Evaluation of ERA5 and NCEP reanalysis climate models for precipitation and soil moisture over a semi-arid area in Kuwait

Evaluation of ERA5 and NCEP Reanalysis Climate Models for Precipitation and Soil Moisture over a Semi-Arid Area in Kuwait

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Received: DD Month YEAR/ Accepted: DD Month YEAR

Abstract In this study, we evaluate the soil moisture and precipitation products obtained from two reanalysis models: the National Centers for Environment Prediction (NCEP) and the European Center for Medium-Range Weather Forecasts (ECMWF). The study centers on Kuwait's semi-arid region, during the wet season (November to May) from 2008 to 2018. For the precipitation-related evaluation dataset, rain gauge records from the Kuwait Automatic Weather Observation System (KAWOS) were used, while the ground-truth soil moisture values were taken from the Climate Change Initiative (CCI-SM). Initially, to ensure CCI-SM reliability, we compare it with in-situ soil sensor measurements deployed at a desert site. The analysis revealed a maximum CCI-SM overestimation in winter, decreasing progressively throughout the year with 20% mean bias. The bias-corrected CCI-SM dataset is used for the comprehensive evaluation of the soil moisture reanalysis data. Accuracy metrics, such as mean bias (MB), correlation coefficient (R), and unbiased Root Mean Square Difference (ubRMSD), were used for this purpose. The results indicate that ERA5 consistently underestimates (~50% MB) soil moisture, but responds well under high soil moisture conditions. NCEP mostly overestimates soil moisture by a similar magnitude, providing even twice as high values during spring months. Mean monthly precipitation (MP) is also overestimated by NCEP, particularly during extreme episodes, yet found to be reliable enough regarding annual accumulated precipitation. ERA5 has shown strong (R

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~0.6–0.9) predictive capabilities under both frontal and convective precipitation conditions, with ~3% median bias for MP, making it a promising alternative data source, particularly in regions with limited weather station coverage.

Keywords ESA CCI, NCEP, ERA5, Soil moisture, Precipitation, Kuwait

1 Introduction

Soil moisture is an important parameter in hydrological, climate, and weather models. In the context of climate applications, soil moisture provides insights into the impact of greenhouse gas emissions on the climate system (Cubasch et al. 2001; Rowntree et al. 1993). In arid regions, soil moisture becomes a sensitive property for climate change and climate models, functioning as a crucial indicator of soil characteristics (Li et al. 2004; Southgate et al. 1996). Numerous factors contribute to the soil moisture levels, including precipitation, plant transpiration, soil evaporation, surface runoff, and underground percolation. Soil moisture within the unsaturated zone undergoes changes due to precipitation recharge and water exchange with both the atmosphere and groundwater. Extensive research has been conducted to understand the water exchange between the vadose zone and the atmosphere, with a primary focus on comprehending soil moisture variations and their impacts on atmospheric boundary layer processes, which in turn influence weather and climate patterns (Bright et al. 2017; Cao et al. 2020; Massad et al. 2019; Pielke and Avissar 1990; Pielke et al. 1991). Soil moisture and precipitation rate, exert control over evaporation and transpiration at the land-atmosphere boundary. As the vaporization of water requires significant amounts of energy, both soil moisture and precipitation play a substantial role in the surface energy flux, ultimately affecting the evolution of weather and climate, particularly in continental regions. Therefore, continuous monitoring of these properties becomes essential to accurately model and forecast any future pattern changes.

Global reanalysis datasets have become important tools for studying climate patterns and trends. They can substitute direct observations, especially when the latter are often unavailable or insufficient in remote areas (Bengtsson et al. 1998, 2004; Brönnimann et al. 2017; Khanal et al. 2023). By assimilating a wide range of observational data, including satellite measurements, ground-based weather stations, and ocean buoys, these datasets reconstruct a comprehensive and consistent picture of past weather conditions across the globe. Two prominent organizations, namely the National Centers for Environment Prediction (NCEP) and the European Centre for Medium-Range Weather Forecasts (ECMWF), are leading in developing reanalysis datasets. The NCEP dataset for instance, incorporates historical observations and numerical weather prediction models to generate a long-term, consistent record of global weather patterns. Similarly, the ECMWF's ERA5 employs advanced assimilation techniques to combine observations with complex numerical models, providing a detailed representation of the Earth's climate system.

The predominant climatic features of the Arabian Peninsula involve high temperatures, typically featuring dry and hot summers along with mild winters, accompanied by low rainfall (Dasari et al. 2022) and significant dust presence (Kokkalis et al. 2018). This results in limited soil moisture and water resources, impacting agriculture and various human activities. Various studies examined the annual and seasonal distribution of precipitation along with trends, employing station data and gridded datasets across the Arabian peninsula (e.g. Alsarmi et al. 2011; Almazroui et al. 2012a,b; Donat et al. 2014; Hasanean et al. 2015). Barth and Steinkohl (2004) explored the role of synoptic scale systems on winter precipitation over the region and demonstrated the role of Mediterranean depressions, the Sudan low, and convective systems. A recent study (Patlakas et al. 2021), revealed that a 3 h event with an average rain rate of 4–5 mm h^{-1} is expected in Kuwait city, Burayadah, Manama, Doha, Dubai, Abu Dhabi, Muscat, and Salalah every 8–10 years. Extreme events over these areas are rather convective with a duration within some minutes to an hour. In the western part of the peninsula, there is a tendency towards wetter conditions. In contrast, in the eastern part, there are more drying trends, although, these are of low significance (Donat et al. 2014). Kuwait is located in the northern edge of Eastern Arabia at the tip of the Arabian Gulf, experiencing 110–190 mm of rainfall annually, featuring a gradual increase from the southwest to the northeast. A distinct rainy season occurs between November to May, with double peaks in January and March (Marcella et al. 2008). The rainfall variability in seasonal and interannual time scales found to be connected with tropical and midlatitude atmospheric systems.

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The availability of global reanalysis products (e.g. soil moisture and precipitation) has revolutionized climatic studies, enabling researchers to analyse long-term climate trends, investigate extreme events, and understand the underlying mechanisms driving changes in various regions. Moreover, these datasets facilitate the development and evaluation of climate models, which are crucial for predicting future climate scenarios and assessing the potential impacts of climate change. Nevertheless, such products should be treated with caution, since they do require ground-truth data for validation, as they might be susceptible to systematic biases and random errors. The main aim of the present work is to understand these biases in the semi-arid area of Kuwait as previously conducted over different regions around the globe (e.g. Zhao and Fu 2006; Fan et al. 2008; Betts 2009; Mao et al. 2010; Wang and Zeng 2012).

This study focuses on evaluating soil moisture and precipitation rates from reanalysis products in comparison to in-situ observations. Our objective is to identify which of the reanalysis model would constitute the best choice for forcing climatic models in the region. More precisely, here we evaluate ERA5 and NCEP reanalysis data, during wet season (months November to May) over Kuwait, for a 10-years period (2008–2018), through comparison of soil moisture and precipitation data obtained from in-situ measurements, as well as homogenized satellite observations from the European Space Agency Climate Change Initiative Plus (ESA CCI). The selection of CCI was due to the lack of in-situ measurements in the study area for such a large time span. Therefore, before using the historical CCI dataset we compare it with the corresponding in-situ observations obtained for a common 28-month period. Our evaluation is performed on a basis of performance metrics such as correlation coefficient, bias, and quadratic distance equations. To our knowledge, such a comparison over the semi-arid area of Kuwait is done for the first time.

The study is structured as follows: Our methodology and data are presented in Sect. 2. The evaluation of the soil moisture and precipitation reanalysis products against observations are presented in Sect. 3 along also with their seasonal variability. Our conclusions and summary are provided in Sect. 4.

2 Materials and methods

2.1 Study area

In this study, two homogeneous desert sites in Kuwait are used. The locations are: (a) the field data area (29.50°N–29.18°N to 47.05°E–47.43°E), established approximately 30 km to the west of the capital, Kuwait City, and (b) the Kuwait Airport Weather Observation Station (KAWOS) (29.24°N, 47.97°E) (Fig. 1). The field data area (36 km x 36 km) was one of the few desert terrains used during the cal/val activities of Soil Moisture Active Passive (SMAP) satellite mission (Colliander et al. 2017). The site consists of four near real-time data transferring stations, equipped with soil moisture sensors. Intensive field campaigns and considerable thermo-gravimetric data collections were archived across the field area, making it a prime site for evaluating volume soil moisture (VSM) measurements. On the other hand, KAWOS site was chosen due to its historical precipitation dataset archive.

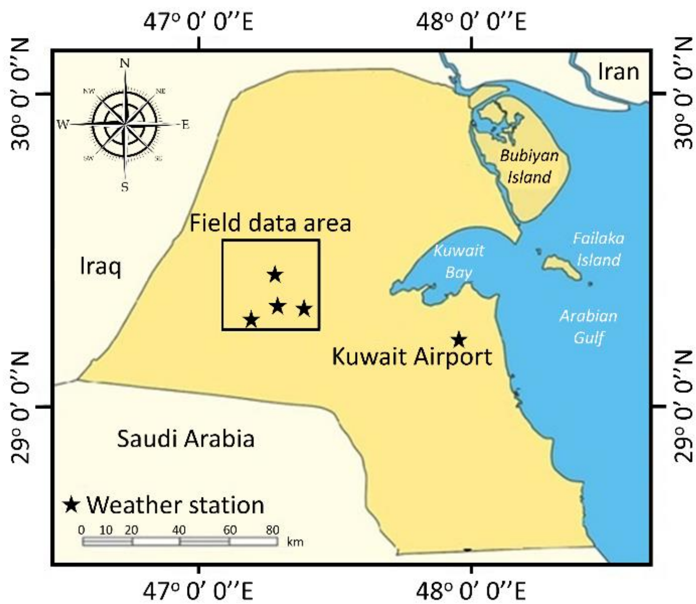

Fig. 1 The weather stations across the State of Kuwait that were used for the evaluation of the models are indicated with the star symbol. Four of them are located inside the field data area (utilized for soil moisture measurements) and one is in Kuwait airport (used for precipitation observations)

2.2 Data and methodology

We use soil moisture (SM) from the field data area, and precipitation-related observations from KAWOS, to evaluate the corresponding products obtained from NCEP and ERA5 reanalysis models. The modeled products, refer to different spatial and temporal resolutions, yet we did not procced to any data upscaling (grid adjustments to a common resolution), to highlight the models' limitations and capabilities on operational level. The nearest neighbor approach was used to match the closest model grid point to a station observation. The evaluation was performed on a monthly basis, during the wet season (November to May) for the time-period 2008 to 2018. A quality-control procedure was applied to remove from our statistics any 24 hr precipitation values equal to 0 mm. A 90% data availability criterion was also applied within each month for each studied property.

The wet season is separated in two periods, namely the winter months (November–February), when precipitation mainly occurs due to synoptic scale precipitations, and the spring months (March–May) which are characterized by mesoscale convective storms. The assessment of precipitation involved the examination of two distinct precipitation-related properties: the mean monthly precipitation (MP), and the mean monthly total precipitation (TP). The MP represents the average value obtained from mean daily precipitation data for each month. Conversely, TP refers to the average value derived from the cumulative hourly precipitation for each day, within the corresponding months. These two precipitation forms were chosen to comprehensively evaluate the performance of the models under various scenarios, including cases of intense or prolonged precipitation events.

2.2.1 In-situ measurements

The soil moisture data collected from sensors in the field data area, refer to the first 5 cm soil depth. The sensors are operating continuously through the years 2015 to 2018, providing data that have been already calibrated with thermogravimetric in-situ measurements at the same depth, during the validation of SMAP mission over the area (Al Jassar et al. 2022). Correspondingly, precipitation data were also collected from KAWOS weather station during the period January 2008 to December 2018 (Fig. 1).

2.2.2 ESA CCI-SM data

The ground-breaking service of ESA's CCI, aims to provide accurate and reliable information about the Earth's climate system. The CCI-SM product combines active and passive spaceborne soil moisture observations of various characteristics (i.e. frequency, spatial resolution, temporal coverage, and polarization), with cutting-edge modelling techniques in order to generate homogenized and comprehensive datasets (Gruber et al. 2019). The data are provided in percentage of saturation (%) for the ACTIVE product, and volumetric (m^3 m^{-3}) units for the PASSIVE and COMBINED products (Dorigo et al., 2015). The unique dataset offers a global coverage with ~ 25 km spatial resolution and daily temporal interval, a multi-decadal archived record, and reasonable surface soil moisture estimates for all land cover types (Dorigo et al. 2017; Gruber et al. 2019). In this study we used the "L3S" (super-collated) processing level of the daily (reference time at 0:00 UTC) CCI-SM product, with 25 km x 25 km spatial resolution, that refers to the depth range 2–5 cm from the surface (Preimesberger et al. 2020). Many studies have been done regarding the evaluation of the CCI-SM using ground-based observations around the globe (e.g. US, China, Canada) (e.g. Dorigo et al. 2015, 2017; McNally et al. 2016; Zhu et al. 2019), but to our knowledge none of them refers over the Arabian Peninsula. Most of them revealed low squared difference (~ 0.034 m^3 m^{-3}) for the CCI soil moisture combined product, making it an excellent candidate to drive climatic and hydrological studies.

2.2.3 Climate model VSM data

The NCEP and ERA5 reanalysis models were chosen for this study. The NOAH and the Integrated Forecast System (IFS) are the land surface schemes used by the two models respectively, to simulate the water movement through the soil, the evapotranspiration, the runoff and other relevant processes. Both schemes have undergone extensive validation and in many cases their performance is comparable (AlSarraf 2022), but the suitability of a particular one for the retrieval of soil moisture depends on various parameters (e.g. the region of interest, the data assimilation technique used etc.). The daily volumetric soil water at the first layer (0–7 cm depth from surface), was retrieved from ERA5 (Jing et al. 2018), with 10 km x 10 km spatial resolution, every 3 hrs. The corresponding product of soil moisture (referring to depths between 0–10 cm below surface level), was retrieved from NCEP reanalysis Daily Averages (Kalnay et al. 1996; Kanamitsu et al. 2002; Ma et al. 2009), with spatial resolution of 250 km x 250 km and temporal interval of 6 hrs. The daily Total Precipitation (mm) product was retrieved by ERA5 with spatial resolution 10 km x 10 km and temporal resolution 3 hrs (Hersbach et al. 2018), while the mean Daily

Convective Precipitation Rate product (kg m^{-2} s^{-1}) was obtained by NCEP reanalysis with 250 km x 250 km spatial resolution and 6 hrs temporal resolution (Schneider et al. 2013).

3 Results and discussion

3.1 ESA-CCI soil moisture evaluation

From almost a four-year period of overlapping measurements and CCI-SM data (May 2015–December 2018), 28 VSM pairs were selected that correspond to the wet season (November – May). The correlation between the monthly VSM from CCI-SM and in-situ observations is significant at the 99% confidence level (R = 0.80), with a slope of 0.47 and intercept 0.08 m^3 m^{-3} (Fig. 2). The horizontal and vertical error bars in Fig. 2 are representing the monthly variability of VSM, confirming the impact of heavy rain events during the year 2018 as a deviation from rest of years' normal trend (see also Fig. 5). For low to moderate VSM values (around 0.02 to 0.12 m^3 m^{-3}) the CCI seems to overestimate and gradually coming closer to in-situ observations, while slightly underestimate for higher soil moistures. The shapes, central tendency measures (i.e. mean and median values), and data dispersion of the VSM distributions from both CCI and the stations, exhibit significant similarity. More precisely, the average VSM during the common months between the two data sets is 0.10 ± 0.05 m^3 m^{-3} from the station, while from the CCI it is 0.13 ± 0.03 m^3 m^{-3}. The insert panel in Fig. 2 shows the ratio VSM_{CCI} / $VSM_{Station}$ highlighting that throughout the wet season the deviation between CCI and the in-situ measurements lies around 20%. During early spring months (March and April), the CCI only slightly overestimates VSM by around 5%. This overestimation gradually increases to 25% during May and early winter months (November until January), taking its maximum value (60%) in February. These deviations can be attributed to the strong precipitation events occurring these months of the wet season, the slightly different range depths below surface at which SM data refers, and the different spatial resolutions between the CCI and the station.

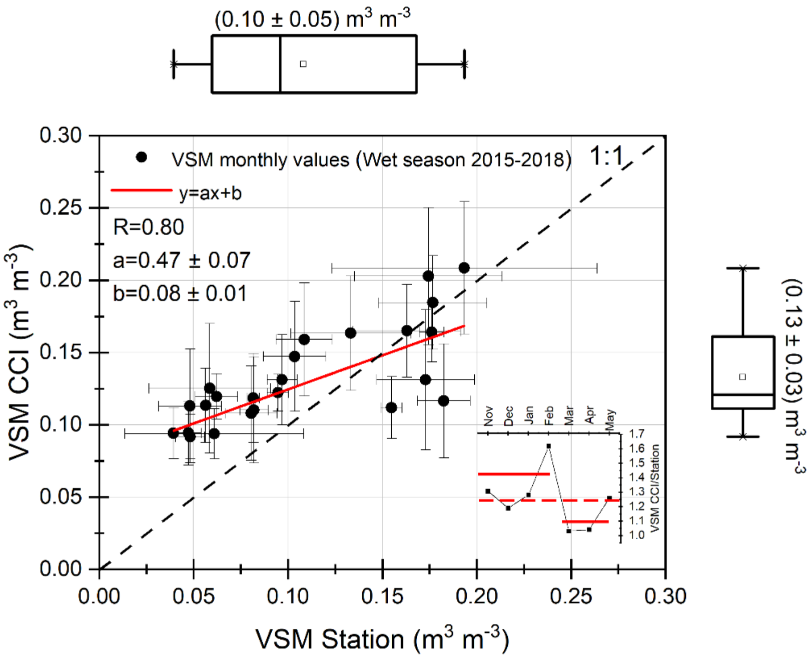

Fig. 2 VSM data (ESA CCI vs Stations) obtained during wet season 2015–2018. The error bars indicate the corresponding monthly variability. The thick red line is the regression line and dashed black line is the 1:1. The whiskers on top and right side are summarizing the statistics of each data set. The internal panel presents the semi interannual cycle of the VSM_{CCI} / $VSM_{Station}$ ratio, the red solid lines correspond to the average between months of close ratio, while the red dashed line shows the ratio from all the months of the wet season

The VSM data over the field area at top 5 cm soil depth extracted from CCI, in-situ stations, and SMAP (the latter not shown here), tails the same pattern throughout the years from 2015 until 2018. A mean absolute bias of 0.043 m^3 m^{-3} is found between CCI-SM and the station VSM and a mean absolute bias of 0.033 m^3 m^{-3} was noted for SMAP VSM values (for wet and dry seasons). These biases were within the range of expected observational error set of both ESA CCI-SM (0.03 m^3 m^{-3}) (Kerr et al. 2016; Dorigo et al. 2017; Portal et al. 2020) and SMAP VSM (to ± 0.04 m^3 m^{-3}) (Baur M et al. 2018; Entekhabi et al. 2010; Entekhabi et al. 2014). The performance of the CCI-SM results from this comparison, as well as many recent studies (i.e. Gruber et al. 2019), indicate the eligibility to use CCI-SM to evaluate soil moisture reanalysis climate model. However, to mitigate any potential bias arising from the over/underestimation of the CCI, we incorporated a bias-correction. The whiskers in Fig. 2, enable us for the evaluation of any biases, relative to the absolute discrepancy between CCI-SM and the in-situ measurements, that may affect our subsequent analysis. The mean absolute bias for the wet season found to be 0.039 ± 0.008 m^3 m^{-3}. By adjusting the monthly mean CCI-SM dataset using this wet mean bias value, we effectively rectified any potential influence. Henceforth, our analysis exclusively employs the bias-corrected CCI-SM product.

3.2 Soil moisture and precipitation analysis

On a seasonal basis, MP seems not to vary significantly during November to May, with a monthly average value 2.6 ± 1.5 mm (Fig. 3). In contrast, TP shows higher variability indicating different precipitation patterns, with maximum values obtained during the months of November and March (41.2 mm and 12.4 mm respectively). During dry season (June to October) no precipitation events have been recorded (Fig. 3). The maximum VSMs are encountered in the period November to February (0.09–0.14 m^3 m^{-3}), while during the spring transit VSMs are decreased due to the shortage of precipitated water, the high temperatures, and the insolation, favouring high evaporating rates.

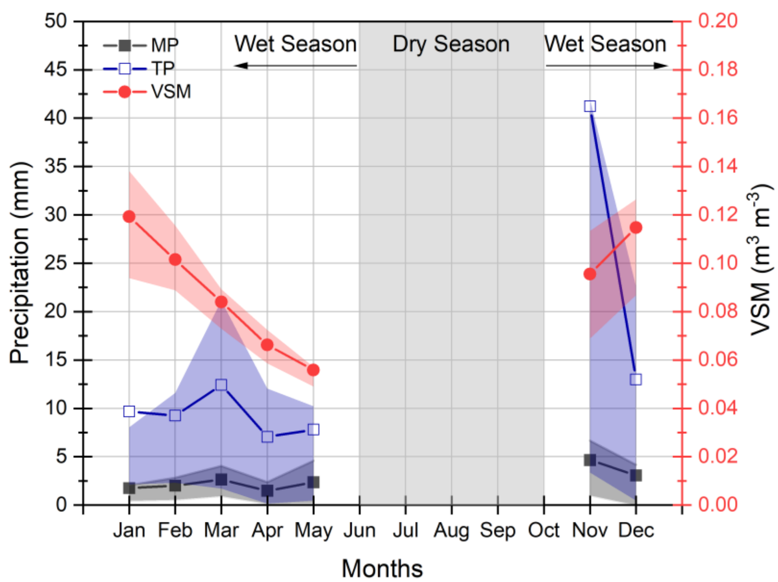

Fig. 3 Annual variability of precipitation-related observations (MP with gray filled squares & TP with blue open squares on left y-axis) and VSM CCI-SM product (red filled circles on right y-axis), obtained over the period 2015–2018. The shaded areas are indicating the first and third quartiles of each parameter

An opposite trend between the precipitation-related parameters and VSM is shown in Fig. 3, for November and December. The high TP value for November is driven by a rare precipitation event, registering around 200 mm, during a single day in 2018 (see also Fig. 5c). Besides this extraordinary rainfall episode that significantly influenced the observed pattern, winter Shamal winds probably blew sea spray from the Arabian sea far inland, resulting in relatively high VSM observations these months (Al Sarraf et al. 2019).

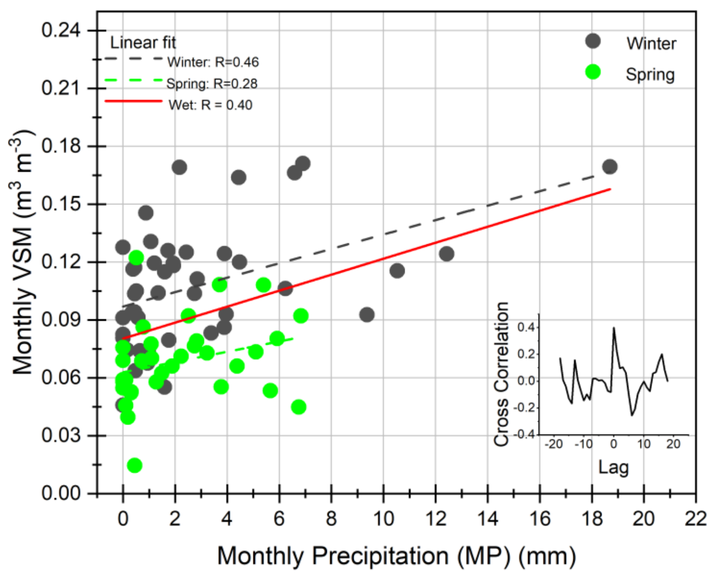

Fig. 4 MP versus VSM during winter (dark filled circles) and spring (green filled circles) months over the period 2008–2018. The thick red line is the regression line between the two datasets. The internal panel represents the time-lag analysis of the data

To analyze the soil moisture variation and relate it to different precipitation amounts, we performed a linear regression analysis between the MP and the VSM. Fig. 4 depicts a scatter plot of MP versus VSM values, comprising monthly observations obtained during both winter (dark) and spring (green) months. Over the study area, a general trend of a weak to moderate correlation magnitude and a positive correlation direction ($R = 0.46$) was found for the whole wet season (red regression line in Fig. 4), supporting the idea that typically, precipitation leads to an increase in soil moisture. When focusing specifically on the spring months, which are characterized by lower precipitation frequency, strength, and higher evaporation rates, the observed correlation weakened ($R = 0.28$), as illustrated by the green dashed regression line in Fig. 4. This suggests that the relationship between precipitation and soil moisture becomes less pronounced during this period. Moreover, the relatively high intercept value of approximately 0.07 m^3 m^{-3} can be attributed to the

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influence of various factors, including the land cover characteristics of the studied area and the rate of evapotranspiration. These factors can significantly impact the baseline soil moisture levels, resulting in a non-zero intercept value. The inset panel in Fig. 4 shows the correlation of the dataset for different time lags. According to this, the maximum correlation coefficient appears for zero time-lag, indicating that the soil moisture and precipitation observations are resulting of the same temporal dynamics and time-dependent interactions between the variables.

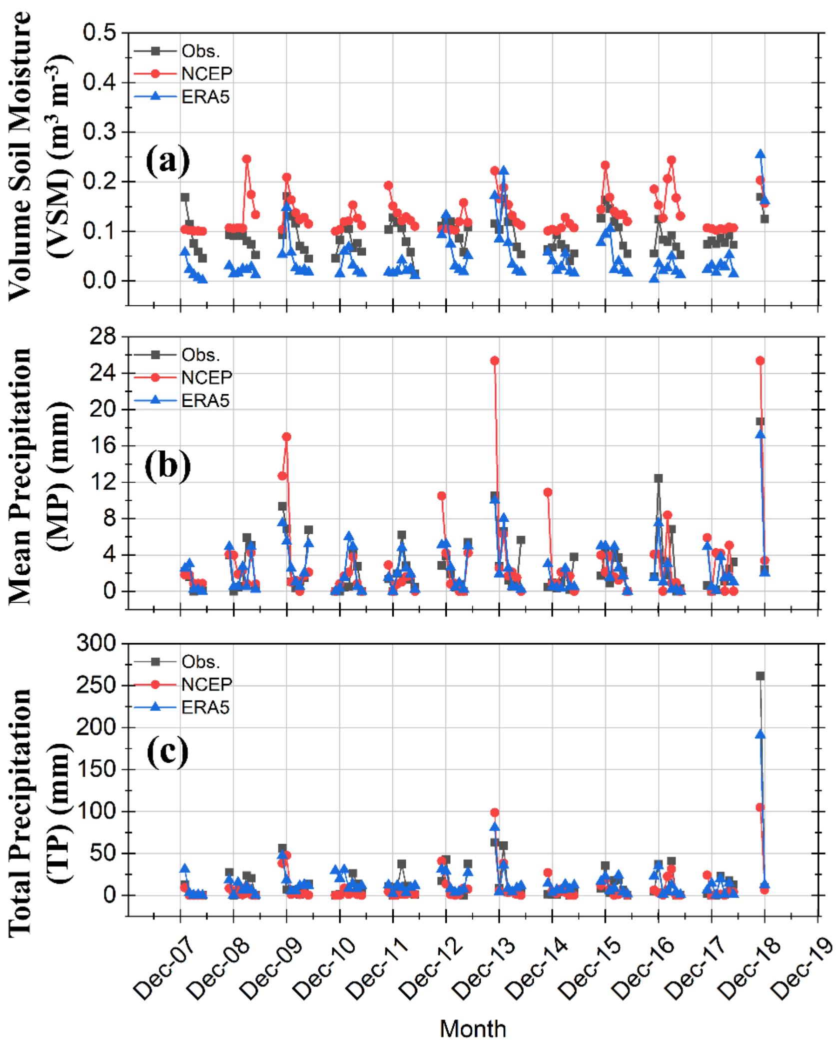

Fig. 5 Mean monthly values of: (a) mean precipitation (MP), (b) total precipitation (TP), and (c) volume soil moisture, obtained from observations (black squares), NCEP reanalysis model (red solid circles), and ERA5 model (blue triangles) during the wet season for the period 2008 – 2018

For the evaluation of VSM reanalysis the bias-corrected CCI product is used, while for the precipitation products, rain gauge records are employed as obtained at KAWOS site

(Fig. 5 black line). The soil moisture data depicted in Fig. 5a are collected over field data area. Meanwhile, the soil moisture and precipitation products obtained from the two models, NCEP (red line) and ERA5 (blue line), were derived over the corresponding grids. In general, ERA5 seems to strongly underestimate VSM values (Fig. 5a), except during moderate to strong rain events, like the ones occurred in 2009, 2013, and 2018 (Fig. 5b and c), during which ERA5 seems to react more realistic compared to NCEP. For MP, both NCEP and ERA5 exhibit a similar trend over time (Fig. 5b). However, NCEP reanalysis tends to overestimate precipitation during heavy rain events, while ERA5 aligns more closely with the in-situ data. In terms of TP (Fig. 5c), the values and variability of the observations, NCEP and ERA5 data, are remarkably similar. This indicates that overall, both NCEP and ERA5 can be considered relatively reliable for estimating precipitation as a cumulative monthly product, but more detailed and accurate VSM estimations can be derived mostly by NCEP, on a monthly basis.

3.3 Evaluation of models' accuracy

In assessing the performance of NCEP and ERA5 reanalysis models, we used the following set of statistical indicators: the correlation coefficient (R), the mean bias (MB), and the unbiased root mean square difference (ubRMSD) (Entekhabi et al., 2010). These metrics can quantify the accuracy and reliability of the models. In addition, the Kling-Gupta efficiency (KG) (Gupta et al., 2009) was also used, as a combined metric involving the correlation coefficient, the standard deviation (SD) and the mean value (μ) of the observed (O) and modeled (M) distributions. KG = 1 indicates a perfect agreement between the model and observation, however according to recent studies (e.g. Andersson et al. 2017; Castaneda-Gonzalez et al. 2018; Knoben et al. 2019) the specific minimum value of KG considered acceptable for good agreement can vary (from values greater than 0.6 to even negative values), depending on the context and application. In this study, KG > 0 is considered a good agreement index, between modeled values and observations. In Table 1, we provide a comprehensive summary of the metrics described above, including their respective mathematical expressions, symbols, as well as the range of values they may take. A summary of the different behaviours of the two models is given in the figures below (Fig. 6, Fig. 7, and Fig. 8), using Taylor diagrams (Taylor, 2001).

Table 1. Statistical metrics used to evaluate the performance of the NCEP and ERA5 models. $\mathbf{M_i}$ and $\mathbf{O_i}$ stands for modeled and observed values respectively, N is the total number of paired values, and the overbar represents the average process.

Metric	Symbol	Definition	Range	Perfect Score
Correlation Coefficient	R	$\frac{\sum_{i=1}^{N}(M_i-\overline{M})(O_i-\overline{O})}{\sqrt{\sum_{i=1}^{N}(M_i-\overline{M})^2(O_i-\overline{O})^2}}$	$[-1, 1]$	1
Mean Bias	MB	$\frac{1}{N}\sum_{i=1}^{N}(M_i-O_i)$	$[-\infty, +\infty]$	0
Unbiased Root Mean Square Difference	ubRMSD	$\sqrt{\sum_{i=1}^{N}\frac{[(M_i-\overline{M})-(O_i-\overline{O})]^2}{N}}$	$[0, \infty]$	0
Kling-Gupta Efficiency	KG	$1-\sqrt{(R-1)^2+\left(\frac{\sigma_M}{\sigma_O}-1\right)^2+\left(\frac{\mu_M}{\mu_O}-1\right)^2}$	$[-\infty, 1]$	1

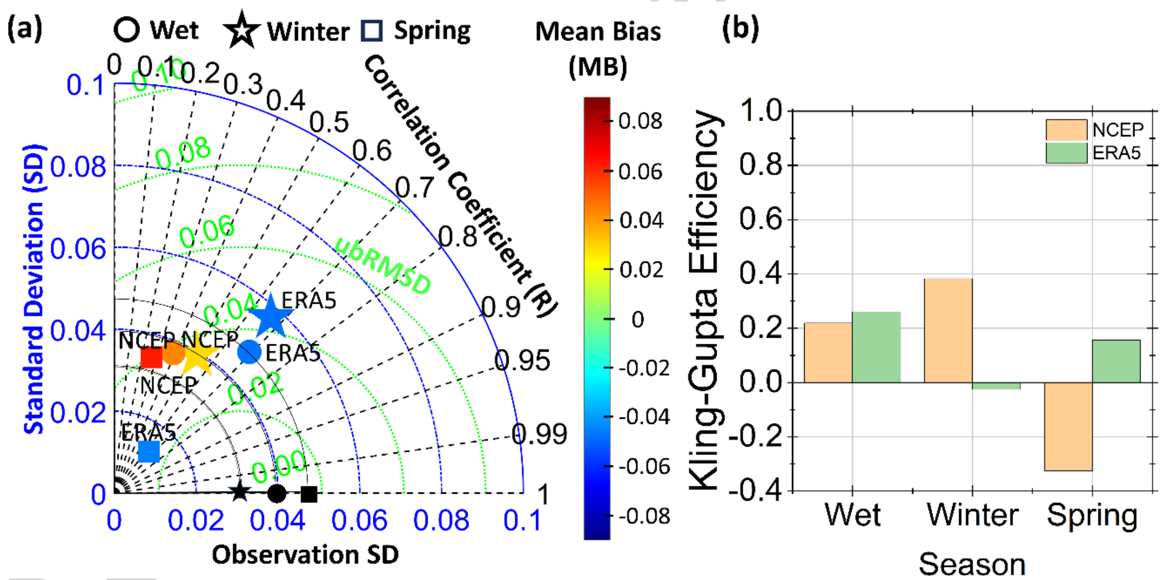

Fig. 6 (a) Taylor diagram illustrating the performance of the evaluated models, regarding volume soil moisture. Colored circles, stars and squares corresponds to wet, winter and spring months, respectively. With the color scale the mean bias level is presented. The black symbols represent the standard deviation of the observational data. The angular distance from the horizontal axis indicates the correlation of the model and measured data. The linear distance of points is proportional to their unbiased root mean square difference (b) The Kling-Gupta efficiency for the two models, during wet season (winter & spring months) over the years 2008–2018

Both ERA5 and NCEP exhibited the ability to accurately predict the VSM trend in the area during the wet season, as shown by the correlation coefficients (0.69 and 0.39, respectively), when compared to CCI-SM (Fig. 6a). While ERA5 shows similar performance during winter and spring months (R = 0.67 and 0.64 respectively), NCEP's moderate performance is limited to the spring months (R = 0.26), while during winter R increases to 0.51. Nevertheless, NCEP demonstrated mean bias (MB) values of 0.04 $m^3\ m^{-3}$ for the wet season. This value ranged from 0.03 $m^3\ m^{-3}$ to 0.06 $m^3\ m^{-3}$ during the winter and spring months, respectively. On the other hand, ERA5 reanalysis consistently underestimated the VSM during the winter and spring months, with a mean MB value around -0.05 $m^3\ m^{-3}$. In terms of unbiased root mean square difference, the ERA5 reanalysis yielded values of 0.03 $m^3\ m^{-3}$, 0.04 $m^3\ m^{-3}$, and 0.01 $m^3\ m^{-3}$ for the wet season, winter, and spring months, respectively. Similar ubRMSD values (0.04 $m^3\ m^{-3}$) obtained by NCEP model as well, for the winter, and spring months. Based on Fig. 6b, it is evident that the NCEP exhibits comparable to the ERA5 performance in terms of soil moisture, specifically during the wet season. Notably, the NCEP performances better during the winter months compared to spring, while the opposite pattern is demonstrated by ERA5, possibly due to their different spatial resolutions and the land-surface models used. Key role may also be played by the convective precipitation that occurs at a smaller scale during spring, while in the winter Kuwait experiences extreme weather events triggered by the passage of strong low-pressure systems and cold fronts, which may contribute to the relatively better performance of NCEP during these months. Large-scale extreme weather events, often resulting from regional or synoptic oscillations, can be observed through the NCEP, which tends to overestimate precipitation during extreme events. Despite this, it may simulate moderate precipitation values effectively (Zhaofei et al. 2012). It's important to acknowledge that NCEP may not be the ideal reanalysis model for mesoscale weather analysis due to its coarse resolution. However, understanding the strengths and weaknesses of each reanalysis model is crucial for any case study (Brönnimann et al. 2007).

Regarding the MP data, the ERA5 showed high linear consistency to the observations, with R values equal to 0.89, and 0.58, for winter and spring months respectively, while NCEP displayed lower values (0.73, and 0.37) for the same periods (Fig. 7a). The ERA5 model exhibited relatively small mean bias values during the wet season (MB = -0.13 mm).

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Specifically, ERA5 slightly overestimates MP during winter (MB = 0.41 mm), while during spring it displayed underestimation (MB = -0.86 mm). A similar pattern is followed by NCEP, which overestimated MP values during winter months (MB = 1.57 mm) but underestimate them in spring (MB = -0.90 mm). For the entire wet season NCEP's MB found to be 0.51 mm. The ubRMSD values for ERA5 found to be around 2.0 mm for both winter and spring months, while for NCEP's overall magnitude error varied from 4.0 mm during winter down to 2.0 mm at spring months.

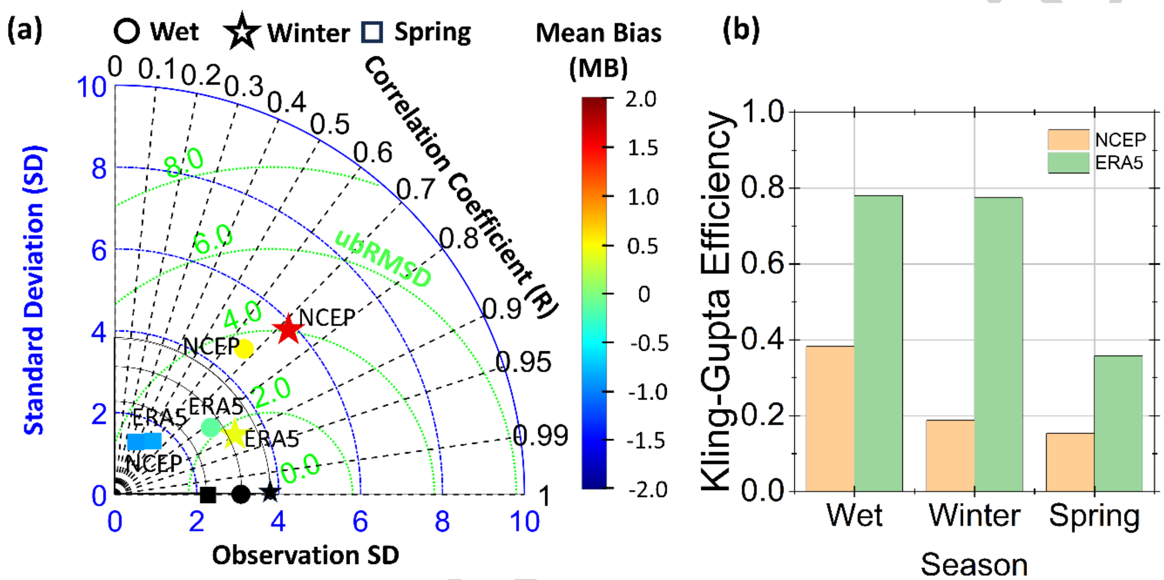

Fig. 7 Similar graphs as in previous figure but for mean precipitation.

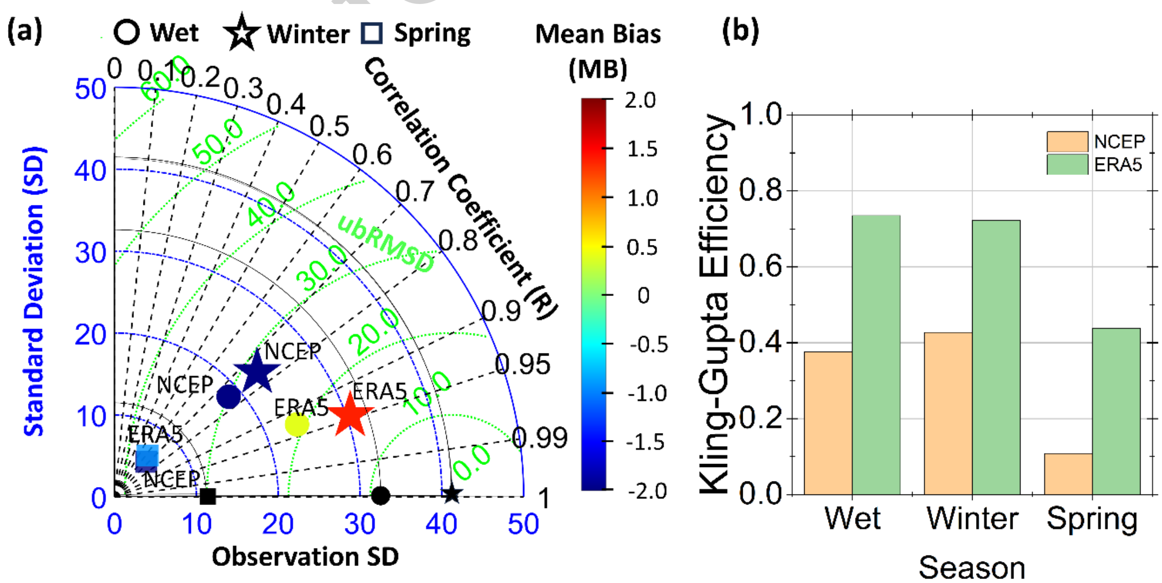

Fig. 8 Similar graphs as in previous figure but for total precipitation

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In terms of total precipitation (TP), the correlation coefficient values for ERA5 were even higher compared to the those found for MP (Fig. 8a). More precisely, ERA5 showed R equal to 0.93 for the entire wet season, with higher values (R = 0.95) appearing during winter, and lower (R = 0.62) during spring months. NCEP follows the same pattern but achieved lower correlation values (R around 0.70). The ERA5 overestimates TP during winter months (MB = 1.36 mm) and underestimates it during spring (MB = -0.94 mm), leading to an overall slight overestimation for the wet season (MB = 0.38 mm). In contrast, NCEP reanalysis significantly underestimates TP, almost at the same magnitude for winter and spring (MB around -5.50 mm). In terms of the model's overall magnitude of error, NCEP displays almost two times higher values compared to ERA5 for the wet season. More precisely ERA5 ubRMSD varied from 15.75 mm to 8.35 mm, for winter and spring months, while the corresponding ubRMSD values for NCEP found to be 27.95 mm and 8.04 mm. The high KG efficiency values shown in Fig. 7b and Fig. 8b, indicate that ERA5 not only follows the observations in time, but also accurately predicts the distributions of the precipitation-related products over the area, especially during the winter months.

In general, ERA5 exhibited a pattern of over- and underestimation for TP and MP, respectively. On the other hand, NCEP reanalysis showed minor over- and underestimation for MP data, but significant underestimation for TP data across all the months of the wet season. The trend in correlation coefficients for ERA5 and NCEP reanalysis was similar for both MP and TP. ERA5 demonstrated a narrower range of ubRMSD values compared to NCEP reanalysis for both MP and TP properties, indicating its overall excellent performance. ERA5 seems to correctly capture the range of values of the precipitation-related products (MP & TP) in wet season, something that can be partly attributed to the use of data assimilation, and the finer horizontal resolution. This is in accordance with similar studies regarding ERA5 seasonal error pattern in Extratropic (Lavers et al. 2022). NCEP shows similar good performance, especially for the TP product, underestimating the amount of precipitation inconsistently with the correlation coefficient. The model simulations have correlations from 0.66 to 0.75 at both precipitation products. The ERA5 seems to slightly underestimate the VSM values, especially during low precipitation events, but successfully capture its seasonal variability.

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4 Conclusions

This study aimed to assess the performance of two models, the ERA5 and NCEP reanalysis, in reforecasting soil moisture and precipitation over Kuwait, during the wet season (winter and spring months), from 2008 to 2018. The evaluation was conducted by comparing their outputs to data obtained from ESA CCI and in-situ observations. To ensure an accurate assessment of the soil moisture product, the CCI-SM data were initially compared to in-situ observations and underwent a bias correction of the order of 0.039 $m^3 m^{-3}$. Afterwards, the bias-corrected data were utilized in our analysis to evaluate the performance of ERA5 and NCEP in terms of soil moisture values. As for the precipitation products, a direct evaluation of the two models was carried out using rain gauge records collected within the study area (KAWOS). The evaluation of the models was primarily based on statistical properties such as correlation coefficient (R), mean bias (MB), and unbiased root mean square difference (ubRMSD).

ERA5 demonstrated an ability to accurately forecast the trend of VSM in the region (R=0.69) during the wet season, but with a mean bias underestimation of -0.05 $m^3 m^{-3}$. On the other hand, NCEP slightly overestimates VSM but captures its time variation moderately. This was indicated by the 0.39 correlation coefficient, and the MB of 0.04 $m^3 m^{-3}$, when compared to CCI-SM. NCEP's moderate performance is limited mostly to spring months, with better performance revealed during winter, while the opposite pattern was shown by ERA5.

In terms of monthly precipitation (MP) data, the ERA5 exhibited strong linear agreement with observations, with R values of 0.89 and 0.58 for winter and spring months, respectively. In contrast, the NCEP reanalysis showed lower values for the same period (0.73 and 0.37 respectively). The ERA5 model demonstrated relatively small MB values (-0.13 mm) during the wet season with slight overestimated MP values during winter (MB = 0.41 mm) and underestimated during spring months (MB = -0.86 mm). Same pattern is displayed also by NCEP model, showing 0.51 mm overall mean bias for the wet season. The RMSE values for ERA5 remained constant around 2 mm for both winter and spring months, while for NCEP, the overall magnitude error varied from 4.29 mm during winter to 2.28 mm in spring.

When considering total precipitation (TP), the correlation coefficient values for ERA5 were even higher (around 0.93) compared to those found for MP, for the entire wet season, with higher values observed during winter months. A similar pattern was also observed for NCEP reanalysis. ERA5 tends to overestimate TP during winter months (MB = 1.36 mm) and underestimate it during spring (MB = -0.94 mm), resulting in an overall slight overestimation during the wet season (MB = 0.38 mm). On the contrary, NCEP reanalysis significantly underestimated TP, with a similar magnitude for both winter and spring (MB around -5.50 mm). In terms of the overall ubRMSD, NCEP displayed values almost twice as high as ERA5 for the wet season, varying from 28.39 mm to 10.17 mm, during winter and spring months.

Based on the results of this study, becomes apparent that ERA5 outperformed NCEP in terms of precipitation-related products, yet a similar performance between the two models was observed for the volume soil moisture, with ERA5 responding better to higher soil moisture values. This can be attributed not only to the different horizontal resolutions but also to the land-atmosphere schemes used. Notably, for precipitation-related products ERA5 demonstrated superior performance not only during winter but also during spring months, due to its ability to capture the localized convective precipitation patterns observed that time of year in the region. NCEP on the other hand due to the coarser resolution performs satisfactory during winter especially for cumulative precipitation and volume soil moisture products. Overall, our findings suggest that the ERA5 precipitation dataset reanalysis holds great potential as a substitute for weather station data in the region. It can serve as a reliable source of precipitation data for future studies in the fields of climatology and hydrology, particularly in Kuwait.

Acknowledgements We are thankful to Kuwait Foundation for the Advancement of Sciences (KFAS) for fully supporting and sponsoring this Project no. CN1742SP01. We are also grateful to Kuwait University (KU) for the administration support.

Author contributions: All authors: Conceptualization; All authors: methodology; Panagiotis Kokkalis, Hala K. Al Jassar, and Hussain Al Sarraf; Panagiotis Kokkalis, Hamad Al Hendi, and Roshni Nair: prepared all figures; All authors reviewed the manuscript

Availability of data and materials: All reanalyses and observational data sets are freely available on request. We thank the NCEP and Copernicus Climate Data Service for the ERA5 data (precipitation and soil moisture), as well as ESA's CCI product of soil moisture. Rainfall gauge observations were provided by the Kuwait Automatic Weather Observation System.

Declarations

Conflict of interest (always applicable and includes interests of a financial or personal nature): None

Ethical Approval (applicable for both human and/ or animal studies. Ethical committees, Internal Review Boards, and guidelines followed must be named. When applicable, additional headings with statements on consent to participate and consent to publish are also required): not applicable

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