Analyzing unexploitable, agronomic, and non-agronomic yield gaps in irrigated barley growing areas of arid and frost-prone regions from Iran

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Research Article

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Abstract

The yield gap analysis is an important topic for researchers worldwide as it aims to identify the factors influencing the gap between actual and potential yields and to enhance food security. In the current study, the APSIM-Barley model was calibrated for three irrigated barley cultivars, validated using 31 field experiment reports, and applied to simulate long-term (1989 to 2019) yields under eight production levels in eight major barley growing locations of Iran (Arak, Hamedan, Kabudarahang, Marvdasht, Neyshabour, Sabzevar, Saveh and Shiraz). Three major yield gaps, namely unexploitable, agronomic and non-agronomic ones, were analyzed. The results revealed a huge difference between potential and actual yields (on average, 5.4 t ha^{-1} yield gap) across the studied locations indicating that the farmers could be able to achieve only 38.6% of the potential yield. Yield gap values varied over locations and seasons. Unexploitable, agronomic, and non-agronomic yield gaps in the studied locations averaged 26.7%, 55.9%, and 17.4% of total yield gap, respectively. The major part of the agronomic yield gap in the studied locations was owing to water limitation, which accounted for ~ 40% of the agronomic yield gap, followed by other agronomic (30%), frost-limited (15.8%), cultivar-limited (13.7%), and sowing date-limited (10.4%) yield gaps. Our findings showed that by improving agronomic management practices, particularly water management and farmers' non-agronomic conditions, the current yield gaps could be reduced considerably in arid and frost-affected locations.

1 Introduction

Following wheat, maize, and rice, barley (*Hordeum vulgare* L.) is the fourth most important staple crop grown to produce feed for animals (Harwood 2019; Miralles et al. 2021). Compared to other staple crops, barley has fewer environmental requirements and inputs, easier crop management, and adapts well to arid and semi-arid Mediterranean regions (Cammarano et al. 2019). Accordingly, along with wheat, corn and rice, it plays a key role in the world's global food security.

On one hand, predictions show that the world's population will increase 35% by 2050, signaling a 70–100% increase in food demand (Van Wart et al. 2013). The production of cereal crops in particular must be increased 50% or even more over the next 50 years so as to meet the growing food demand (Miralles et al. 2021). On the other hand, increased production will impose excessive pressure on water and soil resources and increase the environmental footprint (Zhang et al. 2017). Therefore, the need is urgent to develop highly efficient and sustainable agricultural production systems to feed the growing population (Zhang et al. 2017). One promising strategy to help solve this issue is reducing the yield gap of major crops by improving genetics, crop management, and crop adaptation to the target environments (Chapagain and Good, 2015). Yield gap is defined as the difference between the farmer's actual and simulated potential yields (Lobell et al. 2009; Van Ittersum et al. 2013; Patrignani et al. 2014). Yield gap analysis can supply a quantitative estimate of the possibility of increasing the food production capacity of a given area, which is an important component in designing food security strategies on regional, national, and even global scales (Van Wart et al. 2013). With the achievement of such a goal, production per unit area will be increased through reducing the analyzed yield gaps which results in higher productivity and less environmental impacts (Struik and Kuyper 2017; Soltani et al. 2020).

Types of yield gap differ according to varying levels of limiting/reducing factors. For example, Chapagain and Good (2015) calculated the management gap, genetic gap, and moisture gap for rainfed barley in Alberta, Canada, to be 25%, 12%, and 32%, respectively. In their analysis of the maize yield gap in northeastern China, Liu et al. (2016) investigated three types of yield gap: those caused by non-controllable factors (8%), those resulting from agronomic factors (40%), and those caused by non-agronomic factors (16%, e.g. the lack of capital to purchase fertilizer/seed/water). Research conducted in the southern Amazon on the biophysical and non-agronomic dimensions of yield gaps in soybean, corn, and cotton showed that biophysical yield gaps (due to water and nutrient shortage) accounted for 24% of the potential yield, while unlimited access to machinery, labor, credit, and technological innovations as socio-economic factors led to a yield gap of only 6.1% (Hampf et al. 2018). The researchers concluded that the yield gap could be reduced by improving the management of water and nutrients, determining appropriate sowing dates and cultivars, and to some extent, by removing socio-economic restrictions. Basing their calculations on the Global Yield Gap Atlas (GYGA) and applying the SSM-iCrop2 crop model, Alasti et al. (2022) estimated the total yield gap in Iran's 12 dominant areas of irrigated barley cultivation to be between 3.24 and 4.70 t ha^{-1} (average 4.08 t ha^{-1}). They simulated the average potential and actual yields of irrigated barley in their study locations as 7 t ha^{-1} and 3 t ha^{-1}, respectively. Schils et al. (2018) assessed cereal yield gaps in Europe and found them to be between 10% and 70%. They also stated that by reducing the yield gaps of corn, wheat, and barley from 42–20%, subsequent years would see an increase in cereal production in Europe of 39%, equivalent to 128 million tons.

Barley follows wheat as covering the second largest area in Iran's croplands, occupying ~ 2 million ha and producing ~ 3.5 million tons annually (FAOSTAT 2020). About 0.7 million hectares of cultivated area is for irrigated barley. Nevertheless, the demands for barley for various uses in the country are not met, because the average irrigated yield in the area is as low as 2.95 t ha^{-1}, indicating a huge yield gap which should be analyzed. To date, few long-term assessments have focused on the barley yield gap, particularly those categorizing yield gaps into unexploitable, agronomic, and non-agronomic components for the arid and semi-arid environments of Iran. Accordingly, the current study applied crop simulation modeling to determine different types of yield gap in the major barley growing areas in the country and to analyze the factors affecting them (Fig. 1).

2 Materials and methods

2.1 Description of the study areas

The current study was conducted in eight study locations representative of the major growing areas of irrigated barley in Iran and accounting for 43% of the total area under barley cultivation (Table 1). All study locations have arid or semi-arid climates characterized by low and irregular rainfall, water deficiency, high average temperature and evaporation, intense radiation, soil salinity, low soil fertility, and poor soil structure (Ortiz et al. 2000; Mesgaran et al. 2017; Alori et al. 2020; Ayangbenro and Babalola 2021).

Table 1
Geographical, climatic and soil characteristics of the study locations.

Location	Latitude	Longitude	Altitude (m)	Long-term average annual temperature (ºC)	Long-term average annual rainfall (mm)	PAWC[a] (mm)	HC27 soil code
Arak	34.07	49.78	1703	13.9	302	126	HC17
Hamedan	34.87	48.53	1741	11.5	307	171	HC5
Kabudarahang	35.19	48.69	1680	10.9	310	171	HC5
Marvdasht	29.92	52.89	1605	17.6	305	126	HC14
Neyshabour	36.27	58.80	1213	14.4	241	171	HC8
Sabzevar	36.21	57.65	962	18.3	183	171	HC8
Saveh	35.08	50.37	1112	18.1	200	171	HC5
Shiraz	29.56	52.60	1488	18.0	329	171	HC5

[a] Plant available water holding capacity of each soil. HC27 is a global soil database in a format that is useable for crop simulation models. Refer to Table 4 for properties of each HC27 soil code.

2.2 Crop model

APSIM-Barley (Agricultural Production Systems sIMulator) crop model version 7.10 (Holzworth et al. 2014) was applied to simulate barley yield and yield gaps under different levels of limiting factors (Fig. 2). This model simulates the growth and development of barley on a daily time step in response to various factors such as weather (maximum and minimum temperatures, radiation and precipitation), soil (water and nitrogen), genetic coefficients, and crop management information. It uses 11 crop stages of phenological development for simulation, from sowing to end crop. The initiation of each stage (except for sowing to germination, which is driven by soil water content) is assessed by the accumulation of thermal time. The daily thermal time (in degree days) is estimated using three-hour temperatures which are interpolated from the daily maximum and minimum temperatures.

In potential conditions, the plant grows without limitations of water and nutrients, and the growth rate is determined by solar radiation, temperature, atmospheric CO_2, and crop genetic characteristics (Van Ittersum et al. 2013). Under water-limited constraints, crop growth is directly affected by the actual canopy transpiration, which is estimated as the minimum of crop water demand and soil water supply. Crop water demand is a function of daily crop growth rate, vapor pressure deficit, and transpiration efficiency. Soil water supply refers to the water available in the soil profile for plant uptake which is provided through rainfall or irrigation. Water stress factors are simulated by the model to capture the effects of water shortage on various plant growth processes, included photosynthesis, leaf expansion, phenology, and tillering. Each of these processes shows a different sensitivity to water stress; for example, leaf expansion is more sensitive to water stress than photosynthesis.

Apart from water stress, APSIM-Barley can also simulate the effect of frost stress on crop yield through the reduction in leaf area (senescence) and triggers when the minimum temperature drops below − 5 ºC.

2.3 Model inputs

APSIM-Barley require four types of inputs to simulate barley growth, development, and yield: weather data, genetic coefficients, management practices, and soil properties. Long-term (1989–2019) daily weather data was obtained from Iran Meteorological Organization and comprised maximum and minimum temperatures (°C), rainfall (mm), and sunshine hours. Sunshine hours were converted to daily solar radiation using the Angstrom equation (Wang et al. 2015) to be used in the APSIM model.

Genetic coefficients or cultivar-specific parameters for the three irrigated barley cultivars currently grown in different locations of Iran were obtained through model calibration (Table 2). Model calibration was conducted using a trial and error approach to minimize differences between observed and simulated values for days to flowering, biomass, and grain yield under favorable conditions (Table 3) (Liu et al. 2012). For model calibration, we used a few independent datasets from previous field experiments conducted under various climatic and soil conditions as well as diverse management practices (Table S1).

Table 2
Cultivar-specific parameters obtained from APSIM-Barley model calibration.

Parameter	**Abbreviation**	**Reyhan***	**Bahman**	**Makuie**	**Unit**
Vernalization sensitivity	vern_sens	1	1.5	1.5	-
Photoperiod sensitivity	photop_sens	3.1	4.6	4.2	-
Thermal time during floral initiation stage	tt_floral_initiation	500	500	540	˚Cd
Thermal time from the beginning of grain filling to end of grain filling	tt_start_grain_fill	500	560.5	600	°Cd
Thermal time from the end of grain filling to physiological maturity	tt_end_grain_fill	30	30	35	˚Cd
Potential grain filling rate	potential_grain_filling_rate	0.0027	0.0029	0.0026	$g\ grain^{-1}\ d^{-1}$

* Reyhan: early-maturity cultivar; Bahman: mid-maturity cultivar; Makuie: late-maturity cultivar

Table 3
Results of APSIM model calibration using datasets from Table S1.

	Days to flowering		**Biological yield ($t\ ha^{-1}$)**		**Potential grain yield ($t\ ha^{-1}$)**	
	Observed	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**
Mean	199.2	183	13.96	14.25	5.39	5.52
SRMSE		7 day		13.3%		14.5%
R^2		0.9		0.63		0.61
CRM		+ 0.066		− 0.032		− 0.029
N		9		9		9

SRMSE: Standardized Root Mean Square Error; R^2: Coefficient of Determination; CRM: Coefficient of Residual Mass; N: Number of observations

Management inputs were obtained by questionnaires completed by barley farmers in the study locations. The information obtained from field surveys included type of cultivar used by the farmers, crop density, cultivation methods, planting and harvesting dates, timing and amount of irrigation, soil texture, type and amount of fertilizer, and other management practices. Based on the information obtained from the questionnaires in each location, the dominant practices were applied as input into the APSIM model and for analyzing yield gaps. For instance, in Arak, ~ 90% of farmers sow 'Bahman' cultivar while in Sabzevar, the most farmers use 'Reyhan' cultivar which are dominant in these locations (Table 5). The same approach was applied for sowing date and other management inputs. For example, around 95% of farmers in Shiraz sow barley on 16 November (Table 5). Overall, ~ 300 questionnaires were completed by farmers in the study locations.

Table 4 Simulated types of grain yield under different levels of limiting factors.

Acronym	Yield type	Description
Y_p	Simulated potential yield	The potential yield is the yield of a cultivar in a given location with unlimited nutrients and water and conditions free from pests, diseases, weeds, and abiotic stresses (Evans and Fischer, 1999; Grassini et al., 2009). The potential yield is independent of the soil, and it is assumed that the soil does not have any physical and chemical limitations for crop growth (Evans and Fischer 1999; Van Ittersum et al. 2013). The potential yield is theoretically simulated by the model considering these conditions. Under potential conditions, there is absolutely no water and nitrogen stresses as the Autoirrigation and Autofertilizaiton modules are switched ON in the mode.
Y_{rs}	Simulated research station yield	Simulated yield under the best management practices applied at research stations (i.e., optimal irrigation and fertilization, use of high-yielding cultivars, best sowing dates). This type of yield is also called "attainable yield. Although, both potential and research station yields have the same weather and cultivar, however, research station yields are less than absolute biophysical simulated 'potential yields' even under the best management practices at a given time and in a given ecosystem (Mueller et al., 2012). Under optimal conditions of the research stations, there would be at least a tiny stress over some phonological stages which affects grain yield. The research station yield was simulated based on the management data obtained from the research stations at each location.
Y_w	Simulated water-limited yield	The same as simulated research station yield, except that water is the only limiting factor, and the other factors are held at optimal levels. The amount and timing of irrigation applied by farmers in each region is considered as input for the model.
Y_{cu}	Simulated cultivar-limited yield	The same as simulated research station yield, except that cultivar is the only limiting factor, and the other factors are held at optimal levels.
Y_{sd}	Simulated sowing date-limited yield	Identical to simulated research station yield, except that sowing date is the only limiting factor, and the other factors are optimal.
Y_{fr}	Simulated frost-limited yield	The same as research station simulated yield, except that frost is the only limiting factor, and other factors are held at optimal levels.
Y_{fs}	Farmer's simulated yield	Simulated farmer's yield is based on the average local farmer management practices (only abiotic factors) in each location based on questionnaire answers. This type of yield is simulated by considering the limitations of only sowing date, water, cultivar, and frost. The biotic stresses were included in 'other agronomic yield gap' (Fig. 1).
Y_{fa}	Farmer's actual yield	Average of farmer's observed yields in each location obtained from the Ministry of Agriculture. All stresses of 'abiotic' and 'biotic' plus socio-economic factors affects the actual yield.

* The order of the yields is usually as follows: Yp>Yrs> [Yw, Ycu, Ysd, Yfr]>Yfs>Yfa. All of the barley grain yields at different production levels were simulated by the model except for farmer's actual yield (Yfa) which obtained from the Ministry of Agriculture.

Table 5

Details of management practices by the barley farmers in all study locations obtained from questionnaire.

Location	Sowing date	Cultivar[a]	Number of irrigation	Irrigation method	Water salinity	Use of certified seeds (%)	Soil testing (%)	Soil crusting (%)	Amount of urea application[b] (kg ha^{-1})	Micronutrients application (%)	Land area (ha)
Arak	15 October	Bahman	4	Sprinkler	Low	35	5	55	50–250 (160)	9	0.5–12
Hamedan	8 October	Bahman	4	Sprinkler	Low	41	7	25	50–300 (165)	8	0.8–15
Kabudarahang	2 October	Bahman	4	Sprinkler	Low	38	8	32	50–200 (150)	10	1-12.5
Marvdasht	16 November	Reyhan	4	Basin	Low	30	8	25	75–300 (140)	7	1–10
Neyshabour	15 October	Bahman	5	Basin	Moderate	28	5	35	50–200 (150)	5	0.5-8
Sabzevar	20 October	Reyhan	6	Basin	Moderate	26	5	30	50–200 (150)	5	0.5-8
Saveh	20 October	Reyhan	4	Furrow	Low	42	6	42	50–350 (150)	8	1–14
Shiraz	16 November	Reyhan	4	Basin	Moderate	32	6	50	75–350 (135)	5	1–10

[a] Bahman and Reyhan are mid-maturity and early-maturity cultivars, respectively.

b Values in parenthesis indicate the average.

Soil parameters required by the model, comprising LL (lower limit), DUL (drained upper limit), and SAT (saturated point), were gathered from the HC27 soil profile database (Koo and Dimes 2013; Nehbandani et al. 2020). In HC27, FAO and UNESCO soil maps have been combined with information available in more than 15,000 updated regional and national soil maps around the world to create general soil profiles. According to the HC27, soil parameter estimates (LL, DUL, SAT) are based on three criteria of soil texture (clay, silt, sand), rooting depth as a proxy for water availability (deep, medium, shallow), and organic carbon content as a proxy for fertility (high, medium, low fertility). In general, 27 types of soil profile (3×3×3) are available in HC27 in a format useful for crop models. Locations in the current study have 4 HC27 soil profiles (HC5, HC8, HC14, and HC17) as shown in Table S2.

2.4 Model validation

Independent data obtained from published papers and final reports of research projects on 31 field experiments were used for model validation (Table S1). Model validity was measured by comparing simulated (s_i) and observed (o_i) values using the standardized root mean square error (SRMSE, %) (Wallach et al. 2018) and coefficient of residual mass (CRM) (Willmott 1982) with the following equations:

$$\mathrm{SRMSE} = \frac{100}{\bar{\mathrm{O}}}\sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{Si}-\mathrm{Oi})^2}{\mathrm{n}}}$$

1

$$\mathrm{CRM} = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}\mathrm{Si}}{\sum_{\mathrm{i=1}}^{\mathrm{n}}\mathrm{Oi}}$$

2

where Ō is the mean of the observed values, and n is the number of observations. A lower SRMSE indicates a high simulation accuracy and less error by the model. Negative and positive values for CRM indicate model overestimation and underestimation, respectively (Homaee et al. 2002, Willmott 1982). Linear regression and 1:1 line were also applied to recognize the relationship between observed and simulated values and demonstrate model efficiency. A higher coefficient of determination (R^2) in linear regression indicates higher agreement between the observed and predicted data.

2.5 Simulated grain yields at different levels of limiting factors

Various grain yields at different production levels were simulated by the model for the eight barley growing locations from arid and semi-arid environments. The yields comprised: potential yield (Y_p), research station yield (Y_{rs}), water-limited yield (Y_w), cultivar-limited yield (Y_{cu}), sowing date-limited yield (Y_{sd}), frost-limited yield (Y_{fr}), and farmer's simulated yield (Y_{fs}). The full explanations of the different yields are presented in Table 4. The research station yield was simulated based on the management data obtained from the research stations at each location (Table S3). As mentioned earlier, only four limiting factors were investigated in the current study (water, cultivar, sowing date and frost). The observed research station yields were not used as there might be some other limiting and reducing factors affecting grain yield at the research stations. So, to standardize the yield gap decomposition, the research stations yields were also simulated at each study locations (Table 4). This approach was also applied by Liu et al. (2016). The simulated yields at different production levels were used for yield gap analysis (refer to section 2.6).

Data on farmer's actual yield (Y_{fa}) was obtained from Iran’s Ministry of Agriculture. Actual yields are the average of farmer's observed yields in each location. All stresses of ‘abiotic’ and ‘biotic’ plus non-agronomic factors affects the actual yield. In contrast, simulated farmer's yield was conducted by considering the limitations of only sowing date, water, cultivar, and frost in the current study. Other limiting and reducing factors within farms were considered in “other agronomic yield gaps” (refer to section 2.6).

2.6 Yield gap analysis

Based on the different simulated yields (Table 4), four types of yield gaps were calculated (Fig. 2). Total yield gap, comprising unexploitable, agronomic, and non-agronomic yield gap types, is the difference between the simulated potential yield and the farmer's actual yield. Unexploitable yield gap is estimated as the difference between the simulated potential yield and the simulated research station yield and indicates that reaching the potential yield is not possible in practice because of increased production costs (high use of inputs) and environmental impacts (Tran and Nguyen 2001; Koning et al. 2008; Lobell et al. 2009). The agronomic yield gap is the difference between the simulated research station yield and the farmer's simulated yield, caused by limiting and reducing agronomic factors. Agronomic yield gaps were categorized into five classes based on the particular limiting and reducing factors at each location, which were water, cultivar, sowing date, frost, and other agronomic factors (Fig. 2). Each type of agronomic yield gap was calculated relative to its optimal conditions. For example, to estimate water-limited yield gap, first we found out the optimal amount of irrigation by running the model under different treatments of irrigation regimes. Then, the optimal treatment was compared with the actual amount of water is applied by the farmers (Table 6) at each location. The identical approach was used for other limiting factors.

Table 6
Long-term (1989–2019) simulated climatic characteristics of the study locations.

Location	Cumulative radiation (MJ m^{-2})[a]	Average temperature (ºC)[a]	Frost intensity[b]	Frost frequency (%)[c]	Cumulative rainfall (mm)[a]
Arak	3869 ± 28	9.3	-13.5	100	288 ± 16
Hamedan	4184 ± 26	8.1	-14.8	100	306 ± 14
Kabudarahang	4271 ± 48	7.9	-13.5	100	297 ± 15
Marvdasht	3183 ± 31	10.9	-6.5	82.4	274 ± 23
Neyshabour	3359 ± 22	10.3	-12.7	100	224 ± 14
Sabzevar	2515 ± 28	11.2	-8.4	76.7	159 ± 10
Saveh	2638 ± 32	10.6	-8.1	85.2	168 ± 11
Shiraz	3169 ± 20	11.4	-6.6	50	303 ± 22

[a] Radiation, rainfall and temperature calculated over growing season

[b] Seasonal average minimum temperature when frost occurred. Based on the APSIM-Barley, frost occurs when the temperature drops below − 5 Celsius.

[c] Proportion of the simulated years that frost occurred.

The other agronomic yield gap resulted from agronomic factors other than those investigated in the current study (i.e., water, cultivar, sowing date, and frost), such as improper management of pests and weeds, non-optimal plant density, improper cultivation methods, soil compaction, improper plant nutrition, and use of improper planting equipment.

There should be also a gap between farmer simulated and actual yields which called non-agronomic yield gaps because not determined within the farm but indirectly affects the agronomic practices within the farm. For instance, size of farm owned by the farmers (which indirectly affects mechanization rate), total income (which indirectly affects the affordability to buy fertilizer, pesticides, etc.), gender, age and education (which indirectly affects the acceptance of new technologies in their fields). Very many researchers worldwide also pointed out that these factors are not directly agronomic (e.g. Liu et al. 2016; Beza et al. 2017; Mahmood et al. 2019; Assefa et al. 2020; Worku et al. 2020; Rong et al. 2021).

The other agronomic yield gap is the effect of agronomic management practices on yield reduction (other than the four factor investigated in this study: water, sowing date, cultivar and frost), while the non-agronomic yield gap shows the effect of the farmer's social and economic conditions, which indirectly affects the farmer's management decision and leads to yield reduction. Note that the biotic stresses were included in ‘*other agronomic yield gap’* (Fig. 2) as they are not quantifiable by the model.

3 Results

3.1 Model evaluation

Model evaluation consists of model calibration and validation. The results of model calibration showed that biological yield and potential grain yield were well simulated by the model when compared to the observed data except for days to flowering which was slightly under-estimated (Table 3). For days to flowering, the SRMSE, R^2, and CRM values were 7 days, 0.9, and + 0.066, respectively, while for biological yield and grain yield, the SRMSE values were 13.3% and 14.5%, R^2 values were 0.63 and 0.61, and CRM values were − 0.032 and − 0.029, respectively (Table 3).

The model validation results showed that SRMSE, R^2, and CRM for days to flowering were 7.5 days, 0.88, and + 0.08, respectively. For biological yield (12.9%, 0.65 and − 0.021, respectively), potential grain yield (15.3%, 0.59 and − 0.025, respectively), and water-limited yield (13.2%, 0.78 and − 0.01, respectively), the results were also in the acceptable range, indicating that the model estimated the reality with acceptable accuracy (Fig. 3). According to CRM, however, the model underestimated days to flowering (+ 0.08) and overestimated biological yield (-0.021), potential grain yield (-0.025), and water-limited yield (-0.01) compared with the observed values.

A good agreement was seen between the simulated and observed soil moisture content values during the barley growing season with SRMSE ranging from 9.8–15.2% and CRM ranging from − 0.0068 to − 0.12 (Fig. 4). Based on the model evaluation, it was generally concluded that APSIM was able to reasonably simulate the phenology and grain yield of barley in the studied locations. The model had also been previously tested for simulating the growth and yield of other field crops such as wheat (Deihimfard et al. 2015), maize (Jahangirlou et al. 2023), and canola (Rahimi-Moghaddam et al. 2021) with different Iranian climates, soils, and various management practices, and all indicated that the APSIM model performed well.

3.2 Simulated barley grain yield at different production levels

Simulation results showed that the study locations had high potentials for barley production (Y_p with rates ranging between 7.5 t ha^{-1} for Sabzevar in the northeast of Iran to the highest value of 9.8 t ha^{-1} for Hamedan in the west of Iran (average: 8.8 t ha^{-1}). Among all studied locations, the average simulated research station yield (Y_{rs}) was 7.3 t ha^{-1}, with the lowest (6.2 t ha^{-1}) and highest values (8.2 t ha^{-1}) obtained in Sabzevar and Hamedan, respectively (Fig. 5).

Under limitations of water, frost, and inappropriate sowing date, the simulated grain yield decreased substantially (Fig. 5). The long-term average of simulated water-limited yield (Y_w), simulated frost-limited yield (Y_{fr}), and simulated sowing date-limited yield (Y_{sd}) were found to be approximately 6.1 t ha^{-1}, 6.9 t ha^{-1}, and 7 t ha^{-1}, respectively. Across locations and seasons, the simulated water-limited yield was 5.4–6.6 t ha^{-1}, simulated frost-limited yield was 5.8–7.6 t ha^{-1}, and simulated sowing date-limited yield was 6.1–7.7 t ha^{-1}.

The average farmer's simulated yield (Y_{fs}) was determined to be 4.3 t ha^{-1} ranging from 3.7 t ha^{-1} in Sabzevar to 4.9 t ha^{-1} in Kabudarahang (Fig. 5). Farmer's actual yield (Y_{fa}) in the study locations also varied from 2.7 t ha^{-1} in Sabzevar to 4 t ha^{-1} in Kabudarahang with an average of 3.4 t ha^{-1}, showing a large difference when compared to the average simulated potential yield (8.8 t ha^{-1}). The simulated research station yield have no/little limitations of water, sowing date, frost, and cultivar, but the farmer's simulated yield faces some degree of all the mentioned limitations. In addition to the aforementioned limitations, the farmer's actual yield also has limitations obtained from the questionnaire (e.g., improper management of pests and weeds, non-optimal crop density, soil crusting, improper cultivation methods, improper plant nutrition). Therefore, the farmer's actual yield is lower than the farmer's simulated yield. When averaged across all study locations and years, the barley grain yield at different production levels followed the order of Y_p (8.8 t ha^{-1}) > Y_{rs} (7.3 t ha^{-1}) > Y_{sd} (7 t ha^{-1}) > Y_{fr} (6.9 t ha^{-1}) > Y_w (6.1 t ha^{-1}) > Y_{fs} (4.3 t ha^{-1}) > Y_{fa} (3.4 t ha^{-1}). All of the barley grain yields at different production levels were simulated by the model except for farmer's actual yield (Y_{fa}) which obtained from the Ministry of Agriculture (Table 5).

3.3 Yield gaps

The average total yield gap across all locations was simulated as 5.4 t ha^{-1}, ranging from 4.8 t ha^{-1} in Sabzevar to 6.1 t ha^{-1} in Marvdasht, which shows the large difference between the farmer's actual yield and the simulated potential yield. This gap value is equivalent to 61.4% of the simulated potential yield, meaning that farmers in the study locations have been able to achieve only 37.6% of the potential yield when averaged across locations and seasons. The total yield gap values of Marvdasht, Shiraz, Hamedan, Kabudarahang, and Arak were higher than those of Saveh, Neyshabour, and Sabzevar (Fig. 6). Total yield gap was divided into three components: unexploitable, agronomic, and non-agronomic yield gaps, which comprised, 26.7%, 55.9%, and 17.4% of the total yield gap when averaged across all study locations (Fig. 6).

Compared to unexploitable and non-agronomic yield gaps, the agronomic yield gap, ranging from 53–60%, contributed most to the total yield gap in all study locations (Fig. 6). Water limitation comprised the major part of the agronomic yield gap in the study locations, accounting for ~ 40% of said gap compared with cultivar-limited yield gap (13.7%), frost-limited yield gap (15.8%), sowing date-limited yield gap (10.4%), and other agronomic yield gap (30%) (Fig. 6).

Only three of the eight studied locations showed a gap caused by genetic limitations. In Marvdasht, Shiraz, and Sabzevar, the cultivar used by farmers (Reyhan, Table 6) was not the most optimal for these climates and resulted in cultivar-limited yield gaps of 19%, 13%, and 9% of the agronomic yield gap, respectively (Fig. 6). The cultivar used by farmers in Hamedan, Kabudarahang, Arak, Saveh, and Neyshabour caused no limitation, with cultivar-limited yield (Y_{cu}) values of 8.3, 8, 7.8, 7.2, and 6.6 t ha^{-1}, respectively (Fig. 6).

Almost all studied locations showed a yield gap due to improper sowing date. When averaged across all locations and seasons, the sowing date-limited yield gap was about 10.4% of the agronomic yield gap with the lowest one being in Shiraz (5%) and the highest one in Hamedan (17%) (Fig. 6).

Frost damage resulted in a substantial yield gap in almost all studied locations. The average amount of yield gap due to below zero temperatures was 15.8% of the agronomic yield gap. The highest and lowest frost-limited yield gaps were simulated in Neyshabour with 21% and Shiraz with 11% of the agronomic yield gap, respectively (Fig. 6). Other agronomic yield gap was also substantial in the studied locations, averaging 30% of the agronomic yield gap; the highest (42%) and lowest (18%) values were obtained in Saveh and Hamedan, respectively (Fig. 6).

The non-agronomic yield gap, which is obtained from the difference between the farmer's simulated yield and the farmer's actual yield, varied from 14% in Hamadan to 21% in Sabzevar (Fig. 6).

4 Discussion

4.1 Unexploitable yield gap

The average farmer's actual yield in the studied locations was substantially different from the average simulated potential yield (Fig. 5). The relatively large difference between potential and actual yield values has also been reported for other crops in various regions worldwide, including wheat (Soltani et al. 2020; Zhang et al. 2017), corn (Balboa et al. 2019), rice (Basukala and Rasche 2022; Soltani et al. 2020), potato (Grados, et al. 2020), and soybean (Balboa et al. 2019). The spatial distribution of farmer's actual yield and simulated potential yield showed that the locations with either low actual yield or high potential yield had a higher yield gap and, consequently, a greater potential for increasing current yield. Some parts of the substantial total yield gaps have been defined herein as unexploitable gap (26.7% of the total yield gap). Filling this type of yield gap in the field requires a high amount of water and nitrogen, which would results in a higher production costs and serious environmental impacts. The yield response to the application of more inputs tends to be a decreasing one because of the law of diminishing returns (Koning et al. 2008; Lobell et al. 2009). Other studies have reported different values when quantifying unexploitable yield gap. For example, in Northeast China, the non-controllable yield gap of maize was estimated to be 12.5% of the total yield gap (Liu et al. 2016). Seehusen and Uhlen (2019) calculated the unexploitable yield gap of spring barley in Norway as 46.7% of the total yield gap. Alasti et al. (2022) estimated the unexploitable yield gaps for irrigated and rainfed barley in Iran to be 34.7% and 31.8% of the total yield gap, respectively. These variances in unexploitable yield gaps are explained for the most part by different climates, crops, and management conditions that affect the amount of input usage until reaching the conditions of diminishing returns. Overall, it is difficult, costly and not environmentally friendly to close the unexploitable yield gap in the field as it caused by variable weather conditions and high uncertainty in rainfall, the huge application of fertilizer or crop protection chemicals, or, as noted earlier, where using more inputs would not be profitable (Van Ittersum et al. 2013, Van Wart et al. 2013). In the research stations, the range of irrigation was from 6 to 9 irrigation times in different locations. For example, to simulate the research station yield in Sabzevar, the number of irrigations was 7 times (each 50 mm). While, to simulate the potential yield, automatic irrigation was done by the model and this is not possible in the field with the existing water and technologies. In research stations, despite optimal management, weaknesses compared to the potential conditions still cause a yield decrease. For example, by applying 7 times irrigation (each 50 mm) in Sabzevar, about 25% more water is requied to fill the gap between the research station yield and the potential yield (data not shown).

4.2 Agronomic yield gap

In the current study, a substantial amount of the barley yield gap was associated with agronomic factors (55.9%), namely water, cultivar, sowing date, frost damage, and other agronomic factors, among which water shortage contributed the highest proportion (40%) (Fig. 6). In the studied arid locations, underground water, which is the dominant resource for barley irrigation, has been extremely restricted over the past two decades, such that farmers could only irrigate barley fields 4–6 times per season (Table 5). According to the farmer-completed questionnaires, most of the farmers in the study locations such as Sabzevar and Neyshabour use traditional irrigation methods, especially basin and furrow irrigation (Table 5), with an average irrigation efficiency of 37.2% across locations. In Arak, Kabudarahang, and Hamedan in the west of Iran, despite the widespread use of sprinkler irrigation systems, the water-limited yield gap is still high (Fig. 6). The reasons behind this are the lower number of irrigations (4 times, Table 5) and improper irrigation scheduling (personal correspondence with the farmers). Also, the effect of water limitation has been increased over time due to global warming, as some farmers (particularly those in Sabzevar) stated that they have to irrigate barley even in the winter season because of low rainfall amounts in late winter. Our results are in line with those obtained by Davis et al. (2017) who reported that to close the agronomic yield gap, the allocation of freshwater resources for the irrigation of 14 field crops across 66 countries needs to be increased by at least 146%. They also emphasized that water limitations caused by a lack of water resources and climate change are the main obstacles to reducing the yield gap, especially in arid and semi-arid locations. Using a modeling approach, Zhang et al. (2017) found that the potential yield of wheat decreased because of limited water availability, with an average reduction of 1.9 t ha^{-1} across the major winter wheat production areas of China. Balboa et al. (2019) concluded that irrigation is a very crucial management factor in the western US Corn Belt, responsible for about 50% of both corn and soybean yield gaps which is comparable with the results of the current study (40% of agronomic yield gap). In their study on winter wheat yield gap in the North China Plain using the modeling approach, Lu and Fan (2013) suggested that improving irrigation and fertilizer efficiency through appropriate agronomic practices, such as timely application of water and nitrogen based on crop demand and soil conditions, will substantially reduce the yield gap. Moreover, they suggested improving water storage methods using mulch and sprinkler irrigation instead of furrow irrigation as effective ways to reduce the yield gap.

Across all study locations other than Marvdasht, Shiraz, and Sabzevar, farmers have been using the most optimal cultivar (i.e., Bahman, Table 5) that has adapted to the local climate, so there was no yield gap due to genetic potential. Cultivar-limited yield gaps in Marvdasht, Shiraz, and Sabzevar (Fig. 6) were mainly on the account of cultivating an early-maturity cultivar (Reyhan), which had lower potential than the Bahman cultivar. Simulation results showed that by replacing a mid-maturity cultivar (i.e., Bahman), the simulated cultivar-limited yield for the three mentioned locations increased compared with the common cultivar. The reasons behind the superiority of Bahman in these locations are longer period at the beginning of grain filling (560.5 ºCd which resulted in higher radiation absorption) and higher potential grain filling rate (g $grain^{-1}$ d^{-1}) than other cultivars (Table 2). Therefore, it is essential to use the cultivars adapted to each climate to increase yield and reduce the cultivar-limited yield gap. Zhang et al. (2016) reported that the incorrect selection of a proper maize cultivar by more than half of the farmers in China caused a 19.8% yield gap. Espe et al. (2018) studied the improvement of rice yield through plant breeding in California (USA) and reported that improved cultivars played an important role in increasing rice yield (24.1 kg ha^{-1} $year^{-1}$). Therefore, applying high-yielding cultivars adapted to each location would result in increased yield and reduced the gap. It is worth noting that the superiority of a cultivar in the current study is only based on grain yield. It is likely that a cultivar is being used for other reasons which provide other benefits than yield (e.g. resistance to a disease or pest).

The findings of the current study showed that sowing barley at the inappropriate date in each location based on climatic conditions and cultivar characteristics contributed to an average of 10% of the agronomic yield gap (Fig. 6). Delaying barley sowing was better adapted for Kabudarahang (+ 18 d), Saveh (+ 16 d), Arak (+ 15 d), Hamedan (+ 14 d), Neyshabour, and Sabzevar (+ 10 d), while Marvdasht (-8 d) and Shiraz (-6 d) benefitted from early sowing. By adjusting the sowing date, crops can utilize temperature, solar radiation, and rainfall resources (as main driving factors in crop growth and development) much more efficiently. For example, because of the long growing season in Hamedan and Kabudarahang (data not shown), barley crops received cumulative radiation of 4184 and 4271 MJ m^{-2}, respectively, which could be further increased by delaying the sowing date. In contrast, Shiraz and Marvdasht with a shorter growing season and average temperatures of 11.4 ºC and 10.9 ºC, respectively, received less seasonal cumulative radiation (3169 and 3183 MJ m^{-2}, respectively, Table 6). By applying an early sowing date in these locations, radiation interception could be greatly enhanced. Our findings are similar to Gao et al. (2021) who reported that the high simulated yield of maize in the North China Plain was gained at an early sowing date because of sufficient solar radiation and accumulated temperature. Nunes et al. (2021) also concluded that from the three sowing dates of April 1st, 10th, and 20th for cowpea in Castanhal/Brazil, the most appropriate sowing date was early April because early sowing allowed the crop to make better use of water through transpiration, reduced water loss due to evaporation, and resulted in increased production and decreased water loss. Yao et al. (2021) studied the management factors affecting the winter wheat yield gap in China and found that by adjusting the sowing date, the yield gap could be reduced by 400–1200 kg ha^{-1} (5–15%). In comparison, in our study, by adjusting the sowing date, the yield gap decreased on average by 6.2%. In another study in the Argentinean Gran Chaco region, the optimal range of sowing dates for maximizing soybean yield was estimated to be from early to late December, and any delay in sowing after this date resulted in yield decline by 43 kg ha^{-1} day^{-1} (Madias et al., 2021). Overall, many studies have shown that adjusting the sowing date to better match the crop growth stages and favorable environmental conditions could lead to increased crop yield and reduce the sowing-limited yield gap.

As stated earlier, the frost-limited yield gap comprised, on average, 15.8% of the agronomic yield gap in the studied locations. Frost has occurred in 50–100% of seasons in almost all of the studied locations, meaning that all studied locations are frost-prone environments. However, the intensity of frost occurrence was widely varied across locations and years. In Neyshabour, Hamedan, and Kabudarahang, for example, the intensity of frost damage was much higher (Table 6) than the remaining locations, resulting in a higher frost-limited yield gap (Fig. 6). As reported by the barley farmers in these locations, winter snowfall, especially in recent years, has been decreased (perhaps due to climate change), and this issue has negatively affected the severity of frost. Deihimfard et al. (2019) found that frost damage in cold and semi-arid regions of northeastern Iran did not occur in sugar beet during spring sowing dates, while frequent plant death occurred with all autumn sowing dates. They also reported that in some locations, up to 100% of autumn-sown crops were lost. In the central area of the Huang-huai Plain in China, the reduction in wheat yield due to frost during the 2015–2018 period indicated that the highest and lowest percentages of yield difference compared to normal yield were 18.3% in 2018 and 1.8% in 2017, respectively (Wu et al. 2022).

The other agronomic yield gap resulted from factors other than those investigated in the current study (i.e., water, cultivar, sowing date, and frost) and comprised 30% of agronomic yield gap when averaged across all study locations (Fig. 6). The current results showed that following the water-limited yield gap, other agronomic yield gap had the second largest proportion of the agronomic yield gap in the studied locations. The information provided by farmers on the questionnaire showed that in addition to those investigated in this study, factors such as the improper management of pests and weeds, non-optimal crop density, soil crusting, improper cultivation methods, improper plant nutrition (inadequate supply of inputs), and the use of improper planting implements greatly impacted the agronomic yield gap when compared with the research station yield and should be considered in future research (Table 5). One of the factors of other agronomic yield gap that had an effect on yield gap was the lack of attention to the role of micronutrient elements in plant nutrition in all locations, especially Shiraz, Sabzevar and Neyshabour. This implies that research station simulations have no/little limitations from water, frost, sowing date, and cultivar. In contrast, the simulated farmer's yield have these limitations, plus those above-reported by farmers on the questionnaire. The farmers in the current study, especially those in Sabzevar, Neyshabour, and Shiraz, also reported that the excessive extraction of underground water resources has recently caused the water and soil of these locations to become salty. Overall, this type of gap can be eliminated by applying optimal management practices and utilizing existing technologies (Awio et al. 2022).

4.3 Non-agronomic yield gap

In the studied locations, the average non-agronomic yield gap was 17.4% of total yield gap, which results from so many factors including low farmers' income (e.g., in Neyshabour and Sabzevar which indirectly affects the farmer's affordability to buy fertilizer, pesticides, etc.), the dispersion and small size of cultivated lands (e.g. in Marvdasht, Shiraz, Neyshabour, and Sabzevar) which could indirectly reduce the feasibility of proper management and planning for the optimal use of resources and machinery and lead to an increase in production costs, the advanced age of farmers in Sabzevar, Neyshabour, Marvdasht, Shiraz, and education level (which indirectly affects the acceptance of new technologies in their fields). In addition, fewer than 50% of farmers across all study locations and in Sabzevar, Neyshabour, and Marvdasht in particular, fewer than 30% use certified seeds because they might be expensive to some farmers. It is also worth noting that fewer than 10% and in some locations no farmers implement soil testing before planting because it is hard for them (who have older ages) to accept that soil testing would be beneficial for nutrient application. Soil testing can help reduce the need and subsequent cost of fertilization and avoid soil degradation by improving soil management and ultimately increasing farmers' income (Van Raij et al. 2002). As seen in Table 6, the above-mentioned non-agronomic factors differed among farmers in various locations because of diverse economic and social conditions, anthropological factors, and traditional farming practices. Liu et al. (2016) estimated the maize non-agronomic yield gap in northeast China to be 25% of the total yield gap. They also found that the non-agronomic yield gap had been narrowed at a rate of 10.7% per decade from 1961 to 2010. A study of corn, soybean, and cotton farms in the southern Amazon also showed that the socio-economic factors of unlimited access to machinery, labor, credit, and technological innovation reduced the yield gap by 6.1% (Hampf et al. 2018). Other non-agronomic factors have also been reported, including gender and number of the labor force (Mahmood et al. 2019), and farmer training programs (Abdulai et al. 2020), all of which could indirectly affect agronomic management decisions and, ultimately, crop yield

(Stuart et al. 2016). Estimating the non-agronomic yield gap and determining the factors affecting it would provide a key for further investigations and resolving yield limitations across all study locations.

5 Conclusion

Yield gap analysis is important to recognizing potential sources of enhancement in agricultural yields and developing solutions to reduce these gaps. In the current study, we identified a substantial yield gap when simulated potential and simulated research station yields were compared to the farmer's actual yield in barley growing areas in arid and frost prone locations. The size of the yield gap indicates that over the last two decades, farmers have been able to achieve only 38.6% of the potential yield. The simulated yield gaps were highly location-dependent in relation to the different management practices applied in these locations. The agronomic yield gap in the studied locations, a major component, was caused by water limitations (40%) followed by other agronomic (30%), frost-limited (15.8%), cultivar-limited (13.7%), and sowing date-limited (10.4%) yield gaps. In only three of the eight studied locations, a genetic-limitation gap was seen, which resulted in an average cultivar-limited yield gap of 13.6% of the agronomic yield gap. In the current study the available cultivars that are better suited for each location was investigated. The APSIM crop model may also be used in the future study to show characteristics of optimally adapted cultivars to current or future climate (i.e. ideotyping).

As the research station yield is achievable by farmers, the difference between research station yield and farmer's actual yield (agronomic + non-agronomic gaps) could be eliminated by improving farmers' management practices and supplying the water required by the barley. Under these circumstances, the country's barley annual production could be increased from 3.5 to 7.5 million tons as predicted by the APSIM model.

Declarations

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Authors' contributions:

Mohammad Reza Rahimi: Running simulations, Handling climate and management data, Formal analysis; **Reza Deihimfard**: Conceptualization, Writing original draft preparation, Methodology;

Omid Noori: Handling soil and climate data, Supervision and reviewing

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Figures

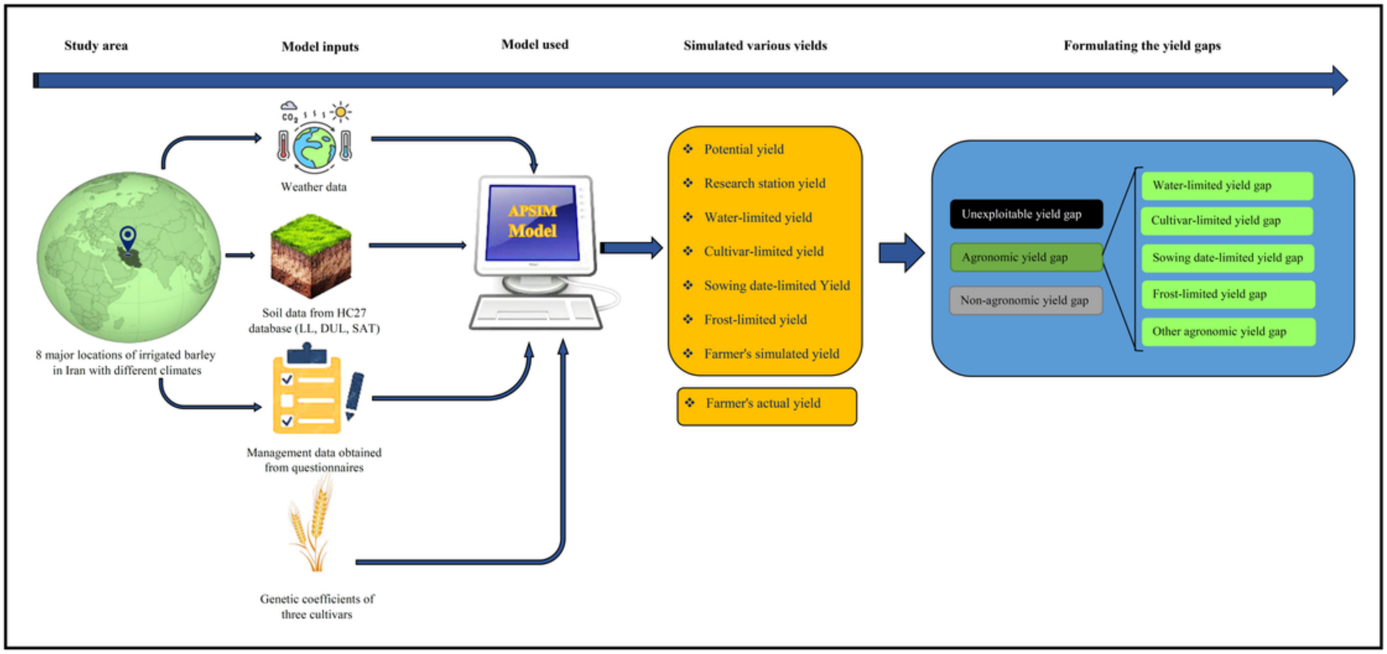

Figure 1

Summary of the steps taken to simulate the various yields and yield gaps in the irrigated barley cultivation areas.

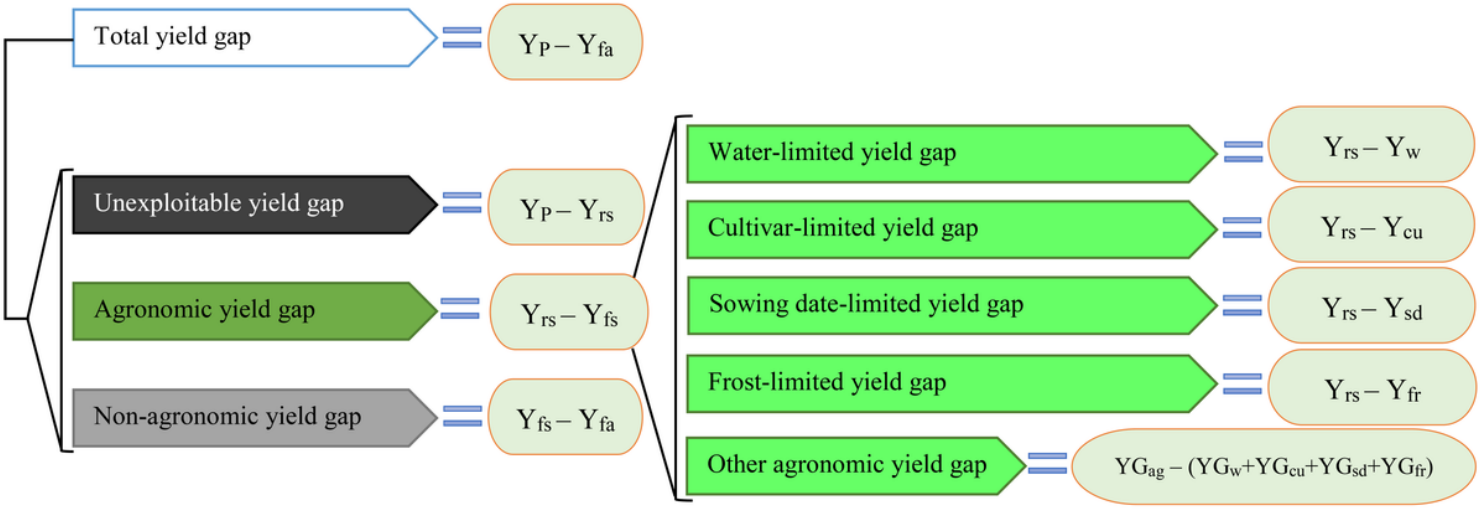

Figure 2

Formulations of different yield gaps simulated using APSIM model. Agronomic yield gap categorized into five groups: water-limited, cultivar-limited, sowing date-limited, frost-limited, and other agronomic yield gaps. Different yields were simulated by APSIM-Barley included: simulated potential yield (Y_p), simulated research station yield (Y_{rs}), simulated water-limited yield (Y_w), simulated cultivar-limited yield (Y_{cu}), simulated sowing date-limited yield (Y_{sd}), simulated frost-limited yield (Y_{fr}), and farmer's simulated yield (Y_{fs}). Farmer's actual yield (Y_{fa}) in each location obtained from the Ministry of Agriculture. Potential and farmer's actual yield are usually the highest and lowest yield, respectively. The order of the yields is often as follows: Y_p>Y_{rs}>[Y_w,Y_{cu}, Y_{sd},Y_{fr}]>Y_{fs}>Y_{fa}. Refer to Table 5 for more details on the definition of different yields simulated by the model. Agronomic yield gap (YG_{ag}), water-limited yield gap (YG_w), cultivar-limited yield gap (YG_{cu}), sowing date-limited yield gap (YG_{sd}), frost-limited yield gap (YG_{fr}).

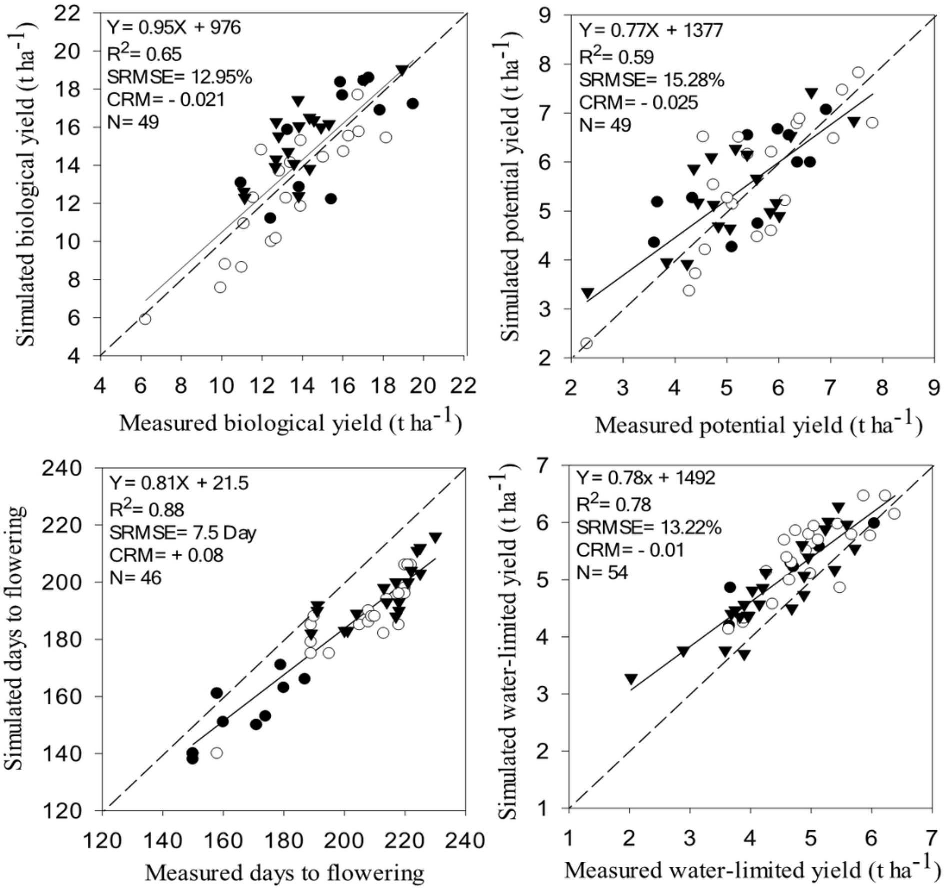

Figure 3

Results of model validation for biological yield, potential grain yield, water-limited yield and days to flowering. Datasets used for model validation is presented in Table S1. Potential and water-limited yields were simulated based upon the “experimental condition” in each experiment (column four of Table S1). Cultivars: Reyhan (●), Bahman (●), Makuie (▼). R^2: Coefficient of Determination; SRMSE: Standardized Root Mean Square Error; CRM: Coefficient of Residual Mass; N: Number of observations.

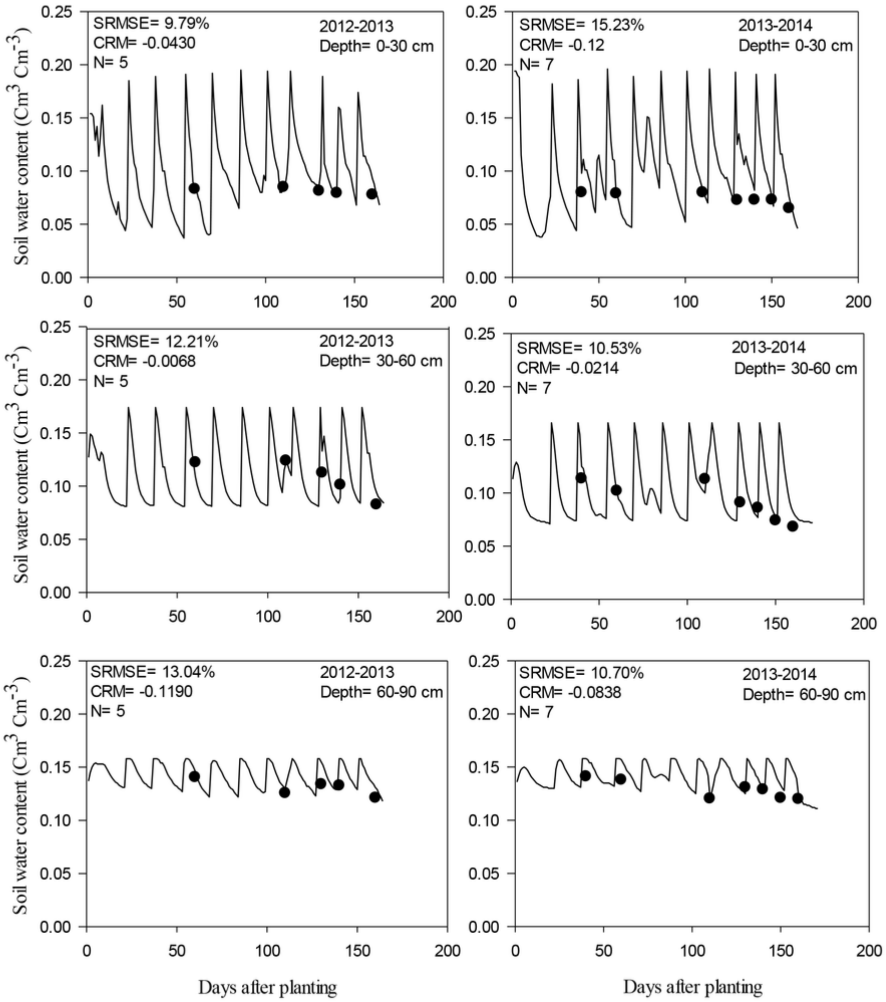

Figure 4

Comparison of simulated (lines) and observed (data points) soil moisture content at the different soil layers in two growing seasons: 2012-2013 and 2013-2014. Data points were obtained from the study of Pirasteh-Anosheh et al. (2017). The seasonal changes in soil moisture contents in the irrigation treatment was used in this study. Soil moisture content was measured before each irrigation at different depths. SRMSE: Standardized Root Mean Square Error; CRM: Coefficient of Residual Mass; N: Number of observations.

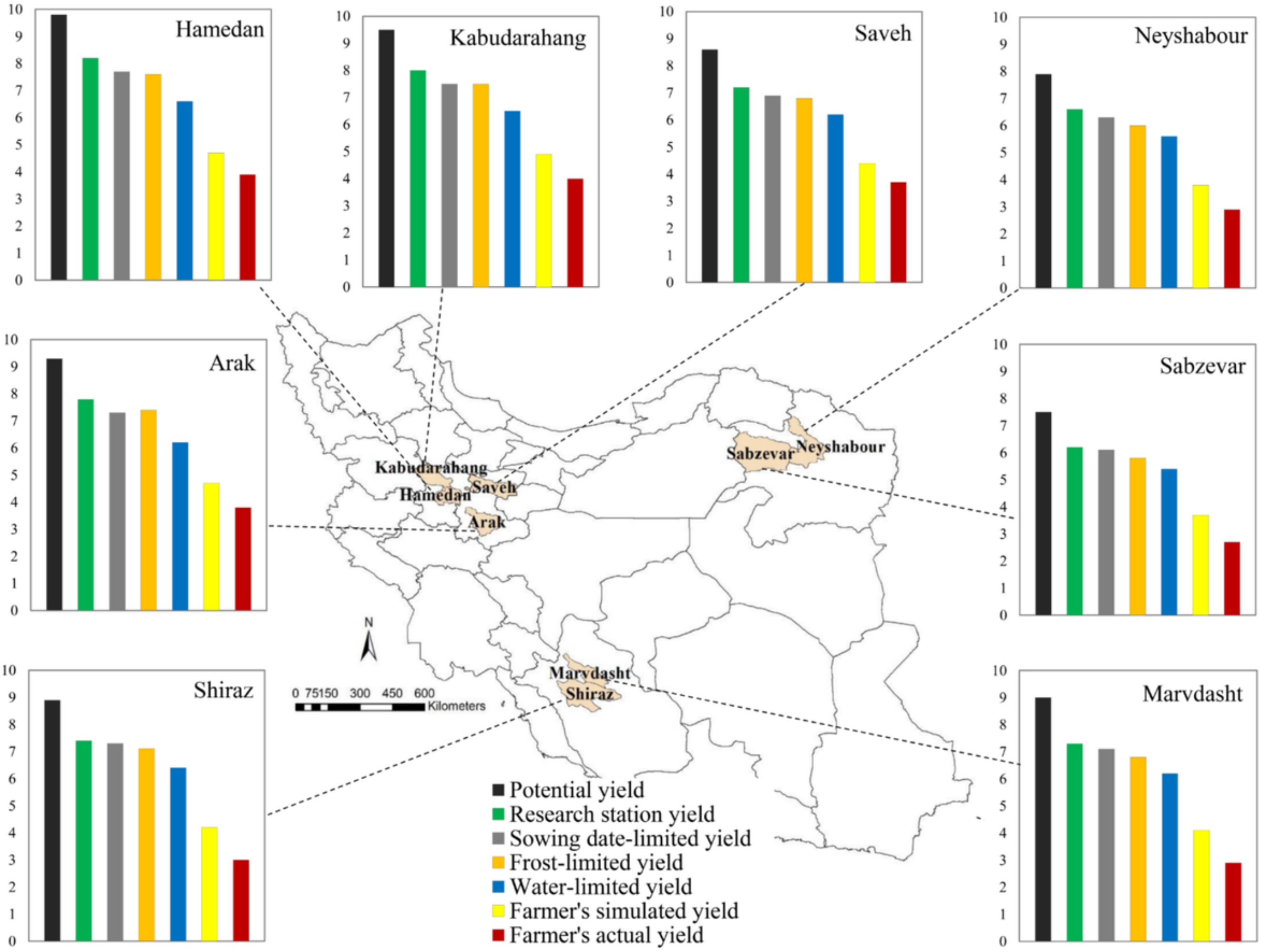

Figure 5

Long-term (1989-2019) average of barley grain yield (t ha^{-1}) at different production levels in all study locations. All type of yields were simulated by the model except for farmer's actual yield which obtained from Iran Ministry of Agriculture. Refer to Table 5 for further explanation regarding the different types of yield.

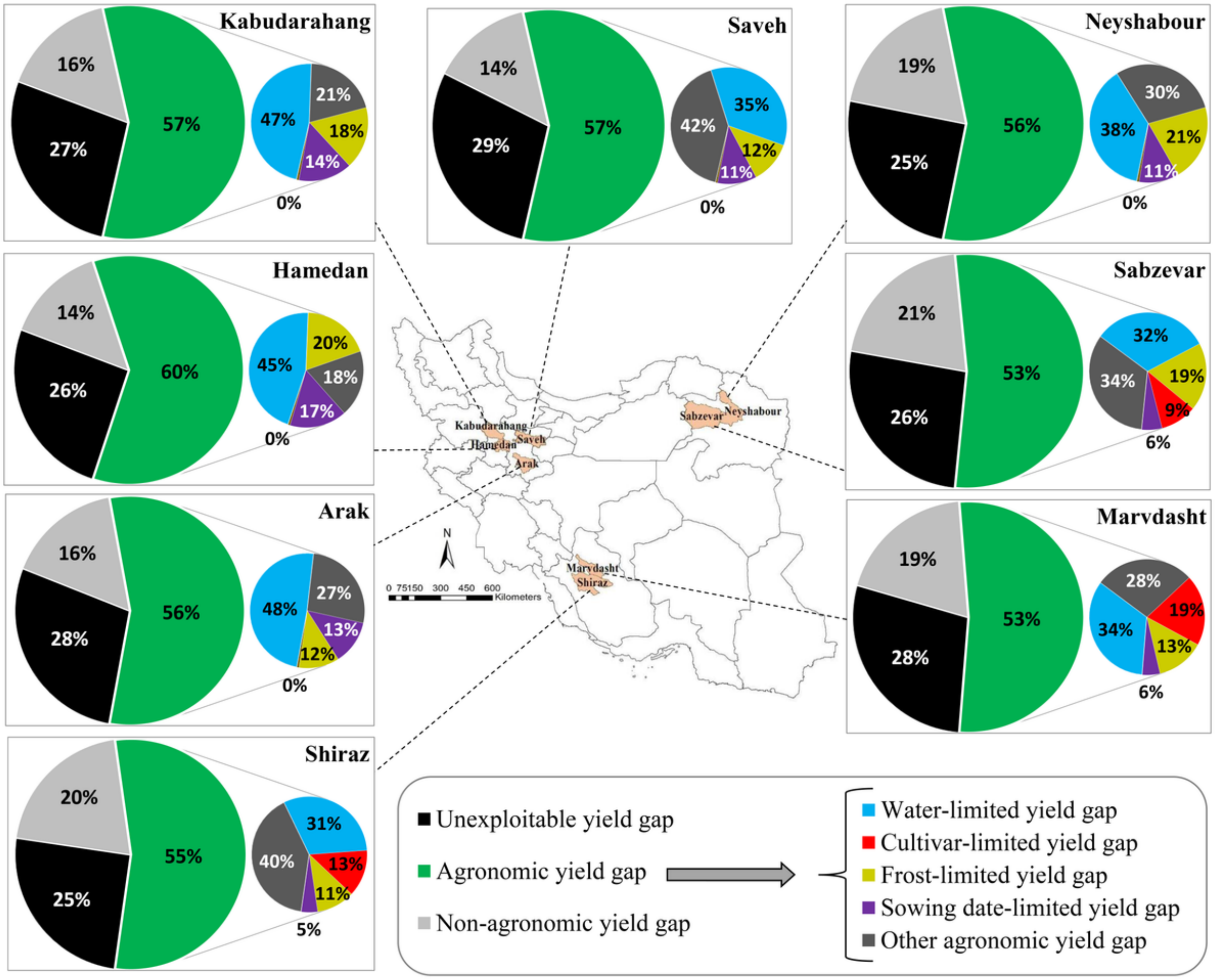

Figure 6

Major yield gaps of barley including unmanageable, agronomic and socio-economic gaps presented in the larger pie charts in all study locations. Agronomic yield gap was categorized into five groups (smaller pie charts): water-limited, cultivar-limited, frost-limited, sowing date-limited and other agronomic yield gaps. Total yield gap is sum of unmanageable, agronomic and socio-economic gaps.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryTables.docx