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Pornchai Taechatanasat
Edith Cowan University

Leisa Armstrong
Edith Cowan University

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Pornchai Taechatanasat [1] and Leisa Armstrong[2]

1 School of Computer and Security Science, Edith Cowan University, Perth, Australia,
Email: ptaecha0@our.ecu.edu.au, pornchai_tae@yahoo.com
2 School of Computer and Security Science, Edith Cowan University, Perth, Australia,
Email: l.armstrong@ecu.edu.au

Abstract

The capacity of farmers and agricultural scientists to be able to make in-season decisions is dependent on accurate climate, soil and plant data. This paper will provide a review of the types of environmental and crop data that can be collected by sensors which can used for decision support systems (DSS) or be further interrogated for real time data mining and analysis. This paper also presents a review of the data requirements for agricultural decision making by firstly reviewing decision support frameworks and agricultural DSSs, data acquisition, sensors for data acquisition and examples of data incorporation for agricultural DSSs.

Keywords: Agricultural data, decision making, sensor devices, data acquisition

Introduction

The productivity of agriculture in Australia is dependent on a number of factors such as changing climate, harsh environmental conditions and changing commodity markets. For farmers in Western Australia, strategic decisions need to be made seasonally to respond to these factors to maintain profitability. These decisions, such as what crop variety to grow, sowing rates, fertiliser and herbicide spraying and other agronomy practices, can contribute greatly to economical sustainability of each farmer.

Many tools are available which assist in the decision process. Various sensors devices and communication devices, such as infrared thermometer, chlorophyll meter, digital camera and NDVI sensor (Pask, 2011), have been designed to capture environmental data. Varieties of ICT software tools in agriculture have been utilised to assist farmers in decision making. Examples of software tools in agriculture are software tools for precision agriculture (Gobbett & Bramley, 2014), mobile communication (Ying & Wu, 2010), cloud computing and internet applications (Bo & Wang, 2011), management software (Siggins, 2011), Decision Support Systems (Andrew, Grundy, & Harris, 2013; Tamayo, Ibarra, & Macias, 2010; Zhong-xiao & yimit, 2008) and GIS software (Esri, 2013).

The effectiveness of these agricultural DSSs is reliant on the type of environmental, crop and other data that is collected by sensors which can be integrated into the DSS or interrogated further using data mining or other analysis techniques. Due to numerous variables affecting crop growth, the accuracy of the existing DSSs using traditional statistics analysis is still in doubt. The quality of input data can be improved by developing reliable data acquisition devices such as the wireless sensor systems. This paper presents a review of the data requirements for agricultural decision making by firstly reviewing decision support

frameworks and agricultural DSSs data acquisition, sensors for data acquisition and examples of incorporating data sets for Agricultural DSSs.

Decision Making Frameworks

Previous studied have reported that the decision makers often make decisions under pressure, with incomplete information, or an overload of information and engage in practices which are hard to evaluate and irrelevant to the organisation and context (Baba & HakemZadeh, 2012). The rational for decision making process has been identified on the research of Franklin (2013). The process consists of the following steps: define the decision situation, identify alternatives, evaluate alternative, select the best alternative and implement the chosen alternative. The basic decision making process has been increasingly applied in various areas, such as in business support application to present graphically information (Hamzah, Sobey, & Koronios, 2010).

There are examples of where agricultural researchers have applied decision making theory to design farmer decision making frameworks. Armstrong, Diepeveen, and Tantisantisom (2010) have proposed an agricultural decision making framework focusing on information flow processes for information dissemination. The flow process was designed to assist decision making for farmers and was based on process for information dissemination to farmers. Reddy and Ankaiah (2005) have also proposed an agricultural decision making framework focusing on an information dissemination system. All these frameworks are reliant on accurate and relevant data sets to provide the means to assist farmer decisions making and to be able to incorporate these processes into decision support systems.

Decision Support Systems

A number of different definitions have emerged to describe a decision support system (DSS). For example, Keen and Morton (1978) defined decision support systems as computer systems that collect resources and use the ability of computer to increase quality of decisions by focusing on semi structured problems. Arnott and Pervan (2005) defined DSS as the area of the information systems' discipline that is focused on supporting and improving managerial decision-making. In addition, Sheng and Zhang (2009) defined DSS as human-computer systems which collect information, process information and provide information based on computer systems. From the definitions above, the term DSS can be considered to be quite broad because the concept of DSS varies depending on author viewpoint. However, Turban et al. (2005) concluded that the main objective of DSS is to support and improve decision-making.

Researchers have reported methods to classify DSSs. For example, Arnott and Pervan (2005) analysed 1,020 DSS articles published in 14 journals from 1990 to 2003. They concluded that DSS can be categorised into seven groups as following: personal DSS, group support systems, negotiation support systems, intelligent DSS, knowledge management based DSS, executive information systems/business intelligence and data warehousing. DSS can be divided into 4 levels (French, Maule, & Papamichail, 2009). The categories are considered according to the domain of activity and level of support. The domain of activity reflects the level of decisions from the personal level to corporate level. Level 0 involves to the presentation and acquisition data. Level 1 is analysis and forecasting information. Level 2 is focused on simulation and

predicting the consequences of the various alternative strategies for decision maker. Level 3 provides evaluation and ranking of alternative strategies. The boundary of each level can be varied. In addition, the level of support can be adjusted. For example, data mining may be categorized into level 2 or level 3 because data mining can be used as expert systems or forecast data.

DSS may be composed of four main components: database, model base, knowledge base and graphics user interfaces (Mansouri, Gallear, & Askariazad, 2012; Turban et al., 2005) . Some authors extend the number of components to five by including users (Marakas, 2003). The functionality of data base is to store, retrieve and organise the raw data that will be used as information to make decisions in the knowledge engine component. The model base consists of the analytical capabilities of qualitative models. The functionality of the knowledge engine is designed to manage of the problem-solving process, the problem recognition and the generation of a final solution. The user interface component is designed to facilitate users' interaction with the system.

Generally, DSS has been classified into three categories based on problems for decision making: structured, unstructured and semi-structured. Structured problems can be solved systematically, while unstructured problems are problems which are un-patterned. Semi-structured problems are problems that cannot verify the optimal decision making (Turban et al., 2005). On the other hand, Zhang, Yang, Lai, and Lai (2012) proposed a different method to categorise DSSs. This method categorises DSSs based on functionalities. The authors categorised DSSs into nine different architectures. The functionality of the DSS is determined by its system architecture. For example,

1. Collecting, managing and providing the organization with external information related to decision questions in domains like policy, economy, society, environment, market and technology.
2. Collecting, managing and providing the organization with internal information related to decision questions in domains like order request, storage status, production capability and finance.
3. Collecting, managing and providing feedback for each alternative decision execution, such as contract processing, material supply plan and production implementation.

Based on the categories above, a general DSS architecture design has been proposed (Zhang et al., 2012). The design is comprised of fundamental modules for DSS: transaction processing system, DSS database, communication technology, data mining modules, decision output and user interface. DSSs are designed for different purpose. Zhang et al. (2012) studied the trends in DSSs' development. The authors point out that DSSs are "projected-oriented" that designs for specific purpose.

Another example of an agricultural DSS architecture design has been proposed by Adinarayana et al. (2012). The architecture design composes of input module, processing data module and output module. Zigbee Mote based WSN and Wi-Fi base WSN are designed to collect environmental data from sensors. The Sensor Observation Service (SOS) database is the processing module of the DSS. Distributed application clients provide the output of the system, which distributes information to users.

Agricultural Decision Support Systems

DSS can be applied to all processes in agriculture. For management problems in farms, intelligent DSSs in agriculture have been introduced to monitor and to assist farmers to make decisions in a timely manner. However, designing a DSS is quite complex; it requires knowledge from various multidisciplinary areas, such as crop agronomy, computer hardware and software, mathematics and statistics to analyse data. For example, to understand crop growth, it is necessary to know how each variable affects crop growth. How many variables affect crop growth? How does temperature affect wheat growth? Each crop requires a different optimum growth temperature. For example, the minimum growth temperature for wheat (Triticum spp. L.) is 3-4 °C and the maximum growth temperature is 30 to 32°C. The optimum growth temperature is 25°C. (Curtis, Rajaram, & Macpherson, 2002).

Adinarayana et al. (2012) proposed an information, communication and dissemination system called GeoSense. The system is designed to help in decision making for precision farming. The system consists of five modules: crop water requirements, rice yield simulation, energy balance and weather profile studies and crop pest and disease prediction (Tripathy et al., 2012). Wireless sensor networks and cloud services were employed to provide real time information to users

Other studies have been undertaken to design DSSs for agricultural systems. For example, work by Adinarayana et al. (2012) designed a DSS to observe and predict pest incidences in rice crops. Other work by Tamayo et al. (2010) implemented DSS for fertilisation, crop growth control and prediction of diseases. Only two types of sensors, temperature and humidity, were utilised in their system for measuring maximum and minimum ambient temperatures, soil temperatures and humidity. Other work by Jiber, Harroud, and karmouch (2011) focused their study on designing a precision agricultural monitoring framework. However, this study was limited as it did not use test beds to evaluate the performance of their monitoring systems.

Andrew et al. (2013) described a list of DSS tools for agriculture as following: 3-PG, APSIM, CABALA, GrassGroTM, GrazFeedTM, MetAccessTM, Yield Prophet. These DSS tools have designed for specific purposes. For example, 3-PG (Siggins, 2011) is a forest growth modelling software for forest managers. APSIM (Agricultural Production Systems Simulator, 2014) is a farming systems simulated crop yield from environmental variables. DSSAT (DSSAT, 2012) is a software program for crop simulation models. DSS tools has been described by Department of Agriculture and Food (2011). DSS tools were divided into four categories in terms of applications: animal and animal products, land water and environment, crop and agribusiness and markets. Examples of crop DSS are MyCrop, ROOTMAP, Yield Calculator and SPLAT.

Agricultural Data for Decision Making

Agricultural data for decision making can categorised into broad three groups: environmental data, crop/plant data and economic data. Environmental data are external variables affecting plant growth. Examples of environmental data are soil, water, temperature, climate, pests and diseases. Examples of crop/plant data include crop growth, crop yield, stress, chlorophyll content, plant dry weight, flowering time, root biomass index, screening and Normalized

Difference Vegetation Index (NDVI) image. Examples for economic data include seeding costs, harvest costs, grain prices, fertiliser and pesticide application. Such categories may be utilised when a researcher is designing a group of variables to be used as input to a DSS to assist decision making.

Climate data such as temperature, relative humidity, solar radiation directly affect plant growth. Each crop requires different level of temperature, relative humidity and solar radiation. The same crop at different crop growth stages requires different level of temperature, relative humidity and solar radiation.

Crop/plant data is an important data for agricultural decision making. Crop growth and crop yield are output from environmental factors affected to crop growth. Many techniques to measure crop/plant data have been described in Pask (2011) such as determining key development stages of plant by farmers, canopy temperature, stomata conductance and water relations, spectral reflectance indices and pigment measurement and NDVI.

Examples of works where agricultural datasets have been use for decision making include work by Bache and Lichman (2013) who described the use of soybean diseases from the machine learning repository. These datasets have also been utilised in research by Jain and Arora (2012) to test their approach for mining multiple patterns to form clusters. The soybean disease dataset consists of 47 objects and 35 attributes, all attributes are categorical. The dataset is divided into four soybean diseases (diaporthe-stem-canker, charcoal-rot, rhizoctonia-root-rot and phytophthora-rot diseases). Examples of the attributes of the soybean dataset are: temp: less than normal, normal, greater than normal, ? (missing attribute values); hail: yes, no, ?; leaves: norm, abnormal,?; etc.

Environmental data, plant data and crop yield were utilised as input of DSS of agricultural yield data (Ruß, 2009). The data consisted of wheat yield data in the years 2003 to 2006 from three different fields, three levels of nitrogen fertiliser were applied with three different plots in each field. Two levels of red edge inflection point (REIP32 and REIP 49) were measured from each plot. REIP is red edge region of the spectrum from 680 to 750nm. REIP values are high when plants have high chlorophyll. The plants' chlorophyll content is correlated with the nitrogen availability. The last input variable is electric conductivity. EM-38 sensors were measured at 1.5 meters depth.

Agricultural Data Acquisition

Precision and accuracy of information is not only related to ways in which data is acquired, but also related to the frequency of collecting data (Malaverri & Medeiros, 2012). High frequency of sampling data increased accuracy of information. However, high frequency of sampling data requires extra investment in tools and is time consuming. Generally, frequencies of acquiring data in agriculture are hourly, daily or weekly. In agriculture, there are substantial numbers of methods for acquiring data for decision making. The standard methods to measurement air temperature, air humidity, radiation and win speed data in agriculture have been suggested in the chapter 3 of Allen, Pereira, Raes, and Smith (1998), detail will be described in next section. Data acquisition in agriculture can be summarised based on the following criteria (Chenghai, Everitt, Qian, Bin, & Chanussot, 2013; ICT International, 2013; Lopes, Olivers, & Arce, 2011; Pask, 2011; Primicerio et al., 2012; Yin,

Liu, Zhou, & Sun, 2013):

1 - **Location to collect data** - Field collection, research trials and farmer demonstration trials are locations in which a researcher can acquire data. Field collection is the most direct and simplest method of collecting data. Both environmental data and plant data have been utilised to determine key developmental stages. Researchers have collected data through research trials, plant breeding and variety trials. Farmers may collect data through farmer demonstration trials.

2 - **Method to collect data** - There are three methods of collecting data: manual, automatic, integration. Manual method is the simplest and direct method to collect data about plants. Example of this method is key developmental stages (Pask, 2011) and sampling soil for moisture, nutrient and root content (Lopes et al., 2011). However, manual methods are time consuming and require collecting data regularly.

Automatic methods have been developed to facilitate farmers and researchers collecting data. Data can be collected in real time. The automatic methods reduce time in recording data manually. Many disciplines, such as computer sciences, biochemistries and physics, have been integrated to create tools for collecting data. For example, X-ray sensors and gamma-ray sensors attached a tractor scan all of a paddy field to create a soil map to assist the farmer to analyse soil properties all over the paddy field.

Integrated methods utilise the advantages of both manual methods and automatic methods. For example, soil water content can be measured by many tools (ICT International, 2013), such as tensiometer. Researchers have a choice of two tensiometer models, jet fill and transducers. Potential between soil water content and water in the tensiometer tube is measured manually, while the transducer tensiometer automatically sends a continuous analogue output signal.

3 - **Tools to collect data** – there are various tools for collecting data in agriculture such as specialised instruments in agriculture, ICT tools in agriculture and weather instruments. Examples of penetrometers, soil moisture probes, chlorophyll meters, tensiometer, near infra-red (NIR) machines and normalized difference vegetation index (NDVI) meters are examples of specialised instruments in agriculture. Examples of ICT tools in agriculture include sensor networks technologies. Environmental sensor and complementary metal–oxide–semiconductor (CMOS) image devices have been designed to integrate with wireless sensor networks (Yin et al., 2013).

4 - **Distance capturing data** – distance capturing data may be categorised into three categories - ground level, aerial and satellite. Satellite imagery or remote sensing has been utilised to assess crop growth and yield variability for precision agriculture (Chenghai et al., 2013; Ma, Chen, Shang, & Zhang, 2006). Unmanned aerial vehicles (Primicerio et al., 2012), weather stations and precision sensors for spraying, are other means of collecting data.

Sensors for Agricultural Data Capture

A variety of sensors have been used to collect agricultural data. These sensors have been used to measure different soil, plant and environment characteristics. Measurement methods for

solar radiation, air temperature, relative humidity, soil nutrients, soil water content, NDVI and wireless sensor will be described.

Solar or shortwave radiation use acronyms Rs and symbol [MJ m^{-1} day^{-1}]. Solar radiation is measured with solarimeters, radiometers or pyranometers. These instruments have a sensor attached on a flat clear surface (Allen et al., 1998).

Air temperature use acronyms T and symbol [℃]. Air temperature can be measured with thermometers, thermistors or thermocouples attached in the shelter. Normally, the air temperature in agriculture use the mean daily air temperature (Tmean) for 24 hour periods calculated from the mean of the daily maximum (Tmax) and minimum temperatures (Tmin) (Allen et al., 1998).

Relative humidity has been defined as the ration between the amount of water the ambient air actually holds and the amount of saturation vapour pressure could hold at the same temperature (Allen et al., 1998). Relative humidity use acronyms RH and symbol [%]. Relative humidity can be measured with hygrometers.

Soil is an important part that provided nutrient to plant. Soil provides air, water and nutrients as a medium of plant growth. Osman (2013) describe that soil are natural unconsolidated materials on the surface of the earth. Osman categories components of soil into four major components: mineral matter, organic matter, water and air. Soil sampling is a direct method to measure proprieties of soil such as gravel, texture, mineral matter, soil water content.

there are seventeen chemical elements have been recognised as essential for plants such as nitrogen, potassium, phosphorus (Osman, 2013). These elements have been categorised into two broad groups: major elements or macro nutrients and minor elements or micronutrients. Plant require macronutrients in large amounts (>1,000 mg kg^{-1}) and require micronutrients are needed in relatively small amounts (<100 mg kg^{-1}). Sampling soil is an efficient, economical and convenience method to test soil proprieties (Lopes et al., 2011). Sampling soil has been utilised to measure moisture or soil water content, nutrient and root content.

Soil water content use acronyms W and symbol (measurement unit) [mm] (Allen et al., 1998). Apart from sampling soil, another method to measure is measured with tensiometers, electrical resistance sensor for soil water tension estimates and gravimetric and volumetric direct measurements (International Atomic Energy Agency, 2008).

Adamchuk, Rossel, Sudduth, and Lammers (2011) studied and classified soil sensor type according to wavelength of sensor, method of detection, active sensors or passive sensors, invasive or non-invasive sensors, stationary operation or mobile operation. In addition, soil properties that can be detected with each sensor type are summarised in table 1. Soil sensor devices can be divided into four groups based on detecting energy: electromagnetic (Gamma-ray, X-ray, optical, microwave, radio wave), electrical, electrochemical, and mechanical.

Table 1 Different types of sensor in agriculture (Adamchuk et al., 2011)

	Sensor type							
Soil Property	Gamma-ray	X-ray	Optical	Microwave	Radio wave	Electrical	Electrochemical	Mechanistic
Chemical								
Total carbon	D	D	D					
Organic carbon	I		D					
:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:
Salinity and sodicity					D	D	D	
Physical								
Colour			D					
Water content	D		D	D	D	D		I
:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:
Clay minerals	I	D	D			I		I

*Soil properties directly (D) or indirectly (I) predictable using different types of proximal soil sensors

NDVI is a technique to measure canopy size and vegetation greenness. Canopy size and vegetation greenness can be used to estimation of early cover, nitrogen content, post-anthesis stay-green and pre-anthesis biomass. The advantages of NDVI measurement are that it is quick, easy and low cost, integrative and non-destructive. The concept of NDVI images have been utilised by many researchers in research focused on plant health (Gamon, Huemmrich, Stone, & Tweedie, 2013; Los, 2013; Luo, Chen, Xu, Myneni, & Zhu, 2013). These research utilised NDVI in broad areas through remote sensing technologies such as satellite. Even though NDVI has been utilised to evaluate plant health as a part of decision making in agriculture, no recent research has been focused on integrating NDVI with DSS in small farm areas.

Examples of works where NDVI have been use for decision making include work by Govaerts and Verhulst (2010) described details for using an NDVI handheld sensor in a small plot area at ground level. An NDVI sensor was utilised in the research of Raun et al. (2001) to predict potential grain yield in winter wheat. An example of research applying NDVI at small plot size is a study of the correlation of NDVI with crop rotation, tillage and residue management (Govaerts & Verhulst, 2010). In addition, an NDVI sensor utilised by Lopes and Reynolds (2012) to determine relationships among NDVI, chlorophyll and phenology.

Wireless sensors (WS) have been developed since the late 20th century. Researchers have been developed wireless sensors as standalone unit and connected as networks called wireless sensors network (WSN). WSN have similar architectures to general computers and can be divided into two main parts: hardware and software. The main hardware in a wireless sensor

is called the sensor node or mote. It consists of six components: micro-controller unit, memory modules, power supply component, input-output component, radio module and antenna (ENORASIS Consortium, 2012). Figure 1 and Figure 2 illustrate timelines of the development of sensor nodes. Only the most prominent models are included in each time frame. There are a number of challenges and constraints in developing wireless sensor networks such as reducing energy consummation, self–management, design issues and security (Dargie & Poellabauer, 2010).

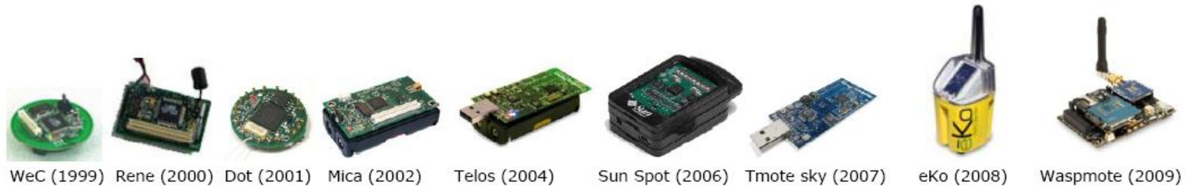

Fig. 1 Time line of the development of sensor node (ENORASIS Consortium, 2012)

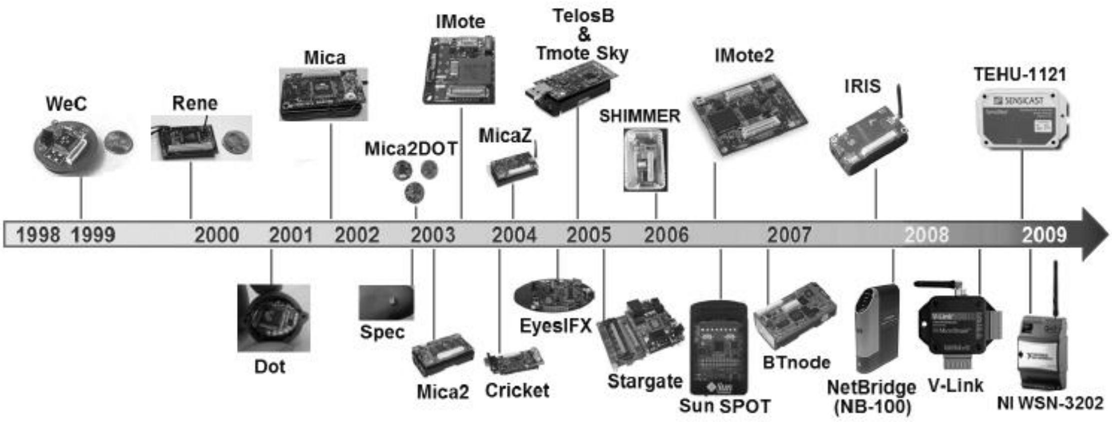

Fig. 2 Time line of the development of sensor node (Akyildiz & Vuran, 2010)

Examples of research utilised sensor and wireless sensors have been reported. Wireless sensor network has been developed to monitor and control system for greenhouses (Phuja, Verma, & Uddin, 2013). Another Example of research utilised sensor and wireless sensors have been reported (Paventhan, Allu, Barve, Gayathri, & Ram, 2012). Both systems have high quality in collect data. However, further research still requires analysing data from the system.

Incorporating data sets for Agricultural DSSs

There are a number of examples of research which has such collected data can be effectively used for Agricultural DSSs which have incorporated real time WSNs , data mining, image processing and DSSs. A number of different techniques have been reported for analysis of agricultural data, including use of crops modelling, traditional statistics, and precision agriculture techniques. There are a number of computer science techniques that have been used to analyse agricultural data for decision making utilizing data mining, digital image processing, neural network and other alternative techniques such as precision agriculture, crop

modelling and traditional statistics.

Multilevel classification using Gaussian Naive Bayes, association rule using rapid association rule mining and multivariate regression mining have been utilised in the similar research of Adinarayana et al. (2012). This method was applied to find the correlation among crops, weather, pests and diseases. These techniques may be suitable to analyse data in this purposed research because the input variables are similar in this study. Other techniques, such as multi-layer perceptrons (MLP), radial basis function (RBF), regression and support vector regression (SVR) (Ruß, 2009, 2013), require further investigation of the possibility of applying them to the dataset in this proposed research.

Some research exists on the use of image processing techniques for quantifying genetic effects of ground cover on soil water (Mullan & Reynolds, 2010). This research used images of early wheat growth stages. Further study is still required to determine the possibility of applying this technique to other stages of crop growth. Another study has determined wheat growth stages using percentages of green colours (Kakran & Mahajan, 2012). The study shows that using colour processing of digital image processing can be determined the age of wheat crop. Other studies using small field plots examined the use of NDVI sensors (Govaerts & Verhulst, 2010; Lopes & Reynolds, 2012). This research using NDVI image with small farms was limited, and further research is required to determine the usefulness of NDVI images.

Various examples exist of how such data sets can be used to develop DSSs to improve decision making for different scenarios. For example, Tamayo et al. (2010) focused collecting data for real time crop monitoring. Other DSSs focused on predicting pest incidence (Adinarayana et al., 2012; Tripathy et al., 2012; Tripathy, Adinarayana, & Sudharsan, 2009). Other DSSs have been applied to different crops, such as rice (Adinarayana et al., 2012), pomegranates (Patil, Kulkarni, Desai, Benagi, & Naragund, 2012) and maize. There is potential to also include data mining techniques to further analyse data to increase accuracy of these agricultural DSSs.

Summary

This paper presented an overview of the agricultural data required for Agricultural DSSs for decision making. The need for accurate environmental, crop and data to incorporate into Agricultural DSS has been highlighted. There is also a need to understand the decision support frameworks and the processes and inputs required to facilitate decision making. The paper presented the types of instrument sensors which can be used for data acquisition. Data acquisition is the first stage for decision support system. Selecting suitable data acquisition methods and tools is directly affecting the accuracy in decision making. Even though, there are substantial sensors and systems designing for acquisition data. However, further research still requires improving accuracy and precision of data, for example, developing new sensors devices and new systems such as wireless sensor network. In addition, training using sensor devices properly for farmers is another research area to assist in the collection of valuable data for decision making.

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