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Outgoing Longwave Radiation over Iraq using Atmospheric Infrared Sounder

Ali M. AL-Salihi[1] and Safaa A. AL-Kinani[1,2]*
[1]Department of Atmospheric Sciences, College of Science, Al-Mustansiriyah University, Baghdad, Iraq.
[2]Department of Environment and Water, Ministry of Science and Technology, Baghdad, Iraq.

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A B S T R A C T

The present paper involves Outgoing longwave radiation (OLR) under clear-sky condition modeling employing three measured meteorological parameters (Air surface temperature, Relative humidity and Cloud fraction). Dataset retrieved from NASA Atmospheric Infrared Sounder (AIRS), from 2003 to 2015 was employed to develop two models to estimate OLR values in Iraq using the multiple linear regression (MLR) and Artificial Neural Network (ANN) approach. For the entire period, the mentioned meteorological parameters were highly correlated with estimated OLR. Comparisons among selected cities (Mosul, Baghdad, and Basrah) for the year 2016 showed close agreement between the estimated and measured OLR. Mosul at the north of the Iraq, showed the lowest root mean square error (RMSE) and correlation coefficient (R) ranged between (1.3853 and 4.4966) and (0.9929 and 0.9993), respectively for the two developed models (MLR and ANN) respectively, indicating model's efficiency and accuracy. Statistical analysis in term of β showed that surface temperature (1.823 to 2.311) tended to provide a high contribute to OLR values. These results indicate the advantage of using the AIRS data and both of correlation analysis and computing system to investigate the impact of the meteorological parameters on OLR over the study area.

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INTRODUCTION

Outgoing longwave radiation (OLR) is classified as type of the radiant energy that leaves out the Earth–atmosphere system to space at a low energy within the sector of the electromagnetic spectrum at a wavelength extended between 4 to 100 μm; this band of radiation called infrared radiation (IR) [1]. It is one of the most essential and critical climate processes that contributed to the radiative budget at the top of atmosphere (TOA), any variation in this fundamental component would cause a long-range imbalance net flux, which eventually alters the climate as it adjusts to restore the balance [2].

Greenhouse gases (GHG) such as (water vapor, carbon dioxide, nitrous oxide, methane, and ozone) in Earth's atmosphere absorbs a particular wavelength of the thermal radiation. As a result, the corresponding absorbing layer of the atmosphere emits more radiation due to the extra that adds to the atmosphere. Some of this radiation is downward back towards Earth, which increases the average temperature of the Earth's surface and performs an important part of the global warming [3].

There are several researchers have examined the influence of OLR in response to a climate change [4], made an investigation about the sensitivity of OLR measured in a clear-sky condition to atmospheric temperature and water vapor. These studies led to that the influence of temperature in OLR change exceeds by water vapor in middle and lower regions of the troposphere and furthermore if clouds introduced into the calculation, it would be same as adding another strong longwave absorber at specific layers in the vertical profile [4].

The new data from AIRS allows to conduct with more researchers [5] measured difference spectrum resolved OLR over the Tropical Pacific. For the period extends between the years 1970-2003 showed the indications of greenhouse gas forcing, and also indicates the sensitivity of the indications to intramural variations in temperature [5]. Moreover, use of a radiative transfer model and investigate the OLR when the atmospheric humidity increases, to confirm the predominance of water vapor as a greenhouse gas to study the impact of changing tropospheric humidity on OLR [6].

Understanding the spatial and temporal variations of OLR is an important issue in expanding knowledge of water balance dynamics on different scales for water resources management and planning [7]. Typically, the highest values of OLR are correlated with the warmest regions of the Earth’s atmosphere, because they radiate the significances amounts of the thermal longwave radiation to space. The cloudless-free equatorial trade wind regions and tropical Pacific are affiliated with such

* Corresponding author: Safaa A. AL-Kinani
E-mail: safaatech@gmail.com

high OLR values, while the areas of intense convection associated with monsoon seem as regions of low OLR [8]. OLR is sensitive and dependent on several meteorological variables, and they have a considerable influence on the OLR, among these are the Earth surface temperature (ST), relative humidity (RH) and cloud fraction (CF) [9].

The aim of this paper is to give an obvious overview of the spatiotemporal variations of the monthly average OLR values over Iraq and three majors selected cities (Mosul, Baghdad, and Basrah) during the period 2003-2015. These values derived from (AIRS). Examine the correlation between OLS and different meteorological variable and developing two different technique (MLR) and (ANN) models in order to estimate OLR over the study area.

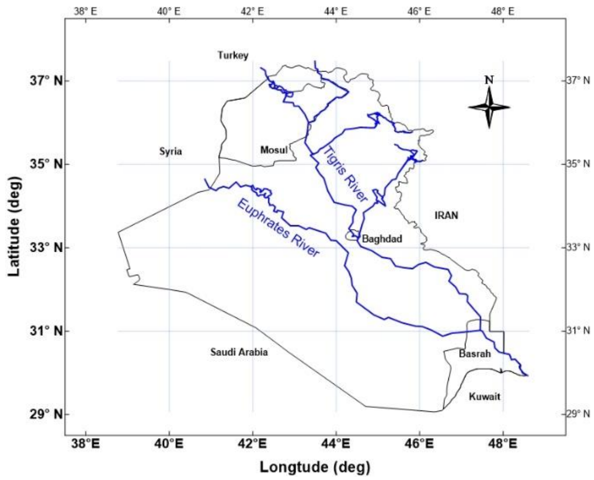

Figure 1.The geographical feature of study area

MATERIAL AND METHODS

Study area and data acquisition

The study area is Iraq which lies in south-western Asia. Located between 29° and 38° N latitudes, and 39°and 49° E longitudes. As shown in (Fig. 1) comprises of 437,072 km^2. The country divided into four major regions: highlands in north and northeast; alluvial plain in central and southeast sections; and desert in west and southwest; rolling upland between upper Euphrates and Tigris rivers, the north of the country mostly composed of mountains [10]. Three cities represented difference geographic regions dispersed across Iraq have been selected in the north (Mosul), alluvial plain in central (Baghdad) and (Basrah) to the southeast regions. As for the characteristic of climate and presented an average air temperature of higher than 48 ºC in July and August to near freezing in January. The mountainous region of northern Iraq receives appreciably more precipitation than the central or south of the country [11]. Roughly 90% of the annual rainfall occurs between October and May. The remaining four months, particularly the hottest ones of June, July, and August are rid except in the north and northeast.

The mean focuses of the research is to develop estimation models for monthly OLR through the year over the study area by processing the satellite dataset for the meteorological parameters including the surface temperature (ST), relative humidity (RH) and cloud fraction (CF). Thirteen years of satellite observation dataset were collected from 1st of January 2003 to 31th December 2015, in order to evaluate and analysis the (OLR) spatiotemporal distribution and to the development of the estimation models. The data of the last year 2016 employed for testing the performance of the estimation.

In present paper, several kinds of a software application were used to cover the process of analysis and mapping of the data that were obtained online from NASA over the study area, including Sigma Stat Statistics, Sigma plot 12.5, Surfer 13, MatlabR2016 and Microsoft Excel, Access 2016.

The (OLR) clear-sky observation and meteorological parameters were retrieved from AIRS instrument in ascending mode (daytime). (AIRX3STM) Level-3 mean monthly gridded data products files extract from the archive data of AIRS website [12] and saves by default in NetCDF files, this is an appropriate file extension that can be re-extracted data from it and arrange into more comprehensive tables using MS. Excel® software. Then perfume an analysis of the downloaded datasets by using Sigma Stat Statistics to find correlations between the selected meteorological parameters and the OLR values using multiple regression equations. Maps that were produced for the study area were conducted by using a grid-based mapping program the Golden Software Surfer® 13.5 to analyze the spatiotemporal distribution of OLR over the study area. The interpolation is applied to produce gridded data files by using the Kriging technique which is used to estimate variable at an unmeasured location from measured values at nearer locations[13]. Sigmplot also used to correlate the estimated and the measured values of OLR, these values of different months and regions were plotted for comparison purposes. MATLAB program was employed to generate an Artificial Neural Network (ANN) as a procedure learning technique to develop another model to estimate OLR from by using meteorological data.

Generally, 168 monthly ascending granules files were downloaded, each file covers a calendar month to acquire the required output data, using the GES-DISC website and through the Interactive Online Visualization and Analysis Infrastructure (GIOVANNI) tool. OLR data acquired from 1°×1° spatial resolution ascending orbits.

Methodology and analysis

The first model built by using multiple linear regressions. Linear correlation and linear regression are the two most useful methods used commonly in the meteorological studies to establish the type of relationship between the various variables and extent of association between one to the other [14]. Regression analysis is the process that was seeking for the estimator and determining how well they estimate the future value. Regression analysis defines an empirical mathematical equation to be employed to estimate an outcome within a particular range of probability represent the future data (the unknown) on the basis of the data collected from the past (the known). The analysis explains how the dependent variable will be influenced by one or more independent variables. The aim of the model is to develop equations to estimate the relationship between the dependent variable OLR and the other combinations of independent variables represented by the selected meteorological parameters ST, RH and CF by using the multiple linear regression methods. The relationships have been examined and correlated in order to conclude empirical equations and the estimated regression coefficients are given under the heading Coefficients (β).

Using the multiple linear regression methods were used to examine the relationships between OLR and ST, RH and CF statistically. The estimative equation for monthly OLR obtained this value by using the terms of β. The multiple regression equations for a response variable y with monitor values y_1; y_2 : :: y_n (where n is the sample size) is as follows:

$$Y_i = \beta_0 + \beta_{1x1i} + \beta_{2x2i} + \beta_{3x3i} + \cdots + \beta_{qxqi} \tag{1}$$

where q is explanatory variables x_1; x_2… x_q with observed values x_{1i}; x_{2i} : : : x_{qi} for i = 1; . . . ; n; β_0 is an regression

Equation constant; and β_1; β_2; β_3; . . . β_q are explanatory variable constants.

The second model was built by artificial neural networks techniques (ANN) which are a class of modern technology known as artificial intelligence. It is a procedure learning technique that simulates the way of a human brain on conserving experiential knowledge. The neural networks mimic this behavior as excessively parallel distributed processor composed of simple processing units that have a natural tendency to making it available for our use as a soft computing tool [15]. In this study. An (ANN) model was developed and applied for estimating the monthly mean OLR values in three selected cities namely Mosul, Baghdad, and Basrah in IRAQ using the other meteorological parameters. A multi-layer feed-forward network with sigmoid hidden neurons and linear output neurons (fit net) was used and trained by Levenberg-Marquardt back propagation training algorithm (LM). There are many connection types and algorithms to learning. The most common type is the Back-Propagation algorithm. This kind of neural network is extensively used in the time series estimation it is consists of two phases a training phase and recall phase.

RESULTS AND DISCUSSION

OLR Climatology

Figure (2): summarized the mean monthly mean values of OLR over three cities Mosul, Baghdad, Basrah for the period from 1st January 2003 to 31th December 2015. The OLR values are different with a maximum in summer and minimum in winter over all considered stations. The OLR values keep increasing start from January and reaching the highest values on July then start to reduce till December. This behavior in the OLR curve is consistent with the three cities and can be well explained because of the cyclic variation in meteorological condition particularly the associated with the verities in the surface temperature, relative humidity at the surface and cloud fraction. They are different in summer and winter. In spite of these variables, there are a noteworthy reduced in OLR values over Basrah city during Summer season (June, July, August) represented through the remains at a relatively constant value (363,362,360.5 W/m^2) respectively and lowest than other two cities (Mosul and Baghdad). This inversion end by the end of August and the OLR curves restored their orders behave. This spatiotemporal inversion of OLR can be well justified by considering that the weather at these times of the year. In the south of Iraq impacts by dust and sand storms. This phenomenon is intimately related and enhanced in these areas because of its closeness to the local desert areas that increase the levels of dust which play a significant role in reducing incoming sunlight by reflecting it and the OLR values would reduce as a result.

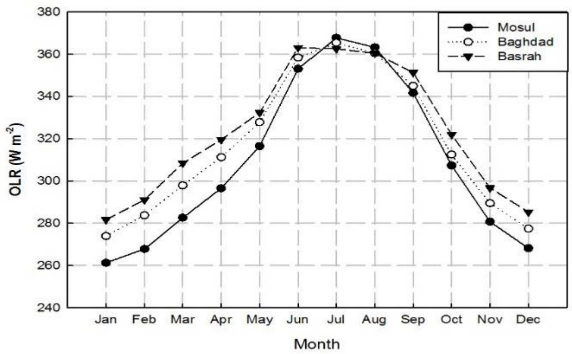

Figure 2.Variability of monthly average OLR values during the period from January 2003 to December 2015 over Northern (Mosul), Middle (Baghdad) and Southern (Basrah) Iraq

Generating Regression Equation OLR Using Standard AIRX3STM Data

The data of the three meteorological parameters (ST, RH, and CF) for the entire period (January 2003 to December 2015) were employed as an estimator (independent variables) to generate the OLR regression empirical equation (estimated OLR value) using the multiple linear regression methods. These data were driven from the standard monthly product AIRX3STM 1°×1° spatial resolution, Version 6 descriptive data. As explained in Section 2.1, the regression regarding β was used to produce the OLR regression equation for data from the entire period in the study area, and from Eq. (1), the formula is given as follows:

$$OLR = \beta_0 + \beta_{st} ST + \beta_{rh} RH + \beta_{cf} CF \tag{2}$$

where β_0 is a constant of the regression equation, and β_{ST}, β_{RH}, and β_{CF}, are explanatory ST, RH, and CF constants, respectively, and for the entire period the equation would be as the following:

$$OLR = 228.092 + (2.357 * ST) + (0.226 * RH) - (28.588 * CF) \tag{3}$$

The analysis conferred a strong relationship between OLR and the three selected meteorological parameters represented by a high value of correlation coefficient (R = 0.980). They are strongly correlated as indicated by the adjusted R^2 of 0.961 for time observations, which mean approximately 96% of the variation in the OLR is interpreted by these independent meteorological parameters (ST, RH, and CF).

In addition, there were another multiple regression processes carried out separately for each one of the three cities (Mosul, Baghdad, and Basrah) during the period from 2003 to 2015 to find the equation constant β and value of R for each city. The meteorological parameters also found to be highly correlated with OLR. Table 1 outlined the multiple regression results for the monthly average data for the three cities.

Generating ANN Using Standard AIRX3STM Data

Meteorological data provided by AIRS within the period (2003-2015) have been used as a dataset to create and train the artificial neural networks whereas data of the year (2016) used for test of the network output evaluation. The input variables that used for building the network were ST, RH, and CF while the target variable was OLR. During the training process, the weights have been adjusted meteorological input data by normalizing and randomizing to remove anomalous behavior of employed data and weight variations. After several training steps and the correlation between input variables and targets are finalized, the recall phase may be run. During perform the mentioned steps, the network output computations are performed using finalized iterations of input data and weights from the training phase to make the outputs of the network (estimated OLR) close to the target (measured OLR). Various numbers of neurons in the hidden layer were examined to find the best model, changed between 5 and 15 neurons. Table 2 shows the RMSE and Regression values for each neurons numbers case. The best validation performance was detected in case 2 with the 10 neurons in the hidden layer. From the highest regression (0.9977, 0.9948, 0.9952) and the lowest RMSE (2.5769, 3.3247, 2.9615) for Mosul, Baghdad and Basrah respectively we proposed the case 2 as the most suitable ANN estimation model. After the network has been well trained, we used these settings on test data (the year 2016), the estimated values were compared with measured data and showed close correlation especially in Mosul city with R=0.9993. This generalization demonstrates the capability of these techniques over unseen (test) data and its ability to yield accurate estimates.

Comparison and Validation of the models

Table (3) Shows computed values of statistical performance indicators (MAPE), (MAE), (RMSE), and (R) that used for finding the credibility of the training and testing procedure in the two models. For the values obtained by (MLR) model, it can be seen that the results of the training procedure values for Basrah city had the maximum values differ from the measured (actual). Values for all statistical indices with highest (RMSE) of (5.6488) and lowermost (R) of (0.9821), the best result found in Mosul city that indices with lowest (RMSE) of (4.9644), highest (R) of (0.9914) and minimum values for all other statistical indices. As for the values of ANN model, Baghdad city had the maximum values differ from the measured values. For all statistical indices with highest (RMSE) of (3.3247) and lowermost (R) of (0.9948), Mosul still had the minimum differ values and best (R) of (0.9977), that made Mosul the closest city to the measured values in both models.

Table (2) furthermore, contained the test procedure values for each model, it can be noticeable from the statistical performance indicators for Mosul city had the highest (R) and lowest values for both (RMSE) and (MAE) in the two models. Baghdad city had the largest difference between the two models. From the comparison that made between the two models, we can conclude that the test values computed in (ANN) model provide us with the best overall performance. For estimating the average monthly OLR compared to values calculated in (MLR) model the result showed the lowest values of (MAPE), (MAE), (RMSE), and highest (R). This advantage exhibits a structure, especially in the northern city of Mosul with quite fine results compared to (MLR) and a lesser extent in the cities of Baghdad and Basrah.

TABLE 1.Estimated regression equation constant β and evaluation statistical criteria

Region	β_0	β_{ST}	β_{RH}	β_{CF}	R	R^2	MAPE	MAE	RMSE
Mosul	247.127	2.093	0.0183	45.574	0.991	0.983	1.3403	4.1365	4.9644
Baghdad	239.891	2.311	0.0722	62.654	0.985	0.971	1.4032	4.4845	5.5730
Basrah	263.196	1.823	0.267	52.896	0.982	0.965	1.4226	4.6275	5.6488

TABLE 2.RMSE and Regression values for three ANN cases

Mosul			Baghdad			Basrah		
Neurons No.	RMSE	R	Neurons No.	RMSE	R	Neurons No.	RMSE	R
5	2.6781	0.9910	5	3.2021	0.9898	5	2.6501	0.9132
10	2.5769	0.9977	10	3.3247	0.9948	10	2.9615	0.9952
15	3.0251	0.9870	15	4.0211	0.9720	15	3.2311	0.9856

TABLE *3*. The statistical performance indicators for training and testing procedures

City	MAPE	MAE	RMSE	R	Model
Mosul					
Training (2003-2015)	1.3403	4.1365	4.9644	0.9914	MLR
Testing 2016	1.2555	3.8759	4.4966	0.9929	
Training (2003-2015)	0.6132	1.9521	2.5769	0.9977	ANN
Testing 2016	0.3621	1.1131	1.3853	0.9993	
Baghdad					
Training (2003-2015)	1.4032	4.4845	5.5730	0.9854	MLR
Testing 2016	1.5429	4.9968	6.7209	0.9844	
Training (2003-2015)	0.7109	2.3301	3.3247	0.9948	ANN
Testing 2016	1.0490	3.4839	5.0367	0.9894	
Basrah					
Training (2003-2015)	1.4226	4.6275	5.6488	0.9821	MLR
Testing 2016	1.1605	3.8753	4.9209	0.9875	
Training (2003-2015)	0.6882	2.2612	2.9615	0.9952	ANN
Testing 2016	0.9711	3.2760	4.3519	0.9917	

Testing values of estimated OLR by the two models (MLR and ANN) versus the measured (actual) values were drawn from the three cities to demonstrate the performance of the two models, and Figure (3) illustrated them. These figures show the profile of the three cities. It can be confirmed that the largest errors according to (RMSE) and (MAE) values of the estimated average monthly OLR values were more observed in Baghdad city. A large positive deviation (model incline to over-forecast) during (April, May, June) months and large negative deviation (model incline to under-forecast) during (July) month. Mosul city had the best closest estimated values to the measured values, as an exhibit in Figure (3) With an advanced of (ANN) curve which behaves almost identically to the measured curve with a good general fitting. The three cities show a tendency to over-forecast through a positive average base error in each city.

In general, the achieved values of (MAPE) for (MLR) model were (1.2%), (1.5%), (1.1%). For (ANN) model were (0.3%), (1.04%), (0.9%) for Mosul, Baghdad, and Basrah respectively for the test period shows that the results of the estimated average monthly (OLR) values have a relatively close agreement with the corresponding measured values for each city. The base errors obtained in these models are very well within acceptable limits and provide good accuracy for long-term prediction, results also show that applying the (ANN) model may be considered as more site dependent than (MLR) model.

Direct comparison between estimated and measured OLR from AIRS using mapping

Figure (4) illustrated the OLR maps over Iraq for January measured from the AIRS [Fig.4 (a)] and estimated OLR [Fig. 4(b)], and the differences between the measured and estimated OLR [Fig. 4(c)]. In the same way, the OLR in April is presented on the right side of the figure. For January, the differences between AIRS and estimated OLR values varied between -7 and 12 W/m^2 over southwestern borders with Saudi Arabia and the north border with Turkey. For April [Fig. 4(c)] shows an underestimation in most Iraqi regions. For July, the maximum differences were in most of Iraq area especially in middle and the alluvial plain. Also, there is a clear underestimation in all Iraqi area as showed in [Fig.4(c)] for October, the maximum differences ranged between -10 in the western north and -2 in the eastern North

Evaluation of estimated OLR with AIRS measured OLR

It’s necessary to evaluate the equation of OLR according to the multiple regression equation models to test the efficiency of this equation. To do this a testing was carried out with a linear regression correlation for four selected months of winter (January), Spring(April), Summer (July) and Autumn (October) in 2016. The OLR equation showed a high correlation coefficient (R) with measured OLR by AIRS for 2016 represented by the values 0.990, 0.982, 0.948, and 0.964 for January, April, July, and October respectively. In all cases, the correlations were statistically highly significant ($p<0.005$). From figure (5), the results indicate that the relation between measured and estimated OLR values is strong linearly with positive correlation, is clear evidence of the accuracy of the regression equations and the results give a good estimation.

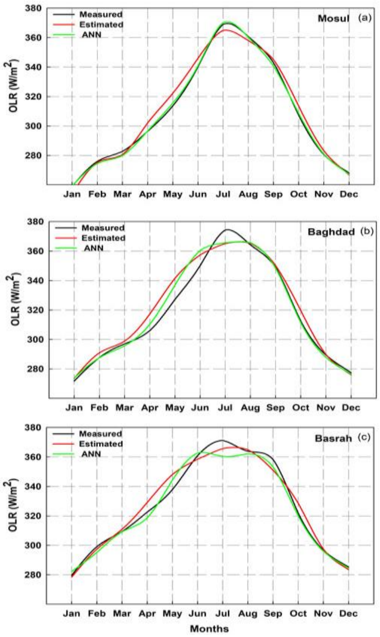

Figure 3.Comparison between measured, estimated and ANN value of OLR over the selected cities

CONCLUSION

There is a strong correlation between OLR and the (ST, RH and CF), this led to lower values of OLR during the winter than summer season because of the variation of these parameters values through the seasons. Linear regression correlation was carried out to validate estimated with measured OLR from AIRS. The results showed that the estimated values were nearly the same as the measured OLR from AIRS, OLR had good accuracy and efficiency in all cases resulting from good correlation coefficients (R, 0.9844–0.9929). Surface temperature had a significant contribution to the high OLR value indicated by the strong positive β (1.823 to 2.311), while relative humidity had positive β associated with OLR (0.0183 to 0.267), cloud fraction in other hand had negative β (45.574 to 62.654). Validation using Artificial Neural Network also was done and presents similar result with a good correlation coefficient (R, 0.9917–0.9993). From this study, we found that AIRS data are useful and suitable to be used to investigate the impact of specific meteorological parameters changes on OLR in IRAQ. It is additionally conceivable to apply the same study with different meteorological parameters and analyses the effects of these new parameters to help to develop a new algorithm/model for further researches.

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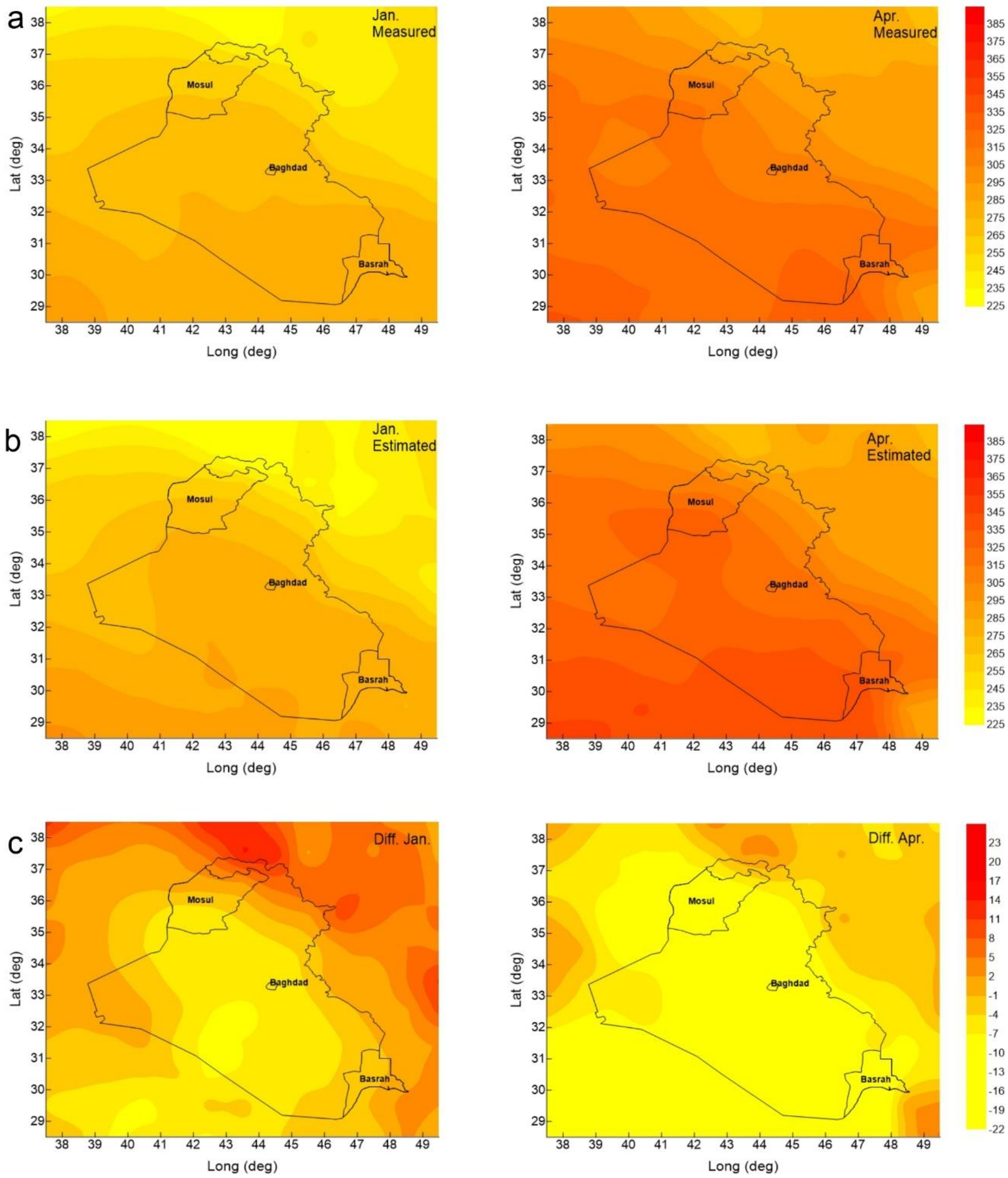
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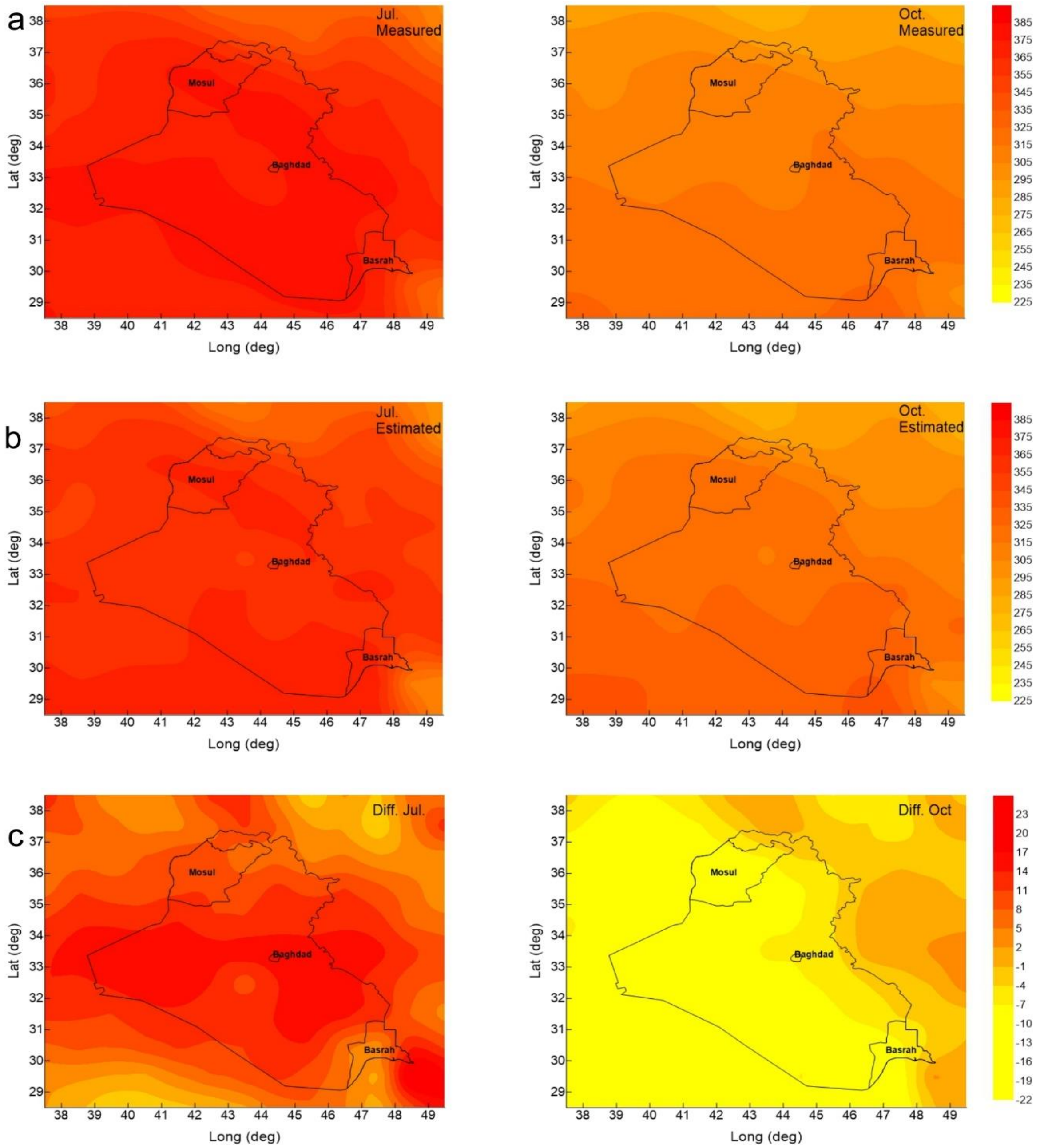

Figure 4. Iraq AIRS OLR (a), Estimated OLR (b), and differences (AIRS – Estimated OLR) (c); left side for January and July while right side for April and October

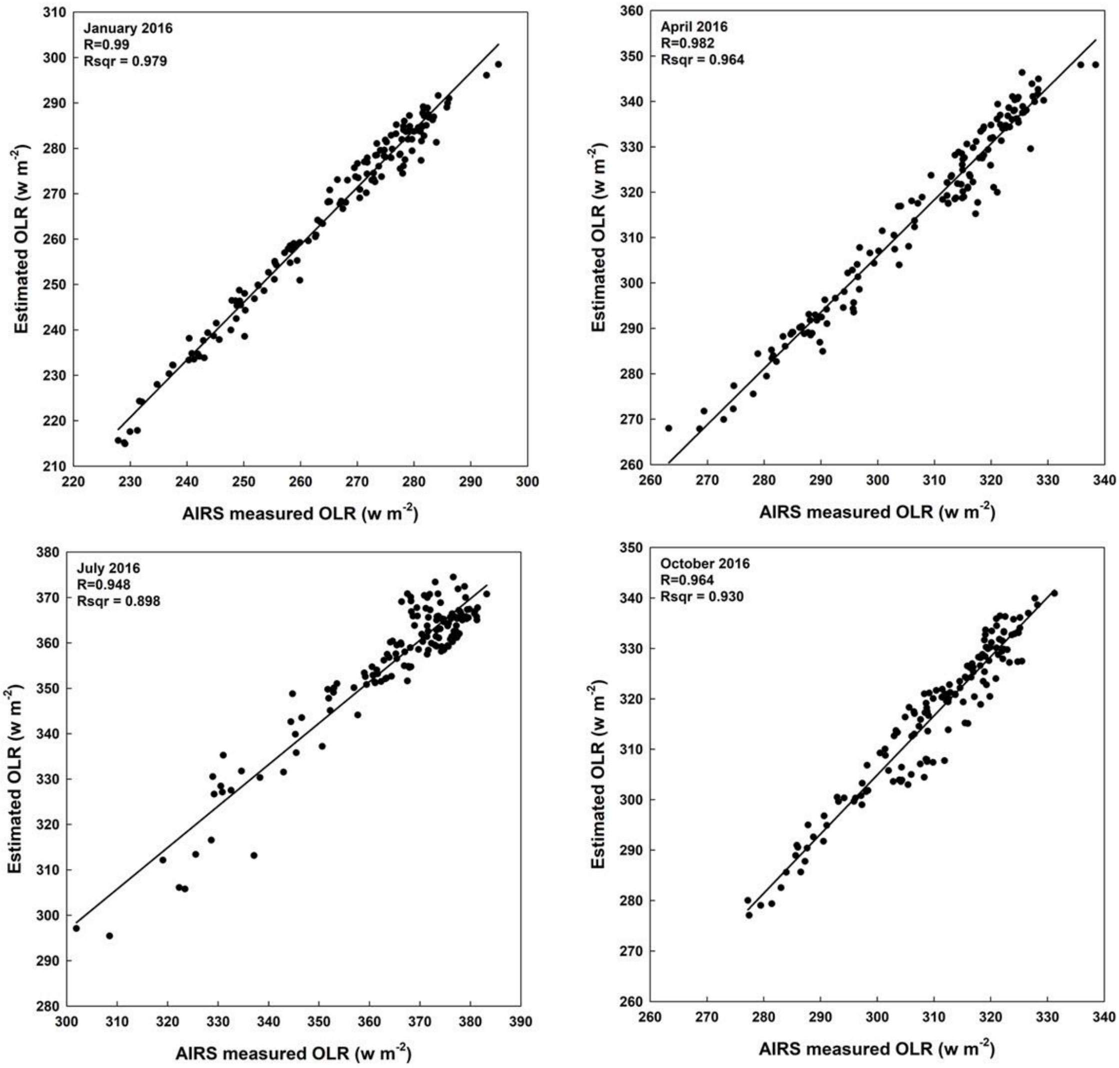

Figure 5. Estimated versus Measured values of OLR from AIRS for January, April, July and October 2016

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Persian Abstract

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چکیده

مقاله حاضر شامل تابش طولانی مدت خروجی(OLR) با استفاده از مدل‌سازی در شرایط آسمان صاف با در نظر گرفتن سه پارامتر اندازه‌گیری هواشناسی(دمای سطح هوا، رطوبت نسبی و میزان جزئی ابر) می‌باشد. داده‌های بدست آمده فرستنده مادون‌قرمز ناسا(AIRS) از سال ۲۰۰۳ تا ۲۰۱۵، با استفاده از دو مدل روش رگراسیون خطی چندگانه((MLR و شبکه عصبی مصنوعی را برای تخمین مقادیر OLR بود. در کل دوره OLR تخمین‌زده شده به مقدار زیادی وابسته به پارامترهای هواشناسی ذکر شده، بود. با مقایسه بین شهرهای انتخاب شده (موصل، بغداد و بصره) در سال ۲۰۱۶ نشان داد که مقادیر تخمین‌زده شده و اندازه‌گیری شده OLR نزدیک به هم بودند. در موصل، شمال عراق، نشان دادند که کمترین میانگین خطای مربع خطی(RMSE) و ضریب همبستگی(R) برای دو مدل استفاده شده(MLR و ANN) به ترتیب در بین محدوده(۱/۳۸۵۳ و ۴/۴۹۶۶) و(۰/۹۹۲۹ و ۰/۹۹۹۳) بود، که نشان‌دهنده‌ی کارایی و دقت مدل است. تحلیل آماری شرایط β نشان داد که در دمای سطح(۱/۸۲۳ تا ۲/۳۱۱) موجب رسیدن به مقدار بالای OLR شد. این نتایج مزیت استفاده از داده‌های AIRS و هر دو روش تحلیل همبستگی و سیستم محاسباتی را برای بررسی تاثیر پارامترهای هواشناسی بر روی OLR در منطقه مورد مطالعه نشان می‌دهد.