Assessing the economic effects of drought using Positive Mathematical Planning model under climate change scenarios

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\section*{HIGHLIGHTS}

- Different types of droughts can have complex economic effects on the cultivation regime.
- Using SPI, water cost coefficient is developed to translate the water deficiency caused by future droughts into added costs.
- Positive Mathematical Planning (PMP) model is used to calculate the future optimal cultivation area for various crops.
- Future cultivation regime is affected by water deficiency, estimated value of the crops, and availability of resources.

\section*{ABSTRACT}

In recent decades, regions all around the world have experienced severe droughts adversely affecting their agricultural production. Climate change, along with limited access to water will alter future production and agricultural development. The purpose of this study is to provide a perspective for the future cultivation regime in the Divandarre region in the Sepidrood catchment in Iran, using historical climatic, agricultural, and economic information. Future precipitation values are determined for three climate scenarios, then downscaled and converted to pixel-based precipitation maps using the Moving Least Squares method. Future droughts are identified using the Standardized Precipitation Index at 3, 6, and 9-month intervals based on precipitation values and the relationship between different types of droughts (meteorological, agricultural and hydrological). We introduce a new coefficient, the water cost coefficient, derived from drought characteristics that captures the added irrigation cost in drought years because of increased water price. Using the Positive Mathematical Planning method and considering limited land and water, predicted future prices and costs based on a linear regression of supply-demand, and the annual water cost coefficient values, an agroeconomic model is built. After prediction of future price and cost based on historical data from 2005 to 2018, we run future scenarios based on various price and cost values to determine the optimal annual cultivation area for each crop from 2020 to 2040. All scenarios indicate a decline in cultivation area for all crops making agriculture less beneficial in the future. The cultivation regime moves away from more water-consuming products with less economic value (e.g. watermelon) toward less water-consuming, more expensive products (e.g. lentils). The findings of this model along with expert economic
1. Introduction

Drought is a common and recurring destructive natural phenomenon that has socio-economic consequences by affecting agriculture. Drought generally occurs when water resources are depleted to such an extent that they can no longer meet the needs of the region. Recent studies have shown that drought has significantly reduced global ecosystem production; in general, droughts are classified into four categories: meteorological, agricultural, hydrological, and socioeconomic (Dracup et al., 1980) (Wilhite and Glantz, 1985). Drought (and specifically agricultural drought) affects agricultural production more than any other natural phenomenon due to the gradual onset and duration of the long-term effects compared to other natural phenomena such as floods. Intergovernmental Panel of Climate Change (IPCC) has reported a significant decline in agricultural production in arid and semi-arid countries (such as Iran), which indicates that food security conditions in these countries are worse than in previous years (P.R. Shukla et al., 2019). It is also predicted that climate change will exacerbate these conditions by increasing the frequency of drought recurrence mainly due to fluctuations in annual rainfall.

Many studies have tried to link hydrological drought to changes in vegetation and, consequently, agricultural drought. Lin et al. (2017) tried to find a relationship between hydrological drought and water-climatic variables, water resources performance, and vegetation in the Xijian River in China. The results of this study show while signal reservoir operation can reduce drought severity in spring and summer, they worsen the autumn droughts. This shows the incapability of a sole water resources management method in reducing drought effects. Sun et al. (2018) tried to determine the severity of droughts in the Yangtze River Basin using WSDI (Water Storage Deficit Index) and information obtained from the GRACE satellite. WSDI can capture the historical drought events and therefore, could be a robust and reliable method for characterization of future droughts. However, the length of data used may not be available for smaller and less developed watersheds. Yu et al. (2014) used the DNDC (DeNitriﬁcation-Decomposition) model to simulate plant growth using the nitrogen uptake process by the plant, taking into account water and temperature stresses. In this model, plant growth is modeled with PGI (Plant Growth Index), mainly focusing on the impact of drought, its severity, and duration on the decline in the growth of maize crops in the United States. Although this model can provide comprehensive yield information for various end-users, it requires very strong and voluminous base data for accurate calibration. In addition, the determination of the coefficients related to the desired plant (such as corn) is done through several experiments, which is very time-consuming and costly. Zargar et al. (2017) tried to determine the tolerance of plants to drought by examining the effect of drought on plant growth and more precisely the process of photosynthesis in different plants. Changes in plants in dealing with drought include reduction of trigger pressure, closure of the stomata during the day, leaf rotation, etc. which depend on the duration of the stress, the growth stage, the genetic potential, and the surrounding environment. To determine these responses, as well as the production of compounds in the plant structure, it is necessary to study the basic metabolic processes of the plant in different stages which is specific to the region and also costly. Drought is a multi-dimensional problem that requires the water sector and the social and agricultural sectors to adapt and plan accordingly to solve it. Savari and Shokati Amghani (2022) used the combined model SWOT-FAH-P-TOWS to develop 12 appropriate strategies to increase farmers’ adaptation to drought. According to the findings, the two strategies “supporting the development and establishment of microcredit organizations and funds using the spirit of empathy and rich culture of farmers to diversify their livelihoods” and “organizing consultative meetings between experts and farmers to combine indigenous and modern knowledge for increasing the effectiveness of drought mitigation programs” are the most effective approaches to deal with drought.

After determining the effects of drought on the growth of agricultural products, these effects are converted to an economic form known as profit and loss functions. There are several methods to determine the economic effects of drought, the most widely used of which are Market Valuation Techniques, Input-Output Analysis, Computable General Equilibrium Analysis (CGEA), Contingent Valuation Method (CVM), Choice Experiments (CE), and determining the optimal point of hydraulic capital. Although many models have been developed using these methods, there are limitations. For example, they require a lot of accurate and detailed information to produce results that may not even be reliable due to a lack of time series, or rapid infrastructural changes in the development of the economic system. The accuracy of the results is also strongly influenced by the structure of resources, environment, and policy constraints. In many cases, the cost and time of implementing these methods are so high that the results are not produced in the design planning horizon and as a result, they lose their practical value. For these reasons, the use of mathematical programming models to assess the effects of climate change on agricultural economics has become widespread today. The reasons for this include fewer empirical constraints in farm modeling, the possibility of defining nonlinear concepts with information, time and computational constraints, and considering endogeneity of the final price and risk behavior in the objective function (Howitt, 1995). In this paper, the PMP method, one of the most widely used mathematical methods in impact assessment, has been used to determine the effects of drought. The selection of PMP is due to a lack of long climatic and economic historical data in the study region, and also large, rapid structural changes because of urbanization, boycotts, and ever-changing governmental policies that cause inconsistencies in data. PMP has proven to be a robust method in case of inconsistent and short-period data.

As discussed, there is a gap that needs to be addressed here. The case study here is the representative of croplands in developing countries that suffer from lack of continuous and reliable climatic and economic data. Large infrastructural changes and abnormalities in historical trends make it even more difficult to interpret this limited data or use more advanced methods. Therefore, the purpose of this study is to prepare a future plan for the cultivation regime in the Divandarreh region in the Sepidrood catchment in Iran, using limited historical climatic, agricultural, and economic information as inputs to a PMP model. This is done in five steps: (1) Predict future precipitation values, (2) Determine future droughts and their properties, (3) Predict future economic crop data, (4) Model calibration, (5) Future simulation to get cultivation areas for different crops. Each step is discussed in detail in the following sections.

2. Study area

The Great Sepidrood catchment is one of the largest water basins in Iran and a subset of the Caspian Sea catchment. The area is 59217 square kilometers and the main river is Sepidrood. The study area, the Divandarreh region in Kurdistan (Figure 1), is part of the Sepidrood catchment, which according to the moisture regime, irrigated and irrigated cultivation (with an area of 122865.5 ha and 5194.3 ha, respectively) is relevant and the relationship between agricultural and meteorological drought will be meaningful. Agriculture is the main activity of the people and irrigated and rainfed crops are both common with the predominant irrigated and rainfed crops in the region being alfalfa and wheat, respectively. In recent
years, the hydrological regime has become more complicated than ever with water shortages and frequent droughts that threaten the food security of the region. According to local authorities, the Sepidrood basin has experienced major droughts in the last 15 years which has aggravated the conditions for various crops with the last one being rice. This problem can seriously threaten the food security in the region and the whole country since rice is the major source of food in Iran, mainly grown in the Sepidrood basin. This problem is intensified in the Divandarre region due to very little access to groundwater making the local agro-economy dependent on rainfall and surface water. Following the main trend in semi-arid parts of Iran, temperature rise and fewer rainfall events have caused large losses to farmers. According to the national statistics organization of Iran, the total rainfall in Kurdistan in the first half of 2020 was 73.4 mm with a 40% decrease compared to the last year with the least value recorded for Divandarre. All the aforementioned reasons make the Divandarre region a perfect fit for the case study.

3. Methodology

The purpose of this study is to provide a perspective for the future cultivation regime in the region using historical, climatic, agricultural, and economic information. Historical precipitation data in this area were collected from 64 precipitation stations and after downsampling, they were converted into pixel-based precipitation maps with a spatial resolution of 1km by 1km using the MLS (Moving Least Squares) method. In this process, three climate scenarios based on CanESM2 were used, which were developed in the framework of CMIP5. CanESM2 includes the following GCMs: CanCM4, OGCM4, CMOC, and CTEM.

Using precipitation data, SPI (Standardized Precipitation Index) values are calculated for three scenarios to determine future droughts and their characteristics (i.e., intensity, magnitude, and duration). Based on drought characteristics, an additional cost parameter as the water cost coefficient is calculated to capture the added cost of water under various drought conditions. Converting qualitative drought properties into economic parameters, PMP (Positive Mathematical Planning) model analyzes all possible cultivation options and chooses the best crop to be cultivated annually (Figure 2). The procedure can be broken down into six steps:

3.1. Data collection and downscaling

Inputs include rainfall, groundwater and land use maps, cost of cultivation and irrigation, crop price, yield, water demand, and cultivation area. Economic data including the cost of production of agricultural products (2001–2018) and the on-farm price of products (2006–2018) as well as base year data are obtained from the national statistics of the Ministry of Agriculture.

The downscaling model used in this study is SDSM (Statistical DownScaling Model), a linking method between a climatic statistical generator and a multilinear fitting method that converts climatic variables at the synoptic scale into local meteorological variables. To better match the observed time series, statistical techniques are used to artificially increase the variance of the downloaded weather time series. Here, SDSM takes daily precipitations at 64 stations from 1961 to 2006 (training: 1961 to 2000; calibration: 2000 to 2006) and after determining the optimal point carrying the largest amount of information, calculates precipitation values for three future RCP scenarios (i.e., RCP 2.6, 4.5, and 8.5) from 2006 to 2040. Although the oldest precipitation values are from 1961, they are very scattered and most of the stations (44 out of 64) have data starting from 1987 which makes it hard to choose a longer calibration period.

3.2. Map generation

Precipitation values at stations need to be converted to pixel-based maps for spatial analysis. Moving Least Squares (MLS) is one of the most important computational frameworks, first proposed by Lancaster and Salkauskas (1981), for analyzing information based on local values, their behavior, and significance through the moving computational domain and kernel weighting functions. In MLS, the estimation is obtained using approximation (regression) in the points that are distributed irregularly as a constraint of distance. More specifically, each point receives a weight proportional to its distance so that neighboring points have more participation in the estimation process. All points within the [local] moving domain participate in the estimation process, while the rest are not considered. A comprehensive explanation of this method is given in Amini and Nasser (2021). Details of the functions used in this article are discussed.

Here, the base function is a second-order quadratic function of two inputs DEM (longitude, latitude, and height) and climatic values (precipitation). Also, r (effective fitting distance) is calculated as follows:

$$r = \sqrt{\left(\frac{x-x_i}{\alpha}\right)^2 + \left(\frac{y-y_j}{\gamma}\right)^2 + \left(\frac{H-H_j}{\rho}\right)^2 + \left(\frac{P-P_j}{\mu}\right)^2}$$

(1)

Where x, y, H, and P are the longitude (degrees), latitude (degrees), height (meters), and precipitation (millimeters), respectively. α, γ, ρ, and μ are distance parameters that need to be optimized. Because of higher convergence speed and efficient computational performance, the Shuffle-Complex Evolution (SCE) optimization approach is used here.
### 3.2.1. SPI calculation

In this study, SPI drought index in 3, 6, and 9-month intervals are used to examine the relationship between meteorological, agricultural, and hydrological droughts. Using pixel-based precipitation data at a monthly scale, SPI values are calculated for the three climatic scenarios for 2020 to 2040.

### 3.2.2. Modeling water deficiency

Droughts reduce the available water resources and thus increase the price of water. Here, water cost coefficient introduces water deficiency to the model to quantitatively assess various drought events and compare the profitability of different crops. The first step in this process is to calculate irrigation costs for future years as a part of the growing stage costs. Assuming irrigation costs change relative to growing costs, irrigation costs for the future are obtained using linear regression.

Deviation from the annual average rainfall cannot capture all drought characteristics. Therefore, the SPI-6 index (SPI in 6-month intervals) is used to identify agricultural drought. Drought begins when the SPI index becomes negative, remains negative, and during the negative period, reaches values less than -1. Using this definition, droughts are identified during the years 2020–2040. Drought characteristics are (1) Intensity: the smallest SPI value in the desired period; (2) Duration: number of months with SPI ≤ −1; 3) Size: Absolute value of SPI values during the drought period. Using these three parameters, the water cost coefficient is calculated as follows:

1. According to Table 1, for any SPI value, a number from 1 to 4 is defined as the drought intensity factor ($f_d$) that shows the intensity of a drought event. As shown in this table, the highest number (4) is for the most intense drought event.

\[ f_w = (f_i * f_d * f_m) + 1 \]

1 is added at the end to make all values greater than 1 (which is an indicator of normal years).

After determining the future drought events for the scenarios RCP 2.6, following the steps above, the water cost coefficients are calculated for each drought event and attributed to the corresponding year (see Table 2).

### 3.3. Economic modeling

In this study, the PMP method is used to build an agricultural production model using nonlinear production cost functions. The PMP uses base year yield data to provide self-calibrating models of agricultural productivity.

#### Table 1. Quantification of drought intensity by the drought intensity factor.

| Qualitative intensity of water conditions | SPI          | Drought intensity factor ($f_d$) |
|------------------------------------------|-------------|---------------------------------|
| Almost normal                            | -0.99 to 0  | 1                               |
| Mildly dry                                | -1.49 to -1.00 | 2                             |
| Very dry                                  | -1.99 to -1.50 | 3                             |
| Severely dry                              | < -2.00    | 4                               |
production and resource use, in line with microeconomic theory, considering the heterogeneity of land and livestock. PMP automatically calibrates the data without using “flexibility constraints”. The resulting models are more flexible in their responses to policy changes, and the underlying factors are recognizable in production variance or resource elasticities. Numerous researchers have used PMP in their studies. For example, water pricing in China (Huang et al., 2016), evaluating the impacts of variations in crop profitability and market innovations on farm profitability, land use and water consumption (Donati et al., 2013), increasing the price and reducing the amount of water, and changing the price of agricultural products to use deficit irrigation (Cortignani and Severini, 2009). The PMP method seeks to accurately calibrate area, production, and price. Kasnakoglu & Bauer used the PMP method in one of the sectional models introduced by Hazel and Norton (1986). The results for the Turkish Agricultural Sector Model showed continuous calibration over seven years (1998).

Here, PMP determines the optimal cultivation area of each crop under different economic and climatic scenarios. Model is formulated as:

$$\max \sum_{i=1}^{6} a_i (p_i - c_i) + \sum_{i=1}^{4} a_i (p_i - c_i)$$

s.t. $$\sum_{i=1}^{6} a_i \leq A_i$$

$$\sum_{i=1}^{4} a_i \leq A_r$$

$$a_i, a_r \geq 0$$

Where:

i and r refer to irrigated and rainfed crops, respectively; p, a, c, and A are the price ($/hectare), cultivation area (hectares), cost ($/hectares), and maximum available area, respectively.

3.4. Model calibration

Calibration is performed for six irrigated crops and four rainfed crops based on the 2015–2016 water year; That is, the areas generated by the model should converge to the base year areas. In the original paper, Howitt (1995) does this by using bounding constraints. In this paper, calibration is done without the need to define tight constraints bounding the variables, by softening the constraints and removing the land costs which makes sense since the majority of farmers are also land-owners in the study region.

3.5. Future scenarios

After calibration, the model runs for future scenarios with price and cost values determined by various prediction functions. Four different functions are used to predict future price, cultivation cost, and irrigation cost. Based on these functions, future scenarios include (1) linear, (2) quadratic, (3) piece-wise linear (4) fixed inflation rate.

4. Results

4.1. Average precipitation by climate scenarios

After running the meteorological model, the average rainfall values for the years 2020–2040, for three climate scenarios are 32.03 mm, 31.55 mm, and 33.00 mm for RCP 2.6, 4.5, and 8.5, respectively. Average rainfall decreases from RCP 2.6 to RCP 4.5 to a small extent but it increases from RCP 4.5 to RCP 8.5 which could be possible due to the change in hydrological regime in the region. However, a single value for average rainfall over the coming years cannot show the temporal distribution of precipitation and therefore, is not enough for drought modeling.

4.2. Drought index by climate scenarios

After obtaining pixel-based precipitation maps, SPI in three intervals (i.e., 3, 6, and 9 months) is calculated (Figure 3). SPI changes almost similarly in RCP 2.6 and RCP 4.5 although SPI magnitude in RCP 2.6 is larger which means more precipitation in wet years and less in dry years. All scenarios show a decrease in precipitation indicating several droughts. However, droughts and wet years lagged for 4–5 years in RCP 8.5 compared to RCP 2.6 and RCP 4.5 which could be due to different temporal distribution of precipitation in RCP 8.5.

4.3. Model calibration

In the original PMP model (Howitt, 1995) variables are bound to change in the range of +0.0001 and -0.0001 from the original values. In this study, however, the calibration is done without tight bounding constraints of variables. By changing the objective function and modifying the costs (i.e., removing the land costs from the total costs), the upper and lower limits are removed and the base year values are reproduced with acceptable accuracy which adds to the model flexibility. The results of this calibration along with the values of the base year by type of cultivation are given in Table 3 and Table 4.

4.4. Prediction of crop prices and costs

Crop prices and costs are the most important economic inputs of the PMP model. Five mathematical functions for extrapolating the price and cost of production are defined in the form of five economic scenarios. Prediction accuracy results based on various error indices are provided in Table 5. Results for crops’ price and cost values based on piece-wise linear regression are represented in the following figures for both observation and trend data sets (see Figures 4-6).

4.5. Economic model results

Droughts will limit access to water and therefore, change the water price. This is an important input to determine the profitability of one crop over another in the cultivation pattern. In this part, the agro-economic model determines the optimum cultivation area for each crop in the

| Drought | Start | End | Intensity | Duration (months) | Magnitude | $f_1$ | $f_4$ | $f_6$ | WCC |
|---------|-------|-----|----------|-------------------|-----------|------|------|------|-----|
| 1       | 2020-10 | 2023-09 | -2.03 | 36 | 28.88 | 4 | 0.52 | 0.43 | 1.90 |
| 2       | 2024-01 | 2028-04 | -2.51 | 52 | 59.07 | 4 | 0.75 | 0.88 | 3.65 |
| 3       | 2028-06 | 2034-02 | -2.97 | 69 | 67.29 | 4 | 1.00 | 1.00 | 5.00 |
| 4       | 2035-11 | 2036-04 | -1.52 | 6 | 4.11 | 3 | 0.09 | 0.06 | 1.02 |
| 5       | 2037-01 | 2037-09 | -1.59 | 9 | 8.69 | 3 | 0.13 | 0.13 | 1.05 |
| 6       | 2037-11 | 2040-09 | -2.47 | 35 | 35.92 | 4 | 0.51 | 0.53 | 2.08 |
future considering water and land availability as well as the crop prices and costs and also supply and demand relationships determined by linear regression models. The PMP model runs four times (number of price and costs prediction scenarios) for each of the three climate change scenarios (RCP 2.6, 4.5, and 8.5). The results are provided in Figures 7 and 8 for irrigated and rainfed crops, respectively.

5. Discussion

Identifying future droughts is an important step in this study that was done using SPI values in 3-, 6-, and 9-month time intervals. In short, SPI-6 best captures agricultural droughts. In Figure 3, it can be seen that intense droughts occur in years with low SPI values but the continuation of a negative SPI could also aggravate the conditions. In the years 2020–2026, the rainfall does not further decrease, but it stays constantly low and causes a major drought, especially in RCP 2.6 and RCP 8.5. This result is only obtainable from the SPI diagram based on the duration concept. A similar case can be observed in the years 2034–2040. SPI-6 results (agricultural drought) are only valid if the general trend is in accordance with SPI-9 results (hydrological drought). In other words, in the long run, agricultural drought leads to the drying of natural water resources causing a severe hydrological drought from 2024 to 2033. There are similar drought events in the early and final years of the modeling period but there is a major drought in the years 2030–2034 with the drought peak in 2032. To further validate the data, SPI-3 is used to indicate short droughts known as meteorological droughts that are used to characterize the beginning and also the most stressful years during a drought period (in here, the years 2022, 2028, and 2039). We can also see a chronological order of meteorological, agricultural, and hydrological droughts from 2025 to 2039. Continuation of hydrological droughts and failure to make appropriate adaptations can lead to socioeconomic drought. Espinosa-Tasón et al. (2022) studied the economic impact of multiyear droughts by applying the economic surplus in Andalusia and found that the effects of hydrological drought on farmers differ according to crop category and whether the system is rainfed or irrigated. In this study, irrigated crops could take advantage of the price effect due to quantity effect losses in rainfed crops.

In order to run future simulations, crops price and cost values need to be determined for the modeling period (2020–2040) using historical data. However, there is a very large jump in the historical cost data between the years 2014 and 2015 (largely due to changes in government policies towards fuel prices and also boycotts) such that values increase more than 10 times on average. Due to this jump, the linear function is unable to predict future prices accurately. The quadratic function can capture this jump, however, due to the sharp increase in exponential function slope after passing the jump, it can lead to extremely high values for price in years to come. The piece-wise linear function can bring the best of both worlds by capturing the large jump in the data and yielding fairly rational price values for the modeling period. In this method, two functions are used to fit two separate sections of the time series. The separation point is defined so that the variance difference between the two sections is maximized. The fourth scenario is defined by multiplying the present values by a fixed value (called the inflation rate). Here, the inflation rate (IR) is applied annually from 2020 to 2040 to price (IR = 0.2), cultivation cost (IR = 0.3), and irrigation cost (IR = 0.4) to get a time series of values throughout the modeling period.

In summary, the best prediction function is piece-wise linear regression (Figures 4 and 5) because it can capture the large jump in the data set with rational future price values. For a more accurate price and cost prediction, we need to conduct economic studies on the supply-demand

Table 3. PMP model calibration results along with base year (2015) cultivation areas for irrigated products.

| No. | Product       | Area in 2015 (ha) | Area from PMP (ha) | Error (%) |
|-----|---------------|-------------------|--------------------|-----------|
| 1   | Cereals       | 570.0             | 570.03             | 0.0044    |
| 2   | Legumes       | 16.1              | 16.10              | 0.0310    |
| 3   | Industrial products | 8.9       | 8.89              | 0.0562    |
| 4   | Cucurbitaceae | 15.4              | 15.39              | 0.0325    |
| 5   | Vegetables    | 64.7              | 64.70              | 0.0077    |
| 6   | Forage plants | 4519.2            | 4519.19            | 0.0001    |

Figure 3. SPI values in 2040–2020 based on three climate scenarios.

Table 4. PMP model calibration results along with base year (2015) cultivation areas for rainfed products.

| No. | Product       | Area in 2015 (ha) | Area from PMP (ha) | Error (%) |
|-----|---------------|-------------------|--------------------|-----------|
| 1   | Cereals       | 91881.5           | 91882.27           | 0.0008    |
| 2   | Legumes       | 30963.5           | 30963.74           | 0.0008    |
| 3   | Industrial products | 10.6           | 9.60              | 9.4348    |
| 4   | Cucurbitaceae | 9.9               | 9.90              | 0.0503    |

Table 5. Error indices for 5 economic scenarios; There is no error for Scenario 4 (Fixed Inflation Rate) because no reference data is available for this method.

| Scenario | R-Squared Cost | RMSRE Cost | MARE Cost | R-Squared Price | RMSRE Price | MARE Price |
|----------|----------------|------------|-----------|-----------------|-------------|------------|
| 1        | 0.60           | 27.10      | 15.95     | 0.80            | 0.52        | 0.37       |
| 2        | 0.89           | 13.80      | 8.14      | 0.88            | 0.31        | 0.22       |
| 3        | 0.87           | 1.54       | 0.65      | 0.93            | 0.36        | 0.25       |
relationships and also determine the growth of the inflation rate in the country due to presidential periods, sanctions, and the relative importance of different products over time. Implementation of such a model is out of the scope of this study.

Except for lentils (Figure 6), the separation point in price prediction happens at the beginning of the time series. Although government subsidies are to prevent an increase in prices for strategic crops (cereals and legumes), the results question the practicality of these subsidies. Obviously, the free market has not followed the desired path of the authorities mainly due to in-between dealers abusing the market conditions in their own favor and leaving farmers in large losses. The primary results of this mismanagement include large immigration toward urban areas and increased joblessness rates. Several studies have pointed out the same result; Movahedi et al. (2021) used structural equation modeling to find the most important factors causing the farmers to abandon agricultural lands. The most effective cause of this phenomenon was the managerial-legal factor including the problem of segmented farms, and not paying enough attention to establishing agricultural incentives. In another study, Boazar et al. (2019) mentions that government plans for water resources management were not efficient and they have switched from supply-side to demand-side management to prevent rice farmers from abandoning their farms or cultivating other crops. In another study, Neisi et al. (2020) analyzed farmers’ drought risk management behavior by using Krejcie and Morgan's table method to sample 350 farmers. She

Figure 4. Observed cost versus fitted cost for different crops (Part 1). The separation point is obvious in all graphs mainly due to large infrastructural changes, sanctions, and the removal of subsidies on necessary raw materials.

Figure 5. Observed cost versus fitted cost for different crops (Part 2). The graphs indicate a huge cost difference ($/ha) for Cucurbitaceae (watermelon and cucumber) and vegetables (tomato and potato) in comparison to other products in Figure 7. This is because these products are not covered by government subsidies and are also more water-consuming which adds to the costs.
found that policies need to make farmers take their own risk management decisions and have access to a variety of tools and strategies. The last step of the modeling process involves future simulations for predicted price and cost while taking into account various climatic scenarios. In general, the cultivation area for all crops decreases in all climate scenarios making it less beneficial to cultivate crops in the future. Drought events are more severe and relatively long in the RCP 4.5 due to less average rainfall leading to constant negative SPI values and therefore, a further decline in the cultivation area for more water-consuming crops. This decline is exacerbated during the drought years for cereals in all three climate scenarios with the RCP 8.5 scenario lagged. Khalili et al. (2021) conducted a quantile regression model to find the effects of drought shocks on household behavior and found that farmers move toward the implementation of coping mechanisms including non-agricultural job opportunities in drought-affected areas of Fars, Iran. As the drought ends, the cultivation area for cereals increases but does not reach the base year value (Figure 7-Cereals). During drought years, cereals are still one of the best crops to grow due to their large demand capacity and the potential for exportation but as the drought duration increases, the profitability of cereals declines. Savari et al. (2022) studied the effect of drought severity on wheat crops and found that further drought aggravation increases the farmers’ vulnerability because of higher vulnerability levels in regions with more critical conditions and longer droughts.

Figure 6. Observed price versus fitted price for major crops. Except for lentils, the separation point is placed at the beginning of the historical data which indicates a constant price increase.

Figure 7. Cultivation area for six groups of irrigated crops under three climate change scenarios for the modeling period (2020–2040). Except for cereals and legumes, RCP 8.5 shows the same pattern as RCP 2.6 and RCP 4.5 with an average lag of 4–5 years because drought events happen later in the RCP 8.5 scenario.
Legumes are the second choice to go to due to the sharp price increase but since this high price is not sustainable (because of low demand), the cultivation area for legumes decreases rapidly (Figure 7-Legumes). Farmers may not be able to benefit from this quick shift in the market due to their common fatalistic behavior and therefore, prior cultivation plans could help them adapt to the market earlier. Zarafshani et al. (2012) mentioned this fatalistic behavior as one of the psychological factors that increase farmers’ vulnerability to droughts because it directs them towards taking more passive coping strategies.

The area of industrial products decreases during the drought years and returns to the previous level at the end of the drought. Industrial products are among the crops with moderate water demand and due to the higher water cost, they are not the best choice in drought years (Figure 7-Industrial Products). Due to the fixed supply-demand relationship, the area for these crops does not increase further than the base year value. Despite higher water demand, the higher relative profitability increases the Cucurbitaceae area slightly during the drought years. Similar to industrial products, due to fixed supply-demand, the area returns to the base year values after the drought (Figure 7-Cucurbitaceae). The same procedure repeats for Vegetables (Figure 7-Vegetables).

As for the forage crops, the area decreases during the drought years since they are among the highest water-consuming crops that reduce the relative profitability (Figure 9-Forage Crops). Forage crops are among the strategic crops since their consumption by livestock. This pattern is also mentioned in other studies in similar semi-arid regions. Mehdipour et al. (2022) analyzed drought adaptation strategies to evaluate rural households’ liveability and found that increased prices in forage crops could damage the livestock population since farmers can no longer afford to feed them finally resulting in a loss of revenue and access to food. Having an overview of the future problems could improve the policies to avoid losses in interconnected sectors.

Rainfed crop cultivation area does also decrease in the long run (Figure 8). However, due to the non-intervention of irrigation costs, the area decreases very slowly. The decreased area for industrial Cucurbitaceae is even smaller because of the fixed supply-demand relationship. Industrial products are no longer economically viable and therefore, are constantly zero. Savari and Moradi (2022) evaluated the effectiveness of drought adaptation strategies and found that the most important adaptation classes under drought conditions were farming strategies and crop management. This was mainly done by a reduction in rainfed wheat cultivation area in Fars simply because it was not economically viable to harvest the crops.

The optimization problem is solved with inequality constraints because, in reality, farmer prefers not to cultivate over not profitable cultivation. This has led to widespread immigration of farmers to cities and the abandonment of agricultural lands. If labor forces are needed in other sectors (such as industry), this will lead to the optimal distribution of manpower but in Iran, this will increase the unemployment rate. Nasrnia and Ashktorab (2021) assessed the drought resilience patterns of rural households. She found that governmental support for occupations such as animal husbandry resulted in more engagement of residents in these activities, leading to increased employment, reduced immigration to urban areas, increased household incomes, and increased household resilience against drought. Proper management with an appropriate cultivation plan can change the drought threat into an opportunity for the farmers. Musolino et al. (2018) conducted an empirical investigation on the distributive effects of drought events in some areas of Southern Europe and found that drought can create not only “losers”, but also “winners” and the key factor to analyze the gains obtained by farmers in price.

One important constraint is the capability of the land for crop rotation (for example, switching between forage crops and vegetables). There are two sides to this problem: (1) Physical constraint and plant physiology: The growing process is different for each crop but given the right machinery and tools, it is possible to implement crop rotation; (2) Economic constraint: there must be sufficient demand for the increased supply of crops which is addressed by linear supply-demand relationships here.

6. Limitations

As with any model, there are limitations to the model implemented in this study. It has been addressed by several studies that identifying drought using only one variable may be subject to bias. In this study, SPI was used to determine droughts which is still the most commonly used drought indicator along with PDSI. This is because the Divandarreh region suffers from lack of continuous and reliable historical climatic data leaving the authors with precipitation as the only reliable historical data. However, using more climatic variables (e.g., temperature, evapotranspiration, etc.) could lead to a more accurate drought identification which will be a future consideration of this study.

Another limitation is the change in crop yield depending on climatic and agricultural conditions. The best way to do this is to build an experimental crop yield model based on climatic and agricultural stress tests. Such data is not available at the moment and the other methods (such as Stewart’s equation) are either too simple or specific to a case study.

One of the most important inputs of the PMP model are future crops’ price and cost values. Currently, these values are determined using piecewise regression method. More elaborate economic models along with expert judgements could increase the accuracy of these predictions. Such models could also provide a more detailed relationship between supply and demand. However, it should be noted that unstable economic conditions in Iran make it extremely difficult to devise reliable economic models. Surveys at farm level could be a beginning point for this purpose.

PMP is the best choice modeling tool given conditions in the study area. However, the model can be improved if more realistic constraints are considered because conceptually, it is an optimization model. These constraints can include manpower, machinery, and movement of products between states. This is only possible if detailed data is available of the import and export of crops at the country level and between states. Physical constraints could also be employed to implement the idea of time lag between crop rotations.

7. Conclusion

Droughts, as the most important threat to food security in an area, reduce the production and quality of agricultural products by changing
the amount and frequency of rainfall. Identifying future droughts can provide a cultivation plan in the modeling period to guide policy-makers and practitioners in mitigating drought effects by optimal use of limited land and water. In this paper, future droughts along with their characteristics (i.e., intensity, duration, and magnitude) are determined by SPI and EDI under RCP 2.6, 4.5, and 8.5. To simulate water deficiency, we introduce a new factor, the water cost coefficient, that shows the actual price of water in drought years. Using the PMP method, an agroeconomic model determines the best cultivation area for each crop given future price and costs based on linear supply-demand relationships. Results of this model could provide the authorities and the farmers with a generic cultivation plan for the modeling period (2020–2040).

Here, linear supply-demand relationships are used to address this problem but more elaborate economic models could yield more accurate prices by considering transportation, import-export, sanctions, etc. The quality of the proposed model could be improved with expert judgments from economists and local authorities by adding more constraints to the optimization problem. Another limitation of this study is that deficit irrigation (not enough rainfall) could lower the quality of crops and therefore, the price. This item is not considered in this study due to the lack of experimental data showing the relationship between water amount and crop yield. There are other formulae connecting crop yield to evapotranspiration and precipitation but they are outdated and also not available locally.

Declarations

Author contribution statement

Ghaffari, Ali: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. Nasser, Mohsen: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data. Pasebani Someeh, Abulfazl: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data. Savari, Mostafa: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data is publicly available from national data websites which are mentioned in the manuscript.

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The authors declare no competing interests.

Additional information

No additional information is available for this paper.

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