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Innovation Model of Agricultural Technologies Based on Intuitionistic Fuzzy Sets

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Abstract: The selection and rational use of mechanization significantly affects the cost of agricultural products. To achieve the best financial effects, it is necessary to optimize the use of existing machine parks. The authors suggest a decision tree for deciding whether to 'innovate or not'. The aim of the research is to define an algorithm that determines whether or not the land is arable, and in this way to help the owner of the family farm in the planning of working hours for agricultural machines, i.e., managing the machine park. The lack of plans, which stems from the lack of accurate data on the appropriate conditions of cultivation, leads to inappropriate use of time and the capacity of the machine park. The decision process is split into four compound variables: biological conditions, economic environment, technological conditions, and expertise and workmanship quality. Linguistic values of these variables are modeled with intuitionistic fuzzy sets, allowing for imprecision in data as well as experts' hesitation.

Keywords: innovation; sustainable farming; fuzzy sets

1. Introduction

Agriculture, and therefore crop farming, faces many problems, which are primarily the result of insufficient investment assets, resulting in Serbian farms having a relatively low competitiveness and lagging behind those in countries of the European Union. The process of European integration will further change the economic conditions, which will be reflected in the further liberalization of agriculture, therefore requiring greater competitiveness. The lowland region of Vojvodina, which is the most developed agrarian area in Serbia, is extremely favorable for crops, primarily due to the good natural characteristics of the land. Cereals are grown on 67% of the total arable land registers, and industrial plants on 24%, while other plants occupy 9% of arable land. However, certain factors, such as lack of financial resources, limited possibility of using bank loans, long-term drought, low agricultural technology, price changes, etc., affect the fluctuations in agricultural production, which makes it difficult to achieve the necessary level of efficiency.

A special issue in Serbian agriculture is ownership transformation, which started in the 1990s due to the transition process from the former socialist countries. While Poland and the countries of the former Yugoslavia partially deviate from the Soviet model of agriculture [1], the agricultural sector in these countries is largely dependent on small individual farms. Such an ownership structure still exists today. The average area of utilized agricultural land per farm in Serbia is 5.45 hectares, and is significantly higher in the region of Vojvodina (10.13 hectares) as a result of greater representation of agribusiness companies, and the completion of the first phase of post-socialist centralization of land in favor of a small number of market-oriented family farms, which in this region account for 99% of the total number of farms. In 1989, the private sector owned 82% of arable land, 97.2% of the tractor and 81.4% of the livestock. However, the private sector, compared to the concentration of fixed capital, is lagging behind the social sector in terms of marketability of production realized through the purchase [2]. The ownership structure of Serbian agriculture is being adjusted to "Western" model of agriculture, i.e., the entrepreneurial model of family farming [3]. Small farms have a significant role in protecting rural areas from environmental degradation, reduction of socio-economic inequalities, etc. [4]; however, agricultural production on small farms in the future cannot be imagined without significant investments in the modernization of production [5].

The interest for this study stems from the importance of crop farming in Vojvodina, the participation of small family farms in the ownership structure, and the impact of various factors on efficiency that make it difficult for rational decision-making in production. Various studies testify to the impact of certain factors on the efficiency of farms. Nowak et al. [6] emphasize the importance of factors on the technical efficiency of agriculture: soil quality, age managers and the surcharges for investments, where soil quality has the greatest impact on efficiency. There is a high proportion of the workforce in variable costs, with the modernization of machinery and advanced methods in production to reduce the costs of operation. In addition to improved technologies that increase productivity and profitability, a significant factor is adequate knowledge of the maximum utilization of inputs (seeds, machinery, fertilizer, chemical inputs, irrigation, etc.), with the preservation of natural resources, which ensures sustainability of the sector [7]. Domanska et al. [8] also point out that technological progress and innovation, in addition to structural transformation (primarily in the former socialist countries), requires changes in quality, while improving the knowledge and skills of farmers. Innovations in agricultural transportation have the main goal to optimize agricultural processes and to make the reproduction cycle in this field sustainable [9].

It is indisputable that the further development of agricultural production in Vojvodina depends on the adoption of scientific knowledge and the implementation of innovative technologies. A large degree of uncertainty is primarily the result of biological processes in nature farming [10], and dependence on weather conditions. Taking into account the various factors that affect production, the selected parameter in the model is land workability, which is determined by the current and predicted meteorological conditions, given that they have the greatest impact on the farming culture.

In accordance with the defined goal of this research, we developed a prototype expert system. Expert systems are an ideal channel for the transfer of new technology and knowledge from the research laboratory to practical application to farms and farmers. Using these systems, one reduces the risk of making the wrong decision and allows agricultural producers to deal with various problems through innovations for sustainable farming.

2. Literature Review

When the difficulties of the comprehensive spreading of model calculations for business optimization are broached, professionals usually plead that innovative information systems are not available; that there is a lack of professionals and computer capacity, and that some companies are averse to model calculations; that most agricultural professionals graduated in times when computer technology was unknown; that only few people deal with model calculations, and research in that field is fragmented, etc. These arguments contain a lot of truth and are broadly known, so as to make their mere listing sufficient. Nevertheless, if we look at the deeper roots of these issues, we should investigate, on the one hand, how we progress towards modernity, and, on the other, what the relationship is between modernization and decision-making proceses. Let's put the optimization problem of company plans into the modernization system of agriculture.

Companies around the world are occupied with two topics: how to innovate their production process and how to modernize the company's decision-making mechanism. These two issues are tightly linked. To have an innovative management in place, not only the means of production and the technical level of manufacture have to be developed, but the decision-making system as well.

The literature on various decision support systems (DSS) in agriculture is abundant. We shall focus our review on systems aiming to ease the decision-making processes for small farmers. Most scholars have presented specialized systems in their papers, focusing on irrigation [11], waste management [12], and fertilizers [13]. Rupnik et al. [14] developed an integrated support system, the AgroDSS. The package incorporates tools for predictive modeling with explanation as well as detection of structural change in time series data.

When it comes to selecting the appropriate machinery, an optimization problem needs to be solved that covers different cropping practices and regional variations in crops. Focused on olive farms, Hafezalkotob et al. [15] developed a MADM procedure for choosing between 6 olive harvesting machines, while Herrera-Cáceres et al. [16] proposed a programming model for olive harvest planning decisions. The model incorporates different land units and maximizes the total amount of oil extracted in the mill. The challenges and prospects of automatic guidance for agricultural vehicles were presented in review papers [17,18], with an emphasis on European farms, while Lindsay et al. [19] proposed a DSS aiming at small-scale producers, helping them benefit from GPS guidance on tractors using farm-specific details. Findings suggest that the described technology is profitable on farm areas of at least 49 ha, which is much bigger than the average farm size in Serbia.

Previous papers have provided impartial solutions to certain challenges burdening small agricultural producers. However, the decision-making process is highly personal, and it is unclear how helpful the DSS really are. McCown [20] states that "In the highly uncertain production environment of Australian dryland farming, personal judgment plays a significant mediating role between perception and action". The author develops a framework for testing the discrepancies between farmers' intuition and analysis. Furthermore, cognitive engineering is used to test various frameworks as to whether they present a concept of mind that is workable for supporting farmers' judgments and decisions [21].

We proceed with papers focusing on determinants for adoption of agricultural technologies. Adoption of new technologies is a multidimensional problem. Empirical evidence shows that determinants for adoption include gender, levels of income, education, climate or geographical position of the farm, farm size, just to name a few. "Farm characteristics such as the size, location, soil properties, slope, proximity to homestead, access to irrigation water and the agro-ecological conditions of the area where the farm is located have also been found to affect adoption" [17]. Comprehensive review of determinants for farmers' adoption is presented in the paper by Knowler and Bradshaw [22]. Rogers [23] states that " … adoption of any innovation or technology is not a single act, but a process with many stages that occurs over a period of time".

Innovation must have specific attributes leading to the provision of services to targeted stakeholders that meet specific needs. These attributes or characteristics must be held in common with innovations related to infrastructure and business processes. Five properties of sustainable innovation have been found, which need to be realized together with the factors of infrastructure mechanisms. These attributes include: (1) alignment between innovation and innovation stakeholder needs; (2) positive relationships between participants in the innovation process; (3) quality of implementation and innovation integrity; (4) innovation efficiency; (5) ownership relationships between participants in the innovation process [24].

Ugur and Mitra [25] investigated the effects that the adoption of new technologies has on employment in less developed countries. The authors concluded that advances in product innovations have a beneficial effect on employment, while process innovations have no effect on employment increase. The effects are negligible for unskilled workers for both types of innovations. Houssou and Chapoto [26] observed no effect of mechanization improvement on input increase. The use of the labor force was not intensified with the use of tractors. Wang et al. [27] proved that demand for machine services increased with large farms, and that better-educated farmers decreased their self-cultivated land by renting it out to less educated ones. Mottaleb et al. [28] investigated over 800,000 farmers in Bangladesh on machinery adoption and found out that physical assets, institutional and physical infrastructure positively affect adoption. It is the same with the irrigation system [29]. Also, women farmers are less likely to own agricultural assets than men. Pannell et al. [30] state that new innovation bears risks and opportunities alike and farmers are eager to try out a new technology that is less risky and with higher expected benefits relative to the prevailing technology as Fountas et al. [31]. When the new technology requires substantial initial investment, the decision is especially uncertain.

It can be concluded that agriculture is not featured by full modernity, i.e., not all its parts are modern, but it would be unrealistic to set it as a goal. There is no sample with cutting edge agriculture in all aspects. Innovation in the machine park of family farms could be elementary need for sustainability of these farms. The need for innovative management and decision-making mechanism, however, means much more than possessing the appropriate data. We have to know what the situation is, but even more we have to know what to do. Once modern computers are at our disposal—hopefully in the near future—then we can, in a contemporary manner, solve not only the generation, handling and processing of data, but also multivariable planning and the optimization of planning through the application of fuzzy sets [32].

Selection and rational use of mechanization significantly affect the cost of agricultural products. To achieve the best financial effects, it is necessary to optimize the use of existing machine parks [33]. It is difficult to make a decision with respect to "modernize or not" on farm-specific jobs when you consider that the decision is made for the next few days under conditions of uncertainty and high risk. This is mostly because of the high number of relevant variables, the inability to measure relevant variables, stochastic, instability and nonlinearity of relevant variables, the lack of information in terms of quantification and measurement operation of relevant variables, insufficient accuracy and availability of information. Treatment of indeterminate, unclear, uncertain, and linguistically described phenomena and situations has encountered difficulties in classical mathematics.

Finally, a paper of Car [34] examined the willingness of farmers to make a shift in farming objectives and even structural changes in order to adopt new technologies.

Many authors have used fuzzy sets in agricultural decisions, such as Cornelissen et al. [35], who used fuzzy models to support decisions regarding sustainable development. Bosma et al. used fuzzy logic to simulate farmers' decisions [36]. The sensitivity of the Fuzzy Decision Support System was tested by Giusti and Marsili-Libelli [37]. Mugera presented an approach for measuring the efficiency of dairy farms with fuzzy data envelopment analysis [38]. Kavdir and Guyer used fuzzy logic application for apple grading [39]. Mota et al. applied fuzzy clustering methods for decision making support in agricultural environment [40].

3. Methods

Modernization as an innovation, essential in both size and importance, has been achieved in agricultural production in cases in which it has been possible to meet biological, environmental, technical and technological and professional conditions in one go. Environmental conditions (in other words: the economic environment): production was also profitable for the production plants and, on top of that, extra inputs—unlike for non-intensive kinds of production—further increased profitability. The market needed and absorbed the increased product volume, and the producers' decision to focus on wheat production took them from the earlier path of necessity to a free path. Technical–technological conditions: the vehicle fleet, chemicals, various equipment and tools needed for production were more or less available at a satisfactory level. Professional knowledge: the producers were able to become familiar with and understand the significance of the intensive wheat sort and its conditions of production, and accepted them. They also created the conditions for the production. Dual conditions—i.e., complexity and ranking—were created in cases where these production systems had been successfully established.

The sustainability of a particular innovation requires a planned change process with clearly defined activities. These activities have to enable continuity of strengthening the infrastructure and innovation attributes [24].

A common characteristic of areas that are, for the time being, underdeveloped, is the lack of complex solutions and their defectiveness, respectively. Even if there is an opportunity to create a comprehensive and complex system to fulfill the necessary conditions, the ranking of conditions still remains an essential issue. Ranking should be made in an order that provides development and does not break it. In the branch of husbandry, for example, we failed to establish a completely satisfactory ranking of solutions (feed production—livestock husbandry—processing). The solution of the first two is ongoing and is progressing well; however, the processing capacities are still narrow.

In this study, the authors used a national Serbian database (Republic Institute for Statistics of Serbia), and the data were taken for the region of Vojvodina, where the area was viewed on the basis of the 45 local governments (municipalities). The total number of farms in this area amounts to 147,624 households, of which 146,269 are family farms, while the rest are legal entities and entrepreneurs. Data were collected in the year 2017. To better understand the problems faced by farmers in Vojvodina, Table 1 shows the main characteristics of agricultural holdings in the region. In addition to the large proportion of small farms (31% of farms were less than 1 hectare), the fragment structure of the estate, with 6 plots per farm on average, affects the efficiency of the production itself. In agricultural production, land cultivation occupies an important place. Therefore, scientists and technologists explore the most effective means of cultivation.

Table 1. Characteristics of farms in Vojvodina (from 45 municipalities). Descriptive statistics.

Variables	Mean	Standard Deviation	Minimum Value	Maximum Value
The share of farms smaller than 1 ha, %	31.03	6.20	17.29	43.80
The share of farms larger than 100 ha, %	1.12	0.59	0.00	2.78
Used agricultural land per hectare (average farm size [ha])	10.13	3.01	2.00	17.10
The share of farms with production of cereals in the total number of holdings, %	71.27	9.40	37.05	87.98
The share of farms with production of industrial crops in the total number of holdings, %	32.63	13.94	8.99	67.57
Total annual work units (AWU)	5296.76	6436.38	290.45	29,238.33
Agricultural holdings without land, %	4.18	2.26	0.81	10.72
The share of farms that can irrigate land in the total number of agricultural holdings, %	19.09	7.54	4.71	35.14
The share of agricultural farms that performed irrigation of the total number of farms, %	4.87	3.04	1.12	13.18
The share of family farms that used credit, %	5.56	1.48	1.50	9.06
The share of farms that have used subsidies in the total number of holdings, %	31.57	8.47	17.10	54.18
The share of farms that have a tractor on their own property of the total number of farms, %	56.73	8.68	35.10	75.45
Number of hectares per tractor (ha/tractor)	12.51	3.66	2.32	20.20
Number of farmers per tractor (active farmer/tractor)	2.36	0.38	1.55	3.51
The share of tractors older than 10 years in the total number of tractors, %	89.17	2.63	82.30	95.62
The share of households with a combine harvester owned, %	6.75	2.23	3.11	11.39
Number of hectares of the combine (ha/combine)	141.58	29.00	92.79	225.14
Number of farmers per combine (an active agricultural/combine)	28.05	9.61	15.93	50.72
The share of the combine over 10 years in the total number of combines, %	89.44	4.60	74.76	98.48
The share of farms that have used a computer, %	4.15	1.41	2.62	10.43
The share of farms that have used the advisory services, %	19.76	5.82	4.98	36.09

Machinery plays an important role in agricultural production, since the machines have radically changed life in the village. The functionality of the new agrarian structure depends on the technical equipment of agriculture.

Indicators of supply of agricultural mechanization: the number of hectares per tractor/combine and the number of active farmers per tractor/combine indicate inefficient use of these machines, as well as a large share of the active agricultural producers in the total population (about 10%). Also, the share of tractors and combines that are more than 10 years old is about 90% of the total number of tractors and combines, which points to the need for investment in new equipment and machinery. However, the current credit policy does not allow credits for small family agricultural holdings, making it impossible for these farms to gain access to investment for the purpose of the improvement of primary machinery. Due to the unfavorable banking conditions and underdevelopment of this type of financing for the agricultural sector, only 5.5% of the total households in the region were willing to take a loan from a commercial bank. In addition, the introduction of new technologies is difficult because of computer illiteracy of farmers, with only 4.15% of farms using computers. In addition, advisory services allow the transfer of new knowledge and information; however, about 20% of farms use the services of consultants, and with some local governments, that share is not 5%. Agricultural producers must invest in education, to adequate management of inputs such as fertilizers, herbicides, irrigation, etc. However, this required large financial investments, as well as the support of the state through measures of agrarian policy. Only 5% of farms irrigated land, where irrigation is available for 19% of agricultural holdings, which indicates the inadequate utilization of capacities. The importance of irrigation in terms of reducing the risk is undeniable.

Fuzzy mathematical modeling can satisfactorily deal with the parameters that are uncertain, vague and subjectively evaluated. The algorithm should be based on the opinion of agricultural experts, the experience of agricultural workers, the available data. Decision trees can serve as algorithms for decision making. If necessary, this model can be developed to an even greater number of levels or restricted to a smaller number of levels, depending on the crop or the type of operation in question.

The decision tree we developed is presented in Figure 1. The input variables can be found on the second, third, fourth and fifth levels of the tree.

An exact and comprehensive analysis is inconceivable without such information, which is provided by a model solving several decision types: optimum production structure, gains, technologies, use of resources, shadow prices, sensitivity analysis, assumptions, simulating and analyzing "what if … " scenarios, etc. Otherwise, there are many uncertainty factors in agricultural production; thus, all calculations contain contingencies.

In traditional, manual calculation, plant managers do not know what to do with such uncertain factors. Yet, calculation results inform us about what will happen if different changes occur. These "what if … " types of results accurately show the degree of the changes' impact on profit, production value or any other indicator we are interested in. Although in the literature we find that the changing processes could appear only once and sequentially, we will assume that they are cyclical [41].

Activities aimed at providing an adaptive prevention system are an integral part of the sustainability process. This system must be sensitive to change. This creates a favorable environment for innovation that will, if necessary, adapt to the system in which they were involved. The innovations to be sustained can be manifested in a wide range of: (a) new prevention programs and strategies, or (b) new infrastructures or business process elements that support the prevention programs or strategies [24].

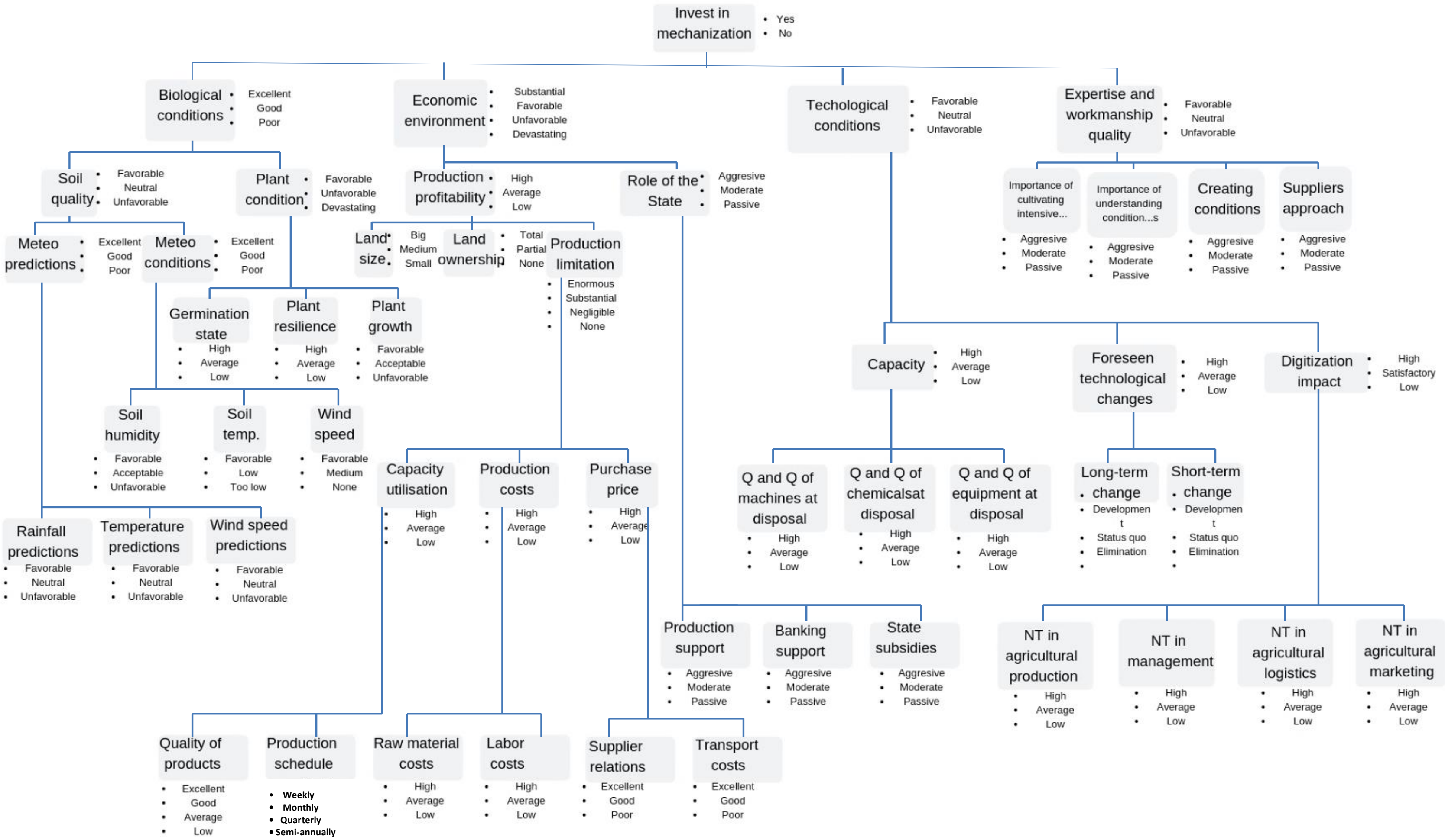

Figure 1. Decision tree—to invest or not in mechanization in agriculture. Abbreviations: Q and Q—quality and quantity; NT—use of new technologies. Expertise and workmanship quality combines the abilities to perceive and understand: 1. the importance of growing intensive sorts; 2. the conditions for cultivating and producing intensive sorts; 3. to create conditions for cultivating and producing intensive sorts.

The decision as to whether to invest or not depends on four compound variables: biological conditions, economic environment, technological conditions and expertise and workmanship quality. The values of these variables are inferred starting from "leaf" variables, 33 in total. The input variables take linguistic values, e.g., "wind speed is favorable" or "quality of products is excellent". Experts' evaluations of these statements are taken as input values, in the form of intuitionistic fuzzy sets (IFS), introduced first by Atanassov [42]:

Let E be the fixed universe and $A \subset E$. The set $A^* = \{\langle x, \mu_A(x), \nu_A(x)\rangle, x \in E\}$, where $\mu_A(x) + \nu_A(x) \leq 1$ is called intuitionistic fuzzy set, and functions $\mu_A(x) : E \to [0,1], \nu_A(x) : E \to [0,1]$ represent the degree of membership and non-membership respectively. The difference $1 - \mu_A(x) - \nu_A(x) \geq 0$ corresponds to the degree of indeterminacy (uncertainty).

Inputs and outputs are defined as intuitionistic fuzzy sets, and implication rules in form of conjunctions of input variables are defined. Conjunction and disjunction of IFSs are defined as:

$$A^* \wedge B^* = \{\langle t(\mu_A(x), \mu_B(x)), s(\mu_A(x), \mu_B(x))\rangle, x \in E\} \tag{1a}$$

$$A^* \vee B^* = \{\langle s(\mu_A(x), \mu_B(x)), t(\mu_A(x), \mu_B(x))\rangle, x \in E\} \tag{1b}$$

where t and s denote t-norm and t-conorm, respectively. t-norm is a generalization of an intersection, while the t-conorm is a generalization of a union. The most commonly used are Min—defined as a minimum of two values $\mu_A(x), \mu_B(x)$; and Max—defined by analogy, reducing Equation (1a) to

$$A^* \wedge B^* = \{\langle Min(\mu_A(x), \mu_B(x)), Max(\mu_A(x), \mu_B(x))\rangle, x \in E\} \tag{2}$$

Min and Max are functions used in our research, although we kept the general notation of $\wedge$ and $\vee$ respectively in the Appendix A. An example of calculation is presented in Table 2. Another example of $\wedge$ and $\vee$ is product (ab) and bounded sum (a + b − ab), respectively.

Table 2. Extract from Appendix A: Obtaining favorable plant condition.

Germination State	$\wedge$	Plant Resilience	$\wedge$	Plant Growth	$\Longrightarrow$	Plant Condition
high	$\wedge$	low	$\wedge$	> acceptable	$\Longrightarrow$	favorable
high	$\wedge$	average	$\wedge$	> acceptable	$\Longrightarrow$	favorable

Notes: > tacit ≥; meaning of "> acceptable": "is better than or equal to acceptable", covering acceptable and satisfactory. Mathematical logic symbols: $\wedge$ conjunction "and"; $\Longrightarrow$ implication "if … then".

4. Research Results

The experts are asked to evaluate each input variable based on its numeric or descriptive value. The universe of discourse (a, b) for input variables include: precipitation (L/m^2), temperature (°C), wind speed (km/h), and cover variables for meteorological predictions and measurements. Germination and plant resilience cover intervals that depend on the plants in question, as well as on the season, and are measured in percentages. Labor costs and other price-related variables depend on the type of field work, season and type of culture. Expertise and workmanship quality is, on the other hand, less numerical in nature and intrinsically vague. The data are obtained through questionnaires disseminated to farm owners. Based on the answers, the experts form an opinion by means of a linguistic variable: aggressive, moderate or passive. Most variables take one of three values: high, medium, low; or aggressive, moderate, passive; or favorable, neutral, unfavorable. We suggest to experts the following pattern (Figures 2 and 3) in choosing the appropriate μ(x) degree:

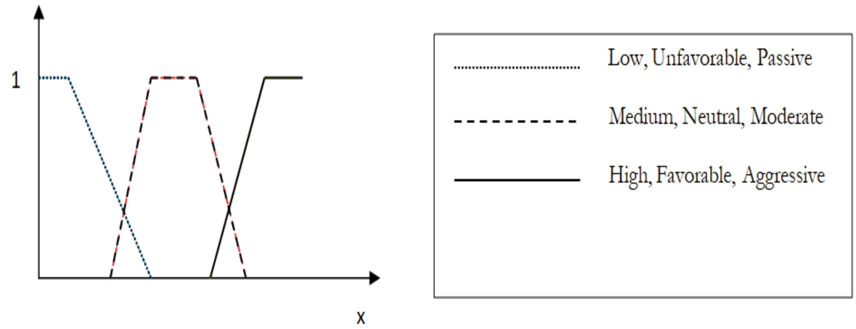

Figure 2. Suggested values for membership degrees in case of three-valued variables.

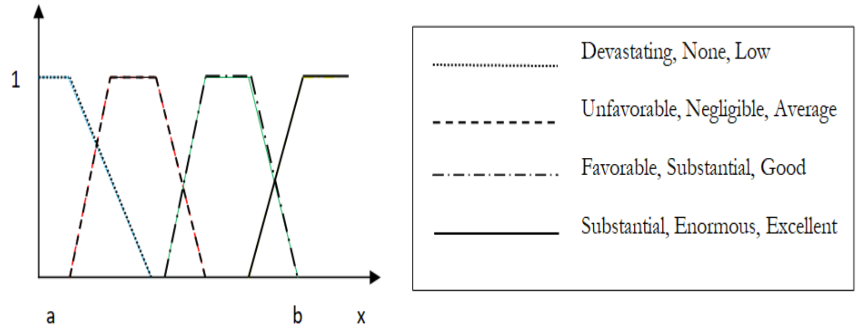

Figure 3. Suggested values for membership degrees in case of four-valued variables.

Instead of just measuring the satisfaction degree, μ(x), experts also measure the level of non-accordance, for example, how much evidence there is for the statement "the quality of products is not excellent". The number provided does not necessarily have to be the difference $1 - \mu(x)$, thereby leaving room for indecisiveness. The comprehensive list of decision rules and inference is presented in Appendix A. Each of the antecedents are in the form of conjunctions; thus, we use (1). Various combinations of antecedents produce the same action/conclusion, for example, Table 2.

To achieve the membership/non-membership degree for favorable plant condition (consequent), we use the membership degree of the disjunction of antecedents by applying Equation (2). Table 3 shows an example of input variables. The third and fourth columns denote the membership and non-membership degrees for the three variables respectively: germination state, plant resilience and plant growth. The t-norm and t-conorm from the definitions Equation (1a,b) were substituted by the most common pair—Min and Max—leading to:

$$\begin{gathered}\mu(\text{plant condition is favorable}) = \text{Max}(\text{Min}(\mu(\text{germination state is low}),\\ \mu(\text{plant resilience is low}), \mu(\text{plant growth is acceptable}), \text{Min}(\mu(\text{germination state is low}),\\ \mu(\text{plant resilience is low}), \mu(\text{plant growth is favorable}), \text{Min}(\mu(\text{germination state is low}),\\ \mu(\text{plant resilience is average}), \mu(\text{plant growth is acceptable}), \text{Min}(\mu(\text{germination state is low}),\\ \mu(\text{plant resilience is average}), \mu(\text{plant growth is favorable})))\end{gathered} \tag{3}$$

When Equation (3) is applied, we obtain the membership degree of favorable plant condition to be 0.2, while the non-membership degree is a total of 0.8, leaving no space for indeterminacy. It is more likely that the plant condition is unfavorable or devastating. The three derived values for the variable plant condition are then used as input values for calculating biological conditions. The comprehensive table with all the calculations is provided in Appendix B. The Appendix consists of the hypothetical entry values for all 33 leaf variables on various levels, as mentioned earlier. Thus, by applying several steps, a final decision takes place as to whether to invest in mechanization or not, taking into account all possible circumstances and all possible values of input/output variables. The final calculation that needs to be performed is to compare two intuitionistic fuzzy numbers: one in favor of mechanization and the second in favor of the status quo. The comparison between values A = (μ_1, ν_1) and B = (μ_2, ν_2) is given with:

$$A \leq B \text{ if } \mu_1(x) \leq \mu_2(x) \text{ and } \nu_2(x) \geq \nu_1(x). \quad (4)$$

Table 3. Extract from the decision tree—biological conditions. Experts' opinions on values of three variables: germination state, plant resilience and plant growth.

Germination State	high	1	0
	average	0.6	0.4
	low	0.2	0.8
Plant Resilience	high	0	1
	average	0.6	0.4
	low	1	0
Plant Growth	favorable	0.8	0.1
	acceptable	0.9	0.1
	unfavorable	0	1

The idea behind the decision tree was to automatize the decision-making process based on formal deduction rules and all the proof gathered when assigning membership values. Up to the moment of decision, the process is free of bias and subjectivity. Nonetheless, the final numerical value associated with the action—to modernize is not a crisp value 0 or 1, but again an intuitive fuzzy set like all of the previously involved variables. In our example (Appendix B), the total amount of proof in favor of modernizing is 0.6, while the membership for the disagreement is 0.4. When it comes to non-modernization, i.e., maintaining the status quo, the degree in favor is only 0.2, while membership for disagreement is 0.7. There is also an indecisiveness degree of $1 - 0.2 - 0.7 = 0.1$. Clearly, the example favors the innovation, based on Equation (4), but it is still up to the decision-maker to gauge whether these figures are high enough to dismiss the risk of action.

5. Conclusions

In agricultural production, land cultivation occupies a significant place. The number of inhabitants on Earth is continuously increasing, while the number of hectares of arable land is stagnating or decreasing; hence, production per unit of arable land needs to grow. We have presented a formalized decision-making process based on fuzzy set theory, more precisely using intuitionistic fuzzy numbers. Such a decision-making algorithm is independent of the type of agricultural activity that is being sought, from the type of agricultural culture that is to be processed, from the geographical location of the agricultural holding. The above-mentioned factors depend on the fuzzy set of variables that affect the decision. The nature of the problem is such that it possesses the characteristics of uncertainty, and a subjective assessment is needed with a wide range of input data. Theory of fuzzy sets with the application of fuzzy logic in decision making allows the treatment, complete examination and analysis of a given problem. There is no possibility of "fitting" a desirable decision by decoding input data, as it also reduces the risk of making the wrong decision. This complete analysis and analysis of the problem would be impossible without fuzzy logic, relying solely on the knowledge, experience and intuition of the expert.

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Appendix A

Rules of inference.

Due to the character and content of the attachment, as well as its scope, it can be seen in its original form at http://bit.ly/2luuAX0.

Appendix B

Decision tree calculations.

Due to the character and content of the attachment, as well as its scope, it can be seen in its original form at http://bit.ly/2HCpAb3.

References

1. Lerman, Z.; Csaki, C.; Feder, G. Evolving Farm Structures and Land Use Patterns in Former Socialist Countries. *Q. J. Int. Agric.* **2004**, *43*, 309–335.
2. Ševarlić, M.M. Changes in the Structure of Farms and Producers Associations in the Republic of Serbia. In *Agri-Food Sector in Serbia - State and Challenges*; Skoric, D., Tomic, D., Popovic, V., Eds.; Društvo agrarnih ekonomista Srbije, Srpska akademija nauka i umetnosti: Beograd, Serbia, 2013; pp. 31–72.
3. Zakić, N.; Vukotić, S.; Cvijanović, D. Organisational Models in Agriculture with Special Reference to Small Farmers. *Ekon. Poljopr.* **2014**, *61*, 225–237. [CrossRef]
4. Galluzzo, N. An Analysis of the Efficiency in a Sample of Small Italian Farms Part of the FADN Dataset. *Econ. Agric.* **2016**, *62*, 62–70. [CrossRef]
5. Morris, W.; Henley, A.; Dowell, D. Farm Diversification, Entrepreneurship and Technology Adoption: Analysis of Upland Farmers in Wales. *J. Rural Stud.* **2017**, *53*, 132–143. [CrossRef]
6. Nowak, A.; Kijek, T.; Domanska, K. Technical Efficiency and its Determinants in the European Union. *Econ. Agric.* **2015**, *61*, 275–283. [CrossRef]
7. Passel, S.V.; Nevens, F.; Mathijas, E.; Huylenbroeck, G.V. Measuring Farm Sustainability and Explaining Differences in Sustainable Efficiency. *Ecol. Econ.* **2007**, *62*, 149–161. [CrossRef]
8. Domanska, K.; Kijek, T.; Nowak, A. Agricultural Total Factor Productivity Change and its Determinants in European Union Countries. *Bulg. J. Agric. Sci.* **2014**, *20*, 1273–1280.
9. Fazekaš, T.; Bobera, D.; Ćirić, Z. Ecologically and Economically Sustainable Agricultural Transportation Based on Advanced Information Technologies. *J. Econ. Agric.* **2017**, *64*, 739–750. [CrossRef]
10. Fess, T.L.; Benedito, V.A. Organic versus Conventional Cropping Sustainability: A Comparative System Analysis. *Sustainability* **2018**, *10*, 272. [CrossRef]
11. Mannini, P.; Genovesi, R.; Letterio, T. IRRINET, Large Scale DSS Application for On-farm Irrigation Scheduling. *Procedia Environ. Sci.* **2013**, *19*. [CrossRef]
12. Repoussis, P.P.; Paraskevopoulos, D.C.; Zobolas, G.; Tarantilis, C.D.; Ioannou, G. A Web-Based Decision Support System for Waste Lube Oils Collection and Recycling. *Eur. J. Oper. Res.* **2018**, *195*, 676–700. [CrossRef]
13. Prabakaran, G.; Vaithiyanathan, D. Madhavi Ganesan, Fuzzy Decision Support System for Improving the Crop Productivity and Efficient Use of Fertilizers. *Comput. Electron. Agric.* **2018**, *150*, 88–97. [CrossRef]
14. Rupnik, R.; Kukar, M.; Vračar, P.; Košir, D.; Pevec, D.; Bosnić, Z. AgroDSS: A Decision Support System for Agriculture and Farming. *Comput. Electron. Agric.* **2019**, *161*, 260–271. [CrossRef]
15. Hafezalkotob, A.; Hami-Dindar, A.; Rabie, N.; Hafezalkotob, A. A Decision Support System for Agricultural Machines and Equipment Selection: A Case Study on Olive Harvester Machines. *Comput. Electron. Agric.* **2018**, *148*, 207–216. [CrossRef]
16. Herrera-Cáceres, C.; Pérez-Galarce, F.; Álvarez-Miranda, E.; Candia-Véjar, A. Optimization of the Harvest Planning in the Olive Oil Production: A Case Study in Chile. *Comput. Electron. Agric.* **2017**, *141*, 147–159. [CrossRef]
17. D'Emden, F.H.; Llewellyn, R.S.; Burton, M.P. Adoption of Conservation Tillage in Australian Cropping Regions: An Application of Duration Analysis. *Technol. Forecast. Soc. Chang.* **2006**, *73*, 630–647. [CrossRef]
18. Keicher, R.; Seufert, H. Automatic Guidance for Agricultural Vehicles in Europe. *Comput. Electron. Agric.* **2000**, *25*, 169–194. [CrossRef]

19. Lindsay, K.; Popp, M.; Ashworth, A.; Owens, P.; Burek, J. A Decision-Support System for Analyzing Tractor Guidance Technology. *Comput. Electron. Agric.* **2018**, *153*, 115–125. [CrossRef]
20. McCown, R.L. A Cognitive Systems Framework to Inform Delivery of Analytic Support for Farmers' Intuitive Management under Seasonal Climatic Variability. *Agric. Syst.* **2012**, *105*, 7–20. [CrossRef]
21. Muzari, W.; Gatsi, W.; Muvhunzi, S. The Impacts of Technology Adoption on Smallholder Agricultural Productivity in Sub-Saharan Africa: A Review. *J. Sustain. Dev.* **2012**, *5*, 69–77. [CrossRef]
22. Knowler, D.; Bradshaw, B. Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research. *Food Policy* **2007**, *32*, 25–48. [CrossRef]
23. Rogers, E. *Evolution: Diffusion of Innovations. International Encyclopedia of the Social & Behavioral Sciences*, 2nd ed.; Elsevier: Orlando, FL, USA, 2015; pp. 378–381.
24. Johnson, K.; Hays, C.; Center, H.; Daley, C. Building capacity and sustainable prevention innovations: A sustainability planning model. *Eval. Program Plan.* **2004**, *27*, 135–149. [CrossRef]
25. Ugur, M.; Mitra, A. Technology Adoption and Employment in Less Developed Countries: A Mixed-Method Systematic Re respectively view. *World Dev.* **2017**, *96*, 1–18. [CrossRef]
26. Houssou, N.; Chapoto, A. Adoption of Farm Mechanization, Cropland Expansion, and Intensification in Ghana. In Proceedings of the International conference of agricultural economists ICAE, Milan, Italy, 8–14 August 2015.
27. Wang, X.; Yamauchi, F.; Otsuka, K.; Huang, J. Wage Growth, Landholding, and Mechanization in Chinese Agriculture. *World Dev.* **2016**, *86*, 30–45. [CrossRef] [PubMed]
28. Mottaleb, K.A.; Krupnik, T.J.; Erenstein, O. Factors associated with small-scale agricultural machinery adoption in Bangladesh: Census findings. *J. Rural Stud.* **2016**, *46*, 155–168. [CrossRef] [PubMed]
29. Zhang, T.; Wang, J.; Teng, Y. Adaptive Effectiveness of Irrigated Area Expansion in Mitigating the Impacts of Climate Change on Crop Yields in Northern China. *Sustainability* **2017**, *9*, 851. [CrossRef]
30. Pannell, D.J.; Marshall, G.R.; Barr, N.; Gurtis, A.; Vanclay, F.; Wilkinson, R. Understanding and Promoting Adoption of Conservation Practices by Rural Landholders. *Aust. J. Exp. Agric.* **2006**, *46*, 1407–1424. [CrossRef]
31. Fountas, S.; Sorensen, C.; Tsiropoulos, Z. Farm machinery management information system. *Comput. Electron. Agric.* **2015**, *110*, 131–138. [CrossRef]
32. Peng, Z.; Wu, L.; Chen, Z. Research on Steady States of Fuzzy Cognitive Map and its Application in Three-Rivers Ecosystem. *Sustainability* **2016**, *8*, 40. [CrossRef]
33. Erdal, G.; Esengun, K.; Erdal, H.; Gunduz, O. Energy Use and Economical Analysis of Sugar Beet Production in Tokat Province of Turkey. *Energy* **2007**, *32*, 35–41. [CrossRef]
34. Car, N.J. Using Decision Models to Enable Better Irrigation Decision Support Systems. *Comput. Electron. Agric.* **2018**, *152*, 290–301. [CrossRef]
35. Cornelissen, A.; Van Den Berg, J.; Koops, W. Assessment of the contribution of sustainability indicators to sustainable development: A novel approach using fuzzy set theory. Agriculture. *Ecosyst. Environ.* **2001**, *86*, 173–185. [CrossRef]
36. Bosma, R.; Phong, L.; Kavmak, U. Assessing and modelling farmers' decision-making on integrating aquaculture into agriculture in the Mekong Delta. *NJAS—Wagening. J. Life Sci.* **2006**, *53*, 281–300. [CrossRef]
37. Giusti, E.; Marsili-Libelli, S. A Fuzzy Decision Support System for irrigation and water conservation in agriculture. *Environ. Model. Softw.* **2015**, *63*, 73–86. [CrossRef]
38. Mugera, A. Measuring technical efficiency of dairy farms with imprecise data: A fuzzy data envelopment analysis approach. *Aust. J. Agric. Resour. Econ.* **2013**, *57*, 501–520. [CrossRef]
39. Kavdir, I.; Guyer, D. Apple grading using fuzzy logic. *Turk. J. Agric. For.* **2003**, *27*, 375–382. [CrossRef]
40. Mota, V.; Damasceno, F.; Leite, D. Fuzzy clustering and fuzzy validity measures for knowledge discovery and decision making in agricultural engineering. *Comput. Electron. Agric.* **2018**, *150*, 118–124. [CrossRef]
41. Hall, G.E.; Hord, S.M. *Implementing Change*; Allynand Bacon: Boston, MA, USA, 2001.
42. Atanassov, K. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [CrossRef]