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Assessment of the effect of precipitation, temperature and potential evapotranspiration of GLDAS model on the outputs of AquaCrop model

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Abstract

Remote sensing (RS) technology can be effective in many agricultural activities due to the associated valuable features such as the ability to take multi-time and multi-spectral images, the ability to distinguish between time and radiometry, and a wide and integrated view of the area. The RS technology also could help to estimate the actual evapotranspiration and to investigate the crop water productivity. In this study, the effect of precipitation, temperature and potential evapotranspiration of the GLDAS model on the outputs of Aqua Crop model in Qazvin synoptic station for two wheat and maize products from 1979 to 2013 have been investigated. Also, the parameters of GLDAS model, the precipitation during 1979-2015 and the evapotranspiration during 1979-2013 were examined. The Penman Monteith method was used to compute the potential evapotranspiration of Qazvin station. The results of the GLDAS model, the precipitation model data and station data, R^2 = 0.97 and NRMSE = 0.38 show that there is a high determination coefficient between these two data sets. The statistical results show R^2 = 0.99 and NRMSE = 0.10 between the evapotranspiration data obtained from the GLDAS model and station data. The results of the statistical evaluation of the outputs of Aqua Crop model, Qazvin station data and the GLDAS model for maize and wheat products showed that the model is more accurate in biomass and yield according to the RMSE and NRMSE indices.

Keywords: AquaCrop Model; Evapotranspiration; GLDAS Model; Precipitation; Water Productivity

INTRODUCTION

Precipitation is one of the most important and variable climatic parameters that changes drastically in the context of time and place. Iran, as an arid and semi-arid country in the Asian region, has an average rainfall of 240 mm per year, which is less than one third of the world average of 860 mm (Safavi, 2006). The agricultural sector, with the consumption of more than 90% of water resources, is the largest and most important consumer of water in the country. Water scarcity is one of the main limitations of agricultural production and consumption management in the agricultural sector that is becoming more necessary due to the increasing population and limited water resources.

Simulation models use a range of plant and environmental parameters to simulate the crop growth and must be calibrated and evaluated before use. One of the newest plant growth simulation models is the Aqua crop model, developed by the FAO experts. The purpose of this model is to create a balance between accuracy, simplicity and ease of use for end users such as the experts and managers of the water organization and economists and policy makers of water resources management who need the simple models to design and analyze different scenarios. The first plant selected for simulation and testing in the Aqua Crop model was maize. The Aqua Crop model was evaluated using the experimental data from six crops season on maize at the University of California and showed that biomass and

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yield were simulated with varying the accuracy under different plant density, planting date and water requirements (Hsiao *et al*., 2009). Alizadeh *et al*. (2010) studied the the efficiency of Aqua Crop model for wheat in Karaj region for 7 and 14-day irrigation periods. The results of this study showed that the model had a good capability in predicting grain yield, water use efficiency, but with increasing the irrigation cycle to 14 days, the accuracy of the model decreased. Rahimi Khob *et al*. (2013) evaluated the Aqua Crop model for forage maize in Qazvin and reported that this model provides the acceptable results for predicting forage maize yield.

Using satellite imagery and remote sensing techniques, a wide range of projects can be completed globally, regionally, nationally, provincially and locally with less cost and time. In addition, the ability to retrieve satellite data at intervals of several hours to several days during the month or year, has made it possible to study changes and monitor terrestrial phenomena. Agricultural and natural resource studies, desertification monitoring, flood degradation, drought, sea and lake water changes, climate change, soil and air pollution, urban and residential changes are considered as tools for accurate management such that many of these studies can be done with satellite information.

The Ground System Information System (GLDAS) model is one of the most up-to-date models based on remote sensing in estimating water balance components. The purpose of this model is to combine the satellite and terrestrial data products, using the advanced surface modeling and simulation techniques in order to achieve the optimal ground state and flow. The model was created by four groups of scientists from the National Aeronautics and Space Administration (NASA), the Goddard Space Flight Center (GSFC), the National Oceanic and Atmospheric Administration (NOAA) and the National Center for Environmental Prediction (NCEP). Using four land surface models (CLM, Mosaic, VIC) and Noah), the system simulates the land surface parameters such as soil moisture and surface temperature and fluxes such as evaporation and sensible heat flux (Rodell *et al*., 2004).

GLDAS uses ground-level (LSM) models that are developed to simulate water-energy exchange processes between the atmosphere and soil. These conceptual models are generally in the category of distributional models and are used to simulate the balance of water and energy at large spatial scales. The LSM models with components such as energy exchange simulator, hydrology, biological processes and carbon cycle are able to provide the appropriate analyzes of water changes on the earth's surface.

The GLDAS model is generated by the offline models, integrating large volumes of observational data, and the Earth Information System (LIS) with a resolution of 0.25 to 1 (Kumar *et al*., 2006).

The Global Surface Information System (GLDAS) model is one of the models that many researchers around the world have studied so far. Bi *et al*. (2016) by examining soil moisture data obtained from the GLDAS model and observational data showed that the LSM model had a more accurate estimate of soil moisture than the Mosaic model on the plateau. Also in this plateau, the GLDAS-2 model has shown a lower efficiency than GLDAS-1 model (Bi *et al*., 2016). Davitt (2011) examined the relationship between evaporation and precipitation from the GLDAS model for a study of climate change and drought in the Plate River Basin. The results showed a significant relationship between these two parameters (Davitt, 2011). Seyyedi *et al*. (2014) obtained the rainfall from runoff simulation at the time of flooding by GLDAS and TRMM in a river basin of the United States from 2002 to 2011 and obtained the acceptable results (Seyyedi *et al*., 2014). Pelroudi Moghadam *et al*. (2015) studied the precipitation and runoff changes using the GLDAS model in Dosti

Dam basin. The results of data analysis showed that in the east and southeast of the study basin, the correlation coefficient between the precipitation and runoff is weaker than the other areas. Wang *et al*. (2011) evaluated the GLDAS / Noah model in the Songhua Basin in China from 2000 to 2006. Based on the comparison between the GLDAS model data and ground observations, a correlation coefficient of 0.76 was obtained for the precipitation parameter and 0.99 for the near-surface air temperature parameter, which indicates the validity of the GLDAS model data for using in water and energy balance (Wang *et al*., 2011).

In this study, the effect of precipitation, temperature and evapotranspiration of the GLDAS model on the outputs of Aqua Crop model for two products of maize and wheat in Qazvin station has been investigated.

MATERIALS AND METHODS

Area of study

Qazvin province with an area of 15821 square kilometers is located between the longitude of 48 degrees and 53 minutes and 36 degrees and 50 minutes and the latitude of 50 degrees and 35 minutes and 35 degrees and 18 minutes in the central region of Iran, respectively.The location of Qazvin province is shown in Figure 1. The average annual precipitation in the province varies from 210 mm in the eastern parts to more than 550 mm in the northeastern heights. In this study, the data from Qazvin synoptic station have been used .The longitude of this station is 50.03 and the latitude is 36.15 and the asssociated height is 1279.2 m.

Receiving and processing the data

Potential evapotranspiration (W m^{-2}) and precipitation (Kg m^{-2} s^{-1}) data from the monthly products of GLDAS-2.0 and the profile soil moisture (Kg m^{-2}) data from the daily products of GLDAS-2.0 were received from Giovanni site for the period 1979 to 2015. For conversion of kg m^{-2} to mm, the coefficient of 10000/1000 and for the conversion of seconds to months, the coefficient of 86400, the number of days per month, was used and the unit of precipitation data was mm/month. A coefficient of 0.035 was used to convert W m^{-2} to mm/day .To convert the potential evaporation to the evapotranspiration of the reference plant, the evaporation pan method and Equation 1 were used.

$$ET_0 = K_{pan} \times E_{pan} \quad (1)$$

In this equation, ET_0 is the evapotranspiration of the reference plant, K_{pan} is the coefficient of the pan and E_{pan} is the amount of evaporation from the pan .The coefficient of the pan depends on the location of the pan and its surroundings and the value varies between 0.5 to 0.85 (Alizadeh, 2010).

Fig. 1. Location of the study area

In this study, a pan coefficient of 0.5 was used to convert the potential evaporation to evapotranspiration of the reference plant. Because there is no the maximum and minimum daily temperature in the GLDAS products, the average daily air temperature for the period 1979 to 2015 was received from the site and then the maximum and minimum temperature of each month were considered .The unit of temperature data was Kelvin, which was converted to the Celsius degrees.

Introducing the Aqua Crop model

The basis for estimating crop performance in the Aqua Crop model is the Doorenbos-Kassam relationship, which is presented in issue 33 of the Food and Drainage Journal of the World Food Organization (FAO). Modifications such as the separation of the actual evapotranspiration (ET) to the evaporation from soil surface (Es) and the transpiration (Ts), as well as yield to biomass (B) and harvest index (HI) have been inferred (Raes *et al*., 2012):

$$\left(1-\frac{Y}{Y_x}\right)=K_y\left(1-\frac{ET}{ET_x}\right) \quad (2)$$

Where Y_x is the maximum yield, Y is the actual yield, ETx is the maximum evapotranspiration, ET is the actual evapotranspiration, and Ky is the ratio between the relative decrease in yield and the relative decrease in evapotranspiration. To calculate the performance of biomass, the Aqua Crop model uses the following equation (Resa *et al*., 2012):

$$Y = f_{HI} \times HI_0 \times B \quad (3)$$

Where HI_0 is the reference harvest index (during the physiological maturity stage), Y is the grain yield, f_{HI} is the coefficient that regulates the reference harvest index.

The model inputs include four categories of meteorological, plant, managerial, and soil information. Table 1 shows the required data for each section (Golabi and Naseri, 2015).

GLDAS model

In the study of global hydrology, climate and carbon cycle, hydrological variables are of particular importance. However, generating this data on a global scale is still a major challenge. The purpose of the Earth Data Collection System (LDAS) is to integrate the satellite data and ground observational data using the advanced surface models and data collection techniques to provide the input hydrological variables to the hydrological and climatic models and to facilitate modeling and pre-modeling. The GLDAS data is generated within the framework of the Land Information System (LIS) software for land surface modeling. The LIS was developed by the Hydrological Science Subgroup at NASA's Goddard Space Flight Center (GSFC). The GLDAS model is supported by NASA's Energy and Water Cycle Studies (NEWS) .To date, GLDAS has generated the spatial and temporal surface data for nearly 40 years (1979 until now).

Table 1. Aqua Crop model input data

Aqua Crop model inputs			
Soil data	**Management data**	**Crop data**	**Climate data**
Soil profile	Irrigation management	Fixed parameters	Precipitation
Groundwater	Field management	User specific parameters	Temperature min
			Temperature max
			Daily evapotranspiration of the reference plant (ET_0)
			Concentration of carbon dioxide in the atmosphere (CO_2)

GLDAS2 model

Model GLDAS-2 is an updated version of Model GLDAS-1 .Currently only the GLDAS-2 model is available on NASA's Giovanni site. The time resolution of GLDAS-2 products is 3 hours. Monthly products are produced by averaging the time of 3-hour products. The basic specifications of the GLDAS-2 model are shown in Table 2.

The GLDAS-2 model data for the early years of simulation (January 1, 1948) were simulated using soil moisture data and the other LSM climatology model parameters. Princeton University global meteorological data are also used as the model input data (Sheffield *et al*., 2006). The model uses the GLDAS General Database for Groundwater Mask (MOD44W: Carroll *et al*., 2009), a combination of GTOPO30 for height, Modified IGBP MODIS 20-category vegetation, and the Hybrid STATSG0 / FAO dataset for soil texture. The ground level parameters of the MODIS satellite have been used in recent versions of GLDAS-2 and GLDAS-2.1 products .While in the GLDAS-1 version and the older versions of GLDAS-2 products (before October 2012), the basic parameters of the AVHRR satellite were used.

GLDAS-2.1 simulation started in January 2000 using the GLDAS-2 simulation conditions. In this simulation, the National Oceanic and Atmospheric Administration (NOAA) and the Global Land Information System (GDAS) for atmospheric analysis, from the Global Climate Rainfall Project Database (GPCP), for precipitation analysis (Adler *et al*., 2003) and finally, the Air Meteorological Agency (AGRMET) AgriculturalMmeteorological Modeling System has been used for the radiation analysis.

Differences between GLDAS-1 and GLDAS-2

GLDAS-1 input data sources have changed several times since 1979 until now. As a result, due to the unreliable input data, an abnormal trend is created in the model output. More information on GLDAS-1 input data is available at http://ldas.gsfc.nasa.gov/gldas/GLDASforcing.php.

GLDAS-2 includes two models GLDAS2.0 and GLDAS2.1. The main purpose of GLDAS2.0 is to use Princeton University Global Meteorological Database to generate reliable climatological data, which currently covers the years 1948 to 2010. GLDAS2.1 is similar to the GLDAS-1 model except that it uses the updated hybrid data, GDAS, GPCP, and the AGMET radiation dataset.

Table 2. Basic specifications of the GLDAS-2 model

Specifications	Contents
-60° تا 90°N	Latitude range
-180° Eتا 180°E	Longitude range
$0.25^{\circ} - 1^{\circ}$	Spatial resolution
3 hours - monthly	Temporal resolution
GLDAS-2.0: 1 January 1948 to 31 December 2010 GLDAS-2.1: January 1, 2000 to date - 1 degree February 24, 2000 to date - 0.25 degrees	Time coverage
360) lon× (150) lat (for 1 degree 1440) lon× (600) lat (for 0.25 degree	Dimensions
(179.5W,59.5S) for 1 degree (179.875W,59.875S) for 0.25 degree	Origin(1st frig center)
NOAH3.3	Land surface models

The GLDAS-2.0 model data is available for the years 1948 to 2010, while GLDAS-2.1 model data from 2000 to now is available with a one-month delay and is updated monthly (Faraji and Kaviani, 2019).

Differences between GLDAS-1 and GLDAS-2.1

The GLDAS-2.1 model has been developed as a replacement for the GLDAS-1 model. The main purpose of GLDAS-2.1 is to provide the up-to-date outputs from the global surface model using the observational data in order to maintain the long-term trend of climate change as much as possible. There were two major issues with GLDAS-1 that were fixed in GLDAS-2. First, the abnormal gradient lines were seen in the Northern Hemisphere in the long wavelength flux entering the Earth estimated by the AGRMET software, which was the main cause of error in this data in the certain years, and second, a significant change in precipitation data in place. There was something special that started in 2009. In addition, the comparison of GLDAS-1 radiation and precipitation has shown that its radiation data compared to accurate the surface radiation balance (SRB) databases, high systematic error (Stackhouse *et al*., 2011) and GLDAS-1 precipitation data compared to the precipitation database (GPCP) that has a small systematic error. The systematic errors listed in the GLDAS-2 version have been corrected using the SRB database for the radiation product and the the GPCP database and the TRMM satellite for the precipitation product (Faraji and Kaviani, 2019). Product specifications of GLDAS-2 model are shown in Table 3.

Statistical evaluation criteria

In this study, the results of GLDAS model with Qazvin station data for two maize and wheat products, by error statistical criteria including Determination Coefficient (R^2), root mean square error (RMSE), normal square root mean square error (NRMSE), Mean absolute error (MAE), mean bias error (MBE) and efficiency modeling (EF) were compared.

Explanation coefficient is one of the most important criteria for evaluating the relationship between two variables x and y, which is displayed dimensionless. This coefficient is directly related to the correlation coefficient. In this way, by taking the square root of the Determination Coefficient, the correlation coefficient between the two series can be obtained. As with the correlation coefficient, the closer the value of the Determination Coefficient is to one, the stronger the relationship between the two variables. If the Determination Coefficient is multiplied

Table 3. Short name, description and unit of each GLDAS-2 model products

Short name	Description	Unit
Evap_tavg	Evapotranspiration	kg m-2 s-1
Qs_acc	Surface runoff	kg m-2
Qsb_acc	Subsurface runoff	kg m-2
SoilMoi0_10cm_inst	Soil moisture (0-10 cm)	kg m-2
SoilMoi10_40cm_inst	Soil moisture (40-10 cm)	kg m-2
SoilMoi40_100cm_inst	Soil moisture (40-100 cm)	kg m-2
SoilMoi100_200cm_inst	Soil moisture (100-200 cm)	kg m-2
SoilTMP0_10cm_inst	Soil temperature (0-10 cm)	K
SoilTMP10_40cm_inst	Soil temperature (10-40 cm)	K
SoilTMP40_100cm_inst	Soil temperature (40-100 cm)	K
SoilTMP100_200cm_inst	Soil temperature (100-200 cm)	K
PotEvap_tavg	The rate of potential evaporation	W m-2
RootMoist_inst	Root zone soil moisture	kg m-2
Rainf_f_tavg	Total precipitation (total rain and snow)	kg m-2 s-1
Tair_f_inst	Air temperature	K

by 100, the value obtained represents the percentage of variance of the variable x, which is described by the variable y Excel software was used to calculate the explanation coefficient.

Error root mean square which is shown like Equation 4 is usually used for accuracy prediction evaluation of one model against the observations. This statistic criterion shows the model variance error in prediction of real amounts. Therefore, the closer to 0 for the amount of this statistic, the model has the less errors in prediction of observational amounts.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{4}$$

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{5}$$

The NRMSE index indicates the level of estimation .The NRMSE classification by Jameson *et al*. (1991) is given in Table 4.

Table 4. Classification of simulation results based on NRMSE

NRMSE	0-10	10-20	20-30	>30
Estimation result	Excellent	Good	Average	Weak

Efficiency Modeling (EF) shows the partial greatness of remained variances in comparison with the data variances. Therefore, the amount of EF is equal to one if the remained variance is equal to the observational data variance. On the other hand, if the amount of EF is equal to 0 or go towards the negative then the mean of observations show a better prediction of the model (Raziei and Pereira, 2013). EM is dimensionless and the amount is between -∞ and +1. The minus amounts of EM show very little accuracy of this model in prediction of the observational amounts and the closer it is to +1, the more accurate is the model.

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{6}$$

Equation 7 is a biased statistic and causes the model performance in over-estimation or lower-estimation If The biased amount would be equal to zero, it shows that the model can predict properly. Moreover, the positive and negative amounts show over-estimation and lower-estimation, respectively.

$$MBE = \frac{\sum_{i=1}^{n} P_i - O_i}{n} \tag{7}$$

Mean absolute error is the difference of mean absolute value of the estimated amount of the model to the actual quantity. The less is its amount, the more is model's accuracy.

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \tag{8}$$

O_i and P_i are the observational and predicted amount, $\bar{O}$ is the mean of the observed amounts and n is the number of data or duration time series.

RESULTS AND DISCUSSION

The results of statistical evaluation of the GLDAS precipitation data with Qazvin synoptic station are given in Table 5.

Statistical evaluation shows that the highest Determination Coefficient was 0.97 in 1987 and 1996 and the lowest was 0.01 in 1992. Determination Coefficient greater than 0.80 in some years shows that more than 80% of the variance in the precipitation data of this station is described by the GLDAS data. The highest value for the EF statistic was 0.92 in 2008. Despite the high power of GLDAS, in the acceptable forecast of precipitation in some years, the very low amount of EF in some years indicates the disability of the model to predict the precipitation in these years. The results of MBE statistics show that the GLDAS model has been underestimated in most of the years under study. The highest MAE statistics was 45.7 mm/month in 1992 and the lowest was 4.83 mm/month in 1995. The maximum value for RMSE was 73.42 mm/month in 1992, the lowest value was 5.95 mm / month in 2008, the highest value was 1.12 NRMSE in 1994 and the lowest value was 0.3 mm in 2002.

Table 5. Statistical evaluation of total monthly precipitation of the GLDAS model with Qazvin synoptic station (mm / month)

NRMSE	RMSE	MAE	MBE	EF	R^2	Year
0.35	8.03	6.28	1.21	0.90	0.92	1979
0.44	11.73	7.93	-4.03	0.82	0.91	1980
0.63	17.28	13.19	-1.36	0.48	0.50	1981
0.42	17.52	10.80	-5.95	0.70	0.75	1982
0.40	9.35	6.72	-0.79	0.77	0.77	1983
0.41	14.99	9.96	-6.18	0.79	0.87	1984
0.40	8.18	5.98	-1.15	0.84	0.91	1985
0.41	10.49	7.89	0.84	0.73	0.73	1986
0.38	12.78	8.50	-6.23	0.89	0.97	1987
0.51	14.99	12.25	-3.07	0.76	0.85	1988
0.38	8.30	5.12	-2.49	0.89	0.96	1989
0.64	14.02	8.07	-0.03	0.63	0.65	1990
0.53	15.48	8.64	-5.03	0.84	0.92	1991
1.00	73.42	45.70	-39.17	-0.60	0.01	1992
0.82	32.08	18.08	-10.64	0.26	0.34	1993
1.12	42.28	19.58	-12.20	0.30	0.50	1994
0.34	6.08	4.83	-0.46	0.91	0.91	1995
0.51	19.37	12.06	-5.23	0.86	0.97	1996
0.42	7.18	5.68	1.69	0.86	0.93	1997
0.37	9.88	8.26	-1.93	0.86	0.95	1998
0.50	10.16	8.02	0.45	0.63	0.56	1999
0.40	10.09	7.09	-3.26	0.84	0.90	2000
0.69	12.92	11.00	0.60	0.43	0.37	2001
0.30	8.40	6.70	-3.62	0.93	0.96	2002
0.62	20.84	13.31	-2.25	0.53	0.55	2003
0.36	9.77	7.34	1.42	0.87	0.86	2004
0.79	18.63	13.41	2.77	0.37	0.39	2005
0.73	21.68	16.57	-3.97	0.53	0.54	2006
0.51	13.70	9.07	0.44	0.69	0.80	2007
0.46	5.95	4.56	1.71	0.92	0.88	2008
0.53	12.95	9.18	2.27	0.78	0.75	2009
0.37	10.86	7.77	-5.40	0.90	0.93	2010
0.70	27.33	19.56	-12.37	0.14	0.26	2011
0.48	12.03	9.43	1.15	0.65	0.45	2012
0.51	12.91	9.70	-1.96	0.69	0.71	2013
0.66	10.68	8.72	4.35	0.73	0.72	2014
0.86	20.87	15.95	14.98	0.34	0.73	2015

The results of statistical evaluation of the GLDAS evapotranspiration data with Qazvin synoptic station are shown in Table 6. The evapotranspiration of Qazvin synoptic station was calculated by FAO Penman-Mantith method and for GLDAS, the potential evaporation was converted from evaporation pan method to the plant evapotranspiration and then evaluated by evapotranspiration of Qazvin synoptic station.

Table 6. Statistical evaluation of total evapotranspiration of the GLDAS model with Qazvin synoptic station (mm / month)

NRMSE	RMSE	MAE	MBE	EF	R^2	Year
0.23	29.15	22.99	-21.44	0.84	0.95	1979
0.31	43.33	33.79	-30.03	0.79	0.97	1980
0.15	17.14	14.07	-12.76	0.92	0.98	1981
0.33	40.94	32.87	-26.12	0.79	0.97	1982
0.26	30.83	26.26	-16.35	0.85	0.96	1983
0.20	22.03	18.26	-13.60	0.92	0.97	1984
0.26	32.12	23.77	-20.34	0.84	0.97	1985
0.25	28.96	23.04	-18.15	0.85	0.96	1986
0.26	30.60	22.37	-15.09	0.84	0.93	1987
0.24	28.40	24.33	-16.50	0.85	0.98	1988
0.25	30.83	26.25	-19.66	0.85	0.97	1989
0.28	34.36	28.53	-18.62	0.81	0.94	1990
0.17	19.04	16.43	-11.92	0.93	0.98	1991
0.19	19.77	15.46	-6.92	0.91	0.95	1992
0.19	19.92	17.81	-7.16	0.92	0.97	1993
0.17	17.66	14.93	-5.26	0.93	0.95	1994
0.16	19.50	18.12	-2.55	0.92	0.94	1995
0.11	12.41	10.24	-3.14	0.96	0.97	1996
0.14	16.59	14.78	-3.32	0.95	0.98	1997
0.11	12.90	10.39	1.48	0.96	0.97	1998
0.12	13.48	10.77	5.45	0.96	0.97	1999
0.11	12.62	11.51	-2.66	0.97	0.98	2000
0.11	13.21	11.10	4.81	0.96	0.97	2001
0.12	14.53	12.25	2.19	0.96	0.98	2002
0.11	12.57	11.33	2.34	0.97	0.98	2003
0.11	13.62	11.66	1.78	0.97	0.98	2004
0.11	13.57	11.28	-0.73	0.97	0.97	2005
0.10	12.98	11.67	0.79	0.97	0.99	2006
0.10	10.96	8.52	1.99	0.97	0.98	2007
0.14	17.51	13.77	-6.92	0.95	0.96	2008
0.25	34.89	27.76	-23.78	0.82	0.99	2009
0.23	31.88	25.77	-21.00	0.85	0.98	2010
0.23	29.49	23.39	-21.66	0.88	0.99	2011
0.24	32.69	26.29	-24.28	0.84	0.98	2012
0.27	39.57	31.92	-28.06	0.77	0.98	2013

Statistical evaluation shows that the highest Determination Coefficient was 0.99 in 2006, 2009, 2011 and 2004 and the lowest was 0.93 in 198. Determination Coefficient greater than 0.90 in some years indicates that more than 90% of the variance in the transpiration-evaporation data of this station is described by the GLDAS data. The highest value for the EF statistics was 0.97 and the lowest value was 0.77 in 2013. The results of MBE statistics show that the GLDAS model has been underestimated in most of the years studied. The highest MAE was 33.79 mm/month in 1980 and the lowest was 8.52 mm/month in 2007. The highest value for RMSE was 43.33 mm/month in 1980 and the lowest value was 10.96 mm/month in 2007 and the highest value of NRMSE was 0.33 in 1982 and the lowest value was 0.10 in 2006 and 2007.

Faraji *et al*. (2018) stated Determination Coefficient 0.82 for the total monthly precipitation of the GLDAS model and Qazvin station during 1995 to 2005. Also, for the evapotranspiration from lysimeter of Ismail Abad station in Qazvin and GLDAS during 1979 to 2003 have been reported Determination Coefficient of 0.95 .The results of Moiwo *et al*. (2012) research also show that the GLDAS transpiration-evaporation with lysimeter transpiration-evaporation data, at best, shows that Determination Coefficient would be 0.92 and RMSE, 0.4.

For the input data of the Aqua Crop model, in the climatic section, the data of precipitation, temperature and evapotranspiration of Qazvin synoptic station and the GLDAS model separately, in the plant part of the model from the data of two wheat and maize, the FAO products from 1979 to 2013 and in other parts from Qazvin station information was used Profile soil moisture of the GLDAS model were evaluated with the Aqua Crop model output of Qazvin station data.

The results of statistical evaluation of the outputs of Aqua Crop model, Qazvin station data and the GLDAS model for maize and wheat products are presented in Tables 7 and 8.

As can be seen in Tables 7 and 8, there is no correlation between Qazvin station data and the GLDAS model and the highest correlation is between the results related to the water requirement for wheat crop. The results show that the model is not accurate enough in estimating evapotranspiration, profile soil moisture and water requirement. The model has a better accuracy for product and biomass performance according to the RMSE and NRMSE indices .Evapotranspiration may be one of the reasons why the model failed to evaluate well. Because GLDAS calculates the potential evaporation, but in Penman-Monteith method, potential transpiration evaporation is calculated.

CONCLUSION

Due to problems such as human error, financial issues, lack of access to all areas and weather problems that exist in the recording of meteorological data, the need for the models that solve the mentioned problems by remote sensing techniques and timely data and to provide for the users accuratly is undeniable. The GLDAS surface model is an important source of information for global water cycle research. In the present study, the precipitation data of the GLDAS model were evaluated with the data of Qazvin station during 1979-2015. Statistical evaluation showed that the GLDAS model has had the good results in some years. Evaporation data the potential of the GLDAS model was converted to the evapotranspiration of the reference plant by evaporation pan method and then evaluated by evapotranspiration data of Qazvin station obtained by FAO Penman-

Table 7. Statistical evaluation of Qazvin station data and the GLDAS model of maize

MAE	MBE	RMSE	NRMSE	EF	R^2	
1.20	0.088	2.238	0.189	-64.405	0.0004	Yield
1.960	0.766	2.369	0.096	-15.729	0.009	Biomass
96.353	-87.235	138.154	0.306	-1.767	0.004	Net irrigation requirement
561.470	550	590.954	0.731	-93.941	0.149	ET_0
413.455	413.455	420.607	0.887	-30.07	0.004	Profile soil moisture

Table 8. Statistical evaluation of Qazvin station data and the GLDAS model of wheat

MAE	MBE	RMSE	NRMSE	EF	R^2	
0.784	-0.749	0.952	0.127	-1.193	0.045	Yield
1.672	-1.609	2.02	0.129	-2.067	0.06	Biomass
166.882	155.764	189.738	0.433	-3.675	0.032	Net irrigation requirement
221.264	217.5	248.547	0.322	-15.01	0.0037	ET_0
152.796	150.572	175.967	0.238	-2.637	0.029	Profile soil moisture

Monteith method during 1979-2013. Statistical evaluation showed that the GLDAS model has had the good results in most years. In this study, the effect of precipitation, temperature and evapotranspiration o fthe GLDAS model on the outputs of Aqua Crop model for two crops of maize and wheat in Qazvin station were evaluated. The results showed that the model does not have a good accuracy. For a more accurate evaluation, it is recommended that more stations should be considered in different climates to achieve the better results. You can also evaluate more products. Due to the fact that the GLDAS model data is updated and modified on a monthly basis, so it is recommended to conduct the present study once every 6 months before using the GLDAS surface model data.

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