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A STATISTICAL APPROACH FOR ESTIMATING WHEAT YIELD USING BOOTSTRAP RESAMPLING FOR RAIN-FED FARMING: A CASE STUDY OF KURDISTAN PROVINCE, IRAN

A. KHOORANI[1], M. FARAJZADEH[2], S. BAZGEER[3]* and P. ZEAEIAN[4]
[1] *Hormozgan University, Dept. of Range and Watershed Management Engineering, Bandar Abbass, Iran*
[2] *Tarbiat Modares University, Dept. of Geography, Tehran, Iran*
[3] *University of Tehran, Dept. of Physical Geography, Tehran, Iran*
[4] *Kharazmi University, Dept. of Geography, Tehran, Iran*

Abstract

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For the purpose of modeling and predicting rainfed wheat (*Triticum aestivum*) yield in Kurdistan province, Iran, five weather parameters, as well as three agrometeorological indices were used, as independent variables in linear regression models during 1991-2003. The independent variables were extracted for different phenological phases during the plant-growing season from sowing to harvest. Backward regression models were used to model rain-fed wheat yield and sensitivity analysis was carried out on the models. On the basis of choosing the best models for each district and Kurdistan province (in the north west of Iran), the bootstrap resampling method was run on them. Both above-mentioned models were validated for 2003-2006 years data by estimating the rain-fed wheat yield. The results show that using bootstrap resampling method for modeling and estimating the crop yield increases the interior accuracy (increasing r, multiple correlation coefficient, from 0.84 to 0.98, and decreasing SEOE, standard error of estimate, from 166 to 47 kg/ha) of the models.

Key words: bootstrap, rain-fed wheat, yield estimation, regression models

Abbreviations: GDD: Growing Degree Days; HTU: Heliothermal Units; PTU: Photothermal Units; WVPD: Water Vapor Pressure Deficit; TD: Temperature Differences; NDVI: Normalized Difference Vegetation Index; IRIMO: I.R. of Iran Meteorological Organization; PET: Mean Evapotranspiration Potential; R: Total amount of precipitation for each phenological stages (mm); R_{day} : Number of days with precipitation (> 0.1 mm) for each phenological stage; $FF_{abs(max)}$: Maximal velocity of wind (daily averages ($m.s^{-1}$)) for each phenological stages; T, T_{max}, T_{min}, and T_b : Average, Maximum, Minimum, and base daily temperature (°C); ESS: Early Seedling Stage; FSAV: The First Stage of Active Vegetative before dormancy stage; DS: Dormancy Stage; SSAV: The Second Stage of Active Vegetative after dormancy stage; RS: Reproductive Stage; MS: Maturity Stage; EGS: Entire Growing Season; SAVRS: Start of second stage of Active Vegetative after dormancy to the end of Reproductive Stage; AAE: The mean Amount of Absolute Error; r: Multiple Correlation Coefficient; SEOE: Standard Error of Estimate; e_a and e_s = actual and saturated water vapor pressure (millibar)

Introduction

Rain-fed wheat, which includes most of the cultivated area of Kurdistan Province, located in the north-west of Iran, is one of the major agricultural crops in the Province. In 2006, Kurdistan province had 11.8% of the cultivated area, which accounted for 13.67% of the rain-fed wheat production of the country (The Ministry of Agriculture, 2009). Agricultural production is under the risk of weather and international

E-mail: khoorani@hormozgan.ac.ir; farajzama@modares.ac.ir; sbazgeer@ut.ac.ir; zeaiean@tmu.ac.ir
*Corresponding author: sbazgeer@ut.ac.ir

markets fluctuation (Labus et al., 2002). Although these risks could never been removed completely, we can minimize their influences by realizing the effective parameters involved in plant growth and crop yield. Among these parameters, climate has more significant role, especially in rainfed crops. It has been suggested that crop yield forecasting and risk analysis tools could be used in regions where the signals of climate variability and forcing (e.g., El Nino/Southern Oscillation) are significant (Hansen et al., 2004; Qian et al., 2009). Due to the semi-arid climate and wide monthly climatic variability and yearly climate fluctuation, modeling and estimating the crop yield is necessary.

Crop growth and production models are divided into three arbitrary categories: simple statistical models, parameterization models, and analog-physical models (Norman, 1979). Statistical models are practical tools to analyze the plant response to the climatic variations (Bair, 1977; Mavi, 1994). Most statistical models are crop-yield weather models; their main advantage is the simplicity and straightforward relation between yield and one or more environmental factors. Regarding environmental outcomes, more significant predictions may be acquired by empirical fits of these regression-type models to real datasets (Barnett et al., 1997) however, the success of a statistical model will be achieved when a logical understanding of biophysical processes, affecting the crop yields with exact predictors, is recognized (Barnett, 2004). Consequently, several studies have been carried out to develop regression relationship between agrometeorological indices and different crop growth stages (Saini and Dadhwal, 1986). Some of the agrometeorological indices such as GDD(Growing Degree Days), HTU (Heliothermal Units), PTU (Photothermal Units), VPD (Vapor Pressure Deficit), TD (Temperature Differences) were calculated during the growing season and used by Sastry and Chakravarty (1982); Thavaprakaash et al. (2007); Bazgeer et al. (2008); Qian et al. (2009). In other studies, the stepwise selection and the Bayesian model averaging for yield gap analysis were compared using 10,000 bootstrap resampling methods drawn from a dataset of 160 plots including 8 years of winter wheat experiments (Prost et al., 2008).

Accuracy of models were enhanced by using different spectral indices obtained from long term satellite data such as Normalized Difference Vegetation Index (NDVI), and by employing them in regression models as independent variables (Aparicio et al., 2000; Boken and Shaykewich, 2002; Hatfield et al., 2008; Qian et al., 2009; 3Bullock, 2011;). Nevertheless, there are some debates of using remotely sensed based data for modeling and estimating crop yield due to some limitations such as obtaining proper images having spatial and temporal resolution in a long period. The other constraint is that the spectral vegetation indices reach a saturated level during last stage of crop development, making it less effective in crop yields forecasting near harvest time (Haboudane et al., 2004). As noted above, the revealed regression models suffer from low accuracy, particularly in case a short period of time is concerned; accordingly the aim of this paper is to provide higher-accuracy (more significant) statistical models for rainfed wheat yield estimation at different plant growth stages in terms of weather parameters and some specific agrometeorological indices. The objective of this research was to evaluate the feasibility of using bootstrap resampling method to select the best meteorological subset as independent variables in regression analysis for estimating wheat yield in Kordistan Province, North West of Iran.

Materials and Methods

The study area is Kurdistan province that located in 34°44′ to 36°30′ N and 45°31′ to 48°16′ E Kurdistan is one of the thirty one provinces of Iran, whose area is 28817 km². It is located in the north west of Iran, bounded by some districts of Iraq on the west. The capital of Kurdistan Province is the city of Sanandaj. Other important districts with their major cities are Marivan, Baneh, Saqqez, Qorveh, Bijar, Kamyaran, and Diwandarreh.

Kurdistan Province is a mountainous region that can be topographically divided into a western and an eastern section at Sanandaj. Because of its elevation and mountains, Kurdistan province has many rivers, lakes, glaciers and caves, which render it rather picturesque. Kurdistan has a generally mild and quite pleasant climate throughout the spring and summer. Winters are long and can be very cold with heavy snowfalls. The population of the province in 1996 was 1,346,383 from which 52.42% were urban dwellers and 47.58% rural dwellers. The sex ratio of the province is 104 (Iran statistics centre, 1996). The major activities of the inhabitants are agriculture and modern livestock farming. Wheat, barley, grains and fruits are the major agricultural products. The chemical, metal, textile, leather and food industries are the main industrial activities in this province.

Data

Rain-fed wheat yield: rain-fed wheat yield data for all Kurdistan province districts, including Bijar, Sanandaj, Saqqez, Qorveh, Marivan and Diwandarreh were obtained from The Ministry of Agriculture for the period 1991-2006. The yield was expressed as the average grain production (kg/ha) for the harvested area. Preliminary analysis showed significant ($p < 0.05$) linear positive trend (i.e., increasing yield over time) during 1991-2006 years in Kurdistan Province

(Figure1a). Although, the area under rain-fed wheat cultivation in this period showed a negative trend in the same period at the 0.05 level of significant (Figure 1b). It might due to immigration from rural areas and some changes in life style (The Ministry of Agriculture, 2009).

Climatic data: Necessary weather parameters of seven weather stations in Kurdistan province for the period 1991-2006 (1993-2006 for Marivan station) were obtained from I.R. of Iran Meteorological Organization (IRIMO). Correlation and nearest neighboring methods were used for retrieval of the missing data.

Agrometeorological indices: The important meteorological variables that influence the growth, development and crop yield include solar radiation, temperature, rainfall (amount and distribution), relative humidity and wind velocity (Hodges and Kanemasu, 1977; Reddy and Reddi, 2003; Meena and Dahama, 2004). These variables and relative parameters that are extracted from them were chosen as independent variables. Three different Agrometeorological indices were also extracted and used in this study. Independent variables in this study are:

Accumulated Temperature Differences (TD) at each phenological stages that were calculated using following equation:

$$TD = \sum_{a}^{b} (T_{\max} - T_{\min}) \qquad (1)$$

Where:

T_{max} = Daily maximum temperature (°C)
T_{min} = Daily minimum temperature (°C)
a = Starting date of phenological phase
b = Ending date of phenological phase

This index was calculated in order to study the influence of temperature variation for wheat yield.

Total Heliothermal Units (HTU) for each phenological stage

HTU is the product of Growing Degree Days (GDD) and bright sunshine hours, which can be calculated using following equation (Reddy and Reddi, 2003):

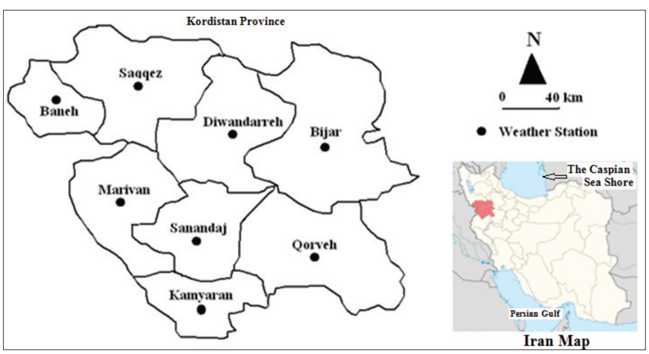

Fig. 1. The location of the study area

$$HTU = \sum_{a}^{b} (GDD \times n) \qquad (2)$$

$$GDD = \sum_{a}^{b} \left[\left(\frac{T_{\max} + T_{\min}}{2} \right) - T_b \right] \qquad (3)$$

Where,

n = Actual sunshine hours
T_b = Base temperature (5°C for wheat crop, Nuttonson, 1955; Gilmore and Rogers, 1958)

We calculated correlation coefficient between GDD, HTU and Photothermal Units (PTU) and found that there is a high correlation between them (with the minimum r = 0.978), therefore we preferred to use HTU in our study.

Total water Vapor Pressure Deficit (WVPD) for each phenological stage was obtained from following equations (Kramer, 1997):

$$WVPD = e_s - e_a \qquad (4)$$

$$e_a = (RH_{mean} \times e_s)/100 \qquad (5)$$

Where,

e_a = actual water vapor pressure (millibar)
e_s = saturated water vapor pressure (millibar) as a function of air temperature (Allen et al., 2000).
RH_{mean} = mean relative humidity (%)

WVPD integrates the effects of both humidity and temperature, and has an important role in plant Evapotranspiration (Rao, 2003).

PET = mean evapotranspiration for each phenological stages based on modified Penman- Monteith method.

Weather parameters include:

R = Total amount of precipitation for each phenological stages (mm)

R_{day} = number of days with precipitation (> 0.1 mm) for each phenological stage

$FF_{abs(max)}$ = maximal velocity of wind (daily averages ($m.s^{-1}$)) for each phenological stages

T = the average daily temperature (°C) for each phenological stages

Accordingly, eight parameters (i.e. TD, HTU, WVPD, PET, R, R_{day}, FF_{absmax}, T) were calculated for different plant growth stages.

In order to elucidate the effect of different weather parameters at different phenological phases, the rain-fed wheat growing season was divided into six different stages from sowing (October 7) to harvesting time (July 10). These stages are: Early Seedling stage, from October 7 to November 6

(ESS); the First Stage of Active Vegetative before Dormancy stage, from November 7 to December 11 (FSAV); Dormancy Stage, from December 12 to March 15 (DS); the Second Stage of Active Vegetative after dormancy stage, from March 16 to May 10 (SSAV); Reproductive Stage, from May 11 to June 9 (RS); and Maturity Stage, from June 10 to July 10 (MS). In order to obtain the best models, regression models were calibrated for each rain-fed wheat yield stage as well as the Entire Growing Season (EGS) and from start of second stage of active vegetative after dormancy to the end of reproductive stage from March 16 to June 9 (SAVRS). Thus, eight regression models were calculated for each study area.

The accuracy of models was confirmed using normality test, co linearity test, variance analysis and data independency test (Chatterjee and Hadi, 2006). Backward regression models were calibrated for 13 years (12 years for Marivan County in the period 1991-2003). The sensitivity analysis was also done on the extracted models and the results that had a robust effect on models were eliminated, as they changed the calibrated models drastically. For this purpose, the model was first calibrated for all 13 years, then a single observation (one year) from the original sample was eliminated, and the model calibrated for remaining observations (12 years). This is repeated repeatedly until each year was eliminated once. Then the validation of models was tested by estimating the rain-fed wheat yield for other three years (2003 to 2006). Since the period was short (13 years), the samples was increased by running bootstrap resampling method on them. Bootstrap resampling method can be used for reducing the uncertainty in the results of selection methods (Chatfield, 1995; Buckland et al., 1997; Miller, 2002). In this method, we generate a large number of datasets from the initial dataset by randomly sampling data with replacement (Efron and Tibshirani, 1993). Therefore, 10,000 new samples were chosen randomly from 13 years data, and extracted regression models were calibrated on this large number dataset again. Finally, these models were used to test the model validation by estimating the rain-fed wheat yield for other 3 years (2003 to 2006).

Model Validation

In order to evaluate the performance of different yield models for estimation of wheat yields, the mean amount of absolute error (AAE) of total difference between estimated yield (Y_e) and reported/observed yield (Y_r) for three years including 2003-04, 2004-05 and 2005-06 were computed as a measure of estimated accuracy.

Results and Discussion

Rain-fed wheat yield in Kurdistan province showed a significant ($P < 0.05$) trend during 1991-2006 ($r= 0.591$). Whereas, rain-fed wheat cultivated area showed a negative trend in the same period. The increasing trend of rain-fed wheat yield may be related to the technological crop advances and crop management improvements such as greater rate and frequency of fertilizer application, improved crop varieties, as proposed by Qian et al. (2009) in their study which was carried out at Canadian Prairie Provinces. Independent variables and their multiple correlation coefficients of the rain-fed wheat yield regression models for Kurdistan province and its districts have been shown in Tables 1 (for backward regression models) and 2 (after running bootstrap resampling method). Figure 2 shows the comparison of rain-fed wheat yield trends for estimated together with reported (observed) data.

According to Table 1 (backward regression models without running bootstrap resampling), the value of multiple correlation coefficient (r) for Kurdistan province is 0.96, and varies from 0.84 for Diwandareh to 0.98 for Qorveh. The Standard Error of Estimates in these models also ranges from 74.69 (kg. ha^{-1}) for Qorveh to 166 (kg/ha) for Sanandaj. Table 2 shows that “r” value in the large dataset created by bootstrap resampling method has been improved and it is higher than that ob-

Table 1
Backward regression models developed for modeling rain-fed wheat yield estimation without running bootstrap resampling, 1991-2003

District	Phenophase	Constant	Independent variables with coefficients	r	SEOE	p-Value
Saqqez	RS	-803.57	TD [3.37]+ VPD [-4.2]+R_{day}[37.89]+FF_{abs}[96.44]	0.94	89	0.01**
Qorveh	EGS	-202.8	HTU [-0.07]+R[1.73]+ PET[-529.1]+T[318.99]	0.97	75	<0.001**
Bijar	RS	-1102.82	VPD [-5.56]+FF_{abs}[-54.57] +T[269.58]	0.87	158	0.01**
Diwandare	SAVRS	-84.01	HTU[0.8]+VPD[-8.01]+R_{day} [17.79] +FF_{abs}[60.02]	0.84	156	0.05*
Marivan	DS	420.4	HTU [1.38]+R[1.43]+T[-69.87]	0.93	119	0.01**
Baneh	RS	-15.96	VPD[-4.98]+R[-12.71]+ PET[453.34]+R_{day}[42.51]	0.96	90	<0.001**
Kurdistan province	RS	-2492.61	HTU[0.46]+VPD[-15.59]+R[-8.9]+PET[564.11]+ T[243.43]	0.96	77	<0.001**

tained from backward regression models without resampling procedure. It ranges from 0.89 in the Diwandarreh model to 0.98 in Qorveh model and the value for Kurdistan province is 0.98. The Standard Error of Estimates in these models ranges from 46.74 kg/ha for Kurdistan province to 122.6 kg/ha for Bijar. The results of models validation are shown in Table 3 (for backward regression models) and Table 4 (after running bootstrap resampling method). The Average of Absolute amount of Errors (AAE) is calculated for all case studies. Based on Mont carlo test (Kroese et al., 2011), there was no significant difference between the obtained AAE by backward regression models and the models that obtained from large dataset by bootstrap method ($p = 0.843$) (Figure 3).

The results from regression models without running bootstrap resampling (Table 1) showed that for Diwandarreh and Marivan districts, the best regression model was obtained from SAVRS and DS data, respectively. For Sanandaj and Qorveh, the best regression models were obtained from EGS data. Based on our results the best stage for estimating winter wheat in Kordistan Province was reproductive stage (May 11 to June 9) using meteorological data collected from the start of second stage of active vegetative after dormancy stage to the end of reproductive stage. Independent variables in five districts have the strongest effect on rain-fed wheat yield at these stages. Because of long time interval from harvest, crop yield estimating based on the data from early stages of crop growth could not led to significant and reliable outcomes. For Marivan districts, due to the high amount of rainfall and moderate climate the best stage for estimating winter wheat was, dormancy stage (December 12 to March 15).

Table 2
Backward regression models after running the bootstrap resampling developed for modeling rain-fed wheat yield estimation, 1991-2003

District	Phenophase	Constant	Independent variables with coefficients	r	SEOE	p-Value
Sanandaj	EGS	3153.28	TD[-1.16]+HTU[0.18]+PET[383.02]+FF_{abs}[57.12]	0.90	122	0.05*
Saqqez	RS	-895.98	TD[3.35]+ VPD [-3.85]+R_{day}[41.48]+FF_{abs}[95.33]	0.95	66	0.01**
Qorveh	EGS	-172.55	HTU [-0.07]+R[1.78]+ PET[-509.46]+T[304.08]	0.98	52	<0.001**
Bijar	RS	-1056.18	VPD [-5.48]+FF_{abs}[-52.38] +T[264.39]	0.90	123	0.01**
Diwandareh	SAVRS	-73.12	HTU[0.73]+VPD[-7.68]+R_{day}[17.69]+FF_{abs}[74.49]	0.89	113	0.05*
Marivan	DS	471.71	HTU [1]+R[1.27]+T[-61.91]	0.94	93	0.01**
Baneh	RS	152.27	VPD [-5.17]+ R[-13.86]+ PET[432.35]+R_{day}[42.9]	0.97	66	<0.001**
Kurdistan province	RS	-2807.3	HTU[0.44]+VPD[-15.59]+R[-5.79]+ PET[729.94]+ T[206.52]	0.98	47	<0.001**

r, Multiple Correlation Coefficient; SEOE, Standard Error of Estimations (kg/ha); GDD, Growing Degree Days; HTU, Heliothermal Units; PTU, Photothermal Units; WVPD, Water Vapor Pressure Deficit; TD, Temperature Differences; RH_{mean}, mean relative humidity; PET, mean evapotranspirantion; R, Total amount of precipitation; R_{day}, number of days with precipitation (> 0.1 mm); FF_{abs}, maximal velocity of wind; T, the average daily temperature; Phenophase, Phenological growth stages of wheat including EGS, Entire Growing Season; RS, Reproductive Stage; SAVRS, Start of second stage of Active Vegetative after dormancy to the end of Reproductive Stage DS, Dormancy Stage; *Significant at 5% level, ** Significant at 1% level.

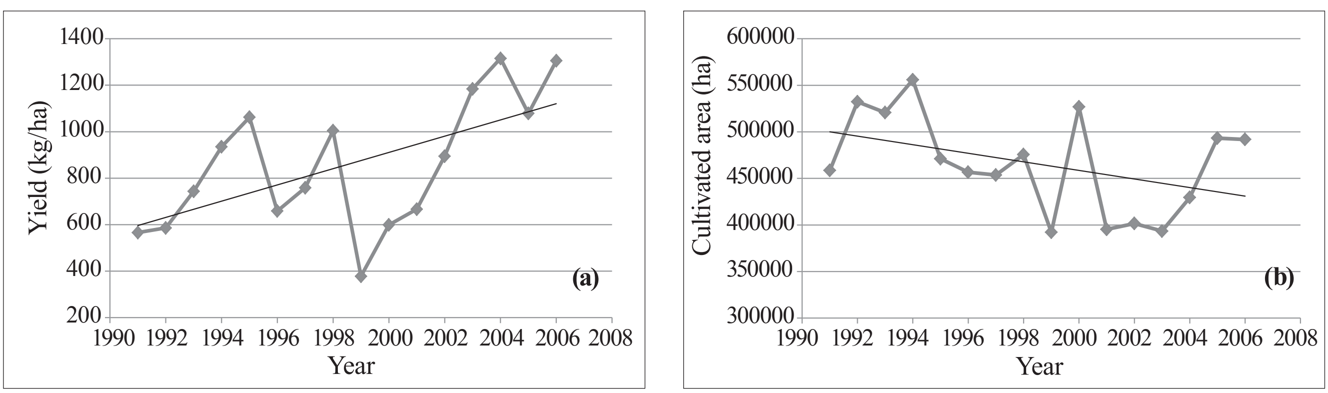

Fig. 2. Trends of yield (a) and cultivated area (b) of rain-fed wheat in Kurdistan province during 1991- 2006

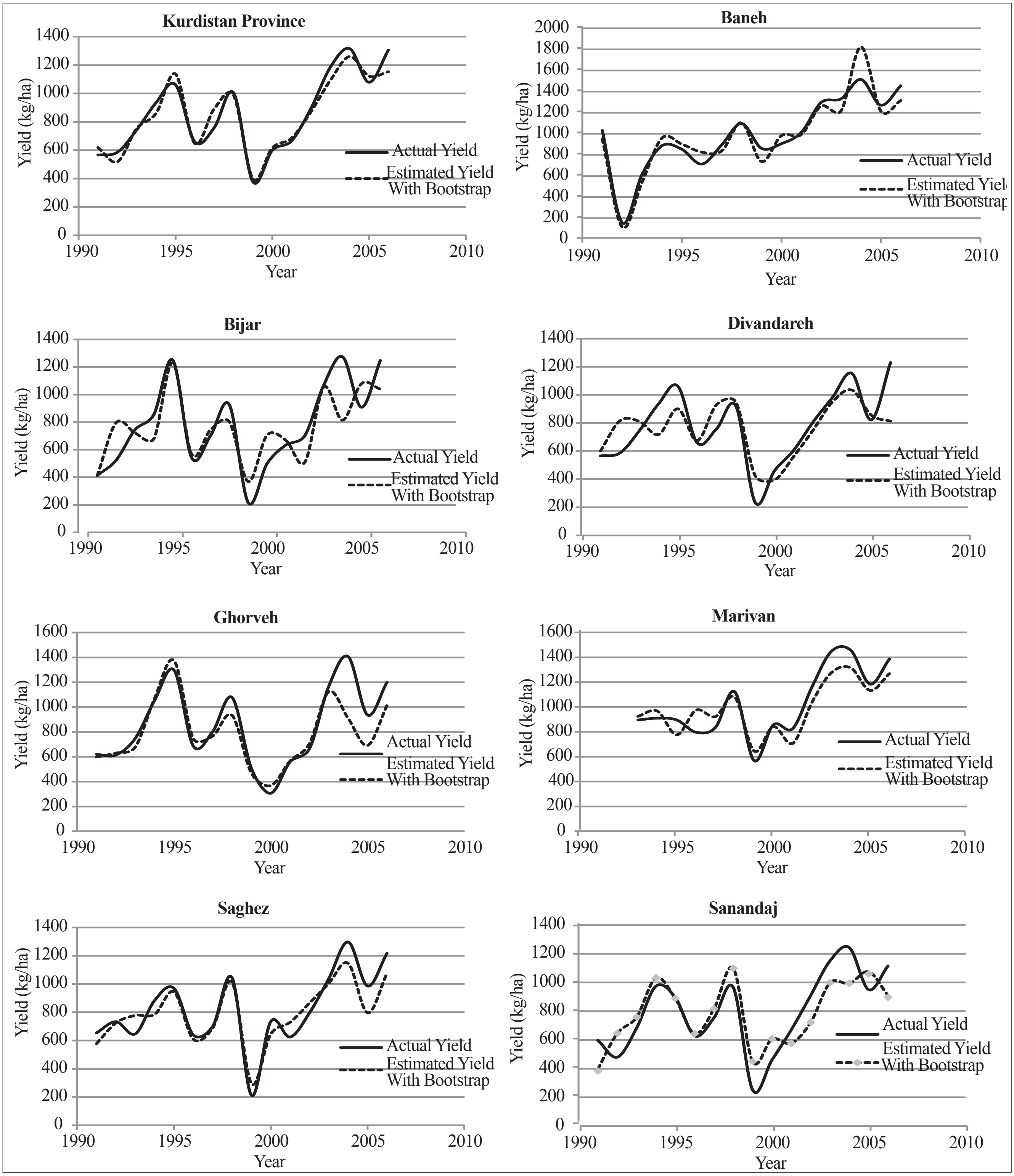

Fig. 3. Reported / Observed (solid line) and estimated (dashed line) rain-fed wheat yield with bootstrap resampling comparison for 1991–2006 in the Kurdistan Province and its districts

The results of running bootstrap resampling method on the regression models for rain-fed wheat yield show a large increase in the regression models accuracy (increasing “r” and decreasing SEOE). Therefore, this study confirms result obtained by Prost et al. (2008) about using this method in climatological studies. The multiple correlation coefficient (r) improved from 0.84 to 0.90, 0.94 to 0.95, 0.97 to 0.98, .087 to 0.90, 0.84 to 0.89, 0.93 to 0.94, 0.96 to 0.97, and 0.96 to 0.98 and standard error of estimate (SEOE) decreased from 166 to 122, 89 to 66, 75 to 52, 158 to 123, 156 to 113, 119 to 93, 90 to 66, 77 to 47 kg/ha for Sanandaj, Saqqez, Qorveh, Bijar, Diwandarreh, Marivan, Baneh and Kurdistan Province, respectively (Tables 1 and 2). On the basis of the results, the value of mean amount of absolute error (AAE) is decreased when using bootstrap resampling as compared to non-bootstrap resampling methods for Sanandaj, Baneh, Bijar districts and Kordistan Province (Tables 3 and 4). Although, AAE is slightly increased in Qorveh, Saggez, Diwandarreh and Marivan.

Conclusion

Based on our results the best stage for estimating winter wheat yield is reproductive stage (May 11 to June 9) using meteorological data collected from the start of second stage of active vegetative after dormancy stage to the end of reproductive stage. For Sanandaj and Qorveh the data of entire growing season can be considered, as well. Using bootstrap method to model rain-fed wheat yield estimation, especially in the studies involving short period data set, the interior accuracy of models could be improved, and it might be suggested that this method is appropriate in modeling the crop yield analysis. It is clear that the result of this study is suitable for studied area and the regions with the same climate condi-

Table 3
Comparison of model estimated and reported/observed rain-fed wheat yield (kg/ha) using backward regression models without bootstrap resampling with AAE, 2003-2006

District	2003-2004		2004-2005		2005-2006		AAE
	Estimated yield	Reported yield	Estimated yield	Reported yield	Estimated yield	Reported yield	
Sanandaj	905	1115	1058	950	973	1243	197
Qorveh	1033	1199	697	936	927	1404	295
Saqqez	1084	1217	827	985	1161	1298	143
Baneh	1312	1456	1213	1272	1904	1516	197
Bijar	1037	1248	1075	908	802	1248	284
Diwandarreh	854	1230	879	822	1030	1153	186
Marivan	1346	1387	1168	1185	1311	1457	68
Kurdistan province	1231	1305	1134	1078	1116	1315	110

AAE, Mean Absolute Amount of Errors (kg/ha)

Table 4
Comparison of model estimated and reported/observed rain-fed wheat yield (kg/ha) using backward regression models after running bootstrap resampling with AAE, 2003-2006

District	2003-2004		2004-2005		2005-2006		AAE
	Estimated yield	Reported yield	Estimated yield	Reported yield	Estimated yield	Reported yield	
Sanandaj	909	1115	1073	950	994	1243	193
Qorveh	1012	1199	691	936	909	1404	309
Saqqez	1074	1217	796	985	1146	1298	161
Baneh	1316	1456	1215	1272	1824	1516	169
Bijar	1040	1248	1098	908	814	1248	280
Diwandarreh	813	1230	856	822	1035	1153	190
Marivan	1269	1387	1134	1185	1323	1457	101
Kurdistan province	1153	1305	1122	1078	1260	1315	84

AAE, Mean Absolute Amount of Errors (kg/ha) tions, but in other areas, the applied methods is useful to extract the best dates to estimate rain-fed wheat yield.

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