Evaluation of CRU TS, GPCC, AgMERRA, and AgCFSR meteorological datasets for estimating climate and crop variables: A case study of maize in Qazvin Province, Iran Postprint

Authors: Faraz GORGIN PAVEH

Date: 2022-12-12T00:00:00+00:00

Abstract

Over the past few decades, meteorological datasets derived from remote sensing techniques have been widely utilized by researchers and water resource managers in agricultural applications. While literature indicates that these datasets are not inherently more accurate than synoptic station data, their advantages—including comprehensive spatial and temporal coverage, accessibility, and free availability—have made them increasingly preferable, sometimes even serving as alternatives to traditional synoptic stations. This study employed four meteorological datasets—Climatic Research Unit gridded Time Series (CRU TS), Global Precipitation Climatology Centre (GPCC), Agricultural National Aeronautics and Space Administration Modern-Era Retrospective Analysis for Research and Applications (AgMERRA), and Agricultural Climate Forecast System Reanalysis (AgCFSR)—to estimate climate variables (precipitation, maximum temperature, and minimum temperature) and crop variables (reference evapotranspiration, irrigation requirement, biomass, and yield) for maize in Qazvin Province, Iran, from 1980 to 2009. Data were first extracted from the four meteorological datasets and a synoptic station within the province to calculate climate variables. Subsequently, the AquaCrop model was applied to compute crop variables, and the results from the meteorological datasets were compared against synoptic station data. All four datasets demonstrated strong performance in estimating climate variables, with AgMERRA and AgCFSR providing more accurate estimations for precipitation and maximum temperature. However, their normalized root mean square error was inferior to CRU TS for minimum temperature. The datasets were also highly efficient for estimating maize biomass and yield in the province. For reference evapotranspiration and irrigation requirement, CRU TS and GPCC outperformed AgMERRA and AgCFSR. Overall, GPCC and AgCFSR emerged as the two best-performing datasets. This study

recommends the use o

Full Text

Preamble

Evaluation of CRU TS, GPCC, AgMERRA, and AgCFSR Meteorological Datasets for Estimating Climate and Crop Variables: A Case Study of Maize in Qazvin Province, Iran

Faraz GORGIN PAVEH[1]*, Hadi RAMEZANI ETEDALI[2], Brian COLLINS[3]

[1]Centre for Crop Science, The University of Queensland, Brisbane 4072, Australia

Abstract

Over the past few decades, meteorological datasets derived from remote sensing techniques have been widely utilized by researchers and water resource managers in agricultural applications. While literature indicates that these datasets are not inherently more accurate than synoptic station data, their advantages—including comprehensive spatial and temporal coverage, accessibility, and free availability—have made them increasingly preferable, sometimes even serving as alternatives to traditional synoptic stations. This study employed four meteorological datasets—Climatic Research Unit gridded Time Series (CRU TS), Global Precipitation Climatology Centre (GPCC), Agricultural National Aeronautics and Space Administration Modern-Era Retrospective Analysis for Research and Applications (AgMERRA), and Agricultural Climate Forecast System Reanalysis (AgCFSR)—to estimate climate variables (precipitation, maximum temperature, and minimum temperature) and crop variables (reference evapotranspiration, irrigation requirement, biomass, and yield) for maize in Qazvin Province, Iran, from 1980 to 2009. Data were first extracted from the four meteorological datasets and a synoptic station within the province to calculate climate variables. Subsequently, the AquaCrop model was applied to compute crop variables, and the results from the meteorological datasets were compared against synoptic station data. All four datasets demonstrated strong performance in estimating climate variables, with AgMERRA and AgCFSR providing more accurate estimations for precipitation and maximum temperature. However, their normalized root mean square error was inferior to CRU TS for minimum temperature. The datasets were also highly efficient for estimating maize biomass and yield in the province. For reference evapotranspiration and irrigation requirement, CRU TS and GPCC outperformed AgMERRA and AgCFSR. Overall, GPCC and AgCFSR emerged as the two best-performing datasets. This study recommends the use of meteorological datasets in water resource and agricultural management for monitoring historical changes and estimating recent trends.

Keywords: climate variables; crop variables; meteorological datasets; precipitation; reference evapotranspiration; irrigation requirement; Iran

Citation: Faraz GORGIN PAVEH, Hadi RAMEZANI ETEDALI, Brian COLLINS. 2022. Evaluation of CRU TS, GPCC, AgMERRA, and AgCFSR meteorological datasets for estimating climate and crop variables: A case study of maize in Qazvin Province, Iran. *Journal of Arid Land*, 14(12): 1361–1376. https://doi.org/10.1007/s40333-022-0108-7

Corresponding author: Faraz GORGIN PAVEH (E-mail: fgorginp@syr.edu)

Received 2022-07-04; revised 2022-11-02; accepted 2022-11-17

1 Introduction

The impact of climate change on agricultural productivity is undeniable, as alterations in precipitation and temperature patterns directly affect crop production and growing seasons. Accurate estimation of temperature and precipitation, along with tracking historical changes, is essential for adapting to these threats. Similarly, precise quantification of crop variables—including reference evapotranspiration, irrigation requirement, biomass, and yield—is critical for agricultural planning.

Ground-based meteorological stations currently provide insufficient temporal and geographical coverage in many regions worldwide. Fortunately, numerous observational options now exist for monitoring global water conditions, with gridded datasets representing a particularly valuable resource. Crop and water simulation models can estimate agricultural water requirements, yield, and other indicators. While several crop simulation models have been reported in literature—such as CropSyst, APSIM, Hybrid-Maize, and CROPWAT—these typically require comprehensive input data on crop growth that are unavailable in most parts of the world. Recent climate and crop prediction research in Iran and other countries has produced significant outcomes, yet issues of accuracy and uncertainty persist, underscoring the need for further investigation.

Satellite-based remote sensing techniques offer cost-effective, wide-ranging, and time-efficient solutions for local, regional, national, and global applications. These datasets encompass various temporal scales, from hourly to annual, enabling examination of changes and monitoring of terrestrial events relevant to agriculture, natural resource management, groundwater, water quality, salinity management, and crop water requirements. Land surface models are critical for providing global-scale hydrological parameters. Although not necessarily more accurate than traditional measurements, these datasets offer complete spatial and temporal coverage—their primary advantage. Applications fall into three categories: (1) historical data for understanding water cycle evolution and studying rainfall and drought trends, enabling continuous evaluation of water resource changes and informed management decisions; (2) short-term meteorological data for rapid decision-making; and (3) model applications providing future precipitation information for long-term planning.

Agricultural management requires precise data across numerous fields, particularly crop yield estimation, which is now considered essential. Climate data constitute a crucial component of plant model inputs, and various databases can help compensate for data gaps, though their accuracy must be assessed. This study estimated minimum temperature, maximum temperature, and precipitation in Qazvin Province, Iran, from 1980 to 2009 using four meteorological datasets: CRU TS, GPCC, AgMERRA, and AgCFSR. Results were compared to a provincial synoptic station using evaluation indices including correlation coefficient (R^2), root mean square error (RMSE), normalized root mean square error (NRMSE), and maximum error (ME). The four datasets were then used to estimate reference evapotranspiration, biomass, irrigation requirement, and maize yield on a monthly scale, with final comparisons made against synoptic station data using the same indices.

2.1 Qazvin Province and Maize

Qazvin Province is located in northwestern Iran, south of the Alborz Mountains, at relatively high latitudes. Despite covering only 1% of Iran's area (1.6×10^{4} km^2), the province contributes approximately 3% of national agricultural production, totaling over 5.9×10^{6} t. Annual precipitation averages 330 mm, ranging from 210 mm in the east to 550 mm in the northeast. The province comprises plain and mountain zones. Table 1 presents monthly maximum temperature, minimum temperature, daily evapotranspiration, monthly evapotranspiration, and precipitation data.

Wheat, barley, maize, and alfalfa are the principal crops in Qazvin Province. This study utilized data from the provincial synoptic station (36°8'59'N, 50°1'47"E; 1279.2 m) collected from 1980 to 2009 (Fig. 1 [Figure 1: see original paper]). Maize was selected as a representative crop, covering over 1.3×10^{2} km^2 of agricultural land. Synoptic station data were used in lieu of documented maize data due to their long-term availability, and were calibrated against actual data to ensure reliability.

2.2 AquaCrop Model

This study employed the AquaCrop model to calculate reference evapotranspiration, biomass, irrigation requirement, and maize yield from both synoptic station and meteorological dataset inputs. Developed by the Food and Agriculture Organization of the United Nations (FAO), AquaCrop is a crop development model designed to assess environmental impacts and water management. As a water-driven model, it simulates crop yields by regulating soil water availability. AquaCrop requires fewer input variables than alternative models while maintaining necessary precision and has proven accurate across numerous experiments under various water management conditions.

The empirical equation of the AquaCrop model is as follows (Dorenbos and Kassam, 1979):

$$1-\frac{Y}{Y_x}=K_y\left(1-\frac{ET}{ET_x}\right)$$

where Y_x and Y represent maximum and actual crop production (kg/m^2), respectively; ET_x and ET represent potential and actual evapotranspiration (mm), respectively; and K_y represents the conversion coefficient between crop yield and water stress.

To avoid confusion, the model separates evapotranspiration into soil evaporation and crop transpiration (Zhu et al., 2021). Reference evapotranspiration (ET_0) was calculated using the FAO Penman-Monteith Equation (Allen et al., 1998):

$$ET_0=\frac{0.408\Delta(R_n-G)+\gamma\frac{900}{T+273}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)}$$

where R_n is net radiation at the crop surface (MJ/(m$^2 \cdot$ a)); G is soil heat flux density (MJ/(m$^2 \cdot$ a)); T is air temperature at 2 m height (°C); u_2 is wind speed at 2 m height (m/s); e_s is saturation vapor pressure (kPa); e_a is actual vapor pressure (kPa); Δ is the slope of the vapor pressure curve (kPa/°C); and γ is the psychrometric constant (kPa/°C).

AquaCrop requires four input data types: (1) meteorological data (daily precipitation, maximum temperature, minimum temperature, and reference evapotranspiration); (2) soil data (texture and organic content); (3) crop data (growth and development factors, evaporation, transpiration, yield, and stress); and (4) management information (irrigation, fertilizer, and surface covering). This study assumed a loam soil texture for Qazvin Province, with 32.2% field capacity and 16.1% permanent wilting point.

2.3.1 Climatic Research Unit gridded Time Series (CRU TS)

CRU TS provides monthly gridded land-based observations dating to 1901, containing 10 observed and calculated variables with no missing values in the defined domain. Accessible data include precipitation, maximum temperature, and minimum temperature (New et al., 1999; Harris et al., 2020). Initially released in 2000, CRU TS employed Angular Distance Weighting Interpolation (ADW) to interpolate monthly anomalies for seven variables onto a 0.50° grid. After thorough review, ADW was selected as the interpolation method, with observed coverage gaps filled by interpolating synthesized data onto a coarser 2.50° grid (New et al., 2000; Mitchell et al., 2004; Mitchell and Jones, 2005; Harris et al., 2014).

2.3.2 Global Precipitation Climatology Centre (GPCC)

Established in 1989 as the in situ component of the Global Energy and Water Exchanges (GEWEX) Global Precipitation Climatology Project, GPCC's primary responsibility is analyzing monthly precipitation over land surfaces using rain gauge observations. The dataset compiles a unique precipitation database from over 85,000 stations worldwide, estimated to represent between 150,000 and 250,000 individual rain gauges (New et al., 2001; Strangeways, 2006; Schneider et al., 2014).

2.3.3 Agricultural National Aeronautics and Space Administration Modern-Era Retrospective Analysis for Research and Applications (AgMERRA)

AgMERRA provides daily time series data globally for 1980–2009 at 0.25° spatial resolution, including daily precipitation, maximum temperature, minimum temperature, relative humidity, and solar radiation (Ruane et al., 2015). Additional details are provided by Reichle et al. (2011) and Ruane et al. (2015).

2.3.4 Agricultural Climate Forecast System Reanalysis (AgCFSR)

AgCFSR includes rainfall data at daily temporal and 0.25° geographic resolution for 1980–2009. The dataset integrates CRU TS, GPCC, Tropical Rainfall Measuring Mission (TRMM), and Climate Prediction Center Morphing technique (CMORPH) databases, combining in situ and satellite data while considering agricultural areas and climatic elements affecting crops (Ruane et al., 2015).

Table 2 summarizes information for all four datasets.

2.4 Evaluation Indices

To determine the suitability of meteorological datasets as replacements for synoptic stations, we identified dataset points closest to the provincial synoptic station and evaluated three measurement methods: (1) K1—using only the single closest point; (2) K4—averaging the four closest points; and (3) K8—averaging the eight nearest points. Data were extracted using each method and compared against synoptic station observations.

For precipitation, maximum temperature, and minimum temperature, the K8 method reduced estimation efficiency and was therefore excluded from climate variable analysis. However, K8 improved crop variable accuracy, so results are presented using K1 and K4 for climate variables and K1, K4, and K8 for crop variables. Monthly dataset data were used to estimate climate variables, with averaged annual data employed for crop variable estimation. Maize production and reference evapotranspiration estimates from CRU TS, GPCC, AgMERRA, and AgCFSR were compared against synoptic station estimates using statistical criteria: R^2, RMSE, NRMSE, and ME.

3.1.1 Minimum Temperature

Figure 2 [Figure 2: see original paper] presents minimum temperature estimates for K1 and K4 in Qazvin Province from 1980 to 2009. As GPCC does not provide temperature data, it is excluded from temperature analyses. All three datasets (CRU TS, AgMERRA, and AgCFSR) estimated minimum temperature efficiently with close agreement. Statistical evaluations appear in Table 3 . All datasets exhibited strong correlations ($R^2 > 0.99$) for both K1 and K4.

For K1, CRU TS performed best with an NRMSE of 5.96%, while AgMERRA and AgCFSR showed NRMSE values of 10.55% and 14.51%, respectively. Despite higher NRMSE values, their ME values were relatively low. For K4, results differed: RMSE increased slightly for CRU TS but decreased significantly for AgMERRA and AgCFSR. NRMSE behavior was similar, decreasing from approximately 6.00% (K1) to 7.55% (K4) for CRU TS and dropping by about 4.00% for both AgMERRA and AgCFSR.

3.1.2 Maximum Temperature

Figure 3 [Figure 3: see original paper] shows maximum temperature estimates from CRU TS, AgMERRA, and AgCFSR for 1980–2009. All datasets estimated maximum temperature with high accuracy and close agreement, showing strong correlations ($R^2 > 0.99$) for both K1 and K4. RMSE values were low, with NRMSE demonstrating high accuracy: 6.32% for CRU TS, 3.82% for AgCFSR, and 1.10% for AgMERRA (K1). AgMERRA performed best for maximum temperature estimation, though AgCFSR showed the lowest ME. Results for K4 were slightly less efficient but remained suitable, with AgMERRA maintaining the best performance (NRMSE = 4.80%), followed by AgCFSR (5.09%) and CRU TS (6.32%).

3.1.3 Precipitation

Figure 4 [Figure 4: see original paper] displays precipitation variation estimates from all four datasets and the synoptic station for 1980–2009. Dataset estimates showed strong correlation with synoptic station data for both K1 and K4. Statistical indices in Table 3 indicate that, unlike AgMERRA, all datasets correlated strongly ($R^2 > 0.50$) with the synoptic station for K1, while all datasets achieved $R^2 > 0.50$ for K4. Although ME values were relatively high, NRMSE values remained below 10.00% for all datasets, with RMSE around 2.0 mm (K1) and 3.0 mm (K4). AgCFSR and AgMERRA performed best, with CRU TS and GPCC ranking third and fourth, respectively, showing similar behavior for K4.

Overall, all datasets efficiently estimated climate variables in Qazvin Province, showing high correlation with the synoptic station and acceptable NRMSE values. AgMERRA and AgCFSR are most suitable for maximum temperature and precipitation estimation, while CRU TS is optimal for minimum temperature.

3.2.1 Reference Evapotranspiration

As GPCC does not provide data for reference evapotranspiration estimation, results are presented for CRU TS, AgMERRA, and AgCFSR (Fig. 5 [Figure 5: see original paper]), with statistical evaluation in Table 4 . CRU TS estimated reference evapotranspiration efficiently, with RMSE values of 156.00–172.00 mm across K1, K4, and K8, and NRMSE below 15.00%. ME values were similar (~360.00 mm), though R^2 was not high.

Table 4 shows poor R^2 values across all methods, leading us to focus on other indices. For CRU TS, efficiency improved when using more points (K8 and K4). AgMERRA and AgCFSR showed similar performance, with AgMERRA slightly outperforming AgCFSR. K4 provided the best reference evapotranspiration estimates for this province.

3.2.2 Irrigation Requirement

Irrigation requirement, calculated as the difference between evapotranspiration and effective precipitation, was estimated to assess all climate variables. Results are shown in Figure 6 [Figure 6: see original paper] and Table 4 . CRU TS and GPCC produced closely aligned, highly reliable results, while AgMERRA and AgCFSR showed less accuracy. CRU TS was most efficient for estimating maize irrigation requirement, with RMSE below 135.00 mm, NRMSE around 18.00%, and ME around 270.00 mm. GPCC was slightly less accurate (NRMSE ~20.00%, RMSE <150.00 mm). The K4 method improved accuracy for CRU TS, while GPCC showed no significant differences among K1, K4, and K8. AgMERRA and AgCFSR were less efficient, with RMSE and NRMSE around 300.00 mm and 40.00% for K1 and K4, and substantially lower accuracy for K8.

3.2.3 Biomass

Figure 7 [Figure 7: see original paper] presents biomass estimates from each dataset compared to synoptic station data. Results differed markedly from previous sections, with all datasets showing close agreement and good RMSE values. NRMSE values were below 5.00% for all datasets, averaging approximately 2.50%. While no single best dataset emerged, GPCC using K8 provided the most accurate maize biomass estimates.

3.2.4 Yield

Yield estimation assumed full irrigation requirement satisfaction and absence of water or salinity stress. Dataset and synoptic station results are shown in Figure 8 [Figure 8: see original paper], with close agreement among estimates. Table 4 shows similar RMSE values and NRMSE below 5.00% across all datasets, with GPCC using K8 performing best.

In summary, all datasets efficiently estimated maize biomass and yield in Qazvin Province. CRU TS was most efficient for reference evapotranspiration and irrigation requirement estimation, though results remained reliable across datasets. Increasing measurement points (K4 and K8) enhanced result reliability.

4 Discussion

Bahrololoum et al. (2020) evaluated CRU TS, AgMERRA, AgCFSR, and GPCC for wheat yield and irrigation requirement simulation in Qazvin Province (1980–2009) using K1, K4, and K8 methods. Their CRU TS evapotranspiration estimates showed R^2 of 0.35 and RMSE of 87.00 mm (K1), 0.25 and 91.00 mm (K4), and 0.27 and 201.00 mm (K8). AgMERRA performed less efficiently ($R^2 < 0.20$, RMSE $>$ 125.00 mm for all methods), while AgCFSR results were similar to AgMERRA. GPCC was most efficient for wheat evapotranspiration estimation. Wheat yield results differed, with AgCFSR performing best (RMSE ~0.22 t/hm^2, $R^2 > 0.70$ for all methods), followed by CRU TS, while GPCC and AgMERRA were less efficient.

Ramezani Etedali and Ahmadi (2021) used GLDAS, GLDAS-CRU, GLDAS-AgMERRA, and AgCFSR to estimate crop yield and evapotranspiration in Qazvin Province (1980–2010), finding AgMERRA and AgCFSR less efficient than CRU TS and GLDAS for potential evapotranspiration estimation. Gorgin Paveh et al. (2020) demonstrated CRU TS superiority over AgMERRA for wheat water footprint estimation. Kakvand et al. (2020) found GPCC more reliable than AgCFSR for maize water footprint estimation, with both datasets more efficient for green water footprint assessment. Ramezani Etedali et al. (2022) showed GPCC outperformed AgMERRA for maize water footprint estimation, with higher reliability for green and total water footprints compared to blue water footprint.

Lashkari et al. (2018) found AgMERRA had strong relationships with maximum temperature in an Iranian province. Ceglar et al. (2017) evaluated four meteorological datasets (AgMERRA, APHRODITE, PERSIANN, and TRMM) for monsoon Asia precipitation estimation, concluding AgMERRA was reliable based on its structure and statistical post-processing. Ahmed et al. (2019) evaluated GPCC, CRU, APHRODITE, and UDel datasets across Pakistan's arid regions, finding GPCC performed best in all climatic zones due to its larger observational station network—results consistent with Duethmann et al. (2013).

Terrain, wind speed, and hill aspect significantly impact precipitation, potentially causing gridded precipitation to misrepresent distribution patterns. Elevation differences also substantially affect precipitation, as extensively documented. White et al. (2008) recommended further regional studies on seasonal precipitation patterns.

5 Conclusions

Given the importance of accurate climate and crop variable estimation and the increasing need for satellite data to supplement traditional measurements, this study evaluated four meteorological datasets (CRU TS, GPCC, AgMERRA, AgCFSR) for estimating climate variables (minimum temperature, maximum temperature, precipitation) and crop variables (reference evapotranspiration, irrigation requirement, biomass, yield) in Qazvin Province from 1980 to 2009.

For climate variables, all datasets proved suitable as synoptic station replacements. CRU TS performed best for minimum temperature, while AgMERRA and AgCFSR showed greater efficiency for maximum temperature and precipitation. For crop variables, all datasets efficiently estimated maize yield and biomass. Reference evapotranspiration and irrigation requirement estimates were less efficient but remained reliable for CRU TS and GPCC. Increasing measurement points (K4 and K8) improved accuracy. Overall, meteorological datasets can effectively estimate climate and crop variables for water resource and agricultural management, enabling monitoring of past variations and future trends. Further research should investigate additional datasets across diverse regions, climatic conditions, and crops.

Acknowledgements

The authors express gratitude to FAO for providing the AquaCrop model and acknowledge the freely available data from CRU TS, GPCC, AgMERRA, and AgCFSR datasets.

References

Abedinpour M, Sarangi A, Rajput T B S, et al. 2012. Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. *Agricultural Water Management*, 110: 55–66.

Ahmed K, Shahid S, Wang X, et al. 2019. Evaluation of gridded precipitation datasets over arid regions of Pakistan. *Water*, 11(2): 210, doi: 10.3390/w11020210.

Allen R G, Pereira L S, Raes D, et al. 1998. Crop evapotranspiration-Guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper 56. Rome: FAO, 300(9): D05109.

Apan A A, Raine S R, Le Brocque A, et al. 2004. Spatial prioritization of revegetation sites for dryland salinity management: An analytical framework using GIS. *Journal of Environmental Planning and Management*, 47(6): 811–825.

Bahrololoum R, Ramezani Etedali H, Azizian A, et al. 2020. Use of gridded weather datasets in simulation of wheat yield and water requirement (Case study: Iran's Qazvin Plain). *Iranian Journal of Ecohydrology*, 7(3): 691–706.

Benevides P, Catalao J, Nico G. 2019. Neural network approach to forecast hourly intense rainfall using GNSS precipitable water vapor and meteorological sensors. *Remote Sensing*, 11(8): 966, doi: 10.3390/rs11080966.

Bosilovich M G, Chen J, Robertson F R, et al. 2008. Evaluation of global precipitation in reanalyses. *Journal of Applied Meteorology and Climatology*, 47(9): 2279–2299.

Bowen G J, Cai Z, Fiorella R P, et al. 2019. Isotopes in the water cycle: Regional- to global-scale patterns and applications. *Annual Review of Earth and Planetary Sciences*, 47: 453–479.

Ceglar A, Toreti A, Balsamo G, et al. 2017. Precipitation over monsoon Asia: A comparison of reanalyses and observations. *Journal of Climate*, 30(2): 465–476.

Confalonieri R, Orlando F, Paleari L, et al. 2016. Uncertainty in crop model predictions: what is the role of users? *Environmental Modelling & Software*, 81: 165–173.

Daly C, Neilson R P, Phillips D L. 1994. A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *Journal of Applied Meteorology and Climatology*, 33(2): 140–158.

Dorenbos J, Kassam A H. 1979. Yield Response to Water. In: Food and Agriculture Organization of the United Nations. Rome, Italy.

Duethmann D, Zimmer J, Gafurov A, et al. 2013. Evaluation of areal precipitation estimates based on downscaled reanalysis and station data by hydrological modelling. *Hydrology and Earth System Sciences*, 17(7): 2415–2434.

El-mageed A, Ibrahim M M, Elbeltagi A M. 2017. The effect of water stress on nitrogen status as well as water use efficiency of potato crop under drip irrigation system. *Misr Journal of Agricultural Engineering*, 34(3): 1351–1374.

Ge Y, Zhang K, Yang X. 2019. A 110-year pollen record of land use and land cover changes in an anthropogenic watershed landscape, eastern China: Understanding past human-environment interactions. *Science of the Total Environment*, 650: 2906–2918.

Golabi M, Naseri A A. 2015. Assessment Aquacrop model to predict the sugarcane yield and soil salinity profiles under salinity stress. *Iranian Journal of Soil and Water Research*, 4(46): 685–694.

Gorgin Paveh F, Ramezani Etedali R, Kakvand P. 2020. Estimation of Wheat Water Footprint Based on CRU and AgMERRA Gridded Datasets. [2022-06-23]. https://osau.edu.ua/en/iv-mizhnarodnyj-yevrazijskyj-kongres-z-silskogo-gospodarstva-ta-pryrodnychyh-nauk/.

Harris I, Jones P D, Osborn T J, et al. 2014. Updated high-resolution grids of monthly climatic observations–the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3): 623–642.

Harris I, Osborn T J, Jones P, et al. 2020. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, 7(1): 1–18.

Hellal F, Mansour H, Abdel-Hady M, et al. 2019. Assessment water productivity of barley varieties under water stress by AquaCrop model. *AIMS Agriculture and Food*, 4(3): 501–517.

Javanmard S, Yatagai A, Nodzu M I, et al. 2010. Comparing high-resolution gridded precipitation data with satellite rainfall estimates of TRMM-3B42 over Iran. *Advances in Geosciences*, 25: 119–125.

Johansson B, Chen D. 2003. The influence of wind and topography on precipitation distribution in Sweden: Statistical analysis and modelling. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 23(12): 1523–1535.

Kakvand P, Ramezani Etedali R, Gorgin Paveh F. 2020. Estimation of Maize Water Footprint Based on GPCC and AgCFSR Gridded Datasets. [2022-06-23]. https://osau.edu.ua/en/iv-mizhnarodnyj-yevrazijskyj-kongres-z-silskogo-gospodarstva-ta-pryrodnychyh-nauk/.

Katiraie-Boroujerdy P S, Nasrollahi N, Hsu K. et al. 2013. Evaluation of satellite-based precipitation estimation over Iran. *Journal of Arid Environments*, 97: 205–219.

Keating B A, Carberry P S, Hammer G L, et al. 2003. An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, 18(3–4): 267–288.

Kreuzer D, Munz M, Schlüter S. 2020. Short-term temperature forecasts using a convolutional neural network An application to different weather stations in Germany. *Machine Learning with Applications*, 2: 100007, doi: 10.1016/j.mlwa.2020.100007.

Lashkari A, Salehnia N, Asadi S, et al. 2018. Evaluation of different gridded rainfall datasets for rainfed wheat yield prediction in an arid environment. *International Journal of Biometeorology*, 62(8): 1543–1556.

Li J, Tian L, Wang Y, et al. 2021. Optimal sampling strategy of water quality monitoring at high dynamic lakes: A remote sensing and spatial simulated annealing integrated approach. *Science of the Total Environment*, 777: 146113, doi: 10.1016/j.scitotenv.2021.146113.

Massah A R, Morid S. 2005. Effects of climate change on Zayandeh Rud river flows. *Journal of Science and Technology of Agriculture and Natural Resources*, 4: 17–27.

Mitchell T D, Carter T R, Jones P D, et al. 2004. A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: the observed record (1901–2000) and 16 scenarios (2001–2100). *Geography*, 55: 25, doi: 10.1002/joc.1181.

Mitchell T D, Jones P D. 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology*, 25(6): 693–712.

New M, Hulme M, Jones P. 1999. Representing twentieth-century space-time climate variability. Part I: Development of a 1961-90 mean monthly terrestrial climatology. *Journal of Climate*, 12(3): 829–856.

New M, Hulme M, Jones P. 2000. Representing twentieth-century space-time climate variability. Part II: Development of 1901-96 monthly grids of terrestrial surface climate. *Journal of Climate*, 13(13): 2217–2238.

New M, Todd M, Hulme M, et al. 2001. Precipitation measurements and trends in the twentieth century. *International Journal of Climatology*, 21(15): 1889–1922.

Olivera Rodriguez P, Holzman M E, Degano M F, et al. 2021. Spatial variability of the green water footprint using a medium-resolution remote sensing technique: The case of soybean production in the Southeast Argentine Pampas. *Science of the Total Environment*, 763: 142963, doi: 10.1016/j.scitotenv.2020.142963.

Ollivier C, Olioso A, Carrière S D, et al. 2021. An evapotranspiration model driven by remote sensing data for assessing groundwater resource in karst watershed. *Science of the Total Environment*, 781: 146706, doi: 10.1016/j.scitotenv.2021.146706.

Ordikhani H, Parashkoohi M G, Zamani D M, et al. 2021. Energy-environmental life cycle assessment and cumulative exergy demand analysis for horticultural crops (Case study: Qazvin province). *Energy Reports*, 7: 2899–2915.

Queyrel W, Habets F, Blanchoud H, et al. 2016. Pesticide fate modeling in soils with the crop model STICS: Feasibility for assessment of agricultural practices. *Science of the Total Environment*, 542: 787–802.

Ramezani Etedali H, Ahmadi M. 2021. Evaluation of various meteorological datasets in estimation yield and actual evapotranspiration of wheat and maize (case study: Qazvin plain). *Agricultural Water Management*, 256: 107080, doi: 10.1016/j.agwat.2021.107080.

Ramezani Etedali H, Gorgin F, Kakvand P. 2022. Study of the performance of two meteorological datasets in estimating the maize water footprint, a case study: Qazvin Plain. *Iranian Journal of Irrigation and Drainage*, 15(6): 1394–1403.

Reichle R H, Koster R D, De Lannoy G J M, et al. 2011. Assessment and enhancement of MERRA land surface hydrology estimates. *Journal of Climate*, 24(24): 6322–6338.

Rodriguez J, Ustin S, Sandoval-Solis S, et al. 2015. Food, water, and fault lines: Remote sensing opportunities for earthquake-response management of agricultural water. *Science of the Total Environment*, 565: 1020–1027.

Ruane A C, Goldberg R, Chryssanthacopoulos J. 2015. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology*, 200: 233–248.

Saeidi R, Ramezani Etedali H, Sotoodehnia A, et al. 2021. Evaluation of AquaCrop model for estimating of changes process of soil moisture, evapotranspiration and yield of maize under salinity and fertility stresses. *Environmental Stresses in Crop Sciences*, 14(1): 195–210.

Salehnia N, Zare H, Kolsoumi S, et al. 2018. Predictive value of Keetch-Byram Drought Index for cereal yields in a semi-arid environment. *Theoretical and Applied Climatology*, 134(3): 1005–1014.

Schneider U, Becker A, Finger P, et al. 2014. GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theoretical and Applied Climatology*, 115(1): 15–40.

Shi H, Li T, Wei J. 2017. Evaluation of the gridded CRU TS precipitation dataset with the point raingauge records over the Three-River Headwaters Region. *Journal of Hydrology*, 548: 322–332.

Stöckle C O, Donatelli M, Nelson R. 2003. CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, 18(3–4): 289–307.

Strangeways I. 2006. *Precipitation: Theory, Measurement and Distribution*. Cambridge: Cambridge University Press.

Valéry A, Andréassian V, Perrin C. 2010. Regionalization of precipitation and air temperature over high-altitude catchments–learning from outliers. *Hydrological Sciences Journal–Journal des Sciences Hydrologiques*, 55(6): 928–940.

Vorosmarty C J, Sahagian D. 2000. Anthropogenic disturbance of the terrestrial water cycle. *BioScience*, 50(9): 753–765.

White J L, Knapp A K, Kelly E F. 2008. Increasing precipitation event size increases aboveground net primary productivity in a semi-arid grassland. *Oecologia*, 158(1): 129–140.

WMO, ICSU. 1990. The Global Precipitation Climatology Project Implementation and data management plan. [2022-08-17]. https://library.wmo.int/index.php?lvl=notice_{display}&id=11757

Worqlul A W, Collick A S, Tilahun S A, et al. 2015. Comparing TRMM 3B42, CFSR and ground-based rainfall estimates as input for hydrological models, in data scarce regions: the Upper Blue Nile Basin, Ethiopia. *Hydrology and Earth System Sciences Discussions*, 12(2): 2081–2112.

Yang H S, Dobermann A, Lindquist J L, et al. 2004. Hybrid-maize A maize simulation model that combines two crop modeling approaches. *Field Crops Research*, 87(2–3): 131–154.

Yao T, Xue Y, Chen D, et al. 2019. Recent third pole's rapid warming accompanies cryospheric melt and water cycle intensification and interactions between monsoon and environment: Multidisciplinary approach with observations, modeling, and analysis. *Bulletin of the American Meteorological Society*, 100(3): 423–444.

Zhu X, Xu K, Liu Y, et al. 2021. Assessing the vulnerability and risk of maize to drought in China based on the AquaCrop model. *Agricultural Systems*, 189: 103040, doi: 10.1016/j.agsy.2020.103040.

Note: Figure translations are in progress. See original paper for figures.