-up Deepfield Robotics (Albert, 2017).

- No single strategy is perfect, and therefore an integrated approach may provide better results. The adoption of such methods may improve the efficiency of cropping systems under sustainable and conservation practices (Bajwa et al., 2015);
- Non-herbicidal weed management strategies by growers will require more knowledge, planning, time, cost and risk than in the past, in spite of ever-increasing farm size (Shanner and Beckie, 2014);
- A weed dynamics model predicts weed flora over the years, depending on cropping system and pedoclimate. This helps towards management rules for reconciling weed-related biodiversity (weed species richness and equitability, weed-based trophic offer for birds, insects and pollinators) and weed harmfulness (crop yield loss, harvest contamination, harvesting difficulty, field infestation, additional crop disease due to weeds) (Meziere et al., 2015).
- In a multilevel approach cropping systems are re-examined in combination with chemical and mechanical (or thermal) methods as a basis for integrated weed management (IWM). IWM can draw from a lot of experience and developments that were done in organic agriculture.

Geo-locating patches where significant weed seed shedding occurs points to key problem areas in next season's crop. An important hypothesis is that late season mapping provides a sound basis for patch spraying of pre-emergence herbicide. Mapping late in the season will allow early detection of herbicide resistance (Gateway to Research, 2017).

The success of chemical treatment of individual weeds or weed patches requires high quality equipment with mechanical and operational spray components suitable to operate under harsh field conditions.

The recent developments in weed control technology has been summarized in a number of review publications (for example: Young and Pierce, 2014, Shanner and Beckie, 2014)

Pest and disease management

Integrated Pest Management (IPM) is a key component of the strategy towards sustainable pesticide use. It emphasizes the growth of a healthy crop with the least possible disruption to agro-ecosystems and encourages natural pest control mechanisms. Harmful organisms must be monitored with adequate methods and tools, where available. Ferguson et al. (2003) discuss the spatial ecology of pests in terms of the roles of environmental factors, behavioural responses and the implications of spatial patterns for yield loss and for developing sustainable integrated crop protection. Their data with insect traps indicate that decision support systems can use sampling strategies which incorporate spatial information to model crop loss more accurately and that there is the potential for spatially targeted applications of insecticide to optimise the influence of biocontrol agents in oilseed rape.

Spatial and temporal effects which can be based on observations integrated in epidemiological models. These models help in evaluating the potential economic impact of the disease and of control measures. Collins and Duffy (2016) used models such models and concluded that a control measure at the outset of the outbreak of maize foliar disease can reduce the spread of the disease at a minimum cost.

The decision-support tools for IPM in the context of precision agriculture can be based on many different sources of information like on-site devices, mobile equipment or airborne or satellite observations if these are of sufficient spatial resolution. These tools can be part of a crop management system that has for a vineyard : (i) an integrated system for real-time monitoring of the components (air, soil, plants, pests, and diseases) of a vineyard or part thereof, and (ii) a webbased tool that analyses these data by using advanced modelling techniques and provides up-to-date information for managing the vineyard in the form of alerts and decision supports for the vineyard part under consideration (Sciaretta et al., 2011). There are emerging commercial services offered to farmers for scouting and decision support, but the spatial or temporal resolution are at this moment not explicitly available (Precision Farming Dealer, 2015)

4 IMPLEMENTATION OF TOOLS FOR SMART FARMING

The above discussion of data availability, information extraction and decision making must be implemented in practice. Major machine manufacturers are including more inexpensive sensors on field equipment, not only on machine monitoring but also on monitoring crops and processes. In addition, on-board intelligence and actuators allow for implementing decisions derived from prepared treatment maps or from on board decision making. All the data about the terrain and crops as well as about the actions (number of seeds and planting depth of each seed, fertilizer dose,..) are geo-referenced. Similarly, drones, small aircraft or new high resolution satellites make it increasingly possible to capture frequent, high-quality images of small sections of field

Major agricultural equipment producers either develop some of the tools themselves, mostly when it involves mechanical or simple electronic hardware. In many cases there is a cooperation with specialized suppliers of hardware who in turn do translational development by incorporating devices that were developed for mass markets outside agriculture. Smart sensors, LAN or IoT on machinery are examples. These developments as well as the discussion with farmer groups make that machinery manufacturers are loosening their rules on proprietary aspects of hard- and software and are more willing to making data sharing possible in a more open environment. This is also the case for developments in drones that are driven by larger markets than just agriculture. Making data-driven decisions to boost profits can be a challenge with different equipment, multiple fields and different activities throughout the season. Therefore, it is convenient that growers can collect field data, get prescriptions and transfer data seamlessly to and from equipment of every equipment manufacturer.

Industrial robotics and automation companies also show a new interest in agriculture. The experience they have gained industry is the basis for their efforts to introduce their robotic systems in a very hard an challenging environment like agriculture. This is a long term effort and one can expect that mergers or acquisitions of smaller start-ups will eventually lead to products that economically feasible in agriculture or at least in some specialized agricultural productions.

It is clear that the volume of data being generated is enormous, creating a technical challenge for those trying to analyze it and extract the useful information for making money-saving or profit generating decisions when farmers operate a tight margins. Creating the infrastructure to handle and analyze that much data is complicated and it attracts companies that can create services to turn this abundance of data into money-saving advice. Combining information like localized weather forecasts with details about topography, water levels in the soil, and the seed that has been planted in a field, such companies can advise farmers about how much fertilizer to put on a field and when, or what the best procedure and timing is for weed disease and pest control. There is growing cooperation between major machinery manufacturers, monitoring service companies and crop management service companies (see for example Climate corp, Pioneer-Dupont, BASF-Maglis, and others).

This also raises the question of data ownership but it requires sharing data. Data that are locked in a steel cabinet cannot help farmers in making decisions to improve the operations and keep their business profitable. All these issues will be part of the recently started large scale EU project, the Internet of Food and Farm 2020 (IoF2020, https://www.iof2020.eu/).

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