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Evaluation of Grid-Based Aridity Indices in Classifying Aridity Zones in Iraq

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ABSTRACT

In this study, the aridity index (AI) based on gridded climate data was validated for defining aridity and classifying aridity zones in Iraq through comparison with the results obtained by the station-based aridity index. Gauge-based gridded climate data taken from Climatic Research Unit Timeseries (CRU TS) were used to determine the annual value of four aridity indices (Lang, De Martonne, Ernic and UNEP AI) over the period 1998-2011. The results showed that the aridity distribution maps derived using grid-based aridity indices were reasonably close to those found using station-based ones. The four aridity indices properly identified similar aridity (dryness) classifications in both the station-based and grid-based aridity maps. The area percentage of each aridity class predicted by grid-based AIs was also compared with that obtained by the station-based AIs. The results showed that the variances between the area percentages predicted by grid-based AIs and those estimated using station-based AIs are fairly slight. The Lang AI exhibited the least variance (0.4%) while the De Martonne AI had the biggest variance (-4.8%). Despite these minor variances, it is however possible to conclude that the grid-based aridity index classified the aridity zones of Iraq as properly as the station-based aridity index did.

INTRODUCTION

Aridity, dryness, and drought events caused by climate changes have become major socio-environmental issues in recent years. They have an adverse influence on ecosystems as well as human livelihoods in many different places of the world (Alizadeh et al. 2020). Particularly, aridity poses a significant, continuing challenge to the majority of global regions (Huang et al. 2017). Aridity is defined as a shortage of moisture that is accompanied by a permanent scarcity of rainfall (Agnew & Anderson 1992). Aridity can increase the risk of desertification in areas with dry, hot climates and little precipitation (Costa & Soares 2012). Iraq is one of the countries that is influenced negatively by increasing aridity. To assess the aridity impact, the aridity indices are used for this purpose. An aridity index may be described as a numerical degree of water deficits and dryness at a certain place (Stadler 2005). Since the start of the 20th century, some numerical indices have been provided for measuring the aridity level (Kimura & Moriyama 2019). The indices proposed by Lang (1920) and De Martonne (1926) are the earliest indices that might be still used to explain the aridity (Traore et al.2020). Those indices applied mean yearly precipitation (in mm) and average annual temperatures in (o C) to measure aridity-humidity in a specific place. Both the indices, in particular De Martonne AI, have been often used to examine the regional distribution and temporal version of the aridity (Croitoru et al. 2013; Quan et al. 2013; Ashraf et al. 2014; Sarlak and Mahmmod 2018; Pellicone et al. 2019; Nistor et al. 2020 and Ullah et al. 2022).

Using the Lang and De Martonne principle, other kinds of aridity indices have been suggested, but they used different statistic values of the temperature in place of the average temperature. Examples of these indices are Emerger AI, which is derived from annual precipitation and the difference between the largest and lowest temperature of the year. Ernic AI, which used annual precipitation and maximum temperature (Stadler 2005). Also, there are other indices (such as the Köppen AI) that depend on temperature and precipitation, however they are not used as regularly as early aridity indices like Lang and De Martonne (Speich 2019).

In 1992, the United Nations Environment Programme (UNEP) suggested a new approach to measure the degree of aridity as a ratio of the mean yearly precipitation (P) to potential evapotranspiration (PET) (U.N.E.P 1992). UNEP definition reflects the effect of the thermal regime in defining the aridity through incorporated PET which is a good indicator of water loss than temperature (Nastos et al. 2013) The UNEP-AI has been applied by several researchers to measure aridity and classify climates on a regional or worldwide scale (see e.g., Haider & Adnan 2014; Cheval et al. 2017; Trabucco and Zomer 2018; Derdous et al. 2021).

To calculate the aridity index accurately, meteorological data over a long period required to be accumulated from numerous weather stations distributed homogeneously over the study area. However, in most cases, such information may be inadequate or unavailable. The best alternative way of obtaining the required data is to use the meteorological datasets produced and made accessible online by international climatic organizations. These databases offer gridded, high-resolution data for climate variables including temperature, precipitation, shortwave radiation, vapor pressure, and PET (Harris et al. 2014, Mistry et al. 2019). The data stored within these datasets are usually generated using extensive analyses of meteorological stations and gauge records from all around the world (Werner et al. 2019). Therefore, they could be relied upon to supply the data required for water resources management, and ecological, agricultural, and climate change studies.

The purpose of this research is to evaluate aridity indices calculated based on gridded data in describing the aridity and classifying the climate in Iraq which is one of the countries suffering increasing dryness. Four aridity indices are used in the study; Lang AI, De Martonne AI, Ernic AI, and UNEP AI. The reason these four indices were chosen over the other aridity indices is because they are commonly used in aridity-related studies. Also, they differ from one another in terms of their data inputs. The results of the aridity mapping and climate classification obtained by grid-based data were compared with those obtained by station-based data to assess the suitability of the gridded data for defining and classifying the aridity in the study area (Iraq).

MATERIAL AND METHODS

Study Area

The study area includes the entire land of Iraq. Iraq is a country located in southwest Asia with a total area of around 435,000 square kilometers. The ground elevation in Iraq ranged from sea level in the south to 3661 meters above sea level in the north (Fig. 1) (Al-Zubedi 2022). In general, the

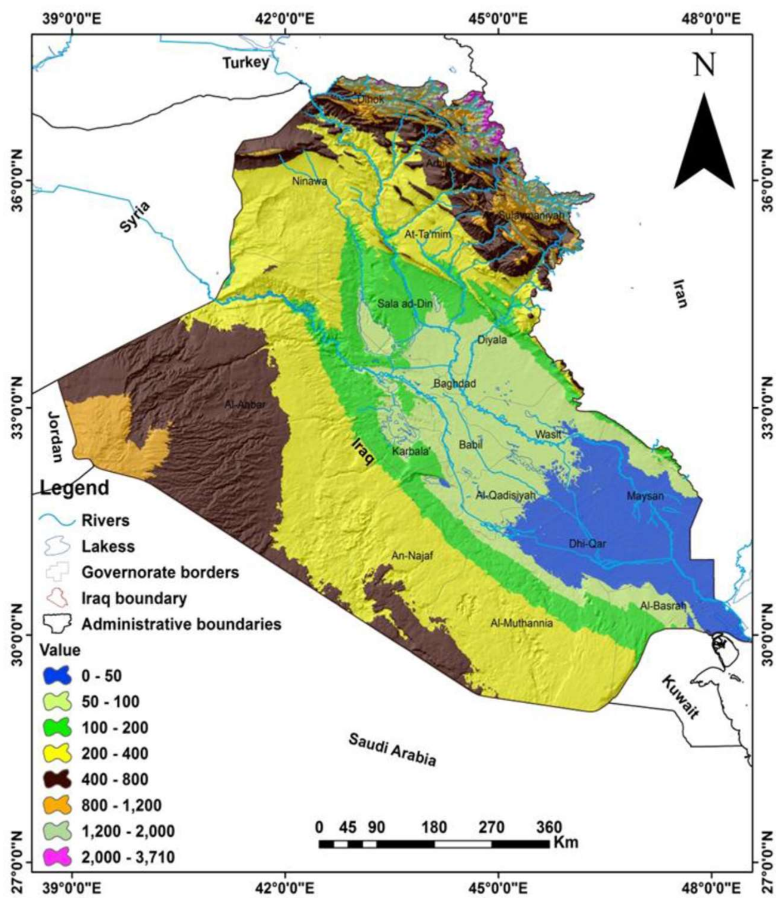


Fig. 1: Location and topographic map of Iraq (Al-Zubedi 2022).

terrain of Iraq is dominated by broad plains, with mountains largely concentrated in the north and northeast (close to the borders with Turkey and Iran).

The climate of Iraq may be described as continental, with an extreme annual temperature range and a relatively small amount of precipitation. The country generally experiences winters that vary between cool and cold, and summers are dry with variations between hot and extremely hot temperatures. The coldest month is January, with temperatures ranging from 5°C to 10°C, while the hottest month is August with temperatures rising up to around 45°C (Salman et al. 2019).

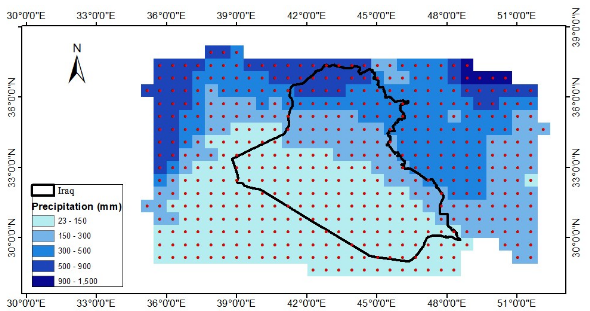
Precipitation falls in Iraq from October to May, with December and February experiencing the largest amount. The mean annual precipitation in Iraq is expected to be between 100 and 180 mm (https://www.britannica.com/place/Iraq/Climate). Most of the country receives less than 100 mm/year, however, the highlands (north-eastern regions of Iraq) may receive up to 1200 mm/year of precipitation (Hameed et al. 2018).

Datasets and Data Processing Methods

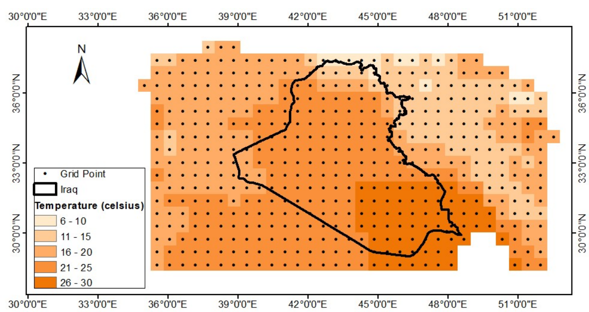
The primary inputs required to determine the aridity indices are climatic data such as temperature (T), precipitation (P), and potential evapotranspiration (PET). The required data are often obtained from historical records of the climatic stations distributed across the study region. However, if such station-based data are either unavailable or insufficient, it is possible to collect them from gridded datasets available on weather and climate websites.

Climate Research Time (CRU-TS) was used in this research to generate required metrological data. More than 4000 gridded stations were generated with the aid of CRU-TS with a grid size of 0.5 degrees. Climate change studies are widely using this method around the world. The data generated by CRU-TS were tested by an accurate quality control tactic to make them a common source of data (Harris et al. 2014).

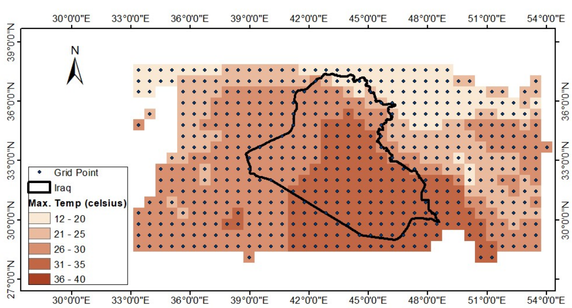
The first step in this method is to download needed gridded data from CRU-TS with a high resolution. These data include the monthly average max temperature, mean and average monthly rainfall, and potential evapotranspiration (PET) for the period from 1998 to 2011. Secondly, spatial processing for the data were done using ArcGIS in order to produce the yearly average for every parameter aforementioned. Fig. 2 shows the annual average layers of



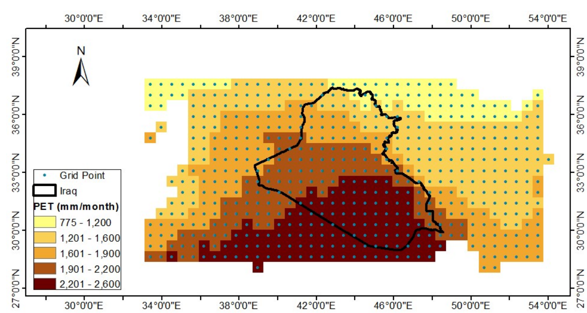
(a) Mean Annual Precipitation



(b) Mean Annual Temperature



(c) Mean Maximum Temperature



(d) Potential evapotranspiration

Fig. 2: Gridded climatology data over the period 1998-2011 was used for calculating aridity indices.

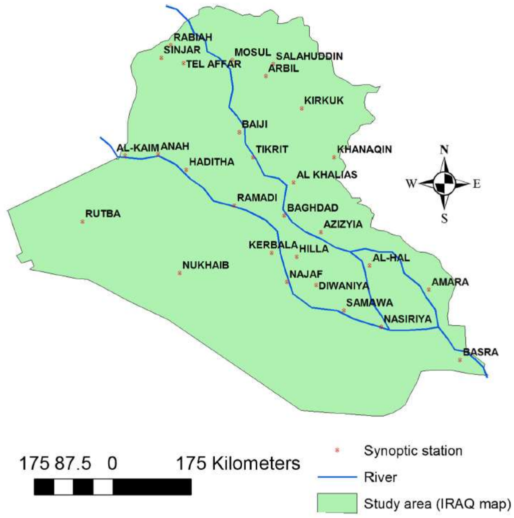


Fig. 3: Location of the meteorological stations in Iraq used by Şarlak and Mahmood 2018.

the max temperature, rainfall, and PET. In the final step, the layers in Fig. 2 were used as input in calculating the aridity index formulas, and four formulas were used (Lang, De Martonne, UNEP, and Ernic).

The station-based values of aridity indices and their distribution were obtained from research conducted by Şarlak and Mahmood in 2018. In their study, the aridity indices of Lang, De Martonne, United Nations Environmental Program (UNEP), and Erinç were computed using historical records of precipitation and temperature from 28 climate stations run by the Iraqi Meteorological Organization and Seismology (IMOS). Fig. 3 illustrates the locations of the meteorological stations utilized in Şarlak and Mahmood's study.

Aridity Index and Its Formulas

As previously mentioned, aridity indices (AI) are usually used to classify aridity zones (dryness-humid regions) according to their degree of dryness. For this purpose, a number of aridity indices have been developed as indicators of dryness and water scarcity. The aridity indices may be broadly classified into two types: those that depend on precipitation and temperature and those that depend on precipitation and potential evapotranspiration (PET) (Quan et al. 2013).

In this paper, four aridity indices had been calculated using gridded climatic data for the period 1998–2011. These indices are Lang, De Martonne, and Ernic index which are based on precipitation-temperature, and UNEP index which are primarily based on precipitation-PET. These indices were frequently utilized in investigating the aridity situations in various regions of the world (Ullah et al. 2022). The equation and inputs required for calculating every aridity index are shown in Table 1.

Based on the magnitudes of the aridity index, the weather of any region may be categorized into different zones in terms of dryness and humidity. Table 2 suggests climate classification recommended for the four aridity indices used in this study. According to the results computed for each aridity index and the related classification scheme, the Iraq areas had been climatically classified and then the spatial distribution for the aridity zones was also obtained.

Table 1: Aridity index formulas and input parameters.

Aridity Index	Formula	Parameters
Lang	AI = P/T	P = annual precipitation (mm)
		T = mean annual temperature (°c).
De Martonne	AI = P/(T+10)	P = annual precipitation (mm)
		T = mean annual temperature (°c).
Ernic	AI = P/Tmax	P = annual precipitation (mm)
		Tmax = mean annual max temperature (°c).
UNEP	AI = P/PET	P = annual precipitation (mm)
		PET = potential evapotranspiration (mm).

Table 2: Classification limits of the Aridity Indices used in the study.

Aridity Indices				
Aridity Zone	Lang	De Martonne	UNEP	Ernic
Hyper-arid	---	---	< 0.05	< 8
Arid	< 20	< 5	0.05 – 0.2	8 - 15
Semi-arid	20 - 40	5 - 15	0.2 – 0.5	15 - 23
Sub-humid	----	15 - 30	0.5 – 0.65	23 - 40
Humid	40 - 60	30 – 60	> 0.65	40 - 55
Very Humid	> 160	> 60	---	> 55

RESULTS AND DISCUSSION

Aridity Mapping

To evaluate the effectiveness of the grid-based aridity index in defining aridity and classifying dryness zones in Iraq, the results of the grid-based calculated indices have been compared to those generated using the station-based indices. Figs. 4 to 7 show the comparison among the aridity distribution maps derived by the four aridity indices (Lang, De Martonne, Ernic, and UNEP AI). The aridity distribution maps were derived from the yearly aridity index values over the duration of 1998-2011 and all selected indices

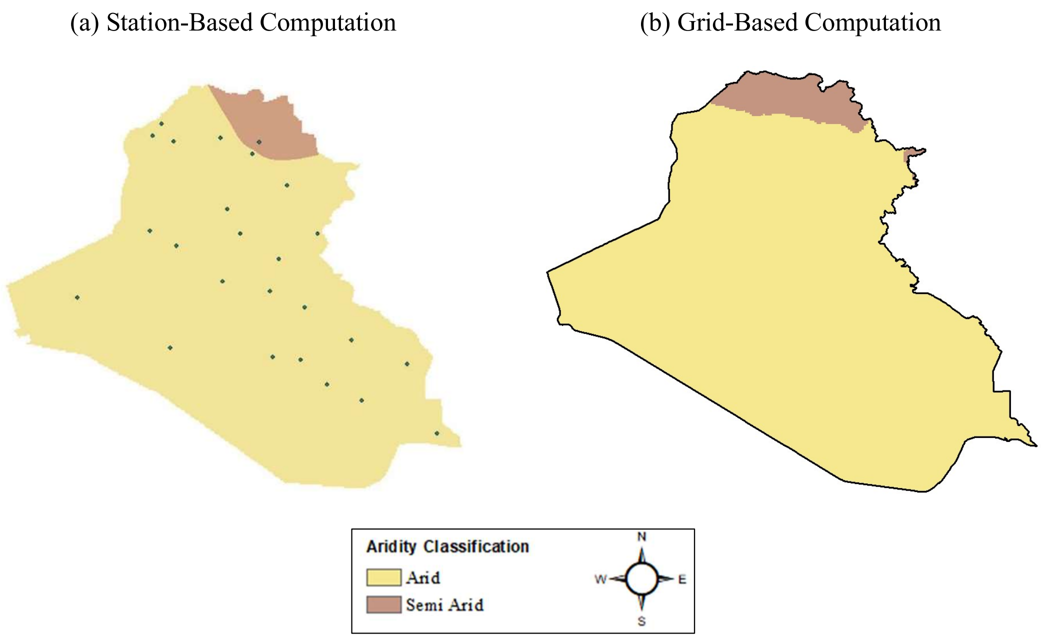


Fig. 4: Aridity distribution maps according to Lang aridity index.

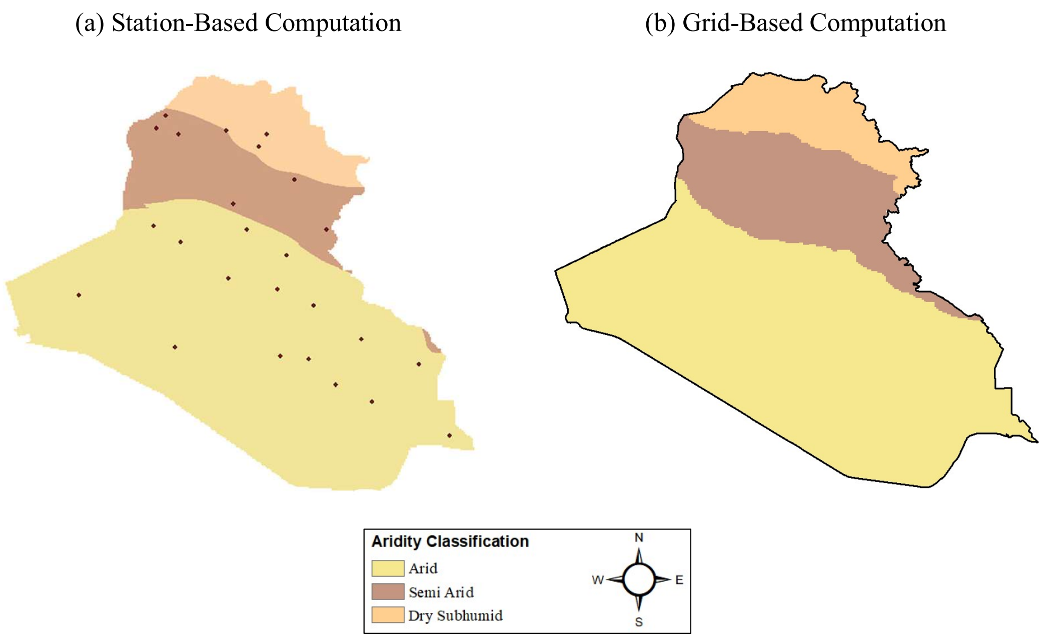


Fig. 5: Aridity distribution maps according to De Martonne aridity index.

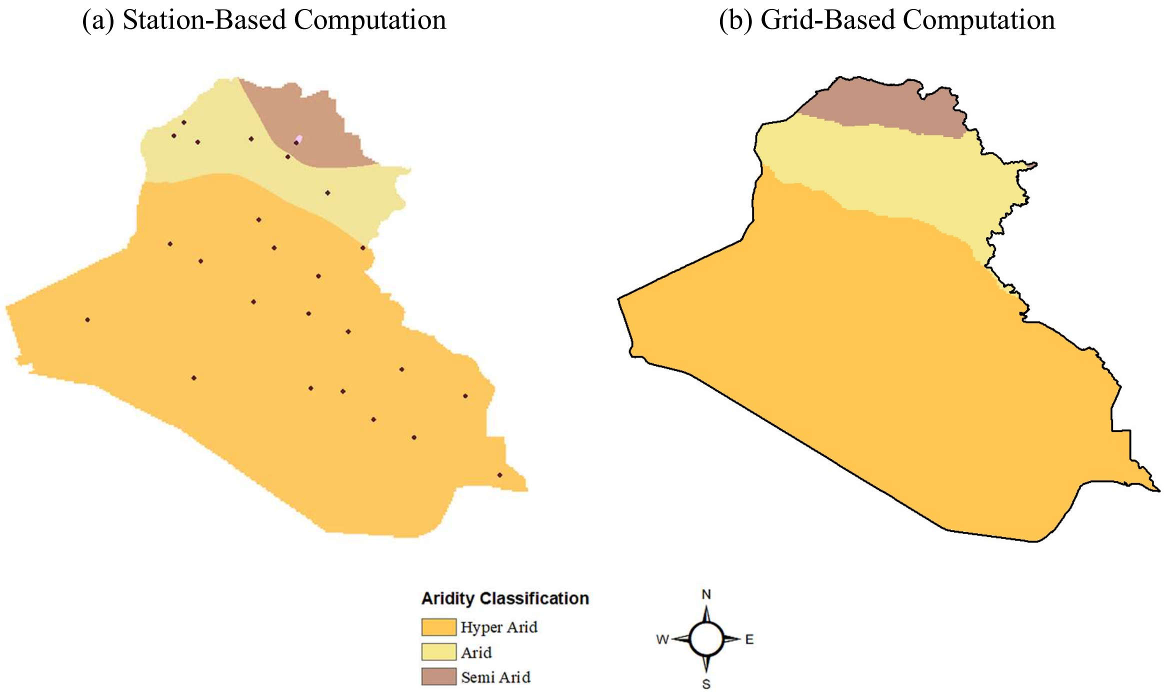


Fig. 6: Aridity distribution maps according to the Ernic aridity index.

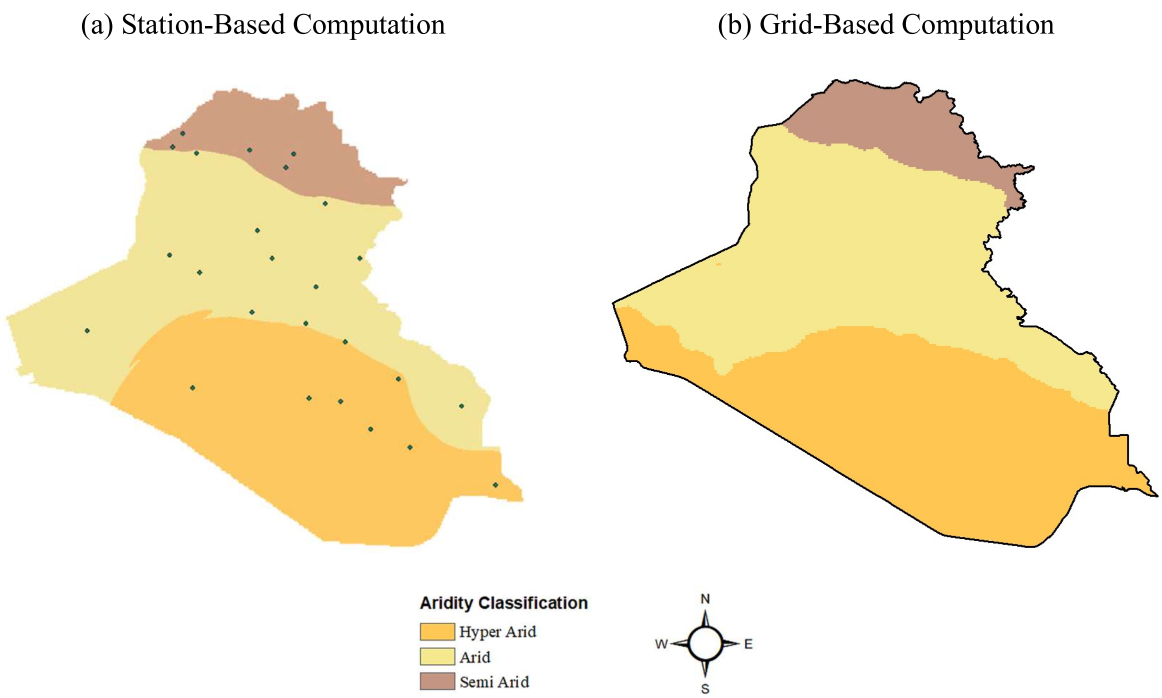


Fig. 7: Aridity distribution maps according to UNEP aridity index.

were computed from gridded and land station weather data. The station-based aridity maps were acquired from a study carried out by way of Şarlak and Mahmood in 2018 while the grid-based aridity maps were generated using gridded data from CRU-TS. Şarlak and Mahmood (2018) utilized historic records of temperature and precipitation from

28 weather stations dispersed over different areas of Iraq (Fig. 3) to calculate the aridity indices.

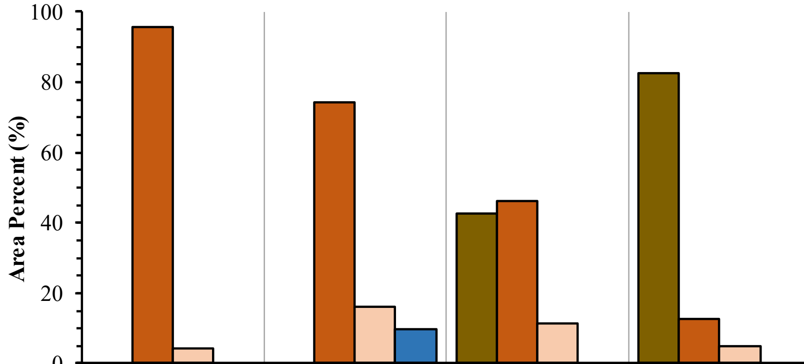
The aridity maps displayed in Figs. 4 to 7 generally imply that the aridity zones of Iraq were identified using gridded data with a distribution that is remarkably close to that found using station data. The four aridity indices properly identified similar climatic classifications in both the station-based and grid-based aridity maps. For instance, the Lang AI was able to identify two classes - arid and semi-arid - when utilizing the station data or the gridded data. For the remaining aridity indices, the same aridity zones were also evidently noticeable for both the station and grid-based maps. Furthermore, when comparing the grid-based aridity maps with those produced using station data, the areas of aridity zones appear to be fairly comparable. Regardless of the data source used, the four aridity indices indicate clearly that the arid climate covers all Iraq regions except a small portion in the north which is classified as sub-humid.

Even though all four aridity indices produced aridity maps and classifications that were closely matched to station-based maps, certain indices appeared to produce results that were more comparable and had less deviation than others. To find out the differences between the grid-based and station-based aridity indices in predicting the aridity classes, the area percentage of each class was calculated and compared as demonstrated in the next section.

Comparison and Variances

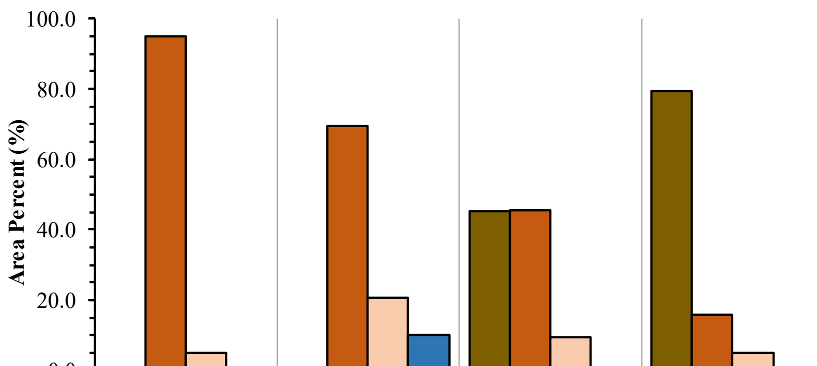
To compare quantitatively the grid-based and station-based calculations of the aridity indices, the area percentages of

(a)



	Lang	De Martonne	UNEP	Ernic
Hyper arid	0	0	42.7	82.6
Arid	95.6	74.1	46.1	12.6
Semi arid	4.4	16.2	11.2	4.8
Dry Subhumid	0	9.7	0.0	0

(b)



	Lang	De Martonne	UNEP	Ernic
Hyper arid	0.0	0.0	45.1	79.3
Arid	95.0	69.3	45.5	15.9
Semi arid	5.0	20.6	9.4	4.8
Dry Subhumid	0.0	10.1	0.0	0.0

Fig. 8: Area percent for aridity classes according to the four aridity indices computed with (a) Station data and (b) gridded data.

aridity classes derived by the four indices were determined. Fig. 8 shows the area percent for aridity classes according to the four aridity indices computed with (a) station data and (b) gridded data.

The area percentages of any aridity class predicted by grid-based and station-based AI do not differ much. The clear similarity between the two graphs reflects the similarity in the aridity classification obtained by the grid-based and that obtained by the station-based aridity indices. Regardless of the data source, the four aridity indices predicted the same climate classes with areas being nearly equivalent. For example, the highest area percent of the arid class was predicted by the Lang index with values being 95.6% from station data and 95% from gridded data (Figs. 8a and b). The dry-subhumid which is the class that was only predicted by De Martonne AI covers the area with percent of 9.7% and 10.1% for gridded and station data respectively.

To give more details onto the differences between the grid and station-based aridity indices, the variance of the area percent for each class were computed. Fig. 9 shows the area percentage variances of the aridity indices computed by station data and gridded data.

Overall, De Martonne and Ernic's AI gave the highest variances, whereas Lang and UNEP's AI exhibited the lowest values. The variances between the grid-based and station-based classes of the De Martonne AI were -4.8 for the arid

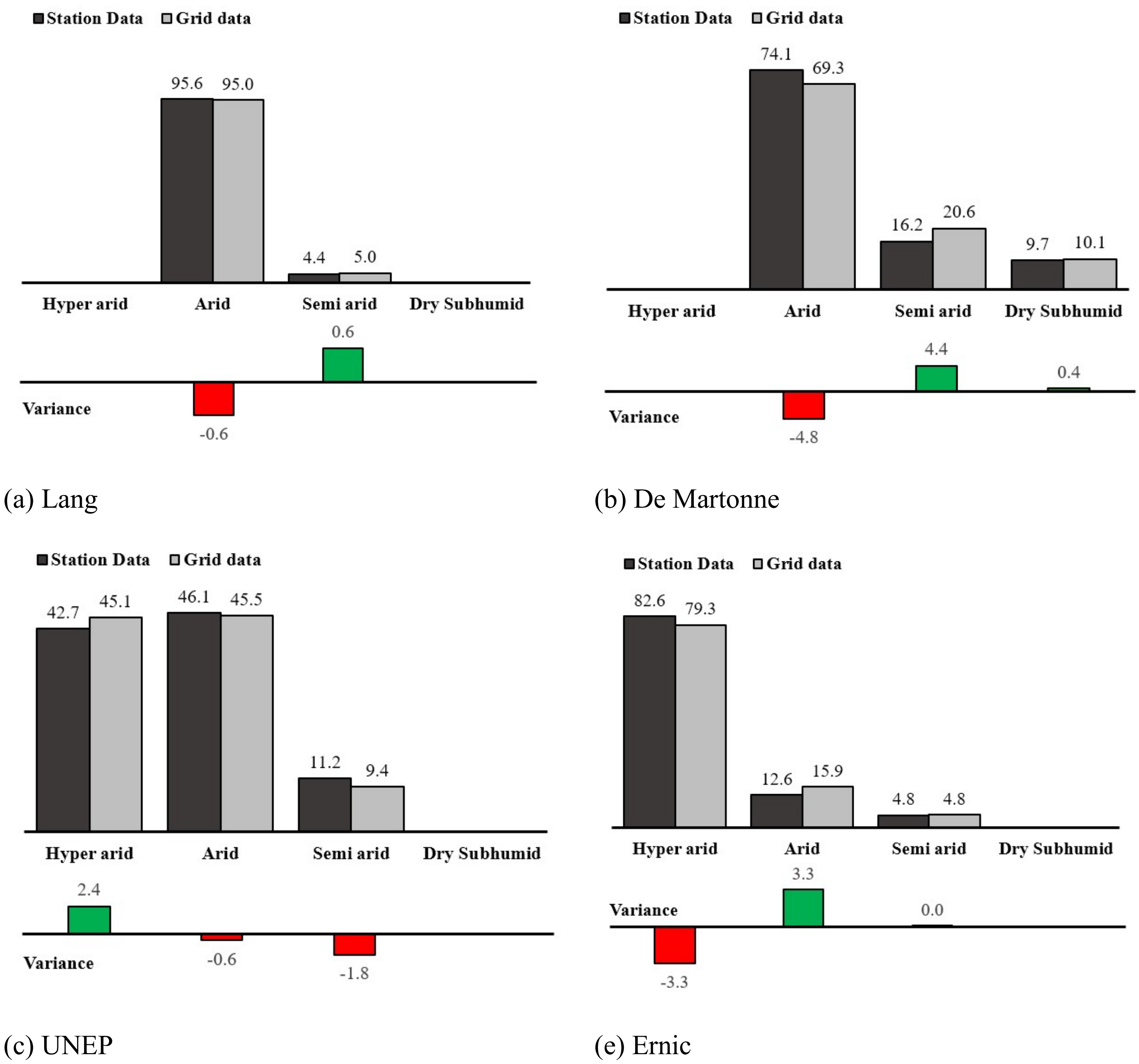


Fig. 9: Variances of the aridity indices computed by station data and gridded data in terms of area percentage of each class.

class and 0.4 for the sub-humid class. In the case of Lang AI, the variances were -0.6 for the arid class and 0.6 for the semi-arid class which was the smallest among the aridity indices used in this study. For the UNEP AI, which is dependent on PET and precipitation, the area percent of the climate classes obtained from station data differed marginally when utilizing gridded data. In the case of UNEP AI, the variances were relatively smaller compared to DE Martonne AI with values of 2.4% for hyperarid (the largest variance) and -0.6% for arid (the smallest variance).

The variances between the results of the classifications obtained by the grid and station-based aridity indices may be attributed to different reasons. One of them, is the class limits of the classification scheme applied by each aridity index. When the difference between the lower and upper limits of a class is large, the variance is expected to be less. Other potential causes for the discrepancies between the grid-based and station-based aridity classifications include differences in temperature and precipitation data obtained from gridded datasets and station records. Also, inaccuracies caused by the interpolation technique that was used to distribute the data spatially could be a source for variances in the results. Despite these minor variations, it is however possible to conclude that the grid-based aridity index correctly forecasted the aridity zones of Iraq in a manner that was consistent with the results obtained when station data were employed.

CONCLUSIONS

In this study, gauge-based gridded climate data taken from Climatic Research Unit Timeseries (CRU TS) were used to determine the aridity index (AI) based on four definitions of aridity (Lang, De Martonne, UNEP, and Ernic). The validation of the grid-based aridity index in defining aridity and classifying aridity zones (dryness-humid regions) in Iraq was assessed by comparing the results with those obtained by station-based aridity indices. The station-based aridity distribution results were obtained from a study conducted by Şarlak and Mahmood in 2018. Şarlak and Mahmood (2018) utilized historical records of temperature and precipitation from 28 climate stations distributed throughout different regions of Iraq to calculate the aridity indices.

First, the aridity distribution maps according to the four aridity indices (Lang, De Martonne, Ernic and UNEP AI) were derived from gridded data for a period 1998-2011. The aridity maps generally implied that the aridity zones of Iraq are identified using gridded data with a distribution that is quite close to that found using station data. The four aridity indices properly identified similar aridity classifications in both the station-based and grid-based aridity maps. Regardless of the data source used, the four aridity indices indicated clearly that the arid climate covers all Iraq regions except a small portion in the north which is classified as a sub-humid.

The area percentage of each climate class predicted by grid-based AIs was also compared with that obtained by the station-based AIs. The findings demonstrated that grid-based predictions of area percentages for every aridity class have some minor differences from those produced by station-based AI. The De Martonne AI demonstrated the largest variance (-4.8%) between the grid-based and station-based classes, and the Lang AI had the smallest variance (0.4%).

Despite these minor variances, it is however possible to conclude that the grid-based aridity index forecasted the dryness zones of Iraq in a manner that was consistent with the results obtained when station data were employed. Therefore, it can be concluded that when gridded data are used, the four aridity indices can effectively determine the degree of dryness and predict aridity zones that are nearly comparable to those generated from station data.

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