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Selection of the Optimum Global Circulation Model that Mimics the Circumstances of Egypt

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Abstract: ***Egyptian researchers in the field of climatic changes and their effects on various sectors, such as agriculture, water resources, health and social usually operate one of the Global Circulation Models (GCMs) and rely on its results. They considered its results as facts and real and they study the impact without reference to the uncertainty in their results. This is a major drawback to study the effect of climate changes on different sectors since there is a persuasive variation in the results of different models. Therefore, the impact analysis may result in building policies and develop alternatives in a way that is related to the real situation of the area under study. It has been found that the best global model or recycling models for the case of Egypt must be neutralized. It is an imperative component for building future policies to study the impact of climate change properly. The current study focuses on assessing the results of GCMs in Egypt. Previous reviews showed that there is no study to address this issue on Egypt. Thus, the following methodology was followed. Forty GCMs in Coupled Model Inter-comparing Project (CMIP5), are analyzed for the variable's precipitation and temperature. These GCMs were Evaluated for Egypt for the climate variable precipitation rate through dividing the entire Egypt area to 110 cells each cell is square 100 km x 100 km. The precipitation and temperature were evaluated through applying five performance indicators. These indicators are listed as follow: i) coefficient of correlation (CoC) , ii) normalized root mean (NRMSE), absolute normalized mean bias error (ANMBE), average absolute relative error (AARE) and skill score (SS).The Payoff matrix (40 GCMs versus 5 indicators) is developed and then the entropy technique for determination of the performance indicators' weights is applied. The Normalization technique was applied for each season out of 4 seasons that are winter, spring, summer and autumn on the performance indicators. These weights are applied to assist for ranking the 40 GCMs. The Ranking of these GCMs were obtained through a multi-criterion decision-making outranking method (PROMETHEE-2). Finally, it is proven that the "MPI-ESM-LR" GCM is found to be the best model for predicting the climate change parameters, (precipitation and temperature), all over Egypt compared to the other 39 models. The MPI-ESM-LR GCM model is developed by the Max Planck Institute for Meteorology in Germany. It is recommended that the results of climate change projects for Egypt up until year 2100 has to apply the output results of the GCM named MPI-ESM-LR rather than other GCMs as long as it gives the most proper results for climate change projection of Egypt.***

Keywords: ***Egypt, Climate change, GCMs, Performance indicators, MPI-ESM-LR model.***

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I. INTRODUCTION

General Circulation Models (GCMs) are numerical models developed in the last decades for the empathy of climate and protruding climate change. GCMs are used for weather forecasting, understanding the climate, and forecasting climate change. There are different applications and usages for GCMs such as understand the current atmospheric circulation, estimate the impact of topography and land usage conditions on monthly and seasonal weather, simulate past climates to improve the understanding of the earth's climate system and estimate future climate changes resulting from natural or anthropogenic processes. Accordingly, scientists of different disciplines can estimate the impact of climate change on hydrology, human health, agriculture, quality of life and more. The International Panel of Climate Change (IPCC) consigns excessive confidence in the ability of general circulation models to mimic future climate and attribute observed climate change to anthropogenic emissions of greenhouse gases expected from human activities in the future [1]. On the contrary, it has been stated that major deficiencies in the models prevent proper simulation of important elements of the climate system, thus large dissimilarities between model predictions and field observations from weather stations frequently exist when comparing the output computed results [1]. Chong-yu and Xu [2] stated that GCMs affirm proficiency at the continental spatial standard; on the contrary they are fundamentally impotent to represent local scale features and dynamics. Consequently, it has been found that there is essential need for evaluating the reliability of GCMs regarding the future prediction.

Raje and Mujumdar [3] return the uncertainties of the results of GCMs appear for the reason of greenhouse gases which are numerically simulated in dissimilar methods. They also referred to designated initial and boundary conditions for each GCM, simulated parameters, and numerical modeling approach. Another important issue is the forthcoming greenhouse gas emissions estimation through the approach of Representative Concentration Pathways (RCP) that is used in simulation models for predicting future climate.

As stated by Raju et al. [4], several authors suggested that uncertainty of GCMs can be minimization by applying the approach of ensemble of different GCMs models, thus this approach shall decrease the uncertainty level during the process of forecasting climate change. Accordingly, some researchers applied multiple GCMs instead of using single GCM output. The use of multiple GCMs are capable of behaved as the core to provide inputs to downscaling techniques. Etemadi et al. [5] stated that GCMs are usually having significant source of uncertainty to quantifying the influences of climate change. They proposed that the uncertainty related to the downscaling and bias correction methods must be considered for enhancing the estimation of the influence of climate change. Kingston and Taylor [6] concluded that GCMs results in uncertainty which is far greater than that coupled with climate sensitivity or hydrological model parameterization. Flato et al. [7] conducted an intensive literature review for studying the uncertainty of GCMs and they summarized the results in what follows:

1. Many studies could not trace strong correlation between ground observations and numerical models' projections;
2. Some studies show that there is feeble correlation between the results appeared from local models and those resulted from regional climatic.
3. It has been realized that the GCMs model's proficiency to simulate the yearly variability of the boundary layer air temperature and the extent of expected warming level was not considered perfectly compatible with the scientific standards.

Flato et al. [7] presented an example of uncertainty of GCMs models for the Northern and Southern Poles of simulation for determining the spreading of fast ice and sea ice which shows improper simulation results. Kharin et al. [8] found that the climate models that mimic present-day warm extremes are having discrepancies in simulating the extreme event in cold zone. Theses discrepancies are larger than that of warm extremes particularly in the ice–covered areas. On the contrary, simulated present-day precipitation extremes are considered adequate in the mild-latitude areas. Raju and Kumar [9] checked the uncertainty of eleven GCMs and they were evaluated for India for the precipitation rate, as a climate variable, using five indicators. The authors used the CoC, NRMSE, ANMBE, AARE and SS for evaluation and testing the eleven GCMs by comparing the observed data and calculated results. The Entropy method was engaged to determine influences' weights of these five indicators [10]. Ranks of these GCMs were conducted through applying the multicriteria decision-making outranking method (PROMETHEE-2). In brief, the eleven GCMs were ranked for four river basins in the peninsular of India. The study concluded that the ensemble of GCMs named: GFDL2.0, MIROC3, BCCR-BCCM2.0, UKMO-HADCM3, MPIECHAM4 and UKMO-HADGEM1 is appropriate for India. The applied methodology can be encompassed to rank GCMs for any selected region. Suppiah et al. [11] chose 15 GCMs that performed well in the Australian region to be tested and evaluated. The selected GCMs are BCCR, CNRM, CSIRO Mark3, GFDL 2.0, GFDL 2.1, IAP, INMCM, MIROC-H, MIROC-M, MIUB, MPI-ECHAM5, MRI, NCAR-CCSM, HADCM3 and HADGEM1. The reliability and consistency of climate models over Australia has been tested by comparing observed data at different locations to the output simulation results of the numerical models for the same locations over the horizon from 1961 to 1990. The climate parameters that were considered in this study were temperature, precipitation and pressure at the sea level for every year for each season out of the four seasons. The study ended to select nine models out of 15 models to construct climate change projections that are namely CSIRO Mark2, DARLAM 125, CCM1, ECHAM4, ECHAM5, GFDL, NCAR PCM, HADCM2 and HADCM3. Gleckler et al. [12] conducted an intensive study for evaluating the GCMs over different areas. They found that there are some models that prove superiority. Finally, they stated that it is not yet possible to determine the best climate model. The model selection certainly will depend on the intended application. Thus, a set of metrics could be developed for a specific application that would truthfully quantify the relative merits of different models. Smith and Chandler [13] tried 22 GCMs models for examining the different future predictions for rainfall over the south-eastern province of Australia. They found that only five models out of the 22 tested models resulted in improper results for rainfall over the study area. The final results indicated that there are relatively trivial increases in rainfall are simulated for summer and autumn, but significant reductions are resulted for both winter and spring. This study was different than other similar studies which indicates that there a significant randomizing in the results of the GCMs since in most of the other studies the number of the reliable models was much less than the improper models. Reifen and Toumi[14] conducted the principle of selecting climate models through comparing between the data measured on the ground and the model results and their level of agreement. In this study they applied the multi-model ensembles approach which results in more precise results than that the depending on single model approach. Thus, they verified for temperature 17 GCMs by comparing the numerical results (as ensembles) contrasted with the observations. The final conclusion was that the multi-model ensemble mean of the selected models provides the most accurate results for having best estimate projections of future climate change. Macadam et al. [15] concluded that GCMs ranking over time is inconsistent. They concluded that such rankings are not convenient for estimating the reliability of anticipated climate changes simulated by GCMs. Therefore, they demonstrate that GCMs performance rankings based on authentic values, which merge biases in climatological means possibly will be reliable over time. Mostafa et al. [16] applied the statistical downscaling method to explore the impact of climate change on rainfall intensity over the Blue Nile Basin. 16 GCMs were studied to check the performance of each model on a series of historical observed rainfall data within the period from 1971 to 2000. The 16 GCMs models were ranked according to the accuracy of performance of the downscaled rainfall data which was compared to the observed data for period of 30 successive years by statistical analysis.

The study ended up that the HADGEM GCM model is the best model to simulate the rainfall over the Blue Nile Basin. From the above-mentioned review, it is clear that the GCMs models are having a special nature due to its highly mathematical and numerical complexity. Given the purpose of using these models that is to predict the climate changes on the global, regional and local levels, a question to be raised herein which is the possibility of the validity and adequacy of these predictions for what will actually happen. The answer of this question is challenging and there are significant discrepancies among the different GCMs as mentioned in the previous review. There are many techniques that have been put on to find out the best and optimum model for different climatic zones. Any user of the GCMs that is interested in future climate forecasting should take into account is the model optimum and gives him the best results compared to other models. Thus, the researcher should always consider that the results of all GCMs models with the measured data from the land truthing stations are historically calibrated in an era starting from at least 30 consecutive years. Through these results, the researcher can choose the best models for the region he wishes to study and then experiment with the model for future periods. Results will be better compared to other models. There are some researchers conducted the assortment for several models and then taking the averages as an ideal way to reduce the expected error. Built on the above, the current study directs on the work of assessing the results of models of global climate change in Egypt, where previous reviews indicated that there is no study to address this issue on Egypt climate. Egypt is a unique case where there are several different climatic zones. For example, the Western Sahara region in Egypt represents about two thirds of Egypt's one-million square km in area, which is considered as a region from the Great Sahara region of Africa. While the Nile Delta and the Northern Coast on the Mediterranean represent the Mediterranean climate region. The southern regions are arid zones. There are also mountainous areas such as the Red Sea chains and South Sinai, which are hot regions with volatile weather, wind and torrents sometimes. Therefore, this study will focus on the selection of climatic models for each region according to the best results. Finally, the results of climatic changes will be determined in Egypt based on the results of the models spatially and are expected to be the technical outputs. From the above-mentioned review, it is clear that GCMs are models of a special nature and have highly multifaceted mathematical and numerical complexity. Given the purpose of using these models is to predict expected the climate changes that will occur at the global level. Through downscaling from the GCMs regional and local climate models can be applied to test the possibility of the validity and adequacy of these predictions. As mentioned in the previous review, there are many techniques that have been applied to find out the paramount models and the most appropriate for different climatic zones. Any user of GCMs models has to consider the optimum model which gives him the best results compared to other models. Thus, the researcher should always consider results of several models and compare these results with the observed field data for a minimum period of 30 consecutive years. Through these results, the researcher can choose the best models for the region he desires to study and then conduct experiments with this model for future periods considers these results will be better than those obtained from other models. On the other hand, there are some similar studies conducted by considering ensembles of different models considering it as an ideal way to reduce the expected error. Based on the above, the current study focuses on the work of assessing the results of models of global climate change in Egypt. Previous reviews showed that there is no study to address this issue on Egypt. Egypt is a special case where there are several different climatic zones. For example, the Western Sahara region in Egypt accounts for about two thirds of Egypt's one million square km area, which is a region that follows the Great Sahara region of Africa. While the Nile Delta and the Northern Coast on the Mediterranean represents the Mediterranean climate region. The southern regions are very dry and almost rainless. There are also mountainous areas such as the Red Sea mountain's chains and South Sinai, which are hot regions with volatile weather, wind and torrents sometimes. Therefore, this study will focus on the selection of the best GCM that is suitable for different climatic region out the available GCMs.

II. METHODOLOGY

The Procedural steps for selection of the best GCM is founded on the developed procedure by Raju and Kumar [9]. Fig. 1 presents the flow chart for the proposed procedure. Thus, the ranking starts after the calculating of the performance indicators. The subsequent step is developing the payoff matrix and rating the performance indicator, then applying the Multi-Criteria Decision-Making techniques. The group decision making has been conducted to select the best GCM that gives the most reliable results for climate change prediction for the period between 2020 till 2100.

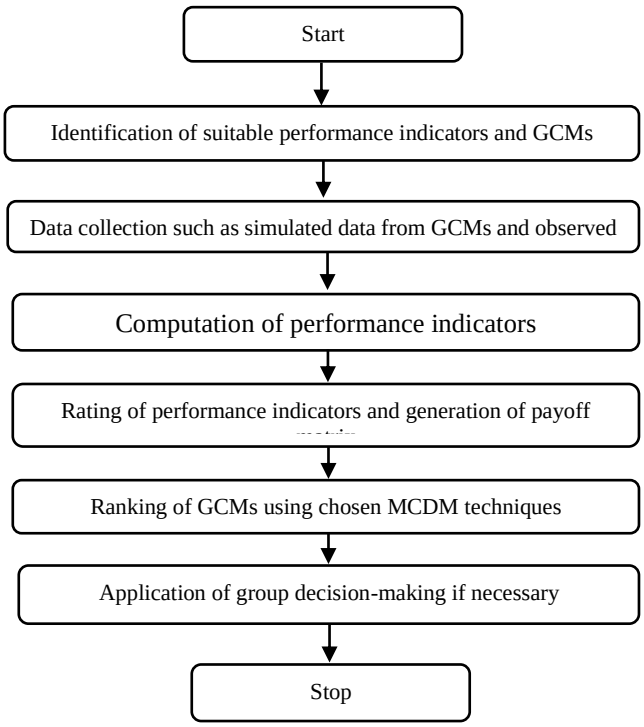

Fig. 1 Flowchart of procedural steps for selection of the best GCM, after by Raju and Kumar [9].

2.1 DATA COLLECTION: SIMULATED DATA FROM GCMS AND OBSERVED DATA

The necessity of selecting the most appropriate GCM for Egypt is an essential issue to conduct the compulsory studies share out with climate change impact. Accordingly, in the existing study performance indicators for evaluating GCMs are selected to be the base for selecting the finest model suitable for Egypt. The mathematical description of these indicators is introduced in what follow. The following step is rating of performance indicators and generation of reckoning matrix. Then, grading of GCMs using Multi-Criteria Decision Making (MCDM) has been the chosen technique that was conducted and merged with the application of group decision-making to select the optimum GCM for Egypt.

Hence, for the current study the one-million km^2 which is the area of Egypt has been divided into 110 cells each cell is 100 km (length) x 100 km (width). The historical observations for each cell were collected depending upon the existing available field weather stations. In the zones where there was not available field data the CRU TS series of data sets were used [17].

In the current study the weather data that is used as the basic data is CRU TS which is the proceeded weather and climate data developed by Climatic Research Unit Time-series. It contains monthly time-series of rainfall, daily temperatures, cloudage, and other climate variables. The CRU's domain is covering the globe areas for the time period from 1901-2015. The data set is latticed to 55.67 x 55.67 km space resolution which concote the analysis of over 4000 worldwide weather station chronicles. Fig. 2 presents a schematic diagram for the used grid pattern that covers the entire area of Egypt. For each cell 4 seasons were considered that are: winter, spring. Autumn and summer. For each cell of the total number used all over Egypt, which is 110 cells (11 x 10) while the cells that are located outside Egypt's boundary were not considered in the calculations. The output results of 40 GCMs were applied on four climatic seasons separately [18]. This has been applied for the period from 1979 to 2005. Accordingly, the processed data for each cell was 4 seasons x 110 cells x 26 years' x 40 models which is equivalent to 457,600 data points.

Fig. 2 Used Grid for Egypt Case with a Cell Size of 100 km x 100 km.

2.2 DEVELOP OF PERFORMANCE INDICATORS

The GCMs are to be evaluated through assess their performance by simulating the historic observations. This supports the choosing GCMs of higher performance so that the relevant output obtained from the best GCMs can be used for further analysis (Mujumdar and Kumar, 2012). A performance indicator can be defined as a measure of any GCM to determine how well it mimics the observed data across space and time. These indicators may provide the basis to assess the confidence level of outputs of GCMs. Thus, hydrological models can be employed for related applications such as watershed management models, groundwater recharge models, coastal protection models and integrated water resources management models.

Different researchers used various performance indicators [9] such as, Sum of Squares of Deviation (SSD), Mean Square Deviation (MSD), Root Mean Square Deviation (RMSD), Normalized Root Mean Square Deviation (NRMSD), Absolute Normalized Mean Bias Deviation (ANMBD), Average Absolute Relative Deviation (AARD), Pearson Correlation Coefficient (CC), Nash–Sutcliffe Efficiency (NSE), and Skill Score (SS). Among all, SSD, MSD, RMSD, NRMSD, ANMBD, AARD are of deviation/error category. In the current study four performance indicators are selected that can be listed as follow:

2.2.1 THE CORRELATION COEFFICIENT (CC)

The first indicator is correlation coefficient which is used to assess the strength between GCMs data and observed data. The value of CC is such that -1 < CC < +1. A CC value of +1 indicates a perfect positive correlation and -1 indicates a perfect negative correlation. If CC is almost closer to Zero. This mean that there is no correlation or a weak correlation and is computed as:

$$CC = \frac{\sum_{i=1}^{T}(x_i - \bar{x})(y_i - \bar{y})}{(T-1)\sigma_{\mathrm{CRU}}\sigma_{\mathrm{GCMs}}} \quad (1)$$

Where, $x_i; y_i$ are observed raw data (CRU) and Global climate models values, And $\bar{x}; \bar{y}$ are averages of observed (CRU) and Global climate models values, whereas σ_{CRU} and σ_{GCMs} are the standard ratio deviations, T is number of time series data [19].

2.2.2 NORMALIZED ROOT MEAN SQUARE DEVIATION (NRMSD)

NRMSD is related to the difference between the detected values (CRU) and the model projected (GCMs), And considered as Non-dimensional forms of the RMSE. NRMSD can be expressed as:

$$\mathrm{NRMSD} = \frac{\sqrt{\frac{1}{T}\left(\sum_{i=1}^{T}(x_i - y_i)^2\right.}}{\bar{x}} \quad (2)$$

Where, $x_i; y_i$ are observed raw data (CRU) and Global climate models values, $\bar{x}$ are averages of observed (CRU) and T is number of time series data. The smaller the value of NMRSD of the estimate, the better the predictive power of the model. An ideal value of Zero is considered [20]

2.2.3 ABSOLUTE NORMALIZED ROOT MEAN SQUARE DEVIATION (ANRMSD)

ANRMSD is the of the mean of the disparity between the measured data and the GCMs simulated values to the mean of measured values. ANRMSD is expressed as:

$$\text{ANRMSD} = \left| \frac{\frac{1}{T}((\sum_{i=1}^{T}(y_i - x_i))}{\bar{x}} \right| \quad (3)$$

Where, $x_i; y_i$ are observed raw data (CRU) and Global Climate Models (GCMs)values, $\bar{x}$ are averages of observed (CRU) and T is number of time series data. Similar to NRMSD, smaller values of ANMBD indicate better performance and it is ideal to have a value of Zero [20] .

2.2.4 AVERAGE ABSOLUTE RELATIVE DEVIATION (AARD)

AARD is defined as the average of the absolute values of relative Deviation. Absolute Relative Deviation is known as the distance between each value in the data set and that data set's mean or median. and is computed as:

$$\text{AARD} = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{(y_i - x_i)}{x_i}\right| \quad (4)$$

Where, $x_i; y_i$ are observed raw data (CRU) and Global climate models' values and T is number of time series data. Similar to previous performances, the smaller the values the superior performance of the model, and a value of zero is indicates the best preferred value [21].

2.2.5 SKILL SCORE (SS)

SS affords a portion of coincidence between two probability density functions (PDFs), which grants contrast through the entire PDF [22] . SS is expressed as:

$$SS = \frac{1}{T}\sum_{i=1}^{nb}\min(f_m \cdot f_0) \quad (5)$$

where: nb is number of cases used to calculate the PDFs for a given region. f_m, f_0 are the frequencies of values in the given case from the selected GCMs and of the observed values in our study the number of cases was taken as constant number for all models , after trying and errors number 8 is the most valuable number for bin for this study , and T is number of time series data. Skill score varies between Zero and one. The higher the score which near to 1.0 value is considered the better the GCMs performance.

The next step is to conduct Transformed Values of performance indicators obtained for the 40 GCMs for each cell out of the 110 cell and for each season out of the four seasons. The procedure is conducted through converted the least values of NRMSD, ANMBD, AARD which are looked-for and giving Neg. signs to represent in maximization standpoint, i.e., (−min) = max.

2.3 CALCULATING THE INDICATORS' WEIGHT

2.3.1 NORMALIZATION

The first step in the multicriterion evaluation is to conduct a normalization for the transformed indicator matrix. The following equation has been used for the normalization technique.

$$k_{aj} = \frac{K_j(a)}{\sum_{a=1}^{T} K_j(a)} \quad (6)$$

Where, k_{aj} is the normalized value, $K_j(a)$ = the indicator value for GCM number (a) and T = the whole number of GCMs (in the current study is 40).

2.3.2 WEIGHTING TECHNIQUE

The Entropy technique [9], [10] were followed for assigning weight for the normalized values of indicators. The purpose of this technique is to assign weight for each indicator of the five selected ones. Thus, the decision can be performed by having the impacts of the five different indicators epitomized to the weight of each indicator. The following set of equation are used within the procedure. The first step in this stage to be calculated is:

$$En_l = -\frac{1}{\ln(T)}\sum_{a=1}^{L} k_{aj}\ln(k_{aj}) \quad (7)$$

Where, En_l is Entropy for each indicator j= 1, 2 ,…., 40) (40 GCMs), $k_{aj}$is the normalized value of the indicator, a is an index for the GCM number, j is the indicator number, and T is the total number of GCMs used (T herein is 40).

The second step is to calculate the Degree of diversification Dd_j as in the following equation:

$$Dd_j = 1 - En_j \quad (8)$$

The third step is to calculate the Normalized weight of indicators r_j as in the following equation:

$$r_j = \frac{Dd_j}{\sum_{j=1}^{J} Dd_j} \quad (9)$$

Accordingly, in the current study for each cell out of the 110 cells that covers Egypt and for four seasons along the year all of the above calculations were performed for each GCM out of the selected 40 GCMs.

2.4 RANKING THE GCMS

Multi-criterion Decision-Making Technique in Deterministic Scenario is applied to rank GCMs within the current study. In the current study four evaluation criteria methods were applied in the current study. These methods are: Compromise Programming, Cooperative Game Theory, Weighted Average Technique and PROMETHEE-2. Thus, each method is used to rank the 40 GCMs separately. Then, an integration through the Group Decision Making Technique was conducted in order to have the final rank for the 40 GCMs through which the best model GCM will be selected for Egypt case. In what follows a brief description for each method of evaluation in addition to the group decision making technique will be described.

2.4.1 COMPROMISE PROGRAMMING

Compromise programming is an evaluation approach that follows the bases upon establishing on distance measure L_{pa} to the optimum solution.

It can be expressed by the following equation:

$$L_{pa} = \left[\sum_{j=1}^{J} (r_j \times |k_j^* - k_j(a)|)^p\right]^{\frac{1}{p}} \quad (10)$$

Where L_{pa} *is* metric value for each GCM (a), $k_j(a)$= indicator's value j for GCM a; r_j = assigned indicator weight j; p = Parameter (1, 2,…….). Thus, GCMs rank is assigned based on L_{pa} values since the lower value of L_{pa} indicates more suitable GCM.

2.4.2 Cooperative Game Theory

This method is depending on ranking the different GCMs based on the measured distant from ideal solution, i.e., as "far-off" as possible to "anti-ideal" solution [9]. The methodology is explained as follow:

$$D_a = \prod_{j=1}^{J} |k_j(a) - k_j^{**}|^{r_j} \quad (11)$$

Where Da is metric value for each GCM (a), $k_j(a)$= indicator j' s value for GCM a; r_j= assigned weight for indicator j. Thus, the rank of the GCMs is built on the value of Da since the higher D_a indicates the most suitable GCM.

2.4.3 WEIGHTED AVERAGE TECHNIQUE

It is a utility-related technique and can be explained as:

$$V_a = \left[\sum_{j=1}^{J} r_j \times k_j\right] \quad (12)$$

Where V_a= metric value for each GCM (a), r_j = assigned weight of the indicator j. Rank the GCMs built on the V_a values. The higher the value V_a the more suitable the GCM.

2.4.4 PROMETHEE-2 METHOD

It is a preference function model and is expressed by the following:

π

$$(a.b) = \frac{\sum_{j=1}^{J} r_j \, Pr_j(a.b)}{\sum_{j=1}^{J} r_j} \quad (13)$$

$$Pr_j = \begin{bmatrix} 0 & if & e_j \le 0 \\ 1 & if & e_j > 1 \end{bmatrix} \quad (14)$$

Where $Pr_j(a.b)$ is a method used the approach of pair-wise comparison to appraise which of each entity is preferred, and e_j = difference between the $k_j(a)$ and $k_j(b)$ of GCMs a and b respectively for indicator j.

Then, the exceeding index of GCM a and b in any GCMs is calculated as follow:

$$\phi^+ = \frac{\sum_1^J \pi_{(a.b)}}{(T-1)} \quad (15)$$

$$\phi^- = \frac{\sum_1^J \pi_{(b.a)}}{(T-1)} \quad (16)$$

The next step is the calculating of the final ranking (net ranking) of GCM (a) in the (T) GCMs group. The higher the value of Net ϕ the more suitable the GCM.

$$\text{Net } \phi = \phi^+ + \phi^- \quad (17)$$

2.5 GROUP DECISION MAKING

In the hassle of choosing the best GCM for Egypt several methods are proposed so as to establish a collective preference based at the aggregation of different individual preferences. However, the reciprocated methods such as multicriteria analysis, linear programming and non-linear programming that focus on a single front-runner usually have some imperfection and mistrust that should be tackled. Accordingly, in the current study the group decision making procedure was selected since it is eminent for as a proper alternative for convoluted problems. Thus, in this approach the preeminent alternative is realized to be the supreme compromise from the far-sightedness of all of the other alternatives implicated in the decision problem. Fig. 3 shows the followed procedure for group decision maker that shows the analysis of the individual priority is performed in filtering, rejecting, and selecting [23].

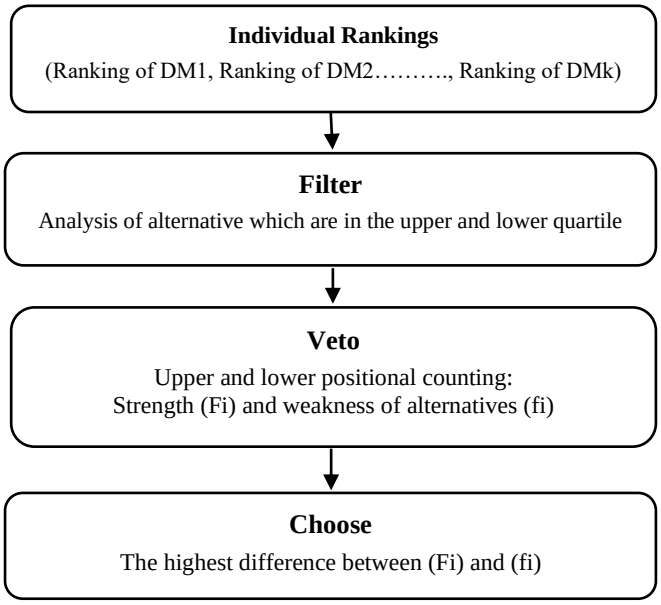

Fig. 3 Applied Methodology for Group Decision Maker, after Morais and de Almeida, [23]

These 3 steps can be briefed described as follows:

1. The first phase consists of analyzing the alternatives which might be in the top and the lower quartiles.
2. In the second phase, a positional count is made of the alternatives, the Strength (Fi) and the Weakness (fi) of the Alternatives, using the equations:

$$F_i = \sum_{k=1}^{m} \sum_{j=1}^{x} (x - j + 1) q_{ij}^k \quad \forall i.k \quad \forall i = 1 \to x \quad (18)$$

$$f_i = \sum_{k=1}^{m} \sum_{j=y}^{n} (j - y + 1) q_{ij}^k \quad \forall i.k \quad \forall i = y \to n \quad (19)$$

Where:

$$q_{ij}^k = \begin{cases} 1 & \text{. if the alternantive i is in the position j for the decision maker k} \\ 0 & \text{. otherwise} \end{cases}$$

In this stage the analysis of the intensity of the Alternative strength which is estimated by the expression: Ni = Fi -fi, taking into consideration that the chosen alternative is being the one that presents the largest value of Ni.

III. RESULTS AND DISCUSSIONS

3.1 PERFORMED INDICATORS

The above five coefficients CC, NRMSD, ANRMSD, AARD and SS are calculated for each cell of the 110 cells that covers Egypt. An example of one cell is presented hereafter. Thus, for each cell out of the 110 cells that represent Egypt, (excluding the cells out of Egypt's boundary), and shown in Fig. 2. All of the calculation for the performance indicators were conducted for each GCM using the relationships indicated by equations (1 through 5) between the observed data and the output results of the different GCMs. Table- I lists the output results of the performed indicators for each model. Table- II lists the entropy values, degree of diversification, and weight of indicators for compromise programming, cooperative game theory and weighted average technique for one season. Table- III lists the entropy values, degree of diversification, and weight of indicators for promethee-2 for one season.

3.2 INDICATORS' WEIGHT

Forty GCMs in Coupled Model Intercomparing Project (CMIP3), namely, ACCESS1-3, ACCESS1-0, bcc-csm1-0, bcc-csm1-1-m,BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CESM1-CAM5., CMCC-CM, CMCC-CMS, CNRM CM5, CSIRO-Mk3-6-0, EC-EARTH, FGOALS-g2, FGOALS-s2, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-H-CC, GISS-E2-R, GISS-E2-R-CC, HadCM3, HadGEM2-AO, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC4h, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-LR, MPI-ESM-MR, MRI-CGCM3, NorESM1-M, and NorESM1-ME are analyzed for the variables, precipitation and temperature. Five indicators, namely, CC, NRMSD, ANMBD, AARD, SS are the performance indicators. Payoff matrix (40 GCMs vs. 5 indicators] is presented in Table- I. Apply entropy technique for determination of weights. Normalization technique equation 6 for each season (4 seasons were selected winter, spring, summer and autumn). The weights are applied in the next step for ranking the 40 GCMs.

Table- I Values of performance indicators obtained for the 40 GCMs for one cell out of the investigated cells that covers Egypt, as an example.

No.	Model ID	CC	NRMSD	ANRMSD	AARD	SS
1	ACCESS1-3	-0.06	4.21	1.55	19.43	0.67
2	ACCESS1-0	-0.07	3.86	0.43	9.49	0.93
3	bcc-csm1-1	-0.08	7.26	1.17	39.48	0.89
4	bcc-csm1-1-m	-0.05	5.37	1.90	18.95	0.77
5	BNU-ESM	-0.07	3.45	0.71	1.15	0.93
6	CanESM2	0.03	3.58	0.60	12.41	0.86
7	CCSM4	0.16	4.13	0.54	8.16	0.95
8	CESM1-BGC	-0.06	4.21	1.55	19.43	0.67
9	CESM1-CAM5	-0.02	3.38	0.32	6.44	0.91
10	CMCC-CM	-0.07	5.43	0.46	7.48	0.94
11	CMCC-CMS	-0.05	5.67	0.43	1.93	0.95
12	CNRM-CM5	-0.05	11.12	2.41	39.45	0.81
13	CSIRO-Mk3-6-0	-0.12	3.60	0.24	5.21	0.95
14	EC-EARTH	-0.04	4.26	0.25	21.32	0.95
15	FGOALS-g2	-0.06	10.27	4.36	107.17	0.65
16	FGOALS-s2	0.00	6.84	0.02	1.88	0.93
17	GFDL-CM3	0.07	3.39	0.47	10.29	0.94
18	GFDL-ESM2G	0.02	5.22	0.01	0.52	0.96
19	GFDL-ESM2M	0.04	3.52	0.56	5.03	0.93
20	GISS-E2-H	0.02	6.87	4.76	65.43	0.25
21	GISS-E2-H-CC	-0.02	10.17	7.07	74.09	0.23
22	GISS-E2-R	-0.14	5.49	2.70	25.70	0.52
23	GISS-E2-R-CC	-0.02	5.70	2.67	55.39	0.62
24	HadCM3	-0.04	4.88	0.38	15.18	0.93
25	HadGEM2-AO	0.17	3.62	0.50	13.15	0.86
26	HadGEM2-CC	0.02	3.47	0.09	10.94	0.94
27	HadGEM2-ES	0.00	3.52	0.11	7.89	0.93
28	inmcm4	-0.04	6.78	0.94	24.75	0.95
29	IPSL-CM5A-LR	-0.13	3.60	0.51	5.06	0.94
30	IPSL-CM5A-MR	-0.05	5.98	0.18	40.33	0.95
31	IPSL-CM5B-LR	-0.02	6.51	0.13	50.27	0.93
32	MIROC4h	0.08	3.87	0.63	11.37	0.93
33	MIROC5	0.08	3.87	0.63	11.37	0.93
34	MIROC-ESM	-0.10	9.94	2.88	94.32	0.83
35	MIROC-ESM-CHEM	0.01	9.99	3.51	68.73	0.81
36	MPI-ESM-LR	0.26	3.54	0.43	10.61	0.90
37	MPI-ESM-MR	0.05	8.29	0.64	1.99	0.90
38	MRI-CGCM3	-0.06	3.97	0.16	19.78	0.94
39	NorESM1-M	-0.07	3.87	0.38	7.15	0.93
40	NorESM1-ME	-0.04	3.53	0.02	5.74	0.95

Table- II Entropy values, degree of diversification, and weight of indicators for compromise programming, cooperative game theory and weighted average technique for one season

Number of GCMs	40		
Indicator	CC	SS	NRMSD
Entropy value Enj	1.59795	0.99274	0.97906
Degree of diversification Ddj	-0.5979	0.00726	0.02094
Weight Rj	1.04948	-0.0127	-0.0367

Table- III Entropy values, degree of diversification, and weight of indicators for PROMETHEE-2 for one season

Number of GCMs	40				
Indicator	CC	NRMSD	ANRMSD	AARD	SS
Entropy value Enj	1.59795	0.97906	0.83148	0.86555	0.99274
Degree of diversification Ddj	-0.5979	0.02094	0.16852	0.13445	0.00726
Weight Rj	2.24137	-0.0785	-0.6317	-0.504	-0.0272

3.3 RANKING OF GCMS

Four methods for ranking GCMs were conducted that are: compromise programming, cooperative game theory, weighted average technique and preference ranking organization method of enrichment evaluation (PROMETHEE-2). Table- IV shows an example of the GCMs ranking applying the methods of compromise programming, cooperative game theory and weighted average technique and PROMETHEE-2. From this Table- IV it can be easily shown the difficulty of selecting any GCM due to the significant randomize in ranking. Any model can have a high rank in one while in the other seasons it has very low rank. Thus, the final stage in evaluation is to select the best suitable model for Egypt as in what follows. Table- V. shows a sample of GCMs ranking for some cells indicated by coordinates (East and North). The ranking was conducted for rainfall and temperature each of them for four seasons. The results show that there are significant variations.

The results of the evaluation shown in Table- V shows that there is no specific path that can determine by any means which of these models is the best in Egypt. From the analysis it was possible to obtain on the cell level, 100 km x 100 km, the top 10 models per cell. The table also shows the order of models according to the degree of credibility of the evaluation. Because of the marked change that does not follow a specific approach, we had to use a more converging method that assists the selection of the finest model for Egypt.

3.4 SELECT THE BEST GCM FOR EGYPT

The group decision making process was applied at each cell out of the 110 cells that covers the entire Egypt. Through the complex calculation to determine the weakness and strength of each model out of the 40 model for the 110 cells spread over 4 seasons for both the rainfall and temperature parameters. Also, the degree of repetition for each model at each cell was also calculated. Finally, it is proven that the "MPI-ESM-LR" is found to be the best model for predicting the climate change all over Egypt.

The MPI-ESM-LR Model couples the atmosphere, ocean and land surface through the exchange of energy, momentum, water and carbon dioxide. It is based on the components of ECHAM6 for atmosphere and MPIOM for ocean as well as JSBACH for terrestrial biosphere and HAMOCC for the ocean´s biogeochemistry. The coupling of atmosphere and land on the one hand and ocean and biogeochemistry on the other hand is made possible by the separate coupling program OASIS3. MPI-ESM has been used in the context of the CMIP5 process ("Coupled Models Intercomparing Project Phase 5") and is currently employed for the MPI-M contributions to CMIP6. MPI-ESM is freely available to the scientific community and can be accessed with a license on the MPI-M Model.

Table- IV Example of three methods for ranking GCMs were conducted that are: compromise programming, cooperative game theory, weighted average technique and PROMETHEE-2 in one season (yellow represents the best model, green represents the 2nd rank and blue represents the 3rd rank)

No.	Model Name	CP	CGT	WAT	PROMETHEE-2

		Lp	Rank	Da	Rank	Va	Rank	Net Phai	Rank
1	ACCESS1-3	0.33	21	0.07	27	0.09	31	-0.44	25
2	ACCESS1-0	0.34	28	0.06	30	0.06	35	-1.66	35
3	bcc-csm1-1	0.38	34	0.05	34	0.17	19	-1.12	31
4	bcc-csm1-1-m	0.34	24	0.08	24	0.13	25	-0.13	22
5	BNU-ESM	0.35	30	0.06	33	0.04	38	-1.96	38
6	CanESM2	0.24	8	0.15	9	0.15	22	1.35	11
7	CCSM4	0.11	3	0.26	3	0.30	7	1.78	7
8	CESM1-BGC	0.33	22	0.07	28	0.09	32	-0.44	26
9	CESM1-CAM5	0.29	14	0.10	18	0.09	30	-0.36	24
10	CMCC-CM	0.36	32	0.06	32	0.11	28	-1.83	36
11	CMCC-CMS	0.34	27	0.07	26	0.14	23	-1.28	32
12	CNRM-CM5	0.43	39	0.00	38	0.34	5	0.25	17
13	CSIRO-Mk3-6-0	0.40	35	0.01	36	-0.01	39	-2.70	40
14	EC-EARTH	0.31	17	0.09	19	0.11	29	-0.11	20
15	FGOALS-g2	0.42	37	0.07	25	0.31	6	-0.04	19
16	FGOALS-s2	0.30	15	0.13	14	0.24	11	-0.22	23
17	GFDL-CM3	0.19	6	0.19	6	0.19	17	1.35	10
18	GFDL-ESM2G	0.26	10	0.14	12	0.20	15	0.05	18
19	GFDL-ESM2M	0.23	7	0.16	8	0.16	20	1.02	12
20	GISS-E2-H	0.29	13	0.14	10	0.27	9	2.00	2
21	GISS-E2-H-CC	0.38	33	0.00	39	0.35	3	1.66	8
22	GISS-E2-R	0.43	38	0.00	40	0.05	37	-1.44	34
23	GISS-E2-R-CC	0.30	16	0.11	17	0.18	18	1.01	13
24	HadCM3	0.32	20	0.08	22	0.12	26	-0.45	27
25	HadGEM2-AO	0.10	2	0.27	2	0.30	8	2.04	1
26	HadGEM2-CC	0.25	9	0.14	13	0.14	24	0.40	15
27	HadGEM2-ES	0.27	11	0.12	15	0.12	27	-0.12	21
28	inmcm4	0.34	25	0.09	20	0.20	16	0.42	14
29	IPSL-CM5A-LR	0.41	36	0.01	37	-0.01	40	-2.48	39
30	IPSL-CM5A-MR	0.34	26	0.08	23	0.15	21	-0.46	28
31	IPSL-CM5B-LR	0.31	18	0.11	16	0.21	14	0.31	16
32	MIROC4h	0.19	4	0.19	4	0.21	12	1.87	4
33	MIROC5	0.19	5	0.19	5	0.21	13	1.87	5
34	MIROC-ESM	0.45	40	0.04	35	0.25	10	-0.82	29
35	MIROC-ESM-CHEM	0.35	31	0.14	11	0.37	2	1.86	6
36	MPI-ESM-LR	0.01	1	0.36	1	0.39	1	1.88	3
37	MPI-ESM-MR	0.28	12	0.18	7	0.35	4	1.36	9
38	MRI-CGCM3	0.33	23	0.07	29	0.07	34	-1.35	33
39	NorESM1-M	0.35	29	0.06	31	0.06	36	-1.94	37
40	NorESM1-ME	0.32	19	0.08	21	0.07	33	-1.12	30

Table- V A sample for two cells shows the ranking of the bets 10 GCMs for each season for rainfall and temperature parameters (red represents MPI-ESM-MR, yellow represents MPI-ESM-LR)

E	*N*	*Rank*	*Rainfall*			
			DJF	*MAM*	*JJA*	*SON*
28	27	1	MPI-ESM-LR	HadGEM2-ES	IPSL-CM5A-MR	IPSL-CM5A-LR
		2	HadGEM2-AO	CSIRO-Mk3-6-0	GFDL-ESM2G	GFDL-CM3
		3	CCSM4	GFDL-CM3	IPSL-CM5A-LR	ACCESS1-0
		4	MIROC4h	inmcm4	HadGEM2-CC	CMCC-CM
		5	MIROC5	HadCM3	HadGEM2-AO	inmcm4
		6	MPI-ESM-MR	MIROC-ESM-CHEM	ACCESS1-0	HadGEM2-CC
		7	GISS-E2-H	CMCC-CM	MPI-ESM-LR	IPSL-CM5A-MR
		8	GFDL-CM3	GISS-E2-H	CMCC-CMS	MPI-ESM-MR
		9	GFDL-ESM2M	MPI-ESM-LR	CMCC-CM	GISS-E2-R
		10	CanESM2	bcc-csm1-1-m	GFDL-ESM2M	HadGEM2-ES

E	N	Rank	Rainfall			
			DJF	MAM	JJA	SON
28	28	1	HadGEM2-AO	HadGEM2-ES	IPSL-CM5A-MR	inmcm4
		2	CCSM4	GFDL-CM3	HadGEM2-AO	ACCESS1-3
		3	MPI-ESM-LR	CMCC-CMS	CMCC-CMS	CESM1-BGC
		4	MPI-ESM-MR	MPI-ESM-LR	MIROC5	ACCESS1-0
		5	MIROC-ESM-CHEM	HadCM3	IPSL-CM5A-LR	MPI-ESM-LR
		6	CanESM2	CSIRO-Mk3-6-0	ACCESS1-0	IPSL-CM5A-LR
		7	MIROC4h	inmcm4	GFDL-ESM2G	HadGEM2-AO
		8	MIROC5	GISS-E2-R	HadGEM2-CC	HadGEM2-CC
		9	HadGEM2-CC	bcc-csm1-1-m	MPI-ESM-MR	HadGEM2-ES
		10	GFDL-ESM2M	GISS-E2-H	CMCC-CM	GISS-E2-R
E	N	Rank	Temperature			
			DJF	MAM	JJA	SON
28	27	1	bcc-csm1-1	CESM1-CAM5	MRI-CGCM3	MPI-ESM-MR
		2	bcc-csm1-1-m	CSIRO-Mk3-6-0	MPI-ESM-MR	bcc-csm1-1
		3	BNU-ESM	bcc-csm1-1	MIROC-ESM-CHEM	FGOALS-g2
		4	ACCESS1-0	MPI-ESM-MR	CSIRO-Mk3-6-0	CESM1-CAM5
		5	MPI-ESM-LR	MIROC-ESM	MIROC-ESM	MPI-ESM-LR
		6	CCSM4	bcc-csm1-1-m	CCSM4	BNU-ESM
		7	CSIRO-Mk3-6-0	MPI-ESM-LR	GFDL-CM3	GISS-E2-H-CC
		8	MIROC-ESM	CCSM4	CNRM-CM5	bcc-csm1-1-m
		9	EC-EARTH	BNU-ESM	CMCC-CMS	HadGEM2-CC
		10	MIROC-ESM-CHEM	MIROC-ESM-CHEM	GFDL-ESM2M	MIROC4h
			DJF	MAM	JJA	SON
28	28	1	MIROC-ESM	MPI-ESM-MR	MPI-ESM-MR	FGOALS-g2
		2	BNU-ESM	CESM1-CAM5	MRI-CGCM3	BNU-ESM
		3	MIROC-ESM-CHEM	BNU-ESM	GFDL-ESM2M	bcc-csm1-1
		4	bcc-csm1-1	CSIRO-Mk3-6-0	CCSM4	MIROC-ESM-CHEM
		5	MPI-ESM-LR	bcc-csm1-1	MIROC-ESM	MPI-ESM-MR
		6	bcc-csm1-1-m	EC-EARTH	GFDL-CM3	MIROC-ESM
		7	FGOALS-g2	MIROC-ESM	CMCC-CMS	GISS-E2-H-CC
		8	CSIRO-Mk3-6-0	bcc-csm1-1-m	bcc-csm1-1	bcc-csm1-1-m
		9	FGOALS-s2	CCSM4	IPSL-CM5A-MR	GISS-E2-H
		10	ACCESS1-0	MRI-CGCM3	IPSL-CM5B-LR	CESM1-CAM5

IV. CONCLUSIONS

Forty GCMs in Coupled Model Inter-comparing Project (CMIP5), are analyzed for the climate variable's precipitation and temperature for Egypt case. These GCMs were Evaluated for the climate variable precipitation rate and temperature through dividing the entire Egypt area to 110 cells each cell is square 100 km x 100 km. These parameters were evaluated through applying five performance indicators. These indicators are CC, NRMSD, ANRMSD, AARD and SS are calculated for each cell of the 110 cells that covers Egypt. The calculation for the performance indicators were conducted for each GCM. A comparison between the observed data and the output results of the different GCMs is conducted and indicated for each cell by the entropy values, degree of diversification, and weight of indicators for compromise programming, cooperative game theory and weighted average technique for one season. Four methods for ranking GCMs were conducted that are: compromise programming, cooperative game theory, weighted average technique and PROMETHEE-2. It has been indicated that there are noteworthy difficulties of selecting any GCM due to the chaotic in ranking. The top 10 models at each cell was defined, then another four methods for ranking GCMs were conducted that are: compromise programming, cooperative game theory, weighted average technique and PROMETHEE-2. The ranking was conducted for rainfall and temperature for four seasons. The results show that is no specific track that can determine by any means to identify the best model for Egypt. From the analysis it was possible to obtain on the cell level, 100 km x 100 km, the top 10 models per cell. The table also shows the order of models according to the degree of credibility of the evaluation. Because of the marked change that does not follow a specific approach, we had to use a more converging method that assists the selection of the finest model for Egypt. The group decision making process was applied at each cell out of the 110 cells through its complex calculation to determine the weakness and strength of each model out of the 40 model for the 110 cells spread over 4 seasons for both the rainfall and temperature parameters. Also, the degree of repetition for each model at each cell was also calculated. Finally, it is proven that the "MPI-ESM-LR" is found to be the best model for predicting the climate change all over Egypt. This model is freely available to the scientific community and can be accessed with a license on the MPI-M Model. The GCM "MPI-ESM-LR" was developed in The Max Planck Institute for Meteorology (MPI-M) in Germany. It is highly recommended to apply this model for Egypt climate change studies as long as it is the most appropriate model for projecting the climate change for Egypt up till year 2100. On the other hand, more studies should be conducted on spatial level for Egypt. That aims to select a specific model that represent each climatic zone in Egypt.

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