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Abstract:

This study is intended to develop predictive models for estimating monthly and daily clear sky global solar radiation on a horizontal surface (\overline{H}) and maximum ultraviolet index (UVI_{max}) for some cities in Egypt. Choosing the preferred model depends on the best and most accurate results. The applicable empirical regression models are confined in multiple linear regression model, factorial regression model and response surface regression model. The investigated models are applied for forecasting daily and monthly clear sky global solar radiation and maximum UVI for cities of Sharm El-Sheikh, Aswan, Safaga and Cairo. The new developing predictive models are calibrated. The regression models for estimating global solar radiation are based on three major predictor variables and their interactions. The predictor variables are cosine solar zenith angle at mid-time between sunrise and solar noon ($\cos(\theta_{\rm ZMT})$), average air temperature (

 \overline{T}) and maximum possible sunshine duration (S₀). The developed empirical models are considered as a simplified statistical approach for daily estimation of \overline{H} because they depend on two monthly constant parameters (S₀ & $\cos(\theta_{\rm ZMT})$) and one daily changeable parameter (\overline{T}). Precision of UVI_{max} forecasting models is based on two parameters, which are accurate prediction results of clear sky global solar radiation and maximum temperature. Some statistical performance indicators measure the results accuracy of empirical

predictive models. The results of the developed models show that the factorial regression models and the response surface regression models give more precised results than the multiple linear regression models. The predicted results of global solar radiation and maximum ultraviolet index overlap the measured data in all months of the year.

Key words: Ultraviolet index, Clear sky global solar radiation, Cosine solar zenith angle, Air temperature and Maximum possible sunshine duration.

1. INTRODUCTION

Ultraviolet (UV) radiation is a form of electromagnetic radiation. The main source of UV radiation (rays) is the sun, although it can also come from man-made sources such as tanning beds and welding torches (American Cancer Society). Ionizing radiation is made up of energetic subatomic particles, ions or atoms moving at high speeds, and electromagnetic waves on the high-energy end of spectrum. the electromagnetic Gamma rays, X-rays, and the higher ultraviolet part of the electromagnetic spectrum are ionizing (Wikipedia, ionizing radiation). Higher energy UV rays often have enough energy to remove an electron from (ionize) an atom or molecule, making them a form of ionizing radiation (American Cancer Society), whereas the lower ultraviolet part of the electromagnetic the below UV. spectrum and all spectrum including visible light (including nearly all types of laserlight), infrared, microwaves, and radio waves are considered non-ionizing radiation (Wikipedia, ionizing radiation).

Solar radiation is an important natural factor because it forms the Earth's climate and has a significant effectiveness on the environment. Solar radiation is radiant energy that emitted by the sun from a nuclear fusion reaction that creates electromagnetic energy. About half of the radiation is in the visible short-wave part of the electromagnetic spectrum. The other half is mostly in the nearinfrared part, with some in the ultraviolet part of the spectrum (AmbientWeather). The estimation of global solar radiation is necessary for utilization the solar energy, design when proper

observation values are missing. The values of solar radiation in clear skies are useful for determination of the maximum performance heating and photovoltaic, moreover, for the design of air conditioning equipment in buildings or for the determination of thermal load their solar installations (El Mghouchi et al 2014).

The ultraviolet is a part of the solar spectrum (UV) that plays an important role in many processes in the biosphere. It has several beneficial influence but it may also be very harmful if UV exceeds "safe" levels. If the amount of UV radiation is enough high the selfprotection ability of some biological kinds is exhausted and the subject may be severely damaged. This is also concerned to the human organism, in specific the skin and the eyes. To avoid the harm from high UV exposures, people should limit their exposure to solar radiation by using protective procedures. The need to reach the public with simple-to-understand information about UV and its possible hazardous effects led scientists to define a parameter that can be used as an indicator of the UV exposures. This parameter is called the UVIndex (UVI). It is associated to the erythemal effects of solar UVradiation on human skin (Vanicek et al 1999).

The UV Dose (UVD) is directly associated to some health effect on humans. A 50% increase in erythemal UVD would consequently increase the rate at which the skin reddens by 50% (Wiegant et al. 2016). However, Hatfield et al., (2009) found statistical relations between exceedance of threshold UVI values and cancer incidence rates by investigating the relation between UV exposure and non-melanoma skin cancer using a statistical model. On the other hand, the acute effects of radiation exposure on skin are well known and result in severe skin burns. As well as, low levels of ionizing radiation to skin have been observed as well. The accompanying erythema, which resembled a burn, was painless; but, chronic radiation dermatitis following repeated exposure is usually extremely painful. Five progressive categories of radiation damage are observed in skin: (1) erythema, (2) transepithelial injury (moist desquamation), (3) ulceration, (4) necrosis, and (5) skin cancer (Miller et al., in press). The UVI is now widely used in many operational weather reports and forecasts. In Europe, for example, there are more than a dozen forecasting centers that release estimated UVI values for countries or regional areas. Different methods are used to predict the UVI.

Operational *UVI* forecasting has already been executed in many countries. The forecast methods vary from simple statistical methods has utilized for local areas to more complicated methods with global coverage and with forecast times from a few hours to several days, either for clear sky or all sky conditions (Vanicek et al 1999).

Several researchers have developed statistical models to predict monthly global solar radiation on a horizontal surface (\overline{H}) using multiple linear regression equations with different independent variables (predictor variables). Some of these predictors (weather parameters) are represented in, mean relative sunshine duration (S/S_0) , mean daily maximum temperature (T_{max}) , mean daily relative humidity (Rh), mean daily rainfall (R), mean daily temperature (\overline{T}) , ratio of maximum and minimum daily temperature and other weather parameters (Falayi et al 2008, Augustine and Nnabuchi 2009, Habbib 2011, Ituen et al 2012, Chen and Li 2012, Adhikari et al 2013, Namrata et al 2016).

El-shanshoury et al (2017), developed the model with multiple regression equation for Sharm El-Sheikh city. This model differs from other searchers empirical models that predict the monthly clear sky monthly global solar radiation future time (H). The developed multiple linear regression model is based on three predictor parameters as independent variables. These parameters are: monthly average cosine solar zenith angle at mid-time between sunrise and solar noon $\cos(\theta_{\text{ZMT}})$, monthly average daily mean temperature (T) and monthly average day length (S_0) . Two predictors are calculated $(S_0 \& \cos(\theta_{\text{ZMT}}))$ and one predictor is measured (T). This model is considered as a simplified statistical approach for daily estimation of H because it depends on two monthly constant predictors (S₀ & $\cos(\theta_{\rm ZMT})$) and one daily changeable predictor (\overline{T}). The developing models for estimating global solar radiation data, using commonly and available meteorological records such as temperature, are calibrated. The results of our previous work deduced that the uses of the above mentioned predictors reduce error rate nearly by 40-50% when compared with other searchers developed models. As well as, UVI_{max} is modeled for forecasting its monthly and daily value. The

statistical prediction UVI_{max} model is based on two independent variables for constructing the multiple linear regression equation. The first predictor is the monthly mean daily clear sky global solar radiation on a horizontal surface (\overline{H}) and the second predictor is monthly average maximum temperature (\overline{T}_{max}). After trying many weather parameters for modeling UVI_{max} , The model's predictors found more parameters that are accurate for UVI_{max} forecasting results than other parameters.

In this work new developed models are utilized with the same parameters of our previous work for estimating \overline{H} and UVI_{max} . The regression models are restricted in multiple linear regression model, factorial regression model and response surface regression model.

2. MATERIALS AND METHODS

The material data of monthly averaged clear sky global radiation on a horizontal surface (\overline{H} in kWh/m²/day) and monthly average air mean and maximum temperature at 10m above the earth ($T \& T_{max}$ in degrees celsius) is obtained from NASA meteorology (NASA). The data covered a period of 22 years (1983 – 2005) for Sharm El-Shiekh, Aswan Safaga and Cairo in Egypt. The latitude and longitude for Sharm El-Shiekh are 27.912° and 34.33°, respectively, for Aswan are 24.0908° and 32.8994°, for Safaga are 26.7453° and 33.95059°, and for Cairo are 30.06263° and 31.24967°. Maximum UVI data is obtained from weather2travel-climate guides (weather2travel).

In this work five developed models are utilized and compared using the same our previous work parameters $(T, \cos(\theta_{\text{ZMT}}) \text{ and } S_0)$ with different techniques. These models are applied for estimating monthly and daily clear sky global solar radiation on a horizontal surface (\overline{H} and H, respectively). As well as, three developed models are used for estimating monthly and daily UVI_{max} by using two parameters (\overline{H} or H and T_{max}). The regression models are multiple linear regression model, factorial regression model and response surface regression model.

Multiple regression designs are restricted to continuous predictor (independent) variables, as main effect ANOVA designs are to categorical predictor variables. Multiple regression designs contain the separate simple regression designs for 2 or more continuous predictor variables. The regression equation for a multiple regression design for the first-order effects includes 3 continuous predictor variables C, T and S is

 $Y = b_0 + b_1 C + b_2 T + b_3 S$ (Hill and Lewicki 2007).

Factorial regression designs are similar to factorial ANOVA designs, in which amalgamation of the levels of the factors are represented in the design. In factorial regression designs, there may be many more such possible combinations of distinct levels for the continuous independent variables than there are cases in the data set. That is, full-factorial regression designs are defined as designs in which all possible products of the continuous predictor variables are represented in the design. For example, the full-factorial regression design for two continuous predictor variables C and T will include the main effects (i.e., the first-order effects) of C and T and their 2way C by T interaction effect, which is represented by the product of C and T scores for each case. The regression equation is $Y = b_0 + b_0$ $b_1C + b_2T + b_3C^*T$. Factorial regression designs can also be fractional, that is, higher-order effects can be omitted from the design. A fractional design for 3 continuous predictor variables C, T and S will include the main effects and all 2-way interactions between the predictor variables is

 $Y = b_0 + b_1C + b_2T + b_3S + b_4C^*T + b_5C^*S + b_6T^*S$ (Hill and Lewicki 2007).

surface regression Quadratic Response response surface regression designs are a hybrid type of design with characteristics of both polynomial regression designs and fractional factorial regression designs. Quadratic response surface regression designs contain all the same effects of polynomial regression designs to degree 2 (second order), and additionally the 2-way interaction effects of the predictor variables. The regression equation for a quadratic response surface regression design for 2 continuous predictor variables C, T is $Y = b_0 + b_1C + b_2C^2 + b_3T + b_4T^2 + b_5C^*T$. As well as, 3 continuous predictor variables C, T and S is

$$Y = b_0 + b_1C + b_2C^2 + b_3T + b_4T^2 + b_5S + b_6S^2 + b_7C^*T + b_8C^*S + b_9T^*S$$
 (Hill and Lewicki 2007).

The suggested modified empirical model of clear sky global solar radiation has been estimated on the basis of measurements of monthly averaged clear sky global radiation on a horizontal surface and monthly average air mean temperature for under investigation states. Also, the empirical model is based on calculation of monthly mean daily extraterrestrial radiation and monthly average cosine solar zenith angle at mid-time between sunrise and solar noon and maximum possible sunshine duration for each state.

2.1. Empirical regression models to estimate monthly average daily clear sky global radiation (\bar{H})

The devolved regression models for estimating \overline{H} are based on three major predictor variables and their interactions. The major predictor parameters are $\cos(\theta_{\rm ZMT})$, T and S_0 . The response variable is monthly averaged clear sky insolation clearness index that calculated to be predictable of \overline{H} . Five empirical models are applied to estimate the monthly and daily average clear sky global radiation. \overline{H} is modeled as follow:

2.1.1. Predictive Multiple Linear Regression (MLR) model

The first-order regression model for three continuous predictor variables (C, T and S) takes the form

Model 1: $\frac{\overline{H}}{\overline{H}_{0}} = b_{0} + b_{1}C + b_{2}T + b_{3}S \qquad (1)$ $\overline{H}_{estimated} = (b_{0} + b_{1}C + b_{2}T + b_{3}S)^{*} \overline{H}_{0} \qquad (2)$

2.1.2. Predictive Factorial Regression (FR) model

The interaction regression model for two continuous predictor variables (C and T) takes the form

Model 2:

$$\frac{\overline{H}}{\overline{H}_0} = b_0 + b_1 C + b_2 T + b_3 C^* T$$
(3)
$$\overline{H}_{estimated} = (b_0 + b_1 C + b_2 T + b_3 C^* T)^* \overline{H}_0$$
(4)

The interaction regression model for three continuous predictor variables (C, T and S) takes the form

Model 3:

$$\frac{\bar{H}}{\bar{H}_{0}} = b_{0} + b_{1}C + b_{2}T + b_{3}S + b_{4}C^{*}T + b_{5}C^{*}S + b_{6}T^{*}S$$
(5)
$$\bar{H}_{estimated} = (b_{0} + b_{1}C + b_{2}T + b_{3}S + b_{4}C^{*}T + b_{5}C^{*}S + b_{6}T^{*}S)^{*} \bar{H}_{0}$$
(6)

2.1.3. Predictive Response Surface Regression (RSR) model

The second-order polynomial regression model for two continuous predictor variables (C and T) takes the form

Model 4:

$$\frac{H}{\overline{H}_{0}} = b_{0} + b_{1}C + b_{2}C^{2} + b_{3}T + b_{4}T^{2} + b_{5}C^{*}T$$
(7)
$$\overline{H}_{estimated} = (b_{0} + b_{1}C + b_{2}C^{2} + b_{3}T + b_{4}T^{2} + b_{5}C^{*}T)^{*} \overline{H}_{0}$$
(8)

The second-order polynomial regression model for three continuous predictor variables (C, T and S) takes the form

Model 5:

$$\frac{\bar{H}}{\bar{H}_{0}} = b_{0} + b_{1}C + b_{2}C^{2} + b_{3}T + b_{4}T^{2} + b_{5}S + b_{6}S^{2} + b_{7}C^{*}T + b_{8}C^{*}S + b_{9}T^{*}S \quad (9)$$

$$\bar{H}_{estimated} = (b_{0} + b_{1}C + b_{2}C^{2} + b_{3}T + b_{4}T^{2} + b_{5}S + b_{6}S^{2} + b_{7}C^{*}T + b_{8}C^{*}S + b_{9}T^{*}S)^{*}\bar{H}_{0} \quad (10)$$

Where, b's are the coefficients of predictor variables, $\overline{H}/\overline{H_0}$ is monthly average clear sky insolation clearness index, \overline{H} is the measure of monthly mean daily clear sky global solar radiation on a horizontal surface, $\overline{H_0}$ is monthly mean daily extraterrestrial radiation KW/m², C represents monthly average cosine solar zenith angle at mid-time

between sunrise and solar noon $\cos(\theta_{\text{ZMT}})$, T represents monthly average daily mean temperature, S represents monthly average day length (S_0) and \overline{T} is daily mean temperature.

The values of the monthly average daily extraterrestrial radiation (\bar{H}_0) can be calculated from the following equation (Duffie and Beckman 2013).

$$\overline{H}_{0} = \frac{24}{\pi} I_{sc} E_{0} \left[\cos\phi \cos\delta \sin w_{s} + \frac{\pi w_{s}}{180} \sin\phi \sin\delta \right] (11)$$
$$E_{0} = 1 + 0.033 \cos \left[\frac{360d_{n}}{365} \right]$$

where, I_{SC} is the solar constant (=1.367 KWm⁻²), ϕ is the latitude of the site, δ is the solar declination, w_s is the mean sunrise hour angle for the given month, and d_n is the number of days of the year starting from the first of January (the Julian day number).

The solar declination (δ) and the mean sunrise hour angle (w_s) can be calculated by the following equations:

$$\delta = 23.45 \sin \left[360 \frac{(d_n + 284)}{365} \right]$$
$$w_s = \cos^{-1} \left(-\tan\phi \tan\delta \right)$$

The maximum possible sunshine duration (S_d) (or monthly average day length) which is related to w_s , can be computed by using the following equation:

$$S_0 = \frac{2}{15} w_s$$
 (12)

Monthly average cosine solar zenith angle at mid-time between sunrise and solar noon is calculated according the following formula (NASA).

$$\cos(\theta_{ZMT}) = f + g[(g - f) / 2g]^{\frac{1}{2}}$$
(13)
where, $f = \sin(\phi)\sin(\delta)$, $g = \cos(\phi)\cos(\delta)$

Average daily mean temperature ($ar{T}$) is calculated as follows:

$$\overline{T} = \frac{(T_{\max imum} + T_{\min imum})}{2}$$
(14)

The estimated daily estimating daily clear sky global solar radiation on a horizontal surface (*H*) is derived from monthly \overline{H} estimation model.

2.2. Empirical regression models to estimate the monthly maximum ultraviolet index (UVI_{max})

The statistical forecasting models for estimation of monthly average maximum ultraviolet index are based on two parameters to construct the regression models. The first parameter is $\overline{H}_{estimated}$ and the second parameter is \overline{T}_{max} . Models 6-8 present the investigated forecasting models.

2.2.1. Predictive multiple linear regression model Model 6:

 $UVI_{max} = \beta_0 + \beta_1 \overline{H} + \beta_2 \overline{T}_{max} \quad (15)$

2.2.2. Predictive factorial regression model Model 7: $UVI_{max} = \beta_0 + \beta_1 \overline{H} + \beta_2 \overline{T}_{max} + \beta_3 \overline{H} * \overline{T}_{max}$ (16)

2.2.3. Predictive response surface regression Model 8: $UVI_{max} = \beta_0 + \beta_1 \overline{H} + \beta_2 \overline{T}_{max} + \beta_3 \overline{H}^2 + \beta_4 \overline{T}_{max}^2 + \beta_5 \overline{H} * T_{max}$ (17)

Where, β 's are the coefficients of predictor variables, \overline{H} and \overline{T}_{max} are considered more accurate effective for UVI_{max} forecasting results than other weather parameters.

2.3. Statistical evaluation

The performance of models will be judged by the statistical indicators such as Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Bias Error (MABE) and correlation coefficient (CC). These indicators are the ones that are applied most commonly in comparing the models of solar radiations. The test of MBE provides information on the long-term performance of the correlation by allowing a comparison of the actual deviation between estimated and measured values term by term (Al-

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Hassany 2014, El-Mghouchi et al 2014). A positive MBE value means an over-estimation of the estimated values and a negative value means an under-estimation of the estimated values (Tian et al 2018). The RMSE is always positive; this test provides information on the short-term performance of the correlation by arranging a term by term comparison of the real differences between the estimated values and the measured values (Almorox 2011). RMSE is a good measure of precision. The MAPE is an overall measure of forecast accuracy (Almorox 2011), computed from the absolute mean relative difference between the global solar radiation of the measured data and those estimated by proposed model (El-Mghouchi et al 2014). The MABE gives the absolute value of bias error and it is a measure of the correlation goodness (Almorox 2011). It is recommended that a zero value for MBE is ideal while a low RMSE, MABE and MAPE are desirable. The correlation coefficient reflects the quality of the model: the higher CC (closed to 1), the highest model quality. The expression of each statistical indicator is given in the following forms (Almorox 2011).

$$\begin{split} MBE &= \frac{\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{i,measured}\right)}{N} , \\ MABE &= \frac{\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{i,measured}\right)}{N} , \\ MABE &= \sqrt{\frac{\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{i,measured}\right)^{2}}{N}} \\ RMSE &= \sqrt{\frac{\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{estimated}\right)^{2}}{N}} \\ CC &= \frac{\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{estimated}\right) \left(\overline{H}_{i,measured} - \overline{H}_{measured}\right)}{\sqrt{\left(\sum_{i=1}^{n} \left(\overline{H}_{i,estimated} - \overline{H}_{estimated}\right)^{2}\right) \left(\sum_{i=1}^{n} \left(\overline{H}_{i,measured} - \overline{H}_{measured}\right)^{2}\right)}} \\ MAPE &= \frac{1}{N} \sum_{i=1}^{n} \left| \frac{\overline{H}_{i,measured} - \overline{H}_{i,estimated}}{\overline{H}_{i,measured}} \right| *100, \quad \text{Where, } N \text{ is Number of the observations.} \end{split}$$

3. RESULTS AND DISCUSSION

3.1. Empirical regression models and the prediction of monthly and daily average clear sky global solar radiation (\overline{H} and H)

Various meteorological data are related to monthly average clear sky clearness index $\left(\frac{\bar{H}}{\bar{H}_0}\right)$. Empirical models are developed to estimate monthly and daily global radiation.

3.1.1. Empirical development regression models for estimating monthly average clear sky clearness index

Regression analysis of five models is employed to estimate the monthly average clear sky global solar radiation (\overline{H}) . The empirical models are equations 1, 3, 5, 7 and 9. The following tables (1-4) show the coefficients of the empirical regression models to estimate $\overline{H}_{\overline{H}_0}$

for Sharm El-Sheikh, Aswan, Safaga and Cairo, respectively.

Table 1: The coefficients of the empirical regression estimation models for Sharm El-Sheikh

	Regression Coefficients									
Models	b_{θ}	<i>b</i> 1	b_2	b_3	b_4	b_5	b_{6}	<i>b</i> ₇	b_8	$b_{\mathscr{D}}$
Model 1	0.6857	0.42213	-0.00295	-0.01031						
Model 2	0.5374	0.47148	0.00192	-0.00825						
Model 3	1.331	0.70484	-0.00903	-0.11461	-0.0317	0.05895	0.00212			
Model 4	0.8843	-1.1197	2.8086	0.01045	0.00072	-0.08043				
Model 5	-43.9871	-28.810	57.884	0.17202	0.00531	8.20306	-0.16303	-0.27083	-4.2050	0.0227

Table 2: The coefficients of the empirical regression estimationmodels for Aswan

Regression Coefficients										
Models	b_{o}	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_s	b_{g}
Model 1	0.5203	-0.01807	0.79727	-0.00353						
Model 2	0.0960	1.1528	0.01204	-0.02533						
Model 3	-1.8382	4.9737	-0.01216	0.17303	-0.04217	-0.3379	0.00294			
Model 4	0.2255	0.4241	1.8283	0.01918	0.00065	-0.0882				
Model 5	-35.6882	7.4866	39.6735	-0.05842	-0.0007	5.63753	-0.07642	-0.00571	-5.4167	0.0079

Table 3: The coefficients of the empirical regression estimationmodels for Safage

Regression Coefficients										
Models	b_{θ}	<i>b</i> 1	b_2	b_3	b_4	b_5	b_6	b_7	b_s	b_{g}
Model 1	0.45123	0.14168	-0.00578	0.02337						
Model 2	0.77901	0.04318	-0.01659	0.01821						
Model 3	1.72539	2.60898	-0.05447	-0.19866	-0.06797	-0.02137	0.007618			
Model 4	1.210684	-2.12527	3.761624	3.06E- 05	0.000929	-0.08158				
Model 5	-40.9489	-1.096	50.47372	-0.11439	-0.00118	6.99859	-0.11606	-0.00577	-6.0232	0.0142

Table 4: The coefficients of the empirical regressionestimation models for Cairo

	Regression Coefficients									
Models	b_{θ}	b_1	b_2	b_3	<i>b</i> 4	b_5	b_6	<i>b</i> 7	b_s	$b_{\mathscr{D}}$
Model 1	0.51251	0.25875	-0.00499	0.008132						
Model 2	0.62571	0.22771	-0.00937	0.007464						
Model 3	1.23308	-0.1230	-0.00957	-0.0800	-0.00707	0.07803	0.000735			
Model 4	0.73562	-0.3226	0.73023	-0.00517	9.6E-05	-0.00653				
Model 5	-44.0632	-10.8823	73.8287	-0.03741	-0.00086	7.73516	-0.08363	0.01431	-7.8058	0.00502

3.1.2. Statistical evaluation of the regression models

The results of the validation of the five models that estimate \overline{H} for Sharm El-Sheikh, Aswan, Safaga and Cairo cities are shown in Table 5.

Table 5: Statistical indicators of accuracy for estimated regression models of Sharm El-Sheikh, Aswan, Safaga and Cairo

Sharm	MBE	RMSE	MAPE	MABE	CC	Aswan	MBE	RMSE	MAPE	MABE	CC
Model 1	-9.8E-05	0.0323	0.4216	0.0274	0.9998	Model 1	0.00032	0.1117	1.3882	0.0910	0.9967
Model 2	-0.00022	0.0336	0.4017	0.0269	0.9998	Model 2	-0.00018	0.0970	1.0706	0.0753	0.9975
Model 3	-0.00147	0.0312	0.3569	0.0240	0.9998	Model 3	-0.01081	0.0680	0.8545	0.0577	0.9991
Model 4	-0.0017	0.0290	0.3071	0.0207	0.9998	Model 4	0.00026	0.0854	0.9185	0.0645	0.9981
Model 5	0.00696	0.0095	0.1205	0.0075	1.0000	Model 5	0.06041	0.0797	1.0022	0.0667	0.9994
Safaga	MBE	RMSE	MAPE	MABE	CC	Cairo	MBE	RMSE	MAPE	MABE	CC
Safaga Model 1	MBE -0.00070	RMSE 0.0801	MAPE 0.9261	MABE 0.0606	CC 0.9982	Cairo Model 1	MBE -0.00072	RMSE 0.0560	MAPE 0.7191	MABE 0.0451	CC 0.9993
Safaga Model 1 Model 2	MBE -0.00070 0.00076	RMSE 0.0801 0.0795	MAPE 0.9261 0.8541	MABE 0.0606 0.0576	CC 0.9982 0.9982	Cairo Model 1 Model 2	MBE -0.00072 -0.00026	RMSE 0.0560 0.0556	MAPE 0.7191 0.6587	MABE 0.0451 0.0418	CC 0.9993 0.9993
Safaga Model 1 Model 2 Model 3	MBE -0.00070 0.00076 -0.00109	RMSE 0.0801 0.0795 0.0411	MAPE 0.9261 0.8541 0.4367	MABE 0.0606 0.0576 0.0299	CC 0.9982 0.9982 0.9996	Cairo Model 1 Model 2 Model 3	MBE -0.00072 -0.00026 0.00097	RMSE 0.0560 0.0556 0.0549	MAPE 0.7191 0.6587 0.6278	MABE 0.0451 0.0418 0.0401	CC 0.9993 0.9993 0.9993
Safaga Model 1 Model 2 Model 3 Model 4	MBE -0.00070 0.00076 -0.00109 -0.00153	RMSE 0.0801 0.0795 0.0411 0.0680	MAPE 0.9261 0.8541 0.4367 0.6782	MABE 0.0606 0.0576 0.0299 0.0455	CC 0.9982 0.9982 0.9996 0.9987	Cairo Model 1 Model 2 Model 3 Model 4	MBE -0.00072 -0.00026 0.00097 -0.00053	RMSE 0.0560 0.0556 0.0549 0.0547	MAPE 0.7191 0.6587 0.6278 0.6435	MABE 0.0451 0.0418 0.0401 0.0412	CC 0.9993 0.9993 0.9993 0.9993

The obtained results of Sharm El-Sheikh and Cairo show that there are a remarkable agreement between the measured and predicted values using different regression models except Model 5 (the secondorder polynomial regression model for three continuous predictor variable). This model gives high accurate results than other models according to the values of RMSE, MAPE, MABE and CC.

The suitable model for Aswan and Safaga cities is different than the suitable one for Sharm El-Sheikh and Cairo. The interaction regression model for three continuous predictor variables (Model 3) fits Aswan and Safaga more than other regression models.

According to the value of MBE, Model 1 is appropriate for Sharm and Safaga as well as model 2 for Aswan and Cairo. But the value of MBE will not be taken into consideration, due to the disadvantage associated with MBE is that the errors of different signs may cancel each other. The smaller the MBE value, the better the model performs. However, some few values in the sum can produce a significant increase in the parameter. The MBE offers information regarding over-estimation or under-estimation of the estimated data;

low values of these mean errors are desirable, though it should be noted that over-estimation of an individual data element will cancel under-estimation in a separate observation (Almorox 2011).

3.1.3. The predictive model to estimate monthly average clear sky global solar radiation (\overline{H})

From the previous analysis of models validation, the best model for estimating the \overline{H} is the model that has three continuous predictor variables. The monthly average clear sky global solar radiation on a horizontal surface for each investigated city is:

For Sharm El-Sheikh, the response surface regression model (model 5, Table 1).

$$\begin{split} H_{estimated} &= (-43.9871 - 28.810C + 57.884C^2 + 0.17202T + 0.00531T^2 + 8.20306S - 0.16303S^2 - 0.27083C^*T - 4.2050C^*S - 0.0227T^*S)^* \ \overline{H}_0 \end{split}$$

For Aswan, the factorial regression model (model 3, Table 2). $\overline{H}_{estimated} = (-1.8382 + 4.9737C - 0.01216T + 0.17303S - 0.04217C*T - 0.3379C*S + 0.00294T*S)* \overline{H}_{0}$

For Safaga, the factorial regression model (model 3, Table 3). $\overline{H}_{estimated} = (1.72539+2.60898C - 0.05447T - 0.19866S - 0.06797C*T - 0.02137C*S + 0.007618*S)* \overline{H}_{0}$

For Cairo, the response surface regression model (model 5, Table 4). $\overline{H}_{estimated} = (-44.0632 \cdot 10.8823C + 73.8287C^2 \cdot 0.03741T - 0.000861T^2 + 7.73516S - 0.08363S^2 + 0.01431C^*T - 7.8058C^*S + 0.00502T^*S)^* \overline{H}_0$

3.1.4. The results of $\overline{H}_{estimated}$ of the best selected model in each city

The values of \overline{H}_0 , $\overline{H}/_{\overline{H}_0}$, $\cos(\theta_{\text{ZMT}})$, T, S_0 , and $\overline{H}_{estimated}$ are presented in Table 6-10. $\overline{H}_{estimated}$ is calculated form the best selected models (Model 5 for Sharm El-Sheikh & Cairo, and Model 3 for Aswan & Safaga (the equations given in the previous section).

Table 6: Monthly average meteorological data and clear sky globalsolar radiation for Sharm El-Sheikh using Model 5

MONTH	H _{measured}	$\overline{H}_{0}_{_{(KW/m^2/day)}}$	$ar{H}_{{}_{measured}} / ar{H}_{0}$	$cos(\theta_{\rm ZMT})$	Т	S_{θ}	$ar{H}_{estimated} ig/ ar{H}_0$	$ar{H}_{estimated}_{_{(KW/m^2/day)}}$
JAN	4.55	6.2563	0.72727	0.47335	15.8	10.4467	0.7295	4.564
FEB	5.58	7.4431	0.74969	0.53653	16.5	11.0364	0.7507	5.587
MAR	6.88	8.9678	0.76719	0.61038	19.6	11.8304	0.7695	6.901
APR	7.88	10.308	0.76443	0.66447	24.0	12.6801	0.7652	7.888
MAY	8.34	11.089	0.75206	0.68588	27.7	13.3882	0.7534	8.355
JUN	8.53	11.349	0.75163	0.68930	30.0	13.7394	0.7518	8.532
JUL	8.30	11.187	0.74197	0.68823	31.3	13.5742	0.7426	8.307
AUG	7.84	10.556	0.74270	0.67545	31.4	12.9619	0.7424	7.837
SEPT	6.98	9.3964	0.74284	0.63373	30.1	12.1415	0.7429	6.980
OCT	5.69	7.8727	0.72275	0.56229	26.5	11.2938	0.7229	5.692
NOV	4.72	6.5046	0.72564	0.48926	21.8	10.5924	0.7265	4.725
DEC	4.22	5.8725	0.71861	0.45275	17.6	10.2591	0.7194	4.225

Table 7: Monthly average meteorological data and clear sky global solar radiation for Aswan using Model 3

MONTH	H _{measured} (KW/m ² /day)	$ar{H}_0^{(\mathrm{KW/m^{2/}})}_{\mathrm{day)}}$	$\bar{H}_{measured} / \bar{H}_0$	$\cos(\theta_{\rm ZMT})$	Т	S_{θ}	${ar H}_{{\scriptscriptstyle estimated}} / {ar H}_{0}$	<i>H</i> _{estimated} (KW/m ² /day)
JAN	4.55	6.8628	0.6630	0.50713	15.8	10.6916	0.66835	4.587
FEB	5.77	7.9584	0.7250	0.56584	16.8	11.1874	0.71999	5.730
MAR	6.89	9.3146	0.7397	0.63264	20.7	11.8569	0.74274	6.918
APR	7.72	10.4358	0.7398	0.67864	26.0	12.5737	0.73035	7.622
MAY	7.86	11.0251	0.7129	0.69370	29.9	13.1697	0.72340	7.976
JUN	8.25	11.1917	0.7372	0.69429	31.7	13.4644	0.72749	8.142
JUL	8.00	11.0731	0.7225	0.69452	32.5	13.3259	0.72113	7.985
AUG	7.47	10.6064	0.7043	0.68701	32.4	12.8112	0.70946	7.525
SEPT	6.93	9.6632	0.7172	0.65304	31.0	12.1194	0.70668	6.829
OCT	5.79	8.3337	0.6948	0.58941	27.3	11.4043	0.70027	5.836
NOV	4.76	7.0876	0.6716	0.52201	21.8	10.8139	0.66989	4.748
DEC	4.22	6.5004	0.6492	0.48779	17.4	10.5343	0.64359	4.185

4.18

Table 8: Monthly average meteorological data and clear sky globalsolar radiation for Safaga using Model 3

MONTH	H _{measured} (KW/m²/day)	$ar{H}_0^{_{(KW/m^{2/}}}_{_{day)}}$	$\bar{H}_{_{measured}}/\bar{H}_{_0}$	$\cos(\theta_{\rm ZMT})$	Т	S_{θ}	$ar{H}_{estimated} / ar{H}_{0}$	H _{estimated}
JAN	4.41	6.4436	0.68440	0.48391	14.7	10.5233	0.68274	4.399
FEB	5.36	7.6037	0.70492	0.54575	15.6	11.0836	0.70688	5.375
MAR	6.42	9.0780	0.70721	0.61747	19.3	11.8387	0.70760	6.424
APR	7.20	10.3519	0.69553	0.66912	24.3	12.6468	0.69021	7.145
MAY	7.50	11.0744	0.67724	0.68861	28.2	13.3198	0.68535	7.590
JUN	7.91	11.3049	0.69969	0.69117	30.5	13.6533	0.69275	7.832
JUL	7.69	11.1562	0.68930	0.69050	31.6	13.4965	0.69117	7.711
AUG	7.10	10.5760	0.67133	0.67931	31.5	12.9148	0.67344	7.122
SEPT	6.23	9.4823	0.65701	0.63993	29.9	12.1346	0.65316	6.194
OCT	5.15	8.0171	0.64238	0.57084	26.0	11.3283	0.64478	5.169
NOV	4.33	6.6850	0.64772	0.49951	20.8	10.6617	0.64696	4.325
DEC	4.00	6.0659	0.65942	0.46368	16.4	10.3453	0.65974	4.002

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Table 9: Monthly average meteorological data and clear sky global solar radiation for Cairo using Model 5

MONTH	H _{measured} (KW/m²/ day)	$\overline{H}_0^{(\mathrm{KW/m^{2/}})}_{\mathrm{day)}}$	$\bar{H}_{measured} / \bar{H}_0$	$\cos(\theta_{\rm ZMT})$	Т	$S_{ heta}$	$\bar{H}_{estimated}$ \bar{H}_{0}	<i>H</i> _{estimated} (KW/m²/day)
JAN	3.86	5.9068	0.65349	0.45335	13.3	10.3004	0.65247	3.854
FEB	4.72	7.1401	0.66106	0.51895	13.6	10.9466	0.66164	4.724
MAR	5.99	8.7551	0.68417	0.59666	16.0	11.8147	0.68207	5.972
APR	7.07	10.2172	0.69197	0.65517	20.1	12.7433	0.69132	7.063
MAY	7.46	11.1074	0.67162	0.68006	23.4	13.5185	0.67114	7.455
JUN	7.76	11.4197	0.67953	0.68502	26.3	13.9037	0.67525	7.711
JUL	7.35	11.2325	0.65435	0.68325	28.2	13.7225	0.65592	7.368
AUG	6.89	10.5087	0.65565	0.66759	28.2	13.0517	0.64956	6.826
SEPT	5.93	9.22796	0.64261	0.62162	26.3	12.1546	0.64455	5.948
OCT	4.76	7.59878	0.62642	0.54590	22.8	11.2281	0.62252	4.730
NOV	3.85	6.16713	0.62428	0.46982	18.9	10.4603	0.62470	3.853
DEC	3.49	5.51261	0.63309	0.43207	14.8	10.0945	0.63201	3.484



Figures 1-4 show the relation between the measured and predicted values of \overline{H} using the suitable empirical development model for each city. It is clear from the figures that there is an excellent correlation and a perfect relationship exists between the measured and estimated

values of monthly average of clear sky global solar radiation. However, the estimated \overline{H} overlaps the measured \overline{H} in all months of the year. Figures 1-4 illustrate also that the values in the month range May-July belong to the maximum value for the global solar radiation. Moreover, the estimated high global solar radiation of the summer months is required for detailed study to get the maximum benefits of solar energy for the production of electric power.

3.1.5. Application of the predictive regression model for estimating daily clear sky global solar radiation on a horizontal surface (H) for Cairo city

To predict the daily clear sky global solar radiation (*H*) in Cairo, substitute the values of $\cos(\theta_{\rm ZMT})$ and S_0 , according to the corresponding month for the day that to be predicted, in the predictive response surface regression model (Model 5, Table 4). \overline{T} is calculated from daily changing maximum and minimum temperature (eqn. 14). For example, to predict *H* of few days for some months, substitute the monthly values of S_0 , $\cos(\theta_{\rm ZMT})$ and \overline{H}_0 (from Table 9, for each month which corresponding that day to be predicted) in the following equation,

 $\bar{H}_{estimated} = (.44.0632 \cdot 10.8823C + 73.8287C^2 \cdot 0.03741T - 0.000861T^2 + 7.73516S - 0.08363S^2 + 0.01431C^*T - 7.8058C^*S + 0.00502T^*S)^* \bar{H}_0$

The results are presented in Table 10.

 Table 10: Some estimated values of daily clear sky global solar

 radiation in Cairo

Date	\overline{H}_{0}	$\cos(\theta_{\rm ZMT})$	\overline{T}	S_{θ}	$H_{estimated}/\overline{H}_0$	H _{estimated} KW/m²/ day
26-4-2018	10.2172	0.65517	(29+18)/2 = 23.50	12.743	0.68581	7.007
29-4-2018	10.2172	0.65517	(35+21.5)/2=28.25	12.743	0.64481	6.588
11-5-2018	11.1074	0.68006	(32+20)/2 = 26.00	13.519	0.66499	7.386
23-5-2018	11.1074	0.68006	(38.5+26.5)/2=32.5	13.519	0.59873	6.650
31-5-2018	11.1074	0.68006	(33+23)/2 = 28.00	13.519	0.65234	7.246
10-6-2018	11.4197	0.68502	(38.5+26)/2=32.25	13.904	0.62627	7.152
27-6-2018	11.4197	0.68502	(42.5+25)/2=33.75	13.904	0.60430	6.901
04-7-2018	11.2325	0.68325	(42+24)/2 = 33.00	13.723	0.60098	6.751
10-7-2018	11.2325	0.68325	(38+25)/2 = 31.50	13.723	0.62240	6.991

From Table 10, it should be noted that whenever the value of average day temperature increases, the value of global solar radiation decreases according to the corresponding days in the same month. That means, there is inversely relationship between the value of average temperature and the value of global solar radiation. The choice of the month range May-July is considered in this work because the effect of UVI is maximum. The prediction value of H is used for forecasting daily value of UVI.

3.2. Empirical regression models and the prediction of monthly and daily maximum ultraviolet index

In this section, three models are applied to estimate the monthly average UVI_{max} (eqns. 15-17) and are compared as attempt to deduce the best of one for each city. There is strong relationship between \overline{H} , \overline{T}_{max} , as independent variable, and UVI, as dependant variable. That refers to try substituting many weather parameters for modeling UVI_{max} . Those model's predictors are found to give more accurate parameters for UVI_{max} forecasting results than other weather parameters.

3.2.1. The predictive model to estimate monthly average UVI_{max}

From the regression analysis and according to accuracy indicators, it has been found that the factorial regression model gives the best results in estimating monthly average UVI_{max} for Sharm El-Sheikh and Cairo. As well as, the response surface regression model gives the best results for Aswan and Safaga. The interaction and second-order polynomial regression models for two continuous predictor variables ($\overline{H} \& \overline{T}_{max}$) are considered the suitable models for applications (Models 7 & 8). The best predictive model for estimation of monthly average UVI_{max} for each investigated city is :

For Sharm El-Sheikh,

 $UVI_{max} = -7.62325 + 1.9181 \,\overline{H} + 0.25144 \,\overline{T}_{max} - 0.0196 \,\overline{H} * \overline{T}_{max}$

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For Aswan,

 $\begin{aligned} & UVI_{max} = -11.7285 + 5.5139 \ \bar{H} + 0.07192 \ \bar{T}_{max} - 0.22392 \ \bar{H}^2 + 0.00879 \ \bar{T}_{max}^2 - 0.05541 \ \bar{H} * T_{max} \\ & For Safaga, \\ & UVI_{max} = -27.0589 + 5.7864 \ \bar{H} + 0.9889 \ \bar{T}_{max} - 1.2353 \ \bar{H}^2 - 0.04814 \ \bar{T}_{max}^2 + 0.33922 \ \bar{H} * T_{max} \\ & For Cairo, \\ & UVI_{max} = -5.2032 + 1.07451 \ \bar{H} + 0.24131 \ \bar{T}_{max} + 0.0011 \ \bar{H} * \bar{T}_{max} \end{aligned}$

The results of the performance indicators show that the error rate for each predictive model is being reduced in varying proportions when compared with each other (Multiple Linear Regression (MLR) model, Factorial Regression (FR) model and response surface regression (RSR) model). The error rate of Sharm El-Sheikh predictive model is reduced by about 10% from MLR model and it has almost the same values of as those of RSR model. The error rate of Aswan predictive model is reduced by about 65% from MLR and 45% from FR models. The error rate of Safaga predictive model is reduced by about 65% from MLR and 50% from FR models. The error rate of Cairo predictive model is reduced by about 65% from MLR and 55% from RSR models. Figures 5-8 show the relationship between the measured and estimated values of monthly average UVI_{max} using the suitable

estimated values of monthly average UVI_{max} using the suitable empirical developed model for each city. It is clear from the figures that there is an excellent correlation and a perfect relationship exists between the measured and estimated monthly average UVI_{max} .



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The estimated value of daily UVI_{max} is calculated from monthly UVI_{max} estimation models, by substituting with the value of daily clear sky global solar radiation on a horizontal surface ($H_{estimated}$) and daily maximum temperature (T_{max}).

3.2.2. Application of the predictive regression model for estimating daily UVI_{max} for Cairo city

For example, to estimate the daily value of UVI_{max} of the same days in Table10, are has to substitute the values of $H_{estimated}$ and daily T_{max} (from Table 10) in the following interaction regression model (FR model):

 $UVI_{max} = -5.2032 + 1.07451 \,\overline{H} + 0.24131 \,\overline{T}_{max} + 0.0011 \,\overline{H} * \overline{T}_{max}$

The results of daily *UVI_{max}* values are presented in Table 11:

Data	Н	T _{max}	Estimated UVI _{max}
Date	<i>estimated</i>		
26-4-2018	7.007	29.0	9.547
29-4-2018	6.588	35.0	10.575
11-5-2018	7.386	32.0	10.715
23-5-2018	6.650	38.5	11.514
31-5-2018	7.246	33.0	10.809
10-6-2018	7.152	38.5	12.075
27-6-2018	6.901	42.5	12.790
04-7-2018	6.751	42.0	12.498
10-7-2018	6.991	38.0	11.771

Table 11: Some estimated values of daily UVImax in Cairo

From Table 11, it should be noted that whenever the value of global solar radiation decreases and maximum temperature increase, the

value of UVI_{max} increases according to each day in the same month. That means, there is inversely relationship between UVI_{max} and global solar radiation. In addition, there is a direct relationship between UVI_{max} and $T_{max.}$

3.2.3. The daily UV dose (DUVD)

It can be calculate as an integral of UV index over the daylight time

as follows:
$$DUVD = \int_{T_0}^{T_{N+1}} UVI(t)dt$$

Where, T_o is the sunrise time and T_{N+1} is the sunset time.

The calculations are performed again using the trapezoid rule that results in the following formula:

$$DUVD = \frac{1}{2} \sum_{j=0}^{N} (UVI_{j} + UVI_{j+1}) \cdot (T_{j+1} - T_{j})$$

The daily *UV* dose is in *UV* Index hours (*UVI h*) if the units of T_j are in hours. To convert *UVI h* units to kJ/m^2 , units that are commonly used to express *DUVD*, are has to multiply the result from the last equation by the factor: 0.09=25*3.6/1000 (Kiedron et al, 2007).

4. CONCLUSION

The statistical empirical estimation models of monthly and daily clear sky global radiation (\overline{H} (for monthly) and H (for daily)) and maximum ultraviolet index (UVI_{max}) is constructed for states of Sharm El-Sheikh, Aswan, Safaga and Cairo. The empirical regression models are applied and compared. The applicable predictive regression models include multiple linear regression model, factorial regression model and response surface regression model. Three major predictor parameters are employed to estimate \overline{H} . The predictor variables are $T, \cos(\theta_{\rm ZMT}), S_0$. The response variable is the variable to

be predictable $\overline{H}/\overline{H}_0$. According to statistical evaluation, the secondorder polynomial regression model for the three predictor variables (response surface regression model) is more applicable for Sharm El-Sheikh and Cairo than the other models. On the other hand, the interaction regression model for three predictor variables (factorial

regression model) fits Aswan and Safaga more than other regression models.

The empirical H developed model is considered as a simplified statistical approach because it depends on two monthly constant parameters ($S_{\theta} \& \cos(\theta_{\text{ZMT}})$), and one daily changeable parameter (\overline{T}). The estimated high global solar radiation of the summer months is required for detailed study to get the maximum benefits of solar energy that to forecast UVI_{max} and for the production of electric power. The regression estimation models of UVI_{max} are based on two parameters. Precision of the developed forecasting model of monthly and daily UVI_{max} is based on maximum temperature (\overline{T}_{max} for monthly

or T_{max} for daily) and accurate prediction of \overline{H} or H. The global solar radiation and maximum temperature are considered more accurate and effective for UVI_{max} forecasting results than other meteorological parameters. The UVI_{max} results show that, the factorial regression model is the best for Sharm El-Sheikh and Cairo. Furthermore, the response surface regression model is more adequate for Aswan and Safaga than other models. The value of UVI_{max} increases with the increase in the value of maximum temperature, so that the increase in the UVI_{max} be linked to the low values of H for each day in the same month. The month range May-July (summer) was chosen in this work because the effect of UVI is maximum. There is an excellent correlation exists between the measured and predicted values for each

of $\overline{H}/\overline{H}_0$ and UVI_{max} . Moreover, the predicted values of $\overline{H}/\overline{H}_0$ and UVI_{max} match the measured data in all months of the year.

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