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SPATIAL SIMULATION OF RICE GRAIN YIELDS BY EMPIRICAL MODELS

Najmeh Koolaeian[1], Ebrahim Amiri[2*], Ebrahim Pazira[1]

[1]Department of Soil Science, Faculty of Agriculture and Natural Resources, Science and Research Branch, Islamic Azad University, Tehran, Iran

[2]Department of Water Engineering, Lahijan Branch, Islamic Azad University, Lahijan, Iran

[*]Corresponding author. E-mail: eamiri57@yahoo.com

ABSTRACT

Rice grain yields can be affected by several parameters including mostly the climate, cultivars, soil types, and the fertilizer managements. In this study, the performance of two empirical models i.e. AquaCrop and artificial neural network models for simulating the grain yields of two most cultivated varieties including the Shirudi (high-yielding) and Tarom (low-yielding) in three contrasting soil series with different fertilizer managements, were calibrated and validated during 2016 and 2017 rice growing seasons for 459 paddy fields in Mazandaran province, northern Iran. Both models were tested by correlation (R^2), normalized root mean square error (nRMSE) and coefficient of residual mass (CRM). Results indicate that the performance of both models were affected by the rice cultivar, soil type and soil fertilizer management for both calibration and validation datasets. The ability of both models proved to be satisfactorily applicable for spatial simulation of rice yields in northern Iran, but AquaCrop model was superior. The higher accuracy was observed in AquaCrop for the Shirudi cultivar (R^2=0.89; nRMSE=5.87%; CRM=0.03) compared to the Tarom (R^2=0.67; nRMSE=10.41% and CRM=0.04) for 2017 dataset demonstrating that the AquaCrop has more performance for high-yielding cultivar. Two models had lower accuracy in Esmaeilkola soil series with deep clay soil texture. The best accuracy was observed in paddy fields with optimum fertilizer managements for both models. Overall, it is possible to suggest that AquaCrop model could be used to simulate the spatial distribution of rice grain yield with an acceptable accuracy at province-scale and is applicable for local climate change related scenarios.

Keywords: yield simulation, fertilizer management, paddy fields, crop productivity model.

INTRODUCTION

Rice is the most staple food for half of the world population which mainly lives in developing countries (Henry, 2013). There is a necessity of accurate simulation to understand the plant reaction to fertilizer, water management and climate change in different soils with inherent soil properties using plant growth simulation models. Application of computer simulating models for rice growth can be helpful for determining the rice yields at province-scale. The simulation of plant growth stages and crop yield make better management for decision makers at large-scale management planning (Farshi et al., 1987). The AquaCrop model is developed by the Food and Agriculture Organization (FAO) as a water-driven model (Farahani et al., 2009). It has been evaluated to simulate water balance and soluble material in a cultivated soil at different bordered conditions including diverse irrigation management from deficit to sufficient which shows good results compared to field measurements (Singh et al., 2008; Foster et al., 2017). AquaCrop model needs less input parameters to simulate crop reaction to water utilization compared to other simulating models (Amiri, 2016). AquaCrop model has been used for simulating many agricultural crops yields such as rice (Xu et al., 2019), soybeans, cotton (Tsakmakis et al., 2018), maize (Rugimbana, 2019), wheat (Emdad et al., 2018) and canola (Zeleke et al., 2011). The AquaCrop parameterization is site-specific and the calibrated variables must be restructured for each experimental site (Farahani et al., 2009). Therefore, site-specifically parameterization of a simulation model with local conditions is prerequisite before using as simulative tools for large-scale implementation. The performance

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of AquaCrop can be affected by fertilizer nitrogen (N) management (Amiri et al., 2014; Amiri, 2016; Babel et al., 2019) and crop genotypes (Seyed Raoufi et al., 2018). The artificial neural networks (ANN) stand out among the different types of models by the calculative techniques with mathematical models simulated form the human's brain neural formation (Abrougui et al., 2019). The ANN as vigorous data-modeling tools attain knowledge by way of experience, becoming able to detect patterns and draw results, therefore can be used for simulation of the rice grain yields. The ability for handling and modeling multiple outputs simultaneously are the main benefits of ANN techniques (Ochoa-Martínez and Ayala-Aponte, 2007). The Mazandaran province is the most important region for the rice production and provide about 50% of rice demand in Iran. The decision makers often need a reliable model for spatial simulation of rice grain yield at province-scale for long and short-term policy programs. There is not still an acceptable model for rice grain yield simulation in Mazandaran province. Therefore, the main objective of this study was to test the performance of AquaCrop and ANN models for spatial simulation of the rice grain yields in paddy fields of Mazandaran province as affected by cultivars, soil types and the fertilizer management within 2016 and 2017.

MATERIAL AND METHODS

Description of the study area

This study was conducted in the Sari city of the Mazandaran province, northern Iran. The paddy fields are the most common agricultural land use in Mazandaran province with total areas of about 210,000 ha. The mean annual precipitation and temperature are 725 mm and 17.3°C, respectively. The different rice cultivars are currently cultivated in the study area but two most common cultivars are the Tarom and Shirudi. Tarom cultivar is a local short-duration rice with low-yielding genotype, and, the Shirudi is an improved local rice with mid-duration and high-yielding genotype. Despite the low yields of Tarom cultivar (averaging 3.5 to 4.5 ton/ha), it is still of public interest due to the good quality, taste and smell which are similar to basmati types and are characterized by tall stature (120 to 130 cm), a weak culm and droopy leaves. The yearly growing season of the rice in the study area commence in April/May and terminate in August/September.

Sampling sites

The study area is located between 53°06´43´´E to 53°09´16´´E longitudes and 36°38´24´´N to 36°39´32´´N latitudes covering the area of 394 ha with mean elevation of 10 m (Figure 1). Three soil series namely Esmaeilkola, Borj and Afratakht in the study area were delineated (Figure 1). The USDA soil classification of the Esmaeilkola, Borj and Afratakht soil series were Typic Halaquepts, Typic Xerofluvents and Fluvaquentic Endoaquolls, respectively. Totally, 459 paddy fields were selected for this study. In brief, 160, 101 and 198 paddy fields were sampled in Esmaeilkola, Borj and Afratakht soil series, respectively. Some paddies were excluded as shown by × symptom (Figure 1) due to the inaccessibility, severe disease/insect infections and the cultivation of cultivars other than Tarom and Shirudi.

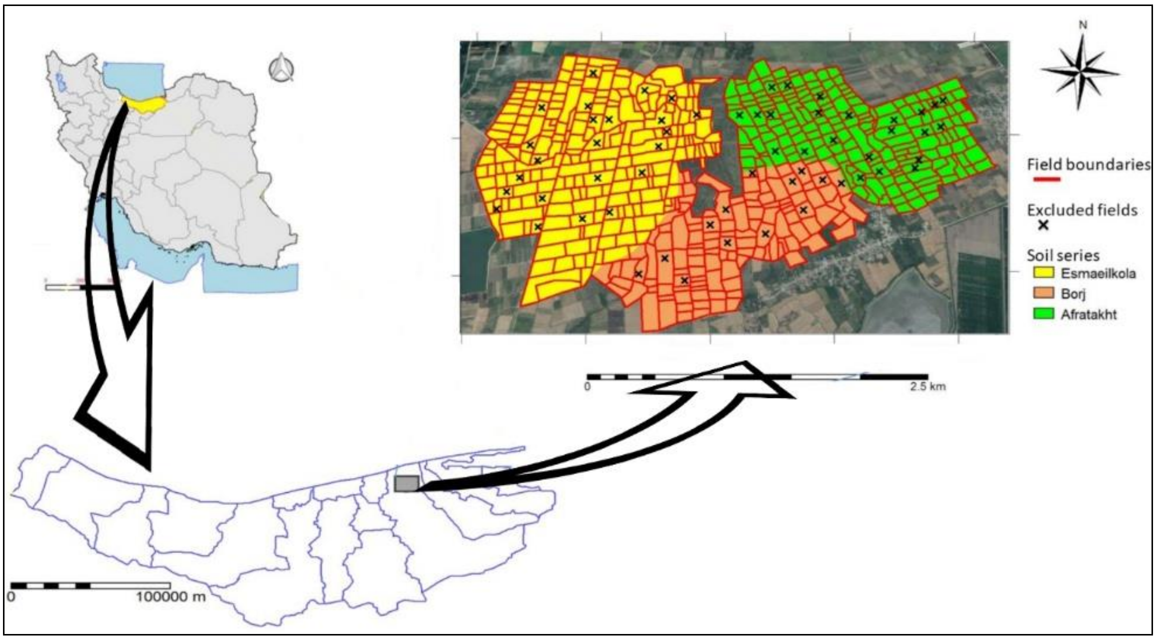

Figure 1. Geographic location of the study area in Mazandaran province (A) and the sampling paddy fields with delineated soil series (B). Red lines show the field boundaries and × indicate the excluded paddy fields.

Soil analysis

The soil composite samples were collected before field preparation from the topsoil, plow pan and subsoil layers in 459 sampling paddies for 2016 and 2017. Soil bulk density, pH and electrical conductivity (EC), organic carbon, total nitrogen (TN), sand, silt, clay, available phosphorous, available potassium were measured based on standard methods. The soil saturated hydraulic conductivity (K_{SAT}) were predicted by the Rosetta software based on the determined soil properties for each soil layers (Schaap et al., 2001).

Paddy fields description

The crop trials were conducted on 2×5 m^2 plots in each 459 paddy fields with triple replications for two successive growing season (2016 and 2017). The recommended N, P, K fertilizer rates were determined in each field according to the soil test results. The AquaCrop model does not consider a soil fertility management for modelling rice response (Van Gaelen et al., 2015). The soil fertility management can be described in the model as expected effect on rice biomass production. All paddies were divided into the three fertilizer management as low, medium and optimum according to the soil test results and their applied fertilizers. The "low fertilizer management" paddies correspond to those fields that received lower than 50% of recommended fertilizer rates that is considered in AquaCrop with 50% of potential biomass production. The paddy fields grouped as "medium fertilizer management" received 50 to 85% of recommended fertilizer rates, meanwhile, the fields that received 85% to 100% of recommended fertilizer rates grouped as "optimum fertilizer management". The medium and optimum fertilizer managements are considered in AquaCrop with 50 to 85 and 85 to 100% of potential biomass production, respectively. The fertilizer application rates of each fields in 2016 were repeated for 2017. All cultivars are grown under full irrigation with continuous standing water with no water stress and no severe disease/inset infections. The 25 to 35 days old seedlings of Tarom and Shirudi cultivars were transplanted at the density of 3 plants per hill on early May in 2016 and 2017 with a spacing of 20 cm×20 cm in each paddy rice field. The weeds, insects, and diseases were controlled by the hand weeding, rice stem borer and chemical spraying in all paddies. The harvest as grain yield at 14% moisture content was measured at physiological maturity in mid-august for both years within 2 m×2 m of each plot.

Climatic data

Daily weather data on maximum and minimum air temperatures and precipitation were collected for the entire growing seasons from Dashte-Naz synoptic weather station. The reference crop evapotranspiration (ET_0) calculator software was used for ET_0 estimation. The annual carbon dioxide (CO_2) concentration at the 385 ppm was set as the default.

AquaCrop model calibration

In this study we used the AquaCrop (version 6.1). AquaCrop is a process-based mechanistic crop model that simulates growth and yield of a range of herbaceous crops under different soil, weather and management conditions on a daily time step. In general, four simulation phases could be distinguished for a complete simulation process namely the simulation of the phenology and crop development, the crop transpiration, biomass production, and yield. The four major components of the AquaCrop including the soil physical and hydraulic properties, crop physiological and productivity (biomass production and harvestable yield), atmosphere (minimum and maximum temperature, precipitation, ET_0 and CO_2 concentration) and field fertilizer managements were needed for AquaCrop calibration in each field. The required soil physical and hydraulic properties for AquaCrop model were determined by consideration of three soil layers, soil texture, K_{SAT} and the depth of restrictive soil layer. In AquaCrop, grain yield is obtained by multiplying biomass by harvest index. In this model, the difference between the simulated and observed grain yields was minimized by using a trial and error approach. The remaining crop parameters were set as default values. The cultivar-specific parameters are affected by location, crop cultivar, the condition of the soil profile and management practices and must be specified separately. All calibrated crop parameters for Shirudi and Tarom cultivars are listed in Table 1.

Table 1. Calibrated crop parameters of rice Shiroudi and Tarom cultivar for AquaCrop model

Description	Shiroudi	Tarom	Units
Base temperature below which crop development does not progress	9	9	°C
GDDays: from transplanting to recovered transplant	100	90	°Cday
GDDays: from transplanting to maximum rooting depth	400	390	°Cday
GDDays: from transplanting to start senescence °C day	1105	1080	°Cday
GDDays: from transplanting to maturity °C day	1215	1150	°Cday
GDDays: from transplanting to flowering 814°C day	728	700	°Cday
GDDays: building up of Harvest Index during yield formation 550°C day	525	515	°Cday
Maximum rooting depth (m)	0.3	0.3	m
Total duration of flowering	16	15	Day
Initial canopy cover	C[1]	C[1]	%
Canopy growth coefficient (CGC)	C[1]	C[1]	%
Maximum canopy cover (CCx)	95	95	%
Canopy decline coefficient (CDC)	C[1]	C[1]	%
Water productivity	18	18	$g±m^2$
Physiological maturity	96	70	days
Harvest index (HI)	41	39	%

[1]: calibrated values

ANN model calibration

The ANN models are the easy to use algorithms without any pre-assumptions for modeling. The main three interconnected layers of the ANN are the input, hidden and output, respectively. In the present study, the multilayer feed-forward network was developed for simulation of grain yield. The back propagation neural network, which uses the Levenberg-Marquardt algorithm, is the simplest in terms of implementation and is also the most popular approach used for training neural networks. The back propagation is a type of supervised learning algorithm, which adjusts the weights and biases according to the target value(s). The back propagation starts by randomly selecting initial weights and then comparing the outputs with the given target value(s) to calculate the difference in mean square error. The errors are then back-propagated through the earlier layers via a negative gradient descent direction for adjusting the weights and bias until at least one stopping criteria is reached. The maximum number of epochs and the mean square error of the network output for each target were the two stopping criteria and were set as 500 and 0 in this study, respectively.

The back-propagation algorithm with multilayer feed-forward network was applied for training dataset in 2016 and its performance was tested for 2017 growing season. Feed-forward networks had one or higher hidden layers with sigmoid activation function. The output layer in this study had pure-line activation function. The input layer consists of neurons (datasets) that previously used as inputs for AquaCrop model. The input dataset consists the daily minimum and maximum temperature, precipitation, ET_0, CO_2 concentration, fertilization rates (N, P, K fertilizers), soil texture, K_{SAT}, depths to the hardpan layer and the crop parameters for calibration of ANN models for 2016 growing season for both cultivars. The output layer was grain yield as the response variable. The ANN methods were conducted by programming using MATLAB software.

Performance of AquaCrop and ANN models

In this regards, the calibrated AquaCrop and ANN approaches were subsequently tested for 2017 growing season with the same rice cultivar. The same crop parametrization in the calibration were used in the validation model for both AquaCrop and ANN models. The average of three replications were used for both calibrating and testing models. Three evaluation criteria including the coefficient of determination (R^2), normalized root mean square error (nRMSE) and coefficient of residual mass (CRM) were used for testing the performance of models. The Eqs. 1, 2 and 3 used for the calculation of three evaluation criteria.

$$R^2 = \left(\frac{\sum_{i=1}^{n}(Oi - O')(Pi - P')}{\sqrt{\sum_{i=1}^{n}(Oi - O')^2}\sqrt{\sum_{i=1}^{n}(Pi - P')^2}} \right)^2 \quad (1)$$

$$nRMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2} \times \frac{100}{\check{N}} \quad (2)$$

$$CRM = 1 - \frac{\sum_{i=1}^{n} Pi}{\sum_{i=1}^{n} Oi} \quad (3)$$

where, n is the number of fields (n=458); *Pi* and *Oi* are the simulated and observed grain yields in each field, and; *O´* and *P´* are the means for the observed and simulated grain yields. Ň is the mean of observed values in fields in 2017 growing season. The simulation models with the lowest nRMSE and CRM, and the highest R^2 value is determined as best simulation method. The nRMSE show the relative difference (%) of simulated versus observed grain yields for 2017 growing season. Based on Jamieson et al. (1991), the nRMSE value of less than 10% is considered as excellent simulation, while the values within 10 to 20% identified as good simulation. The nRMSE values within 20 to 30% show the fair simulation and the values higher than 30% are considered as poor simulation. The CRM show the over- or under-estimation of models. The negative and positive values indicate that the models overestimate and underestimate the observed data, respectively.

RESULTS AND DISCUSSION

Descriptive statistics for rice yields

The significant differences of grain yields in the studied paddies for 2016 growing season were observed (Figure 2). Unsurprisingly, the Shirudi cultivar have significant higher grain yields compared to the Tarom cultivar. There is a pronounced effect of soil fertilizer management on grain yields for both cultivars. The mean grain yields of Shirudi cultivar in Afratakht, Borj and Esmaeilkola soil series were 7972, 8248 and 8592 kg ha^{-1}, respectively, in optimum soil fertilizer management but the low soil fertilizer management led to the decreases of 17.7, 17.9 and 18.5%, respectively. In the Tarom cultivar, the effect of low input fertilizer let to the 17.3, 14 and 17.9% of decreases in grain yields when compared with optimum soil fertilizer management (Figure 2), respectively.

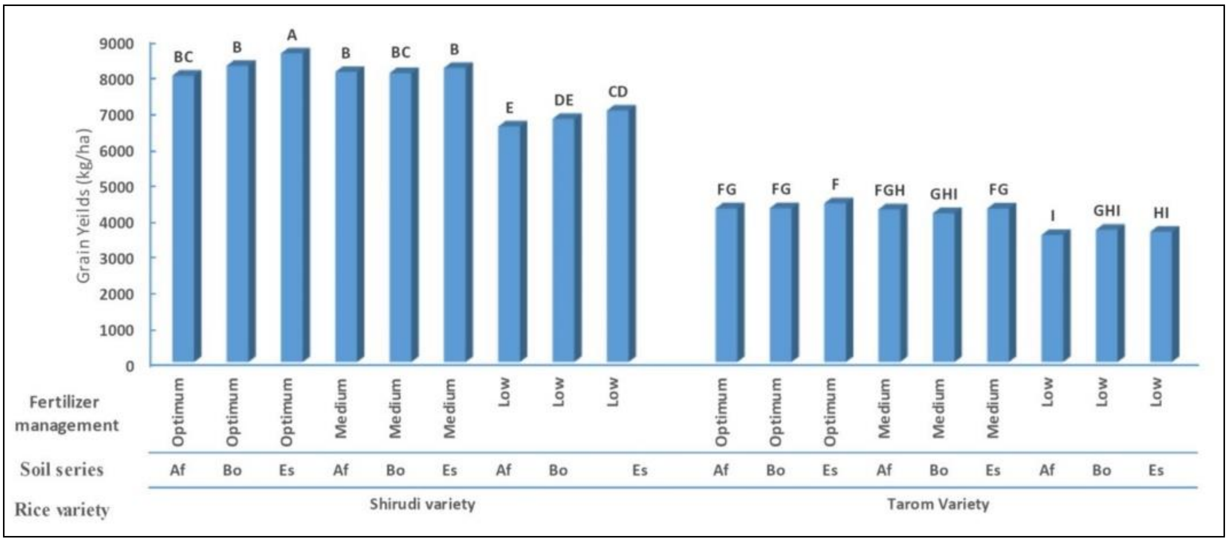

Figure 2. The means of grain yields for Shirudi and Tarom cultivars in different fertilizer management and soil types. The means followed by the same letter(s) in any column are not significantly different at 5% level of significance. Af: Afratakht soil series; Bo: Borj soil series and Es: Esmaeilkola soil series.

Overall performance of models

The scatterplots of the observed and the simulated grain yields by AquaCrop and ANN models were depicted (Figure 3). Results show that both models has high ability for simulation of rice grain yields. The one hidden layer with 25 neurons was the best structure of the ANN model. The AquaCrop had more proficiency for calibrating in 2016 dataset compared with ANN. The R^2, nRMSE and CRM statistics for calibration of the AquaCrop in 2016 dataset were 0.98, 5.97% and 0.03, respectively, that was superior compared with ANN with R^2, nRMSE and CRM values of the 0.98, 7.85 and 0.05, respectively (Figure 3). The simulation of grain yields for 2017 growing season indicated that both has acceptable performance but the more accurate results were for the AquaCrop model (R^2=0.88, nRMSE=7.73% and CRM=0.04) compared with ANN with R^2=0.73, nRMSE=12.28 and CRM=0.09. Also emphasized that the adjusting ANN parameters such as learning rate and number of hidden nodes affected the accuracy of rice yield simulations but still ANN models proved to be superior for accurately simulating rice yields (Ji et al., 2007). The AquaCrop model had excellent simulation by nRMSE of less than 10%, whereas the ANN models had good simulation with nRMSE of the 12.28%. reported the proficiency of the AquaCrop model in Ahvaz, southern Iran indicated that it can simulate the grain biomass and yield via nRMSE of the less than 10% (Andarzian et al., 2011). Showed that ANNs with stochastic partitioning of data is an accurate method to simulate rice grain yield using readily available inputs (Moosavizadeh-Mojarad and Sepaskhah, 2012). Simulation results of AquaCrop in the studied fields can be up-scaled to the province level using the distributed GIS-based as proposed by another work (Alaya et al., 2019).

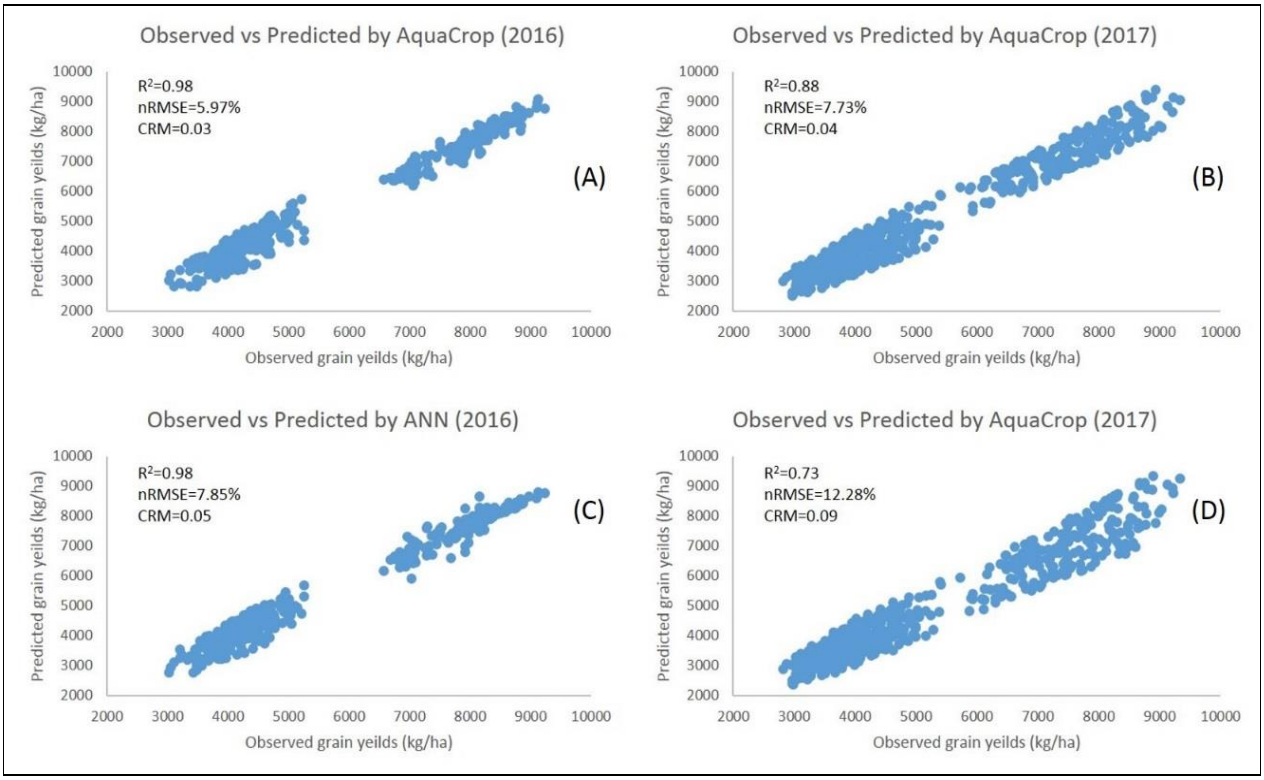

Figure 3. The scatterplots of the observed and simulated rice grain yield by AquaCrop (A and B) and ANN (C and D) models for two growing seasons

Performance of models as affected by rice cultivars

Table 2 shows the comparison of AquaCrop and ANN performance for grain yield simulation of two cultivar. Results show that the simulation performance is affected by the rice cultivars. The R^2, nRMSE and CRM values in AquaCrop model for Shirudi cultivar were 0.90, 4.80 and 0.04, respectively, compared with 0.71, 7.62 and -0.02 for Tarom cultivar in 2016 demonstrating that the AquaCrop model had more accurate simulation for high-yielding cultivar. The ANN simulation for Shirudi was roughly close to the performance of AquaCrop model but still the AquaCrop model was superior with lower error (Table 2). Both ANN and AquaCrop models consist the positive CRM for grain yield simulation in Shirudi cultivars and the negative values for Tarom cultivars showing that the both models have the underestimation of grain yields for high-yielding cultivar (Shirudi) and the overestimation for low-yielding cultivars (Tarom). It could be attributed to this fact that the AquaCrop is a cultivar specific model (Raes et al., 2009; Steduto et al., 2009).

Table 2. Performance of AquaCrop and ANN models as affected by rice cultivars

Year	Simulation model	Rice variety	Y_{obs}	Y_{pred}	R^2	nRMSE	CRM
2016	AquaCrop	Shirudi (n=199)	7976	7652	0.90	4.80	0.04
		Tarom (n=260)	4208	4295	0.71	7.62	-0.02
2016	ANN	Shirudi (n=199)	7976	7662	0.87	7.79	0.04
		Tarom (n=260)	4188	4286	0.68	7.30	-0.03
2017	AquaCrop	Shirudi (n=199)	7526	7315	0.79	6.87	0.03
		Tarom (n=260)	3996	4137	0.67	10.41	-0.03
2017	ANN	Shirudi (n=199)	7526	6994	0.69	10.37	0.07
		Tarom (n=260)	3996	4051	0.60	12.75	-0.06

n: numbers; Y_{obs}: observed grain yields; Y_{pred}: predicted grain yields.

Performance of models as affected by soil series and fertility management

The performance of the AquaCrop model for simulation of rice grain yield in Shirudi and Tarom cultivars were shown in Table 3 and Table 4. The grain yields in Esmaeilkola soil series with deep clay soil texture was weakly simulated, compared with Borj and Afratakht soil series. The R^2, nRMSE and CRM values for in AquaCrop model for Afratakht soil series with high inherent soil quality (higher OC and soil nutrients) for Shirudi cultivar in 2016 were 0.90, 5.00 and 0.04, respectively, that were more accurate than soils beneath Esmaeilkola soil series with 0.79, 8.44 and 0.06 value, respectively. AquaCrop model satisfactorily simulated the effect of cultivar and soil types on grain yield. In ANN model also the best performance was observed in Afratakht soil series (Table 5 and 6) and the lower simulation was for Esmaeilkona soil series, but still the AquaCrop simulation was better due to the higher R^2 and lower nRMSE and CRM. The AquaCrop model had lower performance in Tarom cultivar in all studied soil series compared with Shirudi cultivar. In this regards, the R^2, nRMSE and CRM values in Esmaeilkola soil series for Shirudi cultivar in AquaCrop model for 2017 were 0.68, 11.87 and 0.12 (Table 3), respectively, compared with 0.52, 14.72 and -0.14 values (Table 4) for Tarom cultivar demonstrating that the AquaCrop model had better performance for high-yielding cultivar and in turn the overestimate the grain yield for low-yielding cultivars.

Table 3. Performance indices of AquaCrop models as affected by soil series and fertilizer managements for Shirudi cultivar

Year	Soil series	R^2	nRMSE	CRM	Fertility management	Y_{obs}	Y_{sim}	R^2	nRMSE	CRM
2016	Afratakht	0.90	5.00	0.04	Low	7287	6940	0.50	6.22	0.05
					Medium	8074	7813	0.76	4.06	0.03
					Optimum	7972	7652	0.94	4.65	0.04
	Borj	0.84	7.08	0.05	Low	7521	7082	0.61	6.81	0.06
					Medium	8044	7723	0.90	4.08	0.04
					Optimum	8249	7929	0.87	3.98	0.04
	Esmaeilkola	0.79	8.44	0.06	Low	7778	7387	0.52	9.06	0.08
					Medium	8187	7918	0.69	6.51	0.05
					Optimum	8593	8335	0.69	4.33	0.03
2017	Afratakht	0.81	5.59	0.05	Low	6838	6751	0.62	4.82	0.05
					Medium	7560	7257	0.79	5.87	0.04
					Optimum	7461	7304	0.83	5.80	0.02
	Borj	0.75	9.39	0.09	Low	6697	6501	0.54	6.74	0.06
					Medium	7632	7427	0.59	5.94	0.03
					Optimum	7855	7417	0.75	6.62	0.03
	Esmaeilkola	0.68	11.87	0.12	Low	7350	7189	0.53	10.45	0.12
					Medium	7882	7598	0.58	7.07	0.09
					Optimum	8286	8004	0.68	6.32	0.03

Table 4. Performance indices of AquaCrop models as affected by soil series and fertilizer managements for Tarom cultivar

Year	Soil series	R^2	nRMSE	CRM	Fertility management	Y_{obs}	Y_{sim}	R^2	nRMSE	CRM
2016	Afratakht	0.83	5.99	-0.08	Low	3891	3934	0.71	6.22	-0.01
					Medium	4190	4253	0.80	5.33	-0.01
					Optimum	4258	4281	0.86	6.29	-0.01
	Borj	0.90	6.99	-0.08	Low	4138	4153	0.89	3.19	-0.01
					Medium	4110	4143	0.86	3.39	-0.01
					Optimum	4287	4294	0.95	2.23	-0.00
	Esmaeilkola	0.64	12.80	-0.13	Low	3844	4032	0.57	10.12	-0.05
					Medium	4167	4275	0.51	8.71	-0.03
					Optimum	4204	4418	0.68	8.13	-0.05
2017	Afratakht	0.69	9.82	-0.06	Low	3676	3804	0.66	12.15	-0.08
					Medium	3894	4000	0.65	7.40	-0.03
					Optimum	3748	4071	0.71	6.27	-0.03
	Borj	0.72	11.15	-0.04	Low	3969	3987	0.52	13.54	-0.06
					Medium	4161	4231	0.69	6.06	-0.06
					Optimum	4194	4200	0.79	4.66	-0.03
	Esmaeilkola	0.52	14.72	-0.14	Low	3763	3840	0.56	18.24	-0.24
					Medium	3711	3949	0.69	10.29	-0.16
					Optimum	3987	4228	0.72	6.82	-0.10

In spite of soil series effects on simulation of rice grain yields, the soil fertility management had the pronounced effect on performance of simulation for both models. The low fertilizer management in paddy fields let to the lower accuracy of simulation for AquaCrop (Table 5 and 6) and ANN (Table 7 and 8) models but still the AquaCrop model outperformed the simulation. The results of this study are agreement with another findings (Shrestha et al., 2013). The spatial simulation of the rice grain yields were depicted in the study area (Figure 4). The inappropriate soil fertility management practices in paddy fields may led to adverse effects on grain yields, therefore, the models could bot simulate the rice grain yields effectively. The AquaCrop model simulated the biological yield of rice more accurate compared to other simulation models such as ORYZA2000 and CERES-Rice under different irrigation intervals and nitrogen application levels (Amiri et al., 2014). Some researchers suggested to irrigate rice transplanted in puddled loamy sand soil on every 5th day to get higher irrigation water productivity coupled with statistically similar grain yield as obtained with daily irrigation schedule (Sandhu et al., 2015). The AquaCrop generally simulated grain yield fairly satisfactorily across a range of data sets covering varying levels urea (N) applications from a three-year field experiment. The acceptable performance of AquaCrop model for simulation of rice grain yields on different soil types in the calibration and validation dataset supports the use of the model for evaluation of different fertilizer management strategies in the study area as demonstrated for wheat in Bangladesh (Mustafa et al., 2017).

Table 5. Performance indices of ANN model as affected by soil series and fertilizer managements for Shirudi cultivar

Year	Soil series	R^2	nRMSE	CRM	Fertility management	Y_{obs}	Y_{sim}	R^2	nRMSE	CRM
2016	Afratakht	0.80	6.65	0.06	Low	7287	6940	0.5	6.22	0.09
					Medium	8074	7813	0.76	4.06	0.05
					Optimum	7972	7652	0.94	4.65	0.04
	Borj	0.75	8.58	0.07	Low	7521	7082	0.61	6.81	0.08
					Medium	8044	7723	0.9	4.08	0.06
					Optimum	8249	7929	0.87	3.98	0.04
	Esmaeilkola	0.58	10.85	0.08	Low	7778	7387	0.52	9.06	0.08
					Medium	8187	7918	0.69	6.51	0.05
					Optimum	8593	8335	0.69	4.33	0.03
2017	Afratakht	0.75	7.20	0.07	Low	6838	6751	0.62	4.82	0.08
					Medium	7560	7257	0.83	5.87	0.04
					Optimum	7461	7304	0.79	5.8	0.02
	Borj	0.70	10.73	0.10	Low	6697	6501	0.54	6.74	0.11
					Medium	7632	7427	0.59	5.94	0.03
					Optimum	7855	7417	0.75	6.62	0.03
	Esmaeilkola	0.63	13.04	0.13	Low	7350	7189	0.53	10.45	0.14
					Medium	7882	7598	0.58	7.07	0.09
					Optimum	8286	8004	0.68	5.32	0.03

Table 6. Performance indices of ANN model as affected by soil series and fertilizer managements for Tarom cultivar

Year	Soil series	R^2	nRMSE	CRM	Fertility management	Y_{obs}	Y_{sim}	R^2	nRMSE	CRM
2016	Afratakht	0.85	9.11	-0.08	Low	3891	3934	0.71	6.22	-0.08
					Medium	4190	4253	0.88	12.33	-0.07
					Optimum	4258	4281	0.86	6.29	-0.06
	Borj	0.92	10.13	-0.08	Low	4138	4153	0.60	3.19	-0.09
					Medium	4110	4143	0.71	10.39	-0.08
					Optimum	4287	4294	0.83	8.23	-0.03
	Esmaeilkola	0.61	15.16	-0.12	Low	3844	4032	0.57	13.12	-0.12
					Medium	4167	4275	0.71	8.71	-0.08
					Optimum	4204	4418	0.70	5.13	-0.06
2017	Afratakht	0.70	13.02	-0.10	Low	3676	3804	0.66	12.15	-0.11
					Medium	3894	4000	0.65	7.4	-0.08
					Optimum	3748	4071	0.71	6.27	-0.06
	Borj	0.73	15.37	-0.12	Low	3969	3987	0.52	13.54	-0.13
					Medium	4161	4231	0.69	6.06	-0.07
					Optimum	4194	4200	0.79	4.66	-0.06
	Esmaeilkola	0.49	15.98	-0.15	Low	3763	3840	0.70	18.24	-0.24
					Medium	3711	3949	0.69	10.29	-0.16
					Optimum	3987	4228	0.46	6.82	-0.10

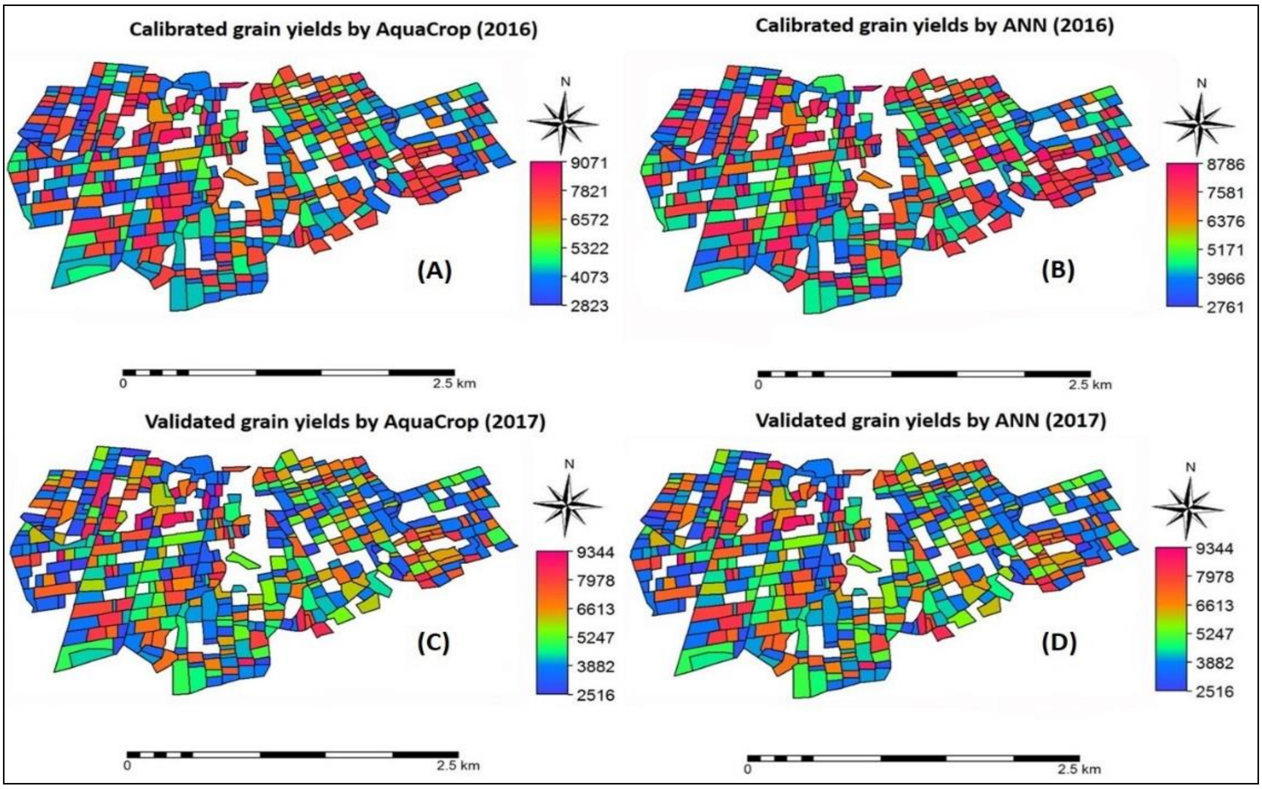

Figure 4. Spatial distribution of the rice grain yields by AquaCrop for 2016 (A) and 2017 (B) and ANN for 2016 (C) and 2017 (D) growing seasons

CONCLUSIONS

The accurate simulation of paddy rice yields can provide a good informative data for decision makers at regional scale. The AquaCrop and ANN efficiencies in three different soil types were studied. More than half of the paddies in the Mazandaran are beneath these three soil types with different cultivars and fertility managements. The best performance of both models was observed in paddy fields with optimum fertilizer managements. Although both models proved to be satisfactorily applicable for spatial simulation of rice yields at province-scale, however, the AquaCrop model outperformed. Moreover, the high accuracy of the AquaCrop were for high-yielding cultivars, fertile soils and the soils with high fertility managements. Generally, results reveal that the simulation accuracy of AquaCrop model in deep clay soil types was lower than other soil types. The simplicity and accessibility of the available input data are the great advantages of the AquaCrop model providing the opportunity to use it as an up-scaling model to the province-level. Results herein emphasized that the recalibration and revalidation of AquaCrop model under low fertilization management and deep clay soil texture is required to explore strategic management options to optimize resource-use efficiency and productivity. Furthermore, it can be suggested that the AquaCrop model has great potential to be reliably used in yield simulation and provide a decision-making basis for climate related scenario studies in northern Iran. Due to the high accuracy of the AquaCrop model in the study areas, the integration of this model with remotely sensed data would be suggested as a useful tool for planning and other management decisions on rice yield.

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