Climate Change and Agricultural Adaptations: Shifting Among Irrigation Sources, Crop Substitution, and the Value of Adaptations

This Draft: February 2025

A B S T R A C T

Given their geographic location and vulnerable agricultural sector, countries in the Middle East have consistently regarded hydro-climatic conditions as a critical and enduring concern. This research examines the main adaptations patterns–shifting among water sources for irrigation and crop substitution in response to climate change. Additionally, this paper evaluates the potential changes in agricultural productivity across Iran's counties due to climate change and examines the benefits of implementing agricultural adaptations. Employing a unique 20-year panel dataset at county level, we find that the utilization of deep and semi-deep wells for irrigation have increased all over Iran when temperature increases, while the share of river, canal, and aqueduct have decreased significantly. We also found that maize, a more heat-resistant crop, has been planted on more land compared to less heat-tolerant crop, especially in warmer regions. Finally, the results exhibit that the adoption of agricultural adaptations significantly enhances the productivity up to US$1,518,895, which is about 41.3% of the total rent in Iran, compared to the not adapted agriculture in all climate zones, based on the projected end-of-century analysis.

Keywords*: Climate Change, Agriculture, Adaptation, Spatial Analysis, C4 and C3 Crops.*

JEL Classification*: Q12, Q15, Q54, D21*

We would also like to thank conference participants at the 29th Annual Conference of the EAERE in Leuven for helpful discussions.

1 Introduction

Climate change is one of the most prevalent and debated topics globally. This phenomenon is largely attributed to the increasing levels of human-induced greenhouse gases, particularly atmospheric carbon dioxide (CO2), along with other trace chemicals (Adams et al., 1988). It is widely acknowledged that the economic impacts of global climate change exhibit significant disparities across different geographical regions. Moreover, these effects can vary significantly among various economic sectors, such as agriculture, which is inherently reliant on critical climatic factors like temperature and precipitation (Adams et al., 1988). Numerous studies conducted over the past decades have explored the effects of climate change on agriculture (e.g., Adams et al., 1988; Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Lang, 2007; Fezzi and Bateman, 2015; Kahsay and Hansen, 2016; Nguyen and Scrimgeour, 2022). The effect of climate change on agriculture could be both negative and positive based on the climate of locations (Mendelsohn et al., 1994).

Recently, there has been a significant increase in studies examining the implementation patterns of various adaptation measures in response to climate change (Di Falco and Veronesi, 2013; Massetti and Mendelsohn, 2018). As explained by Mendelsohn et al. (1994), the adverse effects of climate change on agriculture could be mitigated through the implementation of agricultural adaptations by farmers. Common adaptation strategies include changing crop varieties (Seo and Mendelsohn, 2008; Cui, 2020), irrigation investments (Taraz, 2017), transitioning from crop farming to livestock (Mu et al., 2013), adjusting planting times (Cui and Xie, 2022), use of agricultural inputs, such as pesticides and fertilizers (Jagnani et al., 2021), soil and water conservation practices (Tambet and Stopnitzky, 2021), land adjustments (Cui, 2020; Aragón et al., 2021) and embracing new technologies.

While many of these studies have focused on shifts between different crops (Seo and Mendelsohn, 2008; Cui, 2020), changes in livestock species (Seo et al., 2010), transitions between crop and livestock farming (Mu et al., 2013), and changes in planting dates (Cui and Xie, 2022), shifting among irrigation sources has been overlooked in the literature despite its important implications.

In essence, the detrimental impacts are more pronounced when farming practices remain static compared to scenarios where farmers adapt to the evolving climate conditions (Huang and Sim, 2020). Consequently, studies which examine the effect of climate change on agriculture can be categorized into two main groups. One group examines the effects of climate change on not adapted agriculture using the "production-function approach" and panel regressions (e.g., Deschênes and Greenstone, 2007; Massetti and Mendelsohn, 2011; Chen et al., 2016; Zhang et al., 2017), while the other group considers adaptations in their analysis using the "Ricardian approach" (e.g., Lippert et al., 2009; Mendelsohn and Dinar, 2009; Van Passel et al., 2017; Bozzola et al., 2018).

Although numerous studies have investigated the effects of climate change on agriculture, both with and without adaptations, there has been a lack of comprehensive documentation comparing these two cases to derive the value of adaptations. A recent study by Huang and Sim (2021) addresses this gap by estimating the benefits of adaptations. They suggest that the adaptations could mitigate approximately 65% of the damages from climate change on agriculture in the United States.

This paper first aims to analyze the farmers' decision-making processes regarding the potential adaptation strategies: shifting among water sources for irrigation and crop substitution. Our objective is to understand how farmers adapt to climate changes in Iran, as the country offers a detailed agricultural dataset that enables us to examine the adaptation strategies, particularly shifting among water sources for irrigation. Furthermore, Iran as a country in the Middle East which is subject to water crises and droughts makes it an important case study for examining the impacts of climate change on agriculture. As our second research question, this study emphasizes the importance of adaptations and seeks to quantify their value by estimating the differential impacts of climate change on agriculture with and without these adaptations, employing a methodology similar to that used by Huang and Sim (2021).

To empirically assess adaptations in switching across water sources for irrigation, we employ a fractional multinomial logit model (FM Logit). In this model, the dependent variables are the shares of each water source from three groups of sources used for irrigation. To categorize the irrigation sources, we divide them into three groups: (1) deep and semi-deep wells, (2) surface wells, and (3) rivers, canals (dams), and aqueducts, with the condition that the shares of these sources must add up to 1. Our empirical strategy relies on county-specific normal weather shock which is presumed to be orthogonal to unobserved determinants of the share of irrigation sources, so it offers a possible solution to the omitted variables bias problems (Deschênes and Greenstone, 2007). Moreover, we apply the FM Logit model for analyzing crop substitution between the crops with different levels of heat-resistance as a main adaptation practice by using the crops' planted area share.

We use a unique panel dataset covering the period from 2000 to 2021, with detailed variables reported for each crop in every county. This dataset provides information on the proportion of land irrigated by various water sources, such as deep wells, semi-deep wells, surface wells, aqueducts, canals (dams), and rivers, at the county level. Additionally, it includes data on the crops acreage, which allows us to calculate the acreage share of each crop within counties. Alongside agricultural data, we incorporate the climate data from satellite sources, which cover daily temperature, precipitation, soil moisture, wind speed, and extreme climate indicators dating back to 1980.

Next, we study the climate change impacts on agriculture both with and without adaptations by employing Ricardian approach. The traditional Ricardian model, developed by Mendelsohn et al. (1994), examines how farmland values vary in response to exogenous variables such as climate and soil properties. This model assumes that farmers, who cannot control these external factors, choose their outputs and inputs in a way that maximizes their profits. By conducting a cross-sectional analysis and regressing land values on these exogenous variables, the Ricardian method evaluates their impact on land value. This approach implicitly captures farmers' adaptive behaviors, as they adjust their inputs and outputs to local conditions. However, because these adjustments are not explicitly modeled, the method treats adaptation as a "black box". As a result, it does not reveal the specific changes farmers make to capitalize on their local conditions. Also, one of the preeminent shortcomings of the Ricardian approach is its vulnerability to omitted variables that are correlated with independent variables, leading to biased estimates (Deschênes and Greenstone, 2007; Massetti and Mendelsohn, 2011; Blanc and Reilly, 2017).[1] To address this problem, we use three panels of data from 2006, 2011, and 2016 to produce more reliable and stable estimates by including fixed effects.

To isolate the effect of adaptation, we ensure both scenarios use identical models and variables, capturing only the differences arising from adaptation implementation. We achieve this by applying different fixed effects, allowing us to assess the impact of long-term temperature and precipitation changes on agriculture, as well as the effects of short-term fluctuations.

By incorporating long-term climate data, we observe how agricultural productivity evolves when farmers adapt to climate change. Conversely, analyzing short-term fluctuations enables

[1] For instance, the availability of irrigation influences agricultural results and is linked to long-term climate patterns, as demonstrated in studies from the U.S. (Schlenker et al., 2005), China (Wang et al., 2009), and Africa (Kurukulasuriya and Mendelsohn, 2008).

us to estimate the impact in the absence of long-term adaptation, where farmers rely only on short-run adjustments that could be implemented regardless of climate change.

Our findings indicate that the use of deep and semi-deep wells for irrigation increases by approximately 1% to 3% with a 100℃ increase in the 20-year normal growing season degree-days (*NGDD*). In contrast, the proportion of irrigation from rivers, canals (dams), and aqueducts decreases by about 0.9% to 3.6%. Additionally, the share of surface wells rises by an average of 6.61% with a 100*mm* increase in 20-year normal growing season total precipitation (*NGTP*), while the share of other water sources declines. Furthermore, as temperature and precipitation increase, the planted acres proportion of maize, a C4 crop, increases relative to the alternative C3 crops such as wheat, alfalfa, and barley.

The results also show that agricultural adaptations result in increased productivity and enhanced heat tolerance of agriculture; however, there is a heterogeneity in benefit of adaptations among various climate zones. Also, the effects of climate change on agriculture are not uniform across all regions of Iran; they vary based on the initial climate conditions of each location. Our study reveals that colder counties in the northwestern regions, which constitute a substantial portion of Iran's planting acreage, experience positive effects from climate change regardless of adaptations. Conversely, many of counties in Iran, particularly the southern and central areas characterized by warm and hot climates, face reduced productivity even with or without adaptation practices while effects are less severe in the presence of adaptations.

This study makes a significant contribution to the adaptation literature by analyzing the shift in water sources for irrigation as a key adaptation strategy in response to climate change in a highly sensitive region subject to water crisis, a topic that has not been previously documented in the literature. The other key contribution of this paper, compared to the recent work by Malaekeh et al. (2024) in *Agricultural Economics*, which also focuses on the Iranian region, is that we differentiate between the effects of climate change with and without adaptation. In contrast, their study only examines the impact of random weather shocks without considering adaptation strategies. Furthermore, while Malaekeh et al. (2024) use agricultural profit as their dependent variable, we focus on farmland rent, which is considered as a more reliable proxy for productivity than metrics like net revenue per acre or farmland prices (Lippert et al., 2009; Fisher et al., 2012). This approach to measuring productivity helps to mitigate potential biases inherent in using net revenue per acre and farmland price as indicators.[2] Moreover, by focusing on the Middle East, a region highly sensitive to climate change, we underscore the importance and benefits of agricultural adaptations, thereby addressing a critical gap in the literature.

The remainder of the paper is structured as follows: Section 2, we detail the conceptual framework for crop yield that our study of adaptation strategies relies on. In Section 3, we outline the data sources and summary statistics. The empirical models and reduced forms are presented in Section 4. The findings of our analysis are presented in Section 5. Section 6 presents robustness check. Finally, Section 7 offers concluding remarks and suggest a couple of policy implications stemming from our results.

2 Conceptual Framework of Crop Yield

Consider a farmer who employs a variety of inputs $j = 1, \ldots, J$, including water, fertilizer, chemicals, labor, and machinery, to cultivate crops $i = 1, \ldots, I$. Let $X_{i,j}$ represent the amount of input j used for crop i per unit of land. The vector W_x refers to the prices of these inputs, while H_i stands for the fixed costs related to crop production, such as expenses for renting equipment for tasks like land preparation, planting, and harvesting. The vector $E(p_i)$ represents the expected prices of the crops at the end of the harvest. The total available land is denoted by l, and A_i represents the portion of land allocated to crop i.

Let $q_i\,(X_{i,j}, S_i, C, T)$ represent the yield of crop i, which is determined by the use of inputs $X_{i,j}$, the soil quality of the land dedicated to crop i (S_i), the climate conditions (C), and technological advancements driven by research and development (T). The profit from producing crop i is denoted by π_i. The representative farmer's problem of maximizing profit can be formally expressed as follows:

$$\max_{X_{i,j},\, A_i} \sum_{i=1}^{I} \pi_i = \sum_{i=1}^{I} E(p_i).q_i.A_i - \sum_{i=1}^{I} W_x.X_{i,j}.A_i - \sum_{i=1}^{I} H_i$$

[2] Using land rent instead of farmland prices offers the benefit of avoiding certain factors that heavily distort farmland values, particularly in densely populated areas. For instance, the inflated prices of farmland that might be converted into building land in the near future are unrelated to actual agricultural productivity. Thus, farmland purchase prices often reflect this option value. Moreover, the amount farmers decide to store or sell is factored into the error term in profit regressions. This error is closely tied to yield shocks and, therefore, correlated with weather, introducing endogeneity bias. In years with favorable weather and positive shocks, more is stored and less is sold, while in years with adverse weather, inventories are depleted. This bias tends to push results toward zero.

$$s.t. \quad \sum_{i=1}^{I} A_i \leq l$$

Assuming that interior solutions exist for all decision variables, the optimal levels of input use ($X_{i,j}$) and planted area (A_i), can be determined using the first-order conditions for optimality. The optimal input use for x can be written as:

$$X^{*}_{i,j} = X\,(E(p_i),\, W_x,\, S_i,\, C,\, T)$$

By substituting this expression into the yield function, it follows that crop yield can be represented as a function of expected crop prices, input costs, soil quality, climate factors, and technological advancements:

$$q_i = q_i\,(E(p_i),\, W_x,\, S_i,\, C,\, T)$$

Farmers can implement adaptive measures to lessen the negative impacts of climate change on crop yields. For instance, they might modify their production techniques, switch between irrigation sources such as ground or surface irrigation, or invest in new technologies to conserve irrigation water. These actions help to mitigate the external effects of climate change on agricultural productivity.

3 Data and Summary Statistics

This research utilizes an unbalanced panel data from 2000 to 2021 covering 419 counties across Iran to capture the country's climate heterogeneity. The dataset is compiled from diverse sources, including the National Annual Agricultural Report, satellite-derived climatic and geographic data, National Population and Housing Census, Household Expenditures and Income Surveys. The datasets are described in the following.

National Annual Agricultural Report: Covering period from 2000 to 2021 (except for 2012 and 2014), this dataset comprises detailed information on inputs quantity, planted area, the amount of area irrigated by water sources, agricultural operational expenses, and farmland rent across counties in Iran. The data is categorized by crop, encompassing 19 major crops that collectively represent approximately 95% of all crops cultivated in comparison to the annual agriculture survey (Ministry of Agriculture Annual Survey)[3] which reports all crops' exact planted area and production. We use the latter data for examination of crop substitution adaptation, because it has more exact reports for crops' acreage. The agriculture in Iran is mainly focused on producing grains such as wheat, maize, and barley.

Table 1 presents the average total planted acres of all crops and share of each crop in Iran from 2000 to 2021. In crop substitution analysis (Section 4.2), we focus on the four major crops, including wheat, barley, alfalfa, and maize, which accounts for about 86% of the total planted acres from 2000 to 2021. Among these four crops, maize is categorized as a C4 crop, while the other crops are known as C3 crops which means that maize is more heat-tolerant compared to wheat, barley, and alfalfa.[4]

[Insert Table 1 About Here]

The water sources for irrigation in the data that we used for our analysis in Section 4.1 include deep wells, which typically exceed 100 meters in depth to access water from deep aquifers; semi-deep wells, ranging from 30 to 100 meters, tapping mid-level aquifers; and surface wells, which are shallow, usually less than 30 meters deep, drawing water from near-surface aquifers or water tables. Together, wells account for more than 80% of the water used for irrigation in Iranian agriculture. Other sources include aqueducts, canals (dams), and rivers. Among these sources, semi-deep well has the highest average share for irrigating in Iran with 45.17%, while the least utilized source for irrigation is river with 4.04% (see Table 2).

[Insert Table 2 About Here]

Additionally, Figure 1 depicts the trends in the utilization of irrigation sources in Iran from 2000 to 2021. Overall, there is no clear trend in the usage of all sources combined. However, the area irrigated using semi-deep wells saw a significant increase from 2008 to 2015, before declining back to its 2000 level. Other sources have remained relatively stable with only minor fluctuations. Notably, the use of canals (dams) had become more utilized and situated higher than that of aqueducts and rivers after 2010.

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[3] https://en.maj.ir/

[4] C3 crops follow the C3 photosynthetic pathway, where the first product of carbon fixation is a three-carbon compound (3-phosphoglycerate). These crops, such as wheat, rice, and soybeans, thrive in cooler, wetter environments. C4 crops, on the other hand, utilize the C4 photosynthetic pathway, producing a four-carbon compound (oxaloacetate) in the initial steps of carbon fixation. This pathway is more efficient under high temperatures and intense sunlight, making C4 crops like maize, sugarcane, and sorghum well-suited for hot, dry environments (Sage & Monson, 1998; Taiz et al., 2015).

[Insert Figure 1 About Here]

To gain a better understanding of the distribution of irrigation sources across Iran, Figure 2 displays a map showing the average acreage irrigated by each source at the county level. It is evident that the utilization of each source is concentrated in specific regions. For instance, farmers along the Zagros mountain range, where river density is relatively higher than other regions in Iran, tend to use river water for irrigation more frequently than other parts of Iran. Aqueducts are predominantly used in the eastern regions, particularly from the central to the eastern areas, reflecting their deep historical roots in these regions. Surface wells are most commonly used in the southern parts of the country, while deep wells and canals are highly utilized in certain counties in the western regions.

[Insert Figure 2 About Here]

Besides water sources data, we also focus on utilizing farmland rent data as the dependent variable in the Ricardian approach (Section 4.3). Opting for land rent, instead of farmland values, offers advantages by circumventing certain factors that can distort agricultural prices, particularly in densely populated regions. For instance, elevated agricultural prices in areas slated for potential conversion into non-agricultural use in the medium term are unrelated to genuine agricultural productivity (Lippert et al., 2009). Furthermore, this approach mitigates issue related to farmers' decisions regarding inventory storage, which often introduces measurement errors in profit regressions. This measurement error is intricately linked to yield shocks and consequently correlated with weather conditions, thereby introducing an endogeneity bias towards zero. This bias arises because produced crops storage tends to increase and sales decrease during favorable years with positive weather shocks, while inventories deplete in adverse years with negative weather shocks (Fisher et al., 2012).

Due to the unavailability of farmland rent data for some counties, our sample is restricted to 334 counties out of the total 419 counties. Summary statistic of farmland rent variable is presented in Table 3.

[Insert Table 3 About Here]

Historical Climate Data: To obtain the necessary atmospheric data such as temperature and precipitation, this study utilizes a dataset based on the hourly ECMWF ERA5 data at surface level and referred to as AgERA5 (Boogaard et al., 2020). Data were aggregated to daily time steps at the local time zone and corrected towards a finer topography at a 0.1° spatial resolution.

The correction to the 0.1° grid was realized by applying grid and variable-specific regression equations to the ERA5 dataset interpolated at 0.1° grid.

The equations were trained on ECMWF's operational high-resolution atmospheric model (HRES) at a 0.1° resolution. This way the data is tuned to the finer topography, finer land use pattern and finer land-sea delineation of the ECMWF HRES model. County-level climate measures are calculated as the simple averages of the climate cells within each county. Following the literature (Schlenker et al., 2006; Deschênes and Greenstone, 2007), we use AgERA5 to construct the standard county-level measures of climatic variables: Growing Season Degree-Days (*GDD*), and Growing Season Total Precipitation (*GTP*).

Additionally, we extract the land geographic characteristics such as wind speed, soil evaporation, groundwater runoff, and soil moisture from the NASA Global Land Data Assimilation System (Rodell et al., 2004). Due to the lack of soil characteristics data in Iran, we do not include some of the most common soil variables in the literature such as soil salinity, sand content, clay content, K-Factor, flood risk, permeability, and slope length in our research.

In our investigation, we employ Growing Season Degree-Days (*GDD*) and Growing Season Total Precipitation (*GTP*) as the principal climatic variables. The measure *GDD* quantifies the cumulative exposure to heat within the range of 8℃ to 32℃ during the growing season, extending from April to September. Specifically, on a day with a mean temperature denoted as $\overline{T}$, contributions to Degree-Days (*DD*) are assigned as follows: zero degree-days for $\overline{T}$ below 8℃, $\overline{T}$ - 8 degree-days for temperatures between 8℃ and 32℃, and 24 degree-days for temperatures above 32℃. Then, *GDD*8-32 is computed as the sum of daily degree-days throughout the growing season.

$$DD = \begin{cases} 0, & \overline{T} - 8 \\ \overline{T} - 8, & 8 \leq \overline{T} < 32 \\ 24, & \overline{T} \geq 32 \end{cases}$$

For precipitation, *GTP* represents the total precipitation in millimeters during the growing season. Additionally, we control for Growing Harmful Degree Days (*GHDD*) in our analysis, defined as the sum of degree days over 32℃, where 32℃ contributes zero *GHDD*. Figure 3 illustrates the distribution of growing season degree days and growing season precipitation across counties.[5]

[5] We verify the accuracy of this satellite-derived temperature and precipitation data by comparing it with meteorological station records.

[Insert Figure 3 About Here]

Since the effect of climate change varies among regions with different temperatures (Mendelsohn et al., 1994), it is insightful to understand the share of planted acreage across different climates in Iran to grasp the total effect of climate change. Figure 4 illustrates a histogram of the share of planted acreage and the cumulative share across temperature bins. As depicted in Figure 4, the average temperature is more than 22.5℃ among more than 50% of the counties.

[Insert Figure 4 About Here]

Additionally, we used variables such as top-layer soil moisture, groundwater runoff, soil evaporation, wind speed, the Simple Daily Intensity Index (*SDII*), and the Cold Spell Duration Index (*CSDI*) as our land characteristics variables. The Simple Daily Intensity Index (*SDII*) is defined as the average rainfall rate on "wet days" (Precipitation $\geq 1mm$), measured in mm/day and the Cold Spell Duration Index (*CSDI*) represents the annual count of days contributing to "cold spells", when the minimum temperature remains below 10th percentile. The summary statistics of climatic and geographical variables are provided in Table 4.

[Insert Table 4 About Here]

Climate Change Predictions: The primary emphasis of this study is on medium climate scenario projections, particularly those derived from the medium scenario RCP4.5 and SSP2-4.5 using the CESM2, ACCESS-CM2, CESM1-CAM5, NorESM2, AWI-CM-1-1-MR, CMCC-ESM2, and NESM3 models (please refer to Appendix 1). These models provide daily mean temperature and precipitation data spanning from 2006 to 2100, which we use to construct 30-year normal *GDD*8-32, *GHDD*, and *GTP* for each Iran's county in year 2100.

National Population and Housing Census: National population and housing censuses used to be conducted once a decade in Iran, as stipulated by the national legislation, in the years between 1956 and 2006. The first such census was undertaken by the Department of General Statistics in 1956; subsequent censuses were taken by the Statistical Centre of Iran (SCI) in 1966, 1976, 1986, 1996, and 2006. In 2007, the Cabinet adopted that the time interval for implementation of population and housing censuses be reduced to five years from 10 years, therefore, the next censuses were conducted in 2011 and 2016. By providing accurate statistics and information on the size, structure, and characteristics of Iran's population, this Census serves as an appropriate tool for the country's planners, policymakers, and officials to design and implement social, economic, and cultural programs. Furthermore, this census is considered as one of the fundamental activities in national statistical system due to provision of essential frameworks for implementation of sample surveys within the areas of population and household.[6] We merge this dataset in the years of 2006, 2011, and 2016 to the other datasets, thereby comprising a 3-period balanced panel data.

Household Expenditures and Income Surveys: Conducted annually on a national scale since 1984, this survey provides comprehensive insights into household expenses and incomes.[7] The data has been utilized in this study to ascertain the income per capita and expenditures per capita of each county for the years 2006, 2011, and 2016. Summary statistics of socio-economic variables are presented in Table 3.

4 Empirical Model

4.1 Shifting among Water Sources for Irrigation

To investigate the adaptation strategies adopted by farmers, specifically regarding the shift in water sources for irrigation and changes in crop choices in response to climate change, we employ a panel Fractional Multinomial Logit model (FM Logit). In our analysis of water source adaptation, we classify the sources into three categories based on their marginal depletion costs: (1) deep and semi-deep well, (2) surface well, and (3) river, canal (dam), and aqueduct. We calculate $Share_{it}$ as the proportion of each group's irrigated planting area relative to the total irrigated planting area.

The proportional use of each water source for irrigation falls between zero and one. Due to this constrained range, traditional estimation methods such as linear regression and general linear models are inappropriate (Ramalho et al., 2011). Instead, we adopt the estimation approach developed by Papke and Wooldridge (1996, 2008), who propose a quasi-maximum likelihood estimator (QMLE). This method provides a robust approach to estimate fractional response models without needing to transform boundary values arbitrarily (Ramalho et al., 2011).

Therefore, the conditional mean model for the share of water sources is defined as $E\left[ls_{ij}|x_i\right] = G_j(\beta, x_i)$, where ls_{ij} denotes the proportional share of the j_{th} water source in the i_{th} reporting

[6] https://amar.org.ir/population-and-housing-census
[7] https://amar.org.ir/cost-and-income

district. The parameters β are to be estimated, and x_i represents the explanatory variables, which include climate conditions, extreme events, and fixed effects. As recommended by Koch (2010), ensuring ls_{ij} stays within the unit interval [0,1] can be accomplished by using the Multinomial Logit functional form for $G_j(\beta, x_i)$. Thus, the conditional distribution of the share of water sources among M sources is given by:

$$E[ls_{ij}|x_i] = G_j(\beta, x_i) = \frac{exp(x_i\,\beta_j)}{\sum_{m=1}^{M} x_i\,\beta_m} \tag{1}$$

To ensure proper identification in the multinomial quasi-likelihood function, normalization is necessary for Equation (1) because not all β_j parameters can be individually identified (Mullahy and Robert, 2010). Therefore, $\beta_M = 0$ is used. The estimation function is then given by:

$$E[ls_{ij}|x_i] = \frac{exp(x_i\,\beta_j)}{1+\sum_{m=1}^{M-1} x_i\,\beta_m}, \quad j = 1,2, \ldots, M-1 \tag{2}$$

and

$$E[ls_{iM}|x_i] = \frac{1}{1+\sum_{m=1}^{M-1} exp(x_i\,\beta_m)} \tag{3}$$

Along with Equations (2) and (3), the conditional distribution of water source share also satisfies Equations (4) and (5) and incorporates Equations (6) and (7) for $j = 1, 2, \ldots, M$.

$$E[ls_{ij}|x_i] \in (0,1) \tag{4}$$

$$\sum_{j=1}^{M} E[ls_{ij}|x_i] = 1 \tag{5}$$

$$Pr(ls_{ij} = 0|x_i) \geq 0 \tag{6}$$

$$Pr(ls_{ij} = 1|x_i) \geq 0 \tag{7}$$

Assuming the validity of the functional form of the conditional mean model, and based on the work of Gourieroux et al. (1984) and Mullahy and Robert (2010), we estimate the quasi-maximum likelihood function in a simultaneous and efficient manner.

Based on the estimation results, we focus on analyzing the average partial effects, which evaluate how changes in an explanatory variable affect the distribution of water sources used for irrigation, as discussed by Mullahy and Robert (2010). These partial effects are derived from Equation (1), with the method depending on whether the variable in question is discrete or continuous. For a continuous variable x_k, the effect of x_{ik} on ls_{ij} is obtained by computing the derivative of the expected conditional mean.

$$\frac{\partial E[ls_{ij}|x_i]}{\partial x_{ik}} = \beta_{jk}\left(G_j - G_j^2\right) - \sum_{m=1}^{M-1} G_{mk}\,\beta_{mk} \tag{8}$$

In a similar vein, if x_k is a binary variable, the partial effect is determined by the ratio of the differences in the expected conditional mean associated with the change in x_{ik}.

$$\Delta E[ls_{ij}|x_i] = G_j\,(\beta, x_{i,k=1}) - G_j(\beta, x_{i,k=0}) \tag{9}$$

Using Equations (8) and (9), we can calculate the average partial effects after estimation, with their corresponding standard errors computed using delta methods.

Our empirical approach leverages variations in county-specific normal weather shocks, which are assumed to be exogenous and independent of unobserved factors affecting the dependent variables. This assumption helps addressing potential omitted variable bias issue. We construct a regression model that incorporates variables for temperature, precipitation, two indicators of extreme climate events, and fixed effects. The regression is:

$$E[ls_{iM}|x_i] = \frac{1}{1+\sum_{m=1}^{M-1}\exp(\beta_{1m}NGDD8\text{-}32_{it} + \beta_{2m}NGTP_{it}+\beta_{3m}SDII_{it} + \beta_{4m}CSDI_{it} + \alpha_i + \alpha_t + \epsilon_{it})} \tag{10}$$

where $NGDD8\text{-}32_{it}$ is the 20-year normal growing season degree-days for county i and year t; $NGTP_{it}$ is the 20-year normal growing season total precipitation; $SDII_{it}$ is the simple daily intensity index; $CSDI_{it}$ represents the cold spell duration index; α_i and α_t represent county and year fixed effects, respectively; and ε_{it} is considered as *i.i.d* error term.

4.2 Crop Substitution

In addition to investigating changes in water source use for irrigation, we also aim to explore how farmers adjust their crop choices in response to climate change. To empirically assess the effects of climate change on crop substitution while keeping the total acreage constant, we focus on four key crops: wheat, alfalfa, barley, and maize. These crops collectively represent approximately 86% of the total cropland area in Iran.

We specifically examine the substitution between C4 and C3 crops, given their differing heat resistance levels, with C4 crops being more heat tolerant. Among the crops considered, maize is the sole C4 crop, while the others are C3 crops. Our analysis investigates how climate change influences the acreage of maize (a C4 crop) compared to that of another major crop (a C3 crop).

The goal is to understand how climate change has impacted the comparative advantage of maize. We utilize the fractional logit response model for this analysis:

$$E[ls_{iM}|x_i] = \frac{1}{1+\sum_{m=1}^{M-1} \exp(\beta_{1m} NGDD8\text{-}32_{it} + \beta_{2m} NGTP_{it} + \beta_{3m} SDII_{it} + \beta_{4m} CSDI_{it} + \tau_t + \alpha_i + \alpha_t + \epsilon_{it})} \qquad (11)$$

Where, ls_{iM} represents the planted acreage of the M_{th} crop in the pair groups comprised from maize and alternative crop in the i_{th} reporting district. NGDD8-32$_{it}$ denotes the 20-year normal growing season degree-days for county i in year t; NGTP$_{it}$ indicates the 20-year normal growing season total precipitation; SDII$_{it}$ is the simple daily intensity index; and CSDI$_{it}$ stands for the cold spell duration index. α_i and αt denote county and year fixed effects, respectively, while ϵ_{it} represents the *i.i.d* error term. The term τ_t controls for the trend effects such as technological improvements. The identification relies on the assumption that, after accounting for county fixed effects and national-level shocks, the relative acreage of maize compared to the alternative crop would have changed similarly if the county had experienced the same change in climate normals as other counties.

The dependent variable is a ratio where the numerator is the planted acreage of maize and the denominator is the sum of planted acres of maize and the alternative crop. Including maize acreage in the denominator ensures that the ratio remains between zero and one. The estimated marginal effects reflect changes in the share of maize, with the share of the alternative crop changing in the opposite direction, thus maintaining a zero total change in acreage. Each regression focuses on one alternative crop to analyze the relative acreage of maize with respect to that specific crop.

Similar to the empirical approach described in Section 4.1, our analysis utilizes variations in county-specific normal weather, due to including county and year fixed effects, which are assumed to be exogenous and independent of unobserved factors influencing the dependent variables. This assumption is intended to mitigate potential issue related to the omitted variable bias. The identification assumption rests on the underlying assumption that a country's relative acres of maize with respect to the alternative crop would have changed in the similar way, had the county experienced the same change in climate normal as in other counties.

4.3 Climate Change Impact on Farmland Rent

After evaluating how farmers adapt to climate change over the long term, it is crucial to assess the impact of climate change on agricultural productivity, considering both scenarios: with and without adaptation. In this section, we outline the methodology used to differentiate between adapted and not adapted agriculture.

4.3.1 Fixed-Effects Specification

In this analysis, we employ a panel data technique to provide an assessment of the economic benefits associated with agricultural adaptation against climate change. We focus on a hypothetical climatic variable (w_{it}) for a given county (i) in a specific year (t), encompassing various climate-related factors such as temperature, precipitation, and growing season degree-days. This variable is decomposed into three distinct components:

$$w_{it} = T_i + d_t + \epsilon_{it}$$

Here, T_i denotes the long-term average weather outcome specific to county i, exhibiting variability across different counties. d_t represents the inter-annual weather fluctuation in year t, common across all counties but varying across years and ε_{it} captures the county-specific weather shock. By exploiting permanent inter-county temperature variation (T_i) or common inter-annual temperature fluctuations (d_t), the impact of warming with or without adaptation could be estimated.

Table 5 illustrates the transformation of the generic weather variable under different fixed effects in a balanced panel with two years and two counties. Panel A breaks down each weather observation into three components, namely the county's climate (T_i), inter-annual weather fluctuations (d_t), and county-specific weather shocks (ε_{it}). Then, panel B demonstrates the impact of introducing time fixed effects, wherein the model adjusts by subtracting the yearly weather realizations of each county from the average weather outcome across counties in the same year. Consequently, time fixed effects filter out the common inter-annual weather fluctuation (d_t), leaving only the county-specific climate (T_i) and weather shocks (ε_{it}) in the weather variation. On the other side, panel C explores the incorporation of county fixed effects, transforming the model by subtracting the within-county mean from each county. This adjustment isolates the common inter-annual weather fluctuation (d_t) and county-specific weather shocks (ε_{it}). If the variability in the latter is minimal, the weather variable's impact is primarily identified through inter-annual weather fluctuations. Lastly, panel D showcases the inclusion of both county and year fixed effects, effectively eliminating both cross-sectional climate differences (T_i) and common inter-annual weather fluctuations (d_t). Consequently, the climate change impact is discerned through the variation in county-specific weather shocks (ε_{it}).

[Insert Table 5 About Here]

Our method for estimating the adaptive value relies on the assumption that the weather variable, denoted as $w_{it} = T_i + d_t + \varepsilon_{it}$, can be adequately approximated by $w_{it} \approx T_i + d_t$. This approximation is deemed reasonable under the condition that the county-specific weather shock (ε_{it}) is relatively small. To assess the validity of this assumption, we provide evidence by examining a panel of county-level temperature and precipitation data spanning 1980-2023 for 334 counties in Iran.

Table 6 presents the absolute growing season average temperature variation exceeding specific thresholds (0.4℃, 0.6℃, 0.8℃, 1℃) and growing season total precipitations variation exceeding specific thresholds (40*mm*, 80*mm*, 120*mm*, 160*mm*) with respect to the county-specific temperature shock (ε_{it}). This shock is derived by employing county and province-by-year fixed effects, effectively removing the long-term county-specific temperature component (T_i) and the common inter-annual temperature fluctuation (d_t) within each state (refer to Panel D of Table 5 for clarification). The purpose is to evaluate if our assumption regarding the small variation in county-specific shocks holds true.

[Insert Table 6 About Here]

The findings in Table 6 indicate that the variation associated with the county-specific weather shock (ε_{it}) is minimal. Notably, almost no counties exhibit an absolute value of ε_{it} larger than 1℃, with over 90% of counties having an absolute value smaller than 0.4℃. In contrast, evidence suggests that the variation in the long-term temperature component (T_i) surpasses that of the county-specific temperature shock (ε_{it}). For instance, using province-by-year fixed effects eliminates the inter-annual fluctuation common in a state (d_t), leaving a residual temperature variation mainly driven by the long-term component (T_i) and the county-specific shock (ε_{it}) (see Panel B of Table 5). Table 6 indicates that this residual component exceeds 0.8℃ for approximately 75.04% of counties and 1℃ for 69.95% of counties.

Furthermore, there is evidence that the inter-annual temperature fluctuation (d_t) exhibits greater variation than the county-specific temperature shock (ε_{it}). Using county fixed effects to eliminate the long-term temperature component (T_i) reveals a residual component consisting of the common inter-annual fluctuation (d_t) and the county-specific shock (ε_{it}) (see Panel C of Table 5). Table 6 indicates that this residual component exceeds 0.6℃ for nearly 54.22% of counties and 1℃ for almost 28.52% of counties. Hence, there is substantial evidence suggesting that the common inter-annual temperature fluctuation is notably larger compared to the county-specific temperature shock. As such, we may reasonably approximate w_{it} by:

$$w_{it} = T_i + d_t \tag{12}$$

This suggests that w_{it} is primarily influenced by two factors: long-term cross-sectional weather variations and short-term (common) year-to-year weather fluctuations. For the sake of illustration, let w_{it} represent temperature. We can assess the impact of warming (i.e., an increase in w_{it}) on farmland rent by leveraging the variability in T_i or in d_t to induce alterations in w_{it}. Regrettably, we are unable to discern a comparable distinction in the residual precipitation variation across various fixed effects specifications, as was observed in the case of temperature. This lack of observable differentiation suggests that estimations related to precipitation effects may not meet our expectations or satisfaction.

4.3.2 Reduced Forms

In this subsection, we explain the two panel models which are the same in every regard except for their fixed effects specifications, enabling us to exploit either T_i (d_t) by eliminating the other variation to estimate the effect of climate change on the adapted (not adapted) agriculture.

We utilize spatial models because agricultural productivity and farmland rents in neighboring regions tend to be influenced by similar climatic, economic, and environmental factors. For instance, neighboring counties often share similar soil types, weather patterns, market access, and agricultural practices. Additionally, climate change effects are not isolated but tend to spill over across regions, leading to interconnected responses in agricultural outcomes. Thus, failing to account for this spatial dependence would make results inefficient and/or inconsistent (Polski, 2004).

Hence, we develop our reduced forms controlling for spatial dependence using a spatial weight matrix that contains w_{ij} elements where w_{ij} is a spatial weight defined as the inverse of the squared distance between counties i and j, calculated as the distance between the county centroids as shown in Figure 5. These elements are finite, non-stochastic, non-negative and below 1 (W is row-standardized). By using w_{ij} as weights, the relationship between the dependent variables of counties i and j would be weaker the further apart these counties are.

Due to using the squared distance, we address the issue of non-linear spatial effect which means that as a county is located further, its effect would be weaker exponentially.

[Insert Figure 5 About Here]

To estimate the potential value of adaptation, we will employ two panel models. Since, in climate change studies, there is evidence that agricultural profits and land values across regions are spatially related Schlenker et al. (2006), in both panel models, once we include only the spatial auto-regression term ($\lambda = 0$) which we call this model as Spatial Auto-Regressive Model (SAR) and once only the spatial error term ($\rho = 0$) which we call this model as Spatial Error Model (SEM). The first panel model, where the coefficients on the climatic variables are estimated by exploiting permanent inter-country climate variation, is shown in Equation (13):

$$\begin{gathered} r_{it} = \rho \sum_{j \in N} w_{ij}\, r_{jt} + \sum_{l \in L} E_{itl}\, \alpha_l + \sum_{m \in M} S_{itm}\, \beta_m + \gamma_{pt} + u_{it}, \\ u_{it} = \lambda \sum_{j \in N} w_{ij}\, u_{jt} + \epsilon_{it}\,, \qquad \epsilon \sim N(0,\sigma^2) \end{gathered} \tag{13}$$

where r_{it} denotes farmland rent per hectare in county i and year t; N denotes the set of the n counties; E_{itl} is the l_{th} environmental variable; L denotes the set of the environmental variables; S_{itm} is the m_{th} socio-economic variables that we use as a control; M denotes the set of the socio-economic variables; γ_{pt} is the province-by-year dummy that is used to filter out year-to-year weather and other fluctuations that are common across counties within each province, and also to capture all province-level determinants of farmland rent whether or not they are observed or unobserved, time-varying or time-invariant; and u_{it} is spatial dependent error term; ε_{it} is an *i.i.d* distributed error term.

The second panel model, where coefficients on the climatic variables are estimated by exploiting inter-annual weather fluctuations, is shown in Equation (14):

$$\begin{gathered} r_{it} = \rho \sum_{j \in N} w_{ij}\, r_{jt} + \sum_{l \in L} E_{itl}\, \alpha_l + \sum_{m \in M} S_{itm}\, \beta_m + \tau_i + \theta q_t + u_{it}, \\ u_{it} = \lambda \sum_{j \in N} w_{ij}\, u_{jt} + \epsilon_{it}\,, \qquad \epsilon \sim N(0,\sigma^2) \end{gathered} \tag{14}$$

Notice that Equations (13) and (14) differ only in their fixed effects structure. Here, county fixed effects (τ_i) are included in Equation (14) but not in Equation (13), and province-by-year fixed effects (γ_{pt}) are included in equation (13) but not in Equation (14). Besides fixed effects, Equation (14) includes a time trend (q_t) to partial out trend effects, such as that of technological improvements, from the effect of inter-annual weather fluctuations, and also the effects of adaptation to climate trends that farmers may undertake.

By partialling out province-by-year fixed effects in Equation (13), the effects of the climatic variables on farmland rent in this model will be identified by the variables' within-state permanent inter-county variation. Therefore, as discussed (Mendelsohn et al., 1994), the predicted climate change impact based on Equation (13) would incorporate adaptation behaviors. By contrast, by partialling out the inter-county permanent differences in Equation (14) similar to the model in Deschênes and Greenstone (2007), the effects of the climatic variables in this model will be identified by the variables' inter-annual fluctuations. Since inter-annual fluctuations are transitory and farmers do not permanently adapt to them, the climatic impact estimate based on Equation (14) does not incorporate adaptation behaviors, while it allows for the implementation of short-run adaptations (which are not our interest) that could be adopted regardless of whether climate change occurs.

Our model in Equation (13) contains an underlying assumption that after removing the province-by-year fixed effects, the remaining within-province inter-county climate differences are close enough to the inter-county long-run climate differences. We provide evidence (Figure 6) for this by plotting county level 30-year average degree-days against the remaining yearly degree-days after removing province-year means from each county and adding the long-term state average degree-days.

[Insert Figure 6 About Here]

As presented in the left panel of Figure 6, we find that the remaining variation in degree-days (taking 2016 as an example), after partialling out the province-by-year fixed effects, are nearly identical to the 30-year average degree-days. By contrast, in the right panel of Figure 6, the 30-year county-level average degree-days are quite different to the "unpartialled out" degree-days. The similarity between the partialled out variation in degree-days and the long-run (30-year average) degree-days in the left panel provides evidence that the province-by-year fixed effects have helped to remove inter-annual weather fluctuations, leaving the long-run variation as the remainder. By the same token, the dissimilarity between the "unpartialled out" degree-days and the long-term data suggests that without using province-by-year fixed effects, the former would contain inter-annual weather fluctuations.

5 Results

5.1 Shifting Among Water Sources for Irrigation

From the results of the FM Logit regression, we obtain the marginal effect of a change in *NGDD*8-32 and *NGTP* on the share of each water source group at different average temperatures and precipitations to observe how much a water source group's share would change in different regions. This is because different regions have different marginal costs of water depletion, which affects farmers' decision-making on how much water to extract. The main disparity in the marginal cost of depletion arises from variations in underground water levels, requiring farmers to drill deeper and use more powerful water pumps. Additionally, these sources necessitate advanced drilling technology, more labor, and more time, significantly increasing the construction costs.

It is noteworthy that in FM Logit, the sum of marginal effects on shares is equal to 0, meaning that an increase in one share may lead to a decrease in other shares.

[Insert Figure 7 About Here]

We begin our analysis with deep and semi-deep wells, which are the most commonly used water sources in Iran. Figure 7 illustrates that the marginal effect of a 100℃ increase in *NGDD*8-32 on the share of deep and semi-deep wells is positive across all regions. As shown in Figure 7, there is a concave relationship and the effects range from about 1% to 3% at different temperatures, with a maximum value of 2.93% in regions with an average *NGDD*8-32 of 1,900℃ (please see Appendix 2 for more details). This disparity in effects is closely related to the marginal cost of water depletion from wells. In warmer regions of Iran, farmers need to dig deeper due to lower underground water levels compared to colder regions. Moreover, farmers in colder regions benefit from more rainfall, which adequately meets the water needs of crops. Consequently, despite having a greater capacity of underground water, farmers in colder regions have less incentive to deplete water compared to those in warmer regions with less rainfall and lower underground water level.

Additionally, the marginal effects on the share of surface wells show an increasing trend, ranging from 0.05% to 0.68% for regions with *NGDD*8-32 less than 3,400℃, while the share of surface wells decreases for regions with warmer temperatures. This is likely due to the higher availability of surface wells in regions with moderate temperatures, whereas in warmer regions, the reduced water levels make surface wells less viable.

Furthermore, the share of river, canal (dam), and aqueduct decreases significantly, ranging from 0.73% to 3.62%, with a 100℃ increase in *NGDD*8-32 across all regions with varying temperatures. This decline can be attributed to the fact that these water sources are not consistently available throughout the growing season, whereas wells can provide a more reliable supply of water whenever the crops need irrigation.

We now delve into the marginal effects of *NGTP* on the usage share of water sources in different regions with varying precipitation levels. As shown in Figure 7, the marginal effects of *NGTP* are mostly insignificant at different precipitation levels (please see Appendix 3 for details). As illustrated in Figure 7, the shares of deep and semi-deep wells, as well as rivers, canals (dam), and aqueducts, mainly decrease, while the share of surface wells increases across all regions.

The increase in the share of surface well for irrigation ranges from 2.62% to 8.05% at *NGTP* of 400*mm*. This increase in all regions is primarily because surface wells typically draw water from aquifers that are closer to the ground surface and are directly recharged by precipitation and surface water runoff, in contrast to deep and semi-deep wells, which are replenished over longer terms. Therefore, during periods of high rainfall, the increased amount of water infiltrates the ground and replenishes the shallow aquifers, raising the water level in surface wells. Consequently, as these sources have lower marginal and construction costs, farmers may have more incentive to use surface wells instead of deep and semi-deep wells, which have higher costs and whose water levels do not change significantly with short-term rainfall.

Additionally, farmers may prefer to use surface wells over rivers, canals (dam), and aqueducts, as the latter are less available during the growing season, despite being recharged by increased rainfall. Consequently, the more consistent availability and lower costs associated with surface wells make them a more attractive option for farmers looking to adapt when precipitation increase in all regions with varying precipitation levels.

5.2 Crop Substitution

In this section, we will discuss the results of crop substitution between pairs of crops: maize versus wheat, maize versus alfalfa, and maize versus barley. We anticipate that as temperatures rise due to climate change, the proportion of land dedicated to maize will increase. This expectation is based on the classification of maize as a C4 crop, which exhibits greater heat resistance compared to C3 crops like wheat, alfalfa, and barley.

We present the marginal effects of climate change on the proportion of land allocated to maize across varying temperatures and precipitation levels, aiming to capture the diversity of these effects. Utilizing the FM Logit model, we ensure that changes in the shares of alternative crops are inversely related to the changes in maize acreage, thereby maintaining the total acreage fixed.

[Insert Figure 8 About Here]

Figure 8 shows the marginal effects of a 100℃ change in *NGDD*8-32 on the share of maize planted acres when we take an alternative crop into account (please see Appendix 4 for details). The results demonstrate a nonlinear relationship between *NGDD*8-32 and the proportion of maize acreage compared to wheat. In regions with lower average temperatures (*NGDD*8-32 values below 1,900℃), the increase in maize acreage relative to wheat is minimal, remaining below 1%. However, this change is statistically insignificant, indicating that under cooler conditions, maize does not have a substantial comparative advantage over wheat. As temperature rises, the proportion of maize acreage begins to increase significantly relative to wheat, reaching a peak of 4.24% at an *NGDD*8-32 value of 3,100℃. This suggests that maize becomes more competitive compared to wheat in warmer climates. The relationship then levels off and even shows a slight decline in regions with the highest average temperatures (*NGDD*8-32 values above 3,100℃), although the share of maize planted continues to rise. This could imply that while maize is better suited to warmer conditions than wheat, other factors–such as water availability or specific soil conditions–may restrict its further expansion in extremely hot environments.

Additionally, Figure 8 illustrates the marginal effects of a 100℃ increase in *NGDD*8-32 on the share of maize planted acres relative to alfalfa. Similar to the maize-wheat comparison, the relationship between *NGDD*8-32 and maize share is nonlinear. In regions with lower average temperatures (*NGDD*8-32 below 1,300℃), the change in maize acreage relative to alfalfa is minimal and statistically insignificant as depicted. However, as temperature increases, the comparative advantage of maize over alfalfa becomes increasing until *NGDD*8-32 equal to 2,800℃ where the change in maize share is 4.21%. This indicates a clear shift towards maize cultivation in warmer regions. As same as maize-wheat comparison, the positive change in maize share levels down in the temperatures higher than 2,800℃. Moreover, when we take barley as the alternative crop into account, we do not observe a concave relationship similar to the cases of wheat and alfalfa. The marginal effects of climate change on maize planted acres share is approximately linear and increasing in temperature ranging from 0.30% at *NGDD*8-32 of 700 to 1.55% at 4,300℃, while the majority of effects is insignificant.

The findings align with the expected behavior of C4 crops like maize. As temperature rises, maize acreage increases, while the acreage of alternative C3 crops such as wheat, alfalfa, and barley decreases. This suggests that maize becomes more competitive compared to these other crops in warmer conditions.

We now examine the marginal effects of a 100*mm* increase in growing season total precipitation (*NGTP*) on the share of maize acreage, considering alternative crops. Across all alternative crop cases, Figure 8 exhibit that the increase in maize acreage share decreases as precipitation rises (please see Appendix 5 for details). This indicates that in areas with low precipitation levels, maize has a substantial comparative advantage over the alternative crops. However, this comparative advantage diminishes in regions with high rainfall, although it remains positive overall. The average marginal effects of a 100*mm* increase in *NGTP* on the maize acreage are 12.76%, 24.26%, and 13.93% for the alternative crops of wheat, alfalfa, and barley, respectively. These results are in line with our expectations as C4 crops are more water efficient relative to C3 crops, which implies their comparative advantage in low precipitation regions.

Overall, these results show that Iranian farmers adapt themselves to climate change through measures of shifting among irrigation sources and switching to more heat tolerant and water efficient crops. These adaptations help them to stand against the adverse effects of climate change and to maintain their land productivity and profits.

5.3 Climate Change Impact on Farmland Rent

Now, we aim to obtain the effectiveness of the major adaptations that farmers utilize to offset the consequences of climate change on the agriculture. Hence, we continue to understand the effect of climate change on agriculture in two scenarios of adapted and not adapted farming in order to compare them as an approach for evaluating the benefits of adaptations.

To follow our methodology as described in Section 4.3, we firstly perform diagnostics for spatial dependence using Lagrange Multiplier (LM) tests as described by Anselin (1988). This involves initially assessing the significance of the LM-lag and LM-error tests to determine if there is spatial dependence between the dependent variable and the error terms. If these tests show statistical significance, we proceed with robust tests and choose the model with the lower p-value. The results presented in Table 7 demonstrate significant spatial dependence between the dependent variables (farmland rents) and the error terms across counties in both with and without adaptation cases. Notably, the spatial dependence among the dependent variables is stronger.

[Insert Table 7 About Here]

Based on the established presence of spatial dependence, we proceed to our reduced form analysis. We utilize Equations (13) and (14) to estimate the influence of four climatic variables (*GDD*8-32, *GDD*8-32 *squared*, *GTP*, and *GTP squared*) on farmland rent while controlling for spatial dependence and socio-economic and land control variables. Then, using these estimated equations and climate change projections from climate models, we predict the end-of-this-century impacts of climate change under scenarios with and without adaptation. The benefits of adaptations are quantified by the difference between these two end-of-this-century impact predictions derived from Equations (13) and (14).

Columns (1) and (2) in Table 8 (with a detailed regression table provided in Appendix 6) represent the Spatial Auto-Regressive Model (SAR), whereas columns (3) and (4) illustrate the Spatial Error Model (SEM). Notably, the spatial parameter (ρ) in the SAR yields significant results across both models, irrespective of whether adaptation is included. This indicates a positive spatial correlation and underscores the presence of spatial dependence among counties, implying that the farmland rent in one county is influenced by prices in neighboring counties. This finding underscores the necessity of incorporating spatial effects into our models. On the other hand, the spatial term (λ) in the SEM differs in sign between the models with adaptation and without adaptation, yet remains significant in both cases.

[Insert Table 8 About Here]

Table 8 reveals that, in both the Spatial Auto-Regressive (SAR) and Spatial Error (SEM) models, only the Growing Season Degree-Days (*GDD*) and its quadratic form emerge as significant temperature indicators, regardless of whether adaptation is considered. Additionally, the response of farmland rent to *GDD* displays as an inverted U-shape, consistent with the existing literature.

Quantitatively, there is a noticeable difference between the estimated coefficients of Equation 13 (with adaptation) and Equation 14 (without adaptation). For instance, the optimal *GDD* that maximizes farmland rent is 3,062 degree-days when accounting for adaptation, compared to 2,495 degree-days without adaptation in the SAR. Similarly, in the SEM, the optimal *GDD* for maximizing farmland rent is 2,987 degree-days with adaptation, versus 2,554 degree-days without adaptation. These findings indicate that agricultural production is likely to exhibit increased heat tolerance on average when adaptations practices are implemented.

To visually depict the disparities in the estimated effects between models with and without adaptations, we present the correlation between degree-days and land rent for the SAR in Figure 9. This figure controls for other variables in the regression and utilizes the growing season degree days coefficients derived from Table 8. It is essential to note that these relationships are plotted based on the point estimates of the coefficients for both the linear and quadratic terms of degree-days, so caution is warranted when interpreting the curves. We observe that the optimal degree-days estimated from models incorporating adaptations (Column 2) differs from those estimated by model that does not consider adaptations (Column 1). This suggests that neglecting adaptation could result in larger damages (or lower benefits) associated with higher temperatures. Appendix 7 illustrates the case for the SEM.

[Insert Figure 9 About Here]

Now, we proceed to examine the spatial spillover effects in our context. While the Spatial Error Model (SEM) exclusively captures direct marginal impacts, calculated as the first derivative of a coefficient at the sample mean, the estimated coefficients of the Spatial Auto-Regressive model (SAR) act as intermediate variables for determining these marginal impacts. This implies that a change in an independent variable within one county can influence the dependent variable across all regions due to the presence of spatial dependence and the varying distances among counties. Table 9 presents the average direct, indirect, and total marginal impacts of growing season degree days on farmland rent per hectare in the long-run equilibrium.

[Insert Table 9 About Here]

The average marginal impacts shown in Table 9 indicate that models incorporating adaptation yield more substantial benefits compared to those without adaptation. Specifically, the increase in farmland rent is greater with adaptation in both the Spatial Auto-Regressive and Spatial Error models. This suggests that adaptation allows Iran's agriculture to derive increased benefits from warming, on average, with a small change in growing season degree days. This advantage is primarily due to the fact that most of the cultivated acreage is located in the colder regions of Iran, particularly in the northwestern counties.

Before evaluating the end-of-this-century predictions, we select the best model for assessing the impact by comparing the SAR and SEM based on their alignment with the data. This evaluation is conducted using Akaike's and Schwarz's Bayesian information criteria, which indicate that models with lower AIC and BIC values are more favorable. Analyzing the findings presented in Table 8, we determine that the SAR, particularly with spatial lag, is preferred for both scenarios with and without adaptation. Consequently, we opt to employ the SAR exclusively for our future predictions.

Initially, to shed light on the non-linear warming effect, we illustrate the impact of a uniform 100°C *GDD* increase warming scenario on farmland rent for both cases with and without adaptation on the map. Figure 10 depict that warmer regions are anticipated to witness a decline in productivity as the climate warms, while colder areas may experience relatively better outcomes with the warming trend, regardless of adaptations. Whether the counties experience benefits or harm depends on their current average *GDD* and their position relative to the optimal *GDD*. Specifically, the impact is influenced by whether they are on the left or right side of the optimal *GDD*, as well as their distance from this optimal value.

[Insert Figure 10 About Here]

Figure 10 also underscores the unique advantages of adaptation. Upon comparing the two maps, it becomes apparent that adaptation enhances heat tolerance against the warming effect, leading to improved conditions for all counties when farmers implement adaptive strategies.

We now present climate change effect predictions until 2100 using several prediction models: CESM2, ACCESS-CM2, CESM1-CAM5, NorESM2, AWI-CM-1-1-MR, CMCC-ESM2, and NESM3 under the medium scenarios of RCP4.5 and SSP2-4.5. The welfare change is computed by the change in total farmland rent compared to the average total farmland rent of our sample. Table 10 and Figure 11 showcase the anticipated benefits of adaptation and climate change effects in both scenarios, with and without adaptations until 2100. These projections implement only the SAR as the better fitting model for both with and without adaptation cases.

[Insert Figure 11 About Here]

[Insert Table 10 About Here]

As show in Figure 11, the effect of climate change on the not adapted agriculture is negative across all climate projection models, while it is positive in with adaptation scenario. Our findings in Table 10 highlight the positive impact of climate change on agriculture when farmers adapt to the new climate, with productivity increases ranging from 9.77% to 12.82%. Conversely, there is a loss of productivity when farmers do not adapt, with decreases ranging from –3.64% to –38.39%. Our results for the not adapted agriculture are consistent with the study by Malaekeh et al. (2024), which shows adverse effects of climate change on Iran's agriculture for –21.94% and –29.74% in two scenarios of CESM2 and CMCC-ESM2 until 2080, when the adaptations are neglected by farmers. The projected impacts by the end of this century indicate that agriculture stands to benefit significantly from adaptations. All prediction models demonstrate that the positive effects of climate change with adaptation surpass those without adaptation, resulting in benefits from adaptations ranging from US$439,000 to US$1,518,895,[8] depending on the climate change projections. Our findings on adaptations benefit are consistent with a closely related study by Huang and Sim (2021), which highlights the benefits of adaptations in the United States agriculture sector.

A noteworthy aspect of the results is the variation in end-of-century climate change effects across Iran's diverse climate types. As expected, warmer regions are likely to experience a loss of productivity, while colder regions are likely to benefit from climate change. Therefore, it is insightful to examine the climate change effects across various climate types–extremely arid, arid, severe semi-arid, moderate semi-arid, mild semi-arid, semi-humid, and humid–in Iran (see Iran's climate type categories on the map in Appendix 8).

Figure 12 illustrates the effects of climate change across these different climate types. Interestingly, Figure 12 demonstrates that regardless of the utilization of adaptations, there is a decrease in farmland rent (indicating a loss of productivity) in the extremely arid and arid climate types, which face the highest temperatures and lowest precipitations and comprise 16% of all counties in Iran. The results for other climate types show a positive effect when farmers

[8] During the study period, US$1 is–on average–equivalent to 20,000 Iranian Rials.

adopt adaptations, whereas there is a negative effect in the absence of adaptations for all climate types except the humid regions, which contains 11% of all counties in Iran.

[Insert Figure 12 About Here]

6 Robustness Check

To address potential omitted variable bias, particularly due to the exclusion of irrigation in our initial models when estimating the impact of climate change on farmland rent, we conduct a robustness check by incorporating an irrigation variable into our regressions. Following the approach of Deschênes and Greenstone (2007), we introduce a county-level dummy variable for irrigation. A county is classified as irrigated if its average irrigated acreage constitutes more than 90% of its total acreage.

We re-estimate Equations (13) and (14), now including the irrigation dummy variable to validate our primary results. The findings remain consistent with our main analysis, indicating that the effect of climate change on farmland rent is detrimental when adaptations are ignored, but becomes positive and advantageous in scenarios where agricultural adaptations are implemented. Figure 13 presents end-of-century projections, highlighting that the negative impact of climate change on land productivity is pronounced in most climate prediction scenarios without adaptation, while adaptations may enable farmers to benefit from global warming.

[Insert Figure 13 About Here]

The only notable difference in these results is a reduced magnitude of effects in both adaptation scenarios compared to our main findings, which does not undermine the reliability of our main results.

7 Conclusion

Our comprehensive analysis reveals several key insights into the adaptation practices of Iranian farmers in response to climate change. We observe that the reliance on deep and semi-deep wells for irrigation significantly increases with rising temperatures, particularly in regions with medium average temperatures where the marginal effect peaks. Conversely, the usage of rivers, canals, and aqueducts declines across all temperature ranges, reflecting their inconsistent availability and higher marginal costs. Surface wells, on the other hand, show an increased share in irrigation usage during periods of higher precipitation, attributable to their lower construction and marginal costs and the rapid recharge of shallow aquifers during rainfall.

These findings underscore the critical role of regional variations in the marginal cost of water depletion, driven by factors such as underground water levels, the availability of drilling technology, and the associated costs of water extraction. The observed trends suggest that farmers are making calculated decisions to optimize water resource usage based on the changing climatic conditions, thereby mitigating the adverse effects on their agricultural productivity. However, excessive water extraction from wells beyond the natural recharge rate may not be sustainable for groundwater resources, especially when scarcity pricing is not factored into water costs.[9]

In addition to shifts in water source usage, our study highlights significant trends in crop substitution as a response to climate change. The data indicates a marked increase in the cultivation of more heat resilient crops, such as maize, over traditional less heat tolerant crops like wheat, alfalfa, and barley, particularly in warmer regions. The marginal effects show a nonlinear relationship between temperature increases and maize acreage, with a notable competitive advantage for maize at higher temperatures. However, this advantage levels off in extremely hot regions, suggesting other limiting factors such as water availability and soil conditions.

The relationship between precipitation and crop substitution further supports these adaptation trends. Increased precipitation appears to reduce the comparative advantage of maize over other crops, as reflected in the declining marginal effects on maize acreage share in regions with higher rainfall. This behavior aligns with the water efficiency characteristics of C4 (more heat resilient) crops, which makes them more suitable for low precipitation regions.

Overall, our findings demonstrate that Iranian farmers are actively adapting to climate change through strategic shifts in both water source usage and crop selection. These long-term adaptations not only help in sustaining agricultural productivity but also contribute to maintaining profitability amidst changing environmental conditions. This study underscores the importance of understanding regional disparities in resource availability and costs, which

[9] Blanc and Schlenker (2017) examine how groundwater pumping can temporarily alleviate water shortages, but highlight that it is not a viable long-term solution because it leads to the depletion of resources.

are crucial for designing effective adaptation strategies and policies to support farmers in the face of climate variability.

This study also delves into the intricate dynamics of climate change impacts on Iran's agricultural productivity, emphasizing the role of adaptation strategies. Utilizing both the Spatial Auto-Regressive Model (SAR) and the Spatial Error Model (SEM), we analyzed the effects of Growing Season Degree-Days (GDD) on farmland rent across various counties. The results consistently highlight the critical importance of incorporating spatial dependence in our models, as evidenced by the significant spatial parameters in both SAR and SEM.

The further results underscore a clear distinction between the productivity outcomes with and without adaptations. Specifically, climate change in the presence of adaptations significantly enhance agricultural productivity, with projected increases ranging from 9.77% to 12.82%. Conversely, in the absence of adaptations, climate change leads to notable productivity declines, ranging from –3.64% to –38.39%.

A detailed examination of Iran's diverse climate zones reveals that the impacts of climate change are not uniform. Warmer regions, characterized by extremely arid and arid climates, are expected to suffer productivity losses due to higher temperatures and lower precipitation levels regardless of implementing adaptation practices. In contrast, colder regions, particularly those with moderate to humid climates, stand to benefit from climate change, especially when adaptation measures are implemented.

For policymakers, these insights are invaluable. The evidence presented in this study emphasizes the substantial benefits of supporting farmers in adopting adaptation strategies. Given the financial challenges that individual farmers might face in funding these adaptations, there is a clear role for government intervention. Facilitating access to financial resources and investing in adaptive infrastructure can help mitigate the risks associated with climate change and unlock significant future productivity gains.

In conclusion, this research highlights the nuanced and region-specific impacts of climate change on agriculture in Iran. It calls for targeted adaptation policies that account for local climate conditions and support farmers in making necessary adjustments. By doing so, Iran can not only mitigate the adverse effects of climate change but also harness potential benefits, ensuring a more resilient and productive agricultural sector in the face of a changing climate.

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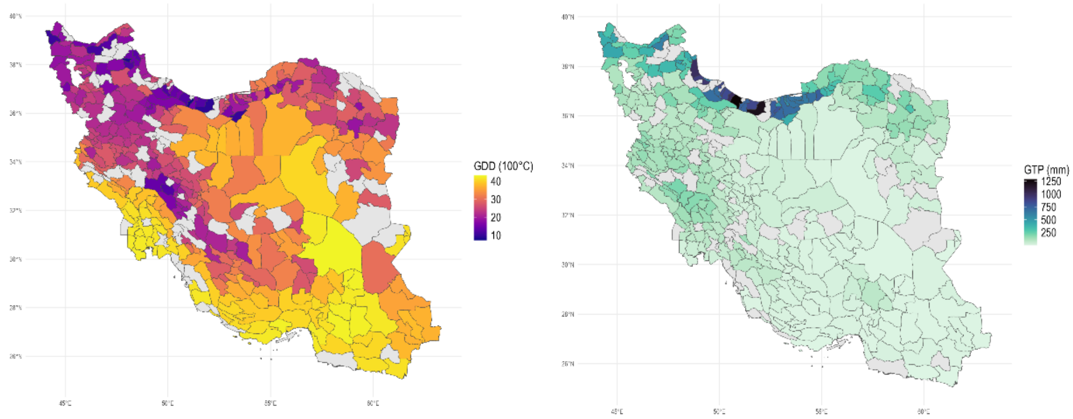
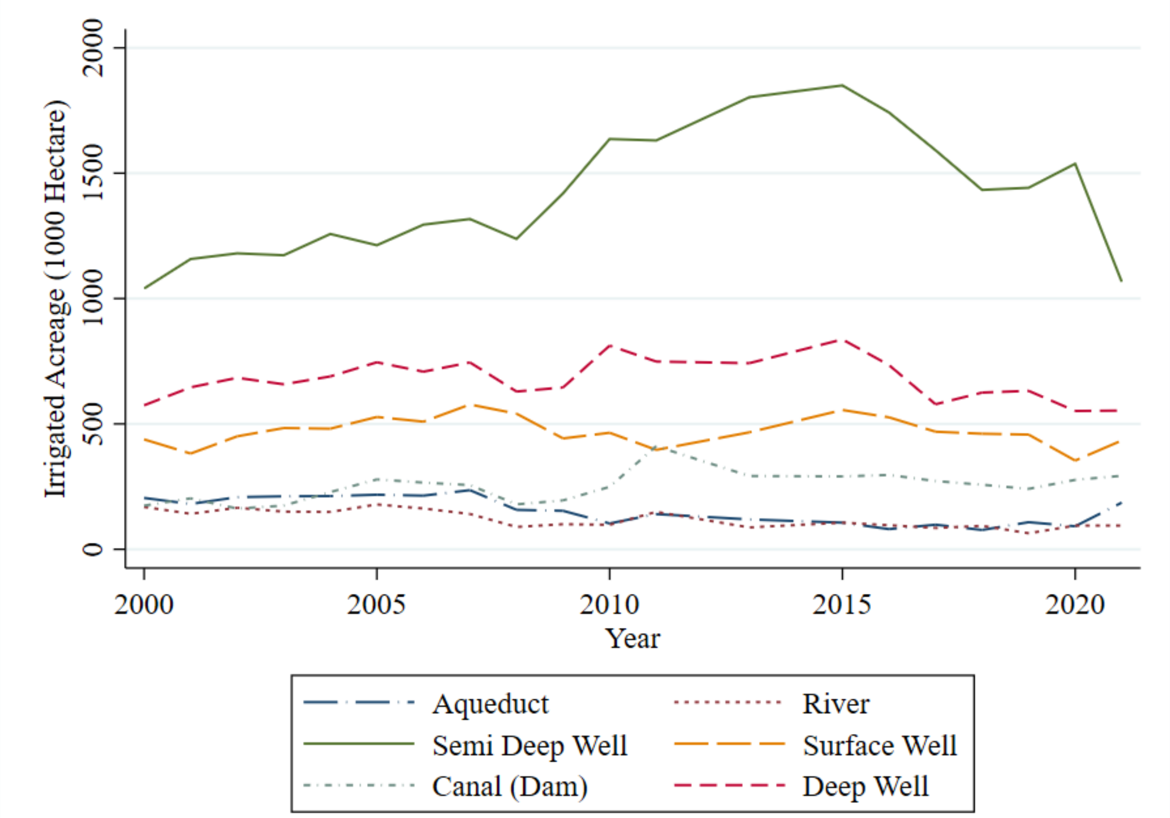
Figures

Figure 1: Iran's Climate Distribution



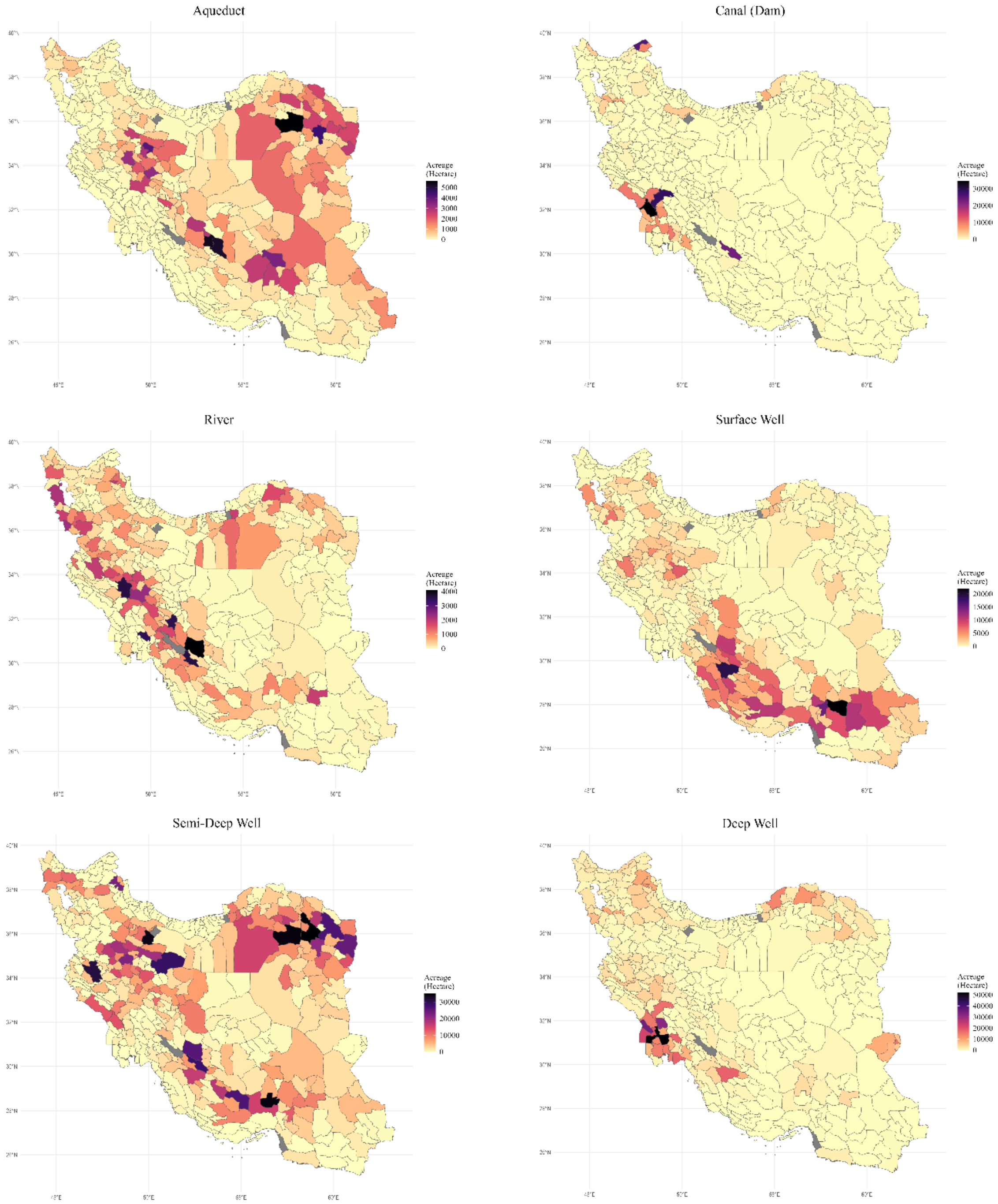
This figure shows the distribution of temperature and precipitation on Iran's map at county-level. The color of each county represents the average growing season degree-days (*GDD8-32*) and average growing season total precipitation (*GTP*) in the left and right panels, respectively. The x-axis and y-axis present longitude and latitude, respectively.

Figure 2: Trend of Irrigation Sources Usage



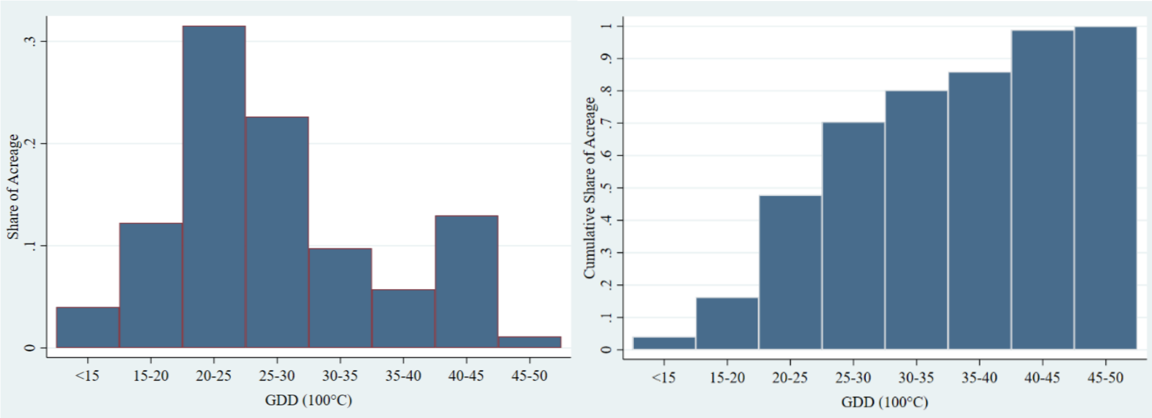
This figure depicts the total national usage of each water source for irrigation from 2000 to 2021 in Iran. The x-axis shows the years and y-axis presents the amount of land irrigated by each water sources in 1000 hectare.

Figure 3: Distribution of Average Water Depletion from Irrigation Sources in Iran



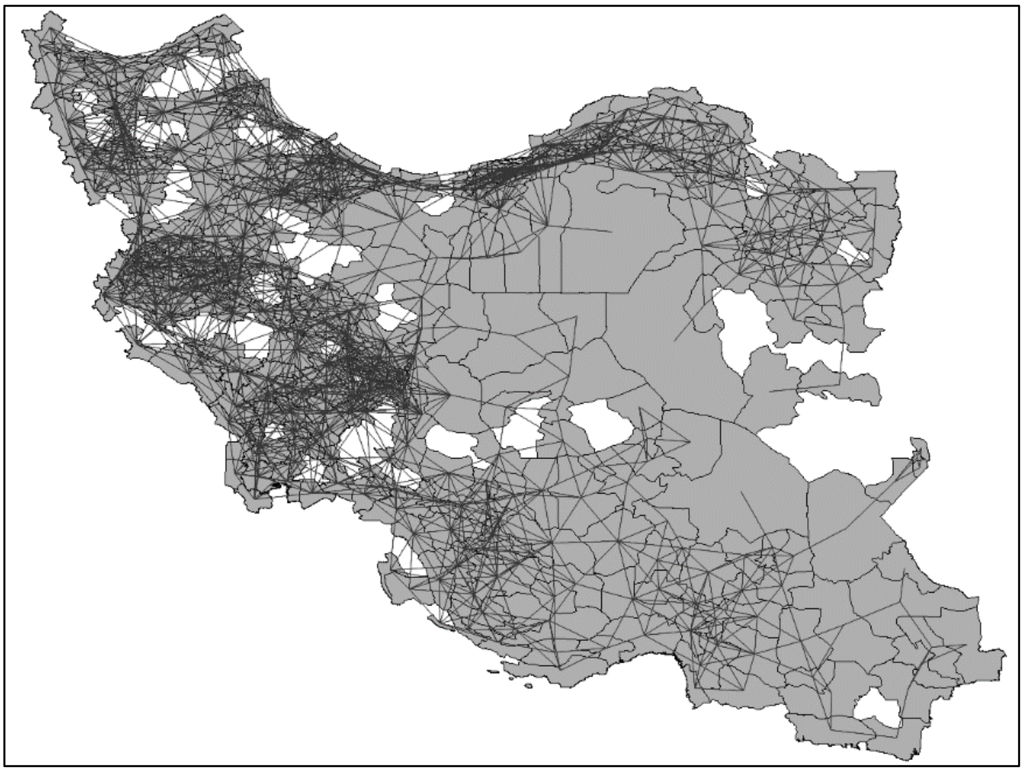
This figure shows the distribution of average water depletion from each irrigation sources between 2000 and 2021 on Iran's map at county-level. The color of each county represents the amount of land irrigated, measured by hectare, by each water source. The x-axis and y-axis present longitude and latitude, respectively.

Figure 4: Probability and Cumulative Density of Cultivated Acreage Among Regions With Different Temperature



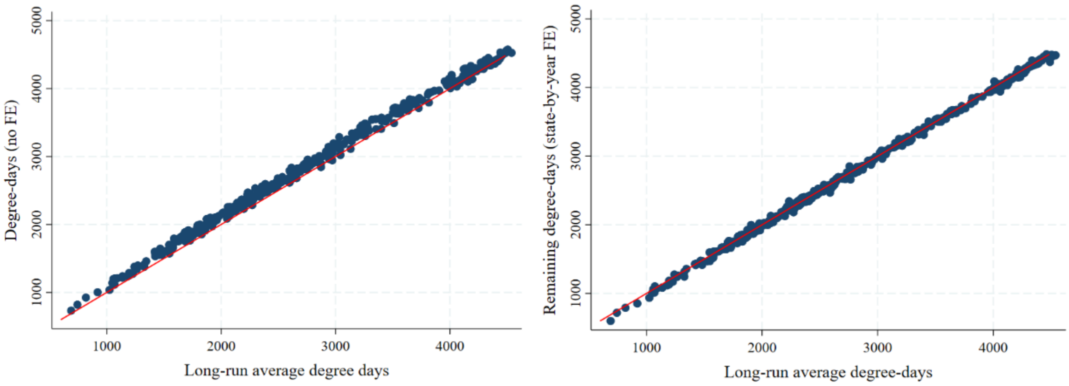
This figure share and cumulative share of farmlands area located in different temperature bins. The x-axis presents 500℃ GDD bins and y-axis shows the share and cumulative share.

Figure 5: Distance Between the County Centroids With a Bandwidth of 135km



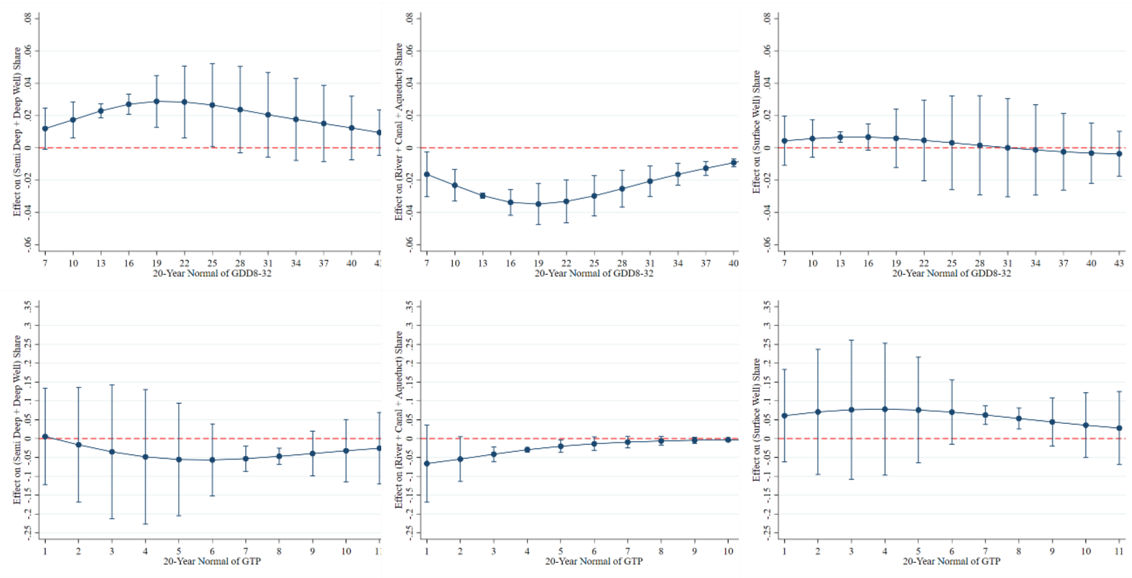
This figure shows the distance between the county centroids with a bandwidth of 135km. The direct lines represent the distance between county centroids for distances less than 135km.

Figure 6: The Efficiency of State-by-Year Fixed Effects in Removing Inter-Annual Temperature Fluctuations



This figure shows the efficiency of province-by-year fixed effects in removing inter-annual temperature fluctuations. The left and right plots depict the value of observations before and after province-by-year fixed effects, respectively. The x-axis presents the long-run average temperature and y-axis shows the temperature in 2016.

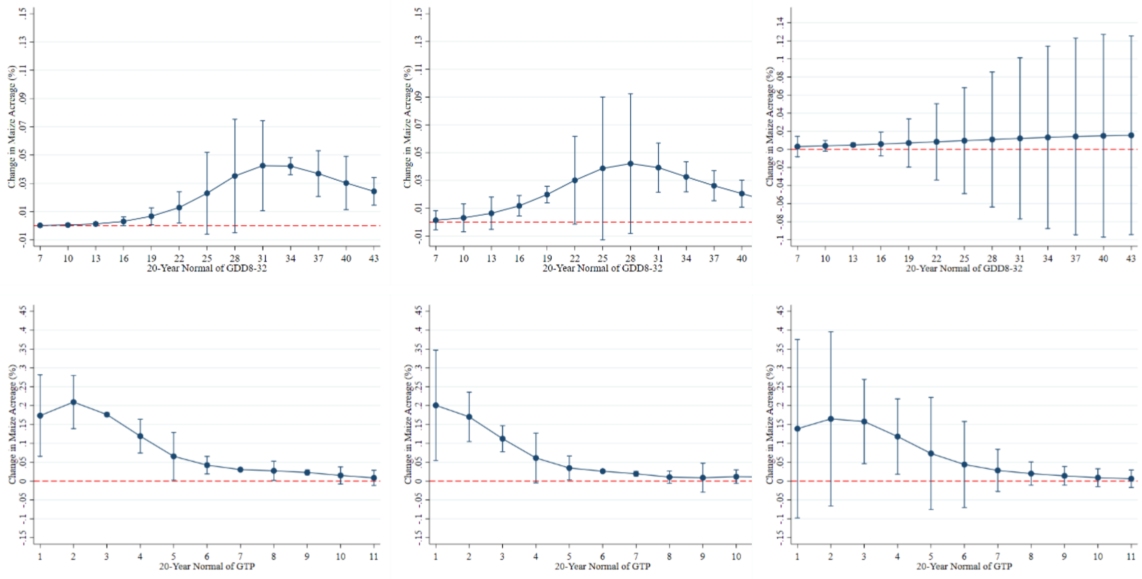
Figure 7: Marginal Effect of NGDD8-32 and NGTP on the Usage Share of Water Sources for Irrigation



a) *Deep and Semi-Deep Well* b) *River, Canal, and Aqueduct* c) *Surface Well*

This figure shows the marginal effects of 100℃ and 100*mm* increase in normal GDD (*NGDD*8-32) and normal GTP (*NGTP*) on the usage of each category of water sources. The plots in top row show the effect of 100℃ increase in temperature and the plots in bottom row show the effect of 100*mm* increase in precipitation. The x-axes show the normal temperature and precipitation in top and bottom rows, respectively. The y-axes show the marginal effect.

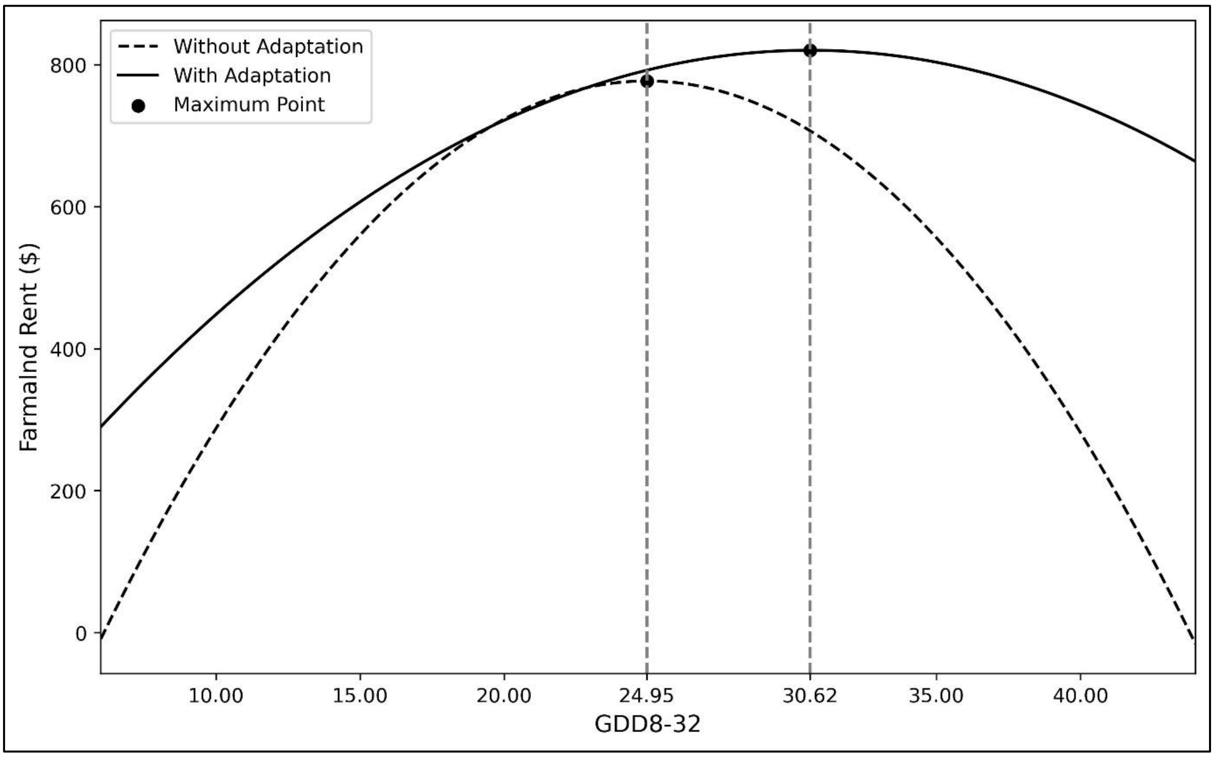
Figure 6: Marginal Effect of NGDD8-32 and NGTP on the Share of Maize Acreage vs Alternatives Crops



a) *Maize vs Wheat* b) *Maize vs Alfalfa* b) *Maize vs Barley*

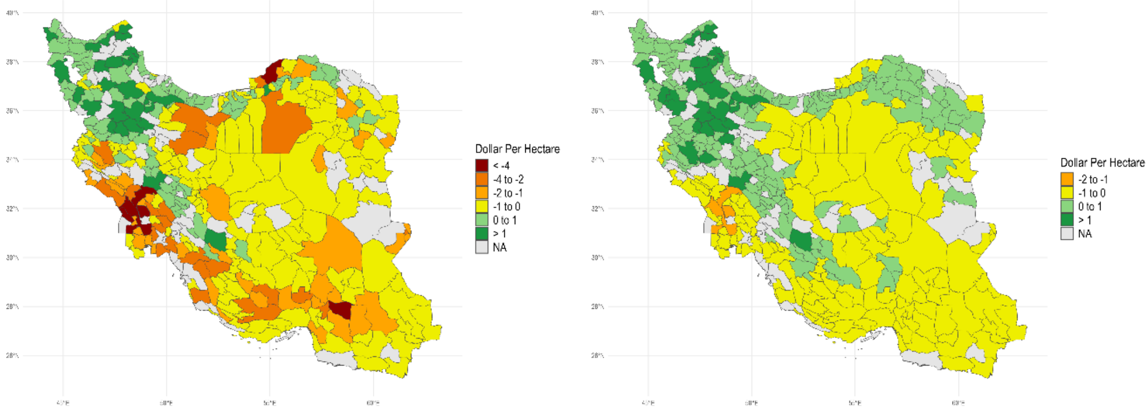
This figure shows the marginal effects of 100°C and 100*mm* increase in normal GDD (*NGDD*8-32) and normal GTP (*NGTP*) on the planted acre of maize versus its alternative crop. The plots in top row show the effect of 100°C increase in temperature and the plots in bottom row show the effect of 100*mm* increase in precipitation. The x-axes show the normal temperature and precipitation in top and bottom rows, respectively. The y-axes show the marginal effect.

Figure 9: The Response of Farmland Rent to Degree-Days (Spatial Auto-Regressive Model)



This figure shows the response of farmland rent to temperature in both adapted and not adapted agriculture scenarios resulted from Equations (13) and (14) for the case of Spatial Auto-Regressive model. The x-axis shows the growing season degree-days (*GDD8-32*) and y-axis present the farmland rent in $.

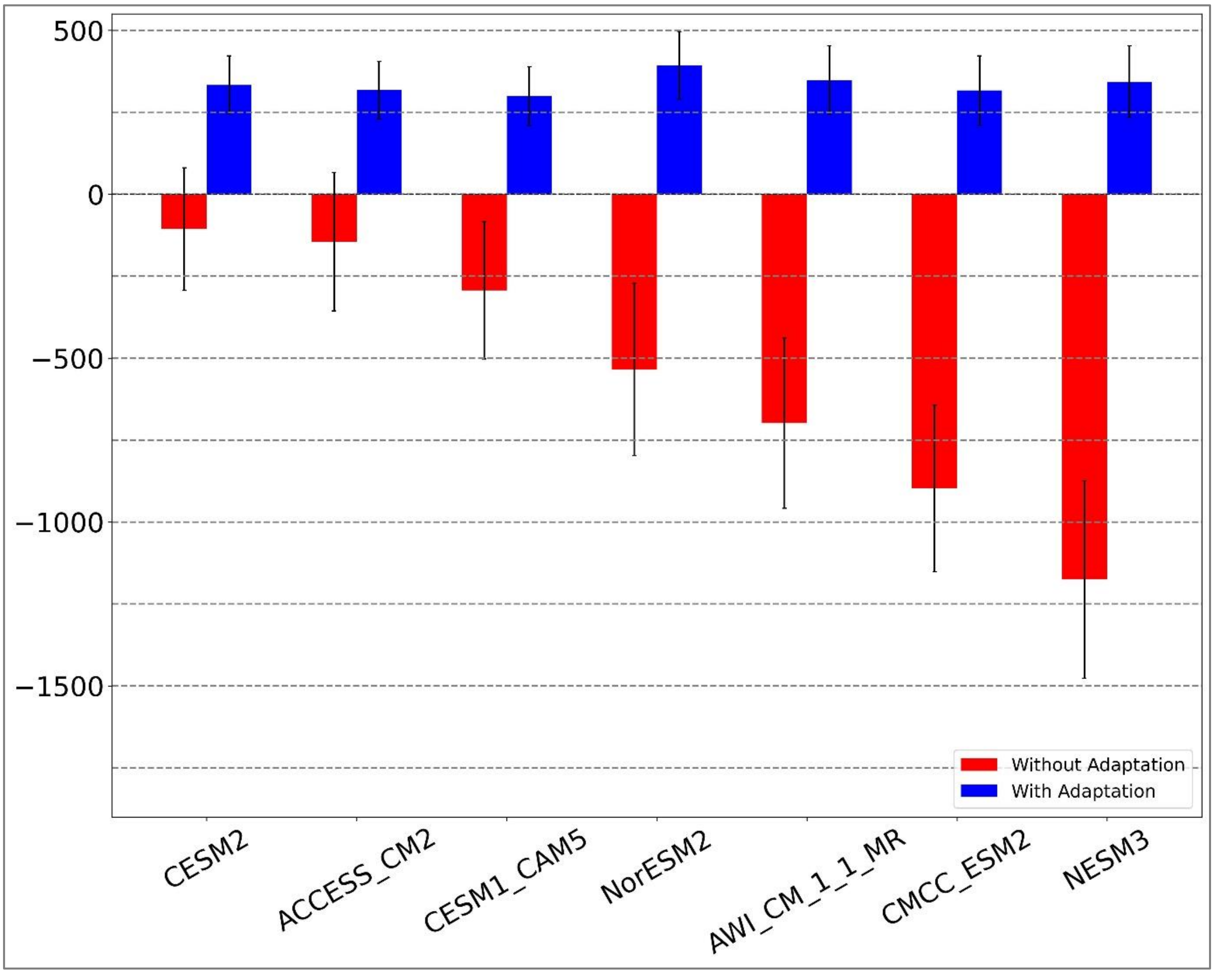
Figure 10: Climate Change Effect on Farmland Rent Based on a Uniform 100℃ GDD Increase Across Counties



a) Without Adaptation b) With Adaptation

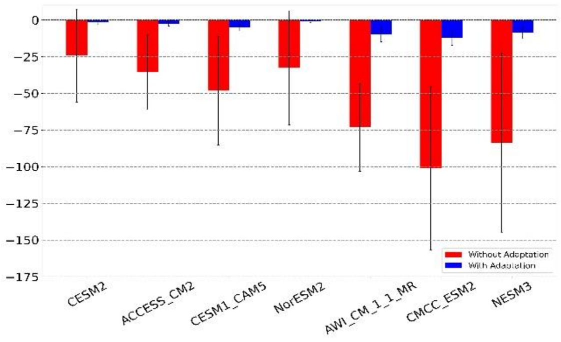
The figure shows the effect of climate change on farmland rent based on a uniform 100℃ GDD increase across counties in both scenarios of with and without adaptation. The effects are measured as dollar per hectare. The x-axis shows the longitude and y-axis shows the latitude.

Figure 11: Prediction of End-of-This-Century Climate Change Effect on Farmland Rent

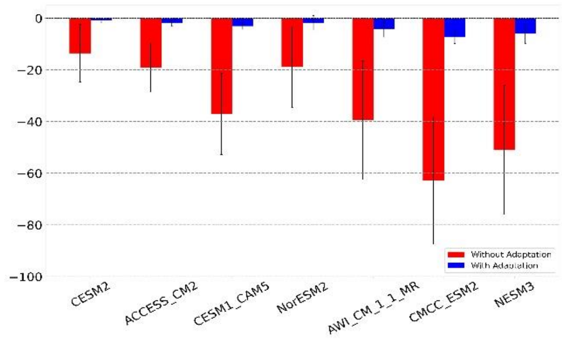


This figure shows the end-of-century prediction of climate change effect on total farmland rent in Iran based on different climate projections in two scenarios of with and without adaptation. The x-axis shows the climate projections and y-axis shows the effect measured in 1000$.

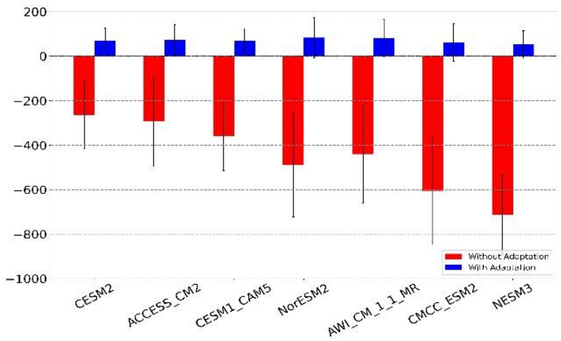
Figure 12: End-of-This-Century Climate Change Effect Prediction in Each Climate Types of Iran



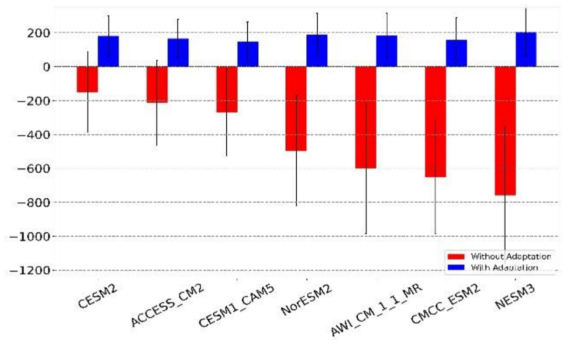
a) Extremely Arid



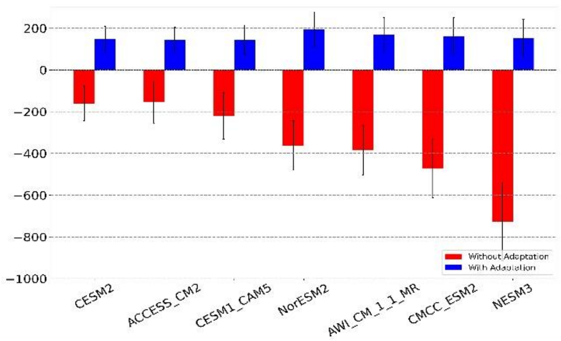
b) Arid



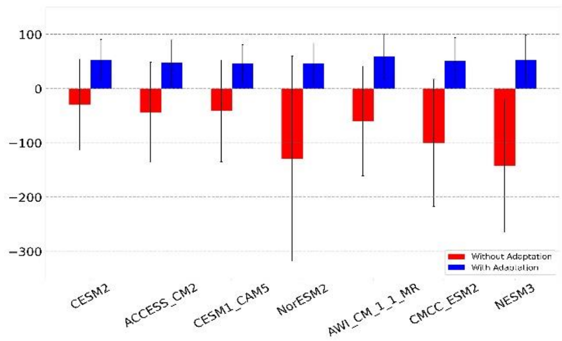
c) Severe Semi Arid



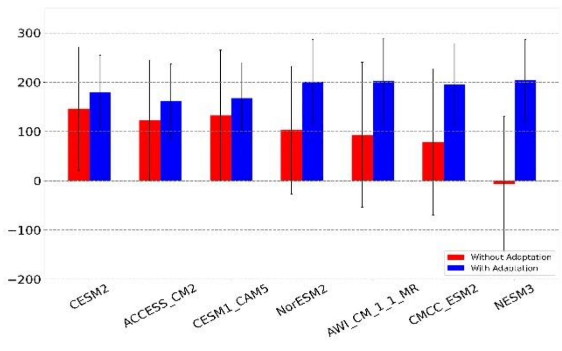
d) Moderate Semi Arid



e) Mild Semi Arid



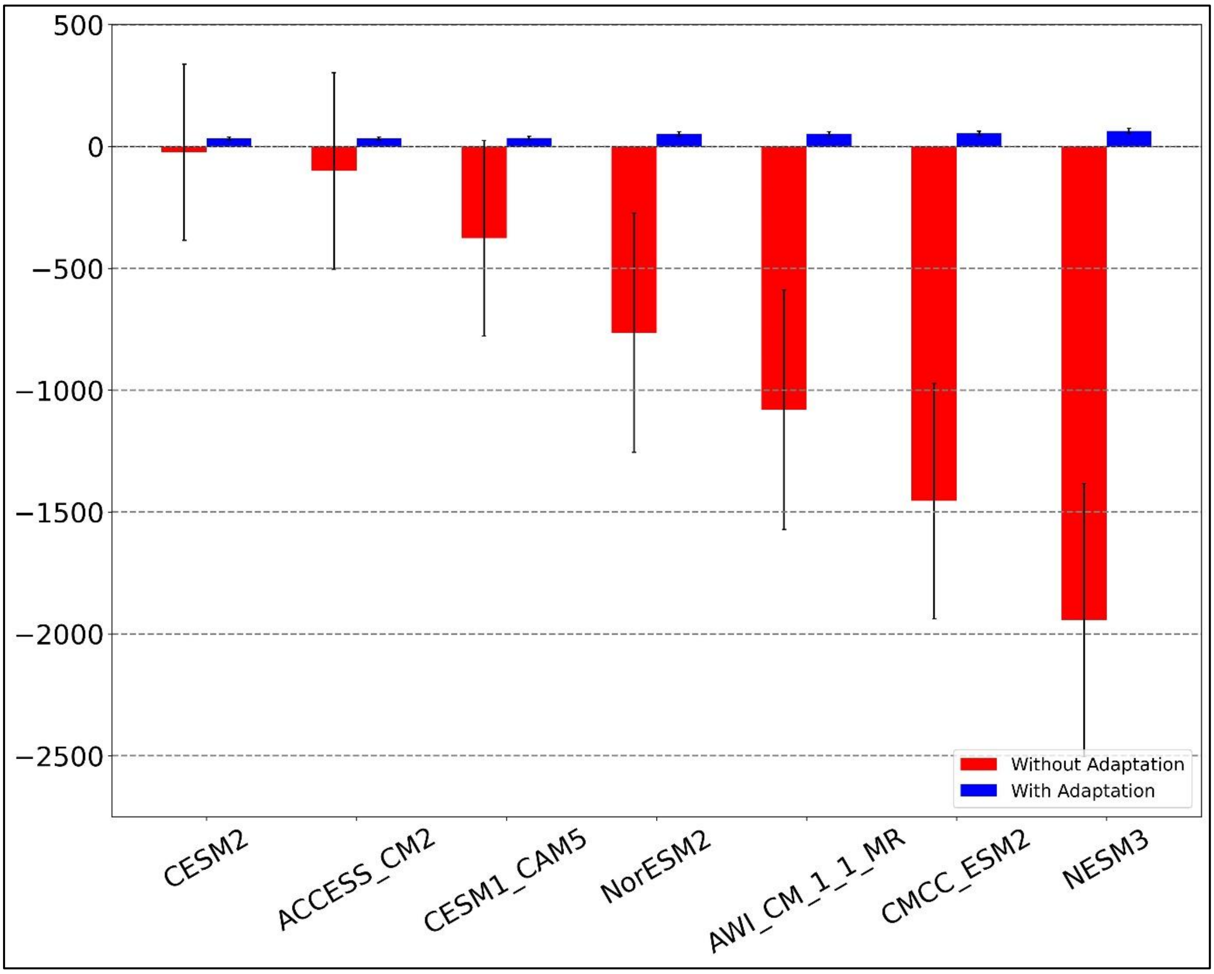
f) Semi Humid



g) Humid

This figure shows the end-of-century prediction of climate change effect on total farmland rent in Iran based on different climate projections in two scenarios of with and without adaptation across Iran's climate zones. The x-axis shows the climate projections and y-axis shows the effect measured in 1000$.

Figure 13: Prediction of End-of-This-Century Climate Change Effect on Farmland Rent – Controlling for Irrigation



This figure shows the end-of-century prediction of climate change effect on total farmland rent in Iran based on different climate projections in two scenarios of with and without adaptation when we control for irrigation in our regressions. The x-axis shows the climate projections and y-axis shows the effect measured in 1000$

Tables

Table 1: Total Planted Area of Crops in Iran from 2000 to 2021

Crop	Planted Area (Hectare)	Planted Area Share	Cumulative Share
Wheat	105,500,000.00	60.90%	60.90%
Barley	26,757,073.00	15.44%	76.35%
Alfalfa	10,586,084.00	6.11%	82.46%
Maize	6,644,221.70	3.83%	86.29%
Potato	2,741,806.70	1.58%	87.87%
Tomato	2,500,169.20	1.44%	89.32%
Watermelon	2,090,148.90	1.21%	90.52%
Beet	1,991,568.40	1.15%	91.67%
Rapeseed	1,911,657.60	1.10%	92.77%
Beans	1,807,106.60	1.04%	93.82%
Cotton	1,787,532.10	1.03%	94.85%
Melon	1,345,785.50	0.78%	95.63%
Sugarcane	1,258,628.30	0.73%	96.35%
Cucumber	1,256,815.50	0.73%	97.08%
Soybean	1,076,185.30	0.62%	97.70%
Clover	1,026,698.50	0.59%	98.29%
Onion	964,657.24	0.56%	98.85%
Sesame	802,740.05	0.46%	99.31%
Sunflower	757,899.56	0.43%	99.74%
Others	434,092.50	0.26%	100.00%

This table presents the total planted area of different crops cultivating in Iran from 2000 to 2021.

Table 2: Total Share of Water Sources for Irrigation

Source	Share
Semi-Deep Well	45.17%
Deep Well	22.01%
Surface Well	15.59%
Canal (Dam)	8.17%
Aqueduct	5.01%
River	4.04%

This table presents the total share of each water source for irrigation in Iran based on the area of land irrigated.

Table 3: Agricultural and Socio-Economic Variables Summary Statistics

	Mean	**SD**	**Min**	**Max**	**N**
Farmland Rent ($)	359.43	279.97	20.20	2,407.86	1,002
Acreage (1000 Hectare)	25.97	31.61	1.00	264.76	1,002
Irrigation Rate	0.63	0.37	0.00	1.00	1,002
Population (1000)	212.53	852.32	4.25	16,968.24	1,002
County Area (km^2)	4,138.28	5,765.57	197.03	55,179.92	1,002
Population Density	80.77	158.17	0.39	25,45.49	1,002
Income Per Capita ($)	737.24	240.68	223.14	2,256.12	1,002

This table shows the summary statistics of agricultural and socio-economic variables. The *Farmland Rent* and *Income Per Capita* have been converted to 2016 prices using CPI reported by Central Bank of Iran.

Table 4: Environmental Variables Summary Statistics

	Mean	**SD**	**Min**	**Max**	**N**
Daily Temperature (℃)	24.19	5.66	10.86	36.04	1,002
GDD8-32 (100℃)	28.75	8.79	7.32	43.12	1,002
GTP (*mm*)	141.87	195.82	0.37	1285.84	1,002
Soil Moisture (kg/m^2)	19.23	3.96	7.68	32.36	1,002
Groundwater Runoff (g/m^2)	12.75	12.72	0.03	63.86	1,002
Soil Evaporation (kg/m^2s)	14.54	4.16	4.82	29.37	1,002
Wind Speed (*m/s*)	2.74	0.67	1.42	7.01	1,002
CSDI	1.74	1.02	0.00	5.00	1,002
SDII (*mm/day*)	2.68	1.60	0.00	7.89	1,002

This table presents the summary statistics of environmental variables.

Table 5: The Consequences of Fixed Effects on the Climate Change Impact Panel Study

	Year 1	**Year 2**
A. No Fixed Effects		
County A	$w_{11} = T_1 + d_1 + \epsilon_{11}$	$w_{12} = T_1 + d_2 + \epsilon_{12}$
County B	$w_{21} = T_2 + d_1 + \epsilon_{21}$	$w_{22} = T_2 + d_2 + \epsilon_{22}$
B. Time Fixed Effects		
County A	$\frac{T_1 - T_2}{2} + \frac{\epsilon_{11} - \epsilon_{21}}{2}$	$\frac{T_1 - T_2}{2} + \frac{\epsilon_{12} - \epsilon_{22}}{2}$
County B	$\frac{T_2 - T_1}{2} + \frac{\epsilon_{21} - \epsilon_{11}}{2}$	$\frac{T_1 - T_2}{2} + \frac{\epsilon_{22} - \epsilon_{12}}{2}$
C. County Fixed Effects		
County A	$\frac{d_1 - d_2}{2} + \frac{\epsilon_{11} - \epsilon_{12}}{2}$	$\frac{d_2 - d_1}{2} + \frac{\epsilon_{12} - \epsilon_{11}}{2}$
County B	$\frac{d_1 - d_2}{2} + \frac{\epsilon_{21} - \epsilon_{22}}{2}$	$\frac{d_2 - d_1}{2} + \frac{\epsilon_{22} - \epsilon_{21}}{2}$
D. Two-Way Fixed Effects		
County A	$\frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4}$	$-\frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4}$
County B	$-\frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4}$	$\frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4}$

This table shows the effect of time, county, and two-way fixed effects on variable for a scenario of two years and counties.

Table 6: Climatic Variations After Using Different Fixed Effects

Temperature	**0.4℃**	**0.6℃**	**0.8℃**	**1℃**
Province-by-Year and County Fixed Effects	8.04%	2.23%	0.82%	0.54%
Only Province-by-Year Fixed Effects	87.80%	81.12%	75.04%	69.95%
Only County Fixed Effects	69.49%	54.22%	39.84%	28.52%
Precipitation	**40*mm***	**80*mm***	**120*mm***	**160*mm***
Province-by-Year and County Fixed Effects	10.19%	2.39%	0.91%	0.59%
Only Province-by-Year Fixed Effects	34.26%	19.38%	11.80%	7.35%
Only County Fixed Effects	30.80%	10.80%	4.43%	2.10%

This table shows the effect of province-by-year, county, and two-way fixed effects on temperature and precipitation variables.

Table 7: Lagrange Multiplier Test Diagnostics for Spatial Dependence

Without Adaptation	Value	p-value
LM-lag	76.13	2.65e-18
LM-error	45.11	1.85e-11
Robust LM-lag	56.91	4.55e-14
Robust LM-error	25.89	3.59e-07
With Adaptation	Value	p-value
LM-lag	81.16	0.00
LM-error	59.49	1.23e-14
Robust LM-lag	22.18	2.48e-06
Robust LM-error	0.50	0.47764

This table presents the results of Lagrange multiplier test diagnostics for spatial dependence of counties in terms of both dependent variable and error term in both scenarios of with and without adaptations.

Table 8: Regression Results of the Effects of Climatic Variables on Farmland Rent

	(1) Without Adaptation	(2) With Adaptation	(3) Without Adaptation	(4) With Adaptation
GDD8-32	218.32**	107.16***	311.03**	109.57***
	(99.17)	(28.41)	(123.82)	(30.56)
GDD8-32 Squared	–4.37**	–1.75***	–6.08**	–1.83***
	(1.83)	(0.51)	(2.29)	(0.58)
GTP	0.91	0.62	0.87	0.61
	(0.67)	(0.51)	(0.84)	(0.49)
GTP Squared	–0.0005	0.0002	–0.0003	0.0002
	(0.0006)	(0.0005)	(0.0008)	(0.0004)
Control Variables	✓	✓	✓	✓
Province-by-Year FE	✕	✓	✕	✓
County FE	✓	✕	✓	✕
Time Trend	✓	✕	✓	✕
Spatial Model	SAR	SAR	SEM	SEM
ρ	0.37**	0.11**		
	(0.055)	(0.055)		
λ			0.38***	–0.20**
			(0.063)	(0.093)
N	1,002	1,002	1,002	1,002
R^2	0.19	0.34	0.16	0.35
Log-Pseudo Likelihood	–7012.69	–7373.72	–7018.53	–7373.47
AIC	14052.99	14945.82	14065.79	14954.63
BIC	14121.73	15426.97	14134.53	15460.33

This table presents the effect of climate change on farmland rent derived from the results of equations (13) and (14) by quasi maximum likelihood estimation. The dependent variable is farmland rent ($). The error terms are clustered at province-level. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 9: Marginal Effects of GDD on Farmland Rent

	SAR		***SEM***	
	Without Adaptation	With Adaptation	Without Adaptation	With Adaptation
Direct Effect	–2.49%***	1.81%***	–2.39%***	1.54%***
	(–3.68)	(5.48)	(–2.53)	(4.62)
Indirect Effect	–0.79%***	0.22%***	–	
	(–3.65)	(6.53)		
Total Effect	–3.29%***	2.03%***	–2.39%***	1.54%***
	(–3.82)	(5.64)	(–2.53)	(4.62)

This table presents the direct, indirect, and total marginal effects of *GDD*8-32 on farmland rent derived from equation (13) and (14) for both Spatial Auto-Regressive and Spatial Error models. The t-statistic values are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 10: The Benefit of Adaptation and Climate Change Effect Predictions Until 2100 in Presence of Both Cases of With and Without Adaptation

	Without Adaptation (%)	With Adaptation (%)	Benefit ($)
CESM2	–3.46 (–1.11)	10.88*** (7.38)	439,000*** (4.16)
ACCESS-CM2	–4.73 (–1.34)	10.36*** (7.05)	462,000*** (3.96)
CESM1-CAM5	–9.57*** (–2.74)	9.77*** (6.53)	592,500*** (5.10)
NorESM2	–17.64*** (–3.98)	12.82*** (7.47)	927,000*** (6.43)
AWI-CM-1-1-MR	–22.81*** (–5.26)	11.37*** (6.55)	1,046,590*** (7.32)
CMCC-ESM2	–29.30*** (–6.91)	10.33*** (5.87)	1,231,540*** (8.64)
NESM3	–38.39*** (–7.65)	11.21*** (6.14)	1,518,895*** (9.29)

This table presents the benefit of adaptations and the effect of climate change on total farmland rent until 2100 in both scenarios of with and without adaptations across various climate projection models. The t-statistic values are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix

Appendix 1: Present and Future of Iran's Climate

	GDD8-32	NGDD8-32	GTP	NGTP
Present	2849.09	2774.76	136.78	137.47
CESM2	3187.22	3231.32	164.07	132.67
ACCESS-CM2	3451.43	3268.98		
CESM1-CAM5	3279.30	3279.13		
NorESM2	3229.71	3381.45		
AWI-CM-1-1-MR	3329.92	3421.17		
CMCC-ESM2	3648.70	3480.98	80.38	89.15
NESM3	3623.10	3565.58	86.14	55.37

This table presents Iran's average *GDD*8-32, *NGDD*8-32, *GTP*, and *NGTP* at present and in 2100 based on different climate projection model

Appendix 2: Average Marginal Effects of NGDD8-32 on the Share Water Sources for Irrigation

NGDD8-32 (100°C)	**Deep + Semi-Deep Well**	**Aqueduct + Canal + River**	**Surface Well**
Average Temperature	0.0239*	– 0.0256***	0.0017
	(0.01362)	(0.00586)	(0.01565)
7	0.0120*	– 0.0164**	0.00440
	(0.00651)	(0.00706)	(0.00776)
10	0.0174***	– 0.0231***	0.00575
	(0.00568)	(0.00499)	(0.00592)
13	0.0229***	– 0.0296***	0.00665***
	(0.00225)	(0.000801)	(0.00165)
16	0.0270***	– 0.0337***	0.00671
	(0.00321)	(0.00409)	(0.00414)
19	0.0288***	– 0.0348***	0.00595
	(0.00815)	(0.00645)	(0.00919)
22	0.0284**	– 0.0331***	0.00466
	(0.0114)	(0.00675)	(0.0127)
25	0.0265**	– 0.0297***	0.00314
	(0.0131)	(0.00637)	(0.0148)
28	0.0237*	– 0.0253***	0.00159
	(0.0136)	(0.00581)	(0.0157)
31	0.0205	– 0.0206***	0.000105
	(0.0133)	(0.00480)	(0.0155)
34	0.0177	– 0.0164***	– 0.00128
	(0.0129)	(0.00341)	(0.0143)
37	0.0151	– 0.0126***	– 0.00243
	(0.0121)	(0.00220)	(0.0121)
40	0.0123	– 0.00914***	– 0.00321
	(0.0100)	(0.00123)	(0.00955)
43	0.00950	– 0.00589***	– 0.00361
	(0.00717)	(0.000128)	(0.00707)

This table presents the average marginal effect of normal growing season degree-days (*NGDD*8-32) on share of water sources for irrigation. The error term is clustered at the province level in all models. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix 3: Average Marginal Effects of NGTP on the Share Water Sources for Irrigation

NGTP (100*mm*)	**Deep + Semi-Deep Well**	**Aqueduct + Canal + River**	**Surface Well**
Average Precipitation	0.00293	– 0.06501	0.06207
	(0.06607)	(0.04993)	(0.06541)
1	0.00537	– 0.0662	0.0608
	(0.0653)	(0.0522)	(0.0626)
2	– 0.0164	– 0.0544*	0.0708
	(0.0775)	(0.0302)	(0.0847)
3	– 0.0352	– 0.0413***	0.0765
	(0.0904)	(0.00998)	(0.0942)
4	– 0.0484	– 0.0295***	0.0779
	(0.0910)	(0.00307)	(0.0893)
5	– 0.0554	– 0.0203**	0.0757
	(0.0761)	(0.00839)	(0.0715)
6	– 0.0566	– 0.0137	0.0704
	(0.0488)	(0.00931)	(0.0435)
7	– 0.0532***	– 0.00923	0.0625***
	(0.0172)	(0.00796)	(0.0128)
8	– 0.0470***	– 0.00629	0.0533***
	(0.0109)	(0.00584)	(0.0142)
9	– 0.0397	– 0.00440	0.0441
	(0.0304)	(0.00406)	(0.0326)
10	– 0.0323	– 0.00316	0.0355
	(0.0423)	(0.00280)	(0.0439)
11	– 0.0256	– 0.00230	0.0279
	(0.0484)	(0.00193)	(0.0495)

This table presents the average marginal effect of normal growing season total precipitation (*NGTP*) on share of water sources for irrigation. The error term is clustered at the province level in all models. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix 4: Average Marginal Effects of NGDD8-32 on the Acreage of Maize vs the Alternatives Crops

NGDD8-32 (100°C)	**Maize vs Wheat**	**Maize vs Alfalfa**	**Maize vs Barley**
Average Temperature	0.03309*	0.04964***	0.01466
	(0.01728)	(0.01361)	(0.03252)
7	0.000234***	0.000558	0.00230
	(0.0000241)	(0.00123)	(0.00612)
10	0.000529***	0.00190	0.00330
	(0.0000966)	(0.00205)	(0.00560)
13	0.00130**	0.00495**	0.00462
	(0.000517)	(0.00211)	(0.00349)
16	0.00316**	0.0109***	0.00630***
	(0.00147)	(0.00106)	(0.000768)
19	0.00691***	0.0211***	0.00831
	(0.00258)	(0.00309)	(0.00742)
22	0.0132***	0.0356***	0.0106
	(0.00503)	(0.0136)	(0.0161)
25	0.0238*	0.0466***	0.0130
	(0.0133)	(0.0171)	(0.0259)
28	0.0363**	0.0491***	0.0154
	(0.0173)	(0.00941)	(0.0352)
31	0.0434***	0.0397***	0.0175
	(0.0134)	(0.00368)	(0.0425)
34	0.0423***	0.0294***	0.0193
	(0.000978)	(0.00916)	(0.0467)
37	0.0363***	0.0246***	0.0205
	(0.00813)	(0.00160)	(0.0470)
40	0.0295***	0.0206**	0.0212
	(0.00845)	(0.00969)	(0.0430)
43	0.0237***	0.0167	0.0211
	(0.00439)	(0.0162)	(0.0348)

This table presents the average marginal effect of normal growing season degree-days (*NGDD*8-32) on the acreage of maize compared to alternative crops. The error term is clustered at the province level in all models. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix 5: Average Marginal Effects of NGTP on the Share of Maize Planted Acres vs the Alternatives Crops

NGTP (100*mm*)	**Maize vs Wheat**	**Maize vs Alfalfa**	**Maize vs Barley**
Average Precipitation	0.19912***	0.20404***	0.15357
	(0.05770)	(0.06329)	(0.12893)
1	0.175***	0.210***	0.141
	(0.0560)	(0.0749)	(0.121)
2	0.210***	0.174***	0.167
	(0.0360)	(0.0307)	(0.117)
3	0.176***	0.110***	0.159***
	(0.00175)	(0.0225)	(0.0535)
4	0.118***	0.0569*	0.117**
	(0.0234)	(0.0341)	(0.0545)
5	0.0648**	0.0329***	0.0718
	(0.0324)	(0.0118)	(0.0753)
6	0.0419***	0.0261***	0.0429
	(0.0119)	(0.000417)	(0.0564)
7	0.0298***	0.0193***	0.0278
	(0.00265)	(0.00170)	(0.0262)
8	0.0251***	0.0118	0.0196
	(0.00900)	(0.00938)	(0.0151)
9	0.0214***	0.0133	0.0135
	(0.00449)	(0.00979)	(0.0139)
10	0.0156	0.0122	0.00830
	(0.00993)	(0.00760)	(0.0168)
11	0.00966	0.00825	0.00462***
	(0.0108)	(0.0109)	(0.000691)

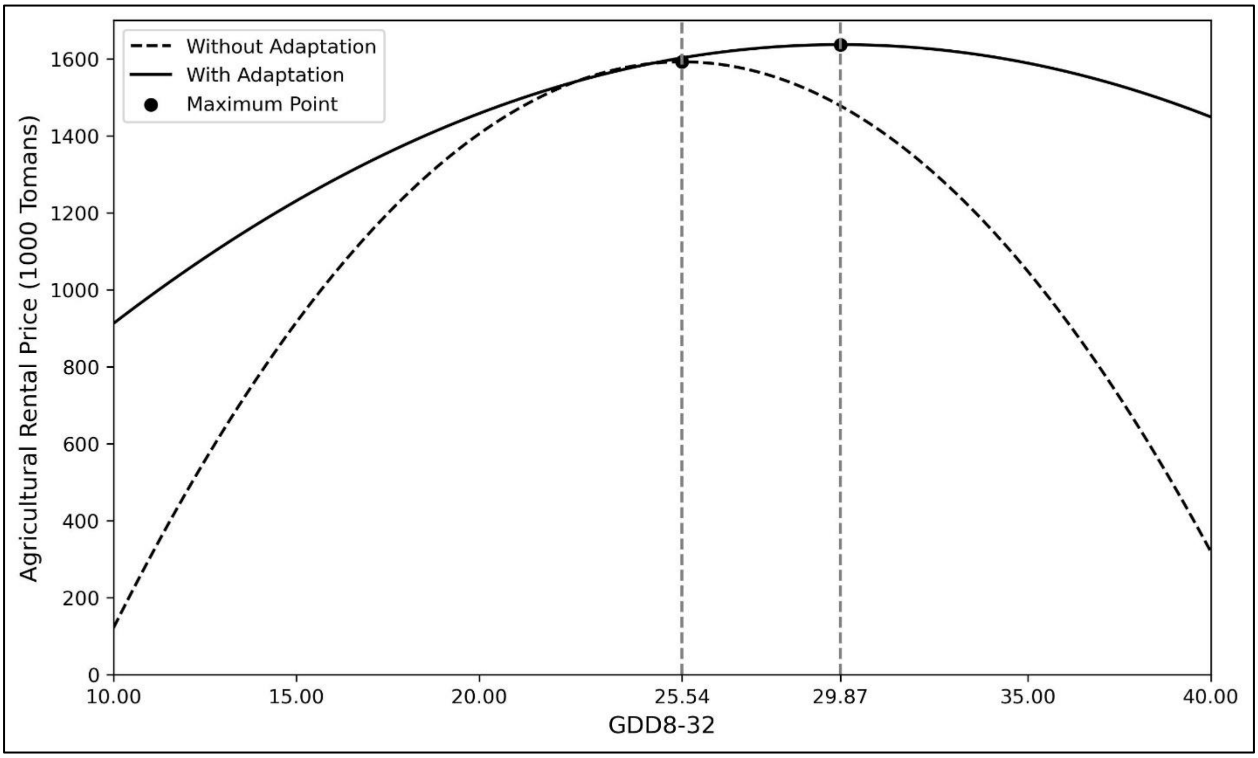
This table presents the average marginal effect of normal growing season total precipitation (*NGTP*) on the acreage of maize compared to alternative crops. The error term is clustered at the province level in all models. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix 6: Regression Results of the Effects of Climatic Variables on Farmland Rent

	(1) Without Adaptation	(2) With Adaptation	(3) Without Adaptation	(4) With Adaptation
GDD8-32	218.32**	107.16***	311.03**	109.57***
	(99.17)	(28.41)	(123.82)	(30.56)
GDD8-32 Squared	–4.37**	–1.75***	–6.08**	–1.83***
	(1.83)	(0.51)	(2.29)	(0.58)
GTP	0.91	0.62	0.87	0.61
	(0.67)	(0.51)	(0.84)	(0.49)
GTP Squared	–0.0005	0.0002	–0.0003	0.0002
	(0.0006)	(0.0005)	(0.0008)	(0.0004)
GHDD32	0.631	0.423	0.419	0.421
	(0.785)	(0.283)	(0.973)	(0.285)
Income Per Capita	–0.762	0.184	–0.541	0.132
	(0.655)	(0.163)	(0.512)	(0.159)
Population Density	–0.338	–0.0357	–0.327	0.0021
	(0.208)	(0.155)	(0.215)	(0.155)
Soil Moisture	19.05	12.43	30.30	16.54
	(15.89)	(11.25)	(19.49)	(11.44)
Soil Evaporation	–26.57***	–17.40***	–27.63***	–19.83***
	(8.633)	(8.649)	(10.87)	(8.476)
SDII	–16.02	–17.37	–23.16	–15.68
	(11.95)	(13.18)	(13.26)	(12.87)
CSDI	8.496	–11.75	6.273	–6.069
	(13.05)	(16.65)	(15.76)	(16.62)
Control Variables	✓	✓	✓	✓
Province-by-Year FE	✕	✓	✕	✓
County FE	✓	✕	✓	✕
Time Trend	✓	✕	✓	✕
Spatial Model	SAR	SAR	SEM	SEM
ρ	0.37**	0.11**		
	(0.055)	(0.055)		
λ			0.38***	–0.20**
			(0.063)	(0.093)
N	1,002	1,002	1,002	1,002
R^2	0.19	0.34	0.16	0.35
Log-Pseudo Likelihood	–7012.69	–7373.72	–7018.53	–7373.47
AIC	14052.99	14945.82	14065.79	14954.63
BIC	14121.73	15426.97	14134.53	15460.33

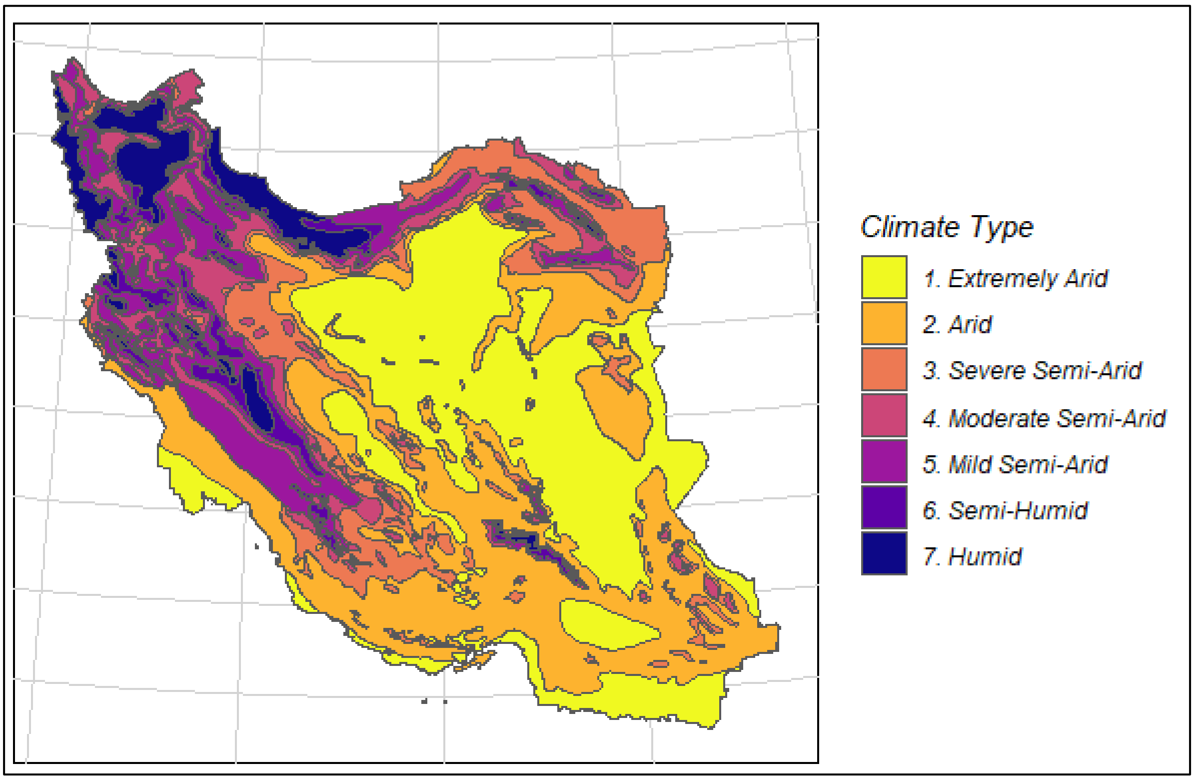
This table presents the effect of climate change on farmland rent derived from the results of equations (13) and (14) by quasi maximum likelihood estimation. The dependent variable is farmland rent ($). The error terms are clustered at province-level. Standard errors are in parenthesis. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix 7: The Response of Farmland Rent to Degree-Days (Spatial Error Model)



This figure shows the response of farmland rent to temperature in both adapted and not adapted agriculture scenarios resulted from Equations (13) and (14) for the case of Spatial Error model. The x-axis shows the growing season degree-days (GDD8-32) and y-axis present the farmland rent in $.

Appendix 8: Iran's Climate Types



This figure shows the seven different climate types of Iran on map.