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Precision Agriculture Impact on Food Production in Brazil

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Abstract. The present study aims to analyze the impact of Precision Agriculture (PA) on food production in Brazil. We applied the multicriteria group decision using the Analytical Hierarchy Process (AHP) to weigh several selected criteria. The group consensus was very high (91.9%). The most critical criteria in level 1 was the machinery input (48.9%), followed by software (44.4%) and human resources (6.7%). In level 2, within the machinery criterion, the sub-criteria soil was the most critical (31.9%), followed by pest control (28.5%). In level 2, within the software criterion, the sub-criteria input management was the most critical one (48.4%), followed by product management (42.3%). The four most significant global priorities are the sub-criteria soil (31.9%), Input management (21.5%), Product management (18.8%), and Pest control (13.9%). Results indicated that the use of PA in grain crops has a high impact on food production (71.1%).

Keywords: multicriteria analysis, agriculture 4.0, grain production.

1 Introduction

The UN's 2030 agenda aims for sustainable development [1], and some actions are needed to increase world food production. However, current production rates meet consumer demands but do not necessarily feed the world population [2]. Information technology (IT) tools have impacted the industrial sector and the agriculture segment in the same way, and it is named Precision Agriculture (PA). PA's use focuses on boosting productivity rates, reducing labor costs, improving work quality and worker safety, and reducing environmental impacts [3,4].

PA is a group of agricultural practices that uses information technology (IT) based on spatial and temporal variability. Such methods manage the agricultural production system carefully, not only in applying inputs or various mappings but also in all the processes involved in production [5,6]. Thus, the potential of PA generates economic and environmental benefits [7,8].

The Analytical Hierarchy Process (AHP) is a multicriteria decision-making approach that includes qualitative information (in the form of judgments) with accessible quantitative data. AHP is a decision-making tool that can help define the general deci-

sion operation by decomposing a complex question into a multi-level hierarchical structure of objectives, criteria, sub-criteria, and alternatives [9,10]. Applications of AHP have been reported in various fields [11-13]. AHP hierarchic structure reproduces the actual trend of the human mind to sort out elements of a system [10]. AHP is a helpful tool for decision-making when professionals deal with complex and interactive systems [14,15]. The present study aimed to evaluate PA use's impact on Brazil's food crop production. This case study is based on grain production (soybeans, corn, and rice).

2 Methods

We applied the Analytical Hierarchy Process (AHP) to analyze PA techniques' impact on Brazil's food production. First, we invited three experts to rate the criteria and weigh them towards the adequate answer of the perceived impact, as shown in Figure 1. The inputs from the group of three experts were computed using the defined concepts (Table 1). The AHP-OS online software [16] was used to process the calculations.

Figure 1 was developed from a literature review carried out on published articles concerning PA and the technologies involved in food production, where the following criteria were selected (1) related topic addressed, (2) year of publication and (3) number of citations. From the literature reviewed, the most used technologies were extracted and divided into criteria and sub-criteria, as identified in Table 1, for later judgment and impact measurement according to the experts. The profile of the specialists were determined as (1) expertise with the PA use and application; (2) presented publication on PA use and application; and (3) proper knowledge on the judgment of the criteria.

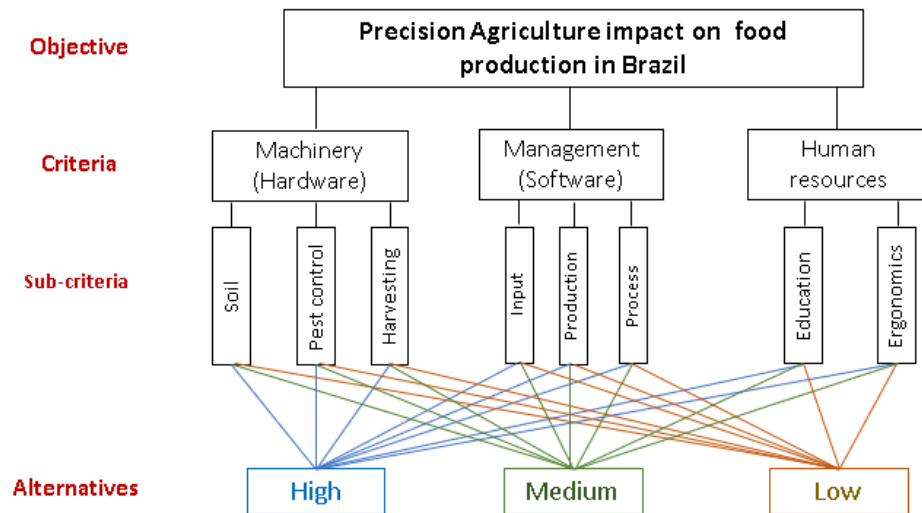


Fig. 1. Scheme of the AHP goal selected criteria, and alternatives for choosing the impact of PA on food production in Brazil

A set of pairwise comparison matrices (A ; Eq. 1) was built. Each element on an upper level was used to compare the elements in the level below [9,10]. The decision of relative weights (w_i) of all pairs of the n elements and these decisions are included as a number (a_{ij}) in a square matrix A (i.e., the comparison matrix):

$$A = (a_{ij}), (i, j = 1, 2, \dots, n) \quad (1)$$

where $a_{ij} = w_i/w_j$ and $a_{ji} = 1/a_{ij}$. The parameters for the pairwise comparison followed a 1-9 scale [9], where: 1 = not a priority; 2 = no to moderate; 3 = moderate; 4 = moderate to high; 5 = high; 6 = high to very high; 7 = very high; 8 = very high to greatest; 9 = highest priority. The weight was assigned to the $(i, j)^{\text{th}}$ position of the pairwise matrix chosen to compare with high sensitivity. The reciprocal of the assigned number was automatically given to the $(j, i)^{\text{th}}$ position. The highest eigenvalue (λ_{\max}) was used to determine the consistency index (CI, Eq. 2).

$$CI = (\lambda_{\max} - n) / (n - 1) \quad (2)$$

Table 1 shows the concepts used for each factor to help normalize the group participants' criteria weight.

Table 1. Selected criteria, sub-criteria, their description, and the references used to support the decision.

Machinery (Hardware)		
Factors	Factor's Description	References
Soil	Agricultural machinery with onboard electronics (plowers and seeders) and an automated steering system. Remotely Piloted Aircraft (RPAs) or Unmanned Aerial Vehicles (UAVs) act in the mapping using a global positioning system (GPS). Sensors to measure organic matter, soil characteristics, and contaminations. Seal mapping using electrical conductivity (ECa) measurements.	[17,18,19, 20,21]
Pest Control	Sensing and mapping to measure productivity, fertility, and compaction attributes, based on topography, terraces, and soil type, for later dosing and localized application. Monitoring of temporal variability. Survey of diseases and diseases through RPAs or UAVs. Optical sensors and sprayers for localized application. Use of multispectral images, together with GIS tools.	[22,23]
Harvesting	Combines equipped with GNSS (Global Navigation Satelite System) and productivity sensors. Harvesters with autopilot and harvest monitor.	[24,25]
Software		
Input Management	Images linked to the interpolation and transformation of data to generate maps of indexes, the health of the crops, soil conditions and management, and even crop productivity estimates. Use of data for decision-making, climate forecast, phytosanitary management, and financial market perspectives. Use the Graphical Information System (GIS), geostatistics, and data mining in databases.	[26,27,28, 29,30,31]

Production Management	Productivity sensors used on production. Use of the Variable Rate Technology (VRT) as inputs at a variable rate. Modeling via geographic information system (SIG).	[24,32]
Process Management	Analytical methods and solutions to process data and build support systems for decision-making in crop management. Use of the Internet of Things. IoT, sensors, and implements reduce operating costs, increase productivity, and create new business opportunities and services. Use computational tools based on artificial intelligence.	[33,34]
Human Resources		
Education	Agricultural production must integrate several areas of knowledge. The education of rural producers directly impacts the adoption of new technologies.	[35,36]
Ergonomics	Use machines and tools to aid in workers' activities and automate exhaustive work.	[37]

3 Results and Discussion

Table 2 shows the hierarchy found by the consultant group. The most critical criteria in level 1 was the machinery input (48.9%), followed by software (44.4%) and human resources (6.7%). In level 2, within the machinery criterion, the sub-criteria soil was the most critical (31.9%), followed by pest control (28.5%). In level 2, within the software criterion, the sub-criteria input management was the most critical one (48.4%), followed by product management (42.3%). The four most significant global priorities are the sub-criteria soil (31.9%), Input management (21.5%), product management (18.8%), and pest control (13.9%).

Table 2. Decision hierarchy of the criteria with corresponding weights.

Decision Hierarchy						
Level 0	Level 1	Level 2	Gib Prio.	High	Average	Low
Precision Agriculture impact on food producti	Machinery (Hardware) 0.489	Soil 0.653	31.9%	0.740	0.195	0.065
		Pest control 0.285	13.9%	0.762	0.176	0.063
		Harvesting 0.062	3.0%	0.475	0.443	0.082
	Software 0.444	Input mgmt 0.484	21.5%	0.745	0.166	0.090
		Prod mgmt 0.423	18.8%	0.681	0.216	0.103
		Process mgmt 0.092	4.1%	0.513	0.309	0.179
	Human resources 0.067	Education 0.875	5.9%	0.658	0.202	0.139
		Ergonomics 0.125	0.8%	0.717	0.212	0.072
				1.0	71.1%	20.3%

Table 3 presents the overall group results and the values registered by each consultant. There was a slight variation amongst the experts' results; however, the AHP group consensus was high (91.9%).

Table 3. Overall results from the group weigh.

Participants	High (%)	Average (%)	Low(%)	CImax (%)
Group	71.1	20.3	8.7	11.9
Consultant 1	69.8	16.2	14.0	30.8
Consultant 2	72.0	21.9	6.1	66.2
Consultant 3	67.7	24.7	7.6	8.4

PA is paving the way for big data in agricultural production [34,26]. Clear documentation of such practices based on new technologies, possibly combined with other technologies such as blockchain, will strengthen the role of these certifications. Such measures can play a significant role in both conventional and organic farming [37]. Additionally, insurance products could become more effective when information unevenness can be decreased when providing information on yields, input use, and environmental conditions to insurance companies.

Worldwide, there are two major issues related to food production. First, enough food needs to be produced to feed the increasing population. Second, the environmental issue needs to be addressed due to the overuse of antimicrobials, fertilizers, and pesticides contributing to the greenhouse effect, directly impacting the soil quality and contamination of the water sources. However, the AP application can contribute to measuring and quantifying the ideal amount for each application, avoiding excess and the environmental impact [22,23].

A crucial aspect needed for the increasing uptake of PA is the improvement of decision support systems and software solutions that assist farmers in most efficiently administering their purchases, planning requirements, and cost calculations [23,33]. The overall vision is to come from precision to decision-making. The advent of machine-learning and deep-learning possibilities has improved the power and consistency of such decision support systems in crops mainly related to chemicals application [4,5,8,29].

An increased interlinkage of agricultural production with upstream industries based on PA technologies might create incentives for more robust vertical adoption in the agrifood sector [7,8]. For instance, highly integrated firms might realize the required integrated data systems more efficiently [18]. The increasing transparency of farming practices and the need to disclose some practices and adjust them to consumer needs might lead to more substantial incentives for backward integration.

The results obtained are based on the judgment of experts based on a literature review. It is recommended for future studies to compare the data obtained with real data on precision agriculture productivity, as well as the impact of each applied technology (criteria and sub-criteria). It is also suggested to explore and survey the impact of using artificial intelligence for decision-making supported by bigdata, as it is one of the most used emerging technologies today.

4 Final Remarks

Advanced technologies will possibly increase the capital intensity of PA, and this could mean that just a few farms can afford it. As a result, this may lead to concentration and rising inequality in the agricultural sector. To avoid such an outcome, diverse technologies must be available for different agricultural systems, ranging from small to large-scale farms and crops. Moreover, different forms of cooperation and PA technology distribution can enable many farms to benefit from the technologies. In developing countries, education is probably the most critical field to expand the potential use of PA. Results indicated that the use of PA might present a high impact on food production in Brazil.

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