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Decision Agriculture

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Chapter 11
Decision Agriculture

Abstract In this chapter, the latest developments the field of decision agriculture are discussed. The practice of management zones in digital agriculture is described for e cient and smart faming. Accordingly, the methodology for delineating management zones are presented. Modeling of decision support systems is explained along with discussion of the issues and challenges in this area. Moreover, the precision agriculture technology is also considered. Moreover, the chapter surveys the state of the decision agriculture technologies in the countries such as Bulgaria, Denmark, France, Israel, Malaysia, Pakistan, United Kingdom, Ukraine, and Sweden. Finally, different field factors such as GPS accuracy, and crop growth are also analyzed.

11.1 Introduction

Decision Agriculture (also referred to as Precision agriculture (PA)) can be termed as the process of adequate amount of farming techniques, i.e., only applying su cient and required amount of nutrients, seeds, water and other farm resources. It helps in avoiding waste of resources while increasing the crop production[97]. This is achieved using various technologies such as creating soil maps, image analysis, variable-rate application, measuring soil moisture and soil chemical content, and automation of farming equipment[14][119][114].

PA's objective is not just to increase the sustainable crop production. It also help towards improving workers condition by automating the repetitive task based on soil moisture and weather readings [33]. It also impact socially by providing more control over environment. It can be used locally or can be expanded over large fields spanning over several kilometers. For example, it is being used to monitor individual testbed in a green house [8] as well as used for controlling pollination of crops[48].

Soil moisture provides information on vegetation and climate state. It also effect the underground communication. therefore, it is important to monitor soil. Scale of soil monitoring can vary from application to application. For a large geographical area, satellites or unmanned aerial vehicles (UAV) are used to perform spectral image

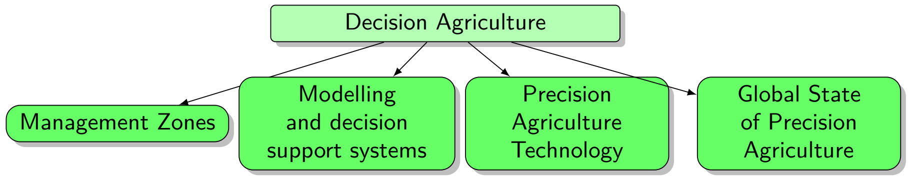

Fig. 11.1: Organization of the Chapter

analysis. However, this approach is limited by bad weather conditions such as heavy clouds which can block the view [33, 52]. these methods rely on number of factors such as quality and post-processing of image, quality of captured videos, instrument calibration, cloud screen, atmospheric correction, normalization of off-nadir effects [51]. The analysis of Global Position System (GPS) microwaves signals in the L-band and cosmic ray neutron probe can be counted as medium level soil monitoring approaches [54]. In-situ measurement techniques are invasive, e.g., gravimetric sampling and can be very time consuming if samples are collected manually. In-situ measurements can be used as a calibration step for large-scale and medium-scale soil monitoring mechanisms. The wireless technology saves the cost for installation and maintenance and provides the facility of real-time information access[29, 118].

The probability of mismatch between the spatial scale of the soil moisture measurement and the one required by the application is high [26, 115]. For example, UG node is deployed several meters way from the sensor which it is assigned to monitor. Upscaling the soil moisture readings to the area where UG node is deployed can help in achieving better communication. The soil moisture readings by WUSN are used as an input to control the CP irrigation system rate. The overall status of the complete field can be obtained by upscaling the data [13, 36, 39]. Just as in-situ soil moisture can calibrate the medium and large-scale soil moisture sensing products, similarly, these remote solutions can be used for upscaling data in WUSN or self-calibration [36, 45]. In coming sections, various solutions for sensing soil moisture are described.

Cyber-Physical System (CPS) is an integration of computational components into engineering systems which are used to detect, react and communicate certain environmental conditions [16] [98] [29, 113]. The CPS aims to create a smart physical and cyber domain by improving machine-to-machine (M2M), human-to-human, and human-to-machine [117]. In precision agriculture (PA), a network of farm machinery can be transformed to a CPS by making them environment-aware and proactive to environmental changes and conditions. To that end, WUSNs extends the PA by transmitting data to an open access media, providing high spatio-temporal resolution of environment properties [17], and not being effected by the farm activities due to buried devices [2, 36]. Moreover, these activities can be automated and controlled by using cloud services. To summarize, a WUSN can be converted to a CPS system by adding actuators which reacts to physical world phenomenons and cloud control applications [117] [61] [113] [38].

A successful agricultural developments impacts the local community, the nation, and the world in a very positive way. It also plays an important role in driving country's economy because everyone is either a producer or a consumer of food, hence, it cannot be ignored. There is also a social responsibility of making better use of limited resources while fulfilling the food needs of the people. The most important resources used in farming are soil and water which makes need of developing underground detection and communication methods more inevitable. To that end, WUSN aims to detect and communicate the farming conditions and parameters in soil, however, face many challenges.

The United Nation resolves to eliminate malnutrition and poverty by 2030. However, the current food production rate of the world is much bigger than the UN's agenda [43, 105]. By 2050, the Wold's population is expected to be 9 billion. The increase in population will eventually increase the demand of human's as well as livestock food by 25% to 70% [35, 52]. Current farming practices are not climate-friendly affecting the food production methods, hence, developing a environmental and climate friendly farming practices is an urgent need of the hour. Meadows and forests can be converted to arable field to increase the food production[27, 49], however, this can disrupt the ecosystem by increasing the green-house effect due to deforestation. Extreme weathers conditions, e.g., drought or prolonged hot weather, can harm crop fields wasting the farmer's hardwork of a complete season.

Instead of creating new fields, a possible solution can be to optimize the usage of current available resources by use of information and technology. Technology can predict exact dose of fertilizers and pesticides to be applied in the crop and produce genetically modified crops. However, consumers are more attracted towards organic food, therefore, these practices are not being adopted in excess[24, 47]. Farms in underdeveloped countries lack means to adopts these improvements. Conversely, optimized water usage has significant advantages to implement agricultural in areas where water is scarce.

Three-fourth ($\frac{3}{4}$) area of the Earth is covered by water, of which only 2.5% of the water is fresh water. From that 2.% of fresh water, 70% is frozen (glaziers and ice caps) and rest (residual 0.75% of freshwater) is in swamps, underground, lakes, rivers, living things, and the atmosphere. 70% of the residual freshwater is used for irrigation [50, 58]. therefore, water is a very valuable and scarce natural resource and must be optimally used by adopting e cient food production technologies [54, 65]

The practical application of Wireless underground communication is limited because of high signal attenuation by soil moisture [2][7][8, 72][17][8][99][104][70]. There has been extensive studies which provide guidance on how communication can be made better in an underground channel. For example, channel model for soil-air communication is presented in [19, 48], channel model considering impacts of various deployment and environmental parameters is presented in [43][46, 70], and a three-wave channel model is given in [8, 71]. these models can be validated by testing them empirically. An outdoor testbed is created to perform this research. This testbed simulate real-life scenarios such as crop rotation, fertigation events which are faced by sensors and transceivers, dynamic weather conditions, and irrigation. Soil moisture level can vary because of because of irrigation and storm, therefore, it would be interesting to study the effect of such variation on communication performance. The performance of communication systems must be measured and analyzed for a long operational period of time to get better understanding the communication in underground environments.

Internet of Things (IoT) provides many sensors (commercial and proprietary) for sensing soil condition and solution for reacting on the basis of sensed information, e.g., applying right amount of water[4][5][22, 51][23][25][49][52][17][54][55][32, 59][119]. However, most solutions are application-specific such as related to data storage, information acquisition, or communication [1]. Therefore, a complete general framework is required with capability of sensing, modeling, decision-making and performing actuation. A cloud-based middle-ware platform accomplish information exchange, provide global data access and management facilities, and gives on-demand processing services [44, 55]. This work develops an autonomous cloud-based application for controlling irrigation system. This model can be used as a guideline for development of PA middleware projects.

CPS models physical processes using data abstraction. Therefore, it is important to give theoretical reasoning for each CPS components and decisions while explaining this system [27, 93]. Introduction o engineering systems into the CPS necessitate the development of a framework containing modeling and abstraction of CPS. Abstract modeling of CPS architecture makes it easier to integrate the components developed by other disciplines[25, 40]. Nevertheless, it has helped many field to make quick substantial improvements, e.g., wireless sensor networks (WSNs).

During the pas decade, developments in WSNs has led to discovering long-rang and/or power-e cient communication protocols [6]. To prolong WSNs lifetime, novel methods of harvesting energy from natural resources (light, vibration, heat) and electromagnetic sources are being investigated. Micro-Electro-Mechanical Systems (MEMS) have contributed to the success of WSNs by providing precise , small and affordable sensors. CPS abstraction enables this alliance of this independent and interdisciplinary studies, e.g., a midlleware issued command or transfer data to various devices without worrying about the data types or underlying network[30, 34].

Wireless Underground Sensor Networks (WUSNs) is a subset area of WSNs which enables the communication between buried underground (UG) nodes and above-ground (AG) devices [6]. Water retention in soil affects the wireless communication. Path loss modeling is also an active research area in UG communication. WUSNs application includes border surveillance, natural disaster detection (e.g. earthquakes and landslides), mine safety, and precision agriculture [2][6].

WUSNs are well-suited for measuring the amount of water and nutrients in the soil. UG devices can be deployed for taking measurement without being visible to farm equipment and machinery. AG nodes can also be deployed in such location where they can communicate wirelessly without being obstructive[2], e.g., nodes can be attached to moving equipment to collect data from all over the farm. Typically, a central data storage and processing is also implemented.

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Precision irrigation applications requires high spatio-temporal resolution for proper working which is provided by the sensor networks. Wireless communication helps in providing remote information access. this information is provided in real-time so that manual manipulation can be avoided to get an idea about the field conditions. [17] used small amount of sensors for measuring soil moisture because of precipitation duration and rainfall cell radius magnitude.

[108] discusses various techniques for estimating exact location of the sensor nodes. In general, examining different soil properties with varying soil moisture level can give an average soil moisture value for the field. [15] calculates location-specific solar radiation intensity values to estimate the evaporation rate corresponding to that certain location. A mobile application is used for this approach. The calculations matched the reading from agriculture station which helped in generalizing the result to all those location which have same radiation conditions. Sensor cluster is then placed in chosen area with following the recommendations given in [17, 33].

The primary task in the WUSN is to determine number of sample readings. It is important because sensing and communicating data consumes large amount of power [17, 20]. Shallow roots and high porosity causes speedy water infiltration and evaporation in soil. Therefore, large sampling rate is needed to overcome this highly fluctuating effect.

11.2 Management Zones in Digital Agriculture

The regions in the agricultural fields with similar characteristic are known as management zones (MZs). Identifying MZs is an ultimate goal of precision agriculture. MZs differs from each other in major factors such as topography, soil type and water and nutrition availability [10]. MZ must be large enough for variable rate application (VRT) and small enough for the precise application. MZ can help in increasing output of farms in terms of cost, yield and quality of production [38]. MZs can be identified on the basis of large variety of attributes, e.g., soil sampling, sensing or plant-based. Combination of these attributes can also be used. Any information obtained for these variables can open new possibilities for crop management.

Soil-based measurement can be used to provide more temporally stable zones. For example, ECa has been used extensively for MZ delineation [37, 50] along with elevation mapping using real-time kinematic-GPS [57, 71, 72, 94]. Soil ECa is suitable for explaining spatial variability for static soil properties, however, it does not explain the spatial variability of yield or quality which strengthens the argument of using the combination of different parameters in the process of MZ delineation for meaningful results. [72, 94] recommends using the combination of crop-based and soil-based MZ for the analyses for temporal variability.

NDVI is also a useful parameter for delineating MZs [21, 33]. It is related to various crop properties such as chlorophyll content, biomass, leaf area [31], crop yield [101] and quality (Johnson et al., 2003). MZ delineation can be classified on the basis of application to inputs, e.g., nutrient MZs (Basso et al., 2012), irrigation MZs [107] and MZs for herbs and pesticides [28, 103, 106]

Nutrition MZs have been found in citrus orchard on the basis of soil variation [95], in wheat crop on the basis of ECa, soil depth and elevation, and in variable rate nitrogen application for increased nitrogen e ciency (Peralta et al., 2015). Nitrogen management in spring wheat has been optimized by using a spatio-temporal Bayesian network [42, 49]. [28, 30] used soil available water, yield data and ECa satellite images to delineate an irrigation MZ and found that soil ECa is extremely useful in forming irrigation MZ for variable rate application of irrigation in pivot systems.

11.2.1 Methodology for delineating MZs

There is no specific methodology to analyze the multi-layer information obtained from the field and delineate MZ [28, 50], hence, evaluating different algorithms and methods for MZ delineation is a challenging task. Several methods have been proposed to delineate MZ based on nature of data sources, agronomic knowledge of the field, and inter-dependencies of data variables. The most common methods for delineating MZ in digital agriculture framework are described below.

Empirical: This simplest and easiest method requires farmers to visually inspect the attribute map or aerial images and delineate the MZ based on their personal experiences from the field. It is an accurate method since the field observations are not scientifically validated and may also incur the personal bias in judgment of the farmer.

Geostatistical: Geostatistical methods have been used to analyze and combine different parameter for producing MZ maps. Due to values spatial dependence, sampling points can be interpolated using geostatistical methods.Maps for the whole field can be generated to study the variability of the properties across the field. All layers of information can be overlaid over each other using interpolation. [3, 25] did MZ delineation using multivariate analysis. In [41, 54], MZ delineation for soil moisture is done for management of water under stressed condition using multivariate geostatistics.

Clustering: Cluster analysis classifies the data into discrete classes or clusters. K-means (also known as c-means), a non-hierarchical clustering technique, divides a multi-dimensional data into k-clusters. Centroid in each cluster is Euclidean distance away from the data points. (Ping et al., 2005) uses k-means to evaluate procedure for MZ delineation in cotton. Fuzzy k-means, an extension to k-means, accounts for the uncertainties related to class boundaries and membership (Dobermann et al., 2003). (Molin and Castro, 2008) shows that principal component analysis (PCA) and fuzzy logic application on soil data and ECa can reliably delineate soil MZ. Many universities have also developed software that perform fuzzy k-means. For example, Management zone analyst (MZA) was developed by University of Missouri (Fridgen et al., 2004) and FUZME developed by University of Sydney, Australia, have been extensively used by researcher all over the world. ZoneMAP automates delineation of MZ from satellite imagery and field data as an input form the user and use the fuzzy k-means as a processing algorithm.

Degree of Agreement: [37, 41] delineate soil productivity zone (SPZ) and yield productivity zone (YPZ) using unsupervised fuzzy k-means clustering. They calculated degree of agreement by matching outcomes of YPZs and SPZs with overall accuracy statistics (matched cells divided by total cells in data sets). Same concept is applied for delineation of MZ in vineyards [44, 100]. Field data is collected analyzed by using crop canopy and soil sensors. Mono-parametric zone maps are generated using fuzzy clustering. This data analysis method can be extended by including comparison bet more parameters, information management during digital agriculture experiments.

Other studies have used combination of statistical and geostatistical methods along with fuzzy clustering method to create management zone. Chlorosis MZs were created in soybean and maize by examining data for pH, yield, NDVI and ECa (Kyaw et al., 2008). They selected NDVI and ECa, using data interpolation and regression analysis, to delineate MZs using MZA [26, 43].

11.3 Modelling and decision support systems in digital agriculture

Decision support systems (DSSs) can be defined as a computerized system which are used for make decisions using the models and databases (see Fig. 11.2). Motivation behind using DSSs is to choose the best alternative from social, economic and environmental point of view. An overview and role of DSSs in agriculture, farm planning and management is presented by [34, 45]. However, due to difference in the context of farmer and scientist, adoption of DSSs in digital agriculture is very low.

For a long period of time, the only objective of agricultural production was to secure profits and no considerations were given to the environmental impact caused by it. Farmers are now facing lot of pressure from environmental protection agencies, public, consumers and bank. Farming practices are now need to be adjusted for the environment protection. However, all production regulations and specifications still cannot guarantee a clean agriculture [37, 47]. As per [40, 45]: The planning and development process in agriculture is a complex problem which, if not face thoroughly, cannot be solved easily. Due to diverse agricultural conditions, one practice may

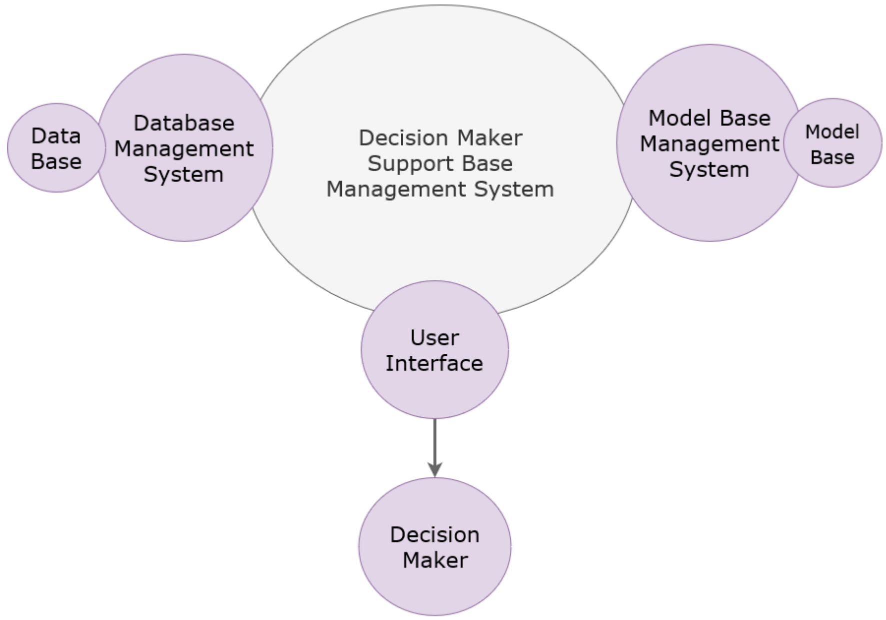

Fig. 11.2: Structure of a basic decision support system (DSS)

different results in different fields. Therefore, decision making in agriculture is not based on set of well-defined rules and regulations instead it is based on experience, knowledge, and skills of producers.

In linear model, several controlled experiments are performed with each experiment observing some variables while others being controlled and standard recommendations are made as an outcome [11, 42]. When linear model is applied in agriculture, research data is analyzed and interpreted as recommendations to farmer. However, in reality, few farmers apply these recommendations make use of linear model in agriculture very rare. [12] summarized that scientific results from experiments in agriculture are not well translated by DSS and adopted by farmers because scientist and farmers does not see the problem in same way. For example, scientists gave more importance to the information related to the quantifiable effect of factors while ignoring the farming environment in which they are occurring.

Scientific publications have to satisfy certain strict rules regarding experiments, technical requirements and statistical procedure to get published. Most of the research is published in peer-reviewed journals with requiring scientists to demonstrate that finding apply to any particular condition of end user. This difference between scientific and a more complex farming world makes it di cult for the farmers to apply the insights from the formal experiments in the real world. This is the area where modeling and validated DSSs can help to bridge the gap between the research and adoption of the research by farmers. Recent advancement in communication technologies have given access of key information to the farmers via cell phones or sophisticated agricultural machinery.

Agriculture sector is disorganized due to uncontrolled variations. These uncontrolled variations (due to site and time specific effect) led to the development of statistical methods by Fisher and co. (Rothamsted Experimental Station, Harpenden, UK) for clarification of experimental effects in agriculture. Fisher's statistical methods allows for the simple evaluation method for publication of scientific work at the expense of adaption and recognition from the end user.

11.3.1 Issues in DSSs

There is a lack of proper DSSs in digital agriculture [35, 46]. Although, DSS are more user-friendly today, however, does not completely addresses the needs of the user. Historically, digital agriculture has more focused on spatial variability, however, temporal variability for the crop and animal production is also being considered now. In addition to spatial and temporal variabilities, digital agriculture also has to deal with uncertainties, human and social issues. Some of the issues are discussed below.

Soil (Spatial): Majority of research in DA is mainly focused on spatial variability. Soil information must be brought down to useful and properly quantified parameters for integration to DSS. Soil sampling is done to assess the physio-chemical properties of the soil and aligns with the goals of digital agriculture if done with adequate planning and spatial statistics. However, it is not possible to always used interpolation for the mapped points due to sampling resolution limitations [32, 33]. Moreover, applications map created by the interpolation may be misleading and detrimental. With the development of proximal and remote methods, sampling can be replaced with sensing at much higher spatial density. The spatial density is so high that interpolation and MZ production can be eliminated. The rapid and high turnover of technology has produced a gap between scientific understanding and technological capability to measure and apply input and outputs of the crop [9, 38].

[35, 53, 56] studied soil properties for site-specific protection and found that heterogeneous soil properties effect the weeds, pests and pesticides behavior. They concluded that information on soil variable properties combined with precision crop protection (PCP) can benefits both economically and ecologically. Another study by (Christensen et al., 2003) proposed a computerized management system which assist in making decision on choosing herbicides and doses of herbicides. The system uses a huge database of herbicides performance on various crops for ranges of weeds at different growth stage. It allowed to rank and make recommendations on e cient herbicides or number of dosses to uses against weeds. [32, 60] reported localized mechanical stress (e.g., compaction during tra c) as one of the possible causes for the high variability in the soil structure within the field.

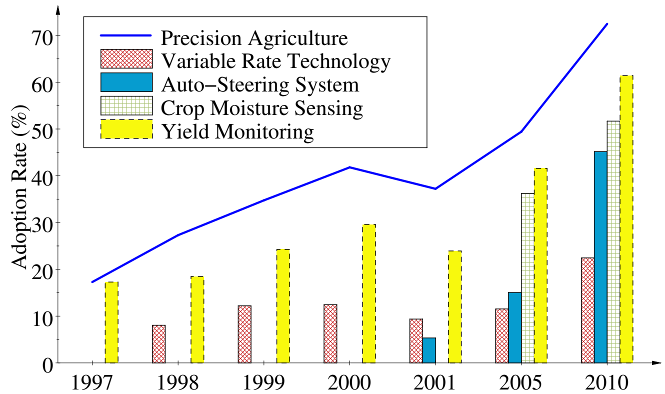

Fig. 11.3: Data by USDA ARMS on PA adoption rate in corn fields [111]

11.4 Precision Agriculture Technology

A total of 32% increase is expected in world's population by 2050. This increase in population will also result in doubling of food demand. Food production is the cause of 70% of water withdrawal in the world. Therefore, there is a dire need of novel technologies which can produce more crop for drop. USDA Agricultural Resource Management Survey (ARMS) publishes information on food production practices, financial conditions, resource utilization, and economic well-being of America's farm household and business. ARMS data shows that precision agriculture is being widely adopted by American farmers. In Fig. 11.3, adoption rate major precision agriculture techniques (represented by bars) is plotted along with the adoption of precision agriculture for corn (represented by line) based on the ARMS data published yearly (USDA ARMS 2015). It can be clearly seen that, for corn, adoption rate for precision agriculture has significantly increased from 17.29% to 72.74% between year 1997 and 2010. Similar trends have been noticed for other crops such as peanuts and soybean. Apart from high adoption rate of precision agriculture in corn production, farmers are adopting the new technologies as they emerge [47, 54].

Crop yield monitoring is one of the most adopted (61.4 %) among all precision agriculture techniques. For guidance and auto-steering, the adoption rate increased from 5.34% to 45.16% in nine years. Auto-steering information allows precise control by using equipment and spatial information of the crop while reducing maintenance cost and extra work for farmers. Although other precision agriculture techniques have seen drastic increase in adoption rates, adoption of variable rate technology (VRT) has been steady relatively. In eight years (1998-2005), VRT's adoption rate has increase from 8.04% to 11.54% only. Crop production has increased significantly by adaptive application of agricultural resources (e.g., fertilizers, pesticides and water etc.) but gathering correct and timely information from the field is also key factor for improving crop growth. It is evident from the fact that after the adoption of crop moisture sensing technology, the adoption of VRT doubled (from 11.54% to 22.44%) in the period of 2005-2010. The same period sees the increase in adoption of crop moisture sensing from 36.21% to 51.68% [25, 50]. This shows that VRT adoption is highly dependent upon the advancement in soil monitoring technologies. Crop moisture sensing has become the most adopted and popular technique in a very short period of time. Yet the techniques are being used with manual data collection or very limited coverage of the field [27].

11.5 Global State of Precision Agriculture

There is not much information available on precision agriculture (PA) adoption all over the world. The most desirable form of information would be published statistics, by known and credible organization, about the farming sector, however, it is very rare. Other useful information may include data obtained from the surveys and interviews of the farmers, opinions from the academics doing research in concerned field and industry reports etc. Though this data is rare and very low, it is still better than guessing [37]. This section aims to provide information on the state of PA adoption all over the world [1].

11.5.1 Bulgaria

Although, there is no o cial data available on PA in Bulgaria [1], however, the first implementation of PA was using lightbar displays for fertilizer application somewhere around 2002-2003, and were extended to be used in sowing and weed control after the invention of automatic steering systems. After 2009, These technologies became famous and were commonly used in Bulgaria. For example, farm machines comes with the advanced equipment such as steering systems, global navigation satellite systems (GNSS) displays, guidance systems for slopes, yield monitoring systems for creating yield maps during harvesting season, and spray control systems for sections. However, these technologies are limited to big farms for oilseeds and grain production located in North Bulgaria only. As per 2016 agricultural census, 2350 large farms with financial capabilities crop and livestock output of greater than 250,000 EUR cover 68% of agricultural area. These farms produce extensively and represents around 45% of the farm output of the country. These big farms are using variable rate application, soil sampling, Geoscan and weather monitoring technology and some of them use precision planting and precision irrigation. Due to lack of access to technology, small scale farms do not implement PA technologies and livestock sector is even far behind in adoption than crop production [31, 72].

PA systems (precision farming systems and different software) are being offered by few companies but they are being implemented by only large farms. Moreover, PA implementation rely majorly on economic profitability and affordability of farmer. To that end, detailed investment information on PA technologies is lacking. Although, the advantages of PA are being debated over many forums, however, a farmer's perspective is lacking. To that end, a survey study results were published in 2018 which shows that, out of 258 randomly sampled set, 49% do not have knowledge about the technologies, 38% have no plan to implement PA and only 4% plan to implement PA [52].

PA technologies are discussed in various universities and scientific institutes of Bulgaria. For example, remotes control methods, such as satellite imagery, are being used to monitor the crop and land conditions at the Space Research and Technology Institute since its inception from 1970s. The Institute is working on many satellite systems projects funded under the 6_{th} and 7_{th} Framework Program, Horizon 2020 and others. Other Institutes, e.g., *Kliment Ohridski*, a Geological-Geographical Faculty from The Sofia University has developed remote methods involving satellite images and drones. The Agricultural University-Plovdiv is offering PA specific master courses under Erasmus projects. It is conducting experiments near Plovdiv city for the development of crops and varieties of maize sunflower, and wheat. Agricultural Hubs also plays an important role in PA adoption. For example, SmartAgriHubs coordinated by Wageningen University under Horizon 2020 Program and Bulgarian AgroHub comes under the European SmartAgriHubs project.

11.5.2 Denmark

In 2019, PA technologies were being used in 28% of the Danish farms which covers 66% of farming land. Denmark is one of the very few countries which o cially collects data on PA via Government o ces using stratified sampling and sample size of 6005 respondents. The survey includes the PA technologies such as: drone images and crop sensors, Global Navigation Satellite Systems (GNSS), software for planning nitrogen applications, sprayer section control. It was found that GNSS guidance, Sprayer section control, drone or satellite images and crop sensors were used 24% (covering 59% of the farmland), 40% (covering 40% of the farmland), 5% (covering 15% of the farmland), and 2% (covering 8% of the farmland) of the Danish farms, respectively. Average farm size in Denmark was 83 ha and the average farmsize adopting GNSS guidance and crop sensor was 202 ha and 342 ha. It shows how, like other countries, large farms have more PA adoption rate than smaller farms [1].

11.5.3 France

France has a largest agricultural area (292 800 km² (53.2% of the surface area of France), about 1/2 ha per inhabitant) and employs 3.4% of the population generating 4.5% of GDP (over 72 billion euros) [1]. It is the largest agricultural country in

European Union covering 18% of agricultural land in Europe. Some of the main productions includes wheat (5_{th} in the world), corn (8_{th} in the world), sugar (7_{th} in the world), wine and milk, livestock and meat products (5_{th} in the world for beef).

The Observatoire des Usages de L'Agriculture Numérique (Digital Agriculture Adoption Observatory - http://agrotic.org/observatoire/chaire-agrotic/) is a partnership of 8 research institutes, 2 universities, and 28 agricultural related companies and collects PA data in France. Some of the observations from the data are given below:

- Software-based variable rate input application is used by 4% French farmers.
- By 2017, remote sensing is used by 1 million ha of farm land with distribution of 85% satellite, 15% using drones/aircraft. Moreover, 10% and 1% of crop and viticulture area, respectively, was being managed by remote sensing.
- Electrical conductivity or resistance sensors are used to map approx. 135,000 ha (> 1%) of French farmland in last decade.
- 20% of the French farms uses soil maps developed by the professionals.
- In 2018, milking robots were being used by 10% of the dairies and other 70% were thinking to acquire it; 10 robots were being used for weeding vineyards and 100 for vegetable crops.

11.5.4 Malaysia

Prof. Siva Kumar Balasundram from Universiti Putra Malaysia (UPM), Department of Agriculture Technology and a Malaysian represntative in ISPA says that, *PA is limited to research purposes and community in Malaysia and there is no adoption statistics reported yet.* It is also confirmed by Dr. Hari Krishna of Sime Darby stating the cost as a reason of low adoption. Dr. Redmond Shamshiri, formerly with UPM and now with Bioeconomy Institute (ATB) Potsdam, Germany, also says that PA in Malaysia is being studies by universities, government research institutes (Malaysian Agricultural Research and Development Institute, the Malaysian Cocoa Boarthe, and Malaysian Palm Oil board) and some startups. The efforts to promote PA in Malaysia includes study tour of Malaysian farmers to New Zealand in 2017 organized by Space Exploration Asia in partnership with Adaptive AgroTech Research Group International, the New Zealand Center for Precision Agriculture, and Massey University of New Zealand. Malaysian Remote Sensing Agency (MRSA) conducted a PA project in rice, however, adoption by farms is very low [1].

11.5.5 Pakistan

In January, 2019, a delegation headed by Dr. Yubin Lane from South China University visited University of Sargodha in Pakistan to introduce and promote PA to researchers and farmers of Punjab province of Pakistan. They, for the first time, practically demonstrated the application and effectiveness of drones technology for precise application of spray in the agricultural campus if the University of Sargodha. The technology e ciently uses the available resources as per requirement and also enables secure crop production [1].

11.5.6 United Kingdom

In 2018, Harper Adams University (HAU) conducted am electronic survey from thousands of UK farmers on farmer mailing lists. The survey shows that 48% of a total of 186,000 respondents uses map-based variable rate technology (VRT) fertilizer, 63% uses GNSS autosteer, 53% uses GNSS sprayer boom control and 15% uses optical nitrogen sensors. It shows them as a leading users of VRT fertilizers as it's adoption hardly exceeds 20% in any other country/region of the world. UK farmers prefers personal training but open to use electronic tutorial materials and willing to pay average 278 euro (339 USD) for annual subscription with web-chat support, if available. 40% were willing to share data for technical help[1].

11.5.7 Ukraine

PA is readily available in Ukraine with many startup companies providing PA services (drones, soil mapping and testing etc.). Big farming companies like Kernel (www.kernel.ua) are providing services such as: yield mapping, satellite images, variable rate technology for fertilizer and seed, and intensive soil sampling. There is no o cial data on PA adoption in Ukraine, however, all indications shows that PA is very limited in Ukraine except for GNSS. Iaroslav Beiko, ISPA member and co-founder of AgriLabs, says that, *"Ukraine is at beginner stage of adopting PA components with 20% usage of automatic section control. The conscience and systematic use of PA complex (field mapping to VRT fertilizers and seeds) is less than 5% of the area"*. Some other industrial sources states higher adoption rate with same underlying story, e.g., SmartFarming website show adoption rate of 30% but with limitation to single technique- an autopilot/guidance system for preventing overlaps and gaps in the fields [1].

11.5.8 Poland

By 2017, there was 14.6 million ha of agricultural land and 10.8 million ha sown land (with 70.7% of Cereal) in Poland [1]. There were 1.4 million farms; 2.5% of which are more than 50 ha covering 31% of agricultural land area. The agricultural land area depends on region of the country, e.g., in southern part it ranges from 4.1 - 30.8 ha and even bigger farms in northern parts. This difference of range explains the difference in adoption of PA in Poland farms. Glaciation increases the potential adoption of PA [32, 36]. PA is also being taught in few universities for research purposes. The current condition of PA in Poland is as follow:

- The PA tools being used includes: GNSS autosteers and lightbars, and auto section control of spreaders, sprayers and planters. These technologies are saving 5-15% for the farmers. Software-based GNSS techniology is being used by very large farms.
- Yield mapping is being used for grains, however, is quite limited due to lack of proper calibration system.
- Soil sampling and soil fertility map is being created by companies and consultants; variable rate application of the fertilizers, using active optical sensors, is being applied on very big farms. Few dozens farms are also using variable rate application of pesticides and variable rate seeding.
- A very few companies are offering soil mapping by management zones using soil electro-conductivity and facility of satellite images for estimating yield potential and biomass production.

11.5.9 Sweden

The ISPA newsletter (May, 2013) presents the report on development in last 6 years and the current condition of PA adoption in Sweden. PA is regarded as one of the important means to increase sustainable food production which also stressed by the National Food Strategy for Sweden by 2017 (Government bill 2016/17:104). The access to useful digital data and digital transformation is beneficial for development of digital equipment in an effort to increase PA adoption [53, 65]. Approximately all farmers in Sweden has access to the digital decision support system which has been proved to be key aspect in spreading of PA[1].

CropSAT, a satellite-based imaging system was launched in 2014 and since its inception is being used in variable-rate application (VRA) of grain crops and nitrogen. This system has paved the way for the development of other imagery systems. It was the first system developed in partnership with university researchers, authorities, private enterprises, and advisory organizations. It is available in multiple languages and can be used globally.

Digital Soil Map of Sweden (DSMS) is an open access soil database. It predicts values for soil texture every 50m and has been used in different decision support systems, e.g., a web-based application Markdata.se. Mark.se can be sued by farmers to produce VRA seeding and prescription files for liming. It is an interactive application which can upload users soil data to become more accurate locally. Drone are still not being used in practical PA in Sweden, however, availability of Solvi.nu, a decision support system for drone images, can make the adoption process faster [20, 71].

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