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Investigating of the best location of solar plants in Turkey by different multiple decision methods

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Highlights

- *Identify optimum locations for development of solar plants in Turkey.*
- *This study applies kam and copula technique.*

Graphical Abstract

In selecting location of solar plants, we relied on the results from applying CCR, BCC, KAM and SFA models. There is not high dependence between the outcomes of the CCR, BCC, KAM models and the SFA models

Aim

Selecting best location of solar plants.

Design & Methodology

We used SFA with copulas and KAM method.

Originality

The first time to select location of solar plants a comparison of the two methods is used.

Findings

There are not high dependence between the outcomes of the CCR, BCC, KAM models and the SFA models.

Conclusion

The CCR, BCC and KAM models shows Usak, Diyarbakir and Rize as the best cities, while the Frontier and SFA with copulas models concur on Elazig and Diyarbakir cities in selecting location of solar plants.

Declaration of Ethical Standards

The authors of this article declare and promised that the materials and methods used in this study do not require ethical committee permission and legal-special permission.

Investigating of the Best Location of Solar Plants in Turkey by Different Multiple Decision Methods

Araştırma Makalesi / Research Article

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ABSTRACT

Exponential development of solar photovoltaic projects during the past decades has vastly relied on findings from location identification analyses. This article draws upon the most important site selection factors in order to identify optimum locations for development of solar plants in Turkey from a subset of thirty selected Turkish cities. This study applies CCR, BCC, stochastic frontier analysis (SFA) and Kourosh and Arash Model (KAM) methods in decision-making. KAM method is a new powerful technique in measuring efficiency of firms (DMUs) and has obtained an important role in economy and managements. It also benefits from the novelty of using copula technique in the SFA methods which has been only recently presented to the literature.

Keywords: Copulas, DEA, KAM, stochastic frontier, technical efficiency.

1. INTRODUCTION

Data Envelopment Analysis (DEA), Free Disposal Hull (FDH) and SFA are well established in the Literature as main instruments to measure efficiency of firms. Nevertheless, DEA and FDH are nonparametric models and therefore, do not place restrictions on functional forms relating inputs and outputs. In other words, in these nonparametric models every deviation from the frontier is considered as inefficiency. SFA is a parametric model where error term represented by two types of variables ($\varepsilon = u + v$). Smith (2008) proposed copula technique in modeling of these u,v error terms. In his proposed models, copulas play an important role in measuring the efficiency of firms. This study also employs KAM Model, which recently presented by Khezrimotlagh et al. (2013) to improve both technically efficient and inefficient DMUs in DEA. A general overview on SFA with copulas and KAM method will be shown in the next Section. Many activities in the literature are using the mentioned methods in evaluation efficiency of firms. Amy et al. (2015) for evaluating the suitability of renewable energy plant site, proposes DEA to assess the efficiencies of plant site candidates by two-stage framework. In the first stage, a fuzzy analytic hierarchy process (FAHP) is adopted to set the assurance region (AR) of the quantitative factors, and the AR is incorporated into DEA to assess the efficiencies of plant site candidates. Kinaci et al. (2016) clarify efficiency scores and ranks of hydroelectricity centers by using data envelopment analysis and stochastic frontier analysis methods. Applying copula technique in the stochastic frontier analysis is an advantage to their study between similar activities. Lutz et al. (2017) studied on the determinants of energy efficiency in the German manufacturing sector based on official firm-level production census data. By means of a stochastic frontier analysis. Huaimo et al. (2018) by data envelopment analysis compared the environmental efficiency of 118 photovoltaic (PV) plants in China. Dehghani et al. (2018) aim at evaluating different areas for solar plants according to a set of social, geographical and technical criteria through a DEA model. The proposed DEA model considers both information of the efficient and anti-efficient frontiers in order to rise discrimination power in DEA analysis.

Installation of a solar plant is very expensive and thus, identifying the optimum location for it is one of the most important initial considerations from investor's side. The main aim of this study is to use some of the most effective factors in evaluating thirty Turkish cities efficiency as target locations for building a solar plant. The final decision relies on efficiency evaluation results using the CCR, BCC, SFA and KAM methods. In the SFA model, we will also include copula technique by using five Archimedean families, which two of them have been recently presented to the literature. These new families have hyperbolic generators and are more flexible in modeling dependence structures. Drawn upon the obtained efficiency scores, we will identify best candidate cities to locate solar plants. The rest of this paper is organized as follows. Section 2 reviews CCR and BCC, SFA including copulas, and KAM model. The reader who is already familiar with the basics of these models may wish to skip directly to Section 3 uses them in an applied setting, with the ultimate purpose of prioritizing thirty Turkish cities viewed as potential locations for installation of solar plants. Finally, Section 4 presents conclusions from the findings in preceding Sections.

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2. MATERIAL AND METHOD

Some factors that are effective for selecting the location of solar plants were proposed. These parameters were then used for determining the priority of cities for location of a solar plant. After careful consideration of previous studies into the plant location problem, certain quantitative and qualitative factors were selected for focus. These factors were utilized by techniques aimed at prioritizing different possible locations of solar plants.

This section is a brief review of CCR and BCC models, SFA with copulas as well as KAM method. References to most important publications are given inside the text for interested readers who are looking for a deeper understanding of these models.

Stochastic Frontier Analysis With Copulas:

Following subsection includes an overview on copulas. Interested readers are referred to see more details in Nelsen (2006).

Copulas and their properties.

A copula is a function $C : [0,1]2 \rightarrow [0,1]$ which satisfies:

(a) for every $u,v\ in\ [0,1], C(u,0) = 0 = C(0,v)$ and $C(u,1) = u$ and $C(1,v) = v$;

(b) for every u1,u2,v1,v2 in [0,1] such that u1 ≤ u2 and v1 ≤ v2, C(u2,v2) −C(u2,v1) −C(u1,v2) + C(u1,v1) ≥ 0.

Copulas functions are powerful technique in modeling dependence structures. Copulas allow us to combine univariate distributions to obtain a joint distribution with a particular dependence structure, in the famous Sklar Theorem: Let X and Y be random variables with joint distribution function H and marginal distribution functions F and G, respectively. Then there exists a copula C such that, H(x,y) = C(F(x),G(y)), for all x,y in R. If F and G are continuous, then C is unique. Otherwise, the copula C is uniquely determined on Ran(F)×Ran(G)1. Conversely, if C is a copula and F and G are distribution

functions, then the function H is joint distribution function with margins F and G. As a result of the Sklar Theorem, copulas link joint distribution functions to their onedimensional margins. This study focuses on Archimedean copulas (AC) which are one of important classes of copulas. These copulas are easy to construct, include many parametric families, and have great variety of different dependence structures.

Stochastic frontier models and copulas

There are seldom efforts in the literature related to the stochastic frontier models based on copulas. Smith (2008) was one of the first scholars who proposed copula technique in SFA. Then Carta and Steel (2012) used copulas to introduce a new methodology for multi-output production frontiers. El Mehdi and Hafner (2013) and Amsler et al. (2014) are among the few who used copulas in SFA.

In this part of our overview, we will explain the main relation between copulas and SFA. Let's consider the traditional stochastic frontier model proposed by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977),

$$\ln yi = f(x;\beta) + \varepsilon i = \beta 0 + \sum \beta n \ln xni + n\ \varepsilon i \qquad (2.1)$$

where yi is the observed scalar output and xi is a vector of N inputs used by the producer i and β is a vector of technology parameters to be estimated. $\varepsilon i = vi - ui$ and $i = 1,...,I$ denotes firms. vi is the noise component, which we almost always consider as a normal distributed variable, and ui is the non-negative technical inefficiency component. They constitute a compound error term, with a specific distribution to be determined, hence the name of composed error model is often referred. Common choices for vi include the exponential, the half-Normal, the Truncated Normal and the Gamma distributions. For ui the Normal distribution is typically selected. More researchers assume that error terms ui and vi are independent. Smith (2008), however, proposed the potential dependence between ui and vi. He used copulas to model this dependence and then estimated the SFA models. Assume that there is potential dependence between ui and vi. ui (and vi) are also independent over i (where $i = 1,...,I$). Let G1 and G2 denote the distribution functions of ui and vi respectively and H be joint distribution function of ui and vi. Then by the Sklar Theorem, there is copula $C\theta$ which satisfies in relation (2.2),

$$H(u,v) = C\theta(G1(u),G2(v)) \qquad (2.2)$$

so its joint density function is as follows,

$$h(u,v)=g1(u)g2(v)c\theta(G1(u),G2(v)). \qquad (2.3)$$

As $\varepsilon = v - u$, by marginal distribution of h we get

$$h(\varepsilon)=\int_0^{+\infty} g1(u)g2(u+\varepsilon)c\theta(G1(u),G2(u+\varepsilon))du. \qquad (2.4)$$

Using $\varepsilon = lny - f(x;\beta)$ in the (2.4) gives density of y. Maximum likelihood estimator (MLE) is a way to obtain more efficient estimator of stochastic frontier models. Clearly, copulas allow us to model marginal distributions separately from their dependence structure, so we have a flexible joint distribution function, whose marginals are specified by the researcher. After estimating stochastic frontier models we desire to calculate technical efficiency of DMUs. This technical efficiency is conditional on expected value as follows

$$TE = E(exp\{-u\}|\varepsilon). \qquad (2.5)$$

By using (2.3) and (2.4) we get

$$TE = \frac{1}{\mathrm{h}(\varepsilon)} \int_{+R} \exp\{-u\} h(u,\varepsilon) du, \qquad (2.6)$$

For more details see Smith (2008), El Mehdi and Hafner (2013). In this study we use loglinear Cobb-Douglas form and we assume that $u \sim N^{+}(0,\sigma u\ 2)$, $u \geq 0$ and $v \sim N(0,\sigma v\ 2)$. Clearly $E(u) = \sigma u\sqrt{2}/\pi$ and $Var(u) = ((\pi - 2)/\pi)\sigma u\ 2$. If we assume that MLE of parameters $\vartheta = (\sigma u,\sigma u,\theta,\beta)$ in (2.4) are $\vartheta ML = (\hat{\sigma u},\hat{\sigma u},\hat{\theta},\hat{\beta})$then by replacing these estimators in (2.6) we get to $TEML$ which is the MLE of TE. 2.2.2. Data Envelopment Analysis

Data envelopment analysis (DEA) is a nonparametric method for evaluating the relative efficiency of decision-making units (DMUs) on the basis of multiple inputs and outputs. In recent years DEA has had a significant role in practical studies in many fields such as energy (Alp and Sözen, 2011; Sözen et al., 2011), banking (Mercan et al., 2003), sport (Anderson and Sharp, 1997; Alp, 2006; Najjari et al., 2016) etc. The first introduction on DEA was practiced by Charnes et al. (1978), who proposed CCR model, also called as Constant Return to Scale (CRS). The CCR model evaluates both technical and scale efficiencies via optimal value of the ratio form. The modified version of the CCR model, BCC model, also known as variable returns to scale, was initially proposed by Banker et al. (1984). This model is used to estimate the pure technical efficiency of DMUs by reference to the efficiency frontier. The primal form of CCR (CRS) model for the efficiency score of DMUk is as follows:

$$\max \quad \sum_{r=1}^{s} u_r y_{rk}$$

Subject to (2.7)

$$\sum_{i=1}^{k} u_i x_{ik}\ 1$$

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{s} u_r y_{rj} \geq 0; \ \ j = 1,2,\dots,n,$$

$$v_i, u_r \geq 0, \ \ i = 1,2,\dots,m, \quad r = 1,2,\dots,s,$$

where n is number of DMUs with s outputs denoted by y_{rk} , $r = 1,\dots,s$ and m inputs denoted by x_{ik}, $i = 1,\cdots,m$. And u_r, v_i are the weights of output r and input i, respectively.

The primal form of input-oriented BCC (VRS) model is considered in this paper, given as follows

$$\min \ \theta_o$$

subject to

$$\theta_o x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \qquad (2.8)$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0$$

$$i = 1,\cdots,m, \quad j = 1,\cdots,n, \quad r = 1,\cdots,s$$

where θ_o is efficiency score of DMUo and x_{io} , y_{ro} (all nonnegative) are i'th input and r'th output of the DMUo respectively, and λ_j is intensity of DMUj. When the θ_o is equal to one, then DMUo is called an efficient DMU.

Kourosh and Arash Model (KAM)

This method has been recently presented by Khezrimotlagh et al. (2013) aimed at improving foundation of DEA and its first definitions. The method tries to increase DEA's power to distinguish DMUs by multiple inputs and outputs with controllable, non-controllable, real and integer data. Unlike current DEA models, KAM provides a methodology based on an introduced epsilon which is able to measure the efficiency score of DMUs where the weights are available or unknown. For more reading on this model, see Khezrimotlagh et al. (2013).

Let DMUs (DMUi, $i = 1,2,\cdots,n$) consist of m non-negative inputs ($x_{ij}, j = 1,2,\cdots,m$) and p non-negative outputs ($y_{ik}, k = 1,2,\cdots,p$) such that, at least one of the inputs and one of the outputs of each DMUs are not zero. Consider an epsilon vector $\varepsilon = (\varepsilon^-, \varepsilon^+)$ in $R^{(m+p)+}$, where ε^- is $(\varepsilon_1^-, \varepsilon_2^-, \dots, \varepsilon_m^-)$ and ε^+ is $(\varepsilon_1^+, \varepsilon_2^+, \dots, \varepsilon_p^+)$. The linear ε -KAM, while DMUl ($l = 1,2,\cdots,n$) is under evaluation, is as follows,

$$\max \ \sum_{j=1}^{m} w_j^- s_j^- + \sum_{k=1}^{p} w_k^+ s_k^+$$

subject to

$$\sum_{i=1}^{n} \lambda_i x_{ij} + s_j^- = x_{lj} + \varepsilon_j^-, \qquad j = 1,2,\cdots,m,$$

$$\sum_{i=1}^{n} \lambda_i y_{ik} - s_k^+ = y_{lk} - \varepsilon_j^+, \qquad k = 1,2,\cdots,p, \qquad (2.9)$$

$$x_{lj} - s_j^- \geq 0, \qquad j = 1,2,\cdots,,m,$$

$$y_{lk} + s_{lk}^+ - 2\varepsilon_k^+ \geq 0, \quad k = 1,2,\cdots,p,$$

$$\lambda_i \geq 0, \ s_j^- \geq 0, \ s_k^+ \geq 0$$

$$j = 1,2,\cdots,m, \quad k = 1,2,\cdots,p, \ i = 1,2,\cdots,n,$$

where w_j^- and w_k^+ are the user-specified weights obtained through values judgments, λ_i: multipliers used for computing linear combinations of DMUs' inputs and outputs. s_j^- and s_k^+ are non-negative slacks, for $j = 1,2,\cdots,m$ and $k = 1,2,\cdots,p$.

Note that when epsilon is zero, linear KAM is the same as the weighted additive model proposed by Charnes et al. (1985).

3.APPLICATION

The main aim of this study is to apply some of the most important efficiency factors in order to indicate the priority among thirty Turkish cities in terms of their suitability for building solar plant. Of course expensiveness of the Solar power plant has important role in selecting these factors. In order to get the best place it is better to consider different conditions and variables like pests (flood, earthquake, hail, etc) and analyzing them carefully. Although, some variables like convection, transportation, price of the land are very important factors to determine. In this study we rely on Sözen et al. (2015) .

Table 1. Thirty candidate Turkish cities with selected parameters

	Land cost	Distance	Earthquakes	Flood	Hail	Snow	Storm	Adversity	Losses	Solar
Bolu	50	5	197	41	23	5	8	6	3	463
Canakkale	300	5	200	202	48	66	141	40	28	355
Ankara	700	13	79	205	116	29	40	25	23	515
Manisa	500	34	303	111	60	38	20	63	21	359
Afyon	100	6	248	100	75	71	73	28	17	359
Kayseri	195	10	16	95	45	40	69	18	15	925
Malatya	75	99	139	91	67	38	35	19	19	660
Icel	120	5	51	84	73	30	37	12	16	1246
Hatay	80	6	87	124	22	12	37	19	14	640
Kayseri	120	83	16	95	45	40	69	18	15	619
Rize	400	6	10	67	3	13	25	9	13	409
Artvin	125	45	75	68	16	39	17	21	11	306
Mugla	130	5	324	96	40	20	55	20	8	220
Hakkari	30	79	93	29	10	12	12	4	4	1403
Sanliurfa	150	28	17	48	56	7	11	7	4	889
Usak	35	120	371	19	14	5	2	4	5	906
Kastamonu	20	214	72	112	66	17	21	10	17	417
Erzurum	75	116	204	119	63	41	42	15	20	622
Elazig	80	50	131	80	54	34	24	10	8	1454
Amasya	275	40	68	71	53	9	6	2	13	511
Gaziantep	70	24	48	43	36	3	6	10	7	678
Tunceli	50	6	206	55	28	22	26	20	12	1080
Nigde	75	110	15	10	18	19	30	1	2	1204
Agri	100	47	115	56	23	30	33	8	8	799
Konya	125	5	30	189	117	148	141	78	26	977
Karaman	50	90	12	23	14	30	26	14	6	834
Diyarbakir	150	14	81	48	44	9	28	9	7	1406
Sanliurfa	70	61	17	48	56	7	11	7	4	1060
Antalya	80	90	180	212	103	43	109	28	21	955
Adana	35	18	126	145	64	28	31	14	24	1396

Table 2. Details of the selected copula families in this study

Family	Generator	τ	λ_L	λ_U	θ interval
Clayton	$\frac{1}{\theta}\left(\frac{1}{t^{\theta}}-1\right)$	$\frac{\theta}{\theta+2}$	$2^{-\frac{1}{\theta}}$	0	$(0,\infty)$
A12	$(\frac{1}{t}-1)\theta$	$\left(1-\frac{2}{3\theta}\right)$	$2^{-\frac{1}{\theta}}$	$2-2^{-\frac{1}{\theta}}$	$[1,\infty)$
coth-copula	$coth(\theta t) - coth(\theta)$	$1+\frac{2}{\theta^2}-\frac{2}{\theta}\coth(\theta)$	$\frac{1}{2}$	0	$[1,\infty)$
csch-copula	$csch(t^{\theta}) - csch(1)$	$\frac{\theta}{\theta+2}$	$2^{-\frac{1}{\theta}}$	0	$(0,\infty)$
Product	$-lnt$	0	0	0	-

Note: τ means usual Kendall's tau to measure dependence or association between variables and A12 family numbered as 4.2.12 in Table 4.1 Nelsen's book that analyzes these parameters and final factors consisting of nine inputs and one output as follows,

Inputs:

1. Distance to power distribution networks (km).
2. Land cost (Turkish Lira).
3. The frequency/probability of earthquakes.
4. The frequency of flooding rains.
5. The frequency of severe hails.
6. The regularity of Snow and blizzard.
7. The recurrence of storms and severe hurricanes.
8. The adversity.
9. Human and financial losses.

Output:

Monthly average solar radiation (h): The primary index for locating solar plants is monthly average solar radiation, which is equal to solar global radiation multiplied by solar duration and divided by the month days. This factor is shown for the selected thirty Turkish cities in Table 1.

In calculations, Matlab software has been used. fminsearchbnd command in Matlab have had an important role in calculating SFA models.

The final decision relies on the results from the CCR, BCC, SFA and KAM methods. In order to provide SFA model for the mentioned Turkish cities in this study, the standard SFA model together with five copula families are used. Details of these families are summarized in Table 2. As stated before, there are two new Archimedean families with hyperbolic generators, namely coth-copula and csch-copula families, recently presented to the literature by Najjari et al. (2014), and Bal and Najjari (2013) respectively. These new families show more flexibility in modeling dependence structures. Moreover, technical efficiency of standard CCR, BCC and KAM models are provided for these data to compare their results by the other models.

In the rest of this article, standard SFA model will be called "Frontier" and SFA with Clayton, A12, coth and csch copulas are called only by copulas names.

Table 3 shows SFA model parameters estimated by using copulas and standard SFA model. Table 4 demonstrates efficiency scores of the mentioned cities by applying different methods, and Table 5 shows correlations between the results from those models. As can be seen in Table 3, dependence parameter θ has different values for families. This value evidences the dependence between u and v. As an example, for the Clayton family, this parameter is $\theta = 1.5389$, and so $\tau = \frac{\theta}{\theta+2} = 0.4348$. Namely, there is 43.48% dependence between u and v. Similarly, for the A12 family this parameter is $\theta = 0.5285$ and $\tau = 0.5638$. The maximum dependence is also shown in A12 family and the minimum dependence belongs to the coth copula, which it is $\tau = 0.4189$. However, last column in the Table 3 shows that all mentioned copula families confirm the dependence between u and v.

Table 4 and Table 5 confirms that CCR, BCC and KAM ($\varepsilon = 0.0001$) models support each other's results. There is 94.67% correlation between CCR and KAM, and 84.96%.correlation between CCR and BCC, while the correlation between KAM and BCC is only 76.49%. This means that results from applying KAM model is very close to CCR results. On the other side, Frontier model and SFA-copulas model will lead to mutually supportive results. In this situation, the maximum correlation between results from the SFA, using Clayton, and csch copulas is 97.06%. There is also high correlation of

Table 3. The estimated parameters of the SFA models

Family	σ_u	σ_v	θ	β_0	β_1	β_2	β_3
Clayton	0.2197	0.2323	1.5389	9.7806	-0.3149	0.0091	-0.1044
A12	0.2149	0.2796	1.5285	10.8491	-0.4477	-0.0913	-0.1559
coth	0.2091	0.2410	1.5336	11.0316	-0.4129	-0.0388	-0.1816
csch	0.2082	0.2118	1.6173	9.6370	-0.3206	0.0175	-0.0762
Product	0.2250	0.1887	-	8.5309	-0.2883	-0.0421	-0.1183
Frontier	0.2132	0.2053	-	10.6964	-0.4528	-0.2100	-0.1698
	β_4	β_5	β_6	β_7	β_8	β_9	τ
Clayton	-0.5143	0.3710	0.0862	0.1554	-0.3154	0.0275	0.4348
A12	-0.5414	0.4475	0.0975	-0.0014	-0.3267	0.2461	0.5638
coth	-0.4017	0.2262	0.0558	-0.0148	-0.1337	0.0545	0.4189
csch	-0.4657	0.3357	0.0538	0.1528	-0.2529	-0.0165	0.4471
Product	0.1109	0.2240	-0.0320	0.2157	-0.3089	-0.2334	-
Frontier	-0.4405	0.4406	0.2070	0.0856	-0.1735	-0.1012	-

92.97% between results of the SFA using coth and csch copulas. Results of the Frontier model has the highest correlation of 80.16% with SFA by using A12 copula and also it has the lowest correlation, 73.13%, with SFA by using csch copula.

Table 4. Efficiency scores of thirty Turkish cities by several methods

DMU	CCR	BCC	KAM(0.0001)	Frontier	Clayton	A12	Product	coth	csch
Bolu	1.0000	1.0000	0.9994	0.2499	0.3478	0.2948	0.2796	0.2584	0.3241
Canakkale	0.3312	1.0000	0.1330	0.5042	0.7087	0.7217	0.4527	0.6896	0.6829
Ankara	0.3135	0.5535	0.1875	0.9123	0.9999	0.9551	0.6765	1.0000	0.9999
Manisa	0.2518	0.4279	0.1208	1.0000	0.9261	1.0000	0.9889	0.8086	0.8833
Afyon	0.2760	0.8333	0.1814	0.1876	0.2976	0.2622	0.3106	0.3055	0.3047
Kayseri	1.0000	1.0000	0.9999	0.5791	0.8081	0.7184	0.6807	0.6925	0.8418
Malatya	0.2968	0.5691	0.1774	0.5711	0.4392	0.4550	0.5985	0.4780	0.4861
Icel	1.0000	1.0000	1.0000	0.5298	0.7681	0.5845	0.8200	0.7436	0.8693
Hatay	0.8471	1.0000	0.4119	0.6703	0.8545	0.7674	0.5468	0.6199	0.8594
Kayseri	0.5294	0.8110	0.2343	0.4851	0.4422	0.4693	0.4329	0.4117	0.4646
Rize	1.0000	1.0000	1.000	1.0000	0.9981	0.9949	0.6128	0.5729	0.9994
Artvin	0.2713	0.9520	0.1289	0.4288	0.4182	0.4280	0.4370	0.3010	0.4110
Mugla	0.2732	1.0000	0.1322	0.1966	0.2879	0.2929	0.1876	0.2626	0.2555
Hakkari	1.0000	1.0000	1.0000	0.9047	0.6783	0.7340	0.8366	0.5779	0.6866
Sanli	1.0000	1.0000	1.0000	0.5194	0.5697	0.5129	0.5053	0.4618	0.5558
Usak	1.0000	1.0000	1.0000	0.8850	0.4649	0.4607	0.9921	0.4105	0.5214
Kastamonu	0.4458	1.0000	0.1736	0.2511	0.1663	0.1563	0.2105	0.1673	0.2001
Erzurum	0.2253	0.4849	0.1435	0.6421	0.4552	0.4982	0.5302	0.5295	0.4969
Elazig	0.9496	1.0000	0.7339	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Amasya	0.7284	1.0000	0.3857	0.5913	0.3460	0.3044	0.4119	0.4084	0.4211
Gaziantep	1.0000	1.0000	0.9999	0.5299	0.4638	0.3933	0.5480	0.3449	0.5035
Tunceli	1.0000	1.0000	1.0000	0.6007	0.8196	0.6904	0.9974	0.6721	0.8684
Nigde	1.0000	1.0000	1.0000	0.2750	0.1939	0.2296	0.3480	0.2562	0.2019
Agri	0.5935	0.8370	0.3410	0.7019	0.6006	0.6729	0.6290	0.6059	0.5958
Konya	1.0000	1.0000	0.9994	0.4183	0.9795	0.7569	0.7911	0.7825	1.0000
Karaman	1.0000	1.0000	0.9935	0.3840	0.3707	0.3818	0.6105	0.2759	0.3847
Diyarbakir	1.0000	1.0000	1.0000	0.9975	1.0000	1.0000	1.0000	1.0000	1.0000
Sanliurfa	1.0000	1.0000	1.0000	0.5165	0.5102	0.4668	0.4997	0.4143	0.5120
Antalya	0.3821	0.5166	0.1943	1.0000	0.8647	0.9995	0.6793	1.0000	0.8688
Adana	1.0000	1.0000	1.0000	0.7702	0.8402	0.6667	0.8764	0.7957	0.9998

4. RESULTS AND CONCLUSION

In selecting location of solar plants, we relied on the results from applying CCR, BCC, KAM and SFA models. For these models nine factors as inputs and one factor as output were used. These factors have been discussed by Sözen et al. (2015) as important parameters in selecting location of solar plants. As can be seen in Table 4 and Table 5 the results from CCR, BCC, KAM models by the SFA models are different. Namely, there are not high dependence between the outcomes of the CCR, BCC, KAM models and the SFA models. The CCR, BCC and KAM models show that Usak, Diyarbakir and Rize as the best cities, while the Frontier and SFA with copulas models concur on Elazig and Diyarbakir cities in selecting location of solar plants. Diyarbakir is the best candidate if only one city desired

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

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