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A Novel Index of Agricultural Drought Measurement: Soil Moisture and Evapotranspiration Revealed Drought Index (SERDI)

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Abstract: Droughts are a common occurrence in various climates and are primarily caused by a prolonged decrease in rainfall. Several factors contribute to droughts, including temperature, wind speed, relative humidity, rainfall timing, amount, and intensity during the growing season. The objective of this study is to establish a new index, named soil moisture and evapotranspiration revealed drought index (SERDI), for displaying dry and wet conditions based on combining both soil moisture and evapotranspiration (Penman-Monteith) to improve drought early warning and its severity globally. For validation of the SERDI with other indices such as LST, VHI, NDVI, and NDWI, different ways used such as R-square, RMSE, MAPE, and P-value to estimate the accuracy, variability of data, the forecast conditions, and how the significance of data. The results showed that the low RMSE and high r^2 were found between SERDI with LST and VHI. In contrast, the low R-square and high RMSE were between SERDI with NDVI and NDWI in most of the semi-arid areas. Furthermore, most of the semi-arid areas from Iran, Iraq, Syria, Jordan, and Israel experienced moderate and severe dry conditions, except some parts of these regions had normal conditions in Iran and Syria. The SERDI analysis revealed a strong correlation between (LST) and a moderate correlation with (VHI) across all study areas. However, the relationship between other indices, like (NDWI) and (NDVI), varied depending on the regions. To conclude, SERDI can be used globally for detecting drought based on soil moisture and evapotranspiration.

Keywords: evapotranspiration; new drought index; semi-arid areas; soil moisture; TerraClimate

1. Introduction

The unpredictability of drought severity is due to a variety of factors, including the frequency and spread of precipitation, evaporation requirements, and the ability of soils to store moisture. There are two common types of drought stress: intermittent drought, which is caused by periods without rain, and terminal drought, which happens at the end of the growing season when soil moisture is used up (Wery, Silim et al. 1993). Droughts occur in many different climates, from wet to dry areas, and are largely due to a decrease in the amount of rain received over an extended period such as a season or year. Temperature, wind speed, relative humidity, and when and how much rain falls during the growing season (including how often it rains, the intensity and length of the rainfall, and when it starts and stops) all play an important role in droughts. Unlike aridity - which is limited to drier areas, droughts are usually temporary and can vary in severity. It's worth noting that there's a difference between heat waves and droughts; heat waves typically last around one week while droughts can go on for months or even years. When these two join forces, the effects on society and economics are drastic (Mishra and Singh 2010).

Drought definitions can be conceptual or operational, with conceptual referring to definitions written in general terms to define the parameters of the concept of drought. The American Heritage Dictionary, for instance, defines a drought as a long period without rain, especially during a planting season. Agricultural experts consistently re-assess the meteorological conditions' effect on the plants during the growing season. Also, operational definitions can be used to identify and analyze droughts in terms of their frequency, severity, and duration for a particular period. This requires data concerning short-term moisture levels or yield departures from the usual, to determine when drought happened. This can help us calculate the chances of droughts with varying degrees of intensity, length, and spatial extent (Wilhite and Glantz 1985). Moreover, Drought is typically characterized as a long-term, significant deficiency of precipitation over a particular region for an extended period. Additionally, definitions have been expanded to include the environmental and societal impacts. This perspective suggests that the effects of drought are contingent on not only how severe the water shortage is, but also the local conditions it affects (Zargar, Sadiq, et al. 2011; Wilhite and Glantz 1985).

Drought indices can provide a numerical value to quantify the drought level, which is more useful than the raw data. These indices are based on various events and conditions, such as climate dryness anomalies (e.g., precipitation), soil moisture loss, or lowered reservoir levels. Additionally, some indices use remote sensing imagery to detect vegetation health as an indicator of drought. Due to a range of factors such as drought characteristics and impacts, plus technological advances in remote sensing, over 150 different drought indices have been developed (Kchouk, Melsen et al. 2021; Yihdego, Vaheddoost et al. 2019; Zargar, Sadiq et al. 2011). Additionally, there is a need for these indices to be tailored to particular climates and water systems, and a current trend of combining existing indices with new ones to cover more issues and applications (Zargar, Sadiq et al. 2011). Different types of droughts require different input variables for forecasting. Meteorological drought analysis relies on precipitation data, while hydrologic drought analysis uses stream flow, reservoir, and lake level data. Groundwater drought is assessed through groundwater level data, and agricultural drought is measured using soil moisture and crop yield data. Various drought indices have been developed for agricultural drought forecasting, based on combinations of precipitation, temperature, and soil moisture. These indices can also be used to assess the impact of a drought and determine its intensity, duration, severity, and spatial extent (Mishra and Singh 2011).

The unclear worldwide patterns in droughts point to potential future increases in regional drought. The agricultural drought, also known as the soil moisture drought, is one of the main causes of uncertainty regarding changes in drought. The physiological functioning of both natural and cultivated ecosystems is severely hampered by soil moisture drought, which can have significant effects on agricultural production (Berg and Sheffield 2018). Changes in precipitation characteristics have probably played a role in the widespread drying of surface soil moisture. This phenomenon is more pronounced in areas with decreasing precipitation. However, the primary factor behind this drying is the increased evaporative demand caused by warmer temperatures (Dai, Zhao et al. 2018). The Penman-Monteith (PM) approach is preferable to the simple Thornthwaite (TH) method, which overestimates drying in energy-limited areas (Mukherjee, Mishra et al. 2018). Estimates of PET-based solely on temperature (e.g., the Thornthwaite approach) may result in PET and drought overestimation (Aadhar and Mishra 2020). There are many indices for drought, but it still requires a more accurate index for detecting drought onset, intensity, and frequency. Several indices used evapotranspiration and soil moisture for drought, but SERDI combined both to detect drought early due to high temperatures and low precipitation. The objective of this study is to establish a new index, named SERDI, for displaying dry and wet conditions based on combining both soil moisture and evapotranspiration (Penman-Monteith) to improve drought early warning and its severity globally. The study highlights that weak, moderate, and strong correlations between indices are normal due to their specific characteristics. This implies that relying on a single index may not provide a comprehensive picture of drought conditions, and using a combination of indices, such as LST and VHI, can be valuable for better monitoring and managing agricultural drought in these regions. Overall, the SERDI analysis provides valuable information for understanding drought patterns, severity, and correlations between indices in semi-arid regions, which can be crucial for drought monitoring and prediction.

2. Methodology

2.1. Study area

The semi-arid regions in the Middle East countries include Iran, Iraq, Syria, Jordan, Israel, and Turkey. It is located between 30 and 60 E and 28 and 40 N. The wide semi-arid areas lie in Iran, which dominates most of central Iran and stretches from the east to the west of the country. Although the province's names were used to show the drought's occurrence, not the entire province has a semi-arid climate, for example, only small parts of Sulaimaniyah and Erbil provinces are located in the semi-arid areas. The temperature and precipitation varied because the semi-arid region covers a huge part of the Middle East. It also has two different semi-arid zones, including cold and hot semi-arid areas. Most importantly, the Köppen classification is used to extract the semi-arid regions in Middle Eastern countries (Peel, Finlayson et al. 2007).

The Köppen climate classification system is commonly used to categorize the world's climates based on the annual and monthly averages of temperature and precipitation. Here are the general Köppen climate classifications for the semi-arid regions of the Middle East (Peel, Finlayson et al. 2007) (Figure 1):

- Iran: BSh (hot semi-arid climate), with some regions classified as BWk (cold desert climate).
- Iraq: BSh (hot semi-arid climate) and BWh (hot desert climate) in the western desert areas in other parts of the country.
- Syria: BSh (hot semi-arid climate) in most parts of the country, with some areas classified as BSk (cold semi-arid climate).
- Jordan: BSh (hot semi-arid climate).
- Israel: BSh (hot semi-arid climate) in most parts of the country, with some areas classified as Csa (hot-summer Mediterranean climate).
- Turkey: BSh (hot semi-arid climate) in the southeastern part of the country, with some areas classified as Csa (hot-summer Mediterranean climate).

It is important to note that these classifications are general and that there can be significant variations in climate within each country due to differences in topography, altitude, and other factors. In addition, climate patterns may be affected by global climate change, which causes variations in average temperatures and precipitation patterns over time.

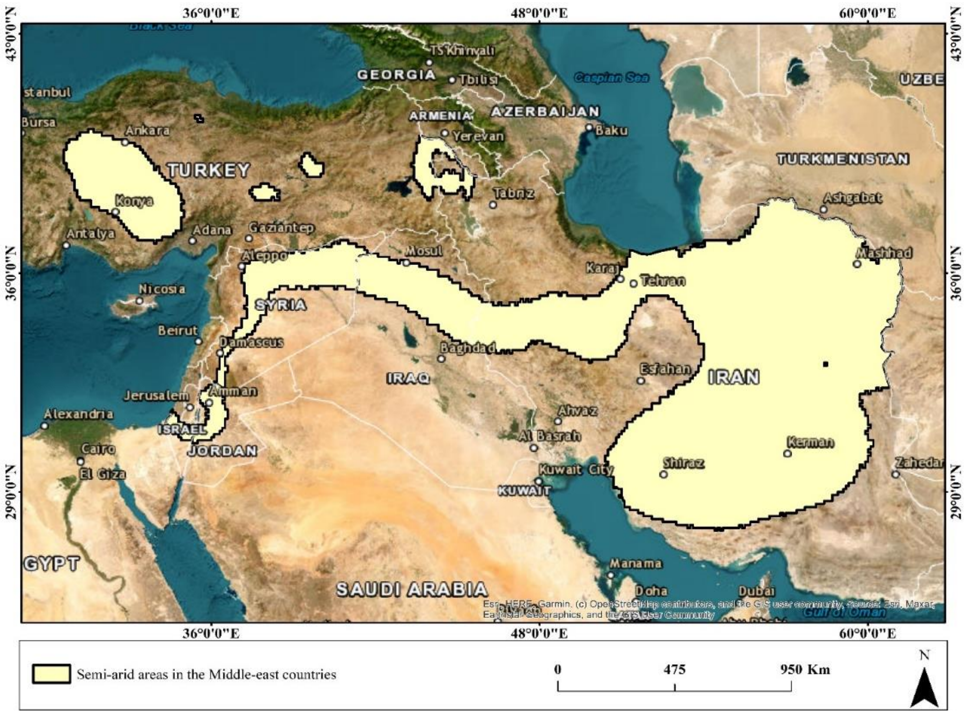

Figure 1. Semi-arid areas in the Middle-east countries.

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2.2. Data

Soil moisture and evapotranspiration data were used in this study. Both data were obtained from TerraClimate which is a dataset of monthly climate and climatic water balance for global terrestrial surfaces and developed by ("IDAHO_EPSCOR/TERRACLIMATE"). We used Google Earth Engine to collect data from TerraClimate. The soil moisture data was derived using a one-dimensional soil water balance model. Also, the reference evapotranspiration data is based on the ASCE Penman-Montieth.

2.3. Methods

Soil moisture and Evapotranspiration Revealed Drought Index (SERDI)

The SERDI is a new drought index that was developed to improve upon existing indices such as the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Evapotranspiration Index (SPEI). The SERDI was developed by researchers at the University of Soran (Scientific Research Center). The SERDI takes into account both soil moisture and evapotranspiration (the combined water loss from plants and the soil surface) to provide a more comprehensive picture of drought conditions. The index will be useful for using satellite data to estimate both soil moisture and evapotranspiration, which allows for more accurate and timely monitoring of drought conditions in future studies. The SERDI is calculated by comparing current soil moisture and evapotranspiration values to long-term averages for the same time of year. If current values are significantly lower than the long-term averages, a drought is indicated. One of the advantages of the SERDI is that it can be used to monitor drought conditions in areas where ground-based data is limited or nonexistent. The SERDI is a promising new drought index that has the potential to provide more accurate and timely monitoring of drought conditions. SERDI was used for the first time in the current study. It includes series equations, which are similar to the steps used for the vegetation health index (VHI).

The Evapotranspiration Condition Index (PETCI) is a drought index that measures the availability of water for vegetation in a particular area. It is often used in conjunction with other drought indices, such as the Soil Moisture Condition Index (SMCI). The PETCI is based on potential evapotranspiration (PET), which is the amount of water that would be lost from an area through evapotranspiration if there were unlimited water available. PET is affected by factors such as temperature, humidity, wind, and solar radiation. One of the advantages of the PETCI is that it provides information specifically about the availability of water for vegetation. This can help to improve drought monitoring and management, especially in areas where vegetation is a key resource. The following equation (Eq. 1) requires a minimum and maximum PET.

$$PETCI = \frac{PET_{max} - PET}{PET_{max} - PET_{min}} \times 100 \tag{1}$$

Where PETCI is the evapotranspiration condition index, and PETmax and PETmin are minimum and maximum evapotranspiration.

The Soil Moisture Condition Index (SMCI) is a drought index that measures the soil moisture conditions in a particular area. One advantage of SMCI is that it relies on actual soil moisture measurements rather than just precipitation data, which can be influenced by factors such as temperature and wind. This makes it a more accurate indicator of soil moisture conditions and can help improve drought monitoring and management. The SMCI is a useful tool for monitoring soil moisture conditions and drought conditions in the United States. It provides a more accurate picture of soil moisture conditions than traditional precipitation-based indices and is widely used in agriculture and water management. The soil moisture requires for this index is based on the following equation (Eq. 2):

$$SMCI = \frac{SM - SM_{min}}{SM_{max} - SM_{min}} \times 100 \tag{2}$$

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Where SMCI is the soil moisture condition index, SM_{min} and SM_{max} are the minimum and maximum soil moisture.

Lastly, the Soil Moisture and Evapotranspiration Revealed Drought Index (SERDI) uses both the Soil Moisture Condition Index (SMCI) and the Evapotranspiration Condition Index (PETCI) in its calculations. By incorporating both indices, the SERDI provides a more comprehensive and accurate picture of drought conditions, taking into account both soil moisture and the availability of water for vegetation. The SERDI was developed to address some of the limitations of traditional drought indices. The SERDI has shown promising results in drought monitoring and prediction, particularly in areas where ground-based data is limited or unavailable. Soil moisture and evapotranspiration revealed drought index (SERDI) using the following equation (Eq. 3).

$$SERDI = (SMCI \times 0.5) + (PETCI \times 0.5) \quad (3)$$

Where SERDI is Soil moisture and evapotranspiration revealed drought index, SMCI, and PETCI are soil moisture condition index and evapotranspiration condition index, 0.5 indicates a coefficient to quantify the relative contribution of SMCI and PETCI in the SERDI. In this study, the following classification scheme for drought monitoring was proposed (Table 1).

Table 1. Classification of normal, wet, and dry conditions based on SERDI.

SERDI Classes	Minimum values	Maximum values
Extreme Dry	<= 0	= <10
Severe Dry	> 10	= < 20
Moderate Dry	> 20	= < 27
Normal	> 27	= < 38
Wet	> 38	= < 50
Extreme Wet	> 50	100

3. Results

3.1. Spatial distributions of dry and wet conditions based on SERDI

SERDI was coined for drought conditions globally, but it was used for semi-arid regions in the Middle East in this study. Figures 2a, b, and c show dry and wet conditions from 2000 to 2002 in the semi-arid regions in the Middle East countries. Severe dry conditions covered most of the semi-arid areas of Iraq and Iran. However, several locations in Iran showed normal conditions, which stretched from the northwest to the northeast and then continued to the southeast (it is almost known as mountainous areas). Also, there was an area in the southwest of Iran that had extremely dry conditions. It is noted that severe drought expanded in huge areas in the central part of the semi-arid region, which stretched from the north to the south of Iran. Both normal and moderate dryness increased in 2001 and decreased in 2000 and 2002. In contrast, severe drought increased in 2000 and 2002 compared to 2001, whereas it decreased in the semi-arid areas of Iran. Although Iraq experienced severe drought in the south of semi-arid areas, it also had normal conditions in several parts. For example, the normal conditions are located in the west and stretched in a thin line in the north of the semi-arid areas, and moderate dryness lies in the south of the normal conditions in Iraq, which are highly expanded in the east of the semi-arid areas in Iraq. Normal conditions increased slightly and severe dry conditions decreased in 2002 compared to 2000 and 2001. On the other hand, moderate drought almost remained unchanged from 2000 to 2001 in the semi-arid areas of Iraq. In addition, Turkey had normal to extreme wet conditions in the all-semi-arid areas due to the fact that Turkey has only cold semi-arid regions compared to other countries in the Middle East. As it was observed, the extreme wetness increased in Turkey in 2001, then slightly decreased in 2002. In contrast, in the eastern semi-arid regions of this country, wet conditions decreased and normal conditions expanded, but in the west, semi-arid conditions remained the same as wet conditions from 2000 to 2002. However, the results showed that all the semi-arid areas in Syria experienced moderate dry and normal conditions, with normal conditions stretching from the northwest to the northeast

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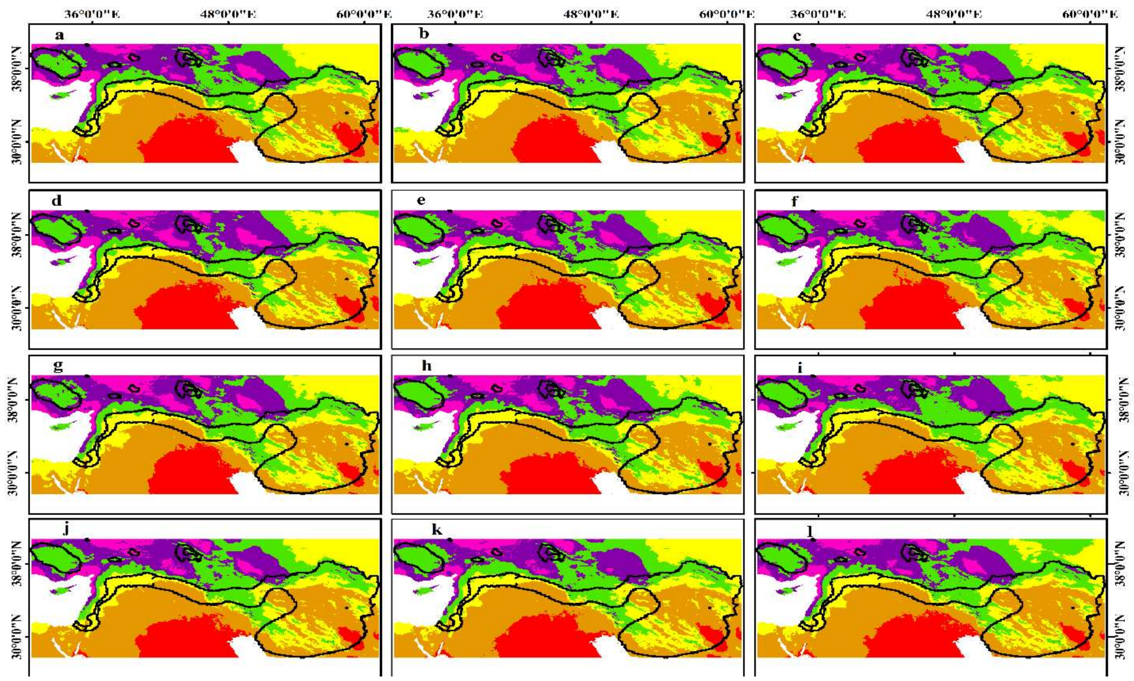
and moderate dry located in the west to the southeast of the country. Both moderate and normal conditions were higher in 2001 than in 2000 and 2002. Moderate dry conditions covered almost all the semi-arid areas in Jordan and Israel, except for the several small portions considered normal conditions, such as the northeast and southeast of Jordan as well as areas near the Mediterranean Sea in Israel. It expanded in 2001 compared to 2000 and 2002.

Figures 2d, e, and f show that normal conditions increased from 2003 to 2005 in the northwest and northeast semi-arid areas of Iran. The wet and extremely dry conditions decreased from 2003 to 2005 in Iran in the northwest and southwest in the semi-arid areas, respectively. In addition, the normal condition dramatically declined and moderate dry increased between 2003 and 2005 in the semi-arid areas of Iraq, Syria, Jordan, and Israel. Also, Severe droughts sharply increased in Iraq and Syria in the south and southwest of semi-arid regions, respectively. Furthermore, normal conditions slightly increased in the north and southeast of east-semi-arid regions in Turkey, but wet conditions remained at almost the same values between 2003 and 2005.

Figures 2g, h, and i showed that normal conditions decreased and moderately dry conditions increased in Iran, Iraq, Syria, Jordan and Israel from 2006 to 2008. Moreover, severe dryness in the central, north, and south as well as extreme dry in the southeast, increased in the semi-arid areas of Iran. Also, wet conditions decreased dramatically in the north and northeast of semi-arid regions in Iran. The semi-arid regions in Iraq and Syria were covered with severe and moderate drought in 2007 and 2008. Furthermore, west-semi-arid areas in Turkey experienced a significant decrease in wet conditions and increased normal conditions between 2006 and 2008. Similar conditions occurred in the north of east-semi-arid areas in Turkey by decreasing wet conditions and an increase in normal conditions. Although all semi-arid regions experienced a decline in normal conditions with the exception of Turkey's semi-arid regions, those southwest of Jordan increased normal conditions in 2008.

Figures, 2j, k, and l illustrate the normal conditions presented in Iran's and Turkey's semi-arid areas. As seen, it stretched from the northeast to the northwest and southeast of semi-arid areas in Iran. Also, the normal condition covered most of the west-semi-arid areas in Turkey. It increased slightly in Syria, but for other countries, it remained constant from 2009 to 2011. Meanwhile, severe dry was high in Iraq and Iran's semi-arid areas from 2009 to 2011, as well as moderate dry covering the semi-arid areas in Syria, Jordan, Israel, the north of Iraq, and around the normal condition in Iran. However, the extreme dryness increased in the southeast of Iran between 2009 and 2011. In addition, the wet condition increased and the normal condition decreased in the semi-arid areas of Turkey from 2009 to 2011.



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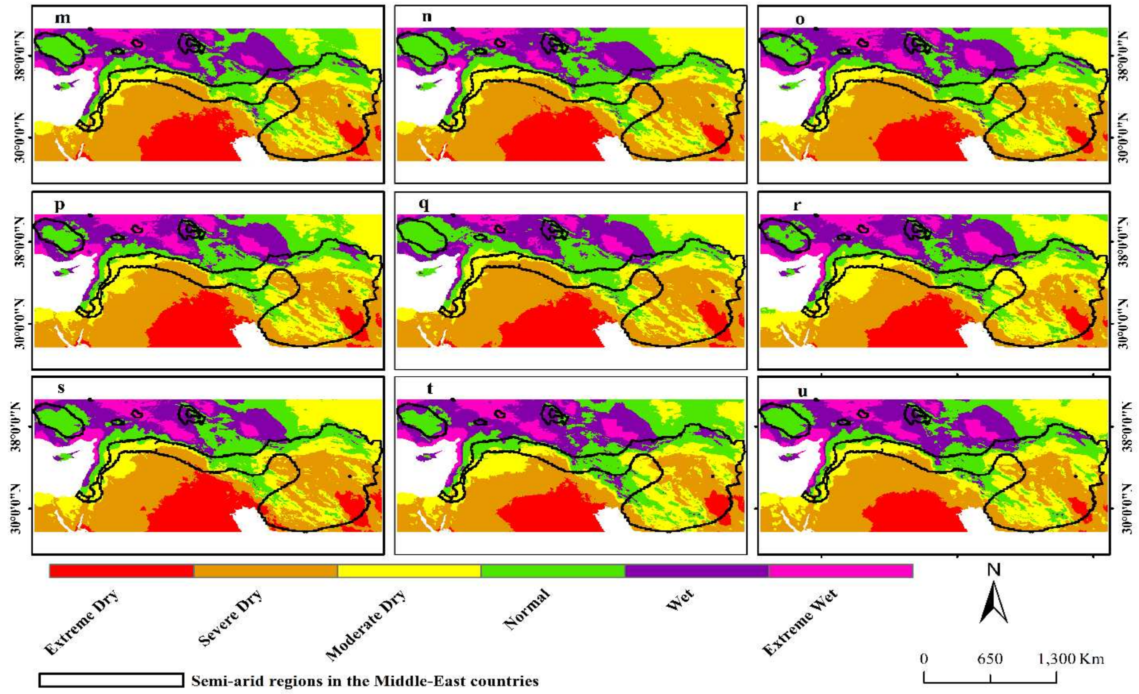

Figure 2. Spatial and temporal distribution of the annual SERDI in semi-arid regions of Iran. (a) 2000; (b) 2001; (c) 2002; (d) 2003; (e) 2004; (f) 2005; (g) 2006; (h) 2007; (i) 2008; (j) 2009; (k) 2010; (l) 2011; (m) 2012; (n) 2013; (o) 2014; (p) 2015; (q) 2016; (r) 2017; (s) 2018; (t)2019; and (u) 2020.

Figures 2m, n, and o showed that wet and dry conditions in the semi-arid areas of the Middle East countries depend on the SERDI. Although the wet and normal conditions decreased in the semi-arid regions of Iran from 2012 to 2013, they slightly started to increase in 2014. Also, severe and moderate droughts have increased in most of the semi-arid areas from 2012 to 2014. Despite the extreme dryness, it covered a large area in the southeast of semi-arid regions in 205, but it noticeably declined in 2014. In contrast, the semi-arid areas in both Iraq and Syria were different because normal conditions decreased and moderate and severe drought started to increase from 2012 to 2014. Meanwhile, severe dryness decreased to moderate dryness in the semi-arid area of Israel from 2012 to 2014. Albeit normal conditions increased in the southwest of Jordan, moderate dry covered most of the semi-arid areas almost all years. Despite the increasing normal condition in 2013, it impacted the wet condition because it reduced the areas with wet conditions in west-semi-arid areas in Turkey. Then, the wet condition began to increase, and the normal condition decreased again in 2014.

Figures 2p, q, and r indicate that severe dry decreased dramatically and normal conditions and moderate dry increased in the semi-arid areas of Iran, Iraq, and Syria in 2017. Although the wet condition was high in the northeast of Iran, it started to decrease in 2016 and 2017. Also, extreme dryness slightly decreased in 2017, after highly covered areas in the southeast in 2015 and 2016. However, severe dryness increased in semi-arid Israel in 2016 even though it always showed severe dryness in all years because the rainfall is between 100mm and 300mm (Fuks, Ackermann et al. 2017). In addition, moderate dry conditions controlled almost all the semi-arid areas in Jordan, except for a small part in the northwest and southwest, which had normal conditions in 2015. Moreover, wet conditions increased in the west-semi-arid areas of Turkey in 2017, after declining slightly in 2016, when they were replaced by normal conditions. Also, the east-semi-arid remained constant with wet conditions from 2015 to 2017.

Figures 2s, t, and u indicate dry and wet conditions in the semi-arid regions of the Middle East countries from 2018 to 2020. It is noted that normal conditions increased dramatically in the semi-arid areas of Iran, Iraq, and Syria, but decreased in Turkey, Jordan, and Israel from 2018 to 2019. Then it increased in Jordan, but for other countries, it reduced slightly in 2020. Moreover, it can be seen that severe drought considerably declined in Iran and Iraq's semi-arid areas from 2018 to 2019, then

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slightly increased in 2020. However, extreme dryness significantly reduced in the southeast in semi-arid areas of Iran from 2018 to 2020. As it was shown, wet conditions substantially appeared in the northeast and west of semi-arid Iran from 2018 to 2019, even though they slightly reduced in 2011. Also, moderate dryness increased in Iraq and Iran's semi-arid regions. In particular, severe and moderate dry conditions covered Israel's semi-arid areas and remained constant from 2018 to 2020. Surprisingly, the wet condition initially increased in 2019, but it declined slightly a year later in the west-semi-arid areas of Turkey. Although extreme wetness occurred in the east-semi-arid areas of Turkey in 2018 and 2019, it diminished completely in 2020.

3.2. Validation of SERDI Based on Common Drought Indices in the Semi-Arid Areas in the Middle-East Countries

To validate SERDI we use relationships and regression of SERDI with drought indices in the Middle-east Semi-Arid areas. The matrix correlation shows that both VHI and LST had a high correlation with SERDI with values of 0.85 and 0.92, respectively, but there was a reasonable correlation between SERDI and other indices such as NDWI and NDVI with values of 0.63 and 0.62, respectively. It means that LST and VHI had a strong relationship and close linear regression with SERDI, and both NDWI and NDVI had a less strong relationship with SERDI compared with the first two indices in Bushehr Province (Supplementary Table S1).

The R-square shows that the variability of the dependent variable SERDI is explained by the explanatory variables such as LST, VHI, NDWI, and NDVI, with values of 85%, 72%, 39%, and 38%, respectively, which means that the variability of SERDI was highly explained by LST and VHI and less explained by NDVI and NDWI. In other words, the strength of the relationship between SERDI and LST, and VHI was high (Supplementary Figure S1).

The RMSE between SERDI and LST, VHI, NDVI, and NDWI is different. The lowest RMSE is between SERDI and LST by 8.3, which means that the LST provides an estimation to predict the SERDI compared to other indices. Besides, the RMSE of VHI was quite good in terms of predicting the SERDI index by 11.3. In contrast, both NDWI and NDVI show a higher RMSE to predict SERDI with values of 16.7 and 16.9, respectively. In general, MAPE values below 10% indicate excellent reliability in prediction, while those between 10% and 20%, 20% and 50%, and greater than 50% reflect useful, reasonable, and untrue forecasting, respectively (Blasco, Moreno et al. 2013). Therefore, both LST and VHI show reasonable forecasts with SERDI due to the values of 24.4% and 32.8%, respectively. While both NDWI and NDVI have inaccurate forecasting with SERDI because the values are 61.8% and 60.2%, respectively. In addition, the P-values indicated that all the indices such as LST, VHI, NDVI, and NDWI as independent variables have a significant relationship with the dependent variable (SERDI), because the P-value is less than the significance threshold, the null hypothesis is rejected (Supplementary Figure S1).

There was a strong correlation found between SERDE and other indices such as LST, NDWI, NDVI, and VHI with values of -0.95, 0.83, -0.69, and 0.81, respectively (Supplementary Table S2). The R-square indicated that it reached 0.9 between SERDI and LST, which is considered the highest value, and it showed that SERDI was explained by LST due to the fact that the R-square is used to identify the strength of a model. In addition, the R- square was good between SERDI and other indices such as VHI and NDWI with values of 0.66 and 0.69, respectively, but it was lower than the normal values between SERDI and NDVI by 0.47 (Supplementary Figure S2).

The RMSE and MAPE are used for identifying errors between two variables. It found that both RMSE and MAPE had the lowest values between SERDI and LST, with values of 5.1 and 18.3%, respectively. However, both matrices (RMSE and MAPE) were a little bit higher between SERDI and other indices such as NDVI, VHI, and NDWI by the values of 12, 9.7, and 9.2, respectively, for RMSE and the values of 54%, 30.5%, and 39.8% for MAPE (Supplementary Figure S2). Moreover, the P-value showed that the SERDI and all the indices had statistically significant information and rejected the null hypothesis, which means that there is a lower than 0.01% risk of assuming that the null hypothesis (no effect of the two explanatory variables) is wrong. Therefore, we can conclude with

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confidence that the three variables of NDVI, LST, VHI, and NDWI with SERDI do provide a significant amount of information (Supplementary Figure S2).

3.2.1. Comparing SERDI with LST and VHI

Table 2 presents the R-Square values between SERDI and LST in various semi-arid provinces in Iran, ranging from 0.819 to 0.905. This shows that the explanatory variable LST explains 82% to 90% of the variation in the dependent variable SERDI, with the provinces of West Azerbaijan and Tehran having the lowest and highest R-square values, respectively. In contrast, there are differences in the R-square values between the VHI and SERDI between the provinces, with Bushehr, Kermanshah, Fars, and Tehran having higher R^2 values (72%, 67%, 66%, and 66%, respectively), and West Azerbaijan, Golestan, and Alborz having lower R- square values (40%, 40.5%, and 56%, respectively).

The RMSE values for SERDI against LST are quite low, with Tehran and West Azerbaijan having the lowest and highest RMSE values of 5.1 and 9.95, respectively. However, for SERDI against VHI, the RMSE values range between 18 and 9.7 for West Azerbaijan and Tehran, respectively. The P-value indicates that all the data are statistically significant, with a P-value ≤ 0.05, which means that the test hypothesis is false or should be rejected.

Regarding MAPE, values below 10% indicate excellent reliability in prediction, while values between 10% and 20%, 20% and 50%, and greater than 50% reflect useful, reasonable, and untrue forecasting, respectively. In this context, the MAPE between SERDI and LST in Tehran suggests useful forecasting due to being lower than 20%, while for other provinces, it is considered reasonable forecasting as it slightly exceeds 20%. Additionally, the MAPE values between SERDI and VHI indicate reasonable forecasting for most provinces in Iran, as they fall between 20% and 50%.

Table 2. The R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas in Iran.

Provinces	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Alborz	0.849	0.848	7.596	21.806	**< 0.0001**	0.556	0.554	13.008	38.974	**< 0.0001**
Bushehr	0.849	0.848	8.316	24.386	**< 0.0001**	0.722	0.721	11.278	32.749	**< 0.0001**
Fars	0.879	0.879	6.736	21.815	**< 0.0001**	0.656	0.655	11.352	34.993	**< 0.0001**
Golestan	0.857	0.856	7.375	22.290	**< 0.0001**	0.404	0.401	15.043	47.351	**< 0.0001**
Kermanshah	0.889	0.888	9.470	20.114	**< 0.0001**	0.670	0.669	16.314	33.464	**< 0.0001**
Tehran	0.905	0.905	5.100	18.268	**< 0.0001**	0.656	0.655	9.721	30.479	**< 0.0001**
West Azerbaijan	0.819	0.818	9.943	21.521	**< 0.0001**	0.401	0.399	18.019	48.709	**< 0.0001**

Table 3 presents the R-square, RMSE, MAPE, and P-value for the semi-arid regions of Iraq. The R-square values between SERDI and LST are high, ranging from 87% to 89%, indicating a strong relationship where the variability of SERDI is well explained by LST. The RMSE values range from 7 to 9.7, suggesting a low average difference between predicted and actual values, signifying good model accuracy. Notably, the scale of the y-axis, representing the dependent variable, influences the interpretation of RMSE values, depending on whether it ranges between (0 and 1 or 1 to 100).

On the other hand, the R-square values between SERDI and VHI are between 68% and 77% for Erbil and Kirkuk, respectively. This indicates a moderate relationship, with VHI explaining a considerable portion of SERDI's variability. The RMSE values show that SERDI predictions by VHI are higher in Erbil (16.2) and lower in Kirkuk (10.4). Regarding MAPE, the forecasts between SERDI and LST, as well as VHI, are reasonable, as all the MAPE values fall between 20% and 50%. The P-value indicates that all the data from all the provinces are statistically significant, with values lower than 0.5, which is the significance level for rejecting the null hypothesis. This suggests that the observed relationships in the data are not due to chance.

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Table 3. The R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas of Iraq.

Provinces	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Erbil	0.885	0.884	9.707	20.604	**< 0.0001**	0.679	0.678	16.179	35.267	**< 0.0001**
Kirkuk	0.893	0.892	7.088	21.633	**< 0.0001**	0.770	0.769	10.389	32.712	**< 0.0001**
Ninawa	0.870	0.870	9.175	22.761	**< 0.0001**	0.725	0.724	13.341	32.400	**< 0.0001**
Sulaimaniyah	0.878	0.878	9.640	20.452	**< 0.0001**	0.750	0.749	13.807	26.926	**< 0.0001**
Diyala	0.869	0.868	7.019	22.159	**< 0.0001**	0.752	0.751	9.638	30.756	**< 0.0001**

Table 4 presents the R-square, RMSE, MAPE, and P-value for the semi-arid regions in Turkey. The R-square values between SERDI and LST are generally high in almost all the provinces, with the lowest R-square recorded in Van province and the highest in Aksaray and Konya provinces. However, unlike other semi-arid regions in the Middle East countries, the R-square between SERDI and VHI is relatively low in the semi-arid areas of Turkey. Although it is low in all the provinces, it remains above 0.5 in the southwestern regions, such as Konya and Aksaray provinces.

Moreover, the RMSE and MAPE values are low between SERDI and LST, indicating good model accuracy, while they are high between SERDI and VHI, suggesting larger prediction errors.

The P-value shows that the data are statistically significant, confirming the validity of the observed relationships.

Table 4. The R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas OF Turkey.

Provinces	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Aksaray	0.901	0.900	9.856	20.465	**< 0.0001**	0.549	0.547	21.032	44.835	**< 0.0001**
Ankara	0.871	0.871	10.439	19.683	**< 0.0001**	0.107	0.103	27.521	94.300	**< 0.0001**
Konya	0.903	0.902	9.785	20.661	**< 0.0001**	0.549	0.547	21.069	46.413	**< 0.0001**
Nigda	0.850	0.849	10.562	19.223	**< 0.0001**	0.332	0.330	22.347	60.017	**< 0.0001**
Van	0.760	0.759	14.755	25.052	**< 0.0001**	0.086	0.083	28.724	90.012	**< 0.0001**

Tables 5, 6, and 7 present the results indicating that the R-square values between SERDI and both LST and VHI are high in the semi-arid regions of Syria, Jordan, and Israel. This reveals a substantial correlation between SERDI and these indices, demonstrating that SERDI in these regions may be adequately described by both LST and VHI. Additionally, both RMSE and MAPE values are low between SERDI and both LST and VHI, with slightly higher values observed for SERDI with VHI. This indicates that the variances of SERDI data with LST and VHI data are not widely spread from the mean, and the forecasts based on MAPE between SERDI and LST and VHI are considered reasonable. Moreover, the P-value confirms that the data between SERDI and both LST and VHI are statistically significant, providing further support for the observed relationships.

Table 5. The R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas of Syria.

Provinces	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Aleppo	0.868	0.867	8.963	24.541	**< 0.0001**	0.770	0.769	11.822	36.442	**< 0.0001**
Al-Hasaka	0.852	0.852	9.941	22.556	**< 0.0001**	0.730	0.728	13.412	29.928	**< 0.0001**
Raqqa	0.860	0.860	7.952	23.906	**< 0.0001**	0.784	0.783	9.888	31.851	**< 0.0001**
Swieda	0.849	0.848	9.000	20.240	**< 0.0001**	0.617	0.615	14.337	40.057	**< 0.0001**

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Table 6. The R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas of Jordan.

Provinces	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Karak	0.879	0.878	6.782	23.432	**< 0.0001**	0.742	0.741	9.907	38.060	**< 0.0001**
Al-Balqa	0.909	0.908	6.720	16.655	**< 0.0001**	0.783	0.782	10.373	29.839	**< 0.0001**

Table 7. the R^2, RMSE, MAPE, and P-value between SERDI with LST and VHI in the semi-arid areas in Israel.

Province	LST					VHI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Hadarom	0.848	0.848	6.983	25.591	**< 0.0001**	0.683	0.682	10.113	38.339	**< 0.0001**

3.2.2. Comparing SERDI with NDVI and NDWI

Table 8 presents the R^2 values between SERDI and NDVI in different semi-arid regions of Iran, showing considerable variation. The province of Alborz scored the greatest R^2 at 61%, indicating that the explanatory variable NDVI accounts for 61% of the variation in the dependent variable SERDI. On the other hand, both Kermanshah and Fars provinces had the lowest R^2 at 0%, meaning that NDVI did not explain any variability in SERDI in these provinces. Conversely, the R^2 values between SERDI and NDWI varied, with Alborz, West-Azerbaijan, and Tehran recording the highest R^2 values (0.78, 0.57, and 0.69, respectively), while Bushehr and Golestan provinces had the lowest R^2 values.

The lowest RMSE values between SERDI and NDVI were observed in Alborz, Tehran, and Golestan provinces (12.1%, 12%, and 13%, respectively). Meanwhile, the lowest RMSE values between SERDI and NDWI were found in Alborz, Tehran, West-Azerbaijan, and Golestan provinces (9%, 9.2%, 15.4%, and 15.7%, respectively). The MAPE analysis revealed inaccurate forecasts between SERDI and both NDVI and NDWI, except for Alborz province in both indices and Tehran province for NDWI, which showed reasonable forecasts. Furthermore, the P-values indicated statistical significance for most of the data, except for the Fars province in the relationship between SERDI and NDVI, where the data was not significant as it exceeded the significance level of 0.05.

Table 8. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Iran.

Provinces	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Alborz	0.613	0.611	12.148	48.246	**< 0.0001**	0.786	0.785	9.041	36.348	**< 0.0001**
Bushehr	0.378	0.375	16.869	60.188	**< 0.0001**	0.390	0.388	16.696	61.749	**< 0.0001**
Fars	0.003	-0.001	19.339	98.544	0.408	0.461	0.459	14.220	70.247	**< 0.0001**
Golestan	0.549	0.547	13.080	56.741	**< 0.0001**	0.349	0.346	15.723	67.645	**< 0.0001**
Kermanshah	0.005	0.001	28.327	112.800	**< 0.0001**	0.524	0.522	19.588	63.652	**< 0.0001**
Tehran	0.476	0.474	12.001	53.953	**< 0.0001**	0.690	0.689	9.231	39.778	**< 0.0001**
West Azerbaijan	0.456	0.454	17.211	64.437	**< 0.0001**	0.567	0.566	15.393	53.539	**< 0.0001**

Despite the low R^2 values between SERDI and NDVI, as well as NDWI, in the semi-arid areas, there are slightly higher values in both Nigda and VAN provinces. For instance, Nigda has R^2 values of 0.43 from NDVI and 0.61 from NDWI, while VAN has R^2 values of 0.47 from NDVI and 0.67 from NDWI. However, the RMSE and MAPE values are consistently high in all the provinces in the semi-

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arid areas of Turkey. The MAPE indicates inaccurate forecasts for all provinces except for VAN province, where a reasonable forecast is observed between SERDI and NDWI (Table 9).

Table 9. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Turkey.

Provinces	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Aksaray	0.107	0.103	29.584	119.815	**< 0.0001**	0.420	0.418	23.829	81.562	**< 0.0001**
Ankara	0.021	0.017	28.806	106.617	**< 0.0001**	0.380	0.378	22.939	73.006	**< 0.0001**
Konya	0.096	0.093	29.834	118.232	**< 0.0001**	0.406	0.404	24.186	81.395	**< 0.0001**
Nigda	0.426	0.424	20.716	79.010	**< 0.0001**	0.614	0.612	16.995	58.076	**< 0.0001**
Van	0.466	0.464	22.025	74.372	**< 0.0001**	0.673	0.672	17.187	45.389	**< 0.0001**

Tables 10, 11, 12, and 13 present the R^2, RMSE, MAPE, and P-values for the semi-arid areas in Iraq, Syria, Jordan, and Israel. The R^2 values indicate that the relationships between SERDI and NDVI, as well as NDWI, are generally low in these countries, except for the Al-Balqa province in Jordan, which has slightly higher R^2 values compared to other provinces. Conversely, the RMSE and MAPE values are high in all the semi-arid areas of these countries, suggesting that the data between these indices do not fit well. The MAPE indicates inaccurate forecasts for all the data between SERDI and NDVI, as well as NDWI, in these regions. Additionally, the P-values indicate statistical significance for the observed relationships in these countries.

Table 10. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Iraq.

Provinces	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Erbil	0.178	0.175	25.904	94.107	**< 0.0001**	0.282	0.279	24.217	79.749	**< 0.0001**
Kirkuk	0.304	0.301	18.069	82.602	**< 0.0001**	0.322	0.320	17.831	75.443	**< 0.0001**
Ninawa	0.186	0.183	22.960	88.806	**< 0.0001**	0.270	0.267	21.745	80.048	**< 0.0001**
Sulaimaniyah	0.320	0.317	22.719	74.265	**< 0.0001**	0.407	0.405	21.299	63.878	**< 0.0001**
Diyala	0.297	0.294	16.213	67.265	**< 0.0001**	0.307	0.304	16.112	61.551	**< 0.0001**

Table 11. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Syria.

Provinces	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Aleppo	0.295	0.292	20.677	84.104	**< 0.0001**	0.352	0.349	19.822	78.413	**< 0.0001**
Al-Hasaka	0.213	0.210	22.923	85.992	**< 0.0001**	0.239	0.236	22.482	81.525	**< 0.0001**
Raqqa	0.189	0.186	19.182	83.193	**< 0.0001**	0.293	0.290	17.891	73.512	**< 0.0001**
Swieda	0.152	0.149	21.329	83.238	**< 0.0001**	0.333	0.330	18.861	65.345	**< 0.0001**

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Table 12. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Jordan.

Provinces	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Karak	0.158	0.155	17.921	87.293	**< 0.0001**	0.321	0.318	16.077	71.991	**< 0.0001**
Al-Balqa	0.449	0.447	16.519	58.896	**< 0.0001**	0.504	0.502	15.628	53.597	**< 0.0001**

Table 13. The R^2, RMSE, MAPE, and P-value between SERDI with NDVI and NDWI in the semi-arid areas of Israel.

Province	NDVI					NDWI				
	R^2	Adjusted R^2	RMSE	MAPE	P-value	R^2	Adjusted R^2	RMSE	MAPE	P-value
Hadarom	0.292	0.289	15.119	65.181	**< 0.0001**	0.439	0.437	13.458	52.091	**< 0.0001**

4. Discussion

Drought indices are highly appreciated to reveal drought onset, intensity, and frequency because drought occurs repeatedly from the beginning of the earth until the end of the earth. Therefore, the SERDI is an index to show drought accurately because it depends on the two most significant variables that highly contribute to drought, such as evapotranspiration and soil moisture data. The SERDI used a similar procedure to the VHI, but the inputs are different. It depends on combining both soil moisture and evapotranspiration. The alteration of evapotranspiration (ET) affects both water availability and the health of ecosystems. Droughts exacerbate ET through increased evaporative demand while simultaneously decreasing the necessary moisture supply, making it challenging to accurately forecast ET anomalies. The heightened ET during droughts rapidly depletes water resources, resulting in sudden-onset droughts and placing significant strain on ecosystems. Our water balance study demonstrates that the combination of ET and drought is widespread worldwide, occurring in 44.4% of months characterized by drought (Zhao, Liu et al. 2022). Evapotranspiration, which is the most important factor in the hydrologic budget alongside precipitation, displays regional and seasonal variations. During droughts, their fluctuations are influenced by weather and wind conditions. The significance of evapotranspiration is heightened during droughts as it continues to diminish the already limited water reserves in lakes, streams, and the soil (Hanson 1991). Drought arises when the loss of water from the leaves surpasses the uptake of water by the roots or its transportation through the plant. Consequently, the disparity between water loss and water intake serves as an indicator of the severity of plant drought (Chen, Lin et al. 2010). Moreover, the severity level of soil drought inevitably escalates as the soil continues to dry (Chen, Lin et al. 2010). However, the water and energy cycles of the land surface are influenced by soil moisture. Alterations in soil moisture levels have a direct impact on the availability of water for plants, which in turn affects their productivity and the yields of crops. Consequently, deficiencies in soil moisture have significant consequences for both agriculture and water supply (Wang, Lettenmaier et al. 2011). Therefore, recent methods utilize rainfall, soil moisture, and vegetation indices to evaluate drought comprehensively. These approaches integrate various temporal and spatial scales, ensuring a holistic understanding of drought conditions (Zeri, Williams et al. 2022). There are several examples of using evapotranspiration and soil moisture in different indices, such as the aridity anomaly index (Gommes, Das et al. 2010), the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano, Beguería et al. 2010), the Evapotranspiration Deficit Index (ETDI) (Nasimhan, Srinivasan et al. 2005), the Aggregate Dryness Index (ADI) (Keyantash and Dracup 2004), the Evaporative Stress Index (ESI) (Anderson, Norman et al.), and the Vegetation Drought Response Index (VegDRI) (Brown, Wardlow et al. 2008). Also, there are some indices used to measure soil moisture, such as the Soil Moisture Anomaly (SMA) (Bergman, Sabol et al. 1988), and the Soil Moisture Deficit Index (SMDI) (Nasimhan, Srinivasan et al. 2005).

The results of the SERDI analysis revealed that a majority of the semi-arid regions in Iraq and Iran experienced severe and moderate dry conditions. However, some areas remained normal due to their higher elevation, such as the Taurus, Alborz, and Zagros mountains. The prevalence of moderate and severe dryness can be attributed to the semi-arid climate, where the average annual rainfall does not exceed 166 mm (Al-Ansari 2013). Jordan, Syria, and Israel exhibited moderate drought, with a few areas experiencing normal conditions, while severe drought was observed in certain parts of Israel. Turkey, on the other hand, had normal, wet, and extremely wet conditions, with the majority of its semi-arid regions remaining in a normal state.

The SERDI analysis demonstrated a strong correlation between LST and a moderate correlation with VHI across all study areas, as evidenced by high R^2 values and a low RMSE. However, the relationship between other indices varied depending on the specific regions. For instance, there was a moderate correlation between NDWI and NDVI in areas with above-normal precipitation, while weak correlations were observed in regions with low precipitation (Alborz and Fars). Furthermore, similar drought conditions were observed between NDWI and NDVI in the northern part of Iran and the majority of Turkey's semi-arid regions. These variations can be attributed to the differences in variables utilized by each index, which can impact their correlation with each other. It is important to note that it is normal to observe weak, moderate, and strong correlations between indices since each index employs distinct methodologies and inputs. Moreover, it is crucial to be cautious with high or statistically significant values of r and R^2, as they may not necessarily correspond to the magnitude of differences between indices. Conversely, small differences between indices can occur even with low or negative values of R (Willmott 1982). Hence, the utilization of LST and VHI can be valuable for detecting agricultural drought, as they exhibit high R^2 values and low RMSE in various regions of semi-arid areas. The limitation of this index is that soil moisture and evapotranspiration data are not available for all areas around the world. Hence, it must depend on the remote sensing data, which is available through the products on the Google Earth Engine (GEE). We suggest that SERDI be developed and examined for the rest of the areas and climate zones around the world. Therefore, further research and testing will be needed to fully evaluate the effectiveness of the index and its potential applications.

5. Conclusion

The SERDI is developed to detect drought by using soil moisture and evapotranspiration, which are obtained from TerraClimate. We used GEE for the SERDI in the semi-arid areas of the Middle East countries. SERDI analysis provided insights into the drought conditions in the semi-arid regions of Iraq, Iran, Jordan, Syria, Israel, and Turkey. The majority of the semi-arid areas in Iraq and Iran experienced severe and moderate dryness, with some exceptions in elevated regions. The prevalence of dryness can be attributed to the low average annual rainfall in these areas. Jordan, Syria, and Israel experienced moderate drought, with sporadic areas of normal conditions and severe drought in parts of Israel. Turkey, on the other hand, had a range of normal, wet, and extremely wet conditions, with most of its semi-arid regions remaining in a normal state.

It is important to acknowledge that weak, moderate, and strong correlations between indices are normal due to their distinct methodologies and inputs. Therefore, the utilization of LST and VHI can be valuable for detecting agricultural drought, as they exhibit high R^2 values and low RMSE in various semi-arid regions. Furthermore, similar drought conditions were observed between NDWI and NDVI in the northern part of Iran and most of Turkey's semi-arid areas. It is important to examine it further and validate it with ground data in future studies.

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