Evaluating the Evolution of ECMWF Precipitation Products Using Observational Data for Iran: From ERA40 to ERA5

Navid Ghajarnia¹, Mahdi Akbari²*, Peyman Saemian³, Mohammad Reza Ehsani⁴, Seyed-Mohammad Hosseini-Moghari⁵, Asghar Azizian⁶, Zahra Kalantari¹,⁷, Ali Behrangi⁴, Mohammad J. Tourian³, Björn Klöve² and Ali Torabi Haghighi²

¹ Department of Physical Geography, Bolin Center for Climate Research, Stockholm University, SE-10691 Stockholm, Sweden

² Water, Energy and Environmental Engineering Research Unit, Faculty of Technology, University of Oulu, Finland

³ University of Stuttgart, Institute of Geodesy (GIS), Stuttgart, Germany

⁴ Department of Hydrology and Atmospheric Sciences, The University of Arizona, Tucson, AZ, USA - 85721

⁵ Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

⁶ Water Engineering Department, Imam Khomeini International University, Qazvin, Iran

⁷ Department of Sustainable Development, Environmental Science and Engineering, KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden

* Corresponding author: mahdi.akbari@oulu.fi

The paper is a non-peer reviewed preprint submitted to EarthArXiv. Also, this manuscript has been submitted in Journal of Hydrometeorology for peer review. Please feel free to contact corresponding author for any question or feedback.
Abstract

ECMWF Reanalysis (ERA), one of the most widely used precipitation products, has evolved over time from ERA-40 to ERA-20CM, ERA-20C, ERA-Interim, and ERA5. Studies evaluating the performance of individual ERA precipitation products cannot adequately assess the evolution in the products. Therefore, we compared the performance of five successive ERA precipitation products using data at daily, monthly, and annual scale (1980-2018) from more than 2100 precipitation gauges in Iran, and applied various statistical and categorical metrics and error decomposition methods. The results indicated that ERA-40 performed worst, followed by ERA-20CM, which showed only minor improvements over ERA-40. ERA-20C considerably outperformed its predecessors, benefiting from assimilation of observational data. Although several previous studies have reported full superiority of ERA5 over ERA-Interim, our results revealed several shortcomings compared with ERA-Interim, in ERA5 precipitation estimates for Iran. Both ERA-Interim and ERA5 performed best overall, with ERA-Interim showing better statistical and categorical skill scores, and ERA5 performing better in estimating extreme precipitations. These results suggest that the accuracy of ERA precipitation products improved from ERA-40 to ERA-Interim, but not consistently from ERA-Interim to ERA5. These findings are useful for model development at global scale and for hydrological applications in Iran.

Keywords: precipitation estimates; statistical evaluation; error decomposition; multi-scale evaluation; ERA; precipitation analysis
1. Introduction

Precipitation is one of the most important components of the hydrological cycle (Eltahir and Bras 1996; Oki and Kanae 2006) and great efforts have been invested in monitoring its spatiotemporal variability (Teague and Gallicchio 2017; Arabzadeh et al. 2020; Koohi et al. 2021). Multiple methods have been developed to measure and monitor precipitation in the field, but accurate estimation of precipitation is still challenging (Adhikari et al. 2020; Foufoula-Georgiou et al. 2020). This difficulty is due to e.g., high spatiotemporal variability in complex topographical regions (Beck et al. 2019) and different sources of uncertainty associated with different measurement methods. These uncertainties significantly impede the study of climate and interconnections of hydroclimatic variables, water resources management, and hydrological forecasts (Sun et al. 2018; Foufoula-Georgiou et al. 2020).

There are three main sources of precipitation data: (1) ground-based data (mainly from precipitation gauge networks), (2) satellite remote sensing (RS) data, and (3) reanalysis datasets (Hosseini-Moghari et al. 2018; Shayeghi et al. 2020; Sun et al. 2018). Each of these has its strengths and weaknesses. Gauges provide the most accurate measurements, but they are geographically sparse, especially in remote areas, inaccessible topographies, and harsh climates (Ghajarnia et al., 2014; Sun et al., 2018). Moreover, gauge observations suffer from sampling errors and undercatch issues (Kidd et al. 2017; Panahi and Behrangi 2019; Ehsani and Behrangi 2021; Song et al. 2021). Precipitation estimation through gauge data interpolation for sparsely gauged regions is also challenging (Akbari et al. 2019; Yong et al. 2016).

Remote sensing precipitation products can mitigate some of the shortcomings of ground-based products by incorporating sensor observations from geostationary satellite thermal infrared (IR) and low-earth orbiting satellite microwave imagers/sounders (Ehsani et al. 2021; Adhikari et al. 2020). However, despite being uniform in space and continuous in time, RS-based precipitation products may have significant biases, due to systematic and random errors in their retrieval algorithms, inadequate temporal sampling, relatively poor performance on snow- and ice-covered surfaces, and the complex relationship between precipitation and RS information (Adhikari et al., 2020; Akbari et al., 2020; Arabzadeh & Behrangi, 2021; Ferraro et al., 2013; Ghajarnia et al., 2015). In addition, according to the World Meteorological Organization (WMO 2017), at least 30
years of historical data are required for climate studies, while many RS-based precipitation products suffer from shorter data records (Bai et al. 2019).

Reanalysis products have been developed by many organizations, mostly in the United States, Europe, and Japan. Such products benefit from use of a data assimilation system that incorporates available observations (in situ and RS data) into a numerical model to obtain the reanalysis outputs (Dee et al. 2011). As they benefit from both observations and modeling, reanalysis products are popular and have been used for various applications, including as input to the WMO assessment of the State of the Climate and in the Intergovernmental Panel on Climate Change (IPCC) assessments and reports (Akbari et al., 2020; Chen et al., 2017; Dee et al., 2011; Ghajarnia et al., 2020; Saemian et al., 2020). Reanalysis products also provide more extended temporal estimations (mainly over 40 years) of land-atmospheric variables, including precipitation (Sun et al. 2018).

European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA) is generally considered one of the most accurate reanalysis products for precipitation studies (Beck et al. 2017, 2019). ERA precipitation products have gradually evolved through five different versions: ERA-40 (Uppala et al. 2005), ERA-20C (Poli et al. 2016), ERA-20CM (Hersbach et al. 2015), ERA-Interim (Dee et al. 2011), and ERA5 (Hersbach et al. 2020) (see Table 1 for a summary of information on these different products). Several studies have evaluated the performance of ERA precipitation products regionally and globally. Studies comparing continental precipitation have found ERA-Interim to be significantly better in capturing monthly precipitation variability than ERA-40 (Simmons et al. 2010). Evaluation of ERA-Interim for precipitation in the United States indicated that the dataset had comparable performance to Global Precipitation Climatology Project (GPCP; Adler et al., 2003) for annual averages in the period 2000-2008 (Balsamo et al., 2010). A recent evaluation of ERA5 for North America (Tarek et al. 2020) indicated consistently lower precipitation bias in ERA5 than in ERA-Interim, and concluded that ERA5 can lead to systematically more accurate hydrological modeling. In a study in mainland China, Jiang et al. (2021) showed that ERA5 can successfully identify the spatial distribution and hotspots of precipitation, but underestimates extreme precipitation.

Although ERA products have been evaluated separately in different regions, there is still a need for specific comparison of performance for the different ERA products that have emerged over time. Previous studies evaluating individual ERA products are not comparable, mainly due
to different evaluation approaches, spatiotemporal scale, and study periods. Many studies have also been conducted across different regions with varying uncertainty in ground truth observations, further impeding comprehensive comparison of ERA products. An exhaustive evaluation of several successive ERA precipitation products for countries with diverse climates and precipitation patterns (such as Iran) can be insightful, revealing critical information on the performance of successive ERA products and contributing to the development and improvement of future versions. While later ERA products are generally expected to show improvements in models, input data, and assimilation methods (Sun et al. 2018), this needs to be verified independently and across different regions.

In this study, we evaluated the performance of five successive ERA precipitation products, using data for Iran, and investigated the improvements in each version compared with its predecessors. Iran's diverse geography and hydro-climatological patterns and access to independent observational data (i.e., precipitation data from gauges not used by global precipitation datasets) provided a unique opportunity to investigate the performance and evolution of the different ERA precipitation products.

A few studies have evaluated the performance of ERA-Interim or ERA5 precipitation products for Iran (Darand and Khandu 2020; Fallah et al. 2020; Khoshchehreh et al. 2021; Shobeiri et al. 2021; Taghizadeh et al. 2021; Shayeghi et al. 2020). However, none of them has focused on a comprehensive comparison of different successive ERA precipitation products to demonstrate their evolution over time. These studies have used different study areas and reference observational datasets, preventing intercomparison of ERA products across Iran based on the results.

The aim of this study was to make a combined assessment of the different ERA precipitation products, using Iran as the study area, to answer the following research questions: (1) What uncertainties and error characteristics are associated with the different ERA precipitation products in estimating precipitation? and (2) do later ERA precipitation products represent an improvement on their predecessors? To this end, we used data from more than 2100 gauges scattered throughout Iran to create the reference dataset, against which outputs from the different ERA precipitation products were compared (Table 1). The recorded data covered a 38-year period (1980 to 2018) and the evaluation was performed at daily, monthly, and annual time scales. To conduct a comprehensive performance evaluation, inspect the error characteristics, and quantify the progress
and evolution of the ERA precipitation products, different types of statistical indices and error
decomposition approaches were employed.

2. Study Area, Datasets, and Methodology

a. Study area

Iran was selected at the study area because most of its existing rain-gauge observations are not
publicly accessible and have thus not been used in previous assessments of global precipitation
products. Iran is located between 25°-40°N and 42°-63°E, and occupies an area of 1,648,000 km²
(Figure 1). The topography of Iran is diverse, with two mountain ranges, the Alborz Chain, which
runs from northwest to northeast, and the Zagros Chain, which runs from northwest to the shores
of the Persian Gulf, and two large deserts (Lout and Kavir) in the center of the Iranian Plateau.
The elevation varies from 25 m below mean sea level (MSL) in northern coastal regions by the
Caspian Sea to 5600 m above MSL in the Alborz Chain. Based on the Extended De Martonne
classification (Rahimi et al. 2013), Iran has a wide range of climates, from perhumid in the
northwest and along the Caspian Sea coast to semi-humid, Mediterranean, semi-arid, and extra-
arid in central and eastern areas.

Precipitation in Iran is influenced by various synoptic systems arriving from the north,
west, south, and southeast (Sabziparvar et al. 2015). The Mediterranean and North
Atlantic cyclones, along with the cold continental air mass, affect northwest and northern Iran,
causing considerable amounts of annual precipitation in the north and northwest (up to 2000 and
500 mm/year, respectively) (Sabziparvar et al. 2015). The Alborz and Zagros Chains largely block
the atmospheric and frontal systems arriving from the north and northwest of Iran, causing an arid
climate in the central region with annual precipitation of less than 50 mm/year (Yazdanpanah et
al. 2017). Summertime Indian monsoon systems influence southern and southeastern parts of Iran,
causing strong winds and sudden rain storms that can result in annual precipitation of up to 200
mm/year in these regions (Sabziparvar et al. 2015).
Figure 1. Map of Iran with the Digital Elevation Model (DEM) background and location of the precipitation gauges (synoptic and TAMAB stations) used in this study.

b. Datasets

1) Observed Precipitation Dataset

Precipitation in Iran is measured by two separate gauge networks, comprising: 1) the Iran Meteorological Organization (IRIMO) network (synoptic stations) and 2) the Iran Water Management Research Institute network (TAMAB stations) (Figure 1). Although observed precipitation at the synoptic stations is regularly reported to the WMO, their stations account for only a fraction of existing rain gauges in Iran. Most of Iran’s rain-gauge observations are not freely accessible to the public and have thus not been used in assessments of global models and products. In this study, we used data from 479 synoptic and 1646 TAMAB stations with records of daily precipitation for the selected study period (1980-2018). Before using the gauge data in assessments, we conducted quality control (QC) tests, which resulted in exclusion of data from six TAMAB precipitation gauges from the reference dataset (see Section 2.3.1).
2) ERA Precipitation Products

The five different versions of ERA (ERA-40, ERA-20C, ERA-20CM, ERA-Interim, ERA5) use models and data assimilation systems to reanalyze archived observations, creating global datasets describing the recent history of the atmosphere, land surface, and oceans (ECMWF 2021). Table 1 provides a summary of the different versions of ERA products and their specifications, differences, and improvements with a main focus on precipitation related issues. A brief description of each dataset is also given below.

3) ERA-40

ERA-40 is a 45-year second-generation reanalysis carried out by ECMWF in 2005 to produce the best possible set of analyses, given the changing observing system and the available computational resources. It began in September 1957, when the observing system had been enhanced, and ran until August 2002 (Uppala et al. 2005). The observations used in ERA-40 were accumulated from various sources with assimilated data provided by a succession of satellite-borne instruments from the 1970s onwards, supplemented with increasing numbers of observations from aircraft, ocean buoys, and other surface platforms, but with a declining number of radiosonde ascents since the late 1980s. The computational cost of ECMWF’s operational four-dimensional variational (4D-Var) data assimilation system was too large to be used for ERA-40. An updated form of the 3D-Var analysis, used operationally at ECMWF between January 1996 and November 1997 (Andersson et al. 1998), was thus adopted in this product (Uppala et al. 2005). ERA-40 estimated global gridded precipitation 1957-2002 with 6-hourly temporal resolution and ~125 km spatial resolution (Table 1).

4) ERA-20CM

ERA-20CM is an ensemble of 10 atmospheric model integrations for the 20th Century (1899-2010) developed at ECMWF (Hersbach et al. 2015). The spatial resolution of ERA-20CM is ~125 km and the temporal resolution is 3 hours (Table 1). Since no atmospheric observations were assimilated in ERA-20CM, this product cannot reproduce the data from actual synoptic gauges. However, the ERA-20CM ensemble product can provide a statistical estimate of the climate over the 20th Century and provides a good reference for the forced low-frequency variability of the
atmosphere in the 20th century. Moreover, ERA-20CM is well suited for projection of global warming and significant events onto other geophysical quantities not directly provided in the forcing data (Hersbach et al. 2015).

5) ERA-20C

The ECMWF’s 20th Century reanalysis ERA-20C (1900-2010), an atmospheric general circulation model, uses the same configuration as the control member of the ERA-20CM ensemble. However, it is forced by observation-based analyses of sea surface temperature, sea ice cover, atmospheric composition changes, and solar forcing (Poli et al. 2016). The resulting climate trend estimations resemble those of ERA-20CM for the temperature and water cycle, but the assimilation of observations adds realism to synoptic time scales compared with ERA-20CM in regions that are covered by observations. The novel feature of ERA-20C compared with its predecessors was the availability of observation-based feedback information. The general quality of ERA-20C and its climate-related agreement with other products improves with the availability of observations (Poli et al. 2016).

6) ERA-Interim

The ERA-Interim project was conducted by ECMWF to prepare a new atmospheric reanalysis to replace ERA-40, which extended back to the early part of the 20th Century (Dee et al. 2011). ERA-Interim covers the period 1979-2019 and its gridded data include a large variety of 3-hourly surface parameters, describing the weather, ocean-wave and land-surface conditions, and 6-hourly upper-air parameters covering the troposphere and stratosphere (Dee et al. 2011). Vertical integrals of atmospheric flux, monthly averages for many parameters, and other derived fields have also been produced and published in the Copernicus portal (Berrisford et al., 2009). The spatial resolution of this dataset is 79 km (Table 1).

7) ERA5

ERA5, the most recent ECMWF reanalysis product, provides a detailed record of the global atmosphere, land surface, and ocean waves from 1950 onwards. Developed to replace ERA-Interim, ERA5 significantly enhanced the spatial resolution of ECMWF reanalysis to 31 km and
provides hourly output and an uncertainty estimate from an ensemble of model runs (Hersbach et al. 2020). In addition, the representation of tropospheric processes appears to be significantly improved in ERA5, as it benefits from a decade of research and developments in modeling physical dynamics and in data assimilation techniques (Hennermann and Berrisford 2018). Therefore, ERA5 can be expected to perform considerably better than ECMWF's previous products. Expected improvements include representation of tropical cyclones, global balance of precipitation and evaporation, precipitation over land in the deep tropics, soil moisture, and more consistent sea surface temperatures and sea ice (Hennermann and Berrisford 2018).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Period/Resolution/Assimilation Scheme</th>
<th>General characteristics / Improvements, strengths, and limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERA-40</td>
<td>1957-2002 6-hourly 125 km 3D-Var</td>
<td>A second generation reanalysis. Key strengths: • Assimilates satellite radiances directly (TOVS, SSM/I, ERS and ATOVS data) • Cloud Motion Winds will be used from 1979 onwards Key limitations: • Tropical moisture (precipitation, total column water vapor) larger than observed from 1991 onward • Precipitation greatly exceeds evaporation</td>
</tr>
<tr>
<td>ERA-20CM</td>
<td>1899-2010 3-hourly 125 km</td>
<td>ERA-20CM includes no data assimilation and is an ensemble of ten atmospheric model integrations forced with SSTs, sea ice concentrations, and radiative forcings. Key strengths: • Capable of providing a statistical state of the climate • Temperature over land is in fine agreement with CRU temperature data Key limitations: • No observational data assimilation and all observational information is incorporated in the boundary conditions and forcing. • Not able to represent actual synoptic stations</td>
</tr>
<tr>
<td>ERA-20C</td>
<td>1900-2010 3-hourly 125 km 4D-Var</td>
<td>Observations assimilated include surface pressures and surface winds over the oceans. Forced with time-varying SSTs, sea ice concentrations, and radiative forcings. Key strengths: • Uses modern, 4D VAR data assimilation scheme Key limitations: • Affected by changes in the observing system • Does not provide the best estimate of the atmospheric state since ~1979, when more complete observations and more comprehensive reanalyses are available ERA-20C strengths compared to ERA-20CM (related to precipitation): • Inclusion of data assimilation</td>
</tr>
<tr>
<td>ERA-Interim</td>
<td>1979-2019 6-hourly 79 km 4D-Var</td>
<td>A third generation reanalysis. Key strengths: • Spatially and temporally complete data set of multiple variables at high spatial and temporal resolution • Improved low-frequency variability and stratospheric circulation Key limitations: • Too intense of a water cycling (precipitation, evaporation) over the oceans ERA-Interim strengths compared to ERA-40 (related to precipitation):</td>
</tr>
<tr>
<td>Dataset</td>
<td>Period/Resolutions/Assimilation Scheme</td>
<td>General characteristics / Improvements, strengths, and limitations</td>
</tr>
<tr>
<td>---------</td>
<td>--------------------------------------</td>
<td>---------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| ERA5    | 1950-present Hourly 31 km 4D-Var     | Represents 10 years of progress made in modeling and data assimilation since the production of ERA-Interim. **Key strengths:**  
- Spatially and temporally complete data set of multiple variables at high spatial and temporal resolution  
- Better able to resolve features like hurricanes than previous generations of the reanalysis  
- Assimilation of data from many recent instruments, including IASI, ASCAT, CrIS, MWHS, MWHS-2, TMI, SSMIS, AMSR-2, GMI.  
**Key limitations:**  
- Non-physical trends and variability may be present in the record due to changes in the observing system  
- Consistency of the representation of globally averaged temperatures in the mid- to upper-stratosphere has not improved in ERA5  
**ERA5 strengths compared to ERA-Interim (related to precipitation):**  
- Better global balance of precipitation and evaporation  
- Better precipitation over land in the deep tropics  
- Higher spatial and temporal resolutions |

References used to summarize information in Table 1: Dee et al. (2011); Hersbach et al. (2015, 2019, 2020); Poli et al. (2016); Uppala et al. (2005); Confluence Mobile - ECMWF Confluence Wiki; ERA-20C: ECMWF’s Atmospheric Reanalysis of the 20th Century (and Comparisons with NOAA’s 20CR | NCAR - Climate Data Guide; ERA-Interim | NCAR - Climate Data Guide; ERA5 Atmospheric Reanalysis | NCAR - Climate Data Guide)

Table 1. Summary of the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA) products used in this study. Models’ general characteristics, improvements, strengths, and limitations related to precipitation estimations are also summarized.

c. Methodology

1) Quality Control of the Observed Precipitation Dataset

Before evaluating the performance of the ERA precipitation products, we applied QC tests on the gauge observations and excluded inhomogeneous and suspicious gauges from the reference dataset. The overall workflow of QC tests implemented in this study is shown in Figure S1 in Supplementary Material (SM). The QC tests were applied to the annual number of wet days with a threshold of 1 mm/day, rather than to precipitation rates following Wijngaard et al., (2003). After constructing the time series of annual wet days for all gauge stations, four statistical homogeneity tests (Standard Normal Homogeneity Test (SNHT; Alexandersson, 1986), Buishand range test
(Buishand 1982), Pettitt test (Pettit 1979), and Von Neumann ratio test (Von Neumann 1941) were performed to check departures of the time series from homogeneity (using the RStudio package by Pohlert, 2016). The predefined null hypothesis of all four tests is that the annual number of wet days in a year is independent and identically distributed. Under the alternative hypothesis, presence of a step-wise shift (break) in the mean or non-random distribution of the time series is assumed (for more details on the definitions of these tests, see SM).

Based on the results of the tests and using the classification scheme developed by Schönwiese & Rapp, (1997) and Wijngaard et al. (2003), gauges in Iran were classified into three categories (Useful, Doubtful, and Suspicious) The Doubtful and Suspicious gauges were re-checked against their closest Useful gauges, using the double mass curve test (Searcy et al. 1960) and a final decision about exclusion of the gauges was then made (for more details on this test, see SM). Only six (of 1640) TAMAB gauges did not pass the QC test and were excluded from the reference dataset used in this study.

2) Spatio-temporal Aggregation of the Reference and ERA Precipitation Dataset

Since the reference and ERA datasets had different temporal resolution, all sub-daily gauge (i.e., reference) data and gridded (i.e., ERA product) data were aggregated to daily time step. Monthly and annual time series were then built from daily values. During the temporal aggregations, monthly (annual) records with more than five days (two months) of missing data in a month (year) were excluded (considered as NaNs).

We employed a slightly modified version of the inverse distance weighting (IDW) method to obtain gridded estimations of precipitation from gauge observations at the spatial resolution of each ERA dataset (Table 1). Using the modified IDW method, three-dimensional distances (including the vertical distance of each gauge from the mean elevation of the grid) were calculated and used as the weights of all gauge stations falling into different ERA product grid cells (see SM for more details). The gridded daily, monthly, and annual time series obtained for the reference observational dataset at the spatial resolution of ERA precipitation products were subjected to statistical analyses and error evaluations.
1) Statistical indices

Kling-Gupta Efficiency (KGE) (Gupta et al. 2009; Kling et al. 2012) was chosen as the statistical index in this study, as it summarizes and combines three measures of model error: correlation coefficient, bias, and variability ratio (Kling et al. 2012). The KGE values were calculated for precipitation estimated by the ERA products compared with the associated observed values in the reference dataset. The revised version of KGE (Kling et al. 2012) was used, to ensure that the bias and variability ratios were not cross-correlated. KGE is calculated as:

\[ KGE = 1 - \sqrt{(1 - CC)^2 + (1 - \beta)^2 + (1 - \gamma)^2} \]  

where \( CC \) is Pearson product-moment correlation coefficient (optimal value is 1), \( \beta \) is bias ratio, defined as the division of simulated and observed mean values (optimal value of 1), and \( \gamma \) is variability ratio, computed by dividing the coefficient of variation (CV) of simulated and observed values by the optimal value of 1 (Kling et al. 2012).

Three additional statistical measures, correlation coefficient (CC), root mean squared standard error (RMSE), and relative bias (RBias) were also calculated, using the following equations:

\[ CC = \frac{cov(p_{est}, p_{obs})}{\sigma(p_{est})\sigma(p_{obs})} \]  

\[ RMSE = \sqrt{\frac{\sum_{t=1}^{T}(P_{t}^{obs} - P_{t}^{est})^2}{T}} \]  

\[ RBias = \frac{\sum_{t=1}^{T}P_{t}^{est} - \sum_{t=1}^{T}P_{t}^{obs}}{\sum_{t=1}^{T}P_{t}^{obs}} \times 100 \]

where \( p_{est} \) and \( p_{obs} \) indicates the estimated and observed precipitation values from the ERA products and reference datasets, respectively. For each pixel, \( cov(p_{est}, p_{obs}) \) is the statistical covariance of observed and estimated precipitation, respectively, and \( \sigma(p_{obs}) \) represents the standard deviation of the dataset. \( P_{t}^{obs} \) and \( P_{t}^{est} \) are observed and estimated precipitation at the time step \( t \) at each grid cell, with \( T \) indicating the total number of time steps in a specific grid cell.

All statistical indices were calculated for the daily and monthly time series. In addition, the observed precipitation data (and their associated ERA estimates) were categorized into four different classes: 0-200, 200-400, 400-600, and >600 mm/year, and KGE was calculated for each
class to evaluate the performance of ERA products for regions with different climates and precipitation regimes (from dry to more humid regions).

2) Categorical contingency table indices

Apart from evaluating the accuracy of models in estimating precipitation rate, it is important to verify their precision in detecting precipitation occurrence. This was done by creating a contingency table based on dichotomous estimations that return *Yes* if the precipitation has happened or *No* otherwise. The contingency table indices were then defined based on the number of *Yes* and *No* events in the reference and ERA products. The threshold specified to separate *Yes* and *No* events in this study was varied from 0 to 25 mm/day, in order to test the functionality of the ERA products in detection of precipitation at different precipitation rates. The contingency table indices applied were probability of detection (POD), false alarm ratio (FAR), Bias, and Heidke skill score (HSS):

\[
POD = \frac{H}{H + M} \\
FAR = \frac{FA}{H + FA} \\
Bias = \frac{H + FA}{H + M} \\
HSS = \frac{2(H \times CN - FA \times M)}{(H + M)(M + CN) + (H + FA)(FA + CN)}
\]

where \(H, M, FA,\) and \(CN\) represent Hit, Miss, False Alarm, and Correct Negative conditions, respectively.

POD represents the success rate of the model in estimating the occurrence of precipitation correctly (optimal value is 1), whereas FAR ratio measures the fraction of estimated precipitation events that were non-rainy days in the observed dataset (optimal value is 0). Bias also measures the ratio of the number of estimated precipitation events to the number of observed rainy days, and indicates whether the model tends to under forecast \((Bias < 1)\) or over forecast \((Bias > 1)\) precipitation. HSS measures the fraction of correct precipitation estimates by the model after eliminating correctly estimated rainy days due to random chance (optimal value is 1). For more information on the definitions and details of the contingency table indices, see Murphy & Winkler (1987) or the website [https://www.cawcr.gov.au/projects/verification/](https://www.cawcr.gov.au/projects/verification/). The *verification* package
in Rstudio, developed by NCAR (2015), was used to calculate the contingency table indices at different thresholds tested in this study.

3) Systematic and Random Error Decomposition

Decomposition of errors to systematic and random components can help determine the source of errors in estimation/prediction models and provides very useful information for evaluating performance and identifying areas for future model enhancement. Systematic errors are reproducible inaccuracies that are consistently in the same direction (higher or lower than observed data), while random errors vary around observed data in different directions. The mean squared difference (MSD) error index, which measures the difference between observed and modeled values, can be decomposed into a systematic component ($MSD_s$) and a random component ($MSD_r$) as (Willmott 1981):

$$MSD = MSD_s + MSD_r$$

$$\frac{\sum_{i=1}^{n}(\hat{P}_{i}^{est} - P_{i}^{obs})^2}{n} = \frac{\sum_{i=1}^{n}(\hat{P}_{i}^{est} - P_{i}^{obs})^2}{n} + \frac{\sum_{i=1}^{n}(P_{i}^{est} - \hat{P}_{i}^{est})^2}{n}$$

where $\hat{P}_{i}^{est}$ is obtained by calculating the least square linear regression relationship as $\hat{P}_{i}^{est} = a + bP_{i}^{obs}$, where $a$ and $b$ are the intercept and slope, respectively.

From the above equations, the ratio ($\frac{MSD_s}{MSD}$) represents the systematic error component, while ($\frac{MSD_r}{MSD}$) or ($\frac{1-MSD_s}{MSD}$) represents the random component of the total MSD value. Apart from the desirability of lower MSD values (total MSD, MSDs, MSDr), a low ratio of systematic error to the random component is preferable, as it reflects a better model algorithm, in the present case capable of capturing the precipitation process (see Ghajarnia et al. (2018) for a graphical illustration of systematic and random error components).

3. Results and Discussion

a. Daily Evaluations

Comparison of scatter plots of daily precipitation estimates for the different ERA precipitation products against gauge observations (Figure 2) and assessment of skill scores revealed improvements in successive versions of the ERA precipitation products at the daily scale. ERA-
40 and ERA-20CM were found to be the worst-performing products among all ERA versions, as indicated by accumulation of points around the horizontal and vertical axes (Figure 2a and 2b), indicating poor performance in capturing precipitation occurrence and rate. ERA-20C estimates outperformed those of the earlier versions (Figure 2c), presumably due to its assimilation of observational data as explained earlier in section 2.2.5 and Table 1. This performance improvement was reflected in higher CC (0.49, ~310% increase compared with ERA-20CM) and lower RMSE (2.9 mm/day, ~10% decrease compared with ERA-20CM) (Figure 2c). In addition, ERA-20C estimates were less concentrated around the horizontal and vertical axes and more directed towards the perfect agreement line. This positive improving trend was also seen for ERA-Interim and ERA5 (Figures 2d and 2e). However, although ERA5 was able to capture more extreme daily observations than ERA-Interim (enhanced distribution of points towards the upper right side of the perfect agreement line), its estimates were more scattered in the plot (especially around the horizontal and vertical axes), indicating more erroneous estimates (Figure 2e). ERA-Interim, the version before ERA5, outperformed all the other products at daily time scale, with the highest CC (0.59, compared with 0.55 for ERA5), lowest RMSE (3 mm/day, compared with 3.8 for ERA5), better RBias (8%, compared with 30% for ERA5), and a better distribution of points around the perfect agreement line (Figure 2d). ERA-5 significantly underestimated precipitation between ~5 and ~25 mm/day). The highest concentration of estimation-observation pairs in all panels was around the zero-zero value, as influenced by the high number of no-rainy days in the time series, especially across the most arid climate regions in central Iran.
Figure 2. Scatter plots of correlation coefficient (CC), root mean squared error (RMSE), and relative bias (RBias) of daily observed and estimated precipitation (mm/day) for (a) ERA-40, (b) ERA-20CM, (c) ERA-20C, (d) ERA-Interim, and (e) ERA5. The color bar shows the density of points in the plot.

Figure 3 shows box plots of daily KGE and its components (CC, bias ratio, variability ratio) for all grid cells, together with the spatial distribution across Iran. ERA-40 showed very poor performance, mainly due to high bias ratio (\(\beta\)) and low CC (Figure 3a). There was a significant improvement in all subsequent ERA precipitation products, as reflected in lower bias ratio and higher CC components (significantly better index values with shorter interquartile range, see Figure 3a-b). Median KGE for ERA-20CM, ERA-20C, ERA-interim, and ERA5 was 0.1, 0.34, 0.45, and 0.39, which was a 93\%, 124\%, 132\%, and 127\% improvement, respectively, compared with ERA-40. Interestingly, there was no significant improvement in ERA products after ERA-40. Again, and in contrast to general expectations, ERA-Interim had slightly higher median KGE (0.06, +16\%), higher median CC (0.02, +4\%), lower bias ratio (0.12, -10\%), and lower variability ratio (0.12, -16\%) compared with ERA5 (Figure 3). This indicates a relatively small decrease in ERA5 performance in precipitation estimation compared with ERA-Interim at the daily scale.

Evaluation of the spatial pattern of KGE for different ERA precipitation products across Iran (Figure 3e) showed that, in addition to the higher spatial resolution, the accuracy of ERA precipitation estimates improved from ERA-40 to ERA5. Compared with ERA-40 and ERA-
20CM, which exhibited lower spatial skill in terms of KGE, ERA-20C, ERA-Interim, and ERA5 showed improved performance for most parts of Iran. In particular, ERA5, ERA-Interim, and partly ERA-20C showed better performance for mountainous regions in western Iran (Zagros Chain) (Figure 3e). However, grid cells located in the northwest and coastal regions around the Caspian Sea were associated with poor representations of precipitation rates, especially by ERA5. Precipitation in central arid areas and the Iranian deserts was mainly misrepresented by all ERA precipitation products, or not included in the analysis due to lack of gauge stations.

Figure 3. Box plots of (a) Kling-Gupta Efficiency (KGE) and its components (b) correlation coefficient (CC), (c) bias ratio, and (d) variability ratio calculated at daily scale in all grid cells by the different ERA products. Red asterisks indicate the mean. (e) Gridded map of KGE for daily precipitation estimates by different ERA products for Iran.
To assess how the ERA precipitation products performed in estimating precipitation of different intensities, KGE and its related components (CC, β, γ) were calculated separately for the four precipitation intensity categories (0-5, 5-10, 10-20, and >20 mm/day) (Figure 4). The size of the sample in each category can be found in Table S1 in SM. Based on the KGE values (Figure 4a), for the category 0-5 mm/day (representing more than 95% of the data, see Table S1), ERA-20C, ERA-Interim, ERA5, ERA-20CM, and ERA-40 provided daily estimates in descending order of accuracy (KGE = 0.2, 0.16, -0.5, -0.27, and -0.31, respectively). However, the order changed to ERA5, ERA-Interim, ERA-20C, ERA-20CM, and ERA-40 as precipitation intensity increased. For example, for precipitation >20 mm/day (around 1% of the sample size) KGE was -0.24, -0.35, -1.34, and < -3 for ERA5, ERA-Interim, ERA-20C, and ERA-20CM/ERA-40, respectively. These trends indicated that the two more recent ERA precipitation products, and in particular ERA5, performed better in capturing extreme precipitation events in Iran. This can be attributed to the higher spatial resolution of ERA-Interim (79 km) and ERA5 (35 km) compared with their predecessors (125 km), leading to better representation of local precipitation processes and intense rainfall. Similar patterns in CC, bias ratio, and variability ratio were found (Figure 4b-d), confirming that ERA5 provided the best performance for the highest rainfall category (>20 mm/day).

Figure 4. Heatmap of (a) Kling-Gupta Efficiency (KGE), (b) correlation coefficient (CC), (c) bias ratio (β), and (d) variability ratio (γ) calculated using daily precipitation time series at different thresholds. Green represents the best value of a particular index for the different ERA products, while red and blue indicate the worst negative and positive index values, respectively. KGE/γ values lower/higher than -3/3 are shown by the same color.
The categorical metrics POD, FAR, and HSS were used to assess the ability of the ERA products in capturing the occurrence or non-occurrence of precipitation events (Figure 5). The POD of the ERA products improved constantly from ERA-40 to ERA5 (0.32 to 0.69) (Figure 5a), indicating higher capability of ERA5 in detecting rainy days compared with its predecessors. This was a particularly important finding considering that ERA5 had the highest spatial resolution of all products.

Despite the improvement in POD for newer ERA precipitation products, the FAR of ERA5 (median 0.58) increased considerably compared with ERA-20C (median 0.47) and the FAR of ERA-Interim (median 0.48) increased slightly, but with larger interquartile range. The higher FAR in ERA5, indicating a higher probability of falsely reporting precipitation events, led to a lower median value of HSS (an overall measure summarizing all categorical metrics) for ERA5 (0.45) compared with ERA-Interim (0.49) (Figure 5b). This indicates that the overall ability of the ERA precipitation products in detecting precipitation events at daily scale in Iran improved from ERA-40 to ERA-Interim, but decreased in the most recent product (ERA5).

The spatial patterns in HSS (Figure 5b) also indicated low detection skill for ERA-40 and ERA-20CM in the study area. HSS improved for ERA-20C estimates and further for ERA-Interim estimates, mostly in the western mountainous region of Iran (Zagros Chain). ERA5 showed slightly weaker performance in terms of HSS, particularly in the northwest and northeast of the country. Figure S2 and S3 in SM also show the maps of spatial distribution of POD and FAR across Iran, based on precipitation estimates of different ERA products.

Calculation of the categorical metrics using different precipitation thresholds for rainy/non-rainy days revealed critical information on the capacity of the different ERA products in detecting precipitation (Figure 6). The FAR, POD and HSS values for different thresholds in ERA-40 and ERA-20CM showed that these products had very little skill in detecting precipitation events in Iran, especially at higher intensities. More than 95% of the precipitation estimates by ERA-40 and ERA-20CM for rainfall events >10 mm/day were false alarms, and these products missed almost all >10 mm/day events (Figure 6a and 6b).

As expected, ERA-20C showed considerable improvement over ERA-20CM and the improvement continued in ERA-Interim and ERA5, with the latter able to capture ~95% of precipitation events with threshold 0 mm/day (Figure 6b). However, this came at the cost of FAR
higher than 0.7, which means more than 70% of ERA5 precipitation estimates for this rainfall category were false alarms. This can be attributed to the higher spatial resolution of ERA5 and its higher potential detection of local spatial precipitation patterns not detected by the reference dataset (due to low number of gauges in those grid cells). In general, high values of both POD and FAR led to higher Bias, as shown in Figure 6d for ERA5 at the threshold <1 mm/day. Overall, the performance of ERA5 in estimating precipitation in the range 0-1 mm/day was lower than that of ERA-Interim.

Figure 5. (a) Box plots of three categorical metrics, probability of detection (POD), false alarm ratio (FAR), and Heidke Skill Score (HSS), showing the range of all gridded values, and (b) spatial distribution of HSS scores in Iran for daily precipitation estimates by the different ERA products.
In terms of HSS (Figure 6c), ERA5 outperformed ERA-Interim for intense precipitation (i.e., higher than 13 mm/day). In addition, there was a much more gradual increase in FAR for ERA5 compared with ERA-Interim, indicating a lower probability of false alarms by ERA5 for more extreme precipitation estimates. These findings, together with the higher POD values for ERA5 at all precipitation thresholds compared with ERA-Interim (Figure 6b), reveal that ERA5 had higher capability in representing extreme precipitation events, despite its overall weaker performance at lower precipitation rates. The enhanced performance at extreme precipitation categories can again be due to the higher spatial resolution of ERA5 compared with ERA-Interim, leading to its higher capability in capturing local precipitation processes.

Figure 6. Plots of the categorical metrics (a) false alarm ratio (FAR), (b) probability of detection (POD), (c) Heidke Skill Score (HSS), and (d) Bias, calculated using different precipitation thresholds for rainy or non-rainy days.

Figure 7 shows the spatial patterns in the systematic and random error components as percentages and as absolute values of MSD averaged over all grid cells across Iran. The lowest systematic error component for all ERA precipitation products was found for ERA-40 (low ratio of systematic error to the sum of systematic and random errors) (Figure 7a). However, it had very high random error values (MSDr) across all grid cells, reflecting high overestimation by ERA-40 and overall poor performance (Figure 7b). ERA-20CM had the next highest systematic error
component, both in terms of percentages (Figure 7a) and absolute mean MSD values (Figure 7b).

Although ERA-20C improved on ERA-20CM’s estimation algorithm and provided lower systematic and random errors, it still suffered from higher mean MSDr error component in precipitation estimates. ERA-Interim was the best-performing ERA precipitation product, giving the lowest relative systematic error for different parts of Iran (Figure 7a) and lower mean MSDs than the MSDr component (Figure 7b). Finally, although ERA5 gave lower relative systematic error value (compared with its random error component), its absolute MSDr and MSD values were higher, which can impact ERA5 precipitation estimates compared with ERA-Interim. These results indicate an overall improvement in ERA products from ERA-40 to ERA-Interim (with decreased systematic error), but slightly decreased performance in ERA5 in terms of both systematic and random error components. This may be caused by the higher resolution of ERA5, but it can also indicate that the ERA5 modeling approach still needs more improvement to better match the spatial resolution of its output.

![Figure 7](image_url)

**Figure 7.** Error decomposition of total mean squared difference error (MSD). (a) Maps of relative systematic (S, top row) and random (R, bottom row) error components (percentages) and (b) averaged absolute values of systematic and random MSD values for the five ERA precipitation products at daily time scale.
b. Monthly Evaluations

To evaluate the performance of ERA precipitation products at monthly time scale, the statistical and categorical evaluation metrics were re-calculated for the monthly time series. Scatter plots of monthly estimates versus observations for all ERA precipitation products (Figure 8) showed considerably improved performance of all products at the monthly scale compared with the daily scale, as was expected. This was reflected in paired points in the scatter plots being better distributed around the perfect agreement line (Figures 8a-e). All products were also more capable of estimating precipitation in wetter months. As found for the daily results (see Figure 2), ERA-40 and ERA-20CM were again the two products with the weakest performance metrics, while ERA-20C had the highest CC (0.78) and lowest RMSE (22.9 mm/month) values. Compared with ERA-Interim and ERA5, ERA-20C estimates were more scattered around lower precipitation rates, indicating underestimation (lower RBias). This can be due to the lower spatial resolution of ERA-20C compared with ERA-Interim and ERA5, resulting in dampening of estimated and aggregated precipitation data over larger grid cells.

Comparisons of the performance of ERA-Interim and ERA5 (Figure 8d-e) indicated that, despite both having the same CC value (0.76), ERA5 achieved better performance in capturing wet months due to its higher spatial resolution, as the points reached closer to the upper right corner of the scatter plot (Figure 8e). However, ERA5 also had higher RMSE (32.5 mm/month) than ERA-Interim (26.7 mm/month).
Figure 8. Scatter plots of correlation coefficient (CC), root mean squared error (RMSE), and relative bias (RBias) of monthly observed (i.e., reference datasets) and estimated precipitation (mm/month) for (a) ERA-40, (b) ERA-20CM, (c) ERA-20C, (d) ERA-Interim, and (e) ERA5. The color bar shows the density of points in the plot.

Monthly estimates by the ERA precipitation products were also evaluated using KGE (for full results, see Figure S4 in SM). Compared with the daily results, the monthly results showed slightly higher KGE median values, of -1.42, 0.3, 0.56, 0.65, and 0.61 for ERA-40, ERA-20CM, ERA-20C, ERA-Interim, and ERA5 respectively. They also showed higher monthly correlations, especially for ERA-40 and ERA-20CM (larger interquartile range towards higher CC in the box plots, see Figure S4a), variability ratio closer to 1 (except ERA-20CM), and similar bias ratio values to those of the daily results. The spatial patterns in gridded monthly KGE maps (see Figure S4e) also showed higher KGE values, particularly for mountainous regions of western and south-western Iran. Overall, based on the monthly KGE calculations in Figure S4, ERA-Interim achieved the best performance of all products. However, the comparable ERA5 skill scores while having considerably higher spatial resolution should also be taken into consideration.
Figure 9. Heatmap of (a) Kling-Gupta Efficiency (KGE), (b) correlation coefficient (CC), (c) bias ratio ($\beta$), and (d) variability ratio ($\gamma$) calculated using monthly precipitation time series at different thresholds. Green represents the best value of an index for the different ERA products, while red and blue indicate the worst negative and positive index values, respectively.

To perform a more in-depth analysis of ERA products at the monthly scale, KGE and its components were also calculated for different mean annual precipitation categories (see section 2.4.1) (Figure 9). These categories included grid cells from dry central regions of Iran to moderate and wet highlands in the northwest or humid and very wet coastal areas by the Caspian Sea in the north (see Table S2 in SM for the size of the data subsets at each category). According to the KGE values (Figure 9a), ERA-Interim was the best performing ERA product in all categories, except over the wettest grid cells with the highest annual precipitation ($\geq$600 mm/year) in which ERA5 outperformed ERA-Interim. Both ERA5 and ERA-Interim improved the estimates of their predecessors for all annual precipitation categories and at the monthly time scale, which is a sign of successful evolution in ERA precipitation estimation products.

Figure 10 shows the pattern of mean monthly precipitation according to the reference dataset and ERA precipitation products. ERA-40, with considerable overestimation, was not able to capture correctly the values or the seasonality of observed mean monthly precipitation (Figure 10a). The performance of ERA-20CM was considerably better than that of ERA-40, but there were still some inaccurate monthly patterns (e.g., in April, July, and December) (Figure 10b). ERA-20C, ERA-Interim, and ERA5 all correctly captured the trend in the mean monthly reference
dataset, but ERA-Interim provided the most accurate monthly estimates while ERA-20C and ERA5 contained relatively constant bias as under- and over-estimations, respectively.

![Figure 10](image.png)

*Figure 10. Long-term average monthly precipitation as estimated by ERA-40 (green), ERA-20CM (light blue), ERA-20C (dark blue), ERA-Interim (orange), and ERA5 (red), and observed precipitation at gauge stations in Iran (dashed black line).*

c. Annual Evaluation

For each ERA product, annual precipitation across Iran was calculated by averaging the estimates over grid cells containing at least one observational gauge. A similar calculation was made for the reference dataset, using the observational gauge data aggregated in the grid cells of the ERA products and applying the modified IDW method (see section 2.3). Finally, the difference between these two time-series was plotted (Figure 11).

As shown in Figure 11, ERA-40 overestimated the reference dataset at the annual scale. This issue was considerably improved in ERA-20CM and ERA-20C, although some erroneous annual fluctuations were observed, particularly in ERA-20CM. ERA-Interim and ERA5 again gave the lowest errors at the annual scale (as well as at daily and monthly scales, see previous sections), with ERA-Interim being closest overall to the reference dataset. ERA5 annual precipitation estimates suffered from a relatively constant positive bias. Therefore, similarly to the daily and monthly results, and contrary to findings in previous studies in Iran (Fallah et al. 2020; Khoshchehreh et al. 2021; Taghizadeh et al. 2021), our evaluations at annual scale suggested that the evolution of ERA precipitation products was quite successful from ERA-40 to ERA-Interim,
but ERA5 had less skill than ERA-Interim across different climates and geographical conditions in Iran. However, it is important to note that the spatial resolution of the estimates improved considerably from ERA-40 to ERA5, which can influence the uncertainties associated with the estimated and reference precipitation datasets created in this study.

![Figure 11](https://example.com/figure11.png)

**Figure 11.** Difference between annual precipitation time series of ERA precipitation products for Iran and values in the reference (observational) dataset.

### 4. Conclusions

This study investigated the performance of the five ERA precipitation products developed to date (ERA-40, ERA-20CM, ERA-20C, ERA-Interim, and ERA5) against a reference observational dataset for Iran. Long-term historical daily precipitation observations from a total of 2119 gauges (479 synoptic and 1640 TAMAB stations) were quality-checked and used to create the reference dataset through spatial aggregation of point-source observations within ERA grid cells. Different statistical and categorical metrics, time series comparisons, and error decomposition methods were applied to investigate uncertainties and error characteristics of the different ERA precipitation products and assess the accuracy of more recent versions compared with their predecessors when applied to Iran. Uncertainties and error values quantified for different spatial regions showed poor performance of all ERA products for coastal areas along the Caspian Sea in the north and for mountainous regions in northwest Iran. The estimates were more accurate (especially ERA-Interim and ERA5 estimates) for western (Zagros mountain chain) and
southwestern and southern (Persian Gulf coast) parts of Iran. ERA-40 was the worst-performing product in all analyses, with considerably high positive bias. ERA-20CM provided marginal improvements over ERA-40 but still contained serious errors, including high relative systematic error for different parts of Iran. By assimilation of observational data into ERA-20CM, ERA-20C provided a considerable improvement in all error indices compared with its predecessors. The two most recent products, ERA-Interim and ERA5, introduced lower error compared with earlier products and showed similar performance based on different evaluation metrics.

In addition to having higher spatial resolution, ERA5 outperformed all other ERA products through more accurate estimation of intense precipitation events in wetter regions of Iran. ERA5 also showed good capability for detecting occurrence of precipitation events, with higher POD values than other ERA products. However, based on the KGE, CC, RMSE indices and lower systematic error, ERA-Interim outperformed ERA5 (and other products) overall. ERA-Interim and especially ERA5 had higher FAR values than their immediate predecessor (ERA20C), which indicates more false alarm errors in their estimates that can be a source of positive bias. ERA-40, ERA20-CM, and to some extent ERA-20C could not correctly simulate the long-term pattern of monthly precipitation changes over Iran, while ERA-Interim and ERA5 showed considerably improved performance, with ERA-Interim being the most accurate ERA product based on the monthly patterns and analyses.

Overall, the findings at different temporal scales, based on various evaluation indices, suggested that the ERA precipitation products improved considerably from ERA-40 to ERA-Interim, but showed slight performance decrease in ERA5 based on some indices. This finding is particularly important, as several previous studies in Iran have identified ERA5 as the best ERA precipitation product, with consistent improvements over ERA-Interim. Differences between the study areas and gauge stations used in the reference datasets might have affected our final results in comparison with previous studies. It should also be noted that despite the marginal decrease in some indices, ERA5 has significantly increased the spatial resolution of precipitation estimations, from 79 km in ERA-Interim and 125 km for other previous products, to 31 km in ERA5 and can thus better capture precipitation patterns in local regions and precipitation extremes. However, the similar difference of spatial resolution between ERA-Interim (79 km) and its predecessors (125 km) and yet considerable improvement of all skill scores in ERA-Interim indicated a more
successful evolution from ERA-40 to ERA-Interim, than from ERA-Interim to ERA5. This suggests that the current modeling capacity of ERA products matches better with spatial resolution of 79 km (ERA-Interim) rather than 31 km (ERA5), for modeling precipitation over Iran.

Acknowledgments

This study was supported by a project funded by Formas, 2017-00,608. Also, University of Oulu Graduate School (UniOGS) and Maa- ja vesitekniikan tuki (MVTT-project number 41878) Foundation grants were other source of support for current research. Furthermore, the authors have no conflicts of interest to disclose

Data availability

The ERA precipitation products used in this study were obtained from:

- ERA-40: https://apps.ecmwf.int/datasets/data/era40-daily
- ERA-20CM: https://apps.ecmwf.int/datasets/data/era20cm-daily
- ERA-20C: https://apps.ecmwf.int/datasets/data/era20c-daily
- ERA-Interim: https://apps.ecmwf.int/datasets/data/interim-full-daily

Authors’ contributions


NCAR, 2015: Package “verification” in R.


Confluence Mobile - ECMWF Confluence Wiki.

ERA5 atmospheric reanalysis | NCAR - Climate Data Guide.

ERA-Interim | NCAR - Climate Data Guide.

ERA-20C: ECMWF’s atmospheric reanalysis of the 20th century (and comparisons with NOAA’s 20CR) | NCAR - Climate Data Guide.