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Applying Integrated Data Envelopment Analysis and Analytic Hierarchy Process to Measuring the Efficiency of Tourist Farms: The Case of Slovenia

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Abstract: This paper examines the efficiency of tourist farms in Slovenia by adopting an approach using a framework of non-parametric programming—Data Envelopment Analysis (DEA) and Analytic Hierarchy Process (AHP), combining the two because the DEA analysis by itself does not take into account all attributes, especially qualitative ones. The beforementioned two methods rank the farm tourism units with respect to their efficiency. By using the DEA method, an input- and output-oriented BCC and CCR model were introduced to upgrade the criteria by including the additional non-numerical criteria of the AHP. The results of the models showed that there are possible improvements on all levels of efficiency, as well as on the criteria of the additional offer of tourist farms, which were analyzed in the AHP model with additional criteria. According to the estimated efficiency, the ranking of tourist farms differed according to the two methods. Within the group of farms assessed as efficient by DEA, the AHP model allowed a more accurate ranking.

Keywords: farm tourism; tourist farms; efficiency; data envelopment analysis (DEA); analytic hierarchy process (AHP); Slovenia

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1. Introduction

Tourism development became an outstanding topic in the nineties [1] and is considered to be an alternative to farming [2]. Tourism became a frequent diversification of agricultural holdings [3] because of the increasing need for short vacations, experience-centered tourist activities, and the growing popularity of the anti-urban style of living [2,4]. As far as farmers are concerned, tourism increases their income, serves other entrepreneurial goals in connection to the farms, and improves the quality of life in the countryside. Farm tourism is an important additional economic support for the farm business, especially in the context of increased land values and agricultural input costs compared to conventional small family farms [5–7]. Ref. [7] claim also that farm tourism can be understood as an improvement of the local community's economic situation.

Despite the financial incentives that tourist farms receive (as well as the growing demand for them and their sustainable potential), they [8,9] are often exposed to market failure [10]. Accordingly, there is the challenge of how to maintain the existence and increase the efficiency of small tourist farms. The efficiency of tourist farms is a critical element in planning economic performance. Although the economic feasibility and low productivity of small-scale tourism farms are questionable, there is no research on economic analysis, including the efficiency of tourism farms [11,12]. Here, efficiency means the level of operational excellence in the rational use of resources and refers to the possibility of decision-making and improvements and the evaluation of the resource allocation [13]. There are many studies in the literature measuring efficiency in tourism, mostly using the Data Envelopment Analysis (DEA) method, which calculates the efficiency of a set of decision-making units (efficient units are assessed with 1). Much of this research is

conducted at the micro level, where researchers determine the effectiveness of hotels, restaurants or travel agencies ([14–29], etc.). However, some research is conducted at the state level. The efficiency of tourist farms has only begun to be researched in recent years; the known research so far has been prepared by Ohe [30], Choo et al. [11] and Arru et al. [12]. Some researchers (such as Jablonsky [31]) proposed combining DEA with Multi-Criteria Decision Analysis (MCDA) methods for instance to rank additionally efficient decision-making units. MCDA is the tool generally used to conciliate multiple evaluation criteria, taking into account the preferences of a decision-maker, which can be often relevant when assessing the relative performance of the DMUs. In fact, a manager is normally not indifferent as to whether a unit turns out to be efficient by using a less-important combination of inputs and/or outputs and by underweighting inputs and/or outputs of high importance to the business concerned [32].

Farm tourism in Slovenia is gradually growing into an increasingly important form of tourism offer [33], but there are no known data on its effectiveness.

The purpose of this research is to fill a gap in research in the field of the efficiency of tourist farms, and to methodologically supplement existing methodologies by using other criteria that affect efficiency and cannot be quantitatively defined. The aim of this paper is to address the tourist farm efficiency problem by:

- Developing a data envelopment analysis (DEA) model to assess the efficiency of tourist farms with accommodation;
- Determining the level of technical efficiency of tourist farms with accommodation in Slovenia, based on DEA models;
- Developing an Analytical Hierarchy Process (AHP) model for evaluating the efficiency of tourist farms with accommodation;
- Analyzing the level of Slovenian tourist farms with accommodation efficiency;
- Comparing the results of both models.

The article is organized as follows. First, the methods for efficiency assessment with the emphasis on DEA and analytical hierarchical process are presented. Then, the study area and data sources are defined, followed by a short description of the methodology and its application to the problem observed. The developed models are described in Section 3. Section 4 presents and discusses the results of efficiency for 45 tourist farms. The article concludes with a summary of the main findings and suggestions for further study.

2. Efficiency Assessment Approaches

Efficiency is the relationship between input and output and refers to the operational efficiency of companies or countries [34]. For this purpose, it is necessary to introduce new technologies and implement various changes [35]. Efficiency is the ratio of output to input in general. Processes that produce more output per input have greater inefficiency. If the maximum possible output per input is provided, optimal efficiency will be achieved. Without using new technologies or making various changes, it is impossible to increase efficiency [35].

Efficiency is central to assessing and measuring performance [36] and can be divided into parametric and non-parametric categories. In parametric methods, production function is presented and changes affecting production are considered (e.g., factor analysis, regression analysis, stochastic frontier approach, etc.). In non-parametric methods, analyses are conducted without presetting the production function through linear programming (e.g., Data Envelopment Analysis, Analytic Hierarchy Process, back error propagation, artificial neural network, etc.) [26,37].

The production function is defined as the ratio of inputs and outputs, and it applies to the operational performance of a firm or country. Thus, it reflects the current status of technology available to the industry. The economic efficiency is correlated to the production function. A tourist farm can be technically inefficient if it operates below the frontier [35,38]. To calculate the efficiency, the introduction of new technologies and various changes are required [36].

Performance can be defined as a combination of efficiency and effectiveness [37]. The difference between efficiency and effectiveness is that efficiency is associated with 'doing things right' and effectiveness with 'doing the right things'. The term efficiency refers to the allocation of resources across alternative uses, while effectiveness determines the ability to reach goals [11]. A measure of efficiency determines the ability of an organization to attain the output(s) with minimum inputs. Efficiency is not a measure of successfulness on the market but a measure of operational excellence in the rational utilization of resources. Efficiency refers to decision-making, possibility of improvements and the benchmarking of resource allocation [13].

Similar to firms and countries, the effectiveness is important in the tourism sector and rural tourism as it is accepted as a natural part of the socio-economic fabric juxtaposed with agriculture [2]. Nowadays, rural tourism is in the process of becoming an important activity expected to promote the employment, vitality, and sustainability of rural communities [39].

For measuring efficiency, which is associated with 'doing things right', two approaches are available: Data Envelopment Analysis (DEA) and Analytic Hierarchy Process (AHP).

2.1. DEA

Data Envelopment Analysis (DEA) is a non-parametric method, based on the use of linear programming, which allows for calculating the efficiency of the studied organizations. Effective organizations constitute the boundary (envelope) within which all organizations are included in the sample. The effectiveness of organizations located within the boundary is determined by the distance to the boundary [31,40,41].

By solving a linear programming problem, DEA calculates efficiency by comparing each unit of production with all other units. The partially linear envelope surface represents the best practice limit—the highest possible level of production achieved for each level of input. Estimates for technical efficiency derived from DEA are obtained through comparisons and observation and do not refer to the estimated frontier. Among other things, DEA allows us to evaluate efficiency in possible situations with multiple outputs and without the assumption of an a priori functional form for the marginal production [40–42].

For all variants of DEA models, Ref. [40] originally assumed that the efficiency of decision-making units is achieved as the maximum ratio of outputs to inputs. This is called the CCR model, after its developers. The result of the analysis of the CCR model is the integrated efficiency, which we call technical efficiency. The CCR scale is constant returns to scale, meaning that a proportional increase in inputs results in a proportional increase in output.

Banker, Charnes and Cooper (the so-called BCC model) upgraded this model in 1984 with the assumption of variable returns to scale, which introduces the assumption of the limited disposal of inputs [43,44].

DEA allows multiple inputs and outputs to be considered simultaneously, without any assumption on the distribution of the data. In any case, efficiency is measured by the proportional change in inputs or outputs, which means that the efficiency of the decision-making units is the subject of analysis. DEA provides some conceptual and practical advantages as it overcomes the complexity arising from the lack of a common measurement scale. DEA also avoids analysis from subjective evaluations in favor of objective evaluations resulting from the weighting of variables during the optimization process [41].

As an empirical methodology, Data Envelopment Analysis (DEA) is well recognized in the evaluation of efficiency and productivity [45]. In particular, DEA has been quite widely used for performance evaluation in various fields [46] and has also been widely used in tourism economics and agricultural economics. Researchers therefore consider the DEA method as a suitable method for measuring the efficiency of services in the tourism and hospitality sector [38,47].

As far as the efficiency-measuring literature is concerned, DEA is quite popular in efficiency measuring in general, but DEA has just recently been used in the tourism and hospitality industry [44]. As far as the DEA application papers are concerned, the share of

tourism is estimated at only 1.34% [46]. In the sphere of farm tourism, only one research paper is traceable—applying DEA to tourist farms in South Korea [6].

2.2. AHP

Analytic Hierarchical Process (AHP) is a method of determining the importance of criteria in multi-criteria decision-making, used to determine weights [48]. The method helps decision-makers find a solution that fits their needs. In the method, the weights and basic benefits of the alternatives are captured using the pairwise comparison method. The weights are obtained by comparing the parameters with each other, and the benefits of the alternatives are obtained by comparing the alternatives. Following this procedure, the criteria are arranged in a hierarchy, so that only a small number of criteria (3–5) are selected at each level. In the AHP method, the importance of the criteria is described with a matrix of comparisons of the importance of the criteria. The relative importance of criteria i and j is evaluated with values from 1 to 9.

The analytical hierarchical processing method is a quantitative method for ranking decision variants based on quantitative assessments of how each variant satisfies the decision-maker's criteria. The AHP method developed a linear additive model of the criteria system, in which the weights at all levels are generally determined based on the comparison of all pairs of criteria [49].

The simplest way used to structure the problem is hierarchically composed of three levels. The goals are at the highest level. The criteria are placed at the middle level. Alternatives (variants) are located on the third, lowest level [50].

Because of its simplicity, ease of use, and high flexibility, the AHP process has been extensively studied and used in almost every application related to multi-criteria decision-making since its development.

Analytic hierarchical process (AHP) is used in various fields. It is used by companies, industry, healthcare, governments, education, etc., as a decision support. In the field of farm tourism, we did not find any research measuring the efficiency of tourist farms using the AHP method, and more generally, in the field of measuring efficiency in tourism using the AHP method, only the research conducted by [51] could be traced.

2.3. Use of Combined Models for Efficiency Assessment

As noted by [52], the combination of AHP and DEA methods is represented to a lesser extent. Most often, AHP generally appears in combination with mathematical programming, QFD, meta-heuristics, SWOT and DEA. The same author [52], believes that the integrated AHP can result in a more realistic and promising decision than the stand-alone AHP.

A combined AHP and DEA method was presented by [53] to solve the relocation of several government agencies from Tokyo. AHP was used to obtain the relative importance of criteria and attributes. Ref. [54] proposed a combined AHP–DEA approach to solve the facility design problem. A computer-aided layout design tool called Spiral was adopted to generate many alternative layouts. Ref. [55] proposed a combined AHP–DEA approach to measure the relative efficiency of slightly inhomogeneous decision-making units.

Jablonsky [31], however, proposed an additional ranking of efficient decision-making units (rated 1 by DEA analysis) using the AHP method and thus a more detailed ranking within the group of efficient units (units with a DEA rating of 1). His research presents two original models for the classification of efficient units in data capture analysis, based on multi-criteria decision-making techniques—goal programming and analytical hierarchy.

Papers combining DEA and AHP methods for tourism sector as well as for farm tourism have not yet been published. In our study discussing the efficiency of tourist farms, the DEA and AHP models were used separately, and the results were compared.

Although AHP has also been a subject of criticism, it is still one of the most widely used MCDA methods in different contexts. There was some concern about ranking irregularities (rank reversal) and compensation between good and bad scores, as the model is

additive. Likewise, because the decision problem is decomposed into smaller subproblems, the number of pairwise comparisons can be substantial. Most critics have been addressed by the method developer himself and as well by Whitetaker [56]. Nevertheless, the AHP is one of the most widely used methods in decision-making because it has many advantages (flexibility, convenience of pairwise comparison, capturing objective and subjective judgments, reducing bias due to inconsistency measures, and ability to deal with group decision problems as well as with risk and uncertainty). Therefore, there is a strong argumentation for its usage, also in combination with DEA. However, other MCDA methods can also be used in combination with DEA, as presented in Table 1.

Table 1. Use of MCDA methods in combination with DEA.

Methods	Application
DEA and PROMETHEE [57]	Evaluation and location strategies formulation
Fuzzy AHP, Fuzzy VIKOR and DEA [58]	Assessment of sectoral investments for sustainable development
Fuzzy TOPSIS and DEA [59]	Employee selection
DEA and IRIS/ELECTREE III [32]	Assessment of performance of biogas plants
DEA and TOPSIS [60]	Decision analysis in emergency management
AHP and DEA [61]	Supplier selection
DEA and ANP [62]	Supplier selection
DEA and OPA [63]	Performance of the suppliers
DEA and DEMATEL [64]	Supply chain performance evaluation

3. Data Sources and Methodology

The combined DEA and AHP model has been used on tourist farms in Slovenia, where tourist farm efficiency was tested in 45 samples with the use of a survey questionnaire. The research was carried out in the form of a questionnaire using the online tool 1KA. The survey was sent to the e-mail addresses of holders with additional tourist activities on their farms and who also had registered farms with rooms. The total number of respondents who participated in the online survey in three intervals was 138. After the initial data analysis as the basis for determining the input and output parameters, we could fully use the data for 45 tourist farms. The rest were excluded due to irregularities and missing answers. The considered sample of tourist farms represents 13% of all tourist farms with accommodation in Slovenia, acting as the representativeness of the sample.

3.1. DEA Model Development

In the development of the DEA model, the online tool MaxDea was used. In the framework of the DEA method, both fundamental models, BCC and CCR, were used. The BCC and CCR models show input-oriented variables, with variable returns to scale (VRS), as well as an output-oriented model, with constant returns to scale (CRS). The result of the analysis of the CCR model is the value of integrated efficiency, called technical efficiency (TE) [40]. The formula for evaluating efficiency in the CCR model is expressed as follows:

$$Max \frac{\sum_{r=1}^{n} (u_{rb})(y_{rb})}{\sum_{k=1}^{m} (v_{kb})(x_{kb})}$$

Under condition of:

$$\frac{\sum_{r=1}^{n} (u_{rb})(y_{rj})}{\sum_{k=1}^{m} (v_{kb})\left(x_{kj}\right)} \leq 1 \text{ for each unit } j$$

$$u_{rb,} v_{kb} \geq \varepsilon \text{ for each unit } r,\ k$$

y_{rj} = output vector r built with unit j
x_{kj} = input vector k built with unit j

u_r = output weight r on basic unit b
v_i = input weight I on basic unit b
j = number of DMU
r = number of outputs
k = number of inputs
ε = small positive number

The BCC model deals with the pure technical efficiency (PTE) of decision-making units, or DMUs. The individual decision-making units (DMUs) in our research are tourist farms. The BCC model and its performance evaluation is shown as the following formula:

$$\max_{u,v,\omega} \theta_b = \sum_{r=1}^{s} u_r \left(y_{rjb} \right) + \omega$$

Under condition of:

$$\sum_{i=1}^{m} v_i \left(x_{ijb} \right) = 1$$

$$\sum_{r=1}^{s} u_r \left(y_{rj} \right) - \sum_{i=1}^{m} v_i \left(x_{ij} \right) + \omega \leq 0$$

$u_r \geq \varepsilon$
$v_i \geq \varepsilon$
$r = 1, 2, 3, \ldots ., s,$
$i = 1, 2, 3, \ldots ., m,$
$j = 1, 2, 3, \ldots ., n,$
ω = free

The total technical efficiency is derived from the ratio between the two models, and it consists of pure technical efficiency (TE according to CRS) and technical efficiency due to volume of business (TE according to BCC) and is calculated as SE = TE_{CRS}/TE_{BCC} [11].

In the next step, the decision-making units, or DMUs, were determined. The lowest level of the tree structure is thus represented by 45 decision-making units, or tourist farms.

The DEA model includes the following inputs:

- Input 1: the number of full-time employees in the basic agricultural activity;
- Input 2: the number of full-time employees contributed, in total, by other family members to basic agricultural activity;
- Input 3: the number of rooms;
- Input 4: the number of beds;
- Input 5: the number of seats;
- Input 6: the number of full-time employees in tourist activity on the farm.

The DEA outputs used were:

- Output 1: the number of tourist arrivals;
- Output 2: the number of tourist nights;
- Output 3: total revenue from the basic agricultural activity;
- Output 4: total revenue from tourism.

3.2. AHP Model Development

According to Saaty and Vargas [50], a three-level hierarchy of goals, criteria and alternatives is most often used when structuring a problem. In the Figure 1, goals are at the highest level, criteria are located at the middle level, and alternatives are at the lowest level. The basic purpose of this type of hierarchy is to decide on the importance of individual elements at the selected level, taking into account all elements at the lower levels.

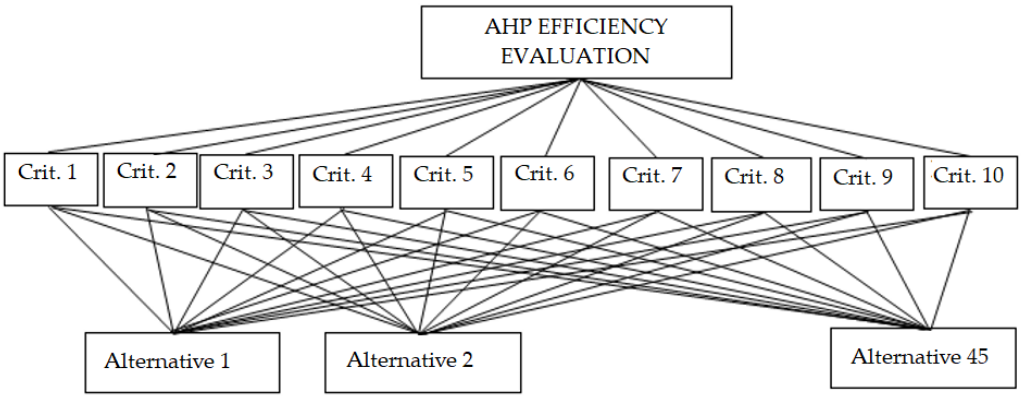


Figure 1. The AHP model structure with basic criteria.

In the process of determining the strength of compared structures in a multi-level hierarchy in the AHP process, the Saaty's formula is used:

$$V(x) = W_1X_1 + W_2X_2 + ... + W_mX_m$$

where:

W_i—weight that belongs to the i-th criterion and measures the importance of this criterion
X_i—the value of the i-th criterion for the alternative X [49].

The value of the function on the alternative x is thus calculated as the sum of the products $W_i \times X_i$, where W_i is the weight that belongs to the i-th criterion and measures the importance of this criterion and x_i the value of the i-th criterion for the alternative x. Here, according to each criterion, it is necessary to evaluate the weights and evaluate the alternatives. The value function $V(x)$ measures the degree of desirability of alternative x. Alternatives are classified using a value function, considering that alternative x is more desirable than alternative y exactly when $V(x) > V(y)$ [65].

To develop the AHP model, we used the computer program Super Decisions, which, along with the Expert Choice software package, is most often used for the needs of AHP modeling. It is a software for decision support, which, in addition to AHP modeling, also enables the use of the analytical network process ANP (Analytic Network Process). Both approaches use the same basic prioritization process based on priorities derived from pairwise comparisons [66].

The first step defines the decision problem, which is represented by evaluations of the efficiency of tourist farms in a selected sample of 45 units (alternatives). The next step structured the hierarchy as shown in Figure 1. The most commonly used hierarchical tree structure occurs when higher pages of attributes depend on lower-level attributes, whereby decision-makers "break" a complex multi-criteria decision problem into their basic components. At the highest level, there is the goal, which in our case represents the AHP efficiency assessment; the middle level of the model is represented by criteria; and at the lowest level alternatives are added, which in our case are represented by tourist farms.

Thus, the first AHP model determined 10 criteria of tourist farms, which correspond perfectly with the inputs and outputs in the DEA models. It was developed for direct comparison with DEA models.

AHP criteria:

- Criterion 1: the number of full-time employees in the basic agricultural activity;
- Criterion 2: the number of full-time employees contributed, in total, by other family members to basic agricultural activity;
- Criterion 3: the number of rooms;
- Criterion 4: the number of beds;
- Criterion 5: the number of seats;
- Criterion 6: the number of full-time employees in tourist activity on the farm;

- Criterion 7: the number of tourist arrivals;
- Criterion 8: the number of tourist nights;
- Criterion 9: total revenue from the basic agricultural activity;
- Criterion 10: total revenue from tourism.

In the next phase, the selection of sub-criteria followed. The structure of the AHP model with included sub-criteria is shown in Figure 2.

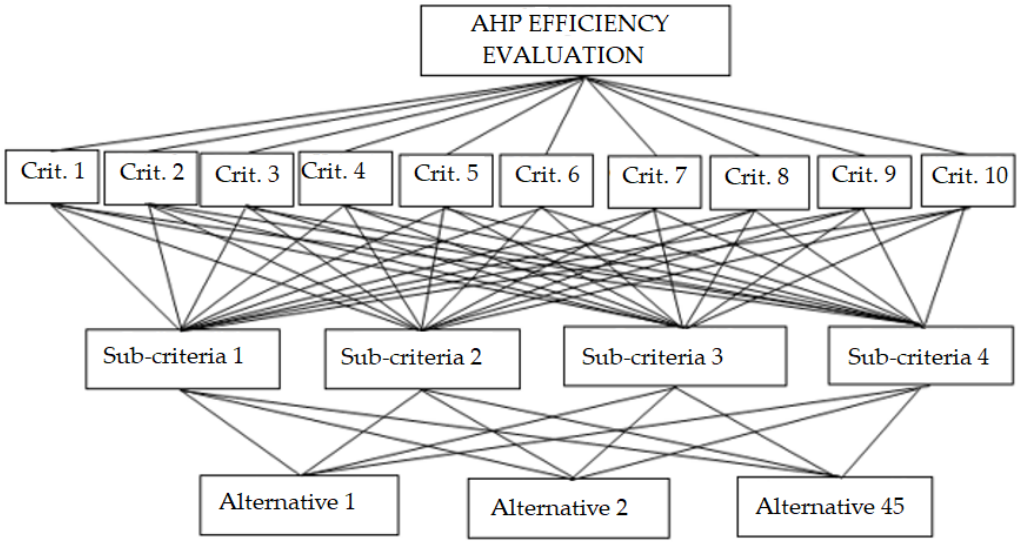


Figure 2. AHP model structure with incorporated sub-criteria.

The second AHP model included additional, non-numerical, criteria that mainly affected the quality of the tourist farm's offer and also the efficiency indirectly. In doing so, we were mainly inspired by some already published research using a multi-criteria assessment of the offers of tourist farms [67,68].

The following sub-criteria were used:

- Sub-criteria 1: additional possibilities on the farm, such as: location near wine road, pets are welcome, house with tradition, beekeeping on the farm, access by bus, camper parking lot, ecological farming, and others;
- Sub-criteria 2: additional activities on the farm, such as: hiking, biking, swimming in a pool, river or lake, sauna, horse-riding, playground for children, hunting, fishing, and others;
- Sub-criteria 3: food and drink services, such as: bed and breakfast, half board, full board, all inclusive, a la carte food service, domestic and local specialty, domestic and local wines, and others;
- Sub-criteria 4: specialized offer, such as: ecological tourist farm, family friendly tourist farm, biker-friendly tourist farm, tourist farm offering healthy vacation, and others.

4. Results

4.1. Results of the DEA Model

BCC and CCR Models

The results (Table 2) of the input-oriented BCC model show that 24 out of 45 tourist farms are technically fully efficient (rating 1), representing 53%. Likewise, 24 out of 45 tourist farms are efficient in the output-oriented BCC model. The average level of efficiency of tourist farms, according to the input-oriented BCC model, is 0.804, and according to the output-oriented BCC model, it is 0.737.

The results of the input- and output-oriented CCR model (Table 2) clearly show the same result. It is known from the DEA literature that the technology exhibits constant returns to scale (CRS) when input- and output-oriented technical efficiencies are equal. If this equality does not hold for each group of inputs and outputs, the technology is

characterized by variable returns to scale (VRS). Thus, 23 tourist farms are technically fully efficient, which represents 51%.

Table 2. Results of input and output oriented BCC and CCR models.

Alternative	BCC-I	Rang	BCC-O	Rang	CCR-I	Rang	CCR-O	Rank
DMU 1	1.000	1	1.000	1	1.000	1	1.000	1
DMU 2	1.000	1	1.000	1	1.000	1	1.000	1
DMU 3	1.000	1	1.000	1	1.000	1	1.000	1
DMU 4	1.000	1	1.000	1	1.000	1	1.000	1
DMU 5	1.000	1	1.000	1	1.000	1	1.000	1
DMU 6	0.719	6	0.671	5	0.670	6	0.670	6
DMU 7	1.000	1	1.000	1	1.000	1	1.000	1
DMU 8	1.000	1	1.000	1	1.000	1	1.000	1
DMU 9	0.573	13	0.289	15	0.252	16	0.252	16
DMU 10	1.000	1	1.000	1	1.000	1	1.000	1
DMU 11	0.546	14	0.190	19	0.189	19	0.189	19
DMU 12	1.000	1	1.000	1	1.000	1	1.000	1
DMU 13	0.584	11	0.387	11	0.371	10	0.371	10
DMU 14	0.870	3	0.903	2	0.828	4	0.828	4
DMU 15	0.752	5	0.171	20	0.129	21	0.129	21
DMU 16	1.000	1	1.000	1	1.000	1	1.000	1
DMU 17	0.263	22	0.252	16	0.176	20	0.176	20
DMU 18	1.000	1	1.000	1	1.000	1	1000	1
DMU 19	0.314	21	0.123	21	0.107	23	0.107	23
DMU 20	1.000	1	1.000	1	1.000	1	1.000	1
DMU 21	0.582	12	0.325	14	0.290	15	0.290	15
DMU 22	1.000	1	1.000	1	1.000	1	1.000	1
DMU 23	0.486	16	0.489	10	0.439	9	0.439	9
DMU 24	0.719	6	0.671	5	0.670	6	0.670	6
DMU 25	1.000	1	1.000	1	0.935	2	0.935	2
DMU 26	1.000	1	1.000	1	1.000	1	1.000	1
DMU 27	0.427	18	0.350	13	0.300	14	0.300	14
DMU 28	1.000	1	1.000	1	1.000	1	1.000	1
DMU 29	1.000	1	1.000	1	1.000	1	1.000	1
DMU 30	1.000	1	1.000	1	1.000	1	1.000	1
DMU 31	1.000	1	1.000	1	1.000	1	1.000	1
DMU 32	0.804	4	0.750	4	0.733	5	0.733	5
DMU 33	0.888	2	0.880	3	0.873	3	0.873	3
DMU 34	0.617	9	0.363	12	0.361	11	0.361	11
DMU 35	0.656	8	0.238	17	0.220	18	0.220	18
DMU 36	0.476	17	0.109	22	0.108	22	0.108	22
DMU 37	1.000	1	1.000	1	1.000	1	1.000	1
DMU 38	0.538	15	0.668	7	0.537	8	0.537	8
DMU 39	0.415	19	0.496	9	0.352	12	0.352	12
DMU 40	1.000	1	1.000	1	1.000	1	1.000	1
DMU 41	1.000	1	1.000	1	1.000	1	1.000	1
DMU 42	0.350	20	0.599	8	0.349	13	0.349	13
DMU 43	1.000	1	1.000	1	1.000	1	1.000	1
DMU 44	0.587	10	0.227	18	0.227	17	0.227	17
DMU 45	1.000	1	1.000	1	1.000	1	1.000	1
Average	0.804		0.737		0.714		0.714	

The basic assumption of the output-oriented CCR model was that farms want to maximize both the number of tourist arrivals and revenue. According to this model, a farm is efficient if it is not possible to increase outputs without reducing the remaining outputs or increasing any of the inputs. The average score of 0.714 shows that the analyzed farms could operate on average at 71% of the current level of output with unchanged input quantities. Farms could increase their output by 29% with unchanged inputs.

Farms that are efficient according to both models operate at the optimal extent of business. Farms with a low CCR efficiency score but are efficient according to the BCC model are locally efficient, but not globally efficient, depending on the scale of operations.

4.2. Results of AHP Model

Firstly, the efficiency of tourist farms using the same criteria as for the DEA model was calculated with the AHP model. Secondly, the efficiency rating according to the AHP model with additional criteria was calculated. The results of both approaches are given in Table 3.

Table 3. Results of AHP model with criteria identical to DEA and with added additional criteria.

Alternative	AHP Assessment	Rank	AHP Assessment Additional Criteria	Rank
DMU 1	1.000	1	0.975	2
DMU 2	0.624	20	0.664	19
DMU 3	0.788	6	0.794	7
DMU 4	0.729	10	0.719	14
DMU 5	0.849	4	0.902	4
DMU 6	0.710	13	0.723	13
DMU 7	0.610	24	0.662	20
DMU 8	0.856	3	1.000	1
DMU 9	0.631	19	0.644	21
DMU 10	0.646	17	0.635	24
DMU 11	0.526	34	0.545	36
DMU 12	0.924	2	0.921	3
DMU 13	0.569	28	0.564	34
DMU 14	0.455	43	0.488	44
DMU 15	0.751	9	0.740	11
DMU 16	0.719	11	0.709	16
DMU 17	0.394	44	0.543	38
DMU 18	0.467	42	0.496	42
DMU 19	0.509	37	0.587	32
DMU 20	0.646	17	0.640	22
DMU 21	0.526	34	0.545	35
DMU 22	0.606	25	0.597	31
DMU 23	0.620	21	0.610	27
DMU 24	0.710	13	0.723	12
DMU 25	0.494	39	0.496	41
DMU 26	0.562	30	0.604	29
DMU 27	0.527	33	0.714	15
DMU 28	0.711	12	0.836	5
DMU 29	0.667	15	0.706	17
DMU 30	0.526	34	0.570	33
DMU 31	0.793	5	0.773	8
DMU 32	0.473	40	0.508	39
DMU 33	0.473	40	0.508	40
DMU 34	0.556	31	0.696	18
DMU 35	0.543	32	0.543	37
DMU 36	0.587	27	0.604	30
DMU 37	0.773	7	0.760	10
DMU 38	0.597	26	0.637	23
DMU 39	0.365	45	0.421	45
DMU 40	0.619	22	0.615	26
DMU 41	0.619	22	0.633	25
DMU 42	0.566	29	0.608	28
DMU 43	0.773	8	0.816	6
DMU 44	0.497	38	0.493	43
DMU 45	0.660	16	0.769	9
Average	0.628		0.625	

In the AHP model using the same criteria as DEA, the lowest score was achieved by the farm with a score of 0.365. Two tourist farms (4%) have an efficiency rating between 0.20 and 0.39, 18 farms (40%) scored between 0.40 and 0.59, 21 tourist farms (47%) scored between 0.60 and 0.79, and 3 farms (6%) scored between 0.80 and 0.99. The average efficiency level of tourist farms is 0.628. The results of the AHP model with added additional criteria (Table 3) show that the lowest score was achieved by the farm with a score of 0.4205. Between 0.40 and 0.59, 15 farms (33) achieved an efficiency rating, 24 tourist farms (53%) scored between 0.60 and 0.79, and 4 farms (8%) scored between 0.80 and 0.99. The average efficiency level of tourist farms is 0.625.

4.3. Comparing the Results of DEA and AHP Models

Comparisons of the results between the models are shown in Table 4. Within DEA, there are minimal differences between the BCC and CCR models. While 24 tourist farms or 53% of the sample are efficient according to the BCC model (score 1), 23 tourist farms or 52% are efficient according to the CCR model. The only difference between the two models is tourist farm 25, which the BCC model defines as efficient, while the CCR model defines it as partially efficient and evaluates it with a value of 0.935, which is also the highest value below the efficiency limit (rating 1).

When comparing the results of the DEA and AHP models (using the same criteria), it may be noted that the AHP model also evaluated tourist farms that were rated as efficient by the DEA model with higher ratings. These are units 1, 2, 3, 4, 5, 8, 10, 12, 16, 20, 28, 31, 37, 43, 45. Meanwhile, the AHP values of the tourist farms are 6, 9, 15, 23, 24, 29, 40 and 4,1 with higher values than the DEA model, since it would otherwise comparatively evaluate them as efficient (rating 1). On the other hand, the AHP model rated certain tourist farms (22, 26, 30) comparatively lower than the DEA model, as it rated them as efficient (rating 1). In the case of certain tourist farms (7, 25), the ratings given differ according to the individual model. For example, unit 25 is efficient according to the BCC model (rating 1), partially efficient according to the CCR model, and according to the AHP model with additional criteria, the values are among the lowest.

Table 4 here below shows the results of both models ranking the farms in terms of efficiency. Within DEA and its sub-models CCR and BCC, it was found that about 50% of tourist farms were efficient, meaning that they reached the efficiency degree 1. The resulting efficiency degree 1 means that the tourist farm is efficient. The remaining tourist farms, which have a lower efficiency degree than 1, were evaluated as partly efficient, implying that the lower the value, the less efficient the tourist farm. As far as the AHP method and inclusion of the additional variables are concerned, it was found that up to unit 11 the AHP ranked in the same order as the DEA. In the continuation, the values of efficiency assessment follow intermittently. It is evident that the AHP model with some additional variables ranked differently than the DEA model, implying that in some cases those additional variables had a significant impact. The AHP was able to provide detailed ranking within the farms that were efficient according to DEA models.

The data in Table 5 show that the ranking according to DEA models for efficient farms is the same, but according to AHP models the ranking within the group of efficient farms differs. It can be also observed, e.g., in the case of farm 18, which was assessed as efficient according to all DEA models, that it was only ranked 42 according to the AHP model with the same criteria.

The AHP model assumes that the criteria (inputs and outputs) are equally important for the basic iteration. The differences in ranking are even more pronounced when additional criteria are included in the AHP model.

In order to assess the results of both methods, the correlation analysis using Spearman correlation coefficient as a non-parametric measure of rank correlation (statistical dependence between the rankings of two variables) was conducted. It assesses how the relationship between two variables can be described using a monotonic function, as pro-

posed by Ataei et al. [69]. Efficiency ranks of both models as input variables were used. The results are presented in Tables 6 and 7.

Table 4. Results of the AHP model with criteria identical to DEA and with added additional criteria.

DMU	AHP Assessment	Ranking	DEA ASSESSMENT							
			BCC-I	Ranking	BCC-0	Ranking	CCR-I	Ranking	CCR-O	Ranking
DMU1	0.9747	2	1	1	1	1	1	1		
DMU2	0.6643	19	1	1	1	1	1	1	1	1
DMU3	0.7944	7	1	1	1	1	1	1	1	1
DMU4	0.7185	14	1	1	1	1	1	1	1	1
DMU5	0.9017	4	1	1	1	1	1	1	1	1
DMU6	0.7226	13	0.71882	6	0.67128	5	0.67032	6	0.67032	6
DMU7	0.6616	20	1	1	1	1	1	1	1	1
DMU8	1	1	1	1	1	1	1	1	1	1
DMU9	0.6436	21	0.57343	13	0.28889	15	0.25195	16	0.25195	16
DMU10	0.6345	24	1	1	1	1	1	1	1	1
DMU11	0.5448	36	0.54575	14	0.19012	19	0.18942	19	0.18942	19
DMU12	0.9208	3	1	1	1	1	1	1	1	1
DMU13	0.5638	34	0.58384	11	0.38674	11	0.371	10	0.371	10
DMU14	0.4879	44	0.86957	3	0.90323	2	0.8284	4	0.8284	4
DMU15	0.7404	11	0.75192	5	0.17108	20	0.12884	21	0.12884	21
DMU16	0.7088	16	1	1	1	1	1	1	1	1
DMU17	0.5425	38	0.2627	22	0.25243	16	0.17596	20	0.17596	20
DMU18	0.4958	42	1	1	1	1	1	1	1	1
DMU19	0.5867	32	0.31447	21	0.12336	21	0.10701	23	0.10701	23
DMU20	0.6398	22	1	1	1	1	1	1	1	1
DMU2I	0.5448	35	0.58182	12	0.32521	14	0.28961	15	0.28961	15
DMU22	0.5966	31	1	1	1	1	1	1	1	1
DMU23	0.61	27	0.48595	16	0.48867	10	0.43889	9	0.43889	9
DMU24	0.7226	12	0.71882	6	0.67128	5	0.67032	6	0.67032	6
DMU25	0.4959	41	1	1	1	1	0.93517	2	0.93517	2
DMU26	0.6044	29	1	1	1	1	1	1	1	1
DMU27	0.7137	15	0.42706	18	0.35011	13	0.30031	14	0.30031	14
DMU28	0.3362	5	1	1	1	1	1	1	1	1
DMU29	0.7057	17	1	1	1	1	1	1	1	1
DMU30	0.5702	33	1	1	1	1	1	1	1	1
DMU31	0.7733	8	1	1	1	1	1	1	1	1
DMU32	0.5075	39	0.8042	4	0.74976	4	0.73286	5	0.73286	5
DMU33	0.5075	40	0.88758	2	0.88028	3	0.87264	3	0.87264	3
DMU34	0.6957	18	0.61743	9	0.36306	12	0.36055	11	0.36055	11
DMU35	0.5426	37	0.65603	8	0.23767	17	0.21991	18	0.21991	18
DMU36	0.6042	30	0.4755	17	0.10892	22	0.10819	22	0.10819	22
DMU37	0.7599	10	1	1	1	1	1	1	1	1
DMU38	0.6374	23	0.538	15	0.66754	7	0.53682	8	0.53682	8
DMU39	0.4205	45	0.41513	19	0.496	9	0.35219	12	0.35219	12
DMU40	0.6145	26	1	1	1	1	1	1	1	1
DMU41	0.6329	25	1	1	1	1	1	1	1	1
DMU42	0.6075	28	0.35016	20	0.59862	8	0.34946	13	0.34946	13
DMU43	0.3156	6	1	1	1	1	1	1	1	1
DMU44	0.4934	43	0.58737	10	0.2273	18	0.22716	17	0.22716	17
DMU45	0.7686	9	1	1	1	1	1	1	1	1

In Tables 6 and 7, the positive correlation between DEA efficiency ranks and both AHP models can be seen. The correlation is weaker with the second model that used additional criteria that can be excepted. Given the value of t-statistics and *p*-values, the null-hypothesis—that there is no correlation between DEA and AHP efficiency ranks—can be rejected.

Table 5. Ranking according to DEA and AHP models.

DMU	CCR-I	BCC-I	CCR-O	BCC-O	SE	AHP—Same Criteria	AHP—Additional Criteria
1	1	1	1	1	1	1	2
2	1	1	1	1	1	20	19
3	1	1	1	1	1	6	7
4	1	1	1	1	1	10	14
5	1	1	1	1	1	4	4
6	27	28	27	27	28	13	12
7	1	1	1	1	1	24	20
8	1	1	1	1	1	3	1
9	38	35	38	38	39	19	21
10	1	1	1	1	1	17	24
11	41	37	41	42	41	34	35
12	1	1	1	1	1	2	3
13	31	33	31	33	35	28	34
14	25	25	25	24	26	43	44
15	43	27	43	43	45	9	11
16	1	1	1	1	1	11	16
17	42	45	42	39	34	44	38
18	1	1	1	1	1	42	42
19	45	44	45	44	42	37	32
20	1	1	1	1	1	17	22
21	37	34	37	37	38	34	35
22	1	1	1	1	1	25	31
23	30	39	30	32	31	21	27
24	27	28	27	27	28	13	12
25	23	1	23	1	27	39	41
26	1	1	1	1	1	30	29
27	36	41	36	35	33	33	15
28	1	1	1	1	1	12	5
29	1	1	1	1	1	15	17
30	35	36	35	36	36	34	33
31	1	1	1	1	1	5	8
32	26	26	26	26	30	40	39
33	24	24	24	25	25	40	39
34	32	31	32	34	37	31	18
35	40	30	40	40	43	32	37
36	44	40	44	45	44	27	30
37	1	1	1	1	1	7	10
38	29	38	29	29	24	26	23
39	33	42	33	31	32	45	45
40	1	1	1	1	1	22	26
41	1	1	1	1	1	22	25
42	34	43	34	30	23	29	28
43	1	1	1	1	1	8	6
44	39	32	39	41	40	38	43
45	1	1	1	1	1	16	9

Table 6. Spearman correlation with basic criteria.

Parameter	BCC-I AHP Assessment	BCC-O AHP Assessment	CCR-I AHP Assessment	CCR-O AHP Assessment
Correlation Coefficient	0.54	0.49	0.54	0.54
Number of cases	45	45	45	45
t-statistics	4.22	3.70	4.16	4.16
Degree of freedom	43	43	43	43
p-value	0.0001	0.0006	0.0002	0.0002
Level of significance	0.05	0.05	0.05	0.05
Reject hypothesis	yes	yes	yes	yes
t-critical	2.02	2.02	2.02	2.02

Table 7. Spearman correlation with additional criteria.

Parameter	BCC-I AHP Assessment-Additional Criteria	BCC-O AHP Assessment-Additional Criteria	CCR-I AHP Assessment-Additional Criteria	CCR-O AHP Assessment-Additional Criteria
Correlation Coefficient	0.45	0.43	0.48	0.48
Number of cases	45	45	45	45
t-statistics	3.32	3.16	3.55	3.55
Degree of freedom	43	43	43	43
p-value	0.0018	0.0029	0.0009	0.0009
Level of significance	0.05	0.05	0.05	0.05
Reject hypothesis	yes	yes	yes	yes
t-critical	2.02	2.02	2.02	2.02

5. Discussion

A similar study based on the analysis of CCR and BCC models by [11], on 196 tourist farms in South Korea, showed that only 6% of tourist farms are technically efficient. Only 24% of tourist farms achieved an efficiency higher than 0.50. The average score of pure technical efficiency is relatively low. Moreover, 10% of tourist farms are efficient in terms of pure technical efficiency, attributed to a lack of management skills.

Compared to the mentioned research, tourist farms in Slovenia achieve a higher level of technical efficiency. At the same time, a large limitation of the database must be pointed out. Nevertheless, it can be assumed that the data obtained from the survey show the real situation well enough.

Table 4 shows that, in addition to enabling a more accurate ranking within the efficient ones, the AHP also enables the inclusion of additional qualitative criteria that the DEA method cannot take into account. Certain differences in ranking between the two AHP models are also shown, indicating that these additional criteria are important, although we have no evidence that they affect performance.

Therefore, the multi-criteria AHP models developed in parallel allowed for performing additional analyses. It turned out that the assessment of efficiency with AHP models enables a more accurate ranking, but significant differences in the criterion itself can be seen (AHP scores are much worse than what was shown in the case of farm 18). The appropriate adjustment of the weights via pairwise comparisons in the AHP model helped to eliminate the anomalies. The inclusion of additional criteria in the additionally developed multi-criteria model turned out to be particularly interesting. The combined use of both methods has proven to be a very useful methodological tool, although some caution is required when interpreting the results.

6. Conclusions

In recent years, much research has been carried out in the field of efficiency in tourism, being stimulated by the ever-increasing competition in the tourism market. The latter has been mainly related to researching the effectiveness of hotels, travel agencies, catering and tourism on a macro level. Despite the growing importance of tourist farms for the economic development of rural areas, the field is still insufficiently researched.

In this paper, the theoretical part of the assignment presents the research that defines the factors of the development of tourism in rural areas and tourism on farms from different perspectives, and in the empirical part, based on a sample of 45 tourist farms from different regions of Slovenia, their technical efficiency using the AHP and DEA methods is assessed.

The DEA method, which is a frequently used method for measuring efficiency, takes into account only quantitatively measurable input and output sources, but does not take into account qualitative categories, which nevertheless affect the efficiency of tourist farms

or the efficiency of the decision-making unit. In this research, we therefore additionally ranked efficient decision units (those rated 1 by DEA analysis) using the AHP method and thus ranked them in more detail within the group of efficient units (units with DEA rating 1).

Accordingly, on the basis of six inputs: the number of full-time employees (FTE) in the basic agricultural activity, the total number of PDM contributed by other family members in the basic activity, the number of rooms, the number of beds, the number of seats and the number of FTE in the tourism activity; and four outputs: the number of overnight stays, the number of total revenues from basic agricultural activity and the number of total revenues from tourism, we developed an input- and output-oriented BCC model, an input- and output-oriented CCR model, and an AHP model based on four additional sub-criteria: additional offer, activities, services and signs of specialized offer, which were developed in the AHP model with additional criteria.

According to the results of the input- and output-oriented BCC and CCR models, 51% tourist farms, respectively, were technically efficient. The AHP model allowed us to rank efficient farms more accurately, but it turned out that only the adjustment of weights in the AHP model provides more comparable results. Farms that are efficient under all models are operating at an optimal scale of operations. Farms with low efficiency scores according to the CCR but are efficient according to the BCC model are locally efficient, but not globally efficient, depending on the scale of operations. The results of the models show that there are possible improvements on all levels of efficiency, as well as in the criteria of the additional offers of tourist farms, which were analyzed in the AHP model with additional criteria.

This contribution adds to a larger volume of literature in the field of measuring the efficiency of tourist farms, and is a methodological addition to the existing methodology. Here, the results of the models can be of help to economic policymakers and rural development program planners, and last but not least, to the makers of tourist farms for improving the efficiency of farms. The originality of the task mainly refers to the inclusion of additional non-numerical criteria in the analysis of the efficiency of tourist farms through multi-criteria analysis, and thus the upgrading of the DEA method with the AHP method.

The findings of this paper may help tourist farm managers to improve the efficiency of their tourist farm. They may also assist managers in obtaining important information for their strategic and operational decisions, to improve performance of their business. The implications for tourist farm operators and researchers and the directions for future research are discussed.

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