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Energy cost optimization of groundwater treatment using biochar adsorption process: An experimental approach

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ABSTRACT

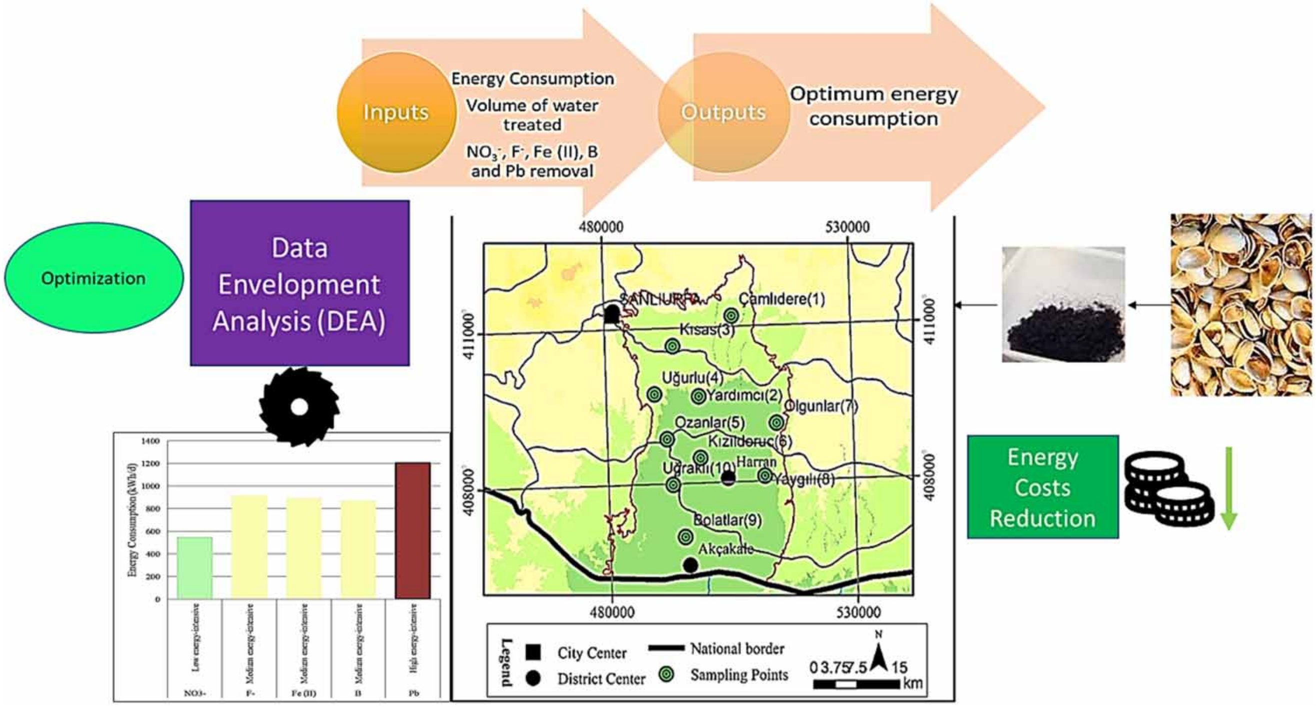
This study has aimed to reduce the energy costs using agricultural waste derived (pistachio shells) biochar application for groundwater treatment. An energy cost indicator has been figured out applying a new quantitative approximation. Data envelopment analysis (DEA) has been applied to optimize the energy costs of groundwater treatment. Energy costs assessment of groundwater treatment has been carried out with regards to nitrate (NO_3^-), fluoride (F^-), boron (B), iron (Fe (II)) and lead (Pb) removal for March (before irrigation) and October (post irrigation) related to 10 observation points in an arid and semi-arid area. When lead removal leads to the highest energy costs in the plant, nitrate removal has the lowest energy costs. The total energy costs would be reduced averagely at 44.5 and 52.5% in March and October, respectively when biochar adsorption was applied in the plant. According to the DEA model, the optimum energy consumption belongs to biochar adsorption in terms of fluorite removal with the value of 434.95 kWh/d. According to DEA analysis, NO_3^- is a low energy-intensive parameter and Pb is a high energy-intensive parameter. The results of the DEA model have been overlapping with the energy cost indicator.

Key words: biochar, Box-Benken method, data envelopment analysis, energy consumption, groundwater resources, optimization

HIGHLIGHTS

- The main aim of this study was to reduce the energy costs using agricultural waste derived biochar application.
- This study is unique in which Pistacia Vera L. derived biochar was firstly used for groundwater treatment.
- Also, lead and boron removal from groundwater using biochar was uniquely investigated.
- The novelty of this research is that a new approach is presented to determine the energy costs of DWTPs.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water and energy supplies are correlated with a complicated relationship defining as the water-energy nexus (Castellet & Molinos-Senante 2016; Ji *et al.* 2020). The municipal water cycle includes two major components which are potable water and wastewater collection, treatment, and distribution. Previous studies have demonstrated that many researchers have majorly concentrated on wastewater treatment as energy issues corresponded to drinking water were less examined (Molinos-Senante & Guzman 2018). Many researchers have ignored energy consumption of water treatment technologies in terms of water-energy nexus and concentrated on water depletion in the energy plants. Energy consumption of the drinking water treatment plants (DWTPs) should be an essential component of the water-energy nexus. DWTPs are energy-intensive plants. Energy consumption is required in huge amounts to treat groundwater properly. Also, higher energy intensity is necessary to treat water for meeting the potable water standards. Also, inlet (raw water) and treated water pumping processes lead to higher energy consumption.

There are many energy costs reduction methods for water treatment. Especially, process modifications and renewable energy alternatives are widely used as minimization techniques. In general, renewable energy systems such as solar panels, photovoltaic systems have been applied to decrease the energy consumptions and the greenhouse gas emissions at drinking water treatment plants (Bukhary *et al.* 2020a, 2020b). Using biomass energy is not only a treatment method but also is an energy consumption reduction method for DWTPs. Biochar is defined as a black carbon generated using thermal or hydrothermal conversion of biomass for environmental purposes. Recently, several researchers have concentrated on the application of adsorbents such as biomass energy sources. Biochar is one of the biomass energy sources. It could adsorb the pollutants from water urgently and uses less energy to fulfill the treatment (Zhang *et al.* 2022). Therefore, biochar could be an alternative treatment method instead of conventional treatment systems due to many advantages. Groundwater pollution due to heavy metals and trace elements (Pb, B, Fe II etc.) and inorganic anions (NO_3^-, F^- etc.) has recently risen at several locations, especially at arid and semi-arid locations (Bilgili *et al.* 2018; Yenigun *et al.* 2021). Harran Plain is one of these locations. Biochar has high cation exchange capacity and important oxygen including functional groups (Zhang *et al.* 2022). Due to its adsorption capacity, biochar application has been applied for NO_3^- and F^- removal from groundwater in this study. Also, biochar could be applied for removing the heavy metals and trace elements from water. Boron, iron and lead removal has been investigated using biochar in this study. From this point of view, biochar adsorption has been examined to mitigate the energy costs in terms of groundwater treatment in this study. Also, biochar application has been a popular groundwater treatment method in recent years. There are limited studies about groundwater treatment using biochar adsorption in the literature. Dewage *et al.* (2018) investigated nitrate and fluoride removal from groundwater using magnetic ferreous derived biochar. Zhong *et al.* (2021) performed a study on arsenic and iron removal from groundwater using rice husk-derived biochar. Lead and boron removal from groundwater using biochar was uniquely investigated in this study. Apart from the previous studies, nitrate, fluorite, and iron removal has been investigated using a new agricultural waste derived biochar. Pistachio shells were used as biochar for groundwater treatment. Pistachio is the local product of the region where the study was carried out. Also, a novelty of this study is that biochar derived from Pistachio shells was firstly applied for groundwater treatment.

This research determines the energy costs of a groundwater treatment plant regarding the water-energy nexus located at an arid and semi-arid area. The main aim of this study is to reduce the energy costs of groundwater treatment using biochar application. Energy costs assessment of groundwater treatment for nitrate, fluoride, boron, iron and lead removal using conventional processes (filtration process) and biochar adsorption in March (before irrigation) and October (post irrigation) related to 10 observation points has been fulfilled in an arid and semi-arid area. An energy cost assessment tool has been developed considering the methodology by Castellet & Molinos-Senante (2016). Also, energy costs of groundwater treatment have been optimized using data envelopment analysis (DEA). Recently, DEA has been widely carried out for economic performance of the environmental plants. To date, many DEA studies have been performed to determine the efficiency of environmental treatment plants using various scenarios (Molinos-Senante *et al.* 2014). Molinos-Senante *et al.* (2014) performed a study on the economic and environmental performance of wastewater treatment plants. They estimated environmental performance using DEA analysis. In this study, DEA analysis was used to optimize the energy consumptions of groundwater treatment. Hernandez-Sancho *et al.* (2011a) determined energy efficiency for wastewater treatment using a non-radial DEA model. DEA methodology has been used to determine the optimum energy consumption of the groundwater pollutant parameters. Also, DEA has been carried out to categorize the groundwater pollutant parameters. Apart from the previous studies, DEA has been used to optimize energy consumption and categorize the groundwater pollutant parameter, such as low, medium, high energy-intensive parameter, in this study. Previous studies used DEA to determine the energy efficiency of DWTPs. Sala-Garrido & Molinos-Senante (2020) compared the energy efficiency of drinking water treatment plants using DEA.

The papers related to energy cost assessment have generally focused on wastewater treatment processes. Castellet & Molinos-Senante (2016) researched the relevance of design parameters to optimal operational parameters of wastewater treatment plants with regards to design and operational flow rates. In several studies, benchmarking methodologies were fulfilled to estimate the energy costs (Hernandez-Sancho *et al.* 2011a; Yapıcıoğlu & Yeşilnacar 2020). Recently, applying cost functions is regarded as a widely used technique. This paper proposes a new comprehensive approach for the determination of the energy costs for groundwater treatment. The originality of this study is that this paper recommends an extensive model of energy cost estimation for a drinking water treatment plant considering water-energy nexus. Current cost assessment methodologies focus mainly on wastewater treatment plants. The novelty of this research is that a new approach is presented to determine the energy costs of a drinking water treatment plant. This cost estimation model has been ensured using the Box-Benken method and sensitivity analysis. The effects of the factors on surface tension to estimate the indicator pollutant parameters (NO_3^-, F^-, B, Fe (II), Pb concentrations) have been statistically examined applying variance analysis (ANOVA). Particularly, the impact of irrigation and process design on energy costs has been investigated. Box-Benken methodology has been applied to evaluate the optimal pollutant concentrations of 10 observation points. NO_3^-, F-, B, Fe (II) and Pb are the important groundwater pollutant parameters in the study area. This research is unique in that it underlines that biochar adsorption could be used as an energy cost minimization technique.

Many studies on this issue have been carried out using several estimation approaches. Landa-Cansigno *et al.* (2020) recommended water reclamation strategies within the scope of a municipal water policies and water-energy nexus. Lee *et al.* (2018) reported the water–energy nexus of freshwater supplies management performing multi-criteria decision analysis. Apart from previous studies, this paper also has aimed to decrease the energy costs and recommend an empirical approach decreasing energy depletions, which also includes a renewable energy product in terms of water-energy nexus. Biochar is a type of biomass energy as a renewable energy type. In this study, this process was carried out as an energy costs mitigation method apart from the other studies.

2. MATERIALS AND METHODS

2.1. Definition of the observation points and biochar adsorption process

The study area is in southeastern Turkey which has the largest irrigation area and the groundwater supplies of the Middle East (Baba *et al.* 2019). Çamlıdere (1), Yardımcı (2), Kısas (3), Uğurlu (4), Ozanlar (5), Kızıldoruç (6), Olgunlar (7), Yaygılı (8), Bolatlar (9) and Uğraklı (10) are the monitoring points of pollution concentrations in the Harran Plain which is one of the arid and semi-arid areas in the world. Figure 1 presents the observation points. Nitrate, fluoride, iron, boron, and lead analysis were fulfilled applying an Inductively Coupled Plasma – Mass Spectrometry (ICP-MS) technique.

Pistachio (Pistacia Vera L.) shells were used and pulverized to generate biochar in this study. Pistachio (*Pistacia Vera L.*) shells were used as agricultural waste. Pistachio (*Pistacia Vera L.)* shells were collected from a local field in Turkey. The adsorption kinetics were fulfilled applying batch experiments. The parameters of slow pyrolysis were 4.5 °C/min of heating rate, 120 minutes of heating duration and 600 °C of temperature. Biochar was investigated to compare adsorption capacities of Fe (II), B, NO_3^-, F^- and Pb. 0.1 g of adsorbent (biochar) was stirred with 50 mL of pollutant solutions, respectively. The last

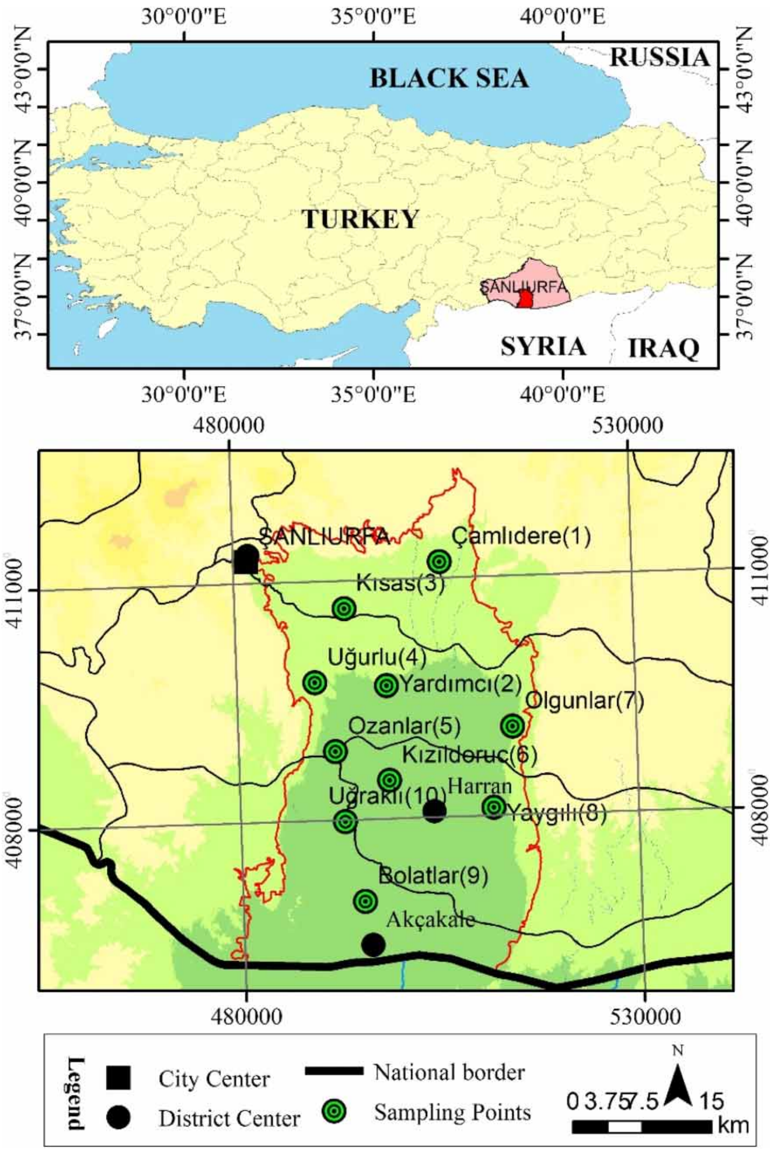


Figure 1 | The map of the study area. *Observation Points: Çamlıdere (1), Yardımcı (2), Kısas (3), Uğurlu (4), Ozanlar (5), Kızıldoruç (6), Olgunlar (7), Yaygılı (8), Bolatlar (9) and Uğraklı (10).

concentrations of pollutants were detected with the technique of ICP-MS and spectrophotometric method. All the analyses were implemented on powder forms of the biochar using vacuum drying. This study is unique in which *Pistacia Vera L.* derived biochar was firstly used for groundwater treatment.

The number of Fe (II), B, NO_3^-, F^- and Pb adsorbed on the biochar (qe) (mol/kg) is determined with the help of Equation (1) (Metcalf & Eddy 2014):

$$qe = ((Bo - Be)S)/B \tag{1}$$

where *Bo* is the initial pollutant concentrations (mM), *Be* is the pollutant concentrations at equilibrium (mM), *S* is the solution volume (L), and *B* is the biochar dosage (g).

2.2. Description of energy costs

Previous studies have confirmed that the water-energy nexus obtains cross-cutting opportunities to reduce urban energy and water demand (Castellet & Molinos-Senante 2016; Molinos-Senante & Guzman 2018). Furthermore, synergistic approaches are important for drinking water treatment authorities to realize the correspondence of water and energy. Energy cost indicator is one of the synergistic approaches which contains available water pollution, water treatment capacity and water amount. Energy cost indicator was determined using a verified numerical methodology in the result of sensitivity analysis. This model was adapted from the method by Castellet & Molinos-Senante (2016) and Hernandez-Sancho *et al.* (2011b). This developed model is based on empirical analyses in this study. The basic model is given in Equation (2) (Hernandez-Sancho *et al.* 2011b):

$$EC = PW^s e^{(\sum \alpha f x f)} \tag{2}$$

where EC = energy cost of the treatment plant; W = mass of wastewater per year; xf = kinds of factors; P, s and α = coefficient of the sensitivity analysis.

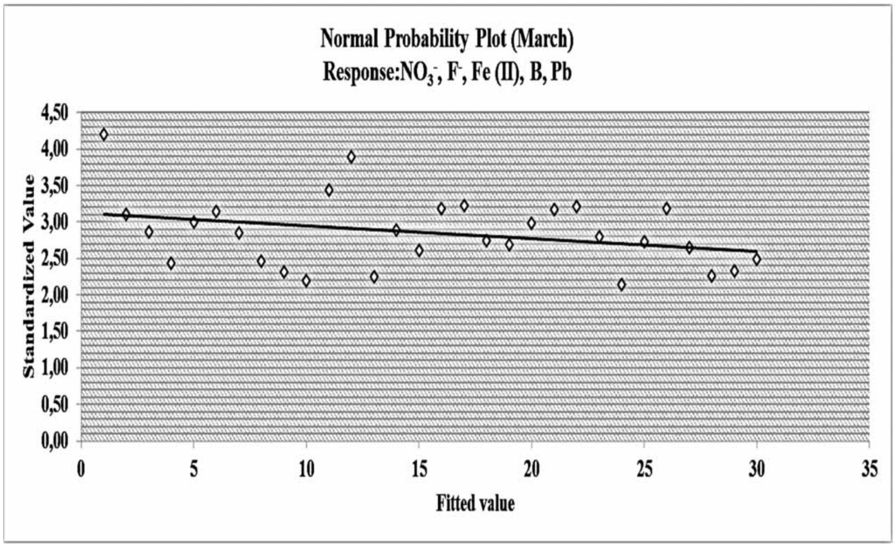
In the derived model, the performance indicator (X) is the variable which defines the correlation of design and operational water treated amount (Equation (2)). Operational flow (Q) (m^3/d) and the design flow of the plant (q) (m^3/d) comprise the performance index (X). Equation (3) presents the estimating of the performance indicator (X) (Castellet & Molinos-Senante 2016).

$$\mathrm{X} = \frac{(q - Q)}{(q)} \times 100 \tag{3}$$

In this paper, coefficients were decided using the Box-Benken method. NO_3^- (x_1), F^- (x_2), Fe (II) (x_3), B (x_4) and Pb (x_5) are the major independent variables. Variable concentrations are analyzed during operation every day and they corresponded to mean values. In the result of sensitivity analysis, the objective function of the framework was defined in Equation (4) by applying Box-Benken methodology. It described the correlation of the data. The regression models obtained multiple linear regressions as the target function at MATLAB. Figure 2 has presented the regression and correlation experiments. The experimental nexus of optimal parameters and independent variables was obtained using multiply regression analysis of empirical data. The optimal parameters (y) could be calculated using the quadric polynomial formulation within the scope of significant variables. The quadric regression model was derived using ANOVA in Equation (4):

$$y = 3.024x_1^2 - 16.6x_2 - 3.2x_3 - 1.6x_4 - 0.5x_5 \tag{4}$$

In the result of the sensitivity analysis, the energy cost assessment tool has been given in Equation (5) for nitrate removal. The coefficients were determined according to the Box-Benken design method. The energy cost assessment tools for fluorite and iron removal are given in Equations (6) and (7), respectively. The energy cost indicator calculation tools of boron and



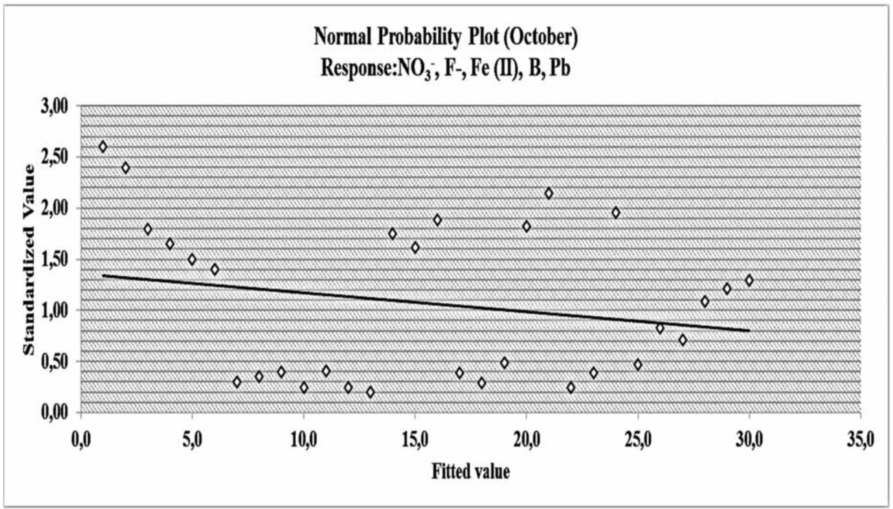


Figure 2 | Normal probability plots for the proposed method.

lead removal are shown in Equations (8) and (9), respectively:

$$ECI = 1989.10^4 W^{0.715} e^{(-16,4[NO_3]+0.66X)} \quad (5)$$

$$ECI = 1989.10^4 W^{0.715} e^{(-0,60[F]+0.69X)} \quad (6)$$

$$ECI = 1989.10^7 W^{0.715} e^{(-0,54[Fe(II)]+0.70X)} \quad (7)$$

$$ECI = 1989.10^7 W^{0.715} e^{(-0,37B]+0.76X)} \quad (8)$$

$$ECI = 1989.10^7 W^{0.715} e^{(-0,18[Pb]+0.83X)} \quad (9)$$

where ECI = energy cost of the DWTP; W = Volume of water treated per year (m^3/year); [NO_3^-] = nitrate concentration after groundwater treatment (ppm); [F^-] = fluoride concentration after groundwater treatment (ppm); [Fe(II)] = iron concentration after groundwater treatment (ppb); [B] = boron concentration after groundwater treatment (ppb); [Pb] = lead concentration after groundwater treatment (ppb); X = performance index.

2.3. Statistical data collection and data interpretation

The effects of the variables for estimating optimal pollutant concentrations have been statistically analyzed with the help of analysis of variance (ANOVA). Response surface method has been carried out using Statistica 7.1. software. The model was applied as it has low standard deviation (0.0059) and high values of R^2 (0.98) and adjusted R^2 (0.96) (October). For March, standard deviation (0.0062) and high values of R^2 (0.99) and adjusted R^2 (0.97) were figured out. Figure 2 presents the converge plot of the recommended methods. Figure 3 demonstrates the empirical correspondence of optimal parameters and independent variables in March.

A multiple linear regression model was performed to reveal a mathematical model for the response. ANOVA results showed that the model was efficient with a R^2 (adjusted) values of 96.00 and 97.00%. The proposed cost model had a β-value of 0.014 which defines the importance. The test results revealed that optimal parameters for October are 9.8 ppm

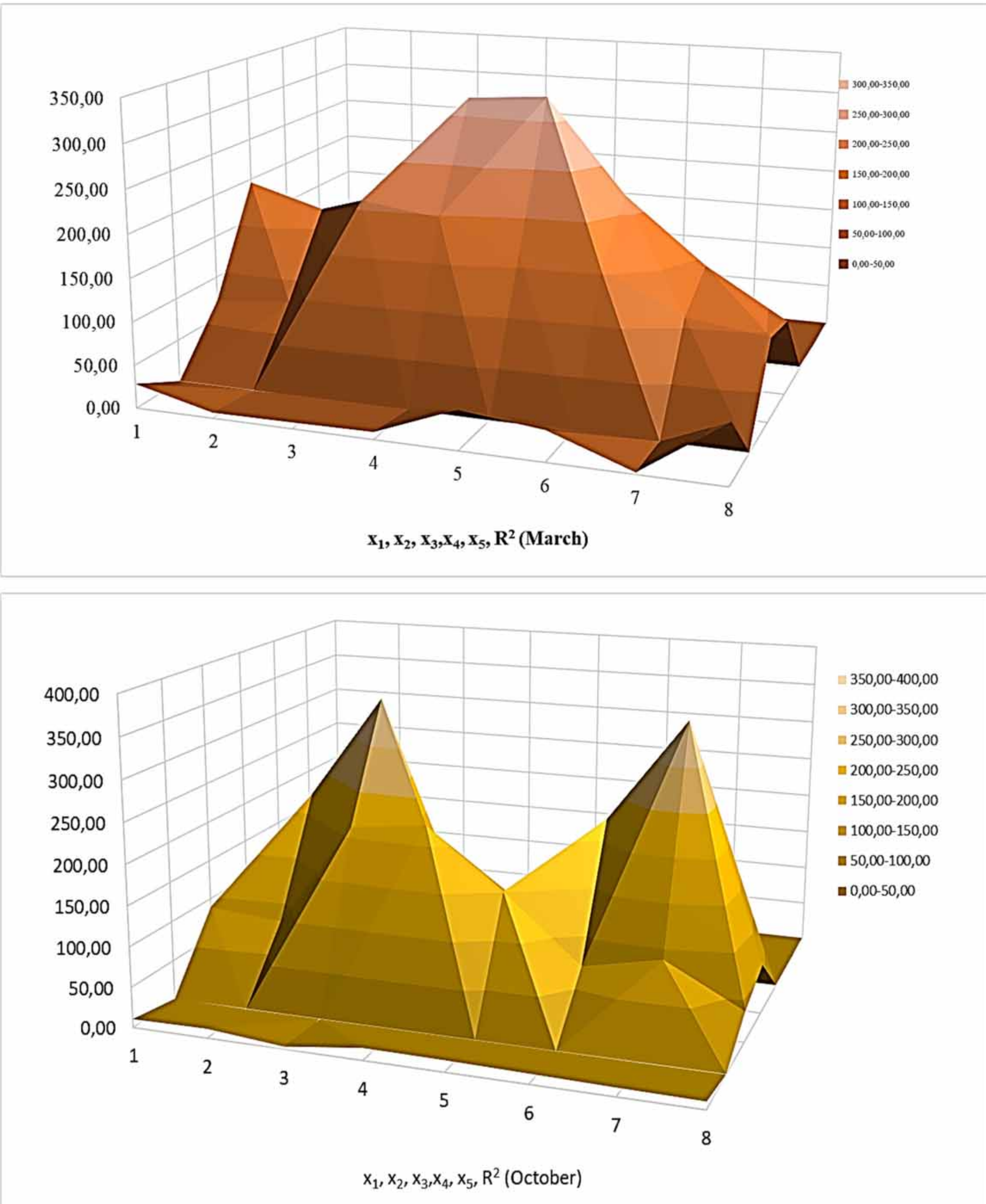


Figure 3 | Response surface.

of NO_3^-, 0.35 ppm of F^-, 18 ppb of B, 24 ppb of Fe (II) and 0.2 ppb of Pb. For March, optimal operating parameters are 16.5 ppm of NO_3^-, 0.85 ppm of F^-, 44 ppb of B, 144 ppb of Fe (II) and 2.25 ppb of Pb. This research proposes a new extended energy costs estimation methodology dependent on corroboration for water treatment. Operational flow (Q) and the design flow of the plant (q) were 2700 and 4000 m^3/d, respectively in March, 2750 m^3/d of operational flow and 4000 m^3/d of design flow corresponded to October.

2.4. Data envelopment analysis

DEA is a non-parametric approach based on linear programming that obtains an index of efficiency in order to assess a performance set of entities which are called Decision Making Units (DMUs) that change inputs into outputs (Sala-Garrido & Molinos-Senante (2020)). According to this study, the inputs are energy consumption, volume of water treated, pollutant (NO_3^-, F^-, Fe (II), B and Pb) removal and the outputs are optimum energy consumption for pollutant removal from drinking water. Figure 4 shows the schematic presentation of DEA model in this study.

The DEA model that carried out Variable Return to Scale (VRS) was regarded as a BCC model (Cooper *et al.* 2011). In this study, the BCC model was used for a DWTP due to its overlapping with characteristics of the plant. The aim is to optimize the energy consumption while producing drinking water while meeting the water quality standards. Also, the categorization of groundwater pollutant parameters has been carried out according to energy intensity using DEA methodology. The basic model is given in Equation (10) (Cooper *et al.* 2011):

$$\begin{aligned}
&\mathrm{Min}\,\theta \\
&\text{s.t.} \\
&\sum_{k=1}^{n} \lambda k X i k \leq \theta X i k 0 \;\; 1 \leq i \leq E \qquad (10)\\
&\sum_{k=1}^{n} \lambda k y r k \;\geq y r k 0 \;\; 1 \leq r \leq P \\
&\lambda k \geq 0 \;\; 1 \leq k \leq n \\
&\sum_{k=1}^{n} \lambda k = 1
\end{aligned}$$

In Equation (10), E ($Xk = X1k, X2k$…………..XEk) defines the vector of inputs and P ($yk = y1k$, $y2k$…………..yPk) defines the vector of outputs. According to the basic model, θ represents the optimum energy cost of drinking water treatment plant and it could be determined by means of Equation (10).

From this mathematical approach, the pollutant removal and energy consumption were correlated with each other for defining the optimum energy consumption using DEA model. The DEA model is given in Equation (11):

$$OptECp = \frac{EC\ x\ W}{\left(\dfrac{ca - cp}{ca}\right)} \qquad (11)$$

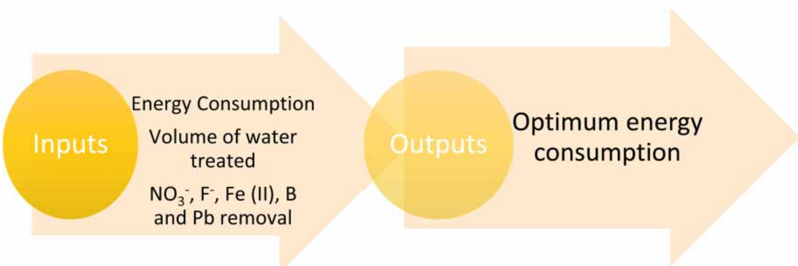


Figure 4 | Schematic diagram of DEA model.

Table 1 | Raw water characteristics before treatment

	Parameter	Observation Well-1	Observation Well-2	Observation Well-3	Observation Well-4	Observation Well-5	Observation Well-6	Observation Well-7	Observation Well-8	Observation Well-9	Observation Well-10
March	NO_3^- (ppm)	22	29	51	37	180	45	47	87	526	113
	F^-(ppm)	0.42	0.46	0.3	0.23	0.84	2.34	0.95	1.3	0.85	1.18
	Fe(II) (ppb)	78	66	671.62	1,557.9	74	78	248.67	230	132	446.86
	B(ppb)	140	92.3	68.2	203	192	1,555.38	375	446	470	547
	Pb(ppb)	3.01	0.97	2.70	8.9	1.02	2.01	1.24	1.17	1.23	5.98
October	NO_3^- (ppm)	7.25	11.95	22.37	27.53	9.32	34.47	5.50	7.99	31.75	34.33
	F^-(ppm)	0.41	0.35	0.24	0.2	0.77	2.05	0.56	0.36	0.91	0.86
	Fe(II) (ppb)	66.19	19.04	416	272	52	62.28	135	32.39	84	247
	B(ppb)	21	19	20	78.76	90.5	1,438	96.17	74.30	353.94	479.58
	Pb(ppb)	1.24	0.2	1.09	1.9	0.91	1.22	1.08	0.19	0.79	2.03

where $OptECp$ = optimum energy consumption per pollutant removal (kWh/d); EC = energy consumption of DWTP per m^3 water treated (kWh/m^3); W = volume of water treated per day (m^3/d); ca = concentration of pollutant in raw water (ppb, ppm); cp = concentration of pollutant in the drinking water (ppb, ppm); $(ca–cp)/(ca)$ = treatment efficiency ($E^{1,2}$).

According to this study, the pollutants (ca and cp) are NO_3^-, F^-, Fe (II), B and Pb in this DWTP. Optimum energy consumption per each pollutant parameter was determined both for conventional and biochar treatment. E_1 and E_2 presents the treatment efficiencies of conventional treatment and biochar adsorption process, respectively.

3. RESULTS AND DISCUSSION

3.1. Energy cost indicator of groundwater treatment

Table 1 presents the analysis results of the groundwater samples before treatment. A conventional water treatment method as filtration process has been applied to treat groundwater treatment. Biochar adsorption has been applied as the alternative

Table 2 | Empirical design matrix related to October

Run Order	x_1 (NO_3^-)	x_2 (F^-)	x_3 (Fe(II))	x_4 (B)	x_5 (Pb)	R^2	Standard deviation (STD)
1	1.5	0.45	72	22	2.6	0.68	0.0094
2	1.8	0.10	71	26	2.4	0.70	0.0090
3	4.6	0.25	68	95	1.8	0.71	0.0085
4	6.5	0.20	150	87	1.65	0.65	0.0087
5	6.6	0.21	321	110	1.5	0.80	0.0081
6	3.3	0.49	282	118	1.4	0.82	0.0080
7	3.2	0.52	231	214	0.3	0.69	0.0077
8	5.5	0.15	87	350	0.35	0.75	0.0095
9	1.8	0.28	88	287	0.4	0.97	0.0090
10	1.9	0.11	211	250	0.25	0.74	0.0091
11	2.0	0.18	150	25	0.41	0.93	0.0088
12	2.5	0.57	89	211	0.25	0.95	0.0068
13	9.8	0.35	24	18	0.2	0.98	0.0059
14	14.5	0.62	121	350	1.75	0.79	0.0086
15	14.3	0.48	170	199	1.62	0.76	0.0060
16	12.5	0.35	164	185	1.89	0.61	0.0079
17	10.5	0.21	245	109	0.39	0.67	0.0071
18	10.4	0.38	84	240	0.29	0.65	0.0075
19	11.0	0.56	121	350	0.49	0.87	0.0073
20	4.2	0.45	93	24	1.82	0.81	0.0069
21	6.8	0.63	211	115	2.15	0.83	0.0066
22	3.5	0.54	215	19	0.25	0.91	0.0066
23	10.5	0.64	89	27	0.39	0.73	0.0069
24	11.6	0.13	81	222	1.96	0.86	0.0067
25	3.2	0.24	212	353	0.47	0.66	0.0064
26	15.1	0.26	223	57	0.83	0.88	0.0063
27	14.3	0.30	151	99	0.71	0.89	0.0070
28	12.6	0.31	69	224	1.09	0.63	0.0068
29	10.8	0.19	89	353	1.21	0.90	0.0065
30	9.5	0.17	38	61	1.29	0.78	0.00764

x_1: NO_3^- (ppm), x_2: F^- (ppm), x_3: Fe (II) (ppb), x_4: B(ppb), x_5: Pb(ppb).
R^2 = 0.98; adjusted R^2 = 0.96, STD: 0.0059.

water treatment method to reduce energy costs. The results confirmed that biochar adsorption could be applied for groundwater treatment in terms of nitrate and fluorite removal using biochar. Approximately 90% of removal efficiency for NO_3^- adsorption was ensured using biochar. In a study by Dewage *et al.* (2018), they reported fluorite and nitrate removal from groundwater could be ensured using magnetic biochar. Fluoride is a geogenic contaminant and has emerged as a crucial problem, especially in arid and semi-arid regions such as Harran Plain. Also, this study showed that pistachio shells derived biochar could adsorb fluorite from groundwater nearly in the value of 91% of removal efficiency. Sadhu *et al.* (2022) investigated fluorite removal from groundwater, and they reported that fluorite removal could be applied using watermelon rind biochar. Inorganic ions could be removed from groundwater using biochar adsorption. Application of nitrate-containing manures leads to contamination at groundwater levels. It leads to nitrate run-off problem. Another ground water pollution is led by separating of rocks and soils enriched by fluoride. Effective treatments are applied to remove nitrate and fluoride from potable water, but they have higher costs. From this point of view, agricultural waste derived biochar is a cheaper biomass

Table 3 | Empirical design matrix related to March

Run order	x_1 (NO_3^-)	x_2 (F^-)	x_3 (Fe(II))	x_4 (B)	x_5 (Pb)	R^2	Standard deviation (STD)
1	4.4	0.52	84	184	4.2	0.74	0.0094
2	102.1	0.12	78	189	3.1	0.76	0.0093
3	14.4	0.25	212	191	2.87	0.71	0.0095
4	12.5	0.35	289	220	2.44	0.80	0.0083
5	10.2	0.38	69	226	3.0	0.82	0.0080
6	5.4	0.10	121	300	3.15	0.73	0.0079
7	32.0	0.16	125	301	2.85	0.81	0.0072
8	3.0	0.18	69	189	2.47	0.85	0.0076
9	35.0	0.25	321	178	2.32	0.77	0.0075
10	81.0	0.48	333	68	3.19	0.65	0.0091
11	78.0	0.35	225	78	3.44	0.67	0.0088
12	18.0	0.34	69	89	3.89	0.83	0.0084
13	16.5	0.85	64	144	2.25	0.99	0.0061
14	16.8	0.55	79	121	2.89	0.90	0.0070
15	22.8	0.43	89	188	2.61	0.68	0.0098
16	20.4	0.45	229	222	3.19	0.95	0.0062
17	10.6	0.41	125	350	3.22	0.65	0.0099
18	88.0	0.80	96	101	2.75	0.93	0.0064
19	76.4	0.79	101	192	2.69	0.69	0.0096
20	3.0	0.80	296	120	2.99	0.70	0.0095
21	4.6	0.56	215	310	3.17	0.73	0.0094
22	12.3	0.18	78	178	3.21	0.61	0.0099
23	28.5	0.24	71	196	2.80	0.64	0.0097
24	6.5	0.26	79	170	2.14	0.83	0.0079
25	7.3	0.75	210	150	2.73	0.91	0.0064
26	8.6	0.83	198	319	3.19	0.88	0.0069
27	45.5	0.24	164	326	2.65	0.94	0.0065
28	35.3	0.63	155	217	2.26	0.66	0.0098
29	2.3	0.39	110	143	2.33	0.89	0.00715
30	68.5	0.78	97	87	2.49	0.63	0.00989

x_1: NO_3^- (ppm), x_2: F^- (ppm), x_3: Fe (II) (ppb), x_4: B(ppb), x_5: Pb(ppb).
$R^2 = 0.99$; adjusted $R^2 = 0.97$, STD: 0.0061.

type to treat groundwater contaminated by nitrate and fluorite. The other groundwater pollutant parameters are heavy metals and trace elements. Iron removal from groundwater was ensured in this study with the nearly 60% of treatment efficiency in this study. Zhong *et al.* (2021) performed a study on iron removal from groundwater using rice husk-derived biochar. They similarly reported that biochar ensured iron oxidation. The other important trace element is boron which is an inorganic ion found mostly in soil, rocks, seawater, and groundwater. In this study, it was found that nearly 94% of treatment efficiency using pistachio *(Pistacia Vera L.)* shells derived biochar. Pb is a heavy metal which has a high pollution risk for groundwater supplies. It could be leached from pesticides to groundwater levels. In this study, approximately 94% of Pb removal efficiency for groundwater treatment was ensured using biochar adsorption.

Empirical design matrix for five factors (NO_3^-(x_1), F^- (x_2), Fe (II) (x_3), B (x_4) and Pb (x_5)) with empirical and calculated responses in the result of Box-Behnken method related to October and March is shown in Tables 2 and 3, respectively.

The relevance test was performed. Degree of statistical relevance is notated by β-value. The results of ANOVA for Box-Behnken method, designed for optimal NO_3^-, F^-, Fe (II), B and Pb concentrations are given in Table 4.

Tables 5 and 6 show the energy cost assessment results in detail. The results revealed that energy cost indicators of Pb removal (ECI, Pb) were higher than that of the other pollutant removal for 10 observation wells in October and March. The highest energy cost index corresponded to Uğurlu Well (4) in terms of Pb removal with the value of 0.95 in March applying conventional treatment. From these results, it could be said that heavy metal removal led to higher energy costs than the other pollutant parameters. The energy cost indicators of all pollutant removal in March were higher than the values in October. It could be considered that irrigation could decrease the energy costs due to the dilution of groundwater composition. From this point of view, it could be said that irrigation could decrease the energy consumption of the potable water treatment plants. The lowest energy cost index related to biochar adsorption process in terms of nitrate removal at Ozanlar (5) well with the value of 0.0000085 in October. It could be originated from that this well is far away from agricultural fields or irrigation dilutes the nitrate leachates. Considering the treatment processes, the energy cost indicators related to biochar adsorption were lower than conventional treatment for all groundwater resources. Figure 4 shows the energy cost assessment based on treatment processes. The analyses confirmed that biochar adsorption was more efficient than conventional processes for treating groundwater supplies. The treatment efficiencies were higher while using biochar adsorption process. This study confirmed that agricultural product derived biochar could adsorb nitrate, fluorite, boron, iron and lead from groundwater resources. The results revealed that biochar adsorption process could be an energy cost minimization method for DWTPs. After lead removal, fluorite led to higher energy costs. Kızıldoruç (6) well had the highest energy costs in terms of fluorite removal using conventional treatment with the value of 0.45 in March. It could be resulted from geogenic formation. Boron removal led to lower energy costs after nitrate removal. The energy costs corresponded to the type of treatment method and groundwater composition.

There are limited studies belong to this topic in terms of groundwater treatment. Groundwater treatment is considered in agricultural activities to grow the agricultural products. Salehi *et al.* (2020) reviewed the water-energy nexus for potable water

Table 4 | ANOVA test results for Box-Behnken method

Resource	Degree of freedom	Adj NO_3^-	Adj F^-	Adj Fe(II)	Adj B	Adj Pb	f-Value	β-Value
Model	13	16.4	0.60	0.54	0.37	0.18	3.40	0.014
Linear	3	15	0.59	0.52	0.36	0.17	1.75	0.200
x_1	1	11	0.68	0.66	0.46	0.26	1.50	0.100
x_2	1	11.5	0.75	0.50	0.50	0.25	3.25	0.150
x_3	1	10.2	0.89	0.61	0.25	0.20	3.05	0.120
x_4	1	9.5	0.91	0.60	0.35	0.19	2.40	0.115
x_5	1	5	0.88	0.24	0.25	0.22	1.15	0.100
Square	1	5.5	4.5	3.5	3.8	0.25	4.00	0.010
x_1^2	1	6.0	6.5	6.2	6.4	6.7	3.50	0.01
Error	10	10.5	10.1	10.2	10.4	10.25		
Total	33	20	2.0	2.5	2.1	2.3		

Table 5 | Energy cost assessment in terms of pollutant removal based on treatment processes in March

Process	Observation Well	NO_3^- concentration (ppm)	ECI, NO_3^-	F^- concentration (ppm)	ECI, F^-	Fe (II) concentration (ppb)	ECI, Fe (II)	B concentration (ppb)	ECI, B	Pb concentration (ppb)	ECI, Pb
Conventional treatment	Observation Well-1	4.2	30.58×10^{-5}	0.23	0.079	36.71	0.0019	65.90	0.0008	1.96	0.81
	Observation Well-2	5.3	31.50×10^{-5}	0.24	0.08	33.70	0.001	46.14	0.00075	0.63	0.25
	Observation Well-3	10	17.85×10^{-4}	0.15	0.02	302.23	0.2	34.79	0.00041	1.76	0.79
	Observation Well-4	7.2	6.85×10^{-4}	0.11	0.01	778.95	0.31	97.52	0.00195	5.78	0.95
	Observation Well-5	33	42.71×10^{-3}	0.46	0.18	37.69	0.005	93.84	0.001	0.66	0.48
	Observation Well-6	8.75	9.02×10^{-4}	1.21	0.45	38.41	0.058	699.92	0.09987	1.31	0.79
	Observation Well-7	9.1	15.24×10^{-4}	0.44	0.13	126.82	0.197	191.40	0.00198	0.81	0.69
	Observation Well-8	17	17.22×10^{-3}	0.65	0.38	112.73	0.1	205.21	0.01956	0.76	0.54
	Observation Well-9	104.1	91.07×10^{-3}	0.47	0.21	68.64	0.09	220.94	0.0298	0.80	0.68
	Observation Well-10	22.1	25.44×10^{-3}	0.6	0.25	227.90	0.198	267.80	0.049	3.89	0.92
Biochar adsorption	Observation Well-1	2.1	17.43×10^{-5}	0.038	0.044	3.12	0.0010	8.41	0.000448	0.391	0.4536
	Observation Well-2	2.75	17.95×10^{-5}	0.023	0.045	5.29	0.00056	4.61	0.0004222	0.127	0.1407
	Observation Well-3	5	10.17×10^{-4}	0.012	0.011	67.16	0.11	6.82	0.0002255	0.351	0.4345
	Observation Well-4	3.5	3.90×10^{-4}	0.025	0.005	82.57	0.173	24.38	0.0010939	1.157	0.5329
	Observation Well-5	17.75	24.34×10^{-3}	0.059	0.102	2.22	0.00285	11.49	0.00058	0.133	0.2784
	Observation Well-6	4.45	5.14×10^{-4}	0.094	0.247	3.92	0.0324	186.65	0.055927	0.261	0.4424
	Observation Well-7	4.55	8.68×10^{-4}	0.095	0.070	12.43	0.1065	41.28	0.0010810	0.161	0.37674
	Observation Well-8	8.5	9.81×10^{-3}	0.143	0.205	16.10	0.0536	57.99	0.0105624	0.152	0.2916
	Observation Well-9	52.1	51.90×10^{-3}	0.077	0.107	10.56	0.0470	28.21	0.015794	0.160	0.3692
	Observation Well-10	11	14.50×10^{-3}	0.047	0.140	44.69	0.1110	32.79	0.027489	0.777	0.506

Table 6 | Energy cost assessment in terms of pollutant removal based on treatment processes in October

Process	Observation Well	NO_3^- concentration (ppm)	ECI, NO_3^-	F^- concentration (ppm)	ECI, F^-	Fe (II) concentration (ppb)	ECI, Fe (II)	B concentration (ppb)	ECI, B	Pb concentration (ppb)	ECI, Pb
Conventional treatment	Observation Well-1	1.25	2.63×10^{-5}	0.20	0.001	31.11	0.0016	9.87	0.00078	0.75	0.76
	Observation Well-2	2.24	2.85×10^{-5}	0.18	0.0097	9.71	0.00099	9.50	0.0007	0.12	0.22
	Observation Well-3	4.32	4.81×10^{-5}	0.12	0.17	187.20	0.18	10.20	0.00039	0.65	0.73
	Observation Well-4	5.4	6.21×10^{-5}	0.11	0,27	136.00	0.3	37.80	0.00175	1.14	0.89
	Observation Well-5	1.8	1.79×10^{-5}	0.36	0.0045	26.52	0.0047	44.37	0.00095	0.55	0.25
	Observation Well-6	6.78	5.96×10^{-5}	1.07	0.05	30.51	0.051	647.10	0.092	0.73	0.7
	Observation Well-7	1	2.21×10^{-5}	0.31	0.191	68.85	0.19	49.05	0.0015	0.65	0.61
	Observation Well-8	1.45	2.95×10^{-5}	0.17	0.08	15.87	0.095	34.18	0.0169	0.11	0.52
	Observation Well-9	6.15	8.09×10^{-5}	0.47	0.075	43.68	0.087	166.35	0.021	0.48	0.615
	Observation Well-10	6.75	9.48×10^{-5}	0.45	0.185	125.97	0.187	235.00	0.04	1.22	0.85
Biochar adsorption	Observation Well-1	0.7	1.26×10^{-5}	0.037	0.0005	2.65	0.000728	1.26	0.000362	0.112	0.3534
	Observation Well-2	1.1	1.36×10^{-5}	0.014	0.0054	1.52	0.000478	0.95	0.000331	0.018	0.1040
	Observation Well-3	2.2	2.30×10^{-5}	0.005	0.0952	41,.60	0.08442	2.00	0.000183	0.098	0.3431
	Observation Well-4	2.65	2.98×10^{-5}	0.022	0.1514	14.42	0.135	9.45	0.0008137	0.172	0.4138
	Observation Well-5	0.9	0.85×10^{-5}	0.054	0.0025	1.56	0.00224	5.43	0.0004465	0.082	0.1175
	Observation Well-6	3.39	2.86×10^{-5}	0.082	0.0275	3.11	0.02351	172.56	0.042412	0.110	0.3227
	Observation Well-7	0.52	1.06×10^{-5}	0.056	0.1033	6.75	0.0893	10.58	0.000703	0.097	0.2860
	Observation Well-8	0.77	1.41×10^{-5}	0.039	0.0432	2.27	0.04465	9.66	0.007959	0.017	0.2449
	Observation Well-9	3	3.88×10^{-5}	0.082	0.038	6.72	0.040368	21.24	0.00987	0.072	0.2890
	Observation Well-10	3.23	4.55×10^{-5}	0.034	0.103	24.70	0.088077	28.78	0.0186	0.183	0.3952

production from humid air. The use of solar and wind energy recommended to reduce the energy costs. Bukhary *et al.* (2020a, 2020b) recommended renewable energy systems to reduce the energy consumption for DWTPs. They recommended solar energy and photovoltaic panels to reduce the energy consumption (Bukhary *et al.* 2020a, 2020b). In this study, a similar renewable energy source (biomass energy) was proposed to minimize the energy costs. Some of the developed models for energy cost estimation were implemented to wastewater treatment plants corresponding operational conditions and treated water amount. Castellet & Molinos-Senante (2016) reported that wastewater treatment plants have lower energy costs if the plants are operated under design conditions. They recommended process modification to reduce the energy costs (Castellet & Molinos-Senante 2016). Similarly, biochar application was recommended to decrease the energy costs in this study. Also, this study revealed that conventional treatment led to higher energy costs from biochar adsorption. Molinos-Senante & Guzman (2018) corresponded greenhouse gas emissions due to energy consumption and energy costs of a drinking water treatment plant. They recommended low carbon technologies such as renewable systems to reduce the energy costs and correspond with carbon dioxide emissions and energy prices. Similarly, biochar adsorption could be regarded as a low carbon process due to the greenhouse gas adsorption ability of biochar.

3.2. Minimization of energy costs

Assessment results confirmed that the ECI values corresponded to October less than March. It could be resulted from the irrigation process in October. Irrigation could dilute the groundwater, so a remarkable decrease was reported on the energy costs. Irrigation could be an alternative technique for the reduction of energy costs for groundwater treatment in terms of water-energy nexus. Zhao *et al.* (2020) similarly reported that agricultural irrigation contains both water and energy consumption, especially in well irrigation districts. In a study by Karimov *et al.* (2021) groundwater recharge was proposed to minimize the energy costs. Schwabe *et al.* (2017) reported a dynamic economic–hydrologic methodology of regional irrigated agricultural surface and groundwater supplies to examine the effects of changes in groundwater costs from energy price increases. They reported that the change of groundwater levels had a high effect on energy costs. Hamidov & Helming (2020) reported irrigated agricultural fields as the key indicator of water-energy nexus in their review study. This study similarly confirmed that an irrigation process could reduce the energy costs of groundwater treatment.

Figure 5 shows the energy cost assessment based on treatment processes. This study confirms that biochar application could be an energy costs reduction technique for drinking water treatment in terms of water-energy nexus. The energy

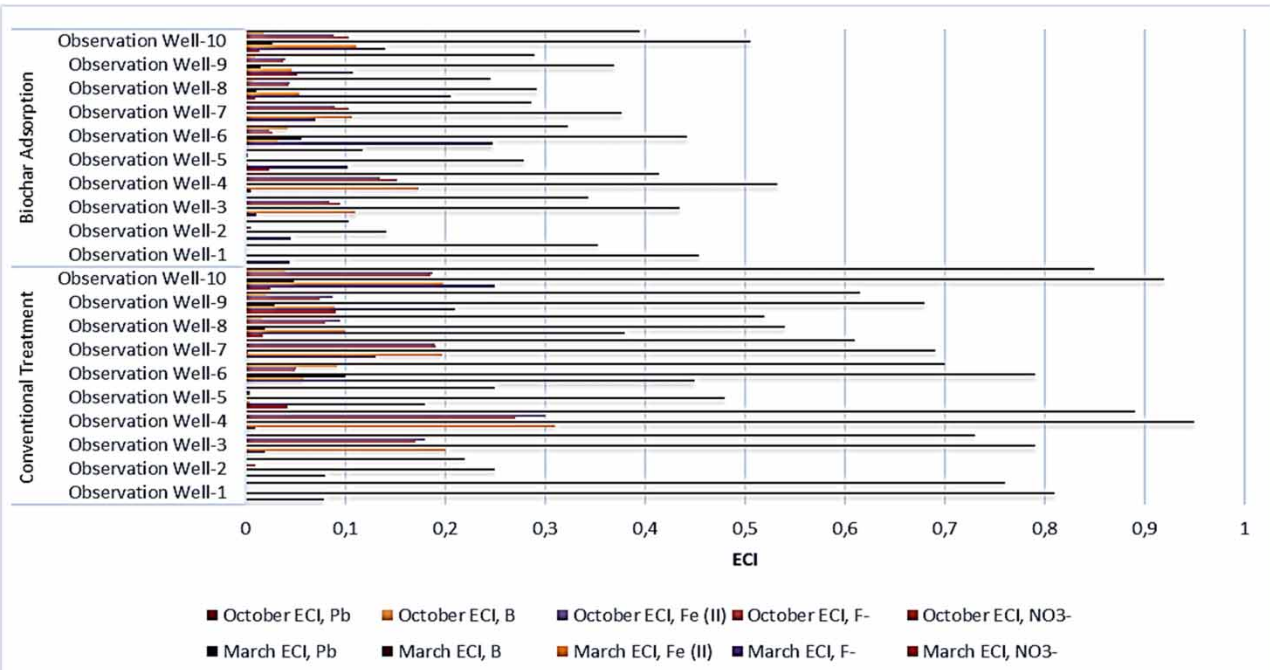


Figure 5 | Energy cost assessment based on treatment processes.

Table 7 | Optimum energy consumption in the result of DEA model

Period/Treatment	Observation Well	W (m^3/d)	EC (kWh/m^3)	OptEC, NO_3^- (kWh/d)	OptEC, F^- (kWh/d)	OptEC, Fe (II) (kWh/d)	OptEC, B (kWh/d)	OptEC, Pb (kWh/d)	E_1, NO_3^-	E_1, F^-	E_1, Fe (II)	E_1, B	E_1, Pb
March (before irrigation) conventional treatment	Observation Well-1	2,700	0.175	583.99	1044.47	892.56	892.72	1350.00	0.8091	0.45	0.529	0.529	0.350
	Observation Well-2	2,700	0.175	578.16	987.95	965.50	944.71	1362.87	0.8172	0.48	0.489	0.500	0.347
	Observation Well-3	2,700	0.175	587.74	945.00	859.09	964.53	1352.54	0.8039	0.50	0.550	0.490	0.349
	Observation Well-4	2,700	0.175	586.66	905.63	945.00	909.36	1349.43	0.8054	0.52	0.500	0.520	0.350
	Observation Well-5	2,700	0.175	578.57	1044.47	963.03	924.18	1350.00	0.8167	0.45	0.491	0.511	0.350
	Observation Well-6	2,700	0.175	586.55	978.45	930.82	859.09	1350.43	0.8056	0.48	0.508	0.550	0.350
	Observation Well-7	2,700	0.175	585.95	880.15	964.29	965.08	1350.00	0.8064	0.54	0.490	0.490	0.350
	Observation Well-8	2,700	0.175	587.25	945.00	926.74	875.18	1351.19	0.8046	0.50	0.510	0.540	0.350
	Observation Well-9	2,700	0.175	589.09	1056.91	984.38	891.66	1354.50	0.8021	0.45	0.480	0.530	0.349
	Observation Well-10	2,700	0.175	587.38	961.29	964.29	925.72	1350.00	0.8044	0.49	0.490	0.510	0.350
October (post irrigation) conventional treatment	Observation Well-1	2,750	0.155	515.05	819.71	804.25	804.25	1068.24	0.8276	0.520	0.530	0.530	0.399
	Observation Well-2	2,750	0.155	524.58	888.02	853.39	852.50	1065.63	0.8126	0.480	0.499	0.500	0.400
	Observation Well-3	2,750	0.155	528.27	869.90	775.00	869.90	1065.46	0.8069	0.490	0.550	0.490	0.400
	Observation Well-4	2,750	0.155	530.26	947.22	852.50	819.71	1070.80	0.8039	0.450	0.500	0.520	0.398
	Observation Well-5	2,750	0.155	506.84	804.25	870.04	836.27	1065.63	0.8410	0.530	0.490	0.510	0.400
	Observation Well-6	2,750	0.155	530.62	745.24	835.67	775.00	1068.88	0.8033	0.572	0.510	0.550	0.399
	Observation Well-7	2,750	0.155	466.85	947.22	869.90	869.87	1065.63	0.9130	0.450	0.490	0.490	0.400
	Observation Well-8	2,750	0.155	484.89	799.22	835.70	789.36	1065.63	0.8791	0.533	0.510	0.540	0.400
	Observation Well-9	2,750	0.155	528.65	888.02	888.02	804.25	1077.77	0.8063	0.480	0.480	0.530	0.395
	Observation Well-10	2,750	0.155	530.57	1044.47	869.90	835.79	1065.63	0.8034	0.480	0.490	0.510	0.400

Period/ treatment	observation well	W (m^3/d)	EC (kWh/m^3)	E_2, NO_3^-	E_2, F^-	E_2, Fe (II)	E_2, B	E_2, Pb	OptEC, NO_3^- (kWh/d)	OptEC, F^- (kWh/d)	OptEC, Fe (II) (kWh/d)	OptEC, B (kWh/d)	OptEC, Pb (kWh/d)
March (before irrigation) biochar adsorption	Observation Well-1	2,700	0.175	0.9045	0.910	0.960	0.940	0.870	522.36	519.23	492.21	502.71	543.10
	Observation Well-2	2,700	0.175	0.9052	0.950	0.920	0.950	0.869	522.00	497.37	513.64	497.36	543.52
	Observation Well-3	2,700	0.175	0.9020	0.960	0.900	0.900	0.870	523.86	492.19	525.00	525.01	543.19
	Observation Well-4	2,700	0.175	0.9054	0.890	0.947	0.880	0.870	521.87	530.90	498.94	536.99	543.08
	Observation Well-5	2,700	0.175	0.9014	0.930	0.970	0.940	0.870	524.19	508.06	487.09	502.58	543.10
	Observation Well-6	2,700	0.175	0.9011	0.960	0.950	0.880	0.870	524.35	492.19	497.50	536.93	543.12
	Observation Well-7	2,700	0.175	0.9032	0.900	0.950	0.890	0.870	523.14	525.00	497.37	530.95	543.10
	Observation Well-8	2,700	0.175	0.9023	0.890	0.930	0.870	0.870	523.66	530.90	508.08	543.12	543.14
	Observation Well-9	2,700	0.175	0.9010	0.910	0.920	0.940	0.870	524.45	519.23	513.59	502.67	543.25
	Observation Well-10	2,700	0.175	0.9027	0.960	0.900	0.940	0.870	523.46	492.19	525.00	502.63	543.10
October (post irrigation) biochar adsorption	Observation Well-1	2,750	0.155	0.9034	0.910	0.960	0.940	0.910	471.80	468.41	444.01	453.46	468.48
	Observation Well-2	2,750	0.155	0.9079	0.960	0.921	0.950	0.910	469.46	444.01	462.57	448.68	468.41
	Observation Well-3	2,750	0.155	0.9017	0.980	0.900	0.900	0.910	472.74	434.95	473.61	473.61	468.40
	Observation Well-4	2,750	0.155	0.9037	0.890	0.947	0.880	0.910	471.65	478.93	450.11	484.37	468.56
	Observation Well-5	2,750	0.155	0.9205	0.930	0.970	0.940	0.910	463.07	458.33	439.44	453.47	468.41
	Observation Well-6	2,750	0.155	0.9017	0.967	0.950	0.880	0.910	472.74	440.71	448.68	484.38	468.50
	Observation Well-7	2,750	0.155	0.9548	0.900	0.950	0.890	0.910	446.44	473.61	448.68	478.93	468.41
	Observation Well-8	2,750	0.155	0.9358	0.893	0.930	0.870	0.910	455.50	477.29	458.33	489.94	468.41
	Observation Well-9	2,750	0.155	0.9055	0.910	0.920	0.940	0.909	470.73	468.41	463.32	453.46	468.75
	Observation Well-10	2,750	0.155	0.9059	0.960	0.900	0.940	0.910	470.52	444.01	473.61	453.46	468.41

costs would be reduced at averagely 44.5 and 52.5% in March and October, respectively if biochar adsorption were applied in this plant considering all pollutant parameters. Based on this, it can be considered that the biochar adsorption process could be an alternative treatment method to decrease energy costs for groundwater treatment instead of conventional treatment methods. The biochar adsorption process reduced nearly 43 and 45% of energy costs in terms of NO_3^- and F^- removal respectively in March. In October, with the effect of irrigation, the reduction value reached up 52 and 50.2% in terms of nitrate and fluorite removal, respectively. Biochar adsorption decreased the energy costs by nearly 44.9, 44.6 and 44.5% in terms of iron, boron and lead removal respectively in March. In October these reductions rose to 53.6, 53.5 and 53.2% in terms of iron, boron and lead removal, respectively.

3.3. Optimum energy consumption of pollutant removal

Optimum energy consumption should be determined at DWTPs for sustainable water-energy nexus. DEA methodology is also an optimization technique. In this study, this optimization method has been underlined apart from the other studies in the literature. Several studies concentrated on determination of energy efficiency at drinking water treatment plants using DEA. Table 7 shows the optimum energy consumptions in the result of DEA in details. Figure 6 represents the optimum energy consumptions of pollutant removal. The lowest optimum energy consumption has corresponded to fluorite removal in terms of biochar adsorption process in October with the value of 434.95 at Observation Well-3 (Kısas (3). It could be resulted from biochar adsorption capacity and irrigation process in October. Biochar could adsorb fluorite in the range of 89–98%. The highest optimum energy consumption (1362.87 kWh/d) belongs to Observation Well-2 (Yardımcı (2)) in terms of lead removal using a conventional treatment method. It could be originated from low treatment capacity of heavy metal using conventional treatment. The treatment efficiency is in the range of 34.7–40% in terms of lead removal. Similarly, the energy cost index of lead removal has the highest value.

The result of DEA shows that optimization of energy consumption for a DWTP is possible using pollutant removal efficiencies. Energy consumption is closely related with volume of water treated and pollutant removal efficiencies. According to the model, treatment efficiencies are the determinant factor to determine the optimum energy consumption. Table 8 presents the statistical analysis of variables at the DEA model. Treatment efficiencies of biochar adsorption have varied in the range of 86.9–98%. Treatment efficiencies (in the range of 34.7–91.30% of pollutant removal) of conventional treatment are lower than biochar adsorption process and it leads to higher energy consumption according to the DEA optimization model. This finding has been consistent with reported previous studies (Molinos-Senante & Guzman 2018; Sala-Garrido &

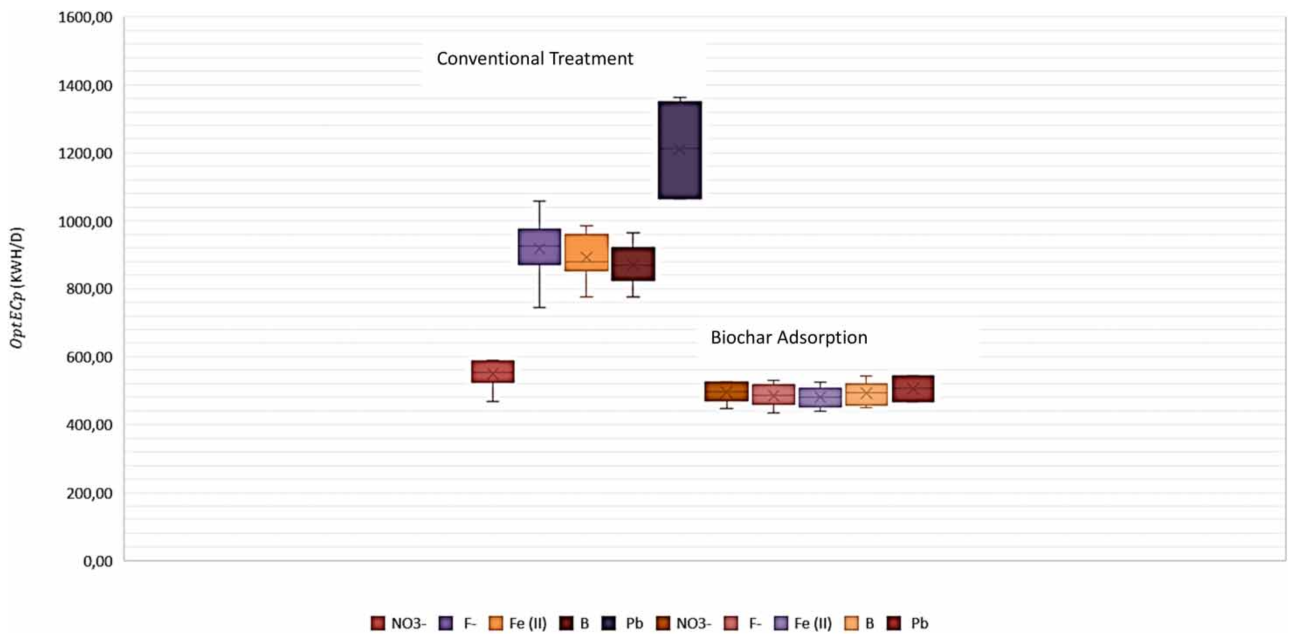


Figure 6 | Optimum energy consumption according to DEA model.

Table 8 | Statistical analysis of variables at DEA model

	Energy consumption (EC) (kWh/m^3)	Volume of treated water (W) (m^3/d)	Nitrate removal efficiency (ENO$_3^-$)	Boron removal efficiency (EB)	Fluorite removal efficiency (EF$^-$)	Iron removal efficiency (EFe(II))	Lead removal efficiency (EPb)
Minimum	0.155	2,700	0.8021	0.49	0.45	0.48	0.347
Maximum	0.175	2,750	0.9548	0.95	0.98	0.97	0.91
Average	0.165	2,725	0.86	0.715	0.71	0.719	0.632
Standard deviation	0.008	0.0075	0.0066	0.0062	0.0054	0.0047	0.0033

Molinos-Senante 2020) which presents substantial variability of energy consumption potential in the operation of water and wastewater treatment plants. The groundwater pollutant parameters were categorized according to optimum energy consumption considering conventional treatment in this study. Biochar adsorption process was ignored due to its reducing capacity of pollutants while categorizing the groundwater pollutant parameters. According to the model, the energy consumption of low energy-intensive (0–600 kWh/d), medium energy-intensive (600–1000 kWh/d) and high energy-intensive (>1000 kWh/d) parameters are considered. Figure 7 shows the categories of groundwater pollutant parameters according to energy requirement. The results revealed that nitrate is the low energy-intensive parameter according to the DEA optimization method considering overall scores. Lead is the high energy-intensive parameter among them. Fluorite, iron and boron are the medium energy-intensive parameters. From this point of view, the results of DEA methodology with energy cost indicators has been overlapped. According to the energy cost assessment, nitrate leads to the lowest energy costs, and it is the low energy-intensive parameter according to the DEA model. Similarly, lead has the highest energy costs, and it is the high energy-intensive parameter. A correlation was formed between two approaches. DEA analysis proves the energy cost estimation tool.

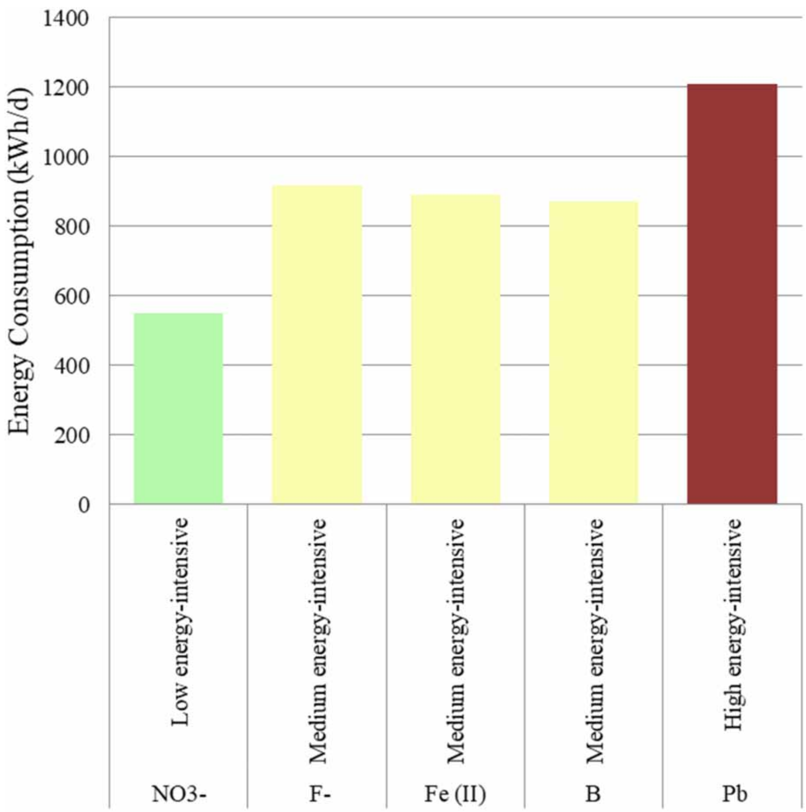


Figure 7 | Categories of groundwater pollutant parameters according to energy requirement.

Sala-Garrido & Molinos-Senante (2020) performed a similar study and the DEA method was used for the determination of energy efficiency of DWTPs. Ananda (2018) reported a study on the determination of water-energy nexus of drinking water sector using the DEA approach. They correlated them with greenhouse gas emissions.

4. CONCLUSION

This paper proposes a model to determine the energy costs of groundwater treatment plants based on pollutant removal and treated water amount. Energy cost indicators of pollutant removal in March (before irrigation) are higher than in October (post irrigation). It could be regarded that irrigation could minimize the energy costs due to the dilution of groundwater content. This study has also shown that cheaper biomass energy could be an alternative energy cost reduction method. When lead removal leads to the highest energy costs in the plant, nitrate removal has the lowest energy costs. The total energy costs would be reduced averagely at 44.5 and 52.5% in March and October, respectively when biochar adsorption was applied in the plant in terms of nitrate, fluoride, boron, iron and lead removal. According to DEA methodology, the optimum energy consumption has corresponded to biochar adsorption in terms of fluorite removal in the value of 434.95 kWh/d. The DEA results reveal that nitrate is a low energy-intensive parameter and lead is a high energy-intensive parameter. The results of the DEA model have been overlapped with the energy cost assessment results.

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CONFLICT OF INTEREST

The authors declare there is no conflict.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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