Agricultural Water Management 258 (2021) 107222

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Investigation of satellite-related precipitation products for modeling of rainfed wheat production systems

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ARTICLE INFO

Handling Editor - Dr. B.E. Clothier

Keywords:
Crop model
DSSAT
CERES-Wheat
Gridded precipitation
Rainfed wheat

ABSTRACT

Precipitation is a very important weather variable for growth and yield of rainfed crops. In many agricultural regions of the world, high-quality precipitation records are not available, and thus, gridded precipitation products (GPPs) have to be applied as an alternative. The main objective of this study was to identify the most accurate GPP for simulating crop yield over a major rainfed wheat production zone in Iran. For this purpose, fifteen global GPPs were evaluated versus the observed precipitation records for the simulation of rainfed wheat growth and development and yield estimation using the Cropping System Model (CSM) CERES-Wheat model embedded in the Decision Support System for Agrotechnology Transfer (DSSAT). The findings showed that multi-source GPPs had generally higher skill for the yield estimation. Considering all statistical and simulation results obtained from three sites during 2000–2010, MSWEP (Multi-Source Weighted-Ensemble Precipitation) was found as the best alternative GPP to the observed precipitation data for rainfed wheat grain yield simulation with normalized root mean square error (NRMSE) of 4.6 and Nash–Sutcliffe efficiency (NSE) of 0.79, while CMORPH (the Climate Prediction Center morphing method) was the weakest with NRMSE of 13.3 and NSE as − 0.81. The results point to differences among GPP, but there is a need to evaluate in other regions if multi-purpose GPPs are in general more reliable than GPPs based on specific sources.

1. Introduction

Cropping System Models (CSMs) are widely used tools for estimating crop development, growth, and yield (Hoogenboom, 2000). As climate change and variability have significant impacts on crop production (Fraisse et al., 2006; Hoogenboom, 2000; Olesen and Bindi, 2002), estimating crop yield using CSMs requires daily weather data as inputs, including solar radiation (S_{RAD}), maximum and minimum temperature (T_{max} and T_{min}), and total precipitation (P) (Hoogenboom, 2000). However, for many agricultural regions, observed weather data (OWD) are not available or do not have sufficient high quality. This is, therefore, a problematic issue for accurate crop yield estimation in these regions (van Wart et al., 2013; White et al., 2011).

Recent studies revealed that gridded weather products (GWPs) are often dependable alternatives for use in crop production system studies using CSMs in regions that lack of high-quality OWD. Some of the conducted studies were summarized in Table 1. Studies indicate that daily S_{RAD}, T_{max}, and T_{min} obtained from GWP may be reliably used for crop simulations, while daily P is often biased (Monteiro et al., 2018; Toreti et al., 2019; van Wart et al., 2013, 2015, White et al., 2008, 2011).

Daily P is the most important weather data for simulating rainfed crops and variability of the CSM outputs is directly correlated to the accuracy of model inputs particularly daily P values (Heinemann et al., 2002), and this enhances the importance of exploring the quality of daily P data (Lashkari et al., 2018; van Wart et al., 2015). There are several available daily gridded precipitation products (GPPs) such as CHIRPS, GPM (the Global Precipitation Measurement Mission) and MSWEP (Multi-Source Weighted-Ensemble Precipitation) that are generated using various sources, including satellites, climate models, and weather

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https://doi.org/10.1016/j.agwat.2021.107222
Received 7 June 2021; Received in revised form 23 September 2021; Accepted 25 September 2021
Available online 5 October 2021

Table 1
The gridded weather products (GWPs) used for crop yield simulation in the previous studies.

Crop (s)	Region (s)	GWPs	References
Maize	China	1. NASA POWER	(Bai et al., 2010)
Rice, Maize, Wheat	Africa, Eastern Asia, Europe, North and South America	1. NASA POWER 2. NCEP reanalysis 2 3. CRU 4. TRMM	(van Wart et al., 2013) (van Wart et al., 2015) (Srivastava et al., 2020)
Coffee, Sugarcane, Soybean, Maize	Brazil	1. AgMERRA 2. ECMWF 3. NASA POWER 4. Xavier	(Battisti et al., 2019) (Duarte and Sentelhas, 2020) (Monteiro et al., 2018) (Valeriano et al., 2018)
Hybrid poplar, Maize	USA	1. NARR 2. NLDAS 3. PRISM 4. Daymet	(Bandaru et al., 2017) (Mourtzinis et al., 2017)
Barley, Wheat	Europe, Mediterranean region	1. AgMERRA 2. MarsMet 3. ERA-Interim	(Cammarano et al., 2019) (Toreti et al., 2019)
Wheat	Northeast Iran	1. AgMERRA 2. APHRODITE 3. PERSIANN 4. TRMM	(Lashkari et al., 2018) (Yaghoubi et al., 2020)
Rice, Wheat	India	1. AgMERRA 2. CHIRPS 3. ERA-Interim 4. NASA POWER 5. PERSIANN 6. PGF	(Parkes et al., 2019)

AgMERRA: AgMIP Modern-Era Restrospective Analysis for Research and Applications
APHRODITE: Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation
ECMWF: European Centre for Medium-Range Weather Forecasts
ERA: ECMWF Re-Analysis
CHIRPS: Climate Hazards group InfraRed Precipitation with Station data
CRU: Climatic Research Unit
NARR: North American Regional Reanalysis
NASA POWER: National Aeronautics and Space Administration, Prediction Of Worldwide Energy Resources
NCEP: National Centers for Environmental Prediction
NLDAS: North American Land Data Assimilation System
PERSIANN: Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
PGF: Princeton Global Forcing data
TRMM: Tropical Rainfall Measuring Mission

stations by applying spatial interpolation techniques and data assimilation method; however, these GPPs have not yet been assessed and inter-compared for rainfed crop yield simulation across relevant regions of the globe.

The primary objective of this paper is to identify the most proper GPP for crop simulation of rainfed crops in the northwest Iran, and also regions with similar environmental attributes. The weather station network over the study region is not sufficiently dense for regional assessments, and there is a particular lack of observed precipitation data. It is a common problematic issue in many agricultural zones, and thus, detecting accurate GPPs can be very useful for crop production systems, especially for yield prediction. Wheat is selected for this research as it is the most important crop in food production globally, and is cultivated in the study areas as a rainfed crop, thus depending on rainfall.

Table 2
List of the selected sites for this study.

Site	Lon. (°E)	Lat. (°N)	Elev. (m)	Province	Climate (Köppen)
Khorramabad	48.28	33.43	1148	Lorestan	BSh
Sanandaj	47.00	35.33	1373	Kordestan	Csa
Tabriz	46.28	38.08	1361	East Azerbaijan	Dsa

Bsh: Semi-arid climate
Csa: Dry summer climate (Mediterranean climate)
Dsa: Humid continental climate

2. Materials and methods

2.1. Study area

Iran is located in southwest Asia and has a dominant arid to semi-arid climate with a long-term annual average rainfall of ~250 mm (Araghi et al., 2019). According to the records from 1978 to 2020, more than 63% of wheat area in Iran are rainfed (Iranian Ministry of Agriculture, 2020), with the northwestern and western provinces as the major regions for rainfed wheat production. Three sites, i.e., Khorramabad in Lorestan, Sanandaj in Kordestan, and Tabriz in East Azerbaijan provinces (Table 2), were selected for this study (Fig. 1).

More than 75% of total wheat production area in these provinces is rainfed, accounting for 30% of rainfed wheat production in Iran. The climate of all the selected sites is semi-arid, which is the general climate for rainfed wheat cultivation. The nearest weather station was selected for each site and their locations were presented in Table 2. The daily observed weather data (OWD) for crop simulation (i.e., S_{RAD}, T_{max}, T_{min}, and P) were obtained from Iran Meteorological Organization (IRIMO) from 2000 to 2010 for each of the selected sites.

2.2. Gridded precipitation product (GPP)

In this study, 15 global GPPs were evaluated, including 13 satellite-related and two gauge-based GPPs (Table 2). The two gauge-based GPPs were solely based on gauge records, while for the thirteen satellite-related GPPs, remotely sensed data of precipitation from different satellites were applied as the main source for generating GPP, or as an auxiliary source for improving the quality of GPP, and thus, "satellite-related" phrase was used in this paper instead of "satellite-derived" and "satellite-based". These 15 GPPs (Table 3) were all generated using spatial statistical interpolation techniques and data assimilation methods. A brief explanation for each GPP is given below.

2.2.1. AgCFSR

AgCFSR [Agrometeorological CFSR (Climate Forecast System Reanalysis)] was originally produced using the NCEP (National Centers for Environmental Prediction) CFSR model outputs for agricultural modeling purposes (Ruane et al., 2015). AgCFSR daily P data is therefore based on CFSR, but some satellite products have been used for quality improvements, including: TRMM, the Tropical Rainfall Measuring Mission 3B42 product (Huffman et al., 2007); PERSIANN, Precipitation Estimation using Remote-Sensing and Artificial Neural Networks (Hsu et al., 1997); and CMORTH, Climate Prediction Center Morphing Product (Joyce et al., 2004). AgCFSR has spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and daily temporal resolution with coverage from 1980 to 2010, and data was downloaded from https://data.giss.nasa.gov/impacts/agmipcf/agcfsr/.

2.2.2. AgERA5

AgERA5 is a daily surface meteorological dataset for agronomic use, based on ERA5 (ECMWF Re-Analysis ver.5), which is published by ECMWF, European Centre for Medium-Range Weather Forecast (Hersbach et al., 2020). For enhancing the quality of P data in ERA5, several

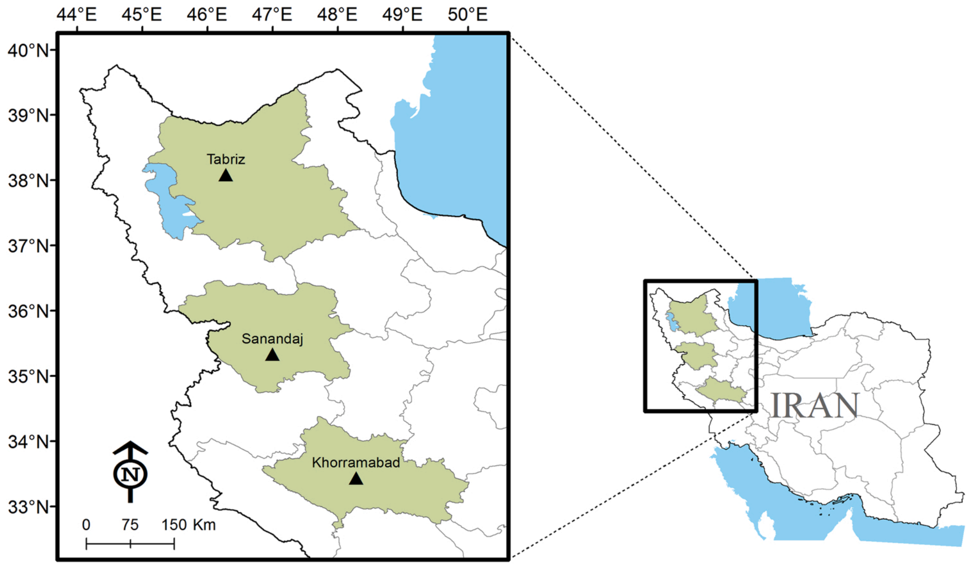

Fig. 1. The study region and the selected sites in Northwest Iran.

Table 3
Summary of gridded precipitation products (GPPs) evaluated in this study.

Product	Resolution	Period	Coverage	Source	References
AgCFSR	0.25° × 0.25°	1980–2010	Global land	NASA (https://data.giss.nasa.gov/impacts/agmipcf/agcfsr/)	(Ruane et al., 2015)
AgERA5	0.1° × 0.1°	1979–present	Global land	ECMWF (https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-agrometeorological-indicators?tab=overview)	(Hersbach et al., 2020)
AgMERRA	0.25° × 0.25°	1980–2010	Global land	NASA (https://data.giss.nasa.gov/impacts/agmipcf/agmerra/)	(Ruane et al., 2015)
CHIRPS v2	0.05° × 0.05°	1981–present	Land 50°S–50°N	Climate Hazards Center, UC Santa Barbara (https://data.chc.ucsb.edu/products/CHIRPS-2.0/)	(Funk et al., 2015)
CMORPH v1	0.25° × 0.25°	1998–present	60°S–60°N	NOAA (https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/archive/)	(Joyce et al., 2004)
CPC	0.5° × 0.5°	1979–present	Global land	NOAA (https://downloads.psl.noaa.gov/Datasets/cpc_global_precip/)	(Xie et al., 2010)
GLDAS CLSM v2.0	0.25° × 0.25°	1948–2014	land 60°S–90°N	NASA (https://disc.gsfc.nasa.gov/datasets/GLDAS_CLSM025_D_2.0/summary/)	(Rodell et al., 2004)
GPCC v2018	1° × 1°	1982–2016	Global land	Global Precipitation Climatology Centre (https://opendata.dwd.de/climate_environment/GPCC/full_data_daily_V2018/)	(Schamm et al., 2014)
GPM 3IMERGDF v6	0.1° × 0.1°	2000–present	Global	NASA (https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_06/summary/)	(Huffman et al., 2019)
MSWEP v2.6	0.1° × 0.1°	1979–2019	Global	gloh2o (http://hydrology.princeton.edu/data/hylkeb/MSWEP_V260/)	(Beck et al., 2019)
PERSIANN-CDR	0.25° × 0.25°	1983–present	60°S–60°N	Center for Hydrometeorology and Remote Sensing, UC Irvine (https://chrsdata.eng.uci.edu/)	(Ashouri et al., 2015)
PGF v3	0.25° × 0.25°	1948–2016	60°S–90°N	Princeton University (http://hydrology.princeton.edu/data/pgf/v3/)	(Sheffield et al., 2006)
POWER	0.5° × 0.5°	1981–present	Global land	NASA (https://power.larc.nasa.gov/data-access-viewer/)	(Stackhouse et al., 2015)
S14FD	0.5° × 0.5°	1958–2013	Global	Institute for Agro-Environmental Sciences, National Agriculture and Food Research Institute, Japan (http://h08.nies.go.jp/s14/)	(Iizumi et al., 2017)
TRMM 3B42 v7	0.25° × 0.25°	1998–2020	50°S–50°N	NASA (https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary/)	(Huffman et al., 2007)

satellite products have been used, including AMSR-2 sensor (the Advanced Microwave Scanning Radiometer 2) on GCOM-W satellite (Global Change Observation Mission – Water); AMSR-E sensor (Advanced Microwave Scanning Radiometer for EOS, Earth Observing Satellite) on Aqua satellite; GMI sensor (GPM Microwave Imager) on GPM (the Global Precipitation Measurement) satellite; MHS sensor (the Microwave Humidity Sounder) on the Metop-A/B satellites; MWHS2 sensor (the MicroWave Humidity Sounder 2) on FY-3-C (Feng-Yun-3C); SSM/I sensor (the Special Sensor Microwave/Imager) on DMSP satellite (Defense Meteorological Satellite Program); SSMIS (Special Sensor Microwave Imager / Sounder) on DMSP satellite; and TMI sensor (TRMM Microwave Imager). AgERA5 covers from 1979 to present with spatial resolution of 0.1°× 0.1° and daily temporal resolution, and data was obtained from https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-agrometeorological-indicators?tab=overview.

2.2.3. *AgMERRA*

AgMERRA (Agrometeorological Modern-Era Retrospective analysis for Research and Applications) is mainly based on NASA (the National Aeronautics and Space Administration) MERRA model, but similar to

AgCFSR dataset, some precipitation products including: TRMM (Battisti et al., 2019), PERSIANN (Hsu et al., 1997), and CMORPH (Joyce et al., 2004) have been applied for improving the accuracy of daily *P* data (Ruane et al., 2015). AgMERRA is a popular dataset in agricultural modeling (Battisti et al., 2019; Lashkari et al., 2018; Toreti et al., 2019; Yaghoubi et al., 2020), and it has a spatial resolution of 0.25°× 0.25° and daily temporal resolution with a coverage from 1980 to 2010. Data was downloaded from https://data.giss.nasa.gov/impacts/agmipcf/agmerra/.

2.2.4. CHIRPS v2

CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) is a quasi-global rainfall dataset, which has been produced for trend analysis and seasonal drought monitoring by combining models of terrain-induced precipitation enhancement with interpolated station rainfall data, and using TRMM (Huffman et al., 2007) data besides station observed records for accuracy enhancement, and also calibrated to global Cold Cloud Duration (CCD) rainfall estimates (Funk et al., 2015). The data coverage comprises land across 50°S–50°N and ranging from 1981 to near-present. CHIRPS has a spatial resolution of 0.05°× 0.05° and daily temporal resolution, and data was downloaded from https://data.chc.ucsb.edu/products/CHIRPS-2.0/.

2.2.5. CMORPH v1

CMORPH (the Climate Prediction Center morphing method) global precipitation product has been created using various remotely sensed data, obtained from TMI, SSM/I, and AMSR-E (which were explained earlier in Section 2.2.2), plus, AMSU-B sensor (Advanced Microwave Sounding Unit-B) on NOAA satellite (National Oceanic and Atmospheric Administration); Meteosat satellites; GOES satellites (Geostationary Operational Environmental Satellite); and MTSAT satellites (Multi-functional Transport Satellites) (Joyce et al., 2004). The spatial coverage is from 60°S–60°N with a resolution of 0.25°× 0.25°. CMORPH is available from 1998 to present with 30 min, hourly, and daily temporal resolution and data was obtained from https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/archive/.

2.2.6. CPC

The CPC (Climate Prediction Center, NOAA) precipitation product is based on records of over 30,000 gauges over the globe that have been collected from multiple sources, and after quality controls, some interpolation techniques are applied to generate the final product (Xie et al., 2010). CPC is available from 1979 to present with a daily temporal resolution, and has global coverage with spatial resolution of 0.5°× 0.5°. This product was downloaded from https://downloads.psl.noaa.gov/Datasets/cpc_global_precip/.

2.2.7. GLDAS v2.0

GLDAS (Global Land Data Assimilation System) coupled with CLSM (Catchment Land Surface Model) have been used to ingest satellite- and ground-based data, using advanced land surface modeling and data assimilation techniques, in order to produce a wide range of land surface data and fluxes (Rodell et al., 2004). Several remotely sensed products have been used for refining the final data, retrieved from TRMM, SSM/I, AMSU, which was explained earlier, plus, MODIS sensor (Moderate Resolution Imaging Spectroradiometer) on Terra satellite. GLDAS-CLSM v2.0 covers lands from 60°S to 90°N with spatial resolution of 0.25°× 0.25° and is available from 1948 to 2014 with a daily temporal resolution. This product was obtained from https://disc.gsfc.nasa.gov/datasets/GLDAS_CLSM025_D_2.0/summary/.

2.2.8. GPCC v2018

The GPCC (Global Precipitation Climatology Centre) daily rainfall product is based on stations observed rainfall data reported in near-real time via the Global Telecommunication System (GTS) (Schamm et al., 2014). GPCC v2018 used in the current study has a global land spatial coverage with 1°× 1° resolution, and is available from 1982 to 2016 with a daily temporal resolution. The kriging interpolation was the major method for the creation of GPCC (Schamm et al., 2014). GPCC v2018 was downloaded from https://opendata.dwd.de/climate_environment/GPCC/full_data_daily_V2018/.

2.2.9. GPM 3IMERGDF v6

IMERG, the Integrated Multi-satellite Retrievals for GPM (Global Precipitation Measurement) is the algorithm that produces the multi-satellite precipitation data for the U.S. GPM team. The 3IMERGDF (IMERG Level 3 Daily Final) produced at the NASA Goddard Earth Sciences (GES) Data and Information Services Center (DISC) uses several remotely sensed data, such as: AMSR-2, TRMM, PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Cloud Classification System), GEOS-5 (Goddard Earth Observing System model Version 5), and many others. This global product (GPM 3IMERGDF v6, hereafter GPM) has a 0.1°× 0.1° spatial resolution that is available from 2000 to present with a daily temporal resolution. GPM v6 was obtained from https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_06/summary/.

2.2.10. MSWEP v2.6

MSWEP (Multi-Source Weighted-Ensemble Precipitation) is a multi-source global precipitation product that was generated using multiple sources including: gauge-based products such as CPC and GPCC, reanalysis datasets such as ERA and JRA55, Japanese 55-year Reanalysis, and satellite-derived products such as CMORPH and TRMM (Beck et al., 2019). MSWEP v2.6 used here has a global coverage with 0.1°× 0.1° spatial resolution, and is available from 1979 to 2019 with 3-hourly, daily, and monthly temporal resolution. This product was downloaded from http://hydrology.princeton.edu/data/hylkeb/MSWEP_V260/.

2.2.11. PERSIANN-CDR

PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record), is originally produced from the PERSIANN algorithm using GridSat-B1 infrared data and adjusted using the Global Precipitation Climatology Project (GPCP) (Ashouri et al., 2015). PERSIANN-CDR (hereafter PERSIANN) covers 60°S–60°N with a 0.25°× 0.25° spatial resolution, and is available from 1983–present with a daily temporal resolution. This product was obtained from https://chrsdata.eng.uci.edu/.

2.2.12. PGF v3

PGF (Princeton Global meteorological Forcing dataset for land surface modeling) was originally generated using NCEP-NCAR (National Centers for Environmental Prediction–National Center for Atmospheric Research) reanalysis data, although some remotely sensed products, such as SSM/I and TRMM, have been also applied to improve the accuracy of *P* data (Sheffield et al., 2006). PGF coverage is from 60°S–90°N with a spatial resolution of 0.25°× 0.25°, and is available from 1948 to 2016 with a daily temporal resolution. PGF v3 was downloaded from http://hydrology.princeton.edu/data/pgf/v3/.

2.2.13. NASA POWER

Daily precipitation in NASA POWER (Prediction of world-wide energy resource – hereafter POWER) is directly retrieved from the MERRA-2 model, GPCP, and TRMM (Stackhouse et al., 2015; White et al., 2008). Although the POWER dataset was originally produced for energy related studies, it has also been used in crop yield simulation research (Duarte and Sentelhas, 2020; Monteiro et al., 2018). POWER has a spatial resolution of 0.5°× 0.5° of the global land and is available from 1981 to present with a daily temporal resolution. POWER was retrieved from https://power.larc.nasa.gov/data-access-viewer/.

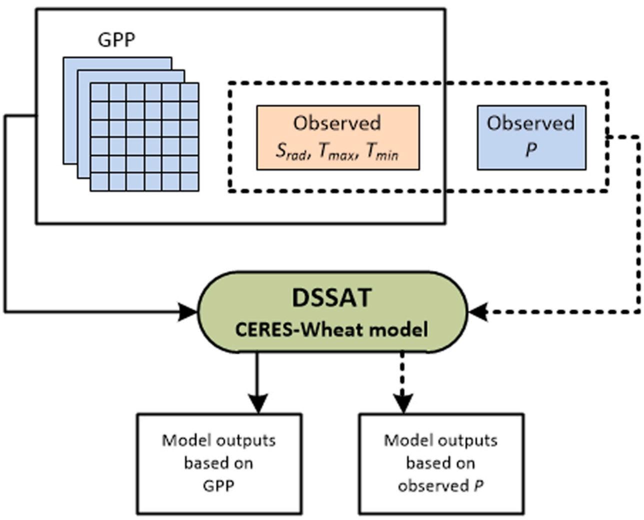

Fig. 2. Schematic diagram of workflow used in the current study (*GPP*: gridded precipitation product, S_{rad}: solar radiation, T_{max}: maximum air temperature, T_{min}: minimum air temperature, *P*: precipitation).

2.2.14. S14FD

S14FD (S14 Forcing Dataset) has been basically created using the JRA-55 model, and some other products, such as GPCC and CRU-TS (Climatic Research Unit Time series), have been used for accuracy enhancement of its precipitation values (Iizumi et al., 2017). S14FD is a global product with a spatial resolution of 0.5° × 0.5° and is available from 1958 to 2013 with a daily temporal resolution. This product was downloaded from http://h08.nies.go.jp/s14/.

2.2.15. TRMM 3B42 v7

Daily accumulated precipitation in TRMM 3B42 (hereafter TRMM) is generated from the 3-hourly TMPA (TRMM Multi-Satellite Precipitation Analysis) which is based on high-quality satellite microwave data with fill-in using microwave-calibrated infrared estimates (Huffman et al., 2007). Covering 50°S–50°N with a 0.25° × 0.25° spatial resolution TRMM v7 is available from 1998 to 2020 with a daily temporal resolution, and was downloaded from https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary/.

2.3. Crop model

In this study, the Cropping System Model (CSM)-CERES-Wheat Version 4.7.5 that is embedded in Decision Support System for Agrotechnology Transfer (DSSAT; www.DSSAT.net) was used for the simulation of wheat growth and development and yield prediction (Jones et al., 2003; Hoogenboom et al., 2019b). DSSAT is a widely used application that includes simulation models for over 42 crops and has been applied for more than 30 years in over 174 countries (Hoogenboom et al., 2019a). The CERES-Wheat model was found to be a reliable tool for simulating various rainfed wheat cultivars across Iran, including the study area (Andarzian et al., 2015; Bannayan et al., 2013; Nouri et al., 2017; Paymard et al., 2019). The Azar-2 cultivar was chosen in this study, as it is the most commonly planted rainfed wheat cultivar in the study area (Nouri et al., 2017). Crop management and soil data, including plant population at seeding, depth, and date of planting, row spacing, soil texture, the genetic coefficients for the Azar-2 cultivar, and fertilizer material and application, were all taken from previously conducted modeling studies in the study area (Nouri et al., 2017).

2.4. Workflow

2.4.1. Statistical analysis of GPPs and observed rainfall

Firstly, precipitation values were extracted from each GPP from the nearest grid point to the selected sites. Considering all sites, the extracted precipitation values from each of the GPPs were compared against the observed precipitation data at daily, 15-day, and monthly time steps, as well as the total precipitation, during the growing season (i.e., October to May) from 2000 to 2010. The statistical analysis was not performed site by site, and all sites were pooled together before the accuracy analysis. This method was conducted to avoid site-based findings and obtain comprehensive site-free results from the GPPs accuracy analysis.

Following previous studies (van Wart et al., 2015), percentage of false wet days (a precipitation event estimated in GPP, but not reported by observations), and false dry days (a precipitation event not estimated in GPP, but reported by observations) of each of the GPPs were also computed versus the observed precipitation records. To compare daily, 15-day, monthly, and total precipitation obtained from GPPs versus observed data during the growing season, the Wilcoxon test was applied. The Wilcoxon test is a non-parametric distribution-free test commonly used to check the mean equality of two series (Wilks, 2011). Null hypothesis of the Wilcoxon test indicates equality of the means of two series.

2.4.2. Accuracy of GPPs for crop modeling applications

As depicted in Fig. 2, to investigate skill of the GPPs for applying in crop modeling, the CERES-Wheat model was firstly run based on the observed weather data (OWD) in each of the selected sites during 2000–2010. Then, the observed rainfall values within the DSSAT weather files replaced by the extracted rainfall values from each of the GPPs, and the crop model was run again. The model outputs (including grain yield and precipitation use efficiency) estimated based on the observed rainfall data and the rainfall values extracted from GPPs were then compared to find the most accurate GPP.

There is uncertainty in crop models outputs because of the assumptions and simplifications considered in model's structure. However, in this context the reference is considered to be the crop model outputs based on observed weather data (OWD), and the results based on GPPs are then used for comparisons. Note that quality control of OWD, including rainfall measured in weather stations (as the stations used in the current study), is typically conducted before data is made publically available by Iran Meteorological Organization (IRIMO).

2.4.3. Evaluation indices

To evaluate the rainfall values extracted from each GPPs and also the CERES-Wheat model outputs, some evaluation indices including: correlation coefficient (r), index of agreement (d), normalized root mean square error (NRMSE), Nash-Sutcliffe Efficiency (NSE), and percent bias (pbias) were calculated (Wilks, 2011):

$$e_i = M_i - O_i \tag{1}$$

$$d = 1 - \left(\frac{\sum_{i=1}^{n} e_i^2}{\sum_{i=1}^{n} \left(|G_i - \overline{O}| + |O_i - \overline{O}| \right)^2} \right), 0 \le d \le 1 \tag{2}$$

$$pbias = 100 \times \frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} O_i} \tag{3}$$

Table 4
Descriptive statistics of the observed and GPP daily precipitation during growing season from 2000 to 2010, and the performance indices and the Wilcoxon test *p*-value (two sided at $\alpha = 0.05$) of GPP versus the observed daily precipitation during growing season from 2000 to 2010 (considering all sites).

Source	Min.	Mean	Median	Max.	S.D.	IQR	Computed versus observed precipitation				
							r	d	NRMSE (%)	NSE	Wilcoxon *p*-value
Observed	0	1.5	0	78.0	4.8	0.3	–	–	–	–	–
AgCFSR	0	1.4	0	50.3	4.3	0.2	0.71	0.83	8.2	0.33	0.00
AgERA5	0	2.5	0.2	69.2	5.3	2.4	0.75	0.85	9.0	0.31	0.00
AgMERRA	0	1.4	0	66.6	4.2	0.6	0.79	0.87	7.2	0.48	0.18
CHIRPS	0	1.8	0	81.6	5.3	0.5	0.58	0.75	8.8	0.23	0.04
CMORPH	0	0.8	0	59.7	3.1	0.1	0.35	0.51	15.2	-1.32	0.00
CPC	0	1.0	0	48.6	3.2	0.3	0.77	0.83	9.8	0.04	0.00
GLDAS	0	1.7	0	81.6	4.2	0.8	0.32	0.54	12.5	-0.56	0.00
GPCC	0	2.2	0	67.2	5.7	1.3	0.72	0.83	8.1	0.49	0.00
GPM	0	1.9	0	133.6	6.0	1.1	0.61	0.75	8.2	0.33	0.00
MSWEP	0	1.6	0	74.9	4.6	0.4	0.78	0.87	7.3	0.46	0.14
PERSIANN	0	1.9	0.5	57.1	3.9	2.3	0.49	0.67	11.6	-0.34	0.00
PGF	0	1.6	0	52.8	4.2	0.8	0.68	0.81	8.6	0.25	0.02
POWER	0	1.0	0	45.8	2.8	0.6	0.74	0.85	10.2	-0.04	0.00
S14FD	0	1.8	0	88.5	5.8	0.3	0.68	0.81	8.5	0.44	0.03
TRMM	0	1.7	0	106.1	6.2	0.1	0.46	0.64	9.4	0.11	0.00

Table 5
Descriptive statistics of the observed and GPP 15-day precipitation during growing season from 2000 to 2010, and the performance indices and the Wilcoxon test *p*-value (two sided at $\alpha = 0.05$) of GPP versus the observed 15-day precipitation during growing season from 2000 to 2010 (considering all sites).

Source	Min.	Mean	Median	Max.	S.D.	IQR	Computed versus observed precipitation				
							r	d	NRMSE (%)	NSE	Wilcoxon *p*-value
Observed	0	22.9	17.4	157.0	24.1	26.2	–	–	–	–	–
AgCFSR	0	21.5	14.8	134.5	20.7	23.2	0.88	0.93	5.5	0.70	0.89
AgERA5	0.2	37.1	32.2	188.4	27.8	32.7	0.81	0.83	7.8	0.39	0.00
AgMERRA	0	21.7	17.0	140.2	21.0	25.2	0.92	0.95	4.8	0.76	0.86
CHIRPS	0	27.0	19.3	201.9	25.5	27.7	0.82	0.90	6.1	0.63	0.00
CMORPH	0	12.3	7.1	96.0	15.3	17.6	0.43	0.57	16.2	-1.61	0.00
CPC	0	15.6	10.8	92.9	16.2	17.9	0.91	0.88	8.5	0.28	0.00
GLDAS	0	22.2	18.2	151.8	18.6	21.0	0.65	0.79	9.9	0.02	0.19
GPCC	0	32.7	25.0	189.7	31.2	36.8	0.87	0.89	5.9	0.65	0.00
GPM	0.1	29.2	20.2	275.0	30.6	30.5	0.86	0.90	5.5	0.70	0.00
MSWEP	0	23.1	17.2	158.4	22.9	26.8	0.92	0.94	4.9	0.73	0.84
PERSIANN	0	29.1	26.0	140.0	19.7	22.7	0.72	0.82	9.1	0.17	0.00
PGF	0	22.3	17.1	134.2	21.9	23.2	0.86	0.92	5.6	0.68	0.64
POWER	0	15.7	12.2	88.1	14.9	16.5	0.91	0.87	9.5	0.09	0.00
S14FD	0	27.4	17.8	199.2	28.2	34.2	0.87	0.92	5.2	0.69	0.04
TRMM	0	26.1	19.0	205.6	26.6	28.0	0.77	0.87	6.6	0.56	0.04

Table 6
Descriptive statistics of the observed and GPP monthly precipitation during growing season from 2000 to 2010, and the performance indices and the Wilcoxon test *p*-value (two sided at $\alpha = 0.05$) of GPP versus the observed monthly precipitation during growing season from 2000 to 2010 (considering all sites).

Source	Min.	Mean	Median	Max.	S.D.	IQR	Computed versus observed precipitation				
							r	d	NRMSE (%)	NSE	Wilcoxon *p*-value
Observed	0.8	45.9	37.2	194.0	36.0	40.9	–	–	–	–	–
AgCFSR	1.2	43.1	35.8	172.7	32.4	42.4	0.92	0.95	4.5	0.80	0.51
AgERA5	6.2	74.2	65.9	310.4	45.7	51.8	0.83	0.81	8.3	0.31	0.00
AgMERRA	1.0	45.6	37.7	160.1	31.7	41.1	0.94	0.97	4.0	0.85	0.66
CHIRPS	0.0	54.1	47.5	282.5	39.6	44.0	0.86	0.91	5.5	0.70	0.01
CMORPH	0.0	24.7	18.1	134.6	24.1	30.7	0.47	0.60	17.3	-1.98	0.00
CPC	0.2	31.2	26.2	146.4	24.5	29.3	0.90	0.86	9.3	0.14	0.00
GLDAS	4.4	44.3	38.6	161.0	28.2	33.2	0.76	0.86	8.3	0.31	0.49
GPCC	0.8	65.4	54.2	271.5	48.1	65.8	0.88	0.87	6.4	0.59	0.00
GPM	4.1	58.4	47.0	329.4	46.5	49.6	0.90	0.91	5.2	0.72	0.00
MSWEP	0.8	46.2	40.3	191.7	34.3	41.2	0.93	0.96	4.2	0.84	0.64
PERSIANN	10.1	58.3	54.8	166.0	29.1	37.5	0.76	0.83	8.7	0.19	0.00
PGF	0.3	46.6	40.1	174.6	32.9	38.9	0.90	0.95	4.8	0.77	0.52
POWER	0.8	31.5	26.6	135.7	22.5	26.0	0.91	0.85	10.3	-0.06	0.00
S14FD	0.1	54.7	46.7	231.1	43.8	57.2	0.90	0.93	4.9	0.76	0.07
TRMM	0.8	52.3	40.2	295.9	42.8	41.3	0.85	0.91	5.4	0.70	0.13

Table 7
Descriptive statistics of the observed and GPP total precipitation during growing season from 2000 to 2010, and the performance indices and the Wilcoxon test *p*-value (two sided at $\alpha = 0.05$) of GPP versus the observed total precipitation during growing season from 2000 to 2010 (considering all sites).

Source	Min.	Mean	Median	Max.	S.D.	IQR	Computed versus observed precipitation				
							r	d	NRMSE (%)	NSE	Wilcoxon *p*-value
Observed	100	295	295	517	108	149	–	–	–	–	–
AgCFSR	112	278	273	445	103	172	0.93	0.96	3.9	0.84	0.64
AgERA5	229	479	450	765	133	149	0.70	0.57	15.5	-1.50	0.00
AgMERRA	104	289	292	445	98	163	0.95	0.97	3.8	0.86	0.69
CHIRPS	146	348	348	654	130	186	0.94	0.91	5.4	0.70	0.13
CMORPH	50	160	153	373	79	93	0.46	0.48	21.1	-3.62	0.00
CPC	59	201	182	382	76	87	0.87	0.72	14.5	-1.17	0.00
GLDAS	151	286	284	448	71	97	0.87	0.88	8.2	0.30	0.54
GPCC	165	421	420	739	173	286	0.85	0.74	9.2	0.12	0.00
GPM	145	376	368	624	142	245	0.94	0.86	6.8	0.51	0.03
MSWEP	108	302	292	532	117	158	0.95	0.96	3.9	0.85	0.72
PERSIANN	208	375	384	547	78	91	0.62	0.64	14.9	-1.30	0.00
PGF	133	287	291	452	79	88	0.93	0.94	5.5	0.69	0.64
POWER	77	203	190	364	70	89	0.88	0.70	15.5	-1.49	0.00
S14FD	104	352	336	595	145	206	0.92	0.89	5.8	0.66	0.16
TRMM	135	337	289	630	133	194	0.84	0.88	6.2	0.61	0.28

$$NSE = 1 - \frac{\sum_{i=1}^{n} e_i^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2}, \ -inf < NSE \leq 1 \quad (4)$$

$$NRMSE = 100 \times \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}}{max(O_i) - min(O_i)} \quad (5)$$

where:M_i: ith extracted value from a GPP or crop model output based on the extracted value from a GPPO_i: ith observed value or crop model output based on the observed valuee_i: ith calculated error$n$: total number of values.

3. Results

3.1. Statistical analysis of GPPs vs. observed precipitation

The best performance of the GPPs when compared to the observed daily precipitation during the growing season was obtained for AgMERRA and MSWEP that both had $r \geq 0.79$ and NSE≥ 0.46 (Table 4). On the other hand, CMORPH had the lowest accuracy among all GPPs. Descriptive statistics of AgMERRA and MSWEP were very similar to those of the observed daily precipitation. Given the *p*-values of the Wilcoxon test, among all GPPs, only AgMERRA and MSWEP had non-significant differences with the observed daily precipitation at $\alpha = 0.05$.

Results obtained for 15-day precipitation during the growing season showed that AgMERRA and MSWEP had the strongest skills, and CMORPH had the weakest skill (Table 5). AgMERRA and MSWEP had values close to the observed 15-day precipitation for almost all descriptive statistics. According to the *p*-values of the Wilcoxon test, there were no significant differences between the observed 15-day precipitation and the GPP products for AgCFSR, AgMERRA, GLDAS, MSWEP, and PGF at $\alpha = 0.05$.

For monthly precipitation during growing season from 2000 to 2010, AgMERRA and MSWEP had the highest skill, and CMORPH had the lowest skill (Table 6). AgMERRA and MSWEP also had descriptive statistics that most closely matched the observed data. Analysis of *p*-values of the Wilcoxon test revealed that AgCFSR, AgMERRA, GLDAS, MSWEP, PGF, S14FD, and TRMM have non-significant differences with the observed monthly precipitation at $\alpha = 0.05$.

Findings gained from statistical analysis of the total precipitation during the growing season from 2000 to 2010 (Table 7) disclosed that AgMERRA and MSWEP had the strongest skills, and CMORPH had the weakest skill. The closest descriptive statistics to the observed total precipitation were also found in AgMERRA and MSWEP. According to the result of the Wilcoxon test, there was no significant difference between the observed total precipitation, and AgMERRA, MSWEP, and some other GPPs (Table 7).

Table 8
False wet days, false dry days, and accuracy [= 100 - (false wet days + false dry days)] of GPP versus the observed daily precipitation during the growing season from 2000 to 2010 (considering all sites).

GPP	False wet days (%)	False dry days (%)	Accuracy (%)
AgCFSR	6.7	10.7	82.6
AgERA5	30.5	0.4	69.1
AgMERRA	6.0	8.2	85.8
CHIRPS	13.5	13.8	72.7
CMORPH	21.8	16.6	61.6
CPC	9.6	3.9	86.5
GLDAS	24.7	12.5	62.8
GPCC	15.4	3.2	81.4
GPM	26.6	7.3	66.1
MSWEP	7.7	4.9	87.4
PERSIANN	31.9	5.3	62.8
PGF	10.8	9.8	79.4
POWER	27.2	0.4	72.4
S14FD	7.7	10.8	81.5
TRMM	11.8	14.8	73.4

3.2. False wet and dry days

Considering all sites during growing seasons from 2000 to 2010 (Table 8), MSWEP had the highest accuracy in terms of accurately representing wet and dry days, and CMORPH had the lowest accuracy. CPC and AgMERRA had the highest accuracy after MSWEP, and GLDAS and PERSIANN had the lowest accuracy after CMORPH.

3.3. Grain yield

Comparing simulated grain yield with GPP products to the model outputs for grain yield (kg ha^{-1}) estimated from the observed precipitation in all sites during 2000–2010 (Fig. 3), the strongest skills were found for AgMERRA and MSWEP. The weakest skill was detected in CMORPH. After CMORPH, the next weakest skills were found in AgERA5 with and PERSIANN.

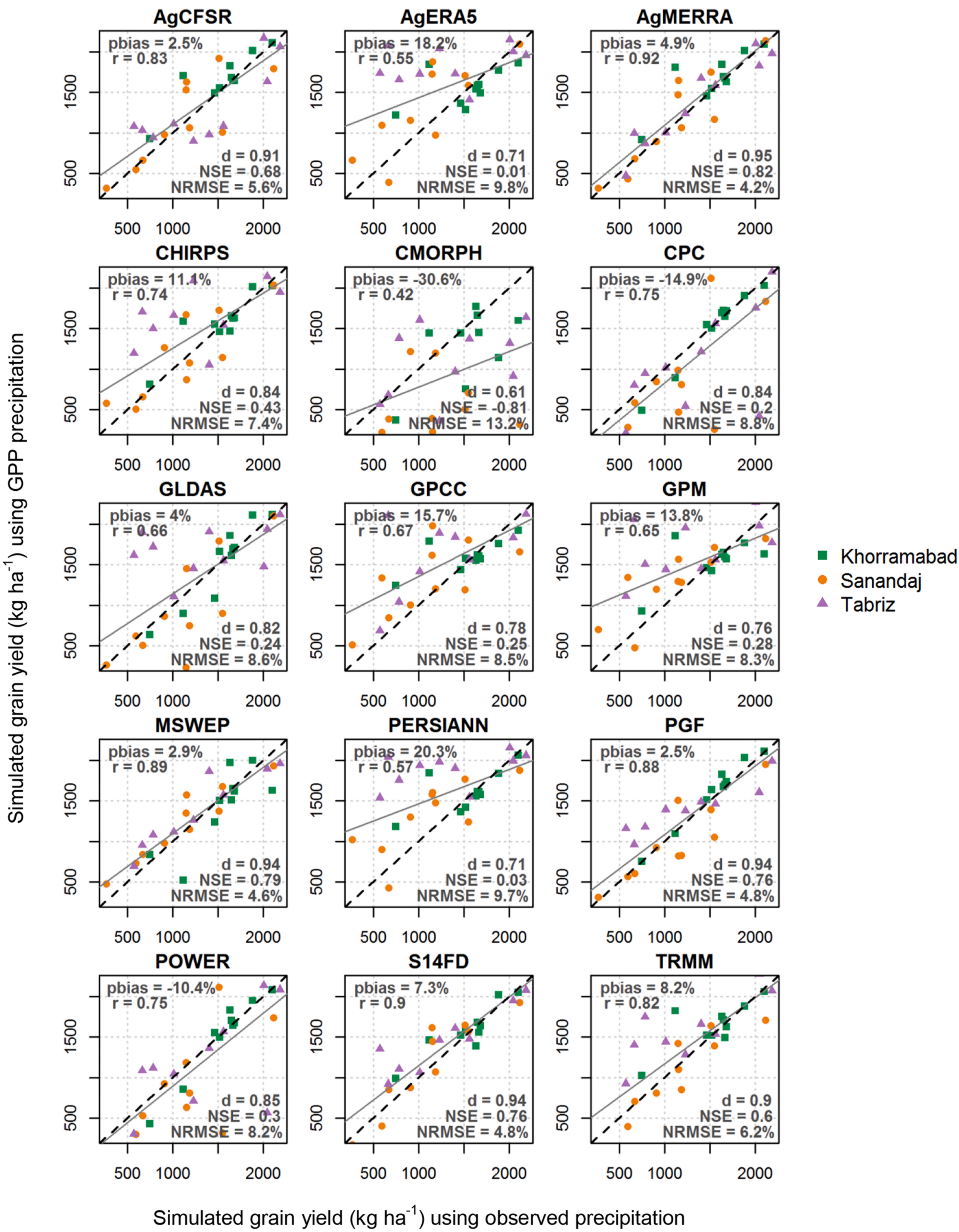

Fig. 3. Evaluation indices for the simulated grain yield based on the precipitation values extracted from each GPP versus the simulated grain yield based on the observed precipitation.

4. Discussion

Simulation of crop yield in water-limited regions is highly dependent on accurate rainfall data, and the available precipitation station network is often insufficient for regional analyses of crop performance using simulation modeling. This calls for the use of gridded estimates of daily precipitation, but there are great differences in the quality of precipitation data from these different GPPs, and the quality of the precipitation data is directly reflected in the quality of the simulated crop yields, as illustrated by the similar performance of the GPPs with respects to precipitation and to crop yield.

Considering evaluation indices computed for the model outputs, it was found that AgMERRA and MSWEP were the GPPs with the highest reliability and the best alternatives for the observed precipitation data for rainfed wheat yield estimation in the study area, whereas CMORPH has the lowest skill. The high skill of AgMERRA for crop modeling was also revealed in previous studies (Battisti et al., 2019; Lashkari et al., 2018; Parkes et al., 2019; Toreti et al., 2019; Yaghoubi et al., 2020). Moreover, previous research has shown higher accuracy of MSWEP daily precipitation against CMORPH, PERSIANN, and TRMM across Iran (Alijanian et al., 2017). Our findings highlight that multi-source precipitation products such as MSWEP has a higher accuracy compared to purely satellite-derived precipitation products such as CMORPH. However, POWER S_{rad}, T_{max}, and T_{min} data were found to be promising source for crop modeling (van Wart et al., 2015; White et al., 2008), but the findings of the current study showed a medium to low accuracy of POWER daily precipitation data.

Considering the findings, MSWEP can be recommended as the best GPP for crop modeling purposes over the study area and similar regions. The main reason is the multi-source structure of MSWEP based on weather stations observations, remote sensing data, and climate models output. MSWEP is also available for recent years and is updated frequently. It has a proper spatial resolution and temporal coverage.

Alongside the results gained in the current study, some general benefits and drawbacks of the investigated GPPs concerning their applicability and retrieval process concern accessibility, and spatial and temporal coverage.

4.1. Accessibility

Ease of downloading is a significant factor that increases the usage of a GWP. The most convenient downloading process in this study was found in PERSIANN and POWER, which had this ability to simply download data for a specific geo-point. MSWEP was in the next rank, which had pre-cutted data for different regions of the globe. For example, the pre-cutted MSWEP file size for each year over the Middle-East was ~25MB. Some products such as AgCFSR, AgERA5, AgMERRA, CHIRPS, CPC, GPCC, and PGF, had one file for each year with global coverage, resulting in considerably larger file sizes compared to MSWEP.

Although the online system of GLDAS, GPM, and TRMM had a perfect option to easily cut the product for a specific region, but unfortunately, the final files were prepared day by day. For instance, for the period selected for the current study from 2000 to 2010, a total of 4018 single files must be downloaded. It would be convenient, if these cutted products were packaged in a single compressed file and then presented to the user. The worst downloading process was for S14FD, where data files of all years with a global spatial coverage had been packaged in a single compressed file with size of ~7 GB.

4.2. Spatial coverage

Most of the assessed GPPs had a global coverage, but some GPPs such as CHIRPS and TRMM had a limited spatial coverage from 50°S–50°N. Such limited GPPs are not useful for the environmental and agricultural studies outside of their bounds. AgMERRA and MSWEP, the two GPPs with the greatest skill in the current study, had a global spatial coverage. This is a distinguished benefit of these GPPs as they can be applied in any zone of the globe.

4.3. Temporal coverage

Availability over the past recent years can be a significant superiority of a GPP. While MSWEP v2.6 is available until end of 2019, AgMERRA was ended in 2010, and this is its major drawback, as it cannot be useful for environmental and agricultural studies after 2010. It is also expected that next versions of MSWEP will include precipitation values for the years after 2019.

5. Conclusions

This study aimed to evaluate multiple gridded precipitation products (GPPs) for rainfed wheat yield estimation in a semi-arid environment using the CERES-Wheat model. To this end, fifteen global GPPs were investigated. Findings showed that multi-source GPPs had higher accuracy. Accordingly, AgMERRA and MSWEP outperformed the other GPPs, while CMORPH was the weakest product. Although AgMERRA was identified as a top GPP in the current research, it cannot be a proper choice for the further studies due to its limited temporal coverage up to 2010, and therefore, MSWEP is recommended for environmental and agricultural research, particularly crop modeling, over the study area. Similar studies for other crops and environments are required to expand the findings of this research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank the three anonymous reviewers whose suggestions and remarks have greatly helped to improve the paper.

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