Using fuzzy logic for estimating monthly pan evaporation from meteorological data in Emara/ South of Iraq

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Abstract:

Evaporation is one of the major components of the hydrological cycle in the nature, thus its accurate estimation is so important in the planning and management of the irrigation practices and to assess water availability and requirements. The aim of this study is to investigate the ability of fuzzy inference system for estimating monthly pan evaporation form meteorological data. The study has been carried out depending on 261 monthly measurements of each of temperature (T), relative humidity (RH), and wind speed (W) which have been available in Emara meteorological station, southern Iraq. Three different fuzzy models comprising various combinations of monthly climatic variables (temperature, wind speed, and relative humidity) were developed to evaluate effect of each of these variables on estimation process. Two error statistics namely root mean squared error and coefficient of determination were used to measure the performance of the developed models. The results indicated that the model, whose input variables are T, W, and RH, perform the best for estimating evaporation values. In addition, the model which is dominated by (T) is significantly and distinctly helps to prove the predictive ability of fuzzy inference system. Furthermore, agreements of the results with the observed measurements indicate that fuzzy logic is adequate intelligent approach for modeling the dynamic of evaporation process.

Key words: Fuzzy logic, Pan evaporation, Iraq, Meteorological data

Introduction:

The accurate estimation of evaporation in the arid and semi-arid region is an essential importance in planning the irrigation practices and water availability. In general, pan evaporation has been widely used as an index of evaporation and for estimating lake and reservoir evaporation. But, It is impractical to place evaporation pans at every point where there is a planned or existing reservoir and irrigation project [1]**,** and even where there is a pan, the measurements may be vitiated by poor maintenance, leading to errors due to many reasons including growth of algae in the water, weed- growth nearby and some incorrect water level measurement.

Recently, the outstanding results using artificial intelligent techniques such as artificial neural networks, fuzzy inference system, adaptive neuro-fuzzy inference system, and genetic programming in the field of evaporation and evapotranspiration have been obtained. Sudheer *et al*. [2] investigated the prediction of class A pan evaporation using the neural networks (NN) model. They used (NNs) for modeling evaporation process using proper combinations of the observed climatic variables such as temperature, relative humidity, sunshine duration, and wind speed. Kumar *et al*. [3] developed the neural networks model to estimate the daily

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grass reference evapotranspiration. They used proper combinations of the observed climatic variables for constructing neural network model. Their conclusions referred that neural networks was a strong promising tool for estimating evapotranspiration. Keskin *et al*. [4] developed fuzzy logic prediction model for daily pan evaporation from measured climatic data. Among the measured climatic variables used to construct the daily evaporation models were the daily observations of air and water temperature, sunshine hours, solar radiation, air pressure, relative humidity and wind speed. They concluded that fuzzy logic offers a promising tool for estimating daily pan evaporation from climatic data.

The abilities of neuro-fuzzy (NF) technique to estimate daily pan evaporation was investigated by Kisi [1]. He used various combinations of daily air temperature, solar radiation, wind speed, pressure and humidity to construct NF models and to evaluate degree of effect of each of these variables on evaporation. He concluded that the NF computing technique could be employed successfully in modeling evaporation process from the available climatic data.

The utility of genetic programming technique to model the evapotranspiration process was explored by Parasuraman *et al*. [5]. They used climatic variables such as net radiation, ground temperature, air temperature, wind speed and relative humidity to model eddy-covariance measured latent heat. Their results showed that the genetic programming evolved equation were parsimonious and understandable and were well suited to model the dynamics of the evapotranspiration process. Kim and Kim [6] applied the generalized regression neural network model embedding the genetic algorithm to estimate and calculate the pan evaporation and the alfalfa reference evapotranspiration, republic of Korea. They used proper combination of the observed climatic variables to build their model. They used an uncertainty analysis to eliminate the climatic variables of the input layer to construct the optimal model. Aytek *et al.* [7] developed an explicit neural network formulation (ENNF) for estimating reference evapotranspiration using daily solar radiation, air temperature, relative humidity, and wind speed. They concluded that the ENNF offered an alternative tool to estimate reference evapotranspiration.

The aim of this study is to develop fuzzy logic intelligent model to estimate monthly pan evaporation with reasonable accuracy from reliable climatic measurements, and subsequently in order to prove the ability of fuzzy logic for estimating evaporation values as a function of climatic variables. The study has been carried out depending on the available data measurements of each of temperature (T), wind speed (W), and relative humidity (RH) of Emara meteorological station ,which is located in the crossing of Latitude 31°78′44.47″ N and Longitude 47°08′27.72″ E, southern Iraq (Fig.1). The climate of the study area is classified within arid to semi-arid region and characterized by the cruelest climatic variable of temperature; it mostly exceeds 48 °C during dry seasons [8].

Fig.1: Location of Emara Meteorological Station.

Review of Fuzzy Logic:

Fuzzy logic is based on the theory of fuzzy sets which relates to classes of objects without sharp boundaries, in which the membership is a matter of degree. In this approach, the classical notation [9] of binary membership in a set has been modified to include partial membership ranging between 0 and 1. The member shape-function (MF) is a curve that defines how each point in the input space is mapped to a membership value (Fig. 2).The generation of a fuzzy model can be based on expert knowledge and historical data. Fuzzy inference is the process of formulating the mapping from a given input to an output equation using fuzzy logic, and then the mapping provides a basis from which decisions can be made or discerned. Basically, fuzzy logic system has four components [10] as follows (Fig. 3); Fuzzification is the process of decomposing a system input and/or output into one or more fuzzy sets, Fuzzy Rules is IF-THEN rule statements which are used to formulate the conditional statements that comprise fuzzy logic, Fuzzy Inference Engine is a process that elaborates and combines rule outputs, and Defuzzification is a process that transforms the fuzzy output into a crisp domain.

The most widespread methodologies for developing fuzzy rules systems are those proposed by Mamdani and Assilian [11] and Takagi and Sugeno [12] methods. The two methods are similar in many aspects, the main difference is that the Takagi-Sugeno output membership functions are either linear or constants while the membership functions of Mamdani are linguistic. A typical rule in a Takagi-Sugeno model has the form [13].

IF input x = 1 and input y = 2 **Then** output is z = ax + by + c

The output level z_i of each rule is weighted by the firing strength w_i of the rule.

For example; for an AND rule with input 1= x and input 2= y the firing strength is:

w_i = And Method ($F_1(x)$, $F_2(y)$)... (1)

where $F_{1,2}(.)$ are the membership functions for inputs 1 and 2. The final output of the

system is the weighted average of all rule output computed as:

$$Final\ output = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \ldots (2)$$

A Takagi-Sugeno rule operates as shown in Figure (4).

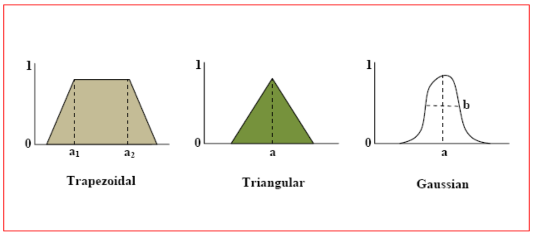

Fig.2: The Different Shapes of Membership Functions

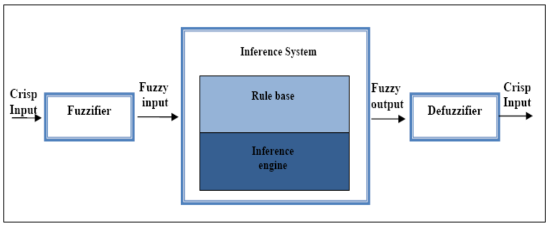

Figure-3: Main Components of Fuzzy Inference Engine

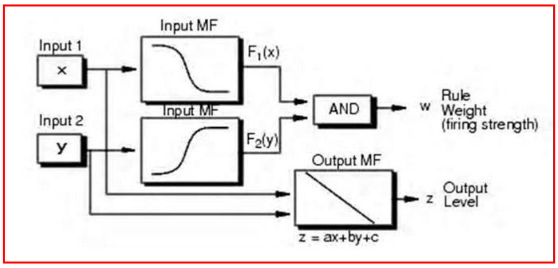

Fig.4: Operation of Takagi-Sugeno Fuzzy Inference Type [13]

Methodology and Data Description:

A total of 262 monthly average observations during the period (1980-2006) for each of temperature (T), wind speed (W), relative humidity (RH), and pan evaporation (E) have been prepared ; input data has been divided into two groups including training set (172 observed points) and testing set (90 observed points). The monthly statistical parameters of the climatic variables are given in Table 1. The $\bar{x}$, x_{min} , x_{max} , S_x , C_k , and R denote the mean, minimum, maximum, standard deviation, coefficient of skewness, and correlation coefficient, respectively. It can see from the coefficient of determination between climatic variables and evaporation (Table 1) that temperature has a significant effect on evaporation.

A fuzzy toolbox in MATLAB environment software is used to build different fuzzy models. A Takagi-Sugeno fuzzy inference engine is selected to generate evaporation predictive model. Membership functions are extracted via subtractive clustering method. By specifying 0.5 for the calculated radius, three Gaussian membership functions are extracted for input variables which are labeled as low, medium, and high for temperature, wind speed, and relative humidity. The same labels are used for evaporation variable.

The performance of the various fuzzy models has been evaluated by using the error statistics root mean squared error (RMSE) and coefficient of determination (R^2). The statistic RMSE indicates the model ability to predict away from the mean, the optimal value is 0. The coefficient of determination R^2 measures the linear correlation between the measured and predicted values, the optimal value is 1. These statistical criteria have been defined as follows [13]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x})^2} \quad \text{... (3)}$$

Where:

x = measured values

$\hat{x}$ = predicted values

n = number of observations

$$R^2 = 1 - \frac{SSE}{SSy} \qquad \text{...(4)}$$

Where

$$SSE = \sum_{i=1}^{n}(x_i - \hat{x})^2$$

(5)

$$SSy = \sum_{i=1}^{n}(x_i - \bar{x})^2$$

(6)

$\bar{x}$ = mean of the measured values.

Table-1: The Monthly Statistical Parameters of Data Set Used in the Study

Data set	Unit	$\bar{x}$	x_{min}	x_{max}	S_x	C_k	R^2
W	m/s	4.03	1.60	9.8	1.47	1.00	0.506
RH	%	46.66	15.00	83.0	18.24	0.22	0.746
T	℃	24.44	8.40	39.6	9.49	-0.05	0.768
E	mm	280.52	24.00	959.6	195.2	0.69	1.000

Application and Results :

Table (2) summarizes statistical errors of the experiments and Figure (5) shows a comparison between the measured and estimated monthly averaged pan evaporation. From table (2), it is obvious that model 1 has the lowest *RMSE* (100.56) and highest R^2 (0.939) for testing period. The fuzzy model whose input was temperature only also performed very well. Due to the fact that temperature is a very easy to measure parameter, estimation of monthly evaporation from this parameter using fuzzy model is a robust and significant. Figure 6 shows fuzzy model built for this study for first model. The membership functions for this model are shown in Figure 7. The IF-THEN rules for this model are:

(1) **IF** T is low **THEN** E is low
(2) **IF** T is medium **THEN** medium
(3) **IF** T is high **THEN** high

Table-2: The RMSE and R^2 of Fuzzy Models in Training and Test Periods

Model No.	*Variables combination*	*Training*		*Testing*	
		RMSE	*R^2*	*RMSE*	*R^2*
Model 1	*W, RH, T*	*66.31*	*0.913*	*100.56*	*0.939*
Model 2	*RH, T*	*70.06*	*0.904*	*104.61*	*0.930*
Model 3	*T*	*77.70*	*0.876*	*106.14*	*0.904*

Discussion:

The available monthly data measurements of observed points T, W, and RH that have been considered for training and testing ranges are 172 and 90, respectively. The development of fuzzy models as functions of (T, W, RH), (T, W), and (T) were obtained with a similar magnitude of correlation coefficients 0.939, 0.930, and 0.904 for models 1, 2, and 3 respectively. Accordingly, it is of interest to observe that fuzzy model is powerful to estimate pan evaporation as a function of (T). This may be because air temperature is the most significant climatic factor which affects evaporation in the southern part of Iraq. It means that the variable (T) alone can effectively characterize most of the variation of pan evaporation values. It considerably reduces the number of climatic variables that are needed to be measured for estimation. The performance of each generated fuzzy model, that was evaluated based on two criteria analysis of RMSE and R^2, provides a harmonious response about the predictive ability of the models.

Conclusion and recommendation:

Three predictive models were generated successfully as a function of air temperature (T), wind speed (W), relative humidity (RH); it is significantly dominated by air temperature to estimate monthly pan evaporation. Furthermore, estimation of pan evaporation by using intelligent models shows excellent correlation and agreements with the observed evaporation measurements, it proves the predictive ability of the generated models. So, according to the fact that temperature is very easy to measure; the estimation of monthly evaporation depending on air temperature by using fuzzy model is significant. In addition, handling of fuzzy logic in MATLAB software is easy and it can be used by anyone not necessarily being familiar with this software.

The results appear to be a promising tool for modeling evaporation process with easy and low-cost constructing strategy. Thus, it would be useful to have the means of estimating pan evaporation from reliable climatic measurements with reasonable accuracy. In general, the study can be further extended by trying different combinations and applying fuzzy logic in other sites and modeling other variables as functions of related contributions.

It is recommended to utilize the integration of satellite images and Geographic Information System (GIS) to develop this strategy for modeling the temporal, spectral, and spatial natural variables in order to construct the Climatic Information System (CIS) in Iraq.

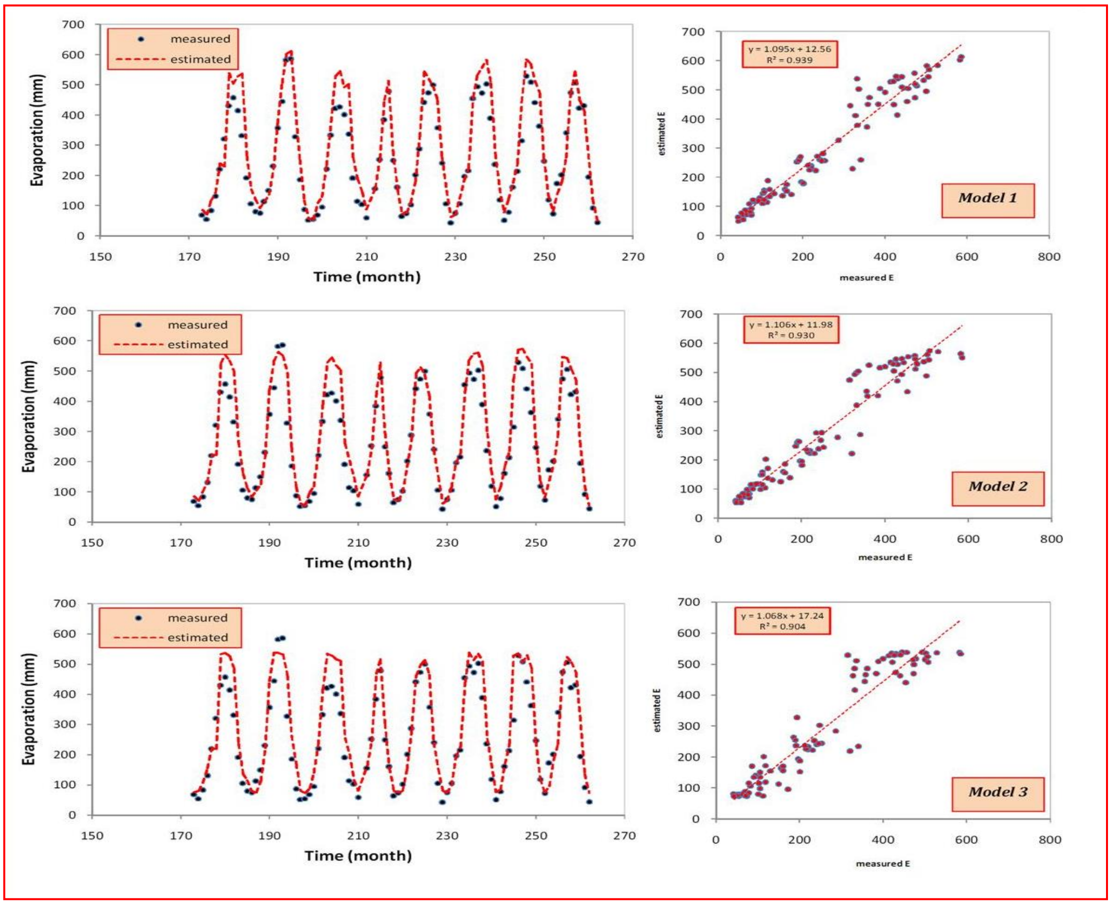

Fig.5: Comparison Between Measured and Estimated Evaporation Using Fuzzy Models for Testing Period.

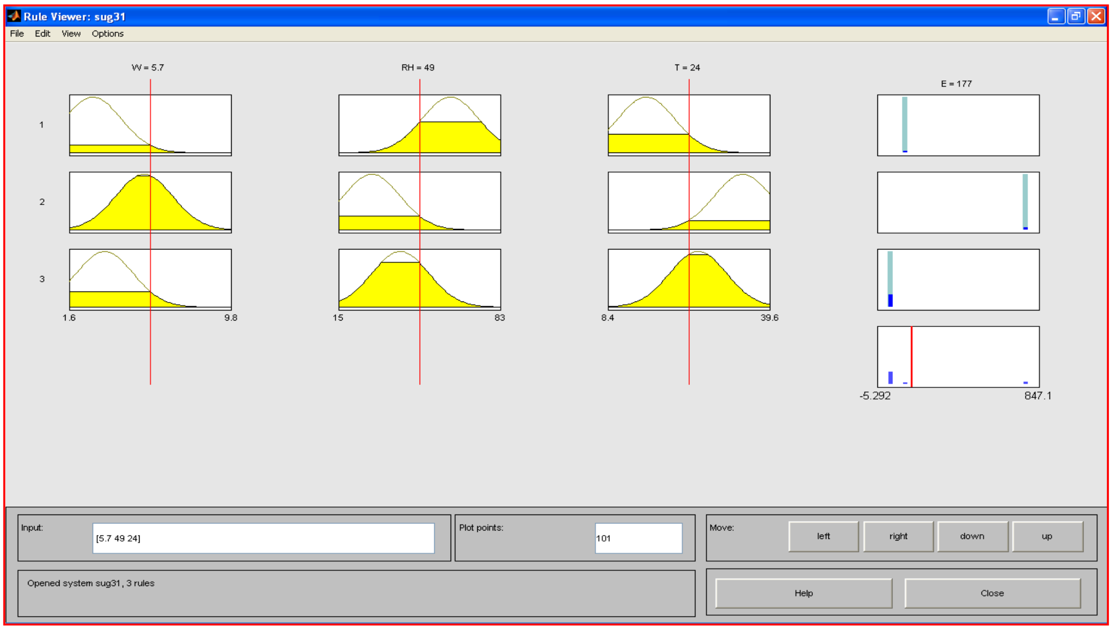

Fig.6: Fuzzy Inference System for First Model.

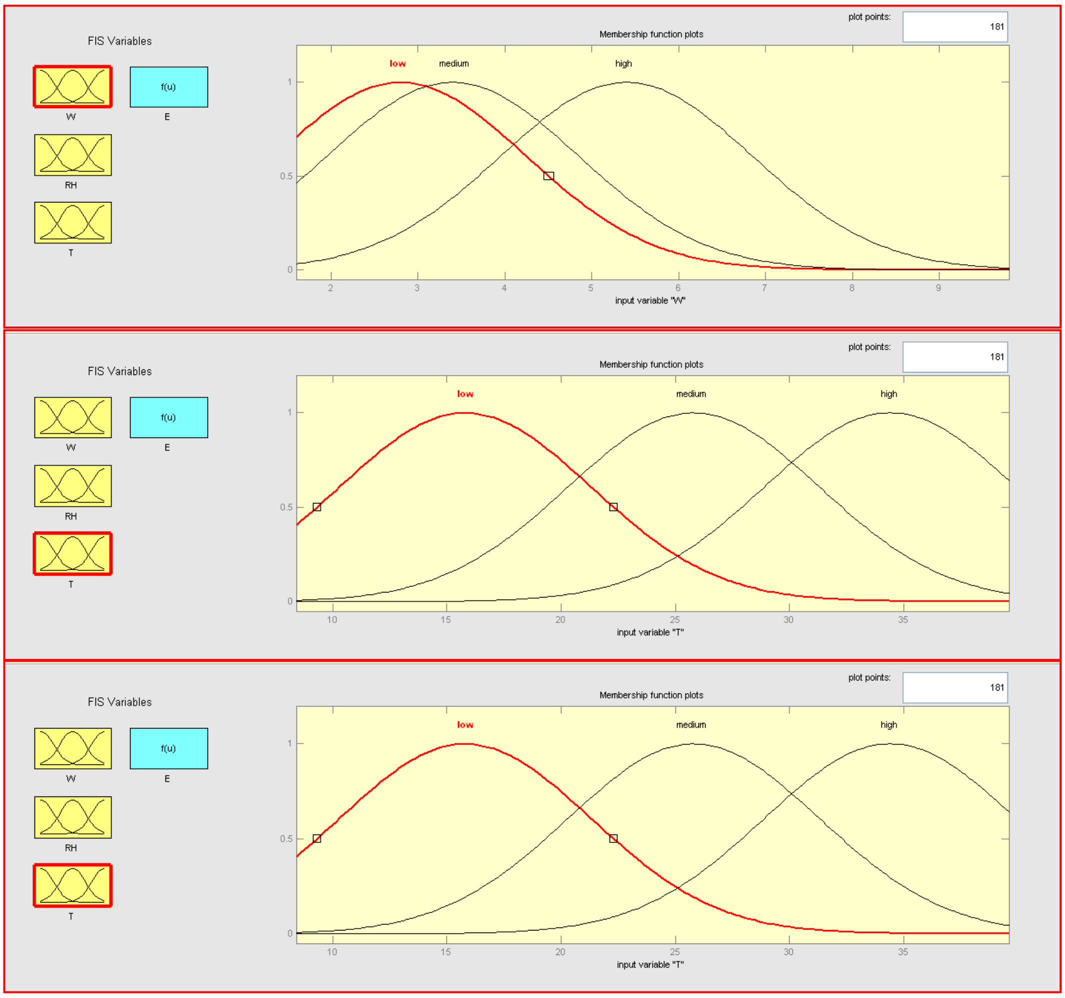

Fig.7: The Membership Functions for Wind Speed, Relative Humidity, and Temperature for the First Model

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استخدام المنطق المضبب لتقدير التبخر الشهري من المعلومات المناخية في العماره/ جنوب العراق

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الخلاصة:

يعد التبخر احد المكونات الرئيسة للدورة الهيدرولوجية في الطبيعة وعليه فان قياس مقدار التبخر ضروري لتقييم المتطلبات المائية فضلاً عن التخطيط لمشاريع الري. ان الهدف من هذه الدراسة هو للتحري عن امكانية تقنية المنطق المضبب للتنبؤ بقيمة التبخر الشهري من المعلومات المناخية الاخرى. اجريت الدراسة اعتماداً على 261 قياساً لكل من معدل درجات الحرارة الشهرية ومعدل سرعة الرياح الشهرية ومعدل الرطوبة النسبية الشهرية والمتوفرة في محطة انواء العمارة الواقعة في جنوب العراق. تم انشاء ثلاث نماذج مضببة باستخدام متغيرات ادخال متنوعة بهدف تقييم تاثير هذه المتغيرات على عملية التنبؤ. استخدم متغييرين احصائيين هما معامل التحديد ومقدار الخطا التربيعي لتقييم ادائية النماذج المطورة. اشارت النتائج بان النموذج الذي تكون متغيرات ادخاله درجة الحرارة والرطوبة النسبية وسرعة الرياح هي الافضل في تخمين قيم التبخر الشهري. فضلاً عن ذلك، فقد برهنت النتائج ايضاً على ان النموذج المضبب الذي يكون متغير ادخاله فقط درجة الحرارة هو الاخر نموذج فاعل في تخمين التبخر. بالاضافة الى ذلك، فان التطابق في القيم المقاسة والمتنبأ بها تؤكد بان المنطق المضبب هو طريقة ملائمة وذكية لنمذجة ديناميكية عملية التبخر.