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The following should be included in all manuscripts submitted to *Agricultural, Environment and Society:*

- ***Generally, should focus on the critical issues that will move agricultural systems forward and improve the living conditions of people.***
- ***Substantial natural science material (particularly farm- or landscape-level, sometimes coupled with social sciences), and***
- ***A thorough examination and discussion of the interconnections between agricultural system components and other systems.***

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Identification of effective factors on acceptance of new irrigation systems for optimum agricultural water management in the Torshiz area

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ABSTRACT

The aim of this research was to identify the factors contributing to the adoption of New Irrigation Systems (NIS) by farmers in the Torshiz region. After gaining a comprehensive knowledge of the study area, a questionnaire was prepared to gather the opinions and views of farmers on the use of these systems. After determining the validity of the questionnaire through expert opinions and its reliability by calculating Cronbach's alpha (0.93), the questionnaire was distributed among 100 farmers and filled out by them in the region. The analysis of the questionnaires was done in SPSS 21 software, and the structural modeling of the effective factors in the acceptance of the systems was done in Smart PLS software. The analysis showed that all of the investigated factors had a significant impact on the acceptance of irrigation systems (T-index greater than 1.96 and significant level less than 0.05). Attitudinal factors were found to be the most influential, followed by economic factors. According to the results, the most significant educational factor was found to be the "suitable cultivation pattern for the region", while the most important economic factor was "various cultivation abilities". In terms of social factors, "using the positive experiences of others in connection with NIS" was identified as the most crucial. Lastly, among the attitudinal factors, it was found that believing that it causes more success in farm management is of the highest importance. Therefore, according to the location of this region, which is located in a hot and dry climate, farmers should be encouraged to accept the use of technology. They can do this by identifying the most suitable cultivation pattern for the region and holding scientific and practical training courses. In this case, it is possible to increase agricultural production and improve water consumption efficiency in the area.

Highlights

- Identify factors influencing farmers' adoption of NIS for better water management in Torshiz, a hot and dry region.
- All investigated factors (educational, economic, social, attitudinal) significantly influence NIS adoption.
- Attitudinal factors have the strongest influence, followed by economic factors.
- Farmers value NIS' potential for success in farm management and efficient water use.

1. Introduction

Water is a valuable and finite resource that plays a crucial role in agricultural production across the world (Martinez-Arteaga et al., 2023). In countries with low average rainfall, agricultural irrigation is a key factor in food and fiber production, and it can consume up to 60% of the available freshwater resources (Koech et al., 2021). The water shortage is currently one of the most pressing issues of the 21st century. This problem is caused by a combination of factors, including climate change and population growth. It poses a threat not only to food security but also to the income security, livelihoods, and overall well-being of rural populations. Furthermore, it endangers regional prosperity and development (Yazdanpanah et al., 2023; Castillo et al., 2021). It is predicted that global water demand will increase by 20–

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30% in the industrial, domestic, and agricultural sectors by 2050, and agriculture will remain the main consumer of fresh water (Martinez-Arteaga et al., 2023). On the other hand, it is expected that the allocation of water resources to different economic sectors and the need to increase the efficiency of water consumption will intensify (Iskandar et al., 2018).

Iran is currently facing a serious water crisis. Water demand has risen substantially, while water resources have decreased significantly across most regions of Iran. This is largely due to prolonged periods of drought. As a result, Iran has earned the fourth position in the Middle East and North Africa region for severe water stress (Rouzaneh et al., 2021). For example, it has been reported that 16 out of 30 river basins in Iran have experienced a drastic decrease in water levels (Ashraf et al., 2019). This can be attributed to climate change, which is expected to reduce water supply and access by 50% by 2050 (Boazar et al., 2019). At the same time, the efficiency of agricultural water consumption in Iran (35%) is very low compared to developed countries, which is more than 70%. Due to the gradual deterioration of the water situation, some methods have been used to reduce this crisis in Iran, among which improving water productivity in the agricultural sector is a vital goal to conserve water and reduce the water crisis (Rahimi-Feyzabad et al. 2020). In addition, due to the increase in demand, limited resources, variation of water level in time and place, and soil pollution, it is necessary to optimize the management of water resources in the agriculture section (Nejadrezaei et al., 2018). In the meantime, new irrigation technologies provide the possibility of controlling and distributing water to meet agricultural water needs (Chuchird et al., 2017). Efficient irrigation practices are responsible for reducing the effects of climate change and creating a positive impact on crop yield, food production, food security, and economic development (Piwowar et al., 2020). For example, technologies such as drip and rain irrigation are a type of agricultural water management that can reduce water shortages by 19% and save up to 35% of agricultural water (Koech and Langat, 2018).

In this context, the studies of the Water and Soil Research Institute and the Agricultural Engineering Research Institute of Iran show that replacing traditional irrigation methods with NIS by improving the efficiency of water consumption can save between 3000 and 6000 cubic meters per hectare (Yazdanpanah et al., 2022). However, irrigation technologies are usually rarely used, especially when a high initial investment is required. Also, a lack of awareness amongst farmers and the public about the different types of irrigation methods is one of the most important and effective issues in the consumption and management of water resources in agriculture. In fact, only 14% of the world's 275 million hectares of irrigated land currently use efficient irrigation methods (Martinez-Arteaga et al., 2023).

The Iranian government is actively taking steps to manage the water shortage challenge in the country. One of them involves encouraging farmers to use new irrigation technology. so, it is investing approximately USD 300 million to support their adoption. According to this plan, the government pays 85% of the total cost of implementing NIS, and the farmer's share remains only 15% (Yazdanpanah et al., 2022). Therefore, with the provision of such government facilities and these conditions of water scarcity and climate change, the cooperation of farmers is necessary for more efficient and sustainable use of water resources due to the relationship between agricultural activities and their environment. Despite the government's efforts to provide appropriate facilities to farmers, the acceptance rate of these systems remains low. Therefore, it is necessary to encourage farmers to adopt these systems and promote the sustainable use of water resources. As a result, the investigation of factors affecting the adoption of new irrigation methods in agriculture has attracted considerable attention among researchers. some researchers, such as Movahedi et al. (2017), Taheri et al. (2018), Menatizadeh and Zamani (2017), Chuchird et al. (2017), Feizabadi and Gorji (2018), Saleh et al. (2022), and Sabbagh and Gutierrez (2023), have conducted research in this field to investigate the factors that influence the adoption of new irrigation methods in agriculture. For example, A study conducted by Saleh et al. (2022) analyzed the factors that influence the adoption of education and irrigation technologies for sustainable food production in the state of Nigeria. The results showed that most of the farmers had a low level of education, which indicates that agriculture in the study area is heavily dominated by the traditional farming system and leads to lower crop yields. Also, the results showed that poor service to farmers was directly related to the acceptance of education and the adoption of irrigation technologies by farmers. Also, Sabbagh and Gutierrez (2023) investigated the factors influencing the adoption of NIS by farmers in Lebanon. By preparing a questionnaire, they used various economic, social, and educational factors to determine the effective factors. The results showed that the hope of farmers to grant facilities to use these systems, the hope of producing more products (higher yield), and the need for less work on the farm are effective in the acceptance of these irrigation systems**.**

The review of research showed that knowledge of the effective factors in accepting new irrigation methods plays an important role in the use of these methods by the target community (farmers). Therefore, due to the great importance of preserving water resources and preventing the wastage of this valuable resource, the current research has been carried out in the Torshiz region of Khorasan Razavi province**.** Considering that the two categories of aridity and desertification caused by climate change will definitely cause serious damage to agricultural and horticultural products, national wealth, and people in arid and semi-arid areas such as the Torshiz region, the use of these methods can play an effective role in making optimal use of available water resources.

To address this issue, the use of NIS can be highly effective in making optimal use of available water resources and increasing yield, quality, and quantity of products while reducing costs and saving water consumption. Moreover, it can also help control the income fluctuations of users, protect and maintain agricultural lands, and prevent and control desertification and wind/erosion crises in the region.

This can also increase the job satisfaction of farmers and their motivation for sustainability. The acceptance of new irrigation technology by farmers depends on various environmental conditions and factors. So, the farmer's level of awareness, income, and profit from the implementation of new irrigation methods can play an important role in their acceptance and development. Therefore, by considering the significant differences that exist in the rural communities of the country in terms of economic, social, and cultural points of view, it is important to examine the effects and reasons for accepting and not accepting new irrigation technology regionally, and the results of this study can be derived from this. The direction is more important**.**

2. Materials and methods

2.1. Study area

The current research is focused on the Torshiz region in Khorasan Razavi province. The region includes four cities, namely Kashmar, Bardaskan, Khalilabad, and Kouhsorkh (Figure 1). The Torshiz region is situated in a dry area located in the north of the Namak Desert. According to the climate classification, the area has a dry and mildly hot desert climate. The average annual rainfall is reported to be 190 mm. The average maximum temperature is 22.5 degrees Celsius, while the average minimum temperature is 11 degrees Celsius. The potential of evaporation and transpiration at the Kashmar synoptic station is 1701 mm per year. Rainfall is limited to the winter and spring seasons. There are no permanent rivers in the plain, and the most important seasonal river is Sheshtaraz. Due to the poverty of water resources, renewable natural resources are very sensitive and fragile, and a lack of attention and unplanned and unprincipled exploitation could lead to the destruction of these resources. Therefore, conducting research on the optimal management of water resources in the region is crucial to ensure their sustainability.

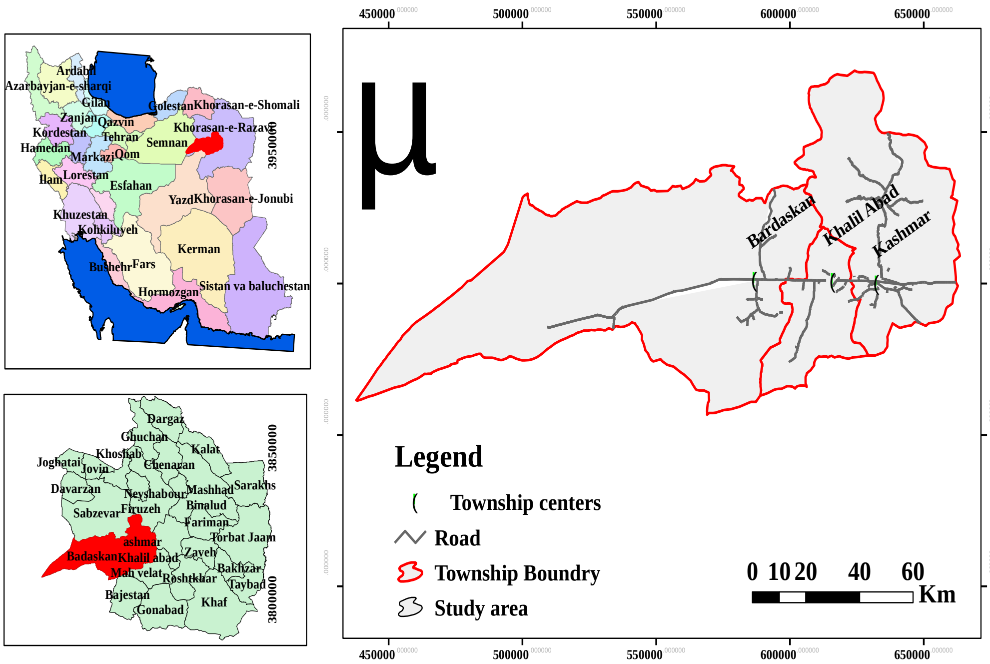

Figure 1. The location of the study area of the Torshiz region

2.2. Method

The purpose of this study was to identify the factors that affect the adoption of NIS for optimal use of agricultural water in the Torshiz region of Khorasan Razavi province. The acceptance of new irrigation technologies varies greatly and is influenced by several factors. Among the factors reported by researchers, household characteristics, farm size, age, education level, farmer's experience, assurance of more income, farmer's investment ability, educational and promotional factors, awareness of the effects of climate change, Government subsidies, cropping patterns, reliability, and risk-taking influence the adoption of irrigation systems for crops (Oyetunde-Usman, Z.; Olagunju, 2021; Martinez-Arteaga et al., 2023**)**. Therefore, in conducting this research, it was tried to investigate different types of influencing factors on the adoption of new irrigation methods and use them in preparing a questionnaire. So, the current research is of the quantitative research type, and in terms of research method, it is descriptive-analytical along with fieldwork. To conduct this research, at the beginning, the previous related research was investigated. The dependent variable of this research is the factors influencing the adoption of NIS, and the theoretical framework and independent variables include economic, social, educational-promotional, and farmers' attitude factors. Descriptive, analytical, and correlation methods have been used to identify the influencing factors in the acceptance of new systems**.**

A questionnaire was used to collect information to identify the influencing factors distributed and filled out by farmers in the Torshiz region of Khorasan Razavi province as water stakeholders. In order to check the validity of the questionnaire, experts in the field were consulted, and the questionnaire's reliability was tested by distributing 30 questionnaires among the target population. These questionnaires were completed and collected, and Cronbach's alpha coefficient was calculated to measure their reliability. Generally, 100 questionnaires were filled out by the target society. SPSS software was used to analyze the data, and Smart PLS was used to prepare the structural model. The questionnaire includes individual social variables (including age, education, main job, place of residence, advertising and promotion, and personal interests) and economic variables (including the scale of farms, ownership of machinery, government credits, provision of cheap electricity, government support, and cooperation in the implementation and limitation of water resources) that have a significant effect on the adoption of NIS. Figure 2 illustrates the steps of the research.

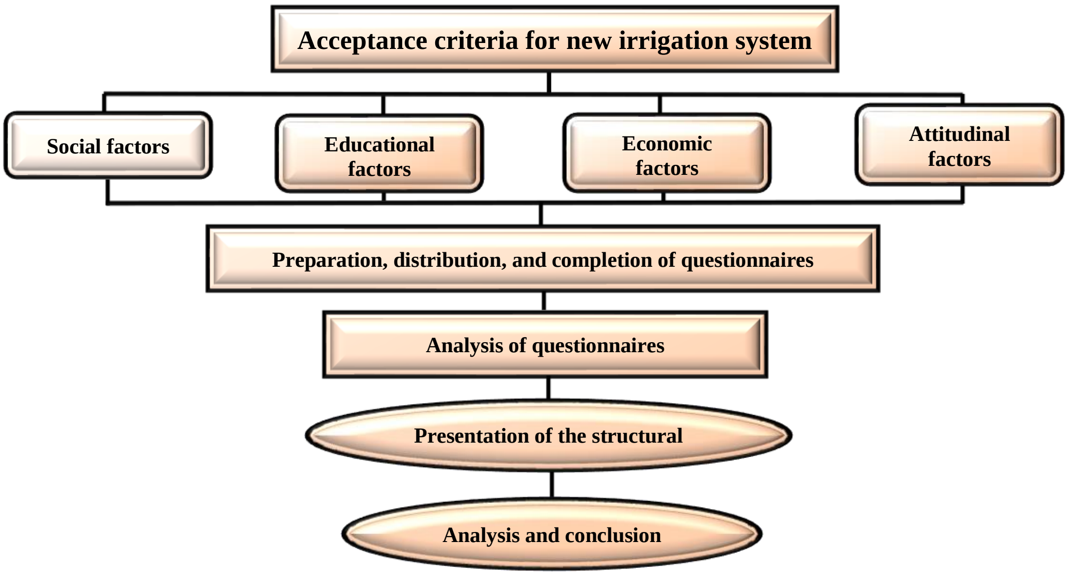

Figure 2. Flowchart of research steps

3. Results and discussion

The aim of the current research was to identify the factors that influence the adoption of these systems by farmers in the Torshiz region. Therefore, decision-makers should identify why farmers' desire for these systems has not been successful despite strong financial and political support. So, this issue was investigated in the present study. In this way, a questionnaire was prepared and completed by the farmers to investigate and identify the factors affecting the acceptance of these systems. Also, in this context, it should be noted that some researchers, such as Lopolito et al. (2022), believe that improving the methods of using water resources in the agricultural sector and innovations such as water-saving techniques are vital strategies to promote economic development (Lopolito et al., 2022).

In this research, a questionnaire was utilized to collect the necessary information. Experts confirmed the validity of the questionnaire, and its reliability was assessed by calculating Cronbach's alpha. The coefficient was calculated at 0.93, indicating that the questionnaire is reliable. In the following, the results of the analysis of the questionnaires are presented.

3.1. Characteristics of farmers

The survey results indicate that the majority of the participants, accounting for 45 percent of the sample, were aged between 30 and 45 years. Most of the respondents had attained a diploma (33 percent), followed by a sub-diploma (24 percent), a post-diploma (23 percent), and a bachelor's degree (20 percent). The survey also revealed that 95% of the land ownership was private, while only 5% was leased. the type of product is mostly in the garden category (73%), followed by agriculture (27%). Most of the farmers produce grapes, pistachios, and wheat**.**

In the next step, the importance and priority of each of the examined items were determined based on the opinion of the farmers. Then, the structural model was prepared based on the results. The results of the investigation are presented below.

3.2. Prioritizing items in each factor

Friedman's test was used to check the same importance of the items in each factor to prioritize the items of each of the educational, economic, attitudinal, and social factors according to the item scale (5-point Likert scale). the results showed that the significant level of Friedman's test is less than 0.05 and the items are not equally important. The ranking of items based on the average of each item is presented in Tables 1 to 4:

According to the results, the most critical educational factor in the region is the item "cultivation pattern suitable for the region", while the least significant is the item "protection technology of productive resources"(Table 1).

Based on the findings, the item "capability of diverse cultivation" is considered the most important economic factor, while the item "investment ability of the farmer" is considered the least important by the farmers (Table 2).

Table 1. Prioritization of educational factors

Educational factors	Mean	Standard deviation	Score
Suitable Cropping pattern for the region	3.4300	0.97706	1
Irrigation calendar according to the cultivation pattern of the dominant crops	3.3900	1.10914	2
Suitable Irrigation Timing	3.3400	1.08451	3
Correct irrigation methods	3.2700	1.06225	4
Risk management in the agricultural sector	3.1200	1.01782	5
Planning for production activity	3.0900	1.08334	6
Production skills in the agricultural sector	3.08	1.125	7
Optimal use of production resources	3.02	1.189	8
Accounting skills in the production sector	2.87	1.236	9
Production resource protection technology	2.86	1.172	10
Friedman's test: 84.649	freedom Degree: 9	Significant level: 0.000	

Table 2. Prioritization of Economic factors

Economic factors	Mean	Standard deviation	Score
Diverse cultivation capability	4.16	5.16	1
Reduction of total irrigation costs in the long term	4.01	1.08	2
Reducing water consumption and costs	3.99	1.03	3
possibility of using irrigation in agriculture and increasing income	3.96	1.09	4
Reduce weed and control costs	3.88	1.09	5
Development and increase of cultivated area	3.81	1.09	6
Increasing the amount of production per unit area	3.74	1.10	7
Reducing fertilizer costs	3.55	1.18	8
Reducing land leveling costs	3.54	1.13	9
Reducing spraying costs	3.50	1.18	10
Reducing labor costs	3.49	1.17	11
Low implementation costs of modern irrigation	3.16	1.39	12
Providing timely facilities and long-term repayment of loans	3.07	1.42	13
The possibility of benefiting from bank facilities	3.06	1.35	14
Sufficient amount of bank facilities	3.05	1.42	15
Low interest rate of bank facilities	3.01	1.37	16
Farmer's investment ability	2.89	1.33	17
Friedman's test: 84.649	freedom Degree: 16	Significant level: 0.000	

According to the results, the item "Using the positive experiences of others in connection with NIS" has the highest importance, and the item "Providing explanatory training in connection with NIS" has the least importance from the users' point of view (Table 3).

Table 3. Prioritization of social factors

Social factors	Mean	Standard deviation	Score
Using the positive experiences of others with NIS	3.08	1.10	1
Appropriate treatment of companies implementing new irrigation methods	3.06	1.11	2
Easy access to after-sales service of spare parts related to NIS	3.01	1.12	3
Easy access to stores supplying spare parts for NIS	2.95	1.18	4
Ensuring security in the area	2.85	1.40	5
Advertisements of sellers and design companies of NIS	2.83	1.11	6
Introducing NIS on radio and television	2.77	4.23	7
Educational visits to areas where NIS have been implemented before	2.65	1.23	8
Participation in training courses related to water management	2.59	1.16	9
Introducing NIS in promotional publications	2.58	1.25	10
Advice of experts and technical specialists to implement NIS	2.58	1.25	11
Providing explanatory training related to NIS	2.56	1.26	12
Friedman's test: 130.73	freedom Degree: 11	Significant level: 0.000	

Based on the findings, the most important attitudinal factor is the one that the item "leads to more success in farm management", while the least important factor is the item "accessibility of farmers to facilities and credits increases", according to the users' perspective (Table 4).

Table 4. Prioritization of attitudinal factors

Attitudinal factors	Mean	Standard deviation	Score
It leads to more success in farm management	4.19	0.92	1
It increases income and profit for the family	4.13	0.92	2
It increases product performance	4.09	0.99	3
It is a suitable method for the production process	4.08	0.94	4
It improves product quality	4.08	0.95	5
It is effective in protecting the environment	4.00	1.12	6
It has tangible results	3.99	0.92	7
It prevents waste of time and capital in agriculture	3.99	1.05	8
Economically, it is associated with cost reduction	3.95	1.02	9
It preserves productive resources	3.82	1.05	10
It creates self-confidence	3.80	1.03	11
It causes acceptance of responsibility	3.77	0.98	12
It causes struggle with traditional thoughts in agriculture	3.71	1.18	13
They are technically feasible	3.71	1.21	14
They are relatively consistent with traditional methods and local knowledge	3.65	1.02	15
It makes family members cooperate together	3.60	1.02	16
Farmers' access to facilities and credits increases	3.53	1.17	17
Friedman's test: 159.34	freedom Degree: 16	Significant level: 0.000	

3.3. Structural equation model

In this section, the validity of the content value of each of the indicators used to design the model is analyzed using the structural equation model method. A complete structural equation model includes path analysis and confirmatory factor analysis. This method is used in research, where the goal is to test a specific model of the relationship between variables. The structural equation model is divided into two phases: confirmatory factor analysis and path analysis. In the measurement part, the relationship between the indicators or the questions of the questionnaire and the factors is investigated, and in the structural part, the relationship of the studied factors with each other is considered to test the hypotheses**.**

There are various methods to implement the structural equation model. one of the newest approaches to the structural equation model is the partial least squares method, which is a method for the structural predictive model. This approach is considered the first option for estimating the model, especially when the number of indicators for each factor is large and there is multiple alignment between them. So, in designing the structural model of the current research, this approach was used to estimate factor loadings and path coefficients (Rezazadeh and Davari, 2013).

The partial least squares method does not require any assumptions about the type of distribution of the measurement variables. Therefore, it is suitable and applicable for data with a non-normal or unknown distribution. In this study, the items to be measured are variables that have an unknown definition and distribution on the Likert scale, and due to their non-normality, the partial least squares method is superior to the covariance-based methods. Covariance-based methods are sensitive to sample size. Smaller samples decrease the statistical power of the method. Also, by reducing the sample size, the assumption of normality of the data cannot be shown well. The partial least squares method estimates the model parameters using the original sample. However, for the correct statistical estimation of the model, it uses the sample reproduction method to determine the confidence interval of the model parameters (Qanavati et al., 2013).

This is a statistical technique that does not require assumptions about the distribution of the measurement variables. This makes it suitable for analyzing data with non-normal or unknown distributions.

3.4. Measurement model

Before applying the structural equation model, it is important to ensure that the structures being studied are valid and that the chosen indicators accurately measure the desired structures. for this purpose, Confirmatory factor analysis (CFA) is used. If the factor load of each indicator with its structure has a T value higher than 1.96, then that indicator has the necessary accuracy to measure the existing structure or attribute. If the indicators of the studied structures have a value of T less than 1.96, they do not have the necessary importance for measurement and should be discarded from the analysis process. According to the review, none of the questions had any problems, and the validity of the constructs showed that the items provided suitable factorial structures to measure the variables studied in the research model.

In structural equation modeling, in addition to construct validity, criteria such as reliability and validity are also evaluated to check the variables. Reliability means that there was the same collection of questions among different respondents. To check reliability, a composite reliability index was used; values higher than 0.7 for each structure indicate its proper reliability (Table 5).

3.5. Structural model

At this stage, considering the completion of the variable refinement phase and the assurance of the accuracy of the indicators in the measurement of related variables, it is possible to test the research hypotheses, which were examined in the form of the structural equation model of the hypotheses, and the direction of the structural model was evaluated. Each path corresponds to one of the hypotheses of the model. Each hypothesis is tested by examining the sign, size, and statistical significance of the path coefficient (beta) between each independent variable and the dependent variable. The predictive effect of the dependent variable will be greater if the value of the path coefficient is higher. By considering the results of the study of the relationships between independent and dependent structures using the relevant coefficient, it is possible to study the significance of the effects between the research structures. The significance of the T-value for each path coefficient should be tested to investigate the significance of the path coefficient or beta; therefore, the bootstrap method was used (Table 6).

Table 5. Examination of AVE values and reliability indices

Factors	Cronbach's alpha	rho_A	Composite reliability	AVE
Educational factors	0.95	0.95	0.96	0.70
Social factors	0.94	0.95	0.95	0.60
Economic factors	0.94	0.95	0.95	0.54
Attitudinal factors	0.97	0.97	0.97	0.64
Acceptance of irrigation systems	0.98	0.98	0.98	0.51

Table 6. Examining the relationships between variables and their significance

	Path coefficient	The standard deviation	T index	Significant level
Educational factors -> acceptance of irrigation systems	0.22	0.02	15.19	0.000
Social factors -> adoption of irrigation systems	0.24	0.02	14.77	0.000
Economic factors -> adoption of irrigation systems	0.33	0.02	20.63	0.000
Attitudinal factors -> acceptance of irrigation systems	0.37	0.03	14.84	0.000

The results show that all the investigated factors have an impact on the acceptance of irrigation systems (T-value greater than 1.96 and a significant level less than 0.05), and the most influential are attitudinal factors and then economic factors. these results are consistent with the results of Movahedi et al. (2017), which investigated the factors influencing the acceptance of pressure irrigation by farmers in Asadabad city, Hamadan province. Their findings showed that attitudinal variables (including perceived usefulness, perceived ease of use, and attitude towards use) had a positive and significant effect on the acceptance of irrigation systems under pressure. Taheri et al. (2018) also investigated the factors influencing the acceptance of the water management plan for the restoration of Lake Urmia by the farmers of Naqdeh city and concluded that there is a significant relationship between the attitude toward the restoration of Lake Urmia and the water management plan. Their findings showed that the variables of knowledge about lake restoration, facilities for accepting the plan, attitude towards lake restoration, and attitude towards the water management plan are the most important factors that recognize the two groups of farmers who accept and do not accept the water management plan. Also, the results of this section are consistent with the results of Haji et al.'s (2020), which investigated and analyzed the factors affecting the acceptance of drip irrigation by sugar beet farmers using a questionnaire. The results showed that attitude variables, perceived ease of use, and perceived usefulness of using new irrigation methods have a significant positive effect on the adoption of drip irrigation technology.

Figures 3 and 4 of the research models are presented in two modes with T-values and path coefficients.

According to the results, various economic, social, educational, and attitudinal factors are effective in the acceptance of NIS by farmers. Detailed Identifying and investigating these factors can play a significant role in developing appropriate policies to promote the use of these methods among farmers. Developing NIS, which optimize and reduce water consumption, in these areas with a hot and dry climate and lands prone to desertification can cause the prosperity of agriculture in the region and the economic growth of local and rural communities. Therefore, it is also effective in protecting the soil and reducing the risks of desertification caused by the abandonment of villages and agricultural lands**.** According to Playan and Mateos (2006), the renovation and optimization of irrigation systems can improve the efficiency of water consumption in agriculture. This process can be particularly beneficial in desert areas and can contribute to the survival of people in rural areas. Also, the results of this section are consistent with the results of other researchers, including Farid et al. (2019), who studied the factors affecting the optimal adoption of irrigation systems among farmers in a region in Pakistan. The results showed that factors such as high economic efficiency, operator deployment, and farmer training are effective in the adoption of these systems by farmers.

Sabbagh and Gutierrez (2023) also investigated the effective factors in the adoption of NIS by farmers in Lebanon. Their results showed that it provides for and has a financial impact on the adoption of these methods by farmers. In this stage, the need for less work and achieving better performance and efficiency of products were also important factors.

According to the results, the factors of "cultivation pattern suitable for the region", "diversity cultivation ability", "using the positive experiences of others" and "more success in farm management" have the greatest impact on the acceptance of these systems by farmers. Therefore, these factors should be considered in planning to convince farmers to use NIS. In this context, Farid et al. (2019) stated that NIS has a suitable efficiency for saving water and increasing the yield of crops**.** However, the most important issue with these systems is their non-acceptance or low acceptance by agricultural communities, despite their proven benefits. So, identifying the factors affecting the acceptance of these systems by farmers can play an important role in the development of these systems. They found out in research that factors such as high economic efficiency, the establishment of operators, and farmer training are effective in the acceptance of these systems by farmers.

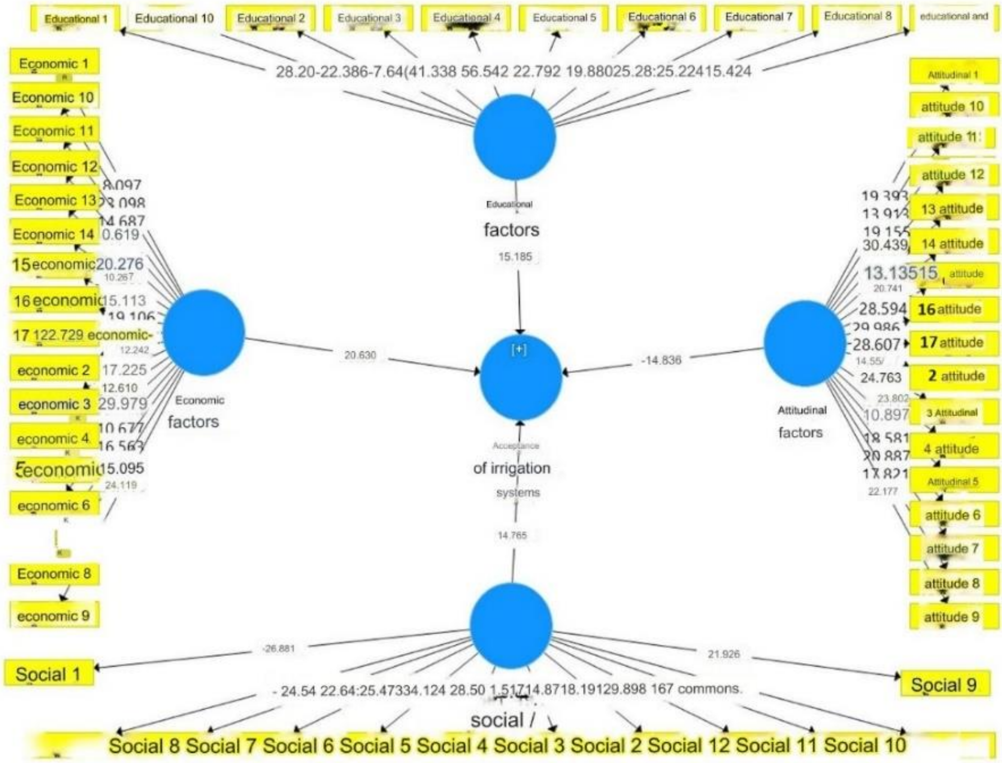

Figure 3. Structural model with T-Values

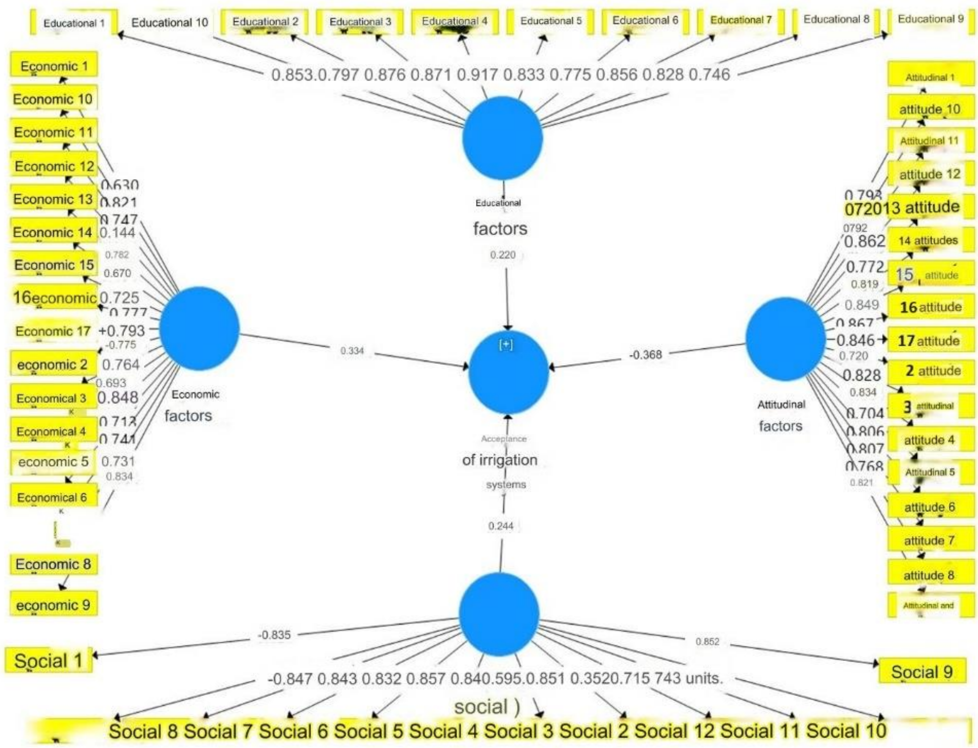

Figure 4. Structural model with path coefficients on paths

It is important to note that the study area has the potential to use renewable energy sources, such as solar energy, to power irrigation systems. This aligns with the principle of sustainable development, which focuses on supporting the economy, society, and environment in a way that meets the needs of the present population without compromising the natural resources and environment for future generations. Sustainable development emphasizes the need to balance the protection and sustainable use of natural resources in managing society. The goals of sustainable development in the water resources field aim to increase the efficiency of water consumption in all regions and at all levels. It also includes maintaining and revitalizing ecological systems related to water resources to optimize water use. In addition, it encourages community participation in the sustainable development of water resources. This issue has been emphasized by Chuchird et al. (2017) in their study. Their research aimed to identify the factors that affect the adoption of agricultural irrigation technologies. After identifying these factors, they also emphasized the importance of the sustainable development of water resources.

It is important to consider various factors when proposing an irrigation system for farmers. These factors include the amount of water available, climatic conditions, soil type, crop type, and water requirements, as well as economic and social conditions, especially the investment ability of farmers. This has been confirmed by Van de Zande et al. (2024) in their research on farmers' preferences for modern irrigation methods. Through questionnaires and interviews, they found out that the cultivation area, crop type, and investment capacity of farmers play a significant role in their acceptance of irrigation methods. Therefore, it is essential to consider these factors when proposing irrigation systems to farmers.

The results of this research can aid in developing effective approaches to increase farmers' positive attitudes towards NIS and encourage their acceptance. Additionally, the findings can provide valuable insights to planners and decision-makers in the agriculture and water sectors, including the Agricultural Jihad Organization, the Ministry of Energy, and the Environmental Protection Organization. The study identified the key factors and behavioral change strategies that can be used to promote the use of irrigation systems and encourage sustainable maintenance of the systems in the area. Thus, the research can be a guideline for justifying and encouraging farmers to adopt optimal agricultural water management technologies and efficient water allocation management.

4. Conclusion

The aim of the present study was to identify the key factors that affect the acceptance of NIS for optimal management of agricultural water resources in the Torshiz region. To achieve this, a questionnaire was developed to gather the opinions and views of farmers regarding the use of NIS after gaining extensive knowledge of the study area. The collected data was analyzed using SPSS 21 software, and the factors that influence the acceptance of these systems were modeled using Smart PLS software. The results of the analysis indicated that all the factors investigated had a significant impact on the acceptance of irrigation systems (T-values greater than 1.96 and significant level less than 0.05), and the most influential were attitudinal factors and then economic factors. The results indicate that farmers have a positive attitude towards NIS and agree that these systems can lead to optimal water management. Therefore, it is recommended to strengthen this positive attitude and provide banking facilities to encourage farmers to use NIS. The study found that among the educational factors, the "suitable cultivation pattern of the region" was the most important, while among the economic factors, "various cultivation ability" was the most significant. Therefore, it is crucial to determine the appropriate cultivation pattern of the region and inform farmers to encourage their participation in projects such as the use of modern irrigation methods. Regarding social factors, "using the positive experiences of others in connection with NIS" was found to be the most important, while among the attitudinal factors, "leads to more success in farm management" was given the highest importance. This shows that if NIS are implemented on trial fields and farmers observe an increase in crop yield, higher economic efficiency, and improved water resource efficiency, they would be more likely to use these methods. This action could be taken by providing suitable incentives, such as long-term bank facilities at low rates. Also, this issue shows the role of education in accepting these systems**.** Therefore, it is necessary to convince farmers to use NIS by holding educational and promotional courses. In fact, agricultural promotion and education are effective managerial strategies to improve agricultural water usage among farmers. These strategies create changes in people's behavior through cognitive, emotional, and psychological aspects. The cognitive aspect results in increased awareness and knowledge; the emotional aspect results in attitude changes; and the psychological aspect results in the development and improvement of people's skills. investigating and determining the behavioral aspects of the learners before each educational action is important to be successful in educational-promotional programs. Ultimately, the future of water depends on whether agriculture can manage and use water sustainably. This requires a series of actions, such as information and educational programs, that may not have clear results in the short term.

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Conflict of interest

No conflict of interest has been declared by the authors.

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Determination of some physical properties of native lentil seeds of Zabol as a function of moisture content

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ABSTRACT

Taking into account the necessity of determination of physical properties to design of storage, handling, and processing systems for agricultural products, the object of this study was intended to determine some physical characteristics of native lentil seed of Zabol such as axial dimensions, surface area, geometric mean diameter, sphericity, filling angle of repose, bulk and true densities, true volume, porosity as well as coefficient of static friction against various surfaces. Analysis of data showed that all physical properties of the lentil seeds were significantly affected with the moisture content in the studied range (4.7% to 19.8% w.b.). The axial dimensions of lentil seeds namely length, width, thickness and also one thousand seed mass of lentil seeds respectively increased from 3.88 to 4.56 mm, 3.69 to 4.21 mm, 2.05 to2.29 mm and 12.14 to 22-73 as the moisture content increased. The values of surface area (11.29-15.12 mm^2) and geometric mean diameter (3.08 - 3.49 mm) of lentil seeds increased with increasing moisture content while the sphericity (79.61 to 76.69%) decreased. The filling angle of repose of the seeds increased significantly with an increase in moisture content. So, it changed from 26.57 at moisture content 4.7 to 29.74 at moisture content 19.8 (w.b. %). The values of bulk and true densities of lentil seeds decreased respectively from 546 to 476 kg/m^3 and 1390 to 1270 kg/m^3 as the moisture content increased. The true volume (6.15 – 6.71 mm^3) and porosity (60.71 to 62.68 %) of lentil seeds increased linearly with increasing moisture content. The values of the coefficient of static friction increased as the moisture content of lentil seeds increased and also the values of this parameter with respect to galvanized iron (0.61-0.64) and fiberglass (0.60-0.64) were greater than that on the glass surface (0.53-0.62).

Highlights

- Determining the physical properties of agricultural products is nessasary to design of processing sytems such as storage, handeling etc.
- Some physical properties of native lentil seeds were determined.
- Physical properties of the lentil seeds were significantly affected with the moisture content.
- Mathematical models predicting the physical properties of the lentil seeds based on the moisture content were developed.

1. Introduction

lentil (*Lens culinaris*) is a small annual legume of the pea family (*Fabaceae*) which is widely cultivated throughout the world. Lentil seed, because of containing high amounts of proteins, cellulose, carbohydrate compounds and folic acid as well as being low in calories, low in fat and cholesterol free is known as a healthy food (Szot et al., 2003). Native lentil seed of Zabol is one of varieties of lentil that is cultivated annually in different regions of Sistan and Baluchestan province. There has been an interest in cultivation of this agricultural product for several reasons, such as its resistance to drought stress, more appropriate price and more marketability compared to other lentil varieties (Ghasemi et al., 2022). It was estimated that cultivated area of that in Sistan and

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Baluchistan province is approximately 1,200 hectares. However, if enough water is available, it can be raised to 3,000 hectares (Jihad, 1399). Determination of physical properties of agricultural materials such as lentil seeds is necessary to design of storage, handling and processing systems (Kashaninejad et al., 2008). When these systems improperly designed, may reduce the quality of agricultural crop which consequently led reduction of waste (Seyedalibeyk Lavasani and Baradaran Motie, 2022). The data based on physical characteristics enable the engineers, food scientists and processors to develop the processes and equipment efficiently (Krishnakumar, 2019; Ghadge and Prasad, 2012). For instance, the axial dimensions of seeds are needed for selecting sieve separators and calculating grinding power during size reduction process (Rameshbabu, et al., 1996; White and Jayas, 2001). In determining the size of grain hoppers and storage facilities, bulk and true densities and also porosity can be useful. In addition, the rate at which heat and moisture are transferred in aeration and drying process can be altered by these parameters (Taheri et al., 2015). The angle of repose and coefficient of friction can be considered as crucial characteristics to design of seed containers and other storage structures (Taheri et al., 2015). Moreover, the magnitude of frictional force determines the amount of power required for the conveyor (Seyedalibeyk Lavasani and Baradaran Motie, 2022). Since, there is no physical study of native lentil seed of Zabol, the aim of this study was to determine some handling and frictional properties of this agricultural crop as a function of moisture content.

2. Materials and methods

2.1. Sample preparation

The lentil seeds used in the present study were obtained from a local mall in Zabol, a city in the eastern south of Iran. After cleaning, the initial moisture content of lentil seeds was determined by hot air oven drying method (ASAE S352.2, 1997). The samples with higher moisture content were prepared by adding distilled water which was calculated from the equation 1 (Kashaninejad et al., 2008).

$$W_2 = W_1 \times [\frac{M_1 - M_2}{100 - M_1}] \quad [1]$$

Where, W_1, W_2, M_1, and M_2 are sample weight (g), distilled water weight (g), final moisture content (w.b. %) and initial moisture content (w.b. %) respectively. At last, the sample was kept at 5C in a refrigerator for at least a week to to ensure the uniform distribution of moisture throughout the product (Gupta and Das, 1997).

2.2. Dimensions, sphericity, one thousand seed mass

As defined in Figure 1, the three principal dimensions were determined randomly measuring the thickness (T), width (W) and length (L) of one hundred lentil seeds using an electronic digital caliper having a least count of 0.01 mm at each moisture level.

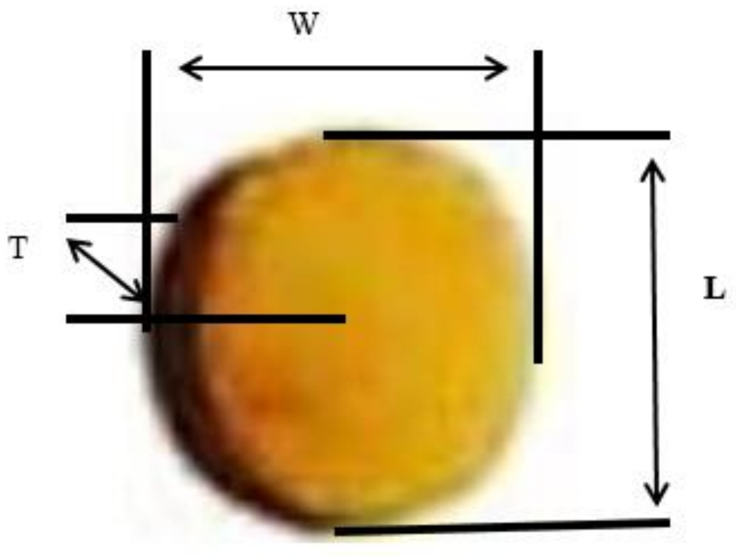

Figure 1. The three principal dimensions defined for lentil seed

To obtain the one thousand seed mass, 5 sub-samples each containing 1000 seeds were randomly selected from the bulk sample and then were weighed with digital balance with an accuracy of 0.001 g (Ghanbarian and Salek, 2014). Degree of sphericity (ϕ) was calculated from equation 2 (Mohsenin, 1980).

$$\phi = \frac{(LWT)^{1/3}}{L} \quad [2]$$

2.3. Geometric mean diameter and surface area

The equations 3 and 4 were used respectively for calculating geometric mean diameter (D_g) and surface area (S) of seeds for each moisture level. (Mohsenin, 1980).

$$D_g = (LWT)^{1/3} \quad [3]$$

$$S = лD_g{}^2 \quad [4]$$

2.4. Bulk density, true density, porosity and true volume

The bulk density was calculated by mass and volume of the circular container with known quantity filled with lentils seeds (Kashaninejad et al., 2006). The true density

(ρ_t) was determined using an electronic balance reading to 0.001 g and a burret. This parameter is expressed as a ratio between the seed mass and the solid volume occupied by the sample (Baümler et al., 2006). True volume (V) of lentil seeds was determined using the liquid displacement method (Mohsenin, 1980). The porosity (ε) of the bulk was obtained from equation 5. (Mohsenin, 1980):

$$\varepsilon = [(\rho_t - \rho_b)/\rho_t].100 \quad [5]$$

2.5. The filling angle of repose

The filling angle of repose (θ_f) is the angle with the horizontal line at which the material will stand when piled. The topless and bottomless cylinder of 10 cm diameter and 11 cm height was used to determine this parameter. The cylinder was placed at the center of a raised circular plate having a diameter of 35 cm and was filled with lentils. The cylinder was raised slowly until it formed a cone on a circular plate (Joshi et al., 1993; Mohammadi Moghadam et al., 2008). The height (H) of the cone and the diameter of sample distribution (D) was recorded. The filling angle of repose (θf) can be calculated from equation 6:

$$\theta_f = tan^{-1}(\frac{2H}{D}) \quad [6]$$

where H and D are expressed as mm.

2.6. Frictional characteristics

The coefficient of static friction for lentil seeds was determined on surfaces of glass, fiberglass, and galvanized iron at different moisture content. A galvanized iron box of 150 mm length, 100 mm width and 40 mm height without base and lid was filled with the sample and placed on an adjustable tilting plate, faced with the test surface. The sample container was raised slightly (5– 10 mm) so as not to touch the surface. The surface with the cylinder resting on it was inclined gradually, until the cylinder just started to slide down. (Kashaninejad et al., 2006). Equation 7 was used to calculate the coefficient of static friction.

$$\mu = \tan(\alpha) \quad [7]$$

Where μ is coefficient of static friction and tan(α) is tangent of angle of inclination.

2.7. Data analysis

The data were subjected to analysis of variance (ANOVA), and significant differences between means were determined by Duncan’s multiple range tests at the 5% significance level. Analysis of data was performed using SAS 9.2 software and regression analyses were performed using Excel software. All these experiments were replicated five times, unless stated otherwise (Ahmadi and Siahsar, 2011).

3. Results and discussion

3.1. Dimensions and one thousand seed mass

Analysis of data (Table 1) shows that there are significant differences among the dimensions and one thousand seed mass of lentil seeds depending on moisture content. The results also indicated that the mentioned parameters have increased linearly with increase in moisture content (Figure 2). The length, width, thickness and one thousand seed mass of lentil seeds ranged from 3.88-4.56 mm, 3.69–4.21 mm, 2.05–2.22 mm and 12.14 - 22.73 g respectively as the moisture content increased from 4.77 to 19.8 (d.b.%).

Szot et al. (2003) expressed the length, thickness and one thousand seed mass of Tina lentil seed (a polish lentil variety) ranged from 5.60-5.93 mm 2.47-2.57 mm and 46.52-58.48 g respectively and of Laird lentil seed (a Canadian lentil variety) ranged from 6.15-6.63, 2.47-2.80 mm and 64.27-72.73 g respectively with increasing the moisture content. In another study, the length and thickness of lentil seeds of Qazvin were measured 6.36 mm and 2.78 mm respectively by Sharifi et al. (2019). thus, it can be found that the lentil seeds of Zabol have smaller dimension and one thousand seed mass in comparison with the mentioned varieties.

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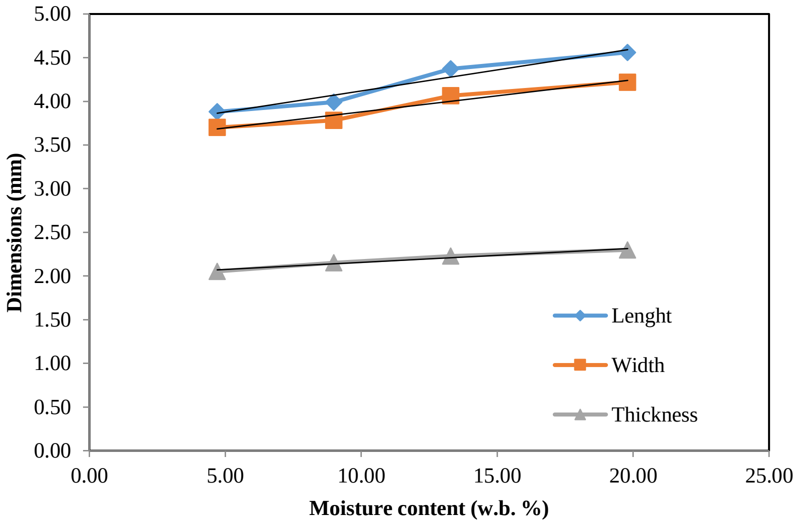

Figure 2. Variation in dimensions of lentil seeds with increasing moisture content

Table 1. Dimensions and one thousand seed mass of the lentil seeds.

Moisture content (w.b %)	Length (mm)	Width (mm)	Thickness (mm)	One thousand seed mass (g)
4.7	3.88±0.2d	3.69±0.2d	2.05±0.14d	12.14±0.07d
9	3.99±0.17c	3.78±0.14c	2.15±0.17c	19.13±0.0c
13.3	4.37±0.2b	4.06±0.2b	2.220.2b	19.81±0.03b
19.8	4.56±0.2a	4.21±0.2a	2.29±0.19a	22.73±0.0a

Means ±SD (standard deviation) within a column with the same lowercase letters are not significantly different at P < 0.05.

The equations 8-11 represent the significant (p<0.05) linear relationships between the dimensions as well as one thousand seed mass and moisture content for the lentil seeds.

$L = 0.0482M_c + 3.6373$ (R^2=0.94) [8]

$W = 0.0368M_c + 3.5112$ (R^2=0.95) [9]

$T = 0.0162M_c + 1.9942$ (R^2=0.96) [10]

$M = 0.636M_c + 11.016$ (R^2=0.83) [11]

Similar trends have been reported for groundnuts gram; guna seeds and green gram (Baryeh, 2001; Aviara, 1999; Nimkar and Chattopadhyay, 2001)

3.2. Surface area

As illustrated in Figure 3, the surface area of lentil seeds increased linearly with increasing moisture content changing significantly from 11.29 to 15.12 mm^2 as moisture content increased (Table 2). Kashaninejad et al. (2008) reported a similar result working with different varieties of soybean. However, Hsu et al. (1991) found the reverse trend for the pistachio. The surface area of lentil seeds of Qazvin has been reported 40.01 mm^2 (sharifi et al., 2019).

Equation 12 indicate a linear relationship between moisture content and surface area of lentil seeds.

$S = 0.2717M_c + 9.864$ (R^2=0.95) [12]

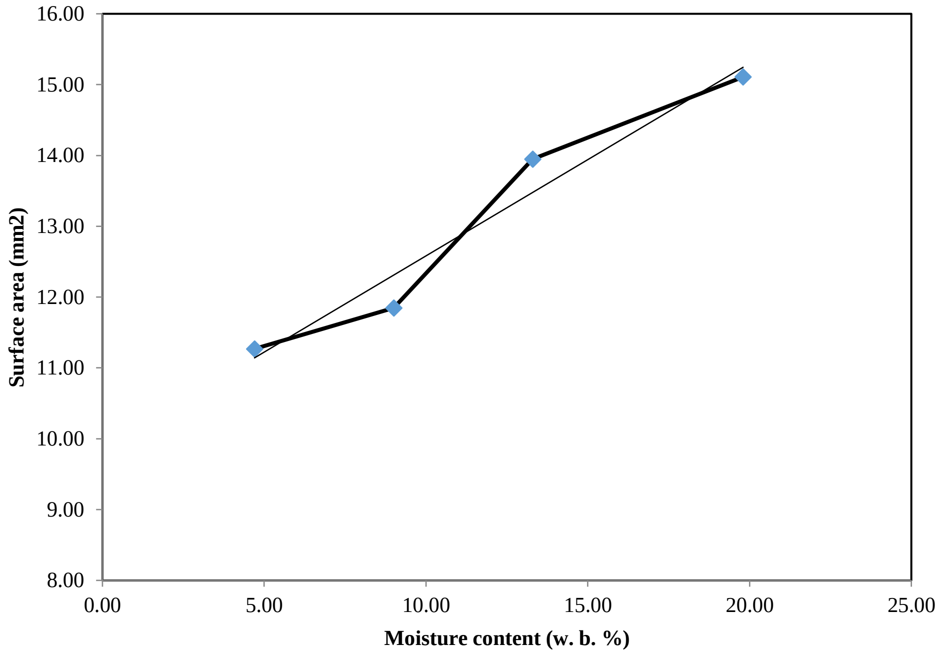

Figure 3. Variation in surface area of lentil seeds with increasing moisture content

3.3. Geometric mean diameter and sphericity

The Figures 4 and 5 indicate that the geometric mean diameters and sphericity of lentil seeds respectively increased and decreased with increasing moisture content. According to Table 2, the values of the geometric mean diameter increased significantly from 3.08 to 3.49 while, the sphericity decreased from 79.61 to 76.69% as moisture content increased. The reduction of lentil seed sphericity indicates that the seeds are inclined towards a rounded shape. However, they are able to slip on flat surfaces as well. Therefore, such a tendency to either roll or slide should be considered in the design of hoppers for milling (Ghadge and Prasad, 2012). Sharifi et al. (2019) reported geometric mean diameter and sphericity value of lentil seeds of Qazvin 3.61 mm and 56 % respectively.

The regression relationship and coefficient of determination between sphericity and moisture content and also for geometric mean diameter and moisture content of lentil seeds are presented by equations 13 and 14. The similar results were reported for soybean seed and millet (McCabe, et al., 1986; Baryeh, 2002).

$D = 0.0292M_c + 2.965$ (R^2=0.90) [13]

$\phi = -0.203M_c + 81.148$ (R^2=0.84) [14]

3.4. The filling angle of repose:

As it can be seen in Table 2, the filling angle of repose of lentil seeds increased significantly from 26.57 at moisture content 4.7 (w.b. %) to 29.74 at moisture content 19.8 (w.b. %). The increase can be explained by the presence of a higher amount of water on the surface of the seeds at higher moisture content resulting in increasing stickiness of the seeds which consequently facilitates sliding of them on each other (Kashaninejad et al., 2008). Similar result reported by Kashaninejad et al. (2008) for different varieties soybean. The equation 15 revealed positive linear relationship between filling angle of repose of lentil seeds and moisture content and its coefficient of determination (R^2).

$$\theta = 0.2234M_c + 25.06 \ (R^2=0.91) \quad [15]$$

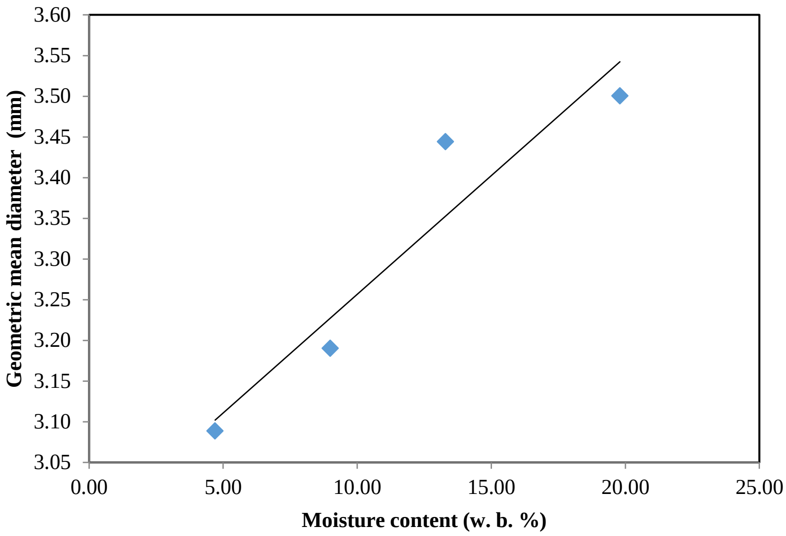

Figure 4. Variation in geometric mean diameter of lentil seeds with increasing moisture content

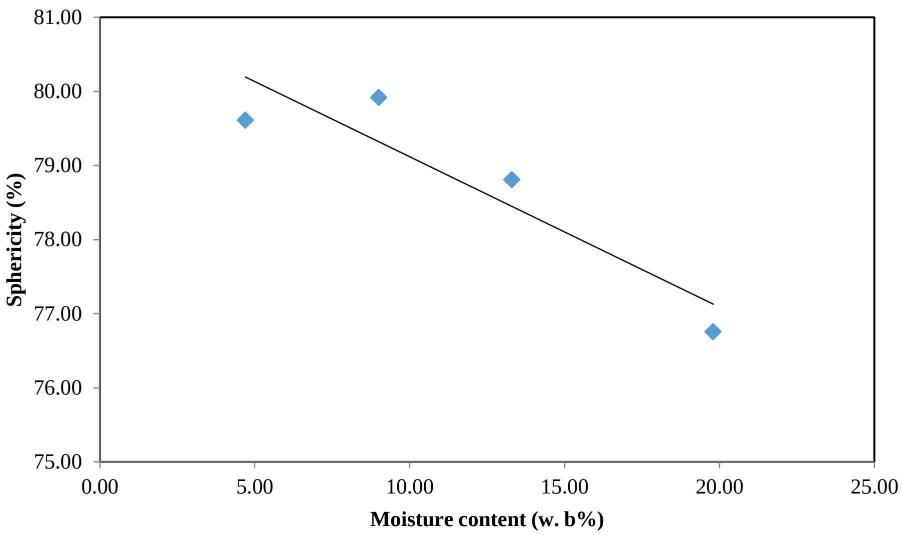

Figure 5. Variation in sphericity of lentil seeds with increasing moisture content

Table 2. Geometric mean diameter, sphericity, surface area and the filling angle of repose of the lentil seeds

Moisture content (w.b %)	Geometric mean diameters (mm)	Sphericity (%)	Surface area $(mm)^2$	The filling angle of repose:
4.7	3.08±0.14c	79.61±0.14a	11.29±1.1d	26.57±0.0c
9	3.18±0.13b	79.89±2.4ab	11.86±0.86c	26.57±0.0c
13.3	3.44±0.2a	78.83±2.8b	13.99±1.6b	27.85±0.0b
19.8	3.49±0.17a	76.69±3.4c	15.12±1.2a	29.74±0.0a

Means ±SD (standard deviation) within a column with the same lowercase letters are not significantly different at $P < 0.05$.

3.5. Bulk density:

As shown in Table 3, the values of bulk density of lentil seeds decreased significantly from 546 to 476 kg/m^3 as the moisture content increased indicating a linear trend between this parameter and moisture content (Figure 6). Similarly, Szot et al. (2003) have reported the bulk density of tina lentil seeds (a polish lentil variety) and laird lentil seeds (a Canadian lentil variety) decreased from 783-747 kg/m3 and 793-731 kg/m3 respectively with increasing moisture content. Also, Sharifi et al. (2019) have reported bulk density 586 kg/m^3 for lentil seeds of Qazvin**.** These results obviously show that the lentil seeds of Zabol possesses lower bulk density in comparison with the mentioned varieties. The decrease in bulk density indicates that the lentil seeds have lower weight increase compared to volume increase with increasing their moisture content. Equation 16 represents the relationship between the bulk density of lentil seeds and the moisture content and its coefficient of determination (R^2).

$\rho_b = -5.039 M_c + 574.5$ (R^2=0.94) [16]

The same findings were reported for cocoa beans, chick pea seeds (Plange and Baryeh, 2003; Konak et al., 2002).

3.6. True volume and true density

The results presented in Table 3 revealed that the true volume and true density of lentil seeds respectively increased and decreased linearly (Figure 6, for true density) as the moisture content increased. The values of the true volume changed from 6.15 to 6.71 mm^3 and values of true density from 1390 to 1270 kg/m3 with increasing moisture content. Similarly, a decrease in the true density has been observed for cotton seeds and chickpeas as the moisture content increased (Ozarslan, 2002; Konak et al., 2002). While, being an opposite trend for cumin seeds (Singh and Goswami, 1996), equations 17 and 18 represent the relationship between moisture content and true volume and true density. There is a similarity between the true volumes of the present paper and the findings reported in previous studies working with lupin, pigeon pea (Ogut, 1998; Shepherd and Bhardwaj, 1986).

$\mathrm{V} = 0.0435 M_c + 5.91$ (R^2=0.95) [17]

$\rho_t = -8.010 M_c + 1437.9$ (R^2=0.96) [18]

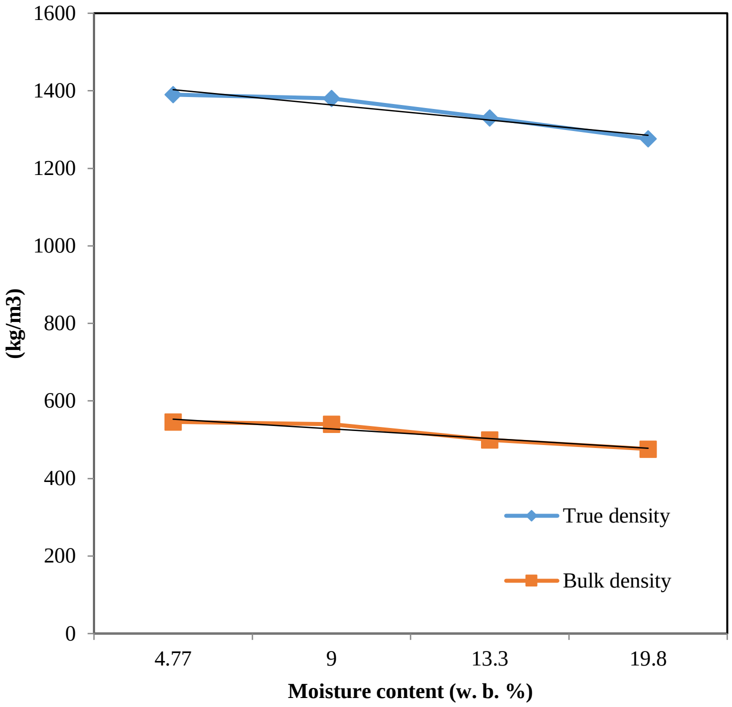

Figure 6. Variation in true and bulk densities of lentil seeds with increasing moisture content

3.7. Porosity*:*

According to Table 3, the porosity of lentil seeds of Zabol increased significantly from 60.71 to 62.68 % with increasing moisture content. Szot et al. (2003) stated the porosity of Tina and Laird lentil seeds ranged from 45.7-47.8 % and 50.3-50.2% respectively with increasing the moisture content. Also, similar trends were reported in lentil seeds (Scanlon et al., 2005) and grape seeds (Ahmadi and Siahsar, 2011). However, a reverse trend was found for pistachio nut by Kashaninejad et al. (2006). The variation in porosity with moisture content followed a linear relationship for lentil seeds (Figure 7), which can be represented by equation 19.

$\varepsilon = 0.1451 M_c + 59.95$ (R^2=0.88) [19]

3.8. Coefficient of static friction:

As the results of Table 4 show the values of the coefficient of static friction of lentil seeds on galvanized iron (0.61-0.64) and fiberglass (0.60-0.64) were greater than that on glass surface (0.53-0.62). In addition, it was found that the coefficient of static friction increased linearly with an increase in moisture content for all the surfaces tested (Figure 8). Increase in static friction coefficient at higher moisture contents have been attributed to an increment in the cohesive force of wet seeds with the structural surface arising from the more stickiness of the seeds as moisture content increases. (Kashaninejad et al., 2008). These findings were confirmed by other researchers (Joshi et al., 1993; Gezer et al., 2002; Carman, 1996). The linear relations between moisture content and the coefficient of static friction obtained for lentil seeds, can be expressed by equations 20, 21, and 22.

$$\mu_{Glass} = 0.0059M_c + 0.5111\ (R^2{=}0.93) \quad [20]$$

$$\mu_{fiberglass} = 0.0029M_c + 0.5815\ (R^2{=}0.92) \quad [21]$$

$$\mu_{galvanized\ iron} = 0.0013M_c + 0.6098\ (R^2{=}0.70) \quad [22]$$

These linear behaviors are in agreement with the results for soybean varieties, and grape seeds (Kashaninejad et al., 2008; Ahmadi and Siasar 2011).

Table 3. True volume, true density, bulk density and porosity of the lentil seeds

Moisture content (w.b %)	Kernel valume (mm3)	True density (Kg/m3)	Bulk density (Kg/m3)	Porosity (%)
4.7	6.15±0.006d	1.39±0.01a	0.546±0.004a	60.71±0.22b
9	6.22±0.02c	1.38±0.004b	0.540±0.0b	60.90±0.11b
13.3	6.54±0.0b	1.33±0.001b	0.500±0.0c	62.32±0.07a
19.8	6.76±0.01a	1.27±0.002d	0.476±0.005d	62.68±0.45a

Means ±SD (standard deviation) within a column with the same lowercase letters are not significantly different at P < 0.05.

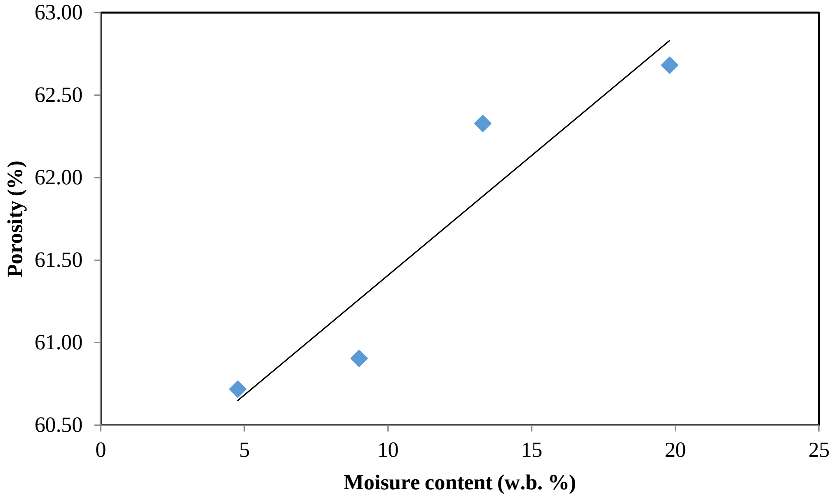

Figure 7. Variation in porosity of lentil seeds with increasing moisture content

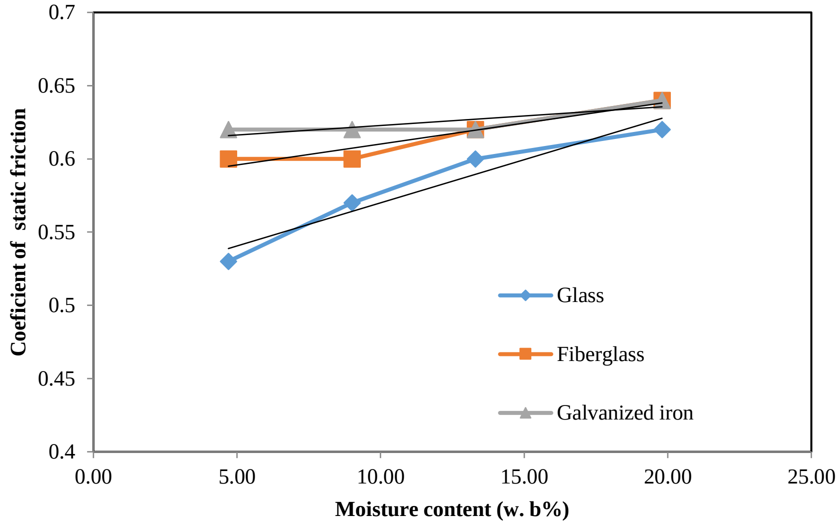

Figure 8. The coefficient of static friction of lentil seeds on different structural surfaces depending on moisture content

Table 4. The coefficient of static friction of the lentil seeds on different structural surfaces at different moisture contents

Moisture content (w.b %)	Glass	Fiberglass	Galvanized iron
4.7	0.53±0.01d	0.60±0.01c	0.61±0.01b
9	0.57±0.0c	0.60±0.0c	0.62±0.0b
13.3	0.60±0.0b	0.62±0.0b	0.62±0.0b
19.8	0.62±0a	0.64±0.0a	0.64±0.0a

Means ±SD (standard deviation) within a column with the same lowercase letters are not significantly different at P < 0.05.

4. Conclusions

The results showed that the physical properties of native lentil seeds of Zabol were significantly dependent on their moisture content. According to the obtained results dimensions, one thousand seed mass, surface area, geometric mean diameter, true volume, porosity, the falling angle of repose, and the static coefficient of friction of lentil seeds increased linearly with increasing moisture content. While, sphericity, bulk, and true densities decreased. Considering the necessity of these parameters to design equipment and machinery for transporting, sorting, handling, processing, drying, and storage of agricultural products, Therefore, the obtained findings represent some physical properties needed for designing storage, handling, and processing systems of native lentil seeds which is accounted a valuable crop in Sistan region of Iran.

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Assessment of environment impacts of forage corn production using LCA: case study in Khorramabad, Iran

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ABSTRACT

Forage corn is an important crop with characteristics that make it attractive for livestock industry. In the west of Iran and the margin of the Zagros mountains, due to the flourishing of animal husbandry, production of forage corn is quite vital. However, such crop production may affect environmental phenomena including global warming, ozone depletion, eutrophication, acidification potential and human toxicity potential. In the present study, the life cycle assessment methodology has been applied to study contaminants production due to forage corn cultivation. Therefore, different environmental impacts, along with the production processes, have been evaluated. The potential environmental impacts are calculated according to the production unit equivalents considered by the global databases. The amount of greenhouse gases emissions due to the production of one ton of forage corn is 118.46 units, as CO_2 equivalent. To consider the impact as ozone depletion, this amount was calculated to be one ton of forage corn equal to 0.0000147 units per kilogram of CEC_{11} production. Eutrophication potential in the production of one ton of forage corn was estimated to be 0.4618 units, equivalent to kilograms of PO_4 production. Improvements in corn production efficiency may result in less contaminants production and lower environment degradation.

Highlights

- The study examines the environmental impacts of forage corn production in western Iran using LCA method.
- The study evaluates the greenhouse gas emissions, ozone depletion, eutrophication, acidification, and toxicity for humans and terrestrial ecosystems as environmental indicators.
- The study shows that the production of one ton of forage corn generates 118.46 units of greenhouse gas emissions equivalent to CO_2.
- The study suggests that improving the efficiency of forage corn production can reduce pollution and environmental degradation.

1. Introduction

Rising global population and their requirement for food, and energy is a challenge which is compounded by increased pressure on natural resources. Decision on how and to what extent humans need to consume resources require precise and sophisticated scientific research and analysis. In this study, Life Cycle Assessment (LCA) methodology has been used. According to this method, it is possible to measure any performance of any given farm on the basis of the amount of inputs that the farmer will provide to the plant and the outputs of it (Brentrup et al., 2004). To evaluate the effects of a production process, a goal and scope of the study should be explained, then it can be used to assess a life cycle inventory and to carry out an impact assessment (Mcgregor, 2002).

Determining a functional unit in the life cycle analysis can be very effective in analysis process. A functional unit is a reference that interconnects the inputs and output of a produced crop. With such unit, the researcher can compare different systems with different structure based on a common basis (Sonesson et al., 2010). The amount of inputs (including fossil fuels and chemical fertilizers),

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production and transfer of agricultural inputs (such as fertilizer application) and field operations (such as plowing and harvesting) can be determined for a functional unit (Khorramdel, 2011). By carefully applying agricultural inputs, the probability of approaching sustainability standards will always increase. One of the methods to preserve natural resources and achieve sustainable development, especially sustainable agriculture, is environmental assessment of the production process of agricultural crops. The life cycle assessment methodology is an accepted method for assessing environmental impacts throughout a product lifecycle (Mir Haji et al., 2012). Many studies have argued that LCA is an appropriate way of quantifying the environmental impact of crops production. In this model, inputs will be collected based on observed data of application of chemical fertilizers, machinery, fossil fuel consumption and other inputs for the production of various crops (Esmaielpoor et al., 2015).

Given the inputs of production and how they can be consumed by plants during their growth, it may be possible to find the proper management production of crops with the least pollutant emissions. It should not be ignored that natural resources will be degraded, and every step towards preserving and sustainable consumption of these resources, helps to sustain resources for human survival on the earth. The purpose of this research is to study a LCA model to assess the environmental impacts of producing one ton of forage corn. It is our aim to evaluate the contaminants emitted by forage corn in Khorramabad, western Iran.

2. Materials and Methods

2.1. Study area

This study targeted Khorramabad location in Lorestan province of Iran (33.46N, 48.33E, 1117 asl). The average annual precipitation of this location is 524 mm and the average annual temperature is 17.07 ° C. Khorramabad is located in a valley between two mountains of the Zagros mountain range. Animal husbandry is also prevalent in this study location, and the production of forage corn is abundant in the region.

2.2. LCA methodology

The review of the life cycle assessment should be included the definition of the goal and scope, the analysis of the inventory, the impact assessment and the interpretation of the results. The data are divided into questionnaire, laboratory, computational and library categories.

2.2.1. Goal and scope

2.2.1.1. Study goal

The results of this research may help to enhance the production of this crop and reduce any hazardous environmental impacts. The scope of this study includes six stages of corn production, in which the inputs and outputs of each stage, including the emissions of each stage into the environment, form the life cycle inventory. Different stages are: tillage, planting, irrigation, fertilization, plant protection and harvesting.

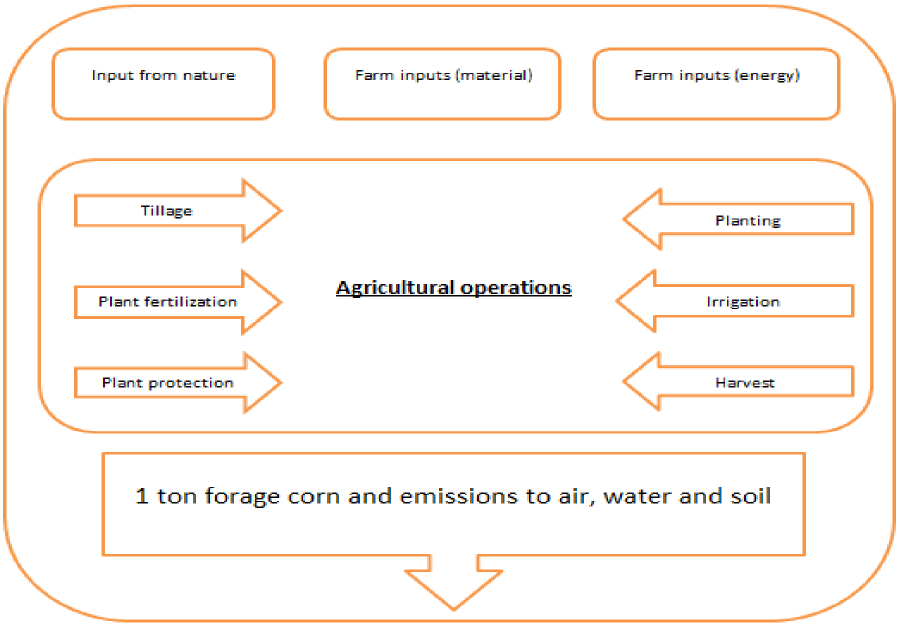

Figure 1. The framework defined for the boundary of the study system of the forage corn field

2.2.1.2. The boundary of the investigated system

The boundary intended for this research was the farm framework. Inputs and outputs data of the study were collected at the defined boundary (Figure 1).

2.2.2. Life cycle inventory

In the second stage, all the necessary resources in the production system for the production of forage corn should be entered exactly in the inventory. All outputs and emissions of the triple-environments would be calculated. According to the Ecoinvent reports, all data are not of a high quality, and in the present study, data has been collected at the L_4 level. This data level has the highest acceptability in the global database.

Collection of data consisted of several steps. At first, information from a questionnaire directly filled up by farmers and some of the relevant authorities. In the next step, the supplementary information of the questionnaire (fossil fuel consumption, electrical energy, etc.) was recorded by the researcher after the evaluation. Final step related to computational information (emissions to air, soil, water, calculation of carbon dioxide consumption from air, etc.) that are calculated using standard Ecoinvent models and to determine the values of the data considered in the functional unit scale.

2.2.3. Functional unit

After classifying information and data, it is essential to consider a functional unit. Functional unit is a scale to understand the connection of a product with another product. Functional unit as a reference can compare different systems based on the common structure (Wiedemann and Mcgahan 2011). It should be noted that life cycle calculations are measured at all stages based on the functional unit (Nemecek et al., 2011b). In this study, the information was collected at scale of one hectare of forage corn farm. Therefore, in order to better understand the results of the life cycle assessment, a functional unit for production of one ton of forage corn is considered.

2.2.4. Life cycle impact assessment

The selection of impact assessment groups should reflect the complete set of environmental issues associated with the cropping system under study, taking into consider the goal and scope of application. In the present research, the main goal is appraisal of environment destruction caused by the production system. Therefore, the impact assessment groups are related to the environmental disturbance with the research objective and it has the best display in the selection of category consequences indexes.

After determining the system boundary according to the goal and scope of the study, the evaluation method would be chosen. The study method of this research has been selected in the SimaPro software from a series of European recipes. The CML-IA recipe instruction evaluates the 11 impacts assessment according to the investigator inputs. Environmental impact assessment has an abbreviation and an equivalent unit that is presented in Table 1 (Goedkoop et al., 2008; Pre consultants, 2003).

Table 1. Impact Squares - Equivalent Units and Specifications

Impact assessment	Unit	Specifications
Natural resources depletion, abiotic (AD)	kg Sb equivalent.	This potential consist of consumption of renewable and non-renewable resources
Abiotic depletion, fossil fuels (ADF)	MJ	The exploitation of fossil fuels, mineral resource and also the potential of fossil resource depletion
Global warming potential (GWP)	Kg CO2 equivalent	The potential share of one material in greenhouse emissions impact
Ozone layer depletion (ODP)	kg CFC-11 equivalent	The value of ozone layer destruction which is its major created by hydrocarbons including Carbon, Chlorine and fluorine
Human toxicity potential (HTP)	kg 1,4-DB equivalent	Damage potential of one unit of released chemical material to environment base on toxicity of a combination and its potential of consumption dose
Terrestrial eco-toxicity (TE)	kg 1,4-DB equivalent	Emissions of toxic substances to soil
fresh-water aquatic eco-toxicity (FEW)	kg 1,4-DB equivalent	Emissions of toxic substances to fresh water
marine eco-toxicity (ME)	kg 1,4-DB equivalent	Refers to impacts of toxic substances on marine ecosystems
Photochemical oxidation (PO)	Kg C_2H_4	The potential has showed the creation of the 1 capacity of ozone of volatile organic material for ozone production
Acidification (AC)	kg SO_2 equivalent	The potential shows the acidification impact of SO2 Another material which has recognized as acidification, are nitrogen oxide and ammonium. Also the impact of SOx is similar to SO2
Eutrophication (EU)	kg PO_4^{-2} equivalent	The potential was used based on PO_4^{-2} , another emission of eutrophication were nitrogen oxidation N_2O and ammonium NH^{4+}

2.2.5. Characteristic coefficient

In the evaluation section, the effect of the phrase "characteristic coefficient" is also applicable to those effects expressed equally. For example, carbon dioxide, methane and nitrous oxide emissions all affect global warming. However, the potential of these gases is different from climate change. For carbon dioxide, it is considered to be 1, and for methane is 21, and for nitrous oxide is 310. Therefore, if one kilogram of nitrous oxide is released into the production process of a product, it is equivalent to releasing 310 units, and expressed as 310 kilograms of carbon dioxide. In this section, the number of 310 is called the coefficient of determination or characteristic coefficient (Bare et al., 2003). Therefore, to express the environmental impact of global warming, it is not necessary to express all the effects of greenhouse gases and can all be expressed in terms of production in carbon dioxide.

2.2.6. Interpretation of the results

There are several basic elements in life-cycle interpretation. These elements can be categorized as follows:

• Identify important issues based on the results from the life cycle inventory process and assessing the life cycle inventory in the overall assessment of the life cycle,

•An assessment that considers completeness, sensitivity and consistency

•Finally, make conclusions, limitations and recommendations.

Use the World Wide Web to set defaults: The World Wide Web used in this research is called the Ecoinvent database. This database is reviewed and updated over time, the latest version (version 3) was used at the time of the current research. The Ecoinvent 3 has more different models and methods than the Ecoinvent 2.

2.3. Investigating uncertainty of data

The Monte Carlo statistical method is used to prevent the exponential growth of data. The application of the Monte Carlo method in mathematics and statistics is very extensive. It is tried to use this method, by random selection, one or a limited number of responses were attempted from the existing answers to arrive at an acceptable solution. This issue becomes valuable when a set of alternatives is available to answer a very large problem and the virtually impossible to test all of them. To access the Monte Carlo method, the square of the standard geometric deviation must be estimated and indicated by the GSD2 abbreviation in the above method. Therefore, the following relationships can be calculated (Roux, 2014):

$$GSD = \exp\left(\sqrt{\frac{\sum_{i=1}^{n}\left(ln\frac{A_i}{\mu_g}\right)^2}{n}}\right) \tag{1}$$

A: Range of numbers and the frequency of alternatives are in the range of i to n, μ_g. It will be obtained from the following equation:

$$\mu_g = \sqrt[n]{A_1 A_2 \ldots A_n}$$

After the Monte Carlo method has been introduced for quality as "life cycle inventory entries", trial data were introduced into SimaPro.

Number of test questionnaires (n): The following formula is used to determine the number of sample individuals and can be calculated according to the following equations (Snedecor and Cochran, 1989):

$$n = \frac{N\times(S\times t)^2}{(N-1)d^2+(S\times t)^2} \tag{2}$$

$$d = \frac{S\times t}{\sqrt{n}} \tag{3}$$

t: 1.96 (at 95% probability level), s: advances the standard deviation of society, d: desirable accuracy probability, N: size of society and n: sample size.

It should be noted that performing uncertainties in research data manually is a complex task. The SimaPro software has an uncertainty analysis evaluation file. Among four methods of estimating the uncertainty of SimaPro, Monte Carlo method was chosen in this study. In the evaluation columns, lognormal values were entered. The software, by entering the value of variance, according to the coefficient of variation, evaluates uncertainty in all of the environmental effects separately. It should be noted that the longest evaluation of SimaPro software is the assessment of uncertainty and this process requires a long time.

2.4. SimaPro software

The software used for the Life Cycle Assessment Methodology is called SimaPro. SimaPro version: 8.3.0, report version V_3, language: English. The side software that is used during the process of collecting and performing the steps of the article are; Excel, Grapher v12.7.855, Math type v6.8, and Edraw max v8.4.

2.5. The source of emissions data

The crop production emissions in the triple environments, were calculated using equations and references in the Ecoinvent (Table 2).

Table 2. Resources used to calculate emissions.

Environment	Emissions	Data sources
Air	NH_3, CO_2, NO_X, N_2O, CH_4, SO_2 & CO & etc	Bengona et al., 2015; Nemecek, 2007; Nemecek, 2011; Agrommon, 2009
Water	Phosphate, Nitrate, cadmium, lead, zinc & etc	Bengona et al., 2015; Nemecek, 2007; Nemecek 2011; The emission model SALCA-P and SALCA-NO_3, 2006
Soil	Cadmium, lead, zinc & etc	Nemecek 2007; Nemecek 2011; Robert and stauffer, 1996

3. Results and Discussion

3.1. Life cycle inventory (LCI)

Field inputs and outputs were collected as detailed as possible. The results were calculated in terms of functional unit. Results are presented (Table 3) after the statistical evaluations and data uncertainty analysis.

3.2. Cut off the important paths of inputs

According to the employed method for planting forage corn in the studied area, at first materials and operations of agriculture should be evaluated. Then at each production stage different materials will be also used that should be considered and thus emissions related to different production stage will be examined separately. A separate calculation of emissions at the interpretative stage will be very beneficial. In setting up the inventory, the materials used were listed with all the details on the L_4 level. Default data was extracted from the Ecoinvent database for setting energy consumption inventories.

The data for all farm input was evaluated by default values extracted from reports of Ecoinvent. After setting and choosing the default, each data was verified based on conditions of Iran. Emissions to the environment, given the laboratory data and licensed models of the Ecoinvent were calculated. Based on the study conducted on use of electricity energy for irrigation water pumping in the agricultural process, it has been observed that the environmental release of the process is equal to 230-830 units per kilogram of CO_2 production across different regions. Therefore, irrigation water management and the use of more efficient processes, such as sprinkler irrigation and drip irrigation, are highly recommended (Schlesinger, 1999; Ghasempour, 2016).

Table 3. The part of life cycle inventory.

Inputs	Unit	Amount	Comment
Inputs from nature			
Water, in ground	m^3	139.308	Ecoinvent report and This study
Carbon dioxide, in air	kg	467.233	Nemecek and schntzer, 2012
Land occupation, annual crop	ha	0.0205	Nemecek and schntzer, 2012
Inputs from technosphere (material)			
Seed	kg	0.735	This study
N fertilizer, urea	kg	8.95	This study
P fertilizer, triple superphosphate	kg	3.61	This study
Pesticide, unspecified	kg	0.0895	This study
Agricultural machinery	h	0.167	This study
Chopper harvesting	ha	0.0205	65hp, 1250kg
Inputs from technosphere (energy)			
Labor	h	1.962	This study
Electricity	kwh	52.112	Ecoinvent report and This study
Diesel, burned in agricultural machinery	MJ	147.1898	Ecoinvent report and This study

3.2. Life cycle assessment of production stages

According to results obtained by the life cycle assessment, the amount of greenhouse gas emissions to exacerbate global warming threats to produce one ton of forage corn is 118.46 the unit equivalent of producing kilograms of CO_2. Disposal of abiotic depletion resources related to fossil fuels has been fulfilled in the production of one ton of corn equal to 1726.38 MJ. Eutrophication potential of the product unit in Khoramabad is estimated to be 0.4618 kg equivalent to PO_4 production. In a similar experiment in 2013, on corn fodder plant, the amount of autoclaving potential was 0.41 kg equivalent to PO_4 production (Bacentti et al., 2013). The contribution of each of the stages of production to the impact assessment is represented in Figure 2.

It is noteworthy that in the same experiment, by using two tons of organic fertilizers per hectare, they have succeeded in achieving global warming potential of 29.75 unit, equivalent of producing kilograms of CO_2 (Bacentti et al., 2013). Therefore, depending on the type of cropping system and the type of farm inputs, farmers are generally exposed to the amount of publications in the environment. Numeric values of the environmental impact for one ton of forage corn is given in Table 4..

Table 4. The amounts of different environmental impacts for production one ton of forage corn. CML-IA recipe

Impacts assessment	Value calculated without uncertainty assessment	Median	Mean	SD (Standard deviation)	CV (Coefficient of Variation)
AD	0.000633	0.000599	0.000637	0.000196	30.72108
ADF	1726.383	1301.889	1751.615	2829.887	161.5587
GWP	118.463	91.22857	120.1522	177.1907	147.4718
ODP	1.47E-5	1.16E-5	1.48E-5	1.87E-5	126.4954
HTP	51.38039	46.66575	51.72478	32.93569	63.67488
FEW	23.04889	20.70289	23.20639	14.88244	64.13079
ME	151730.5	146095.9	151610.4	41575.27	27.42244
TE	0.26878	0.236646	0.271491	0.250925	92.42493
PO	0.033666	0.02731	0.034044	0.042638	125.2436
AC	0.735621	0.587642	0.743328	0.970134	130.5123
EU	0.461843	0.449245	0.462899	0.086714	18.73279

With regard to the column diagram, the effect of chemical fertilizers was significant in most cases but this evaluation is not at the data level of the L4, because there were not adequate details. Even the expression of the category of fertilizer also makes statements on the level of L3 for example, represent phosphorous fertilizer or nitrogen fertilizer. In the impact assessment of abiotic depletion (fossil fuels), the use of chemical fertilizers is important. It is noteworthy that each chemical fertilizer has different effects on the impacts assessment in the life cycle inventory.

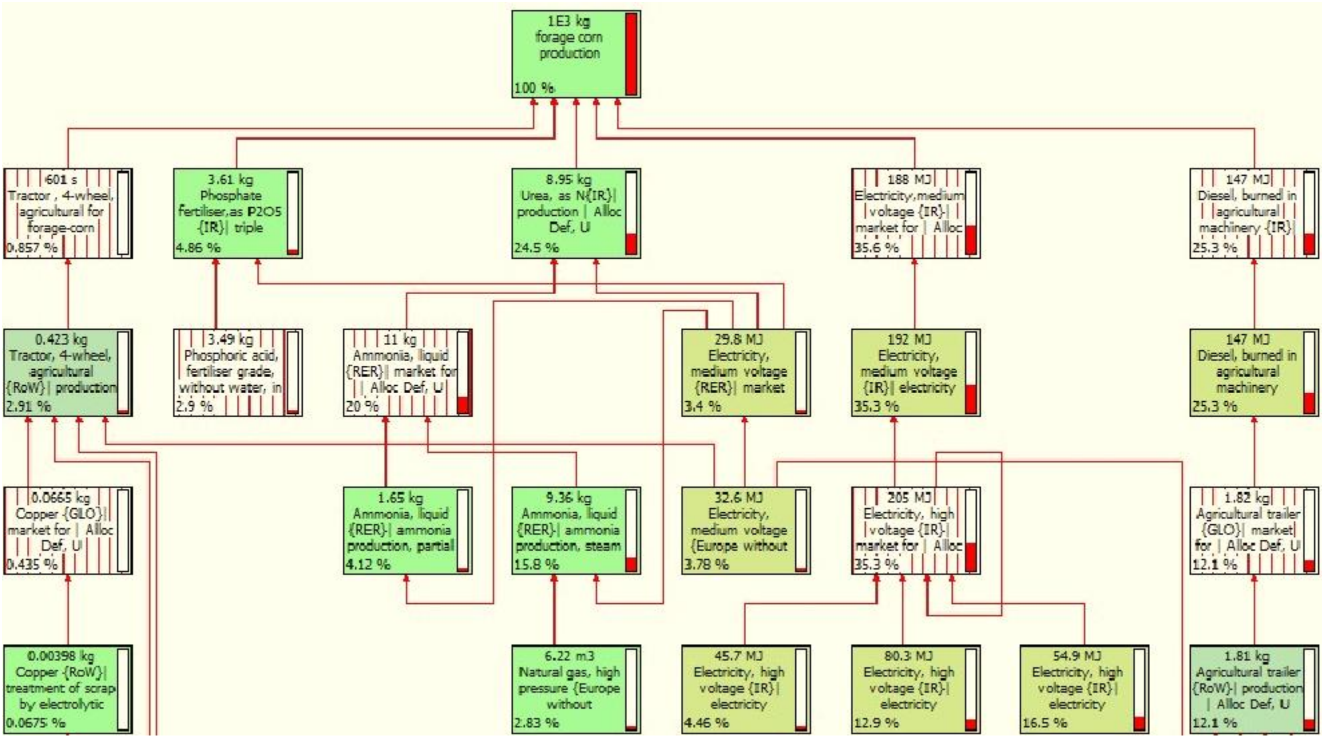

Figure 2. Paths of the important inputs to produce a ton of forage corn.

3.3. Impact assessment of production inputs

In order to clarify the subject and understand better the production processes in the present experiment, various inputs of production were individually examined. After defining a life cycle for each input separately, the results became more appealing. The mesh was in the impact category of abiotic depletion and phosphorus fertilizer impact was significant. More details of the thread, as fallow:

- In the abiotic depletion effect class, triple superphosphate fertilizer plays the dominant role in the life cycle inventory defined for the life cycle assessment.
- In the abiotic depletion (fossil fuels) effect class, nitrogen fertilizer impact was also significant. Further details indicated that urea fertilizer application in the fertilization stage had an impact on the environmental damage of this category.

In Figure 4, the effect of field inputs on the impacts assessment has been shown to be effective. As described above, in addition to defining a flowchart, generating life cycle assessment is useful for each inventory inputs. According to Figure 2, irrigation of forage corn cultivation has a greater effect on the use of chemical fertilizers. Forage corn irrigation is done using electric energy and well water extraction. According to experimental results, the use of electricity has the greatest impact on greenhouse gases emission in irrigation process. This step increases the entry of nitrate and phosphate into groundwater and results subsequently in a more powerful formation of other environmental impacts. Increasing the concentration of other substances in the surrounding ecosystems causes the collapse of ecosystems balance. The presence of nitrate and phosphate is essential for plant growth, but increasing its concentration in water causes excessive growth of algae in freshwater. Further, this will reduce the amount of oxygen in the water and ultimately lead to the deterioration of the ecosystem (Guinee, 2002).

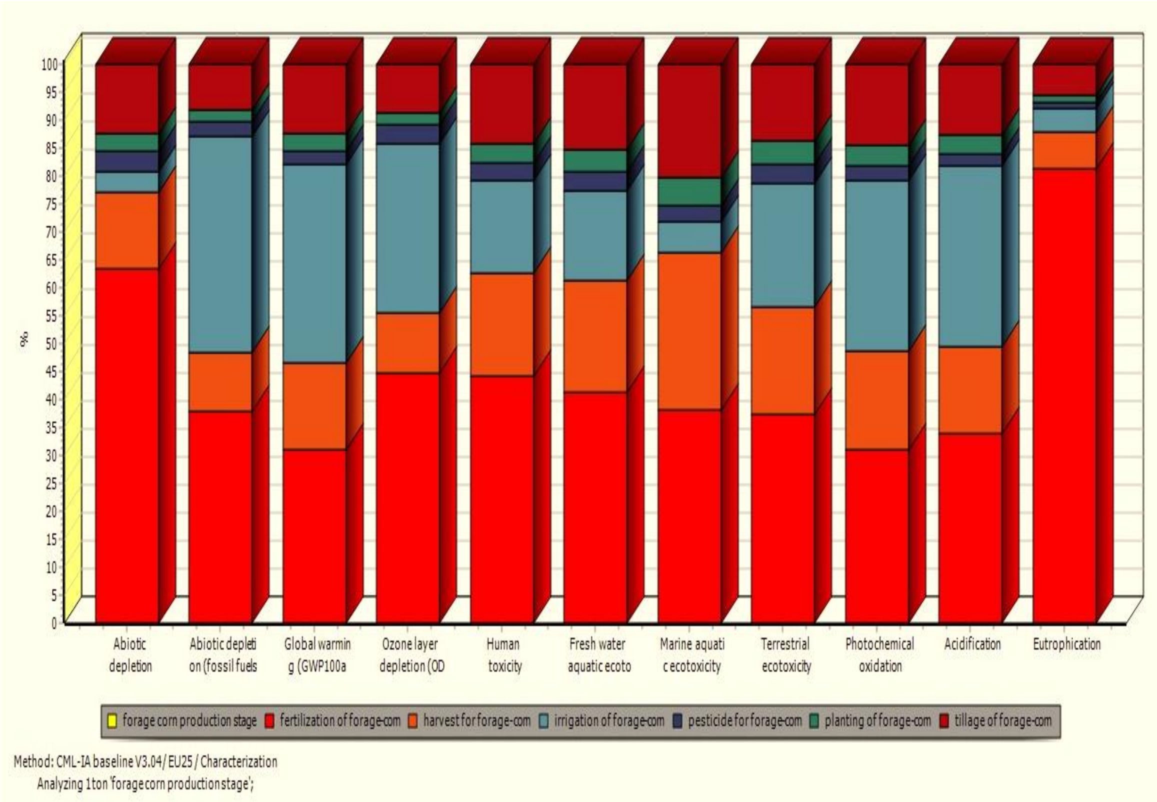

Figure 3. Column chart impacts assessment for production stages of one-ton forage corn. CML-IA recipe.

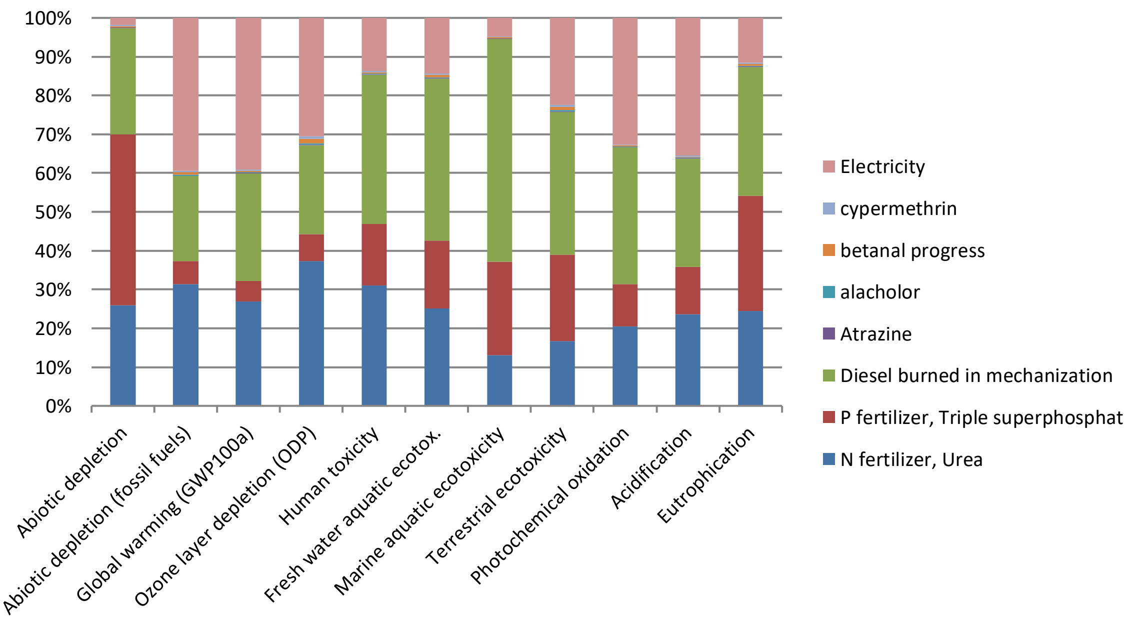

Figure 4. Column chart effect of farm inputs on impacts assessment. CML-IA Recipe.

The ozone layer depletion by chlorine and bromine adds to the amount of harmful ultraviolet light that causes the surface to warm up. The ozone depletion potential is represented by the reference unit of kilogram of CEC_{11} production. After evaluating the data, this potential for one ton of forage corn equal was 0.0000147 units per kilogram of CEC_{11} production. A large amount of emission factors associated with this environmental impact due to the use of pesticides and herbicides during the agricultural process. Carbon, chlorine and fluorine are the most important substances that have the property of ozone depletion (Guinee, 2002).

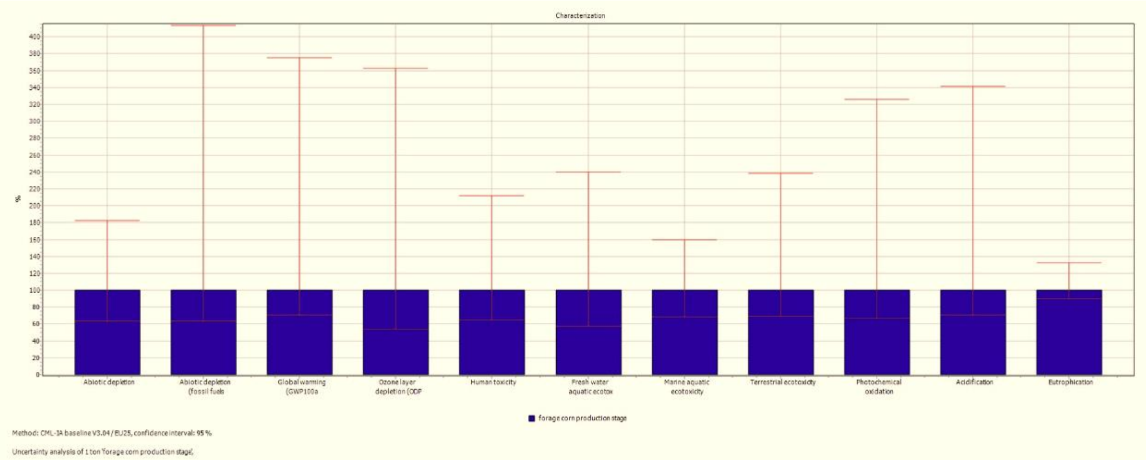

Figure 5. Results of uncertainty assessment for one ton forage corn production.

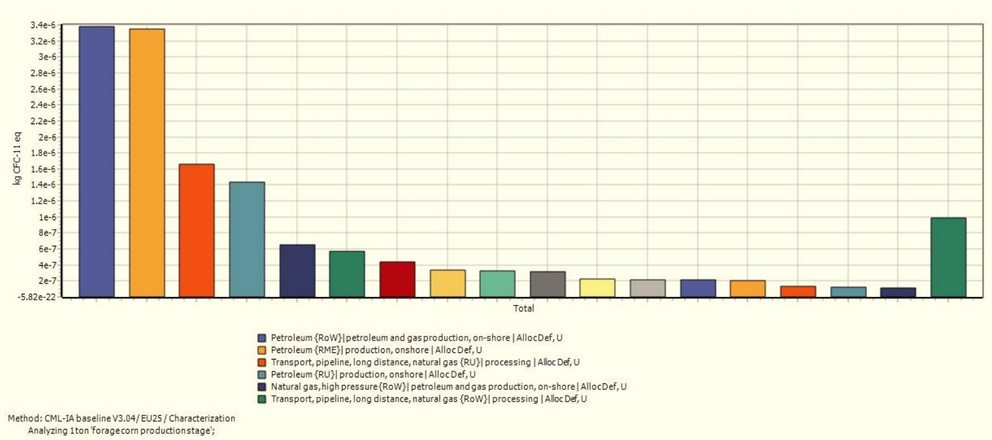

Figure 6. The most effective inventory entries in the environmental impact of the ozone layer depletion.

3.4. Uncertainty analysis of research data

The results obtained from the average data may not be the same for all research farms. Given the average value, the data in the fields is higher or lower than this value. Therefore, considering the difference in the data, the environmental impact values would be certainly different. By analyzing data, an uncertainty range is defined for each environmental impact. This range starts from the values before the average and continues up to values above the average. The graph of the uncertainty analysis of one ton of forage corn is presented in Figure 5.

The most uncertainties in the data are seen in the environmental impact of ozone depletion (ODP). It is necessary to mention, there are farms in the studied area that can impose more than the average ozone depletion. The potential of this environmental impact may be a range of 40 percent less or about 400 percent higher than the average (Fig 4). Subsequently, the effects of global warming and abiotic depletion fossil fuel are in the next category.

The results indicated that photochemical oxidation and acidification of picks were approximately at the same level. The rest of the environmental impacts are shown in Figure 5. According to the life cycle inventory evaluation information, it can be interpreted that which inputs had the most effect on the environmental impact of ozone depletion and what are the uncertainties of the inputs.

According to Figure 6, the greatest impact is seen for fossil fuel inputs and transportation. These materials can be referred to fossil fuels and natural gas. Highest consumption of natural gas in the life cycle inventory is the urea fertilizer production. The uncertainties in this environmental effect are probably due to infrastructure differences (distance to the main road and distance with the manufacturer), topography (land slope) and machinery (power of machinery, used equipment). The green column on the right side of the graph shows the effect of other things in the inventory.

4. Conclusion

4.1. Life cycle assessment conclusion

Considering the global issue of food security and food shortage with current production situation, many people around the world are challenging to provide food. Therefore, it seems reasonable to enhance production management than reducing inputs. Reforming the infrastructure for production is very necessary and should be reconsidered through government institutions. Revision of cropping pattern can be beneficial with respect to the conditions of region and natural resources. Considering climatic conditions, topography, natural resources and mechanization of each region are appropriate steps in choosing the suitable crops (Hassani et al., 2016).

Another issue in the study area was about those instruments which were not developed and historically improved. For example, a tractor with a plow was used for sloping lands and flat lands. Therefore, due to the increased duration of agricultural operations and increased fuel consumption, one ton of forage corn in steep lands will be more polluting. The adaptation of the equipment and the power required for their use in tillage may help to reduce environmental emissions.

When a tractor is over-powered, fuel consumption and greenhouse gas emissions increases. In this way, this stage will result in more environmental damage. Therefore, any improvement in developing the proper mechanization infrastructure are very beneficial. Most farmers may not be able to purchase the right equipment and the farmer only considers the financial situation at the time of purchase. In this situation, government agencies can help the farmers and reducing environmental damage through the purchase of appropriate equipment and facilating the availability of advanced equipment in the area. It is very important to pay attention to financial situation of farmers as the first production level in terms of agricultural infrastructure reform (Hassani and Ramroudi, 2017).

Therefore, according to this study, environment friendly production of forage corn is possible only by modifying the pattern of its production. An improved management can be able to progress towards the least-polluting production, along with the consideration of manufacturing infrastructure and more precise programs for application of chemical fertilizers, chemical pesticides, fossil fuels and other required inputs.

4.2. Long-term emissions conclusion

It should be noted that environmental pollutants will increase through accumulation in nature during their production process across many years however the values quoted in this study are based only on the study year. The SimaPro software has the ability to calculate historical environmental impacts. Considering farm inputs and environmental impact indicators, a long-term scenario can be developed. Aquatic and atmospheric environments due to fluidity may not be appropriate in this scenario. Providing a scenario for continuation of the current production process is necessary. To forecast the future and to provide a scenario based on the results, several separate environmental impacts of inputs can be considered for production one ton of forage corn.

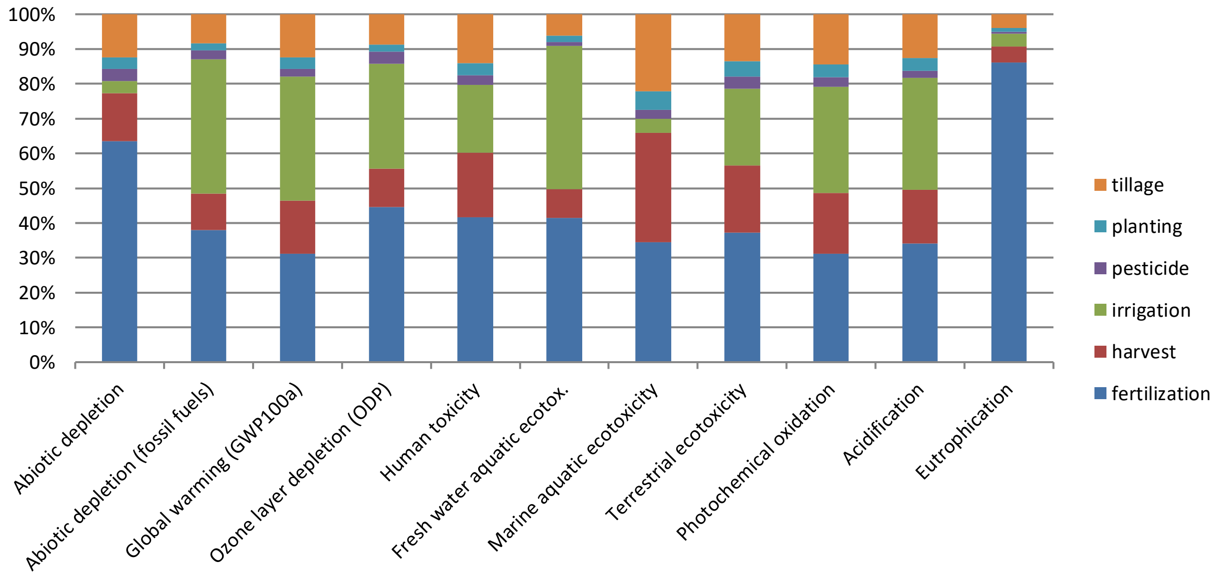

Figure 7. Long term environmental impact assessment based on current production inputs. CML-IA Recipe.

Considering the assumptions of the whole column in Figure 7 and comparing it with Figure 3, most changes are in the effects of eutrophication, fresh water aquatic toxicity, human toxicity and ozone layer depletion. Environmental impacts of chemical pesticides will not be exceeded annually, and their accumulation in the biological environment will have adverse effects. There is a general belief among farmers that more application of chemical fertilizers and more irrigation leads to higher yield and consequently higher profits from the agricultural process. Over time, chemical fertilizers appear to be a powerful factor for eutrophication. The use of chemical fertilizers also increases the impact assessment of human toxicity in long term and leads to a higher pollution. Therefore, modifying the management of inputs and production of forage corn can directly affect the improvement of the production scenario. This increase in the percentage of chemical fertilizers used in the impact assessment of ozone layer depletion and fresh water aquatic ecotoxicity is also clearly visible. In addition to fertilizer use, the application of chemical pesticides, and the processes of tillage and planting in long-term have more effects on aquatic ecosystems. Looking at the long-term scenario graph, other percentages can also be deduced. It should be noted that the values in the long-term scenario are predicted by the percentage of stages and avoided by providing numerical values in prediction.

4.3. Uncertainty analysis conclusion

In uncertainty analysis, the results indicate the uncertainty distance of the data from the mean. This distance included values both beyond and above mean value. It may be possible to set precise plans for the management measures to reduce environmental impacts. Considering the uncertainty results of this study, there are many differences in inputs, energy consumption, publications, mechanization, and many others. One reason for these differences can be the field topography. On steep slopes, machinery and tools, in addition to increasing the operating time, use more fossil fuels. The lack of tools and methods of instrumentation can be the next factor. In many cases, in the studied area, the actual level of the farm is different from the farmer estimate. As a solution farmer can measure the area with a GPS device and is quite helpful and effective in applying the inputs, more accurately. Regarding the use of chemical pesticides, it should be noted that determining economic loss level and accurate calibration of spraying equipment can be effective in correctly applying this input. Using water pumps according to the needs of the fields and adjusting the duration of irrigation can be effective in reducing electric energy and water consumption.

Recommendations and suggestions:

- Knowing farms with less environmental impacts and management of other fields can be recommended as an environmental strategy.
- Factors that reduce environmental impacts can be investigated. If these factors are identified, it may be possible to further reduce the hazard impacts on environment.
- The results of the studies can be used to land use planning and prevent the cultivation of inappropriate land.

5. Acknowledgment

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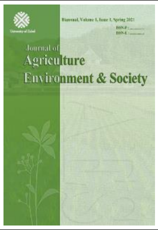

Response of physical dimension changes and fruit quality of Khatouni melon to chemical fertilizer application

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ABSTRACT

To investigate the effect of commonly used chemical fertilizers on certain quantitative and qualitative characteristics of Khatouni melon ecotype, an experiment was conducted in a randomized complete block design at the research farm of Ferdowsi University of Mashhad. The treatments included: T1: control (no fertilizer applied), T2: nitrogen fertilizer from urea at a rate of 120 kg/ha, T3: phosphate fertilizer from triple superphosphate at a rate of 120 kg/ha, and T4: potassium fertilizer from potassium sulfate at a rate of 100 kg/ha. Results indicated that the use of potassium fertilizer led to a 17% increase in melon fruit length compared to the control. The application of fertilizers T2 and T3 resulted in a 14% and 15.5% increase in fruit length, respectively, compared to the control. The fruit lengths for treatments T2, T3, and T4 were 38 cm, 38.6 cm, and 39.3 cm, respectively. The highest middle diameter of the melon (14.5 cm) was obtained from treatment T3 and the lowest from treatment T1. The number of seeds per fruit was 649 in the control, with a 3% and 6% increase observed with T2 and T4 treatments, respectively. The highest and lowest flesh thickness were recorded from treatments T2 (3.66 cm) and T1 (3.00 cm), respectively. The highest (3.16 kg) and lowest (1.97 kg) fruit weights were obtained from treatments T4 and T1, respectively. Treatment T2 resulted in a 33% increase in fruit weight compared to the control. The highest positive and significant correlation was found between single fruit weight and fruit length (r=0.82*) and middle diameter (r=0.82*). The highest sugar content was observed in treatments T2 and T4.

Highlights

- The study investigates the effects of different chemical fertilizers on the growth characteristics of the Khatouni melon ecotype.
- The study identifies that applying chemical fertilizers, particularly potassium and nitrogen, significantly enhances the quantitative and qualitative characteristics of Khatouni melons.
- The paper shows that the use of chemical fertilizers significantly improves both the growth and quality of Khatouni melons.
- Overall, this article highlights the importance of macronutrient fertilizers (nitrogen, phosphorus, and potassium) to maximize yield and quality and has an impact on improving the characteristics of Khatouni melon.

1. Introduction

Melon (*Cucumis melo* L.) is an annual plant from the Cucurbitaceae family and is one of the most important horticultural crops in arid and semi-arid regions of the world. The plant's high thermal requirement is advantageous for cultivation in these areas (Kashi and Abedi, 1998). With a wide variety of cultivars and landraces, melon cultivation has a broad distribution. In Iran, melon is cultivated on 76000 hectares under irrigation farming and 1400 hectares on rainfed lands , yielding a production of 20191 kg/ha and 827.6 kg/ha, respectively, totaling approximately 1,549,394.3 tons (Statistics of the

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Ministry of Agriculture Jihad, 2024).

Melon fruit, in addition to its sugar content, is a rich source of vitamins A, C, beta-carotene, and potassium. It is free of cholesterol and contains small amounts of fat, sodium, vitamin E, folic acid, iron, and calcium, making it suitable for consumption as fresh fruit or juice. Studies have shown that in the United States, high-fat and high-protein diets often lead to health issues that can be mitigated by incorporating melon, potentially improving many health conditions and overall wellness (Lester, 1997). The physical characteristics of melon are influenced by genetics, environmental conditions, and agricultural management practices. The interaction of these factors can affect processing industries and consumer acceptance (Valverde et al., 2006).

One of the key strategies for increasing crop yield is the use of mineral nutrients, and fertilizer trials play a significant role in determining the quantity and quality of plant production. The structural components of many macromolecules within the plant body and its final products are formed through the uptake of mineral nutrients, primarily from the soil. This uptake process depends on the hydration of these elements and is influenced by the quantitative relationships between ions and molecular complexes of elements in the soil. Therefore, the availability of nutrients is closely tied to these soil chemistry interactions.

Soil, as a crucial medium for production, experiences fluctuations in its mineral content and reserves. Continuous use of soil resources without replenishment can lead to a decline in its productive capacity. The nutritional components present in plants, such as proteins, fats, acids, vitamins, and minerals, determine the quality of plant products, including flavor and aroma compounds. These attributes are influenced not only by genetics but also by agricultural management practices. The application of specific mineral nutrients alters the synthesis of these compounds; for instance, excessive use of potassium compounds enhances the metabolism of carbohydrate synthesis, while an abundance of nitrogen shifts assimilates towards the production of amino acids and amides. Therefore, heavy nitrogen fertilization increases the production of nitrogenous organic compounds (crude protein), whereas high potassium fertilization boosts the synthesis of carbohydrates and fats (Alizadeh, 2022).

Phosphorus is a key component of essential molecules such as nucleic acids and phospholipids. The storage form of phosphate in seeds and fruits is myo-inositol hexakisphosphate (phytate). Phytate production occurs during the maturation phase. Plants, along with phytate, transfer important mineral elements such as magnesium and phosphate to the embryo and young seedling for phosphorylation processes. Studies have shown that phosphorus deficiency in plants and fruit trees negatively affects flower, seed, and fruit production due to impaired nucleic acid and protein synthesis (Hagh Paraste Tanha, 1992).

The optimal amount of nitrogen for the growth of cucurbit family plants depends on the species, location, climate, soil characteristics, and crop management practices (Van Eerd and O'Reilly, 2009). Research by Simsek and Comlekcioglu (2011) on melons demonstrated that nitrogen treatments at 0, 30, 60, and 90 kg/ha during fruit development significantly affected various fruit attributes (fruit weight, fruit length, fruit width, seed cavity diameter, and dry matter weight). Specifically, the greatest fruit width (18.7 cm) was observed with the zero-nitrogen treatment, while the greatest fruit length was achieved with the 30 kg nitrogen treatment. Additionally, Kirnak et al. (2005) found that applying nitrogen levels of 0, 40, 80, and 120 kg/ha to a melon variety (*Cucumis melo* L. cv. Polidor) resulted in fruit diameters of 19, 26, 31, and 35 cm, respectively. Similar results were obtained in this study regarding fruit length, with the treatments resulting in lengths of 11, 16, 19.5, and 22 cm in the first year under non-stressed irrigation conditions.

In another study, Drake et al. (2002) evaluated the response of apple trees to nitrogen fertilization, concluding that the highest fruit firmness and skin color quality were achieved with the lowest nitrogen application rates. Nava et al. (2008) reported that potassium fertilization led to reduced fruit firmness in apples over two years of testing. They attributed the decrease in fruit firmness to the concurrent increase in fruit size, which resulted from potassium application. Given the limited information available on the structural role of different chemical fertilizers in affecting melon fruit characteristics, this study aims to evaluate the quantitative responses of melon fruit to the application of various chemical fertilizers (urea, phosphate, and potassium) under field conditions.

2. Materials and methods

This experiment was conducted at the research farm of the Faculty of Agriculture, Ferdowsi University of Mashhad, using a randomized complete block design with three replications. The experimental treatments included: T1: control (no fertilizer applied), T2: nitrogen fertilizer from urea at a rate of 120 kg/ha, T3: phosphate fertilizer from triple superphosphate at a rate of 120 kg/ha, and T4: potassium fertilizer from potassium sulfate at a rate of 100 kg/ha (Saber Ali and Nasrabadi, 2020; Keshtehgar et al., 2020). All phosphate and potassium fertilizers, along with 40% of the urea fertilizer, were applied before planting to the respective plots, while the remaining nitrogen fertilizer was applied in two splits, three weeks after planting, with a one-week interval between applications. The soil of the experimental site was loamy sand, and a soil sample was analyzed at the soil laboratory before the experiment to determine the soil physical and chemical properties (Table 1).

The land had been left fallow the previous year, and preparatory operations were carried out in April and May. Each experimental plot consisted of two rows, each 3 meters wide and 4 meters long, with a plant spacing of 60 centimeters within the rows. Direct sowing was performed on May 5, 2023. Melon seeds of the Khatouni variety were procured and disinfected with the fungicide Carboxin-Thiram before planting. Seeds were sown in pre-heated soil, with five seeds planted per hole at a depth of 5 centimeters. After germination and at the four-leaf stage, thinning and earthing up around the plants were carried out. Irrigation was conducted weekly with furrow irrigation methods. Maintenance operations included mechanical weed control and pesticide applications to combat aphids and melon flies.

At the stage of fruit maturity, after removing the border effects, fruits from five plants were harvested. For each of three fruits per treatment, quantitative and qualitative traits were measured: length, highest middle diameter, fruit width, peel thickness, flesh thickness (measured with a caliper), and number of lobes. The mean values of these measurements were recorded as representatives for each treatment.

To measure seed count, seeds were separated from the fruit, thoroughly washed, dried in the shade, and then manually counted. The number of fruits produced per plant was recorded along with their weights, and the average weight per fruit was noted as the single fruit weight per plant.

For sugar content analysis, the colorimetric method was used (Dubois et al., 1956). In this method, the reaction of sugars with sulfuric acid and phenol produces a yellowish-orange color. For this purpose, 50 grams of fruit flesh were mixed with 200 cc of 96% ethanol for 60 seconds. From the resulting mixture, 20 microliters were taken and mixed with 20 microliters of phenol, 5000 microliters of sulfuric acid, and 1980 microliters of distilled water. The absorbance was measured using a spectrophotometer at a wavelength of 490 nm. The sugar concentration in the solution (x) was determined using a standard curve {y=mx+b}, where y represents absorbance and x represents sugar concentration in micrograms per milliliter. The percentage of sugar in the total fruit flesh was then calculated. Data analysis was performed using SAS software version 9.4. Mean comparisons were conducted using Duncan's multiple range test at a 5% probability level.

Table 1. Physical and chemical characteristics of field soil before planting

P	K	N	Organic carbon (%)	C/N	Electrical conductivity Ds.m^{-1}	Bulk density g.cm^{-3}	pH
(mg/kg)							
9	192	0.11	1.1	11	2.1	1.2	7.5

3. Results

The evaluation of the effects of individual chemical fertilizers on the traits studied revealed that certain traits did not exhibit the expected behavior in this experiment. For example, the fertilizer treatments did not significantly affect traits such as the number of fruits per plant, peel thickness, and the number of lobes (Table 2). In the case of the number of fruits per plant, it was anticipated that urea, due to its role in amino acid production and accumulation, and the high rate of transport of these compounds via the xylem and phloem to organs with elevated protein synthesis (such as young leaves and reproductive organs), would promote the formation of reproductive tissues and structures. Although this did not happen as expected, there was still a 6% increase compared to the control. Regarding the number of lobes per fruit, while no statistically significant difference was observed, the application of phosphate fertilizer (T3) resulted in an 11% increase in the number of lobes compared to the control (Table 3). The use of urea fertilizer (T2) increased the fruit peel thickness to 3.93 mm, with the lowest value observed in the potassium fertilizer treatment. Lotfi et al. (2015) reported a peel thickness of 3.8 mm for Khatouni melon in their study. Additionally, Rekha et al**.** (2017) showed that the highest number of fruits in bell peppers (8.23 fruits per plant) was obtained with the application of chemical fertilizer at the recommended rate, while the lowest number (6.78) was recorded for the organic fertilizer treatment.

Table 2. Analysis of variance (means of squares) for quantitative and qualitative traits of melon fruit under different fertilizer treatments

S.O.V	df	Number of seeds per fruit	Number of lobes	Fruit peel diameter	Percentage of sugar	Diameter of the fruit	Fruit flesh thickness	Fruit length	Weight of single fruit	fruits per plant
Block	2	3247^{ns}	1.75^{ns}	0.270^{ns}	0.770^{ns}	0.000^{ns}	0.060^{ns}	10.3^{ns}	0.004^{ns}	0.009^{ns}
Treatment	3	10437**	0.555^{ns}	0.453^{ns}	2.20**	4.72*	0.243*	27.8*	0.963**	0.010^{ns}
Error	6	5658	0.305	0.136	0.728	0.805	0.034	5.22	0.020	0.004
CV		11.6	4.31	6.54	5.47	9.64	7.56	8.64	10.5	11.2

ns, *, and **: denote no significant, significant at 5 and 1% probability levels, respectively

Table 3. Effects of nitrogen, phosphate and potassium fertilizers with control on fruit characteristics in melon

Treatment	Number of seeds per fruit	Number of lobes	Fruit peel diameter(mm)	Diameter of the fruit (cm)	fruit flesh thickness (cm)	Fruit length (cm)	Weight of single fruit (kg)	fruits per plant
T1*	649ab	9.00a	3.33a	11.6b	3.00b	32.6b	1.97c	1.33a
T2	673ab	9.66a	3.93a	13.8ab	3.66a	38.0a	2.95b	1.42a
T3	559b	10.0a	3.33a	14.5a	3.50ab	38.6a	3.15a	1.23a
T4	692a	9.33a	3.00a	14.0ab	3.33ab	39.3a	3.16a	1.33a

In each column, means sharing at least one common letter are not significantly different at the 5% probability level according to Duncan's multiple range test.

*: T1: Control (without adding fertilizer), T2: Nitrogen fertilizer from urea source at 120 kg/ha, T3: Phosphate fertilizer from triple superphosphate source at 120 kg/ha, and T4: Potassium fertilizer from potassium sulfate source at 100 kg/ha

3.1. Length and diameter of melon fruit

The effect of potassium on the growth of meristematic cells cannot be solely attributed to its impact on turgor. However, for guiding growth processes in meristematic tissue, a low apoplastic pH is necessary, within which potassium's effect on ATPase activity is evident at a pH of 6.5. Additionally, potassium has a close synergistic relationship with plant hormones such as indole acetic acid and cytokines, which influence the formation of new tissues by activating certain related enzymes (Cocucci and Dalla Rosa, 1980). The experiment showed that the application of potassium fertilizer resulted in a 17% increase in melon fruit length compared to the control. The shortest fruit length was recorded in the control treatment (Table 3). The range of melon fruit length varied between 32.6 cm and 39.3 cm across different treatments. The use of fertilizer treatments T2, T3, and T4 resulted in increases of 14%, 15.5%, and 17%, respectively, in fruit length compared to the control. Kokabi and Tabatabai (2011) found that when potassium concentration combined with calcium increased from 1.5 to 3, the fruit length of Galia melon reached its maximum value of 18.1 cm, representing a 6% increase compared to the 1.5 concentration. In another study, Kirnak et al (2005) reported that under optimal irrigation conditions, increasing nitrogen fertilizer led to an increase in the fruit length of muskmelon over two consecutive years. In the present study, the fruit length in the urea, phosphate, and potassium treatments were 38 cm, 38.6 cm, and 39.3 cm, respectively. Regarding the middle diameter of the melon fruit, the highest value (14.5 cm) was obtained from treatment T3, which represented approximately a 20% increase compared to the control. The middle diameter of the fruit in treatments T4, T2, and T1 were 14 cm, 13.8 cm, and 11.6 cm, respectively. A study indicated that the ratio of fruit length to width in the Mashhadi melon variety ranged from 2.15 to 2.31 across different poultry manure fertilizer treatments, showing significant effects from the various treatments (Norouzi et al., 2010)

3.2. Number of seeds per fruit

The results from the analysis of variance table indicated that the fertilizer treatments had a significant effect ($p \leq 0.01$) on the number of seeds per fruit (Table 2). The range of variation in the number of seeds per fruit was 649 in the control, with approximately 3% and 6% increases observed with the application of fertilizer treatments T2 and T4, respectively, compared to the control. The use of phosphate fertilizer (T3) resulted in a 19% decrease in the number of seeds per fruit compared to the control. Notably, the increase in the number of seeds per fruit was observed with treatments T2 and T4, while the application of treatment T3 led to a reduction in seed number (Table 3). Investigations reveal that the amount of phosphorus absorbed by the plant depends on the extent of root development. An increase in mineral phosphorus in the plant leads to the accumulation of this nutrient in older leaves, while younger leaves contain relatively high levels of organic phosphate, mostly in the form of nucleic acid phosphates. Consequently, when other essential co-factors for the plant are not supplied optimally, such as magnesium, the transfer of phosphate to the embryo and seedling for phosphorolysis processes is restricted. As a result, some fertilized seeds do not grow due to reduced synthesis of nucleic acids and proteins, leading to a decrease in seed number (Hagh Paraste Tanha, 1992).

3.3. Fruit flesh thickness

The experimental treatments had a significant effect ($p \leq 0.05$) on fruit flesh thickness (Table 2). The highest and lowest values for fruit flesh thickness were obtained from the urea treatment (3.66 cm) and the control (3.00 cm), respectively (Table 3). In this experiment, the effect of potassium on fruit flesh thickness was not significant with the other two treatments T2 and T3. However, it was significant with the control treatment (without adding fertilizer).Kokabi and Tabatabai (2011) found that increasing the potassium concentration in the nutrient solution (increasing the potassium-to-calcium ratio) to 3.5 resulted in a minimum fruit flesh thickness of 3.06 cm, while ratios of 1.5 and 2 resulted in fruit flesh thicknesses of 3.5 cm and 3.53 cm, respectively, in the same study. In another study, Kim et al (1991) reported that increasing potassium concentration in the fruit reduced both the size and weight of the melon. It appears that although polygalacturonic acid in the cell wall complex and calcium compounds such as calcium pectate play a role, potassium is critically important for inducing cellular turgor. The stability of fruit flesh thickness is dependent on the ratio of potassium to calcium (Mignani et al., 1995).

3.4. Fruit weight

Chemical fertilizer treatments had a significant effect on the weight of individual fruits (Table 1). The highest fruit weight (3.16 kg) and the lowest (1.97 kg) were obtained from the potassium fertilizer treatment (T4) and the control (T1), respectively. The difference between the T3 and T4 treatments was only 10 grams. The effect of the urea fertilizer treatment (T2) resulted in a 33% increase in fruit weight compared to the control. A study by Kokabi and Tabatabai (2011) reported different findings regarding the effect of potassium on the weight of individual melon fruits. The results of the correlation table showed that the highest significant positive correlation existed between individual fruit weight and fruit length ($r=0.82^*$) and fruit diameter ($r=0.82^*$) (Table 4). The positive effect of potassium fertilizer on increasing the weight of individual melon fruits (an increase of approximately 38% compared to the control) seems to be related to its physiological characteristics, as potassium enhances phloem loading with assimilates and long-distance transport. Potassium can depolarize the membrane to some extent via H+-antiport, and this depolarization increases ATPase activity, which in turn strengthens membrane transport. Additionally, in the presence of potassium, the ATP and NADPH synthesis systems are enhanced. Therefore, the increase in photosynthesis in the presence of potassium can be attributed to the reduced resistance of stomatal and leaf tissue cells to CO_2 entry, as well as to the increased activity of RUBP carboxylase. When the potassium content in the leaf dry matter was 1.28%, 1.98%, and 3.84%, the CO_2 assimilation rate increased by 11.9, 21.7, and 34 mg m^2 h^{-1}, respectively (Demming and Gimmler, 1983). In this way, in the presence of potassium, the synthesis of macromolecules such as cellulose, starch, and proteins is enhanced, ultimately leading to an increase in individual fruit weight.

Table 4. Correlation coefficients among melon fruit traits under chemical fertilizer and control treatments

	1	2	3	4	5	6	7	8	9
V1	1								
V2	-0.14^{ns}	1							
V3	-0.08^{ns}	0.82**	1						
V4	0.09^{ns}	0.63*	0.47^{ns}	1					
V5	-0.31^{ns}	0.82**	0.53^{ns}	0.72**	1				
V6	0.13^{ns}	0.69*	0.62*	0.34^{ns}	0.31^{ns}	1			
V7	-0.43^{ns}	0.70*	0.43^{ns}	0.32^{ns}	0.82**	0.33^{ns}	1		
V8	-0.45^{ns}	0.41^{ns}	0.64*	0.27^{ns}	0.34^{ns}	0.17^{ns}	0.21^{ns}	1	
V9	0.39^{ns}	-0.10^{ns}	0.02^{ns}	-0.20^{ns}	-0.15^{ns}	-0.00^{ns}	-0.07^{ns}	0.00^{ns}	1

ns, *, and ** : represent non-significant, significant at 5% and 1% probability level, respectively
V1: number of fruits per plant, V2: weight of single fruit, V3: fruit length, V4: flesh thickness, V5: fruit diameter, V6: Sugar content (%), V7: peel thickness, V8: number of lobes and V9: number of seeds per fruit

3.5. Sugar content

The results of the analysis of variance indicated a significant effect of fertilizer on the sugar content of melon ($p \leq 0.01$) (Table 2). The lowest sugar content was observed in the control treatment, while the highest was recorded in both the potassium and nitrogen fertilizer treatments (Figure 1). However, the three fertilizer treatments did not show statistically significant differences in melon sugar content. A study by Kultur et al. (2001) demonstrated that sugar content and its accumulation in melon are dependent on the photosynthetic assimilation of canopy leaves after ripening. Their findings also indicated that genotype has a significant and notable effect on sugar content, with significant differences observed between genotypes. In their experiment, spatial factors did not significantly affect the increase or change in sugar content. Martuscel et al (2014) found that improvements in melon flesh firmness, soluble solids, and carotenoid content occurred when phosphorus levels were increased from zero to 200 kg per hectare. Another study showed that the adequate application of potassium significantly improved tomato flavor, lycopene content, color, and flesh texture (Gruda et al., 2018). It appears that as melon ripens, the sugar content in each lobe increases. The sugar accumulated in the vacuoles represents a larger proportion compared to other parts of the cell, and the increase in vacuolar sugar serves as a basis for cellular turgor and growth in fruit size. Sucrose begins to accumulate in the fruit 28 to 42 days after planting, and the potential for further sugar increase exists beyond this period, which may occur a week before fruit maturity (Ofosu-Anim and Yamaki, 1994).

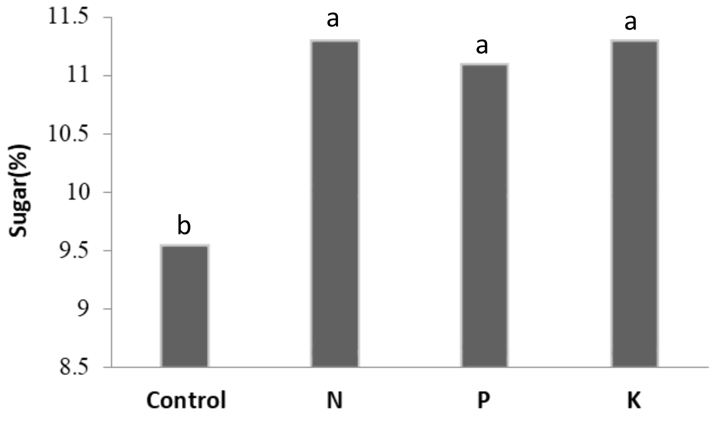

Figure 1. Impact of chemical fertilizer treatments on sugar content in Khatouni melon ecotype.

In general, the results of this study demonstrated that chemical fertilizers had a significant impact on improving vegetative, reproductive, and quality traits of melon. Potassium fertilizer resulted in the highest values for traits such as individual fruit weight, fruit length, and the number of seeds per fruit. In contrast, urea fertilizer had a greater effect on the number of fruits per plant, fruit thickness, and the number of lobes in the fruit compared to the other treatments. Phosphate fertilizer had an intermediate effect between urea and potassium. Therefore, the variations observed in the examined traits due to the fertilizer treatments can be attributed to the specific effects of each fertilizer. Based on these findings, the integration of these fertilizers along with essential micronutrients seems necessary to enhance the centric characteristics of the fruit.

4. Discussion

The yield of cucurbit crops is closely related to the development of vegetative plant biomass. Thus, by making the nutrients needed by the plant readily available, chemical fertilizers accelerate the physiological processes of the plant to improve growth and fertility, which has an impact on increasing the vegetative and reproductive tissues, such as leaves and fruit. The leaves of cucurbits serve as the primary source of nutrient translocation to the developing fruits. As such, the longevity and health of the leaves, particularly their ability to remain green and functional, directly influence the fruit's size, quality, and flavor (Aitbayeva et al., 2022). Poonam et al. (2014) demonstrated that the fruit yield of watermelons significantly increased with all levels of nitrogen (N), phosphorus (P_2O_5), and potassium (K_2O) applications, owing to the water-soluble quality and the effectiveness of conventional fertilizers. These results were more pronounced when compared to the generally recommended dose and control treatments.

The findings from this study underscore the significant impact that different chemical fertilizers have on some growth characteristics and quality of Khatouni melon fruits. By assessing the centric dimensions (e.g., length, diameter, weight, and flesh thickness) of the fruits under the influence of nitrogen, phosphate, and potassium fertilizers, we gain insights into how these nutrients alter both the physical and biochemical properties of the melon.

4.1. Implications for agricultural practices

The results of this experiment highlight the importance of selecting the appropriate type and quantity of chemical fertilizers for maximizing yield and quality in melon cultivation. While nitrogen is essential for enhancing flesh thickness and overall fruit size, potassium plays a crucial role in boosting fruit length, weight, and sugar content. Phosphorus, on the other hand, appears to have a more moderate effect, primarily influencing fruit diameter and seed production.

Given the significant increase in fruit length, diameter, and weight with the use of potassium and nitrogen fertilizers, farmers in arid and semi-arid regions, such as those cultivating Khatouni melons, may benefit from targeted fertilization strategies. The findings also reinforce the importance of soil nutrient management, as the availability of essential elements like potassium and nitrogen directly impacts the metabolic processes associated with fruit development.

Conclusion

This study evaluated the effects of chemical fertilizers (nitrogen, phosphorus, and potassium) on some growth and yield characteristics of Khatouni melon, a notable cultivar in arid regions. The results demonstrate that the use of these fertilizers significantly influenced several key traits, such as fruit length, middle diameter, flesh thickness, number of seeds per fruit, and overall fruit weight. Potassium fertilizer led to the greatest increase in fruit length (17% increase) and overall fruit weight (3.16 kg). Nitrogen and phosphorus also contributed to improvements, with nitrogen showing a notable impact on flesh thickness and fruit weight, and phosphorus enhancing middle diameter and other growth characteristics.

Moreover, the use of these fertilizers significantly increased the sugar content of the fruits, particularly with the nitrogen and potassium treatments. The positive correlation between fruit weight and other physical attributes such as length and middle diameter further highlights the critical role of chemical fertilizers in optimizing melon yield. These findings emphasize the importance of selecting appropriate fertilizers for improving both the quantity and quality of melon production, particularly in regions where maximizing agricultural output is essential for economic and food security reasons.

The study concludes that potassium, nitrogen, and phosphorus fertilizers play crucial roles in enhancing the growth and quality of melon fruit. This knowledge can inform future cultivation practices, aiming to improve yield and the nutritional content of melons grown in similar climatic conditions. The study provides valuable insights for farmers and agricultural scientists seeking to improve melon production through informed fertilizer management. Further research may be needed to explore the long-term effects of these fertilizers on soil health and sustainability.

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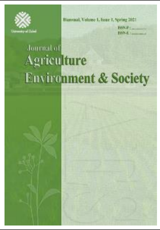

Optimizing grain filling period of spring wheat in the warm and humid agro-climatic zone of northern Iran

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Triticum aestivum

ABSTRACT

To optimize the grain filling period of commercial wheat cultivars, an experiment was conducted at two agricultural research stations in the warm and humid agro-climatic zone of northern Iran. The experiment was conducted as a split plot with four replications. The main plots consisted of five sowing dates: 1 November (SD1), 16 November (SD2), 1 December (SD3), 16 December (SD4), and 31 December (SD5), and four spring wheat cultivars, namely Ehsan, Tirgan, Meraj, and Kalateh, were the subplots. The results indicated that the highest yield was obtained from SD3 (5892.2 kg ha^{-1}). Despite the one-month difference between SD1 and SD3, the grain filling period remained unaffected, providing suitable conditions for plant height and resistance to lodging across the different cultivars. At SD3, optimal conditions were established for the wheat cultivars regarding temperature, day length (DL), relative humidity (RH), and energy use efficiency during the grain filling period. Both SD2 and SD3 exhibited the highest energy use efficiency. The grain yield at SD1 decreased due to severe plant lodging, while exposure to terminal heat and drought stresses, and shortened grain filling period reduced yield at SD4 and SD5. For the early anthesis cultivar, i.e., Kalateh, the grain yield was significantly higher than that of the other cultivars. The grain filling period for the early anthesis cultivar was not significantly different from the others, allowing the plant to escape terminal heat and drought stresses, thereby increasing energy use efficiency and, consequently the grain yield. Therefore, the early anthesis cultivar is highly suitable and recommended for cultivation in the studied zones where terminal heat and drought stresses are prevalent at optimal sowing dates.

Highlights

- Highest wheat yield was 5892.2 kg/ha at Dec 1 sowing (SD3) in northern Iran.
- SD2 & SD3 optimize grain filling with max energy use efficiency.
- Early anthesis cv. Kalateh yields highest, escapes heat/drought stress.
- SD1 yield drops due to lodging; SD4 & SD5 suffer heat & short grain fill.
- Grain filling period stable at SD1-SD3, key to yield in humid zone.

1. Introduction

Wheat (*Triticum aestivum* L.), a globally significant crop, has the largest area (220.4 million hectares, 2023) under cultivation worldwide (FAO, 2025). In Iran, wheat is the most significant agricultural product in production and area under cultivation, playing a crucial role in both the economy and food security (Ghaffari, 2013). Climate change, particularly the increased greenhouse gases, has altered temperature and rainfall patterns (IPCC, 2018), reducing crop yields, including wheat (Asseng et al., 2015). Nevertheless, climate change may even lead to an increase in yield in certain regions. Since 1980, the grain yield trends of the Azar-2 wheat variety, a widely cultivated type, have shown a kg ha^{-1} increase in cold regions but a 14.4 kg ha^{-1}decrease in warm and temperate regions (Deihimfard et al., 2023).

Terminal heat and drought stresses have been the primary causes of decreased wheat yield in many parts of

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the world, including Iran (Farooq et al., 2011). Environmental stresses during anthesis and the grain-filling period can lead to reduced fertility and a shortened grain filling period (Farooq et al., 2014). Aligning susceptible developmental stages with non-stress conditions during the growing season can help the plant escape environmental stresses (Farooq et al., 2014). Determining the appropriate sowing date to leverage optimal conditions is a key strategy to mitigate the adverse effects of terminal heat and drought stresses (Andarzian et al., 2015). Delayed planting, due to lower winter temperatures, affects emergence and leaf development and exposes critical stages such as anthesis and the grain filling period to terminal heat stress. This results in a substantial reduction in dry matter and shortens vegetative and reproductive periods. (Farooq et al., 2014). Conversely, early sowing dates lead to the accumulation of excessive growing degree days (GDD) during the vegetative period, resulting in lodging that negatively impacts grain yield (Gupta, 2017). Plant development is divided into several phenological stages to better understand its life cycle (Salazar-Gutierrez et al., 2013). The length of the growing season and the phenological stage are determinants of grain yield, with each plant requiring a certain amount of temperature to reach each phonological stage (Aslam, 2017). Any change during these stages can alter one or more yield components, ultimately affecting economic performance. Therefore, manipulating these stages can increase yield (Andarzian et al., 2015).

In addition to temperature, photoperiod (PPD) is a major environmental factor determining the anthesis period (Daba, 2016). Plant development is a function of both temperature and day length (DL) (Zhang et al., 2015), where the expression of wheat development genes is regulated in response to prevailing environmental conditions (Slafer, 2012). Agro-climatic indices such as GDD, DL, PPD, photo-thermal unit (PTU), helio-thermal unit (HTU), hydro-thermal unit (HYTU), heat use efficiency (HUE), helio-thermal use efficiency (HTUE), photo-thermal use efficiency (PTUE), and hydro-thermal use efficiency (HYTUE) have been used to investigate plant phenology and its relationship with grain yield (Ahmad et al., 2017; Singh and Singh, 2014).

Under climate change conditions, these agro-climatic indices are also subject to change. Monitoring these indices allows for the assessment of crop response to climate change at different developmental stages (Parmesan et al., 2015). Developmental stages are estimated more accurately using GDD than calendar days. Therefore, GDD is recommended for studying the relationship between growth duration and temperature, based on a direct relationship between temperature and growth (Ahmad et al., 2017). Previous research on the effect of temperature on phenology has been conducted using cumulative GDD in wheat (Salazar-Gutierrez et al., 2013; Aslam et al., 2017, Li et al., 2012). This study aims to investigate the grain yield of spring bread wheat cultivars at different sowing dates to optimize the grain filling period based on the agro-climatic indices in the warm and humid agro-climatic zone of northern Iran.

2. Materials and methods

2.1. Field experiments

The experiments were conducted at two agricultural research stations in Gorgan and Gonbad, Golestan province, within the warm and humid agro-climatic zone of northern Iran, during the cropping seasons of 2017-2018 and 2018-2019. The geographical and meteorological characteristics of the two test stations over the two years of the experiment are presented in Table 1.

Table 1. Meteorological data of two agricultural research stations during two years of the experiment (2017-19)

		Accumulated day length (hour)	Precipitation (mm)		Evaporation (mm)		Accumulated actual sunshine (hour)		Mean minimum temperature (°C)		Mean maximum temperature (°C)		Mean temperature (°C)		Mean relative humidity (%)	
Month	**Location**	**2017-2018 2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**	**2017-2018**	**2018-2019**
Nov	Gorgan≠	306.1	73.8	55.5	61.1	42.2	167.1	143.9	9.3	7.4	20.3	18.3	14.8	12.8	76.5	76.4
	Gonbad§	304.5	38.6	32.4	68.2	50.6	174.3	154.6	10.0	7.8	21.9	19.4	15.9	13.6	67.6	71.0
Dec	Gorgan	300.2	18.7	22.0	35.6	28.5	141.7	120.3	3.4	5.5	15.0	15.7	9.2	10.6	80.6	83.3
	Gonbad	298.0	19.5	57.0	42.4	39.5	153.8	125.8	4.7	6.8	17.3	16.1	11.0	11.4	72.2	78.9
Jan	Gorgan	309.2	70.2	156.6	27.9	36.9	129.0	156.2	3.2	2.4	12.3	14.9	7.8	8.6	82.7	80.8
	Gonbad	307.3	92.2	105.8	28.5	45.5	129.0	172.4	3.5	4.6	13.3	16.4	8.4	10.5	78.8	71.6
Feb	Gorgan	304.0	35.8	76.8	29.1	31.3	232.0	303.2	4.9	3.5	13.1	13.4	9.0	8.5	83.9	80.4
	Gonbad	303.0	44.2	121.6	41.8	37.9	233.2	338.8	5.6	3.9	14.2	15.1	9.9	9.5	80.3	77.2
Mar	Gorgan	371.4	28.7	209.9	61.7	65.2	125.3	166.6	8.0	6.6	20.0	17.8	14.0	12.2	80.0	77.6
	Gonbad	371.3	38.4	187.6	62.0	64.8	128.1	179.7	8.7	6.7	21.0	19.6	14.9	13.1	78.3	73.3
Apr	Gorgan	394.7	37.9	74.8	78.3	77.8	144.0	147.1	9.1	10.1	19.8	20.1	14.5	15.1	77.5	80.6
	Gonbad	395.6	42.5	62.3	75.5	68.7	139.7	152.8	9.2	10.6	20.1	22.0	14.6	16.0	77.0	76.3
May	Gorgan	438.5	5.2	2.7	172.0	169.9	235.3	238.4	14.8	16.6	30.8	30.3	22.8	23.4	64.8	68.8
	Gonbad	440.3	27.5	11.2	163.5	160.3	241.4	240.2	14.5	16.6	31.3	31.8	22.9	23.7	62.0	64.1

≠Gorgan: Latitude 36° 54' N; Longitude 54° 25' E; Altitude 6 m
§Gonbad: Latitude 37° 16' N; Longitude 55° 13' E; Altitude 45 m

2.2. Plant materials

The plant materials consisted of the latest wheat (*Triticum aestivum* L.) cultivars released for the region. These included four spring bread wheat cultivars: Ehsan (a predominant cultivar in the zone), Tirgan, Meraj, and Kalateh. The pedigree and characteristics of these cultivars are listed in Supplementary Tables 1 and 2. The cultivars were planted on five sowing dates as follows: SD1 (November 1), SD2 (November 16), SD3 (December 1), SD4 (December 16), and SD5 (December 31). Soil preparation practices included plowing and discing.

2.3. Experimental design

The experiment was conducted in a split-plot arrangement based on a randomized complete block design (RCBD) with four replications. The five sowing dates were randomly located in the main plots, while the four wheat cultivars were randomly placed in the subplots. Each cultivar was planted in 12-square-meter plots (1.2 m wide and 10 m long) using experimental plot seeders (Wintersteiger, Austria). The seeding rate for all plots was 350 seeds per square meter.

2.4. Crop protection

The amounts of chemical fertilizers were determined based on soil properties (Supplementary Table 3). Accordingly, all potash fertilizer, sourced from potassium sulfate, and all phosphate fertilizer, sourced from diammonium phosphate, were applied as base and topdressing. Urea, as the nitrogen source, was also applied as both base and topdressing. Additionally, chemical control of grassy and broadleaf weeds was achieved by mixing Granstar and Topic herbicides (at 20 g/ha and 1 L/ha, respectively). Throughout the growing period, agro-technical recommendations were uniformly applied to all treatments.

2.5. Phenological development and harvesting

During the experimental period, phenological stages such as emergence (Zadoks 11), heading (Zadoks 55), anthesis (Zadoks 65), and physiological maturity (Zadoks 90) were recorded. Days to reach each specific developmental stage was calculated based on when 50% of the plants in each plot reached that stage. The lodging score of the stem at the physiological maturity stage was calculated using Equation (1) (Fischer et al., 1987).

Lodging score= (% of plot area lodged × angle of lodging relative to the vertical /90) × 100 (1)

At the end of the cropping seasons, the harvest was conducted using a small plot combine harvester (Wintersteiger, Austria), and then the grain yield and yield components of each plot were measured using a digital scale.

2.6. Agro-climatic indices

The agro-climatic indices at each phenological stage, such as DL, PPD, GDD, PTU, HTU, HYTU, HUE, HTUE, PTUE, and HYTUE, were calculated [14]. The calculation of PPD was performed using the data related to the DL from the stage of emergence to anthesis, as shown in Equation (2) (Aslam et al., 2017):

$$PPD = 1 - 0.004 \times (20 - DL)^2 \quad (2)$$

For calculating GDD, Eq. (3) was used:

$$GDD = \sum (Tmin + Tmax) / 2 - Tbase \quad (3)$$

The base temperature and maximum threshold temperature were considered to be zero and 35°C, respectively (Andarzian et al., 2015). To investigate the interaction between the bright period and temperature units, PTU and HTU indices were employed. PTU is the product of GDD and DL on any given day, while HTU is the product of GDD and actual bright sunshine hours on any given day (Ahmad et al., 2017).

$$PTU \text{ (degree-days hours)} = \sum(GDD \times DL) \quad (4)$$

$$HTU \text{ (degree-days hours)} = \sum(GDD \times \text{No. of actual sunshine hours}) \quad (5)$$

HYTU was obtained by multiplying GDD by mean RH (Ahmad et al., 2017).

$$HYTU \text{ (degree-days percent)} = \sum(GDD \times \text{mean } \%RH) \quad (6)$$

The energy use efficiency indices, such as HUE, PTUE, HTUE, and HYTUE, were obtained by dividing the grain yield by the sum of units according to the relevant indices [Aslam et al., 2017).

$$HUE\ [(kg/ha)/(degree\text{-}days)] = \text{Grain yield / Accumulated Heat Units} \quad (7)$$

$$PTUE\ [(kg/ha)/(degree\text{-}days)] = \text{Grain yield / Accumulated PTU} \quad (8)$$

$$HTUE\ [(kg/ha)/(degree\text{-}days)] = \text{Grain yield / Accumulated HTU} \quad (9)$$

$$HYTUE\ [(kg/ha)/(degree\text{-}days)] = \text{Grain yield / Accumulated HYTU} \quad (10)$$

2.7. Statistical analysis

First, Bartlett's test was performed for the uniformity of error variances then the data analysis was performed using SAS 9.1.3 (SAS Institute Inc., Cary, NC, USA) with PROC GLM, and the comparison of means was carried out using least significant different (LSD) at the 5% probability level.

3. Results

3.1. Grain yield and yield components

The combined analysis of variance revealed a significant location effect on grain yield, 1000-grain weight, and spikes per square meter (Table 2). Both grain yield and spikes per square meter were significantly higher in Gorgan than in Gonbad (Table 3). The year effect on grain yield, biological yield, yield components, and plant height was also significant (Table 2). Notably, spikes per square meter, 1000-grain weight, and harvest index were significantly higher in the first year, while the biological yield, grains per spike, spike length, and plant height were higher in the second year (Table 3). Sowing date significantly affected biological yield, grain yield, yield components (except grains per spike), harvest index and plant height (Table 2). The highest grain yield was observed at SD3 (December 1), in the order of SD3 (5892.2 Kg/ha) > SD2 (5436.2 Kg/ha) > SD4 (5059 Kg/ha) > SD1

(4465.5 Kg/ha) > SD5 (4028.9 Kg/ha) (Table 3). However, the biological yield, spike length, and plant height decreased with delayed sowing date (Table 3). The combined analysis of variance confirmed significant differences between cultivars in terms of grain yield, yield components, and plant height (Table 2). The yield of the Kalateh cultivar was significantly higher than the others. Additionally, spikes per square meter in the Kalateh and Tirgan cultivars were significantly higher than in the Ehsan and Meraj cultivars (Table 3). The height of the Kalateh cultivar was significantly shorter than the other cultivars, in the order of Ehsan > Meraj > Tirgan > Kalateh (Table 3).

Table 2. Combined analysis of variance for grain yield, yield components, spike length and plant height in bread wheat cultivars at different sowing dates in two cropping seasons (2017-19)

S.O.V	df	Biological yield	Spike m^{-2}	Grain/spike	1000-Grain weight	Grain yield	Harvest index	Spike length	Plant height
Place (P)	1	26892863 ns	57111**	27.0 ns	87.2**	10240594**	308.11 ns	3.83 ns	409.7 **
Year (Y)	1	154335957**	7097**	342.4*	1915.9**	3961613**	2442.05**	163.88**	8922.1**
P×Y	1	22630749 ns	2221*	73.2 ns	73.2*	1273989 ns	26.45 ns	0.08 ns	90.6*
Error1	12	10525286	414	44.6	8.3	3202467	106.91	0.39	17.0
Sowing Date (SD)	4	127721105**	34566**	42.6 ns	200.5**	35449683**	1501.20**	10.91**	798.0**
P×SD	4	3483033 ns	9104**	91.8*	107.8**	4860312**	376.18**	1.63**	18.5 ns
Y×SD	4	16563953**	31643**	78.6*	40.6**	2774509**	367.90**	2.86**	187.0**
P×Y×SD	4	8849635*	8732**	60.6 ns	48.6**	2253814**	158.85*	0.64 ns	29.7 ns
Error2	48	2821257	1186	30.5	5.2	373372	43.04	0.37	12.0
Cultivar (C)	3	1312091ns	9737**	3173.1**	881.7*	9727177**	561.47**	46.44**	1014.9**
SD×C	12	2664889ns	1585	38.4 ns	9.4 ns	157188 ns	33.37 ns	0.52 ns	13.6 ns
Y×C	3	17406259**	1904	147.8**	31.0**	1022383*	91.14*	8.58**	55.5**
P×C	3	10625052**	3776**	14.9 ns	21.4*	217524 ns	53.30 ns	1.62**	47.7**
P×Y×C	3	11821334**	6174**	6.0 ns	25.4**	455122 ns	46.21 ns	0.32 ns	29.8 ns
Y×SD×C	12	1642948 ns	1351 ns	89.0**	5.6 ns	162208 ns	17.83 ns	0.21 ns	8.2 ns
P×SD×C	12	1870394 ns	689 ns	30.1 ns	17.2**	252657 ns	41.62 ns	0.58 ns	10.3 ns
P×Y×SD×C	12	1666147 ns	972 ns	35.0 ns	12.2*	227934 ns	28.75 ns	0.54 ns	31.9**
Error3	180	2537527	936	27.48	6.0	326597	32.12	0.40	11.69
CV%		11.01	9.27	13.75	5.62	11.48	16.11	6.67	3.46

* and **: Significant at the 5% and 1% probability levels, respectively.
ns: Non-significant.

Table 3. Mean comparison for effect of location, cropping season, sowing date and cultivar on grain yield, yield components, spike length and plant height in four bread wheat cultivars.

S.O.V	Biological yield	Spike m^{-2}	Grain/spike	1000-Grain weight	Grain yield	Harvest index	Spike length	Plant height
				Place				
Gorgan	14750.0a	343.33a	38.43a	43.10b	5155.2a	36.15a	9.63a	97.78a
Gonbad	14170.2a	316.61b	37.84a	44.14a	4797.5b	34.19a	9.41a	100.05a
				Cropping season				
2017-2018	13765.6b	334.68a	37.10b	46.07a	5087.6a	37.93a	8.80b	93.63b
2018-2019	15154.6a	325.26b	39.17a	41.18b	4865.1b	32.41b	10.23a	104.20a
				Sowing date				
SD1	15847.0a	352.53a	38.58a	45.58a	4465.5d	28.58d	10.08a	103.35a
SD2	15574.7a	330.91b	38.00a	45.31a	5436.2b	35.72b	9.79b	101.62b
SD3	14584.7b	342.09ab	38.98a	43.19b	5892.2a	41.75a	9.43c	98.40c
SD4	13969.6c	332.98b	36.83a	42.52b	5059.0c	36.72b	9.15d	96.26d
SD5	12324.5d	291.31c	38.28a	41.52c	4028.9e	33.08c	9.12d	94.97e
				Cultivar				
Ehsan	14497.0a	318.55b	33.65b	47.45a	4675.04c	33.16c	10.51a	102.04a
Tirgan	14610.8a	338.26a	31.80c	45.24b	5102.06b	35.76b	9.60b	98.28b
Meraj	14427.6a	322.55b	43.89a	40.20d	4715.76c	33.08c	8.69c	101.21a
Kalateh	14305.0a	340.50a	43.20a	41.60c	5412.55a	38.68a	9.26b	94.15c

Means in each column, followed by at least one letter in common are not significantly different at the 5% probability level-using Tukey test.
SD1 (1 November), SD2 (16 November), SD3 (1 December), SD4 (16 December) and SD5 (31 December).

Table 4. Temperature and relative humidity during the grain filling period under different sowing dates of four bread wheat cultivars

Sowing Date § / Cultivar	Mean minimum temperature (°C)	Mean maximum temperature (°C)	Mean temperature (°C)	Mean minimum relative humidity (%)	Mean maximum relative humidity (%)	Mean relative humidity (%)
SD1	9.85e	21.18e	15.44e	58.90a	96.06a	77.48a
SD2	10.99d	23.13d	16.94d	55.00b	95.19b	75.10b
SD3	12.06c	25.21c	18.48c	50.42c	94.01c	72.22c
SD4	12.78b	26.63b	19.52b	46.80d	92.71d	69.75d
SD5	13.78a	28.36a	20.85a	43.98e	91.92e	67.95e
Ehsan	12.51a	26.01a	19.10a	48.70c	93.11c	70.90c
Tirgan	11.76b	24.71b	18.08c	51.34b	94.16b	72.75b
Meraj	11.85b	24.88b	18.21b	51.07b	94.05b	72.56b
Kalateh	11.44c	24.01c	17.59d	52.97a	94.58a	73.78a

Means in each column for each factor followed by at least one letter in common are not significantly different at the 5% probability level-using Duncan's multiple range test. § SD1 (1 November), SD2 (16 November), SD3 (1 December), SD4 (16 December) and SD5 (31 December)

3.2. Temperature and RH during the grain filling period

During the grain filling period, the minimum, maximum, and mean temperatures increased with a delay in sowing from SD1, While the minimum, maximum, and mean RH decreased with delayed sowing (Table 4). The grain filling period for the Kalateh cultivar occurred at milder temperatures and higher relative humidities compared with other cultivars (Table 4).

3.3. Period length and DL

The maximum and minimum lengths of the phenological period were obtained at SD1 and SD5, respectively (Table 5). However, the three initial sowing dates were not significantly different concerning the grain filling period (Table 5). The Kalateh and Ehsan cultivars required the least and most time, respectively, to reach heading, anthesis, and physiological maturity. There was no significant difference among cultivars for grain filling duration (Table 5). At heading, anthesis, and maturity, the highest DL was obtained at SD1 and SD2. The accumulative DL at SD3 was significantly higher during the grain-filling period than the other sowing dates (Table 5). At all phenological stages, the highest and lowest DL was observed in the Ehsan and Kalateh cultivars, respectively. However, during the grain filling, there was no significant difference between cultivars (Table 5).

Table 5. Mean comparison for effect of sowing date and cultivar on time period and day length of phenological stages in four bread wheat cultivars

	Time (No. of days from sowing)				DL (h)			
Sowing Date § / Cultivar	Heading (55)#	Anthesis (65)	Physiological Maturity (90)	Grain filling (65-90)	Heading (55)	Anthesis (65)	Physiological Maturity (90)	Grain filling (65-90)
SD1	137.02a	143.75e	184.22a	40.47a	1415.67a	1497.46a	2026.96a	529.50b
SD2	131.16b	137.14b	177.05b	39.91a	1370.97b	1445.90b	1980.46b	534.56b
SD3	123.27c	129.09c	169.72c	40.63a	1310.86c	1385.39c	1939.31c	553.92 a
SD4	116.08d	120.53d	157.69d	37.16b	1265.54d	1323.83d	1836.44d	512.60c
SD5	108.48e	112.47e	144.09e	31.63c	1216.94e	1272.26e	1712.70e	440.45d
Ehsan	125.83a	131.84a	169.66a	37.83a	1349.62a	1426.91a	1943.30a	516.39a
Tirgan	122.61c	127.98c	166.05c	38.08a	1308.44c	1376.87c	1892.27c	515.40a
Meraj	123.16b	128.61b	166.61b	38.00a	1315.32b	1385.00b	1899.87b	514.87a
Kalateh	121.20d	125.96d	163.89d	37.93a	1290.61d	1351.09d	1861.26d	510.18a

Means in each column for each factor followed by at least one letter in common are not significantly different at the 5% probability level-using Duncan's Multiple Range Test. # Zadoks growth scale. § SD1 (1 November), SD2 (16 November), SD3 (1 December), SD4 (16 December) and SD5 (31 December).

3.4. GDD

At heading, anthesis, and physiological maturity, SD1 significantly accumulated the highest GDD, which decreased significantly with a delay in sowing (Table 6). However, during the grain filling period, the highest GDD was recorded at SD3, followed by SD4, SD2, SD1, and SD5 (Table 6). At all phenological stages and during the grain filling period, the lowest and highest GDD was accumulated in the Kalateh and Ehsan cultivars, respectively, in the order of Ehsan > Meraj > Tirgan > Kalateh (Table 6).

3.5. PPD

The results showed that SD1 had the highest PPD, while SD5 had the lowest PPD (Figure 1). Among the cultivars, Ehsan had the highest PPD, followed by Meraj, Tirgan, and Kalateh (Figure 1).

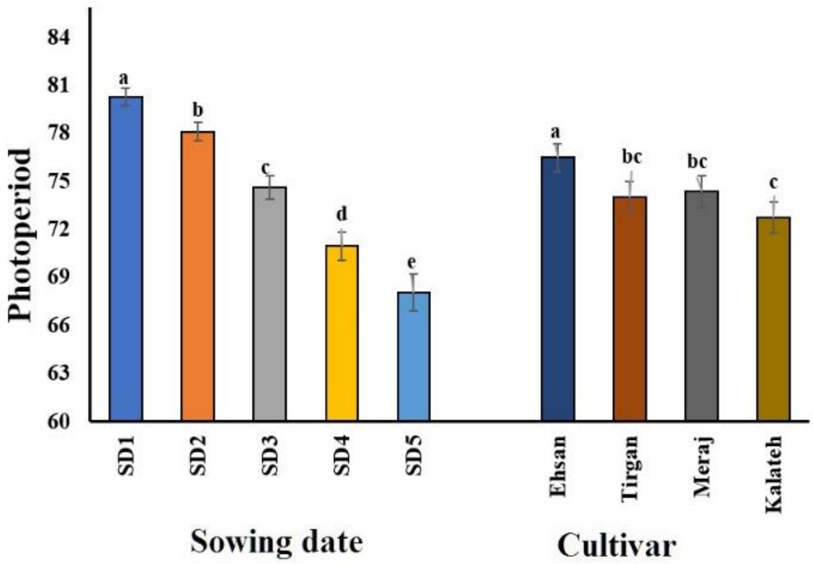

Figure 1. Photoperiod under different sowing dates in bread wheat cultivars during two cropping seasons.

For each factor, means followed by at least one letter in common are not significantly different at the 5% probability level using Tukey test. SD1 (1 November), SD2 (16 November), SD3 (1 December), SD4 (16 December) and SD5 (31 December).

Table 6. Mean comparison of the agro-climatic indices at phenological stages and grain filling period in four bread wheat cultivars

	GDD (degree-days)				HUE [(kg/ha)/(degree-days)]			
Sowing Date § / Cultivar	Heading (55)#	Anthesis (65)	Physiological Maturity (90)	Grain filling (65-90)	Heading (55)	Anthesis (65)	Physiological Maturity (90)	Grain filling (65-90)
SD1	1520.82a	1609.76a	2236.65a	626.89e	2.97e	2.81e	2.01c	7.20b
SD2	1412.36b	1499.38b	2181.20b	681.83c	3.86c	3.63c	2.50b	8.06a
SD3	1315.97c	1402.62c	2157.53c	754.92a	4.53a	4.24a	2.74a	7.82a
SD4	1266.81d	1338.92d	2064.83d	725.91b	4.02b	3.79b	2.45b	7.00b
SD5	1227.39e	1287.58e	1945.58e	658.00d	3.32d	3.16d	2.07c	6.33c
Ehsan	1387.47a	1474.74a	2190.14a	715.40a	3.44c	3.23c	2.16c	6.64c
Tirgan	1340.29c	1418.70c	2105.83c	687.13b	3.85b	3.63b	2.42b	7.49b
Meraj	1347.72b	1427.75b	2118.00b	690.24b	3.51c	3.31c	2.21c	6.81c
Kalateh	1319.20d	1389.41d	2054.66d	665.25c	4.15a	3.93a	2.64a	8.18a
	PTU (degree-days hours)				PTUE [(kg/ha)/(degree-days)]			
SD1	15778.63a	16860.62a	25089.38b	8228.76d	0.29c	0.27c	0.18d	0.55c
SD2	14867.86b	15957.29b	25129.12b	9171.83c	0.37b	0.34b	0.22b	0.60a
SD3	14170.48c	15278.62c	25626.72a	10348.10a	0.42a	0.39a	0.23a	0.57b
SD4	14053.79d	14997.43d	25060.12b	10062.69b	0.36b	0.34b	0.20c	0.51d
SD5	14090.80d	14888.80e	24086.26c	9197.46c	0.29c	0.27c	0.17e	0.45e
Ehsan	15086.74a	16206.89a	16206.89a	26036.83a	0.32c	0.29c	0.18c	0.48c
Tirgan	14485.30c	15480.15c	15480.15c	24836.86c	0.36b	0.33b	0.21b	0.55b
Meraj	14578.49b	15595.76b	15595.76b	25009.02b	0.32c	0.30c	0.19c	0.50c
Kalateh	14218.71d	15103.41d	15103.41d	24110.57d	0.38a	0.36a	0.22a	0.61a
	HTU (degree-days hours)				HTUE [(kg/ha)/(degree-days)]			
SD1	7422.21a	7825.93a	11223.39b	3397.46d	0.62e	0.58e	0.40d	1.34a
SD2	6807.23b	7231.42b	11246.05b	4014.63c	0.81c	0.76c	0.49b	1.38a
SD3	6140.97c	6486.88c	11397.52a	4910.63b	1.00a	0.94a	0.53a	1.23b
SD4	5939.34d	6299.64d	11377.36a	5077.72a	0.88b	0.82b	0.45c	1.02c
SD5	5816.00e	6173.87e	11118.93c	4945.06b	0.73d	0.69d	0.36e	0.84d
Ehsan	6634.02a	7023.83a	11897.75a	4873.92a	0.74c	0.70c	0.40d	1.00d
Tirgan	6384.49c	6752.54c	11181.24c	4428.70b	0.83b	0.78b	0.46b	1.20b
Meraj	6408.64b	6811.04b	11282.64b	4471.60b	0.76c	0.71c	0.42c	1.08c
Kalateh	6273.47d	6626.78d	10728.97d	4102.18c	0.90a	0.85a	0.51a	1.37a
	HYTU (degree-days percent)				HYTUE [(kg/ha)/(degree-days)]			
SD1	114865.5a	121863.0a	169720.4a	47857.3c	0.039d	0.037d	0.026d	0.094c
SD2	107498.5b	114561.4b	164827.8b	50266.4b	0.051b	0.048b	0.033b	0.109a
SD3	101879.4c	109023.2c	162474.5c	53451.3a	0.058a	0.054a	0.036a	0.110a
SD4	98383.7d	104029.5d	153986.6d	49957.1b	0.051b	0.049b	0.033b	0.101b
SD5	95439.4e	99891.7e	143893.4e	44001.7d	0.042c	0.040c	0.028c	0.094c
Ehsan	106635.3a	113532.6a	163540.8a	50008.2a	0.044c	0.042c	0.029c	0.095c
Tirgan	102948.2c	109211.7c	158266.0c	49054.3b	0.050b	0.047b	0.032b	0.105b
Meraj	103550.0b	109905.5b	159034.3b	49128.8b	0.045c	0.043c	0.029c	0.095c
Kalateh	101319.6d	106845.3d	155081.1d	48235.9c	0.054a	0.051a	0.035a	0.113a

Means in each column for each factor, followed by at least one letter in common are not significantly different at the 5% probability level-using Duncan's multiple range test. # Zadoks growth scale. **§** SD1 (1 November), SD2 (16 November), SD3 (1 December), SD4 (16 December) and SD5 (31 December).

3.6. PTU and HTU

In the heading and anthesis stages, the highest values of PTU and HTU were accumulated in SD1 and SD2. During the grain filling period, the highest PTU was obtained in SD3, followed by SD4, SD5, SD2 and SD1, whereas the highest HTU accumulated in SD4 followed by SD5, SD3, SD2 and SD1 (Table 6). The results confirmed that in the phenological stages and also in the grain filling period, the highest PTU and HTU were observed in Ehsan and Kalateh cultivars, respectively, in the order of Ehsan> Meraj> Tirgan> Kalateh (Table 6).

3.7. HYTU

The HYTU in the phenological stages decreased in the order of the sowing date: SD1> SD2> SD3> SD4> SD5. However, during the grain filling period, SD3 and SD2 accumulated the highest HYTU, respectively, in the following order: SD3> SD2> SD4> SD1> SD5 (Table 6). Similar to the mentioned agro-climatic indices (PPD, GDD, PTU, HTU and HYTU), the highest HYTU was obtained in Ehsan, followed by Meraj, Tirgan and Kalateh, respectively, in all phenological stages and during the grain filling period (Table 6).

3.8. Energy use efficiency

HUE, PTUE, HTUE and HYTUE indicated that the energy use efficiency at heading, anthesis and physiological maturity at SD3 and SD4 were significantly higher than at other sowing dates (Table 6). In the grain filling period, the highest HUE, HTUE, PTUE and HYTUE were observed at SD2 and SD3 (Table 6). In all phenological stages and the grain filling period, the Kalateh and Ehsan cultivars had the highest and lowest energy use efficiency, respectively (Table 6).

4. Discussion

Climate change represents an important research challenge for plant scientists. The rise in greenhouse gas emissions and the impact of increased carbon dioxide levels have led to changes in temperature and precipitation patterns (IPCC, 2018), resulting in reduced yields for many crops, including wheat (Lobell et al., 2011; Asseng et al., 2015). Identifying the optimal planting date is a vital strategy for mitigating the effects of heat stress and drought at the terminal cropping season (Amrawat et al., 2013).

The decrease in fertile spikes and 1000-grain weight at late sowing dates was due to warm and dry weather and the reduced grain-filling period (Andarzian et al., 2015). Delayed sowing dates exposed the grain-filling period to higher temperatures and lower relative humidity (Table 4). The reduction in fertile spikes could be attributed to the decreased duration of stem elongation at late sowing (Slafer, 2012). High temperatures negatively affected the biological yield, grain yield, and some yield components (Farooq et al., 2011). It should be noted that the biological yield is directly related to the length of the growing period, with temperature being the most important factor influencing the development and growth of plants (Liu et al., 2016). As such, the biological yield decreased in the order of sowing dates: SD1 > SD2 > SD3 > SD4 > SD5 (Table 3). There was a significant and positive correlation between the biological yield and growing period (Figure 2a).

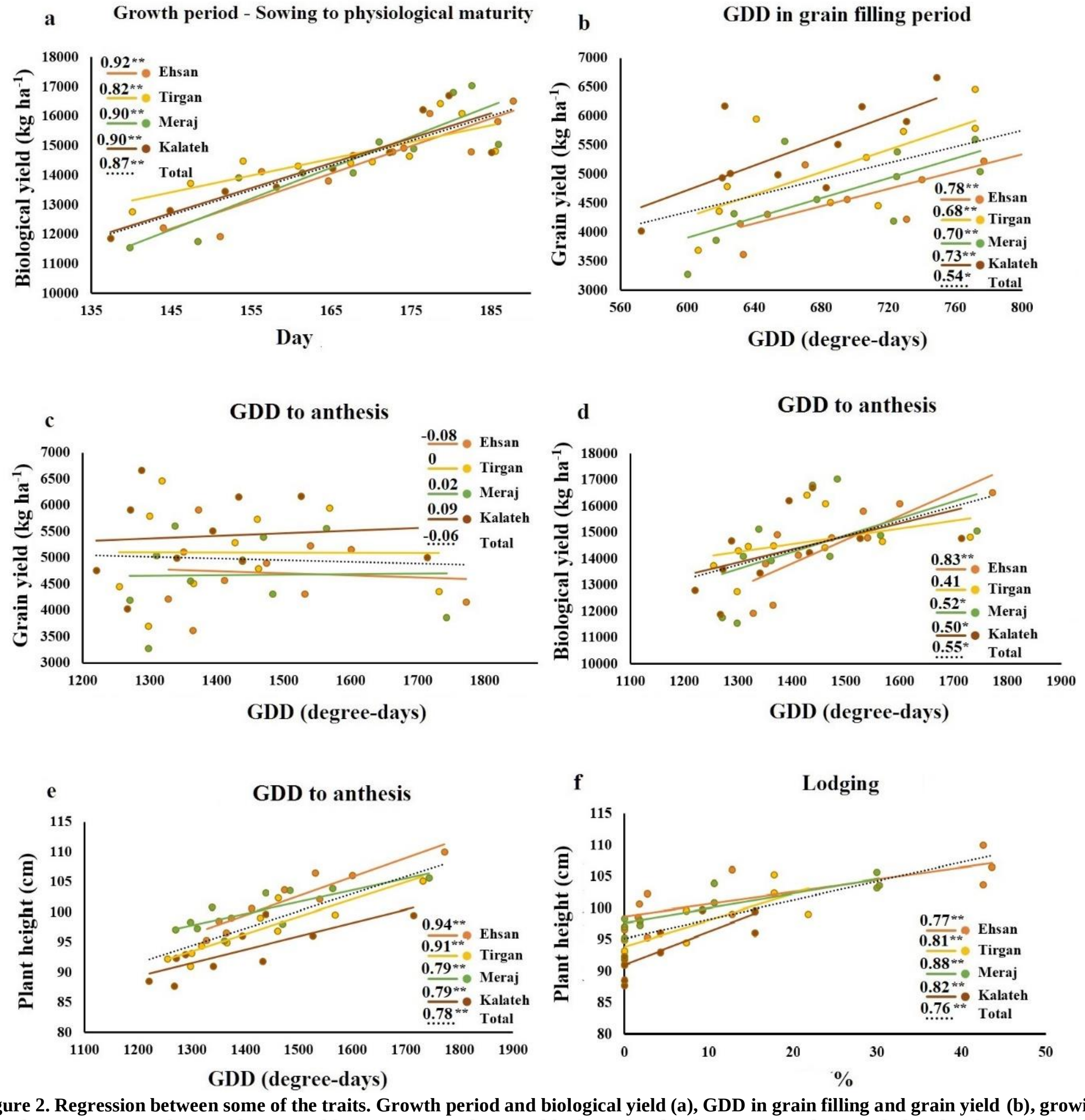

Figure 2. Regression between some of the traits. Growth period and biological yield (a), GDD in grain filling and grain yield (b), growing degree days (GDD) to anthesis and grain yield (c), GDD to anthesis and biological yield (d), GDD to anthesis and plant height (e), lodging and plant height (f).

The grain yield and spikes per square meter in the Kalateh cultivar were higher than in the other cultivars (Table 3). Kalateh is an early-anthesis cultivar (Table 5), and its anthesis occurred at milder temperatures (Table 4);

thus, producing more fertile spikes was plausible. Climate change and global warming have altered and accelerated the phenological stages of plants, thereby reducing yield performance (Asseng et al., 2015; Zhang et al., 2015). The ability to control the length of phenological stages is crucial for adapting to specific environmental conditions and determining breeding strategies based on them (Mkhabela et al., 2016). In the warm and humid agro-climatic zone of northern Iran, the grain-filling period occurs in April and May. A comparison of the two-year climatic parameters of the experiment with the long-term weather data showed that in April and May of the two years of the experiment, the mean minimum, mean maximum, and daily mean temperatures increased. Moreover, the mean relative humidity increased in April and decreased in May (Table 7). An increase of one degree Celsius in world temperature has reduced wheat yield by 4.1-6.1% (Liu et al., 2014). A two-month difference between SD1 and SD5 resulted in a reduction in the phenological period of the crop at different stages, with the number of days to heading, anthesis, and physiological maturity decreasing by 28.54, 31.28, and 40.13 days, respectively (Table 5). The reduction in growing period might be attributed to higher temperatures at late sowing dates (Asseng et al., 2015). In this study, the differences in phenological stages were due to variability in the climatic parameters at the different sowing dates (Aslam et al., 2017) Meanwhile, the reduction in days to maturity and other phenological stages of wheat has been reported to have a direct relationship with higher temperatures (Andarzian et al., 2015; Salazar-Gutierrez et al., 2013; Aslam et al., 2017). Therefore, yield reduction due to temperature changes in delayed sowing dates can be expected because of the reduction in the length of developmental stages of wheat (Andarzian et al., 2015). Adjusting the sowing date to minimize the effects of terminal heat and drought stresses effectively maintains yield performance (Sylvester-Bradley et al., 2012). The control of plant phenology through the sowing date is very important to prepare optimal conditions for assimilate transport and partitioning during the grain-filling period (Reynolds et al., 2012).

Despite the one-month difference between SD1 and SD3, the grain filling period was not affected. However, in the two final sowing dates (SD4 and SD5), the grain filling period decreased significantly due to the increase in temperature and decrease in humidity (Table 5). It is well known that crops require the accumulation of a certain amount of heat to grow and reach each of the phonological stages (Ahmad et al., 2017). The ability to predict the phenological stages leads to improved control and management of pests and weeds, and facilitates the selection of appropriate breeding strategies (Mkhahela et al., 2016). In terms of GDD, SD1 had significantly the highest value at heading, anthesis, and physiological maturity. However, during the grain filling period, the highest GDD was observed in SD3, which was significantly higher than other sowing dates (Table 6). During the grain filling, a positive and significant correlation was observed between GDD and the grain yield of different cultivars (Figure 2b). However, at anthesis, no significant correlation was observed between GDD and grain yield (Figure 2c). Moreover, at anthesis, the high and positive correlation of GDD with the biological yield and plant height caused severe lodging in plants, especially in the two initial sowing dates (Figure 2d,e). The early anthesis cultivar, Kalateh, had a lower lodging percentage than other cultivars in the first three sowing dates, which did not lodge even at the last three sowing dates. This could be attributed to lower GDD and plant height in the Kalateh cultivar (Figure 2e,f). The late anthesis cultivar, Ehsan, had higher lodging than that of other cultivars because of the accumulation of more GDD and higher plant height (Figure 2f). Based on the results, SD2 and SD3 provided the optimal conditions for sufficient GDD accumulation, plant height, and yield performance in the different cultivars.

Under normal conditions, where biotic and abiotic stresses are unlikely to occur and the plant does not lodge, longer phenological stages such as more days to anthesis and physiological maturity can produce higher yield (Camargo et al., 2016). At heading, anthesis, and maturity, the highest DL was obtained in SD1 and SD2 (Table 5). It is worth mentioning that during the grain filling period at SD3, accumulated DL was significantly higher than those of the other sowing dates (Table 5). In the grain filling period, a positive and significant correlation was observed between DL and grain yield in different cultivars (Figure 3a). However, there was no significant correlation between DL and the grain yield at anthesis (Figure 3b). In the phenological stages, the highest and lowest DL was observed in the late anthesis cultivar (Ehsan) and the early anthesis cultivar (Kalateh), respectively. However, during the grain filling, there was no significant difference between cultivars (Table 5).

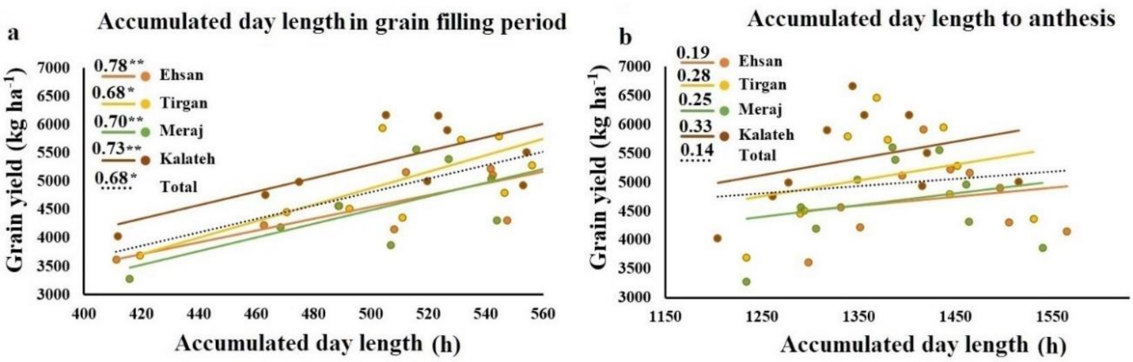

Figure 3. Regression between grain yield and accumulated day length in grain filling period (a) and anthesis (b).

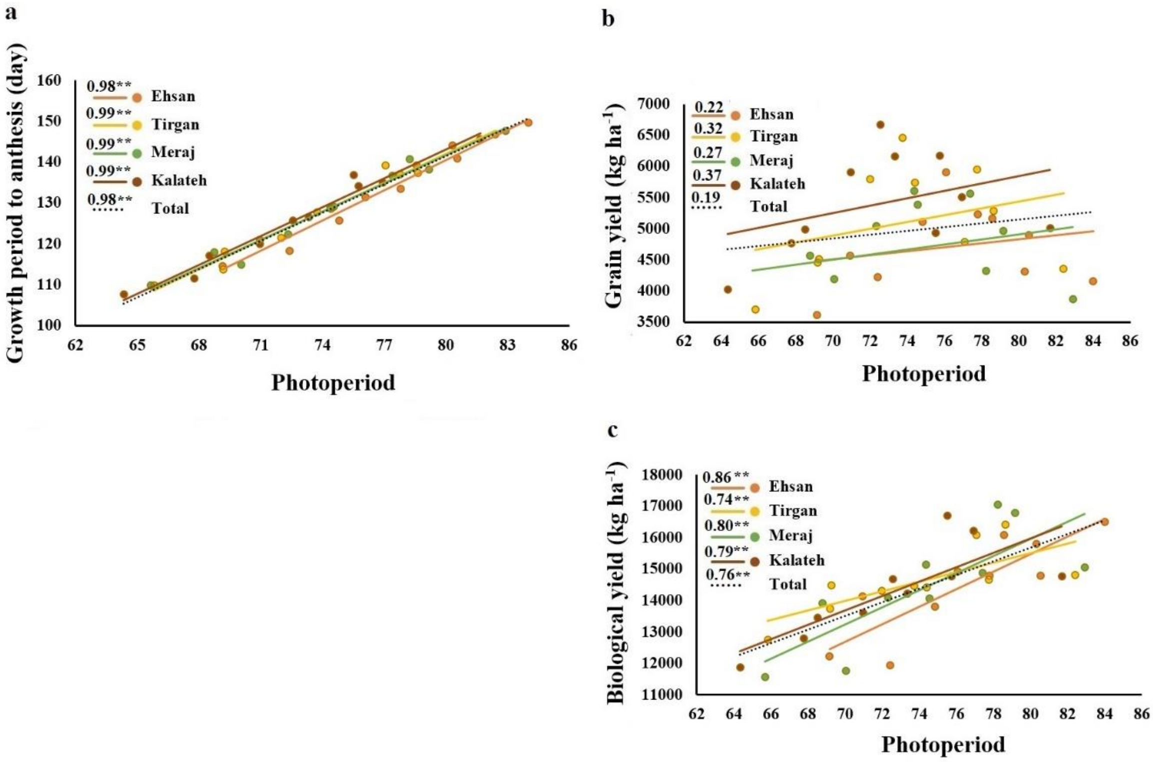

Figure 4. Regression between photoperiod with days to anthesis (a), grain yield (b), and biological yield (c).

In wheat, emergence to the beginning of anthesis, in addition to temperature, is also affected by the PPD (Ahmad et al., 2017). Thus, wheat anthesis is sensitive to both PPD and DL (Zhang et al., 2015). The developmental response of plants sensitive to PPD begins and reaches a maximum during a certain day and accelerates the development of long-day plants such as wheat (Perez-Gianmarco et al., 2018). Here, the results showed that SD1 had the highest PPD values, whereas SD5 had the lowest PPD values (Figure 1). The highest and lowest PPD values were related to the late anthesis cultivar (Ehsan) and the early anthesis cultivar (Kalateh), respectively (Figure 1). There was a very strong positive correlation between PPD and days to anthesis in different cultivars (Figure 4a). Furthermore, no significant correlation was observed between PPD and the grain yield in any cultivars, while the correlation between PPD and the biological yield was positive and significant (Figure 4b,c).

As the beginning and end of each phenological stage occur due to the effect of temperature and the length of the bright period, the PTU and the HTU must be used to predict the exact stages of both anthesis and maturity (Singh and Singh, 2014). Overall, PTU is the product of GDD and the potential sunshine hours, while HTU is the product of GDD and actual sunshine hours (Ahmad et al., 2017). In the phenological stages, the highest PTU and HTU were observed in SD1 and SD2. During the grain filling period, the highest PTU was related to SD3, while SD1 accumulated the lowest value (Table 6). Thus, SD3 provided the optimal conditions for the cultivars regarding temperature, potential sunshine hours and actual sunshine hours during the grain filling period. Other researchers reported receiving more PTU on the early sowing dates than the delayed ones (Singh and Sing, 2014). In the grain filling period, a positive and significant correlation was observed between PTU and the grain yield in different cultivars (Figure 5b). Nevertheless, at anthesis, the correlation between PTU and grain yield was not statistically significant for different cultivars (Figure 5a). The early sowing date accumulated lower HTU during the grain filling period, which reduced the yield performance at SD1 (Tables 3 and 6). On the other hand, higher HTU in SD4 and SD5, despite a significant reduction in the grain filling period, was attributed to the overlap of high temperatures and maximum sunshine hours during the grain filling period. As a result, no significant relationship was observed between HTU and the grain yield at anthesis and the grain filling period (Figure 5c,d). The reduction of HTU in different stages of wheat development has also been attributed by other researchers to delay in sowing (Amrawat et al., 2013).

The HYTU in the phenological stages decreased in the order of the sowing date: SD1 > SD2 > SD3 > SD4 > SD5. However, SD3 and SD2 accumulated the highest HYTU during the grain-filling period, respectively (Table 6). Here, it should be noted that as the minimum, maximum, and mean relative humidity decreased during the grain filling period (Table 4), the maximum HYTU in SD3 and SD2 indicated the optimal conditions to employ humidity and heat in the grain filling period, which has played an essential role in the final grain yield (Gudadhe et al., 2013). In this regard, a positive and significant correlation was observed between the HYTU and the grain yield in different cultivars during the grain filling period (Figure 5f).

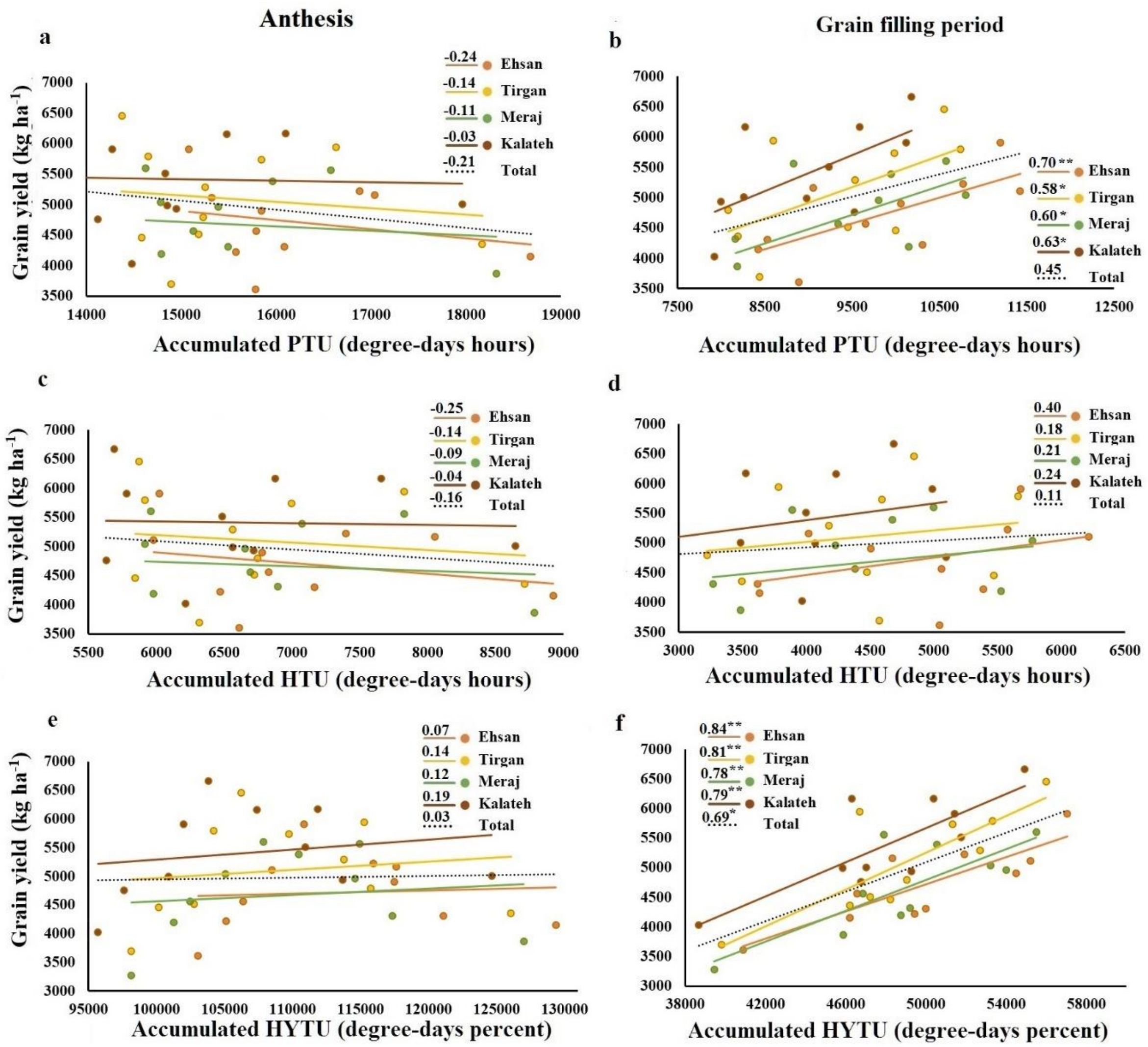

Figure 5. Regression between the agro-climatic indices at anthesis and grain filling period with grain yield.

The results confirmed that in the phenological stages and also in the grain filling period, the highest and lowest agro-climatic indices such as GDD, PTU, HTU, and HYTU were observed in the late anthesis cultivar (Ehsan) and the early anthesis cultivar (Kalateh), respectively (Table 6).

The accumulation of the mentioned indices was directly related to the growth period, so that a positive and significant correlation was observed between these agro-climatic indices and the days to anthesis (Figure 6a-d). Accordingly, the higher values of the agro-climatic indices in the Ehsan cultivar and the lower values in the Kalateh cultivar were due to the differences in their late and early anthesis and maturity, respectively (Table 5). Therefore, days to anthesis was higher in the Ehsan cultivar compared to the Kalateh cultivar; 6.2, 6, 6.4, 5, and 7 days to anthesis in SD1, SD2, SD3, SD4, and SD5, respectively (data not displayed). There was no significant difference between Ehsan and Kalateh for the grain filling period at different sowing dates. The decrease in the agro-climatic indices during the grain filling period in the early anthesis cultivar (Kalateh resulted from the coincidence of the grain filling period with mild weather conditions. So, the minimum, maximum, and mean daily temperature during the grain filling in the early anthesis cultivar (Kalateh) was less than that of the late anthesis cultivar (Ehsan). Conversely, in the same period, the relative humidity in the early anthesis cultivar was higher than in the late anthesis cultivar (Table 4).

Energy efficiency is a function of genetic factors that regulate plant phenological stages by selecting an appropriate sowing date (Singh et al., 2016). The energy use efficiency indices (HUE, PTUE, HTUE, and HYTUE) in the phenological stages were significantly higher at SD3 and SD4 (Table 6). While in the grain filling period, the highest energy use efficiency was observed in SD2 and SD3 (Table 6).

The early sowing date prevents the plant from utilizing the maximum GDD during the grain filling period, in contrast in the late sowing date, the plant receives less GDD due to a shortening of the phenological stages and consequently, the grain yield and energy efficiency are reduced (Gupta et al., 2017). In all phenological stages and the grain filling period, the early anthesis cultivar (Kalateh) and the late anthesis cultivar (Ehsan) had the highest and lowest energy use efficiency, respectively (Table 6). In different cultivars, a positive and significant correlation could be observed between HUE, HTUE, PTUE, and HYTUE with the grain yield during anthesis and the grain filling period (Figure 7). These results showed that selecting an appropriate sowing date for wheat is crucial for managing the climatic conditions, which could lead to achieving the maximum energy efficiency and grain yield (Solanki et al., 2017).

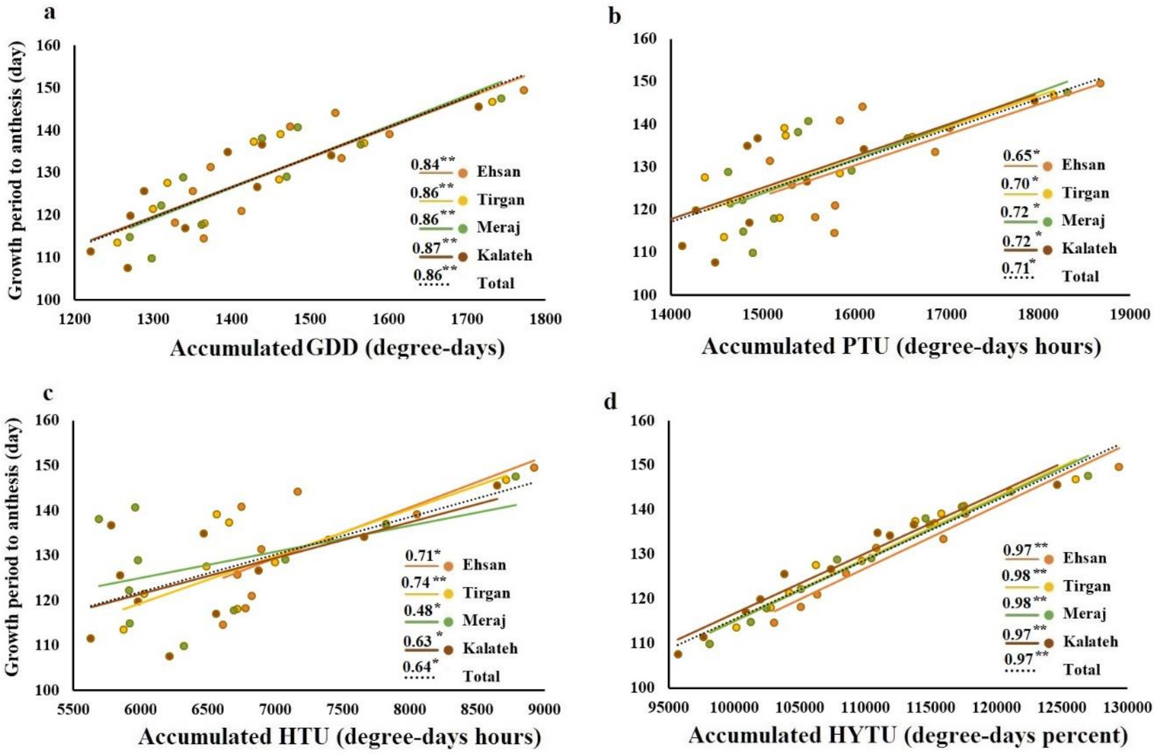

Figure 6. Regression between the agro-climatic indices and growth period at anthesis.

Table 7. Mean comparison of the climate parameters during two years of experiment with long-term average in April and May.

Parameter	Location	Long-term average (34 years)		Average experiment (2 years)	
		April	May	April	May
Mean minimum temperature (°C)	Gorgan	8.8	13.8	9.8	14.0
	Gonbad	8.8	13.7	9.8	13.3
Average maximum temperature (°C)	Gorgan	19.7	25.0	20.3	27.0
	Gonbad	20.9	26.6	21.4	27.9
Mean temperature (°C)	Gorgan	14.2	19.4	15.1	20.5
	Gonbad	14.8	20.2	15.6	20.6
Mean minimum relative humidity (%)	Gorgan	57.3	52.9	63.8	46.5
	Gonbad	56.6	50.3	58.5	43.5
Mean maximum relative humidity (%)	Gorgan	91.1	89.5	94.8	86.9
	Gonbad	91.8	89.1	95.5	92.5
Mean relative humidity (%)	Gorgan	74.2	71.2	79.3	66.7
	Gonbad	74.2	69.7	77.0	67.5
Precipitation (mm)	Gorgan	50.6	43.3	55.1	37.4
	Gonbad	52.1	40.0	46.3	41.0
Evaporation (mm)	Gorgan	85.1	124.6	71.0	132.7
	Gonbad	75.6	120.9	71.1	124.5

Meteorological data for Gorgan and Gonbad weather stations from its inception (1984).

5. Conclusion

The SD2 and SD3 provided suitable conditions for plant height and resistance to lodging in different cultivars. Also, these two sowing dates provided optimal conditions for different cultivars in terms of climatic parameters and energy use efficiency during the grain filling period. The grain yield decreased due to severe plant lodging at SD1, exposure to terminal heat and drought stresses, and a reduced grain filling period at SD4 and SD5. In addition to determining the optimal sowing date, the release of new commercial cultivars adapted to the climatic conditions also plays an important role in increasing yield. The grain filling period of the early anthesis cultivar, Kalateh, was not significantly different from other cultivars. Nevertheless, the grain filling period in the early anthesis cultivar, Kalateh, occurred sooner than other cultivars. This helped the crop escape terminal heat and drought stresses, increased energy use efficiency, and consequently increased grain yield. Therefore, the early anthesis cultivar is suitable and advisable for cultivating in the studied zones where terminal heat and drought stresses are common at optimal sowing dates.

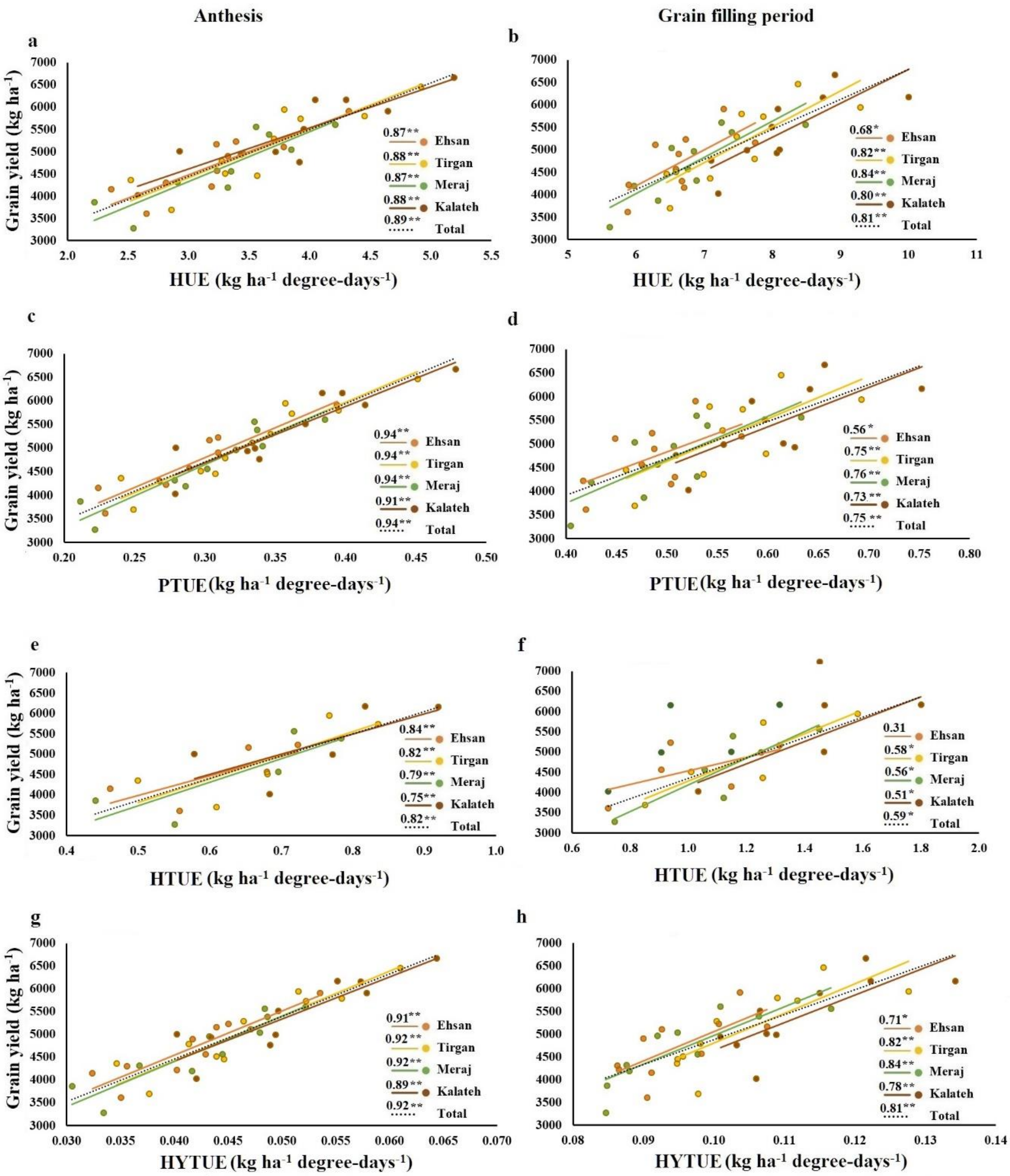

Figure 7. Regression between energy use efficiency in agro-climatic indices and grain yield.

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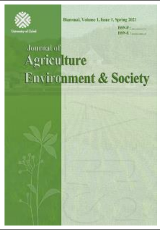

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Forecasting air temperature in Zabol city: a comparative study of SARIMA, BP-FFNN, and RNN-LSTM models

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ABSTRACT

This study compares three models, Back -Propagation Feed-Forward Neural Networks (BP-FFNN), Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM), and Seasonal Autoregressive Integrated Moving Average (SARIMA), for temperature prediction using historical air temperature data from Zabol City, Iran. The dataset consists of daily average air temperature observations, and the models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Median Absolute Percentage Error (MDAPE), and Coefficient of Determination (R^2) metrics. The BP-FFNN model outperformed the RNN-LSTM and SARIMA models, achieving the lowest values for RMSE (0.018), MAE (0.013), and MDAPE (1.59%). It demonstrated accurate temperature predictions with a strong correlation between predicted and actual values (R^2=0.99). The RNN-LSTM model showed comparable results, capturing long-term patterns with RMSE of 0.042, MAE of 0.031, and MDAPE of 3.53%. The SARIMA model provided insights into seasonality and autocorrelation, achieving RMSE of 0.042, MAE of 0.03, and MDAPE of 3.65%.The study's findings have implications for weather forecasting, climate research, and energy management systems. The superior performance of the BP-FFNN model suggests its reliability for accurate temperature prediction, while the RNN-LSTM model offers an alternative approach for capturing long-term patterns. The SARIMA model contributes insights into seasonality and autocorrelation. The study highlights the strengths and limitations of each model and their practical applications in temperature forecasting. In conclusion, the BP-FFNN model effectively predicts temperatures in Zabol City while the RNN-LSTM and SARIMA models provide alternative approaches for capturing long-term patterns and understanding seasonality. The study's results advance temperature prediction techniques and have practical implications for various fields reliant on accurate temperature forecasting.

Highlights

- This study highlights the applications of forecasting air temperature in Zabol City, recognizing its importance in energy generation and agriculture.
- The study demonstrates the use of statistical approach and two deep neural network algorithms for averaged temperature prediction, showcasing advanced techniques.
- A comparative analysis of three approaches is conducted, providing insights into their respective strengths and limitations in averaged temperature forecasting.
- The study identifies the potential for enhancing accuracy through a hybrid deep neural network algorithm, emphasizing the importance of combining different models or techniques to achieve improved predictions.

1. Introduction

Accurately predicting air temperature at a specific location and time is crucial for various applications, including energy generation and agriculture. With climate experts warning about the potential environmental impacts of rising temperatures, the need for reliable temperature

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forecasting becomes even more critical (Abrahams and Carr, 2017). However, The prediction of air temperature presents significant challenges due to its multidimensional and chaotic nature within the broader weather data system (Kirchgässner et al., 2013). Nevertheless, advancements in weather observation data availability have facilitated the development of data-driven forecasting approaches (Cifuentes et al., 2020). The primary challenges in air temperature prediction involve understanding the interrelationships among weather variables and building robust models capable of revealing hidden patterns in the data (Zhang et al., 2020).

Air temperature prediction plays a critical role in various applications, including agriculture, industry, energy, the environment, and tourism (Abdel-Aal, 2004). These applications encompass areas such as short-term load forecasting for power utilities (Li et al., 2016), the development of air conditioning and solar energy systems (García and Balenzategui, 2004; Ruano et al., 2006) adaptive temperature control in greenhouses (Altan Dombaycı and Gölcü, 2009), prediction and assessment of natural hazards (Camia et al., 1999), and the estimation of cooling and energy consumption in residential buildings (Ben-Nakhi and Mahmoud, 2004; Mihalakakou et al., 2002). Accurate temperature forecasting is essential in conjunction with analysing additional relevant factors, as it enables effective planning for infrastructure upgrades, insurance decisions, energy policies, and business growth (Smith et al., 2007). Given the wide-ranging significance of temperature predictions across these domains, there is a growing demand for reliable and precise temperature forecasting methods.

Traditional numerical weather prediction (NWP) models based on physical equations have been widely used for temperature forecasting. However, these models rely on prior knowledge and substantial computational resources (Bauer et al., 2015). In contrast, machine learning techniques, particularly deep learning, offer an alternative by uncovering hidden patterns in the data without the need for prior knowledge. These approaches show promise in weather forecasting and prediction, surpassing the limitations of physics-based models (LeCun et al., 2015).

In recent years, air temperature forecasting has garnered significant attention in domains such as agriculture, energy management, and climate modeling. Various methods have been explored to accurately predict the air temperature. One such method is the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which effectively captures temporal dependencies and seasonal patterns in time series data (Box et al., 2015; Hyndman and Athanasopoulos, 2018). SARIMA has been successfully applied to forecast air temperature in different regions and time scales, capturing both short-term fluctuations and long-term trends (Al Dhaheri et al., 2017).

In addition to SARIMA, machine learning models have gained prominence in time series forecasting. The Back Propagation Feed-Forward Neural Network (BP-FFNN) is one such model that captures complex patterns and non-linear relationships (Bishop, 2005). Researchers have employed BP-FFNN for air temperature prediction, achieving competitive results by effectively capturing the intricate relationships between temperature and meteorological variables (Kuligowski and Barros, 1998; Roy, 2020; Smadi and Mjalli, 2007).

Shi et al. (2015) introduce ConvLSTM, a convolutional LSTM network, for prediction of the future rainfall intensity. ConvLSTM outperforms other models in capturing spatiotemporal correlations and accurately predicting future rainfall intensity (Shi et al., 2015). Their study demonstrates the successful application of deep learning techniques to address the challenging problem of precipitation forecasting. Another popular approach is the Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) model, which captures long-term dependencies in sequential data, making it suitable for air temperature prediction (Hochreiter and Schmidhuber, 1997). RNN-LSTM has shown improved accuracy compared to traditional methods, particularly in capturing nonlinear patterns and long-term trends in air temperature dynamics (Jingxiao et al., 2021; Tran et al., 2021).

In summary, the forecasting of air temperature has been extensively studied using various methods including SARIMA, BP-FFNN, and RNN-LSTM. These models have demonstrated their effectiveness in capturing the complex patterns and temporal dependencies present in air temperature time series data. Furthermore, hybrid models combining multiple approaches have shown improved forecasting performance. In this study, we aim to compare and evaluate the performance of SARIMA, BP-FFNN, and RNN-LSTM models for forecasting and one-step-ahead prediction of air temperature using a dataset consisting of approximately 4,000 samples and seven features.

The remainder of the paper is organized as follows: Section 2 introduces the dataset from Zabol City, Iran, and the models are implemented. Section 3 presents the results which are obtained. Section 4, concludes the paper by summarizing the key findings and suggesting future research directions.

2. Material and Methods

2.1. Data Collection and Pre-processing:

Zabol City in southeastern Iran presents a compelling case for studying the interplay between topography and weather patterns. To explore the intricate dynamics that shape the environment of Zabol, we compiled an extensive dataset from (TuTiempo.Net, 2010-2021) for each day from 2010 to 2021. This dataset encompasses various features such as average, minimum, and maximum wind speed, humidity, average temperature, maximum temperature, and minimum temperature, providing valuable insights into the City's climatic patterns. With scorching temperatures exceeding 40 degrees Celsius during the summer, Zabol is one of the hottest places on Earth, posing challenges for residents and necessitating effective water management and adaptation strategies.

In this research, we go beyond analysing historical climate data and focus on temperature forecasting in Zabol City. By leveraging advanced statistical and machine learning models, and considering factors like solar radiation, air pressure, and geographical features, we aim to deliver accurate and reliable temperature predictions for the region. The forecasting aspect of our study holds significant implications for key sectors such as agriculture, energy management, and urban planning, as it enhances our understanding of Zabol climate dynamics. By integrating temperature forecasting into our analysis, stakeholders can make informed decisions based on trustworthy projections, enabling effective planning and decision-making processes.

By employing a range of statistical and machine learning models, we seek to advance our comprehension of Zabol weather conditions and provide stakeholders with the tools to make data-driven choices. Figure 1 indicates the flowchart of the pre-processing and post-processing approaches with three models.

To prepare the data for modelling, a preprocessing step was applied using the Min-Max normalization method. This technique rescales the data to a fixed range, typically between 0 and 1, by subtracting the minimum value and dividing by the range of the data. Min-Max normalization was chosen as it preserves the relative relationships between the values and is suitable for neural network models. This step ensures that all features are on a similar scale, preventing any one feature from dominating the model's learning process. The Min-Max normalization technique has been widely used in time series analysis and forecasting (Radhika and Shashi, 2009).

2.2. Proposed Statistical and Neural Network Architectures

In this section, we will present a concise overview of statistical method and two deep neural networks that have been employed in the field of forecasting.

The SARIMA model captures complex dynamics in time series data by incorporating both seasonal and non-seasonal components. It combines autoregressive (AR) dependencies, moving average (MA) components, differencing operations, and seasonality patterns for comprehensive analysis and forecasting (Atasever et al., 2022). Optimal SARIMA parameters were determined using grid search or automated methods such as the Akaike information criterion (AIC) or Bayesian Information Criterion (BIC) (Box et al., 2015; Hyndman and Athanasopoulos, 2018). The dataset was divided into training and testing sets, and the SARIMA model was fitted to the training data. It was then used to make one-step-ahead predictions on the testing set.

The SARIMA model offers flexibility and robustness in time series analysis, allowing the identification of dependencies, trends, and seasonality for accurate forecasting and insights into underlying dynamics. Its performance can be assessed using statistical metrics like root mean squared error (RMSE) and AIC to measure goodness of fit and predictive capabilities.

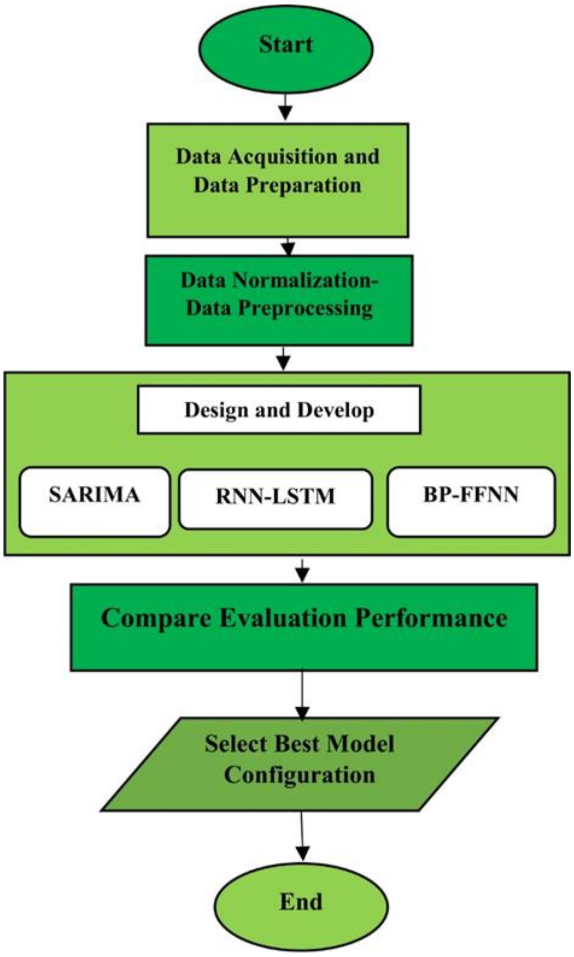

Figure 1. Schematic Flowchart of the study

The BP-FFNN is a powerful machine learning model known for capturing complex patterns and non-linear relationships (Bishop, 2005). Before training, the dataset was split into training and testing sets, and feature normalization techniques such as MinMax normalization were applied. The BP-FFNN model, with multiple hidden layers and appropriate activation functions, was trained iteratively using the Backpropagation algorithm to optimize the network weights based on prediction errors. After training, the BP-FFNN model was evaluated on the testing set, generating one-step-ahead prediction.

The BP-FFNN model belongs to the family of artificial neural networks and features a feed-forward architecture where information flows from input to output layers. The back propagation algorithm plays a crucial role in training, adjusting weights based on the error gradient. This iterative learning process allows the BP-FFNN to optimize performance and capture the underlying dynamics of time series data. Once trained, the model can forecast future values by leveraging past observations. The learned representations within the network enable it to capture intricate patterns and relationships, facilitating accurate forecasts and revealing underlying trends and dynamics in the data (Yang and Wang, 2018).

The RNN-LSTM model is a powerful deep learning model designed to capture long-term dependencies in sequential data (Hochreiter and Schmidhuber, 1997). Similar to the BP-FFNN model, the dataset was split into training, validation and testing sets, and feature normalization techniques such as Min-Max normalization were applied. The RNN-LSTM model, consisting of LSTM units with recurrent connections, was trained using historical data to capture temporal dependencies (Hochreiter and Schmidhuber, 1997). After training, the model was evaluated on the testing set, generating one-step-ahead prediction.

The RNN-LSTM model overcomes the vanishing gradient problem of traditional RNNs by utilizing LSTM units, specialized memory cells that retain and update information over long time spans (Hochreiter and Schmidhuber, 1997). This allows the model to effectively model long-term dependencies in time series data. The architecture of the RNN-LSTM includes an input layer, one or more LSTM layers, and an output layer. The input layer receives the sequential time series data, while the LSTM layers process the data, updating hidden states and cell states at each time step. The output layer produces predictions or classifications based on the learned representations from the LSTM layers. The recurrent connections in the LSTM layers enable the network to learn and leverage temporal dependencies inherent in the time series data (Hochreiter and Schmidhuber, 1997).

The two algorithms, the BP-FFNN and the RNN-LSTM have been implemented using the widely-used deep learning framework, Keras (Chollet, 2021). The BP-FFNN model consists of two hidden layers, each composed of 10 neurons. The RNN-LSTM model utilizes two LSTM layers which first LSTM layer consists of 100 neurons and the second LSTM with 50 neurons, followed by a dense layer.

In terms of activation functions, all models employ the rectified linear unit (ReLU). The RMSE has been chosen as the loss function, and the Adam optimizer is utilized with a recommended learning rate of 0.01 in BP-FFNN model and 0.001 in RNN-LSTM model. Training models involve 150 epochs with a batch size of 512 in the BP-FFNN model and a batch size of 32 in the RNN-LSTM model. The predictions are made for the subsequent day as well as the following last year (from 2020 to 2021). These configurations ensure that the models are optimized and trained effectively for average air temperature prediction. For the SARIMAX model, the seasonal and non-seasonal components of the temperature data are captured using appropriate parameters.

2.3. Evaluation Metrics

To assess the forecasting performance of each model, we employ several evaluation metrics. These metrics include:

- RMSE: It is the square root of the average squared difference between the predicted and actual air temperature values and provides a more interpretable measure of prediction error. Lower RMSE values indicate better accuracy (Liu et al., 2019).

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{predicted}-X_{observed})^2} \tag{1}$$

- Mean Absolute Error (MAE): It calculates the average absolute difference between the predicted and actual air temperature values, providing a measure of the average magnitude of the prediction error (Liu et al., 2019).

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|X_{predicted}-X_{observed}\right| \tag{2}$$

- Mean Directional Absolute Percentage Error (MDAPE): It quantifies the average absolute percentage difference between the predicted and actual air temperature values. MDAPE provides a measure of the average percentage error in capturing the magnitude of temperature changes (Liu et al., 2019).

$$MDAPE = median(\sum_{i=1}^{N}\frac{\left|X_{observe}-X_{predicted}\right|}{X_{observed}})\times 100\% \tag{3}$$

- R^2(R-squared): R-squared is a statistical measure that indicates the proportion of the variance in the dependent variable that can be explained by the independent variable(s) in a regression model. It represents the goodness fit of the model, indicating how well the model's predictions match the actual data (Liu et al., 2019).

$$R^2=1-\frac{\sum_{i=1}^{N}(X_{observe}-X_{predicted})^2}{\sum_{i=1}^{N}(X_{observe}-\bar{X})^2} \quad , \tag{4}$$

Where $X_{predicted}$ is the prediction data, $X_{observed}$ is the real data, N is the number of real data and X_{bar} is the mean value of the dataset. These metrics provided measures of accuracy, prediction error magnitude, the proportion of variance explained by the models, and the average absolute percentage difference between predicted and actual values. By calculating these metrics, we compared and evaluated the performance of the SARIMAX, BP-FFNN, and RNN-LSTM models in forecasting air temperature.

2.4. Experimental setup

In this study, the proposed network models were trained and evaluated using specific hardware and software environments. The hardware consisted of an Intel Core i7-8750H processor and Nvidia GeForce GTX 1070 GPU, providing powerful computing ability and memory bandwidth. Deep learning frameworks like Tensor Flow or PyTorch were utilized for model implementation and training. The Nvidia GeForce GTX 1070 GPU accelerated the training process due to its parallel processing capabilities. Python, along with libraries like Pandas and NumPy, was used for data manipulation and pre-processing tasks. This hardware and software setup ensured efficient analysis and reduced computational time.

3. Results and discussions

3.1. Performance Comparison of Forecasting Models

We evaluated the performance of three forecasting models, namely SARIMA, BP-FFNN, and RNN-LSTM, on the task of air temperature prediction in the Zabol City dataset. The models were trained and tested using a dataset consisting of 4000 samples with 7 features and a target variable of average air temperature. In this subsection, we present a comprehensive analysis of the results obtained from each model and discuss their strengths and weaknesses.

Neural network approaches in weather prediction have utilized a range of meteorological and geographical variables as input factors. These variables encompass air temperature, wind speed and direction, air pressure, precipitation, solar radiation, relative humidity, cloudiness, latitude, longitude, and altitude (Bilgili and Sahin, 2009; Hou et al., 2022). Specifically, air temperature, relative humidity, precipitation, and wind speed are commonly used inputs for air temperature predictions. While different types of neural network approaches have incorporated various meteorological variables as inputs, simpler techniques like multi-layer perceptron (MLP) (Jallal et al., 2019) and feed-forward neural network (FFNN) (Kisi and Shiri, 2014) have included geographical inputs such as latitude, longitude, and altitude. However, it is important to acknowledge the challenges in selecting the optimal input variables for a specific neural network approach due to the complexity of the problem and the limited number of studies available on this topic.

Furthermore, it has been observed that neural network techniques are primarily employed for short-term air temperature forecasting. Limited studies have been dedicated to medium- and long-term air temperature prediction, with a focus on utilizing RNN and LSTM models known for their ability to capture temporal trends in air temperature time series (Thi Kieu Tran et al., 2020). RNN and LSTM models have demonstrated their effectiveness in long-term forecasting of hydrologic variables (Liu et al., 2019; Thi Kieu Tran et al., 2020). The accuracy of these models primarily depends on the selection of input variables and the structure of the network. Incorporating additional data, such as rainfall, air pressure, and humidity, in deep learning methods has shown to enhance air temperature predictions.

Error! Reference source not found. summarizes the p erformance of the forecasting models based on several evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Median Absolute Percentage Error (MDAPE), and Coefficient of Determination (R2). The evaluation results are as follows:

Table 1. Comparison of error evaluation results for One-Step-Ahead prediction of air temperature across different models

Model	RMSE	MAE	MDAPE	R^2
BF-FFNN	0.018	0.013	1.59%	0.99
SARIMAX	0.042	0.03	3.65%	0.96
RNN-LSTM	0.042	0.031	3.53%	0.96

From the results in **Error! Reference source not f ound.**, it is evident that the BP-FFNN model outperformed the SARIMA and RNN-LSTM models in terms of all evaluation metrics with values of MAE (0.013), RMSE (0.018), MDAPE (1.59%), and R^2 (0.99), which are indicated in bold font. However, the RNN-LSTM model demonstrated a similar level of performance to the SARIMA model, with comparable values of MAE (0.031 vs. 0.03), RMSE (0.0421 vs. 0.0424), MDAPE (3.65% vs. 3.53%), and R^2 (0.964 vs. 0.96).

Figure 2 displays the comparison between the actual air temperature values and the temperature predictions made by the BP-FFNN model. The model exhibits a close fit to the actual values, indicating its effectiveness in capturing the underlying patterns in the temperature time series.

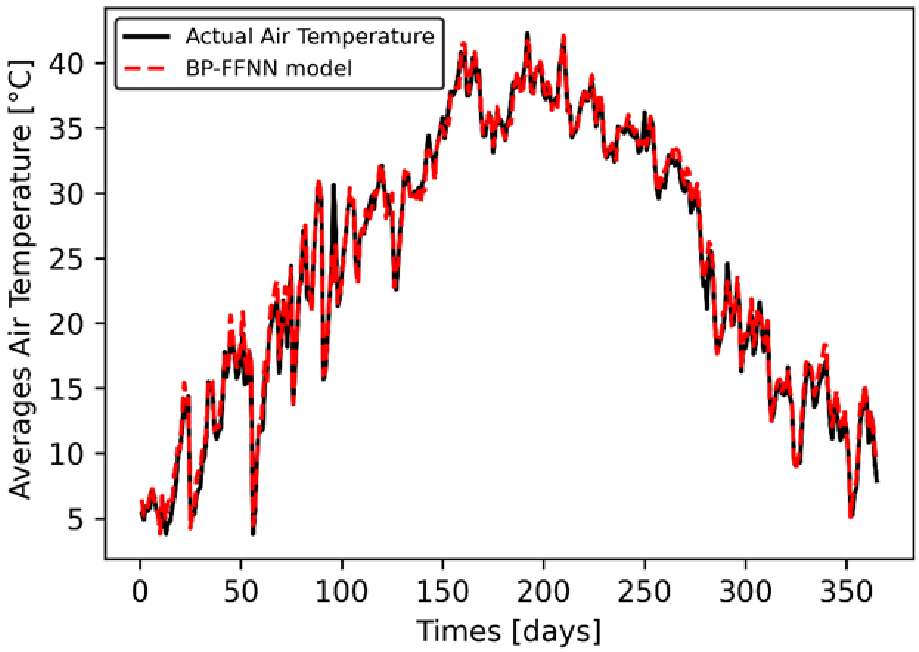

Figure 1. Comparison of BP-FFNN Temperature Predictions and Actual Values

Similarly, in Figure 3, the RNN-LSTM model, and in Figure 4, the SARIMA model, demonstrate good agreement with the actual values, capturing the fluctuations and overall trend in the temperature time series. The performance of this models comparable to that of the BP-FFNN model, indicating its effectiveness in capturing the complex relationships within the data.

The best-performing model obtained using the auto_arima function is a SARIMA model with an autoregressive (AR) component of order 2, a differencing (I) component of order 1 to ensure stationary, and a moving average (MA) component of order 2. The model does not include any seasonal AR, differencing, or MA terms as denoted by the absence of seasonal components. The amount of time taken for model estimation and fitting was determined to be about 30.60 seconds.

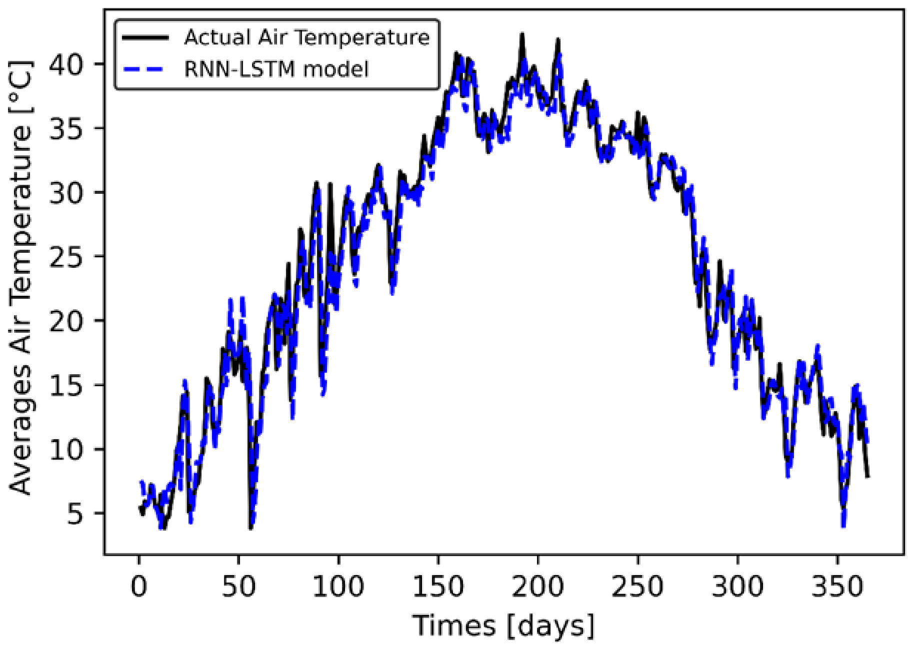

Figure 3. Comparison of RNN-LSTM Temperature Predictions and Actual Values

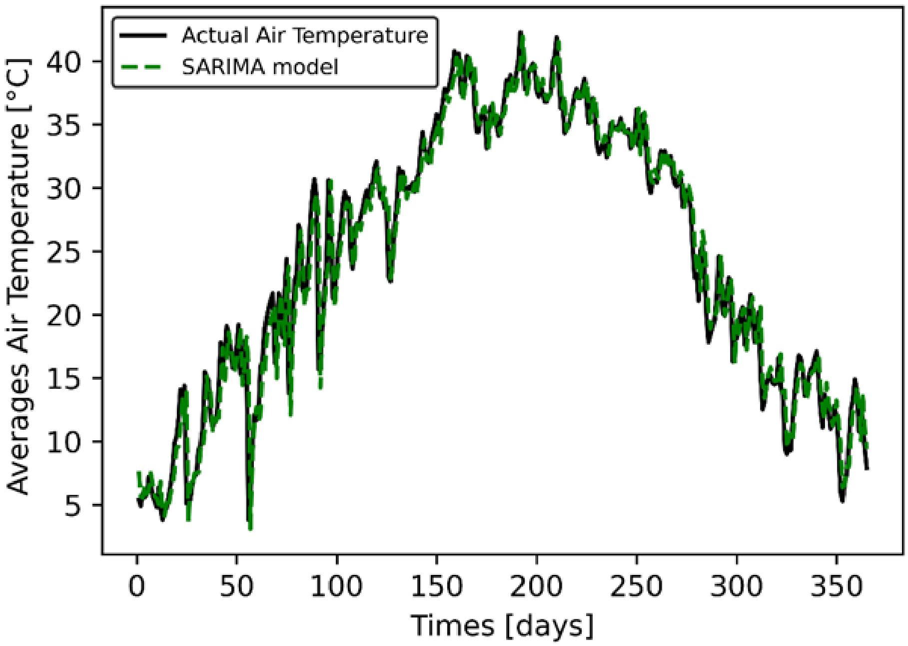

Figure 4. Comparison of SARIMA Temperature Predictions and Actual Values

In contrast, the SARIMA model exhibited higher errors and a lower R^2 value compared to the BP-FFNN model. Although it showed reasonable accuracy, the SARIMA model was outperformed by the more advanced deep learning models.

In summary, The performance of BP-FFNN models is influenced by their network configuration, including the number of hidden neurons and layers (Fahimi Nezhad et al., 2019; Park et al., 2019). The determination of the optimal configuration to avoid under fitting and over fitting often relies on trial and error due to the absence of specific guidelines (Jallal et al., 2019). While increasing the size of hidden layers and neurons can enhance the ability of neural networks to learn complex processes and improve their forecasting capabilities, it has been observed in several studies that adding more layers and neurons does not always lead to increased accuracy (Fahimi Nezhad et al., 2019; Jallal et al., 2019). Therefore, selecting the most suitable methodology for air temperature forecasting remains challenging based on the existing literature. The BP-FFNN model demonstrated superior performance, exhibiting better predictive capabilities compared to the other models. The results of the RNN-LSTM and SARIMA models were found to be relatively similar and closely aligned. Both models yielded comparable forecasting outcomes, suggesting that they possess similar forecasting capabilities for the given dataset. However, it is worth noting that the performance of these models was slightly lower compared to the BP-FFNN model. In this study, the BP-FFNN model proved to be a promising option, demonstrating its potential for accurate and reliable predictions in the context of daily air temperature forecasting.

4. Conclusions

In this study, we conducted a comprehensive analysis of three different models, namely BP-FFNN, RNN-LSTM, and SARIMA, for air temperature prediction. Our results demonstrated that the BP-FFNN model outperformed the other models, exhibiting the lowest Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Median Absolute Percentage Error (MDAPE), and highest Coefficient of Determination (R^2). This highlights the exceptional capability of the BP-FFNN model to capture complex patterns and non-linear relationships in the temperature data.

The RNN-LSTM model also showed promising performance, delivering comparable results to the BP-FFNN model. This finding underscores the effectiveness of RNN-LSTM in capturing long-term dependencies in sequential data. The RNN-LSTM model's ability to retain and update information over extended periods enables it to effectively model the dynamic nature of temperature data. This makes RNN-LSTM a valuable tool for analyzing and forecasting temperature patterns.

Additionally, we explored the application of the SARIMA model using the auto_arima function. The SARIMA model provided valuable insights into the relationship between the current and past values of the temperature series. It offered a deeper understanding of the underlying dynamics and seasonal components present in the data. The SARIMA model's ability to capture temporal patterns can be advantageous for interpreting temperature trends and identifying recurring patterns in the dataset.

While our study demonstrates the effectiveness of deep learning models (BP-FFNN and RNN-LSTM) and the interpretability of the SARIMA model in temperature prediction, it is important to acknowledge certain limitations. One limitation is the reliance on historical data, which assumes that future temperature patterns will follow similar trends. Changes in environmental factors, unforeseen events, or long-term climate variations may introduce uncertainties that could impact the accuracy of predictions. Additionally, the performance of the models may vary depending on the specific geographical location and the availability of high-quality and consistent temperature data.

Despite these limitations, our work provides several key advantages. Firstly, it highlights the potential of deep learning models for accurate temperature prediction, which can benefit various applications in weather forecasting, climate modeling, and environmental analysis. Secondly, our study sheds light on the interpretability of the SARIMA model, facilitating a deeper understanding of temperature dynamics and seasonal variations. Lastly, the comparative analysis of these models contributes to the advancement of temperature prediction methods, guiding researchers and practitioners in selecting appropriate models based on their specific requirements and datasets.

In conclusion, our study demonstrates the superior performance of the BP-FFNN model, the comparable performance of the RNN-LSTM model, and the interpretability of the SARIMA model in temperature prediction. These findings contribute to the growing body of knowledge in the field and have practical implications for various applications. Further research can focus on refining the models, incorporating additional variables, and exploring ensemble approaches to enhance the accuracy and reliability of temperature predictions.

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