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Agricultural expansion and its impacts on climate change: evidence from Iran

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Abstract

Excessive concentration of greenhouse gases in atmosphere emitted from human activities has been considerably changing the world's climate, especially in the last 50 years. Agriculture, as humans' food production system, has undoubtedly interrelated with climate change (CC). During current decades, the impacts of CC on agriculture have been properly investigated; however, the impacts of agriculture on CC have received lower attention. This may be due to the scarcity of long-term spatiotemporal climatic and agricultural data to analyze coupling trends and interactions. Benefiting from a comprehensive database and using structural equation modeling, this study seeks to investigate the contribution of agriculture to CC in Iran for more than half a century. For this, two indicators were developed to evaluate structural characteristics of agricultural expansion (AEI) and CC at the province level. Then, the effect of AEI on CC was investigated using the structural equation modeling technique. The results showed that AEI has not had a positive contribution to raising the long-term average surface temperature. Precisely, the provinces with a higher level of surface temperature have had a lower AEI, indicating that other sectors outweigh agriculture in exacerbating long-term CC in the country. Nevertheless, Iran still needs to improve and sustain its agricultural practices and technologies. The main conclusion of this study is that if the government and policymakers aspire to manage CC, they should have a more holistic and systematic view. In other words, not only do they need to consider all drivers of CC, but they also have to pay close attention to the network of relationships among the drivers.

Keywords Global warming · Agriculture and climate change · Agricultural management · CO_2 emission · Sustainable agriculture

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1 Introduction

Agriculture expansion (AE) and climate change (CC) regulation are two highly interrelated and major global issues. The majority of studies have emphasized such interrelation and its importance, especially in recent decades, characterized by a huge surge in average global temperature (Agovino et al., 2018; Bryan et al., 2013; Lin & Huang, 2019). A stable climate is perhaps the most important environmental factor determining the sustainability and efficiency of agricultural production systems. CC can diversely influence AE in a complex way. Short-term changes in climate conditions, precipitation patterns, and temperature, for instance, will increase the possibility of crop failure and excessive proliferation of pets, reducing both the quantity and cost of food produced. Considering the anticipated trend in world's population, this will cause serious concerns for food security worldwide. This situation would more severely influence developing and underdeveloped countries where many people are poor and the birth rate is the highest. To compensate for low production due to unstable climate conditions, people would expand their agricultural activities and areas which consequently encourage deforestation and agricultural land conversion (ALC). Therefore, there is no doubt that AE also affects CC; however, the impact of AE on CC is less available (Maeda et al., 2021). AE influences CC through different mechanisms such as the emission of greenhouse gases (GHGs) and land use change (LUC) (Azadi et al., 2022; Nelson et al., 2012; Ng et al., 2023). Considering emission of GHGs, Smith et al. (2014) and Lenka et al. (2015) reported that agriculture contributes to about a quarter (~10–12 Gt CO_2 eq/yr) of anthropogenic GHG emissions, principally including three groups of GHGs (methane, nitrous oxide, and carbon dioxide). Methane is released mainly from livestock digestion processes and stored animal manure, and nitrous oxide is emitted from organic and mineral nitrogen fertilizers. According to the US Environmental Protection Agency (EPA), 9% of GHG emissions in 2016 were associated with the agriculture sector (especially livestock, soils, and rice production) in the USA (EPA, 2019). In EU-28, 10.3% of total GHG emissions were associated with the agriculture sector. Food and agriculture organization (FAO) estimated that GHG emissions of agriculture have increased from 4.6 Gt CO_2 eq yr^{-1}[1] in the 1990s to 5.3 Gt CO_2 eq yr^{-1} in 2011. Moreover, this amount of CO_2 is expected to substantially increase to 30% by 2050, provided that greater reduction efforts such as declining energy use are not devoted (Tubiello et al., 2014).

Agriculture also impacts CC through incentivizing different land use and cover changes (LUCC) including deforestation (Baude et al., 2019; Beillouin et al., 2022; Kertész et al., 2019; Shrestha et al., 2022). Empirical evidence asserted that LUCC alters the land surface energy fluxes (Anita et al., 2010); however, the severity of the effect varies based on LUCC characteristics. Maeda et al. (2021) showed that climatic impacts of deforestation significantly differ based on land uses/activities developed afterward. It was shown that commercial agriculture land use is producing more negative impacts on surface temperature and local climate compared to other land uses such as rural settlements. Mounting evidence suggests that LUCC affects not only the local climate but also the regional and global climate. Nonetheless, the exact patterns of these changes have remained poorly understood (Fahrenkamp-Uppenbrink, 2013). LUCC affects the quality of different dimensions of the environment. For instance, it influences water quality, air quality, and biologic diversity through changes in runoff, hydrologic cycle, carbon storage, habitat loss, and disturbance

[1] Gigatons of CO_2 equivalent per year.

to resource availability (Azadi et al., 2022; De Palma et al., 2018; Mantyka-Pringle et al., 2015; National Research Council, 2012; Ponpang-Nga & Techamahasaranont, 2016; Shrestha et al., 2022).

The land use change trend has been taking place on a very large scale today because of humankind's technological advances. In the past (thousands of years ago), people converted forests into other land uses using fire, primitive tools, and grazing to facilitate hunting and agriculture, but today, advanced technology has led to rapid changes in land use on a very large scale (FAO, 2018). In Iran land use change, especially agricultural land conversion (ALC), has considerably increased during current decades and this has caused numerous socioeconomic and environmental impacts. ALC has a negative association with AE, meaning that when ALC increases, the AE decreases (Azadi & Barati, 2013; Azadi et al., 2015; Barati et al., 2015). In the USA, urban and agricultural areas expansion, energy development, and forestry practices changes have been the main drivers of land use change (National Research Council, 2012). These large-scale changes may contribute to increased CO_2 concentrations in the atmosphere which is one of the most important environmental problems of today.

Although our knowledge about the impacts of LUCC on climate through GHG emissions is lacking, empirical evidence suggests that one of the most important outcomes of these emissions is global warming. Overall, the temperature of the Earth's equilibrium is controlled by a few factors, including incoming sunlight; absorbed and reflected sunlight; and infrared radiation released, absorbed, and re-emitted in the atmosphere, mainly by greenhouse gases (GHGs) (Li et al., 2023; Wuebbles et al., 2017). Any changes in these factors through the addition of GHGs will contribute to CC by reducing the radiative balance of the earth. Any changes in this balance will result in changes in temperature, precipitation, and other climate variables through a complex set of physical couplings (Li et al., 2023; Usgcrp, 2017). These changes will create an additional loop, which means more global warming. Figure 1 illustrates the changes in global surface temperature, relative to 1951–1980 average temperatures (as anomaly baseline[2]), and CO_2 as the most important GHG. Based on this graph, a direct correlation exists between these two variables ($r=0.95$, $P<0.001$).

Literature review shows that studies examining the impacts of AE on CC have three major characteristics. Firstly, the impact of AE on CC has not been frequently studied; however, adequate CC mitigation and adaptation policies require a complete understanding of the effect of AE on CC. Secondly, studies have mainly measured specific characteristics of AE such as cropland expansion (Sampaio et al., 2007), cash-crop plantation (June et al., 2018), change in cropping system (Ashraf et al., 2019), and their influences on micro and regional climate. Although these studies provide important implications for decision making, they only show the change in the surface sensible heat flux which consequently changes surface temperature. Therefore, an integrated analysis of pathways by which AE influences CC is required to quantify the overall effect of AE on CC. Thirdly, the majority of studies analyze AE–CC interactions within a small period of time, mostly lower than 10 years (June et al., 2018), undermining their abilities to uncover dynamics of AE–CC interactions over time. This study attempts to bridge the current knowledge gap in analyzing the impact of AE on CC by developing a comprehensive indicator composed of diverse forms of land use changes and agricultural activities indices that exacerbate GHGs emissions and land surface temperature. The study also applies a wider time frame and a large geographical area to capture both possible spatial and temporal variations in AE–CC interactions.

[2] Anomaly baseline is the average of variable(s) such as temperatures during a period of time (here 1951–1980).

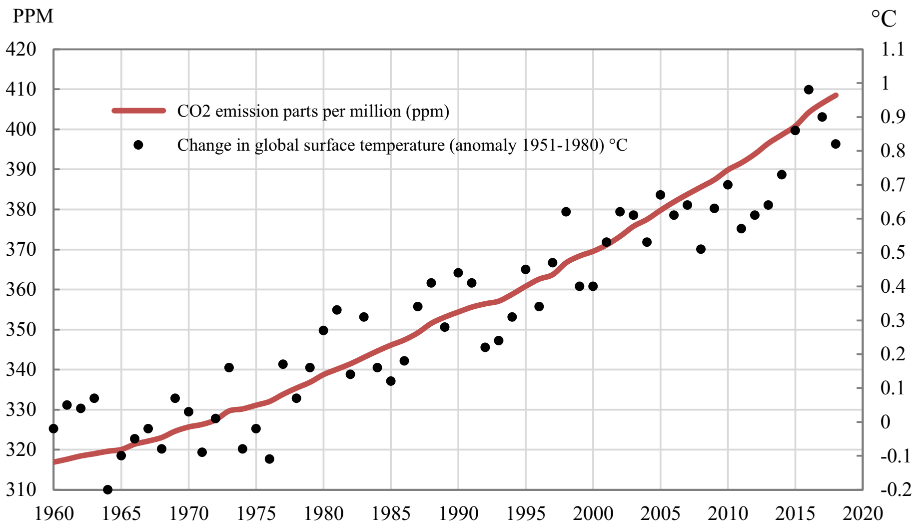


Fig. 1 Correlation between global surface temperature and carbon dioxide (Source of data: NASA/GISS. https://climate.nasa.gov/vital-signs/global-temperature/)

In Iran, it is widely claimed that the agricultural sector is a major source of GHG emission (Reisinger et al., 2013) and the amount of agricultural GHG emission has been experiencing an upward trend since the last two decades (Mohammadi et al., 2014). There are no specific data about agricultural CO_2 or other GHGs emissions from the agricultural sector at the country, province, or other local levels in Iran. However, empirical studies are essentially needed to support these claims. The only clear evidence is that Iran's CO_2 emissions increased drastically between 1990 and 2015, rising by 5% annually, whereas the global average for the same period was 2.3% (Central Bank of the Islamic Republic of Iran, 2018). Iran is the 11th country in the world, emitting 716.8 million tons of CO^2 and 1.64% of global GHGs (Friedrich et al., 2017). It is also the biggest emitter of GHGs in the Middle East (Mansouri Daneshvar et al., 2019).

To the best of our knowledge, this study is the first to analyze and statistically model the long-term spatiotemporal impacts of AE on CC in Iran for the duration of 57 years. This indicates the novelty and relevance of this study. More importantly, this study considers specific variations in AE and CC relationship for different geographical regions in the country which would provide significant policy implications for national policymakers. Moreover, while the majority of previous studies have attempted to reveal underlying forces behind a phenomenon, LUCC for instance (Li et al., 2020; Shahbazian et al., 2019), analyzing the mechanism of the impact of driving forces has received scarce attention. Specifically, this study seeks to answer the following main questions: (1) Have CC and AE changed in Iran (among provinces) significantly? (2) Has AE played an important role in CC in Iran? (3) How has the temperature changed in Iran during recent decades? To achieve these goals, this paper has been structured as follows. Section 2 discussed the methodology of the paper. In this section, the study area was first explained in brief. Then, the procedures of the calculation and development of AE and CC indicators were discussed. In Sect. 3, the results of the study were obtained, discussed, and compared with other studies. Finally, Sect. 4 prepared a brief conclusion of the paper and provided some suggestions for further studies.

2 Methods and materials

2.1 Study area

The study area was the Islamic Republic of Iran (Iran) in western Asia. Iran is located between the Caspian Sea in the North and the Persian Gulf and the Sea of Oman in the South. Based on the latest official census data, the population of Iran was about 80 million in 2016 (its current estimation is over 81 million inhabitants). Iran's land area is about 1,648,195 km^2. More than 82% of its area is located in the arid and semiarid zones of the world. Iran has a diverse climate ranging from hyper-arid (35.5%) to wet (10%) (Amiri & Eslamian, 2010). The average precipitation in Iran is less than 1/3 of the world (860 mm). Iran has extreme temperature changes (sometimes from -20 to $+50$ °C) over its different geographical areas. Severe drought and lack of adequate rainfall are the two main recognized features of Iran's climate. Agriculture is one of the main economic sectors of Iran. According to the last official census data of Iran (2017), the share of the agricultural sector in GDP and employment is about 11% and 18%, respectively (Statistical Center of Iran, 2017). More than 50% of rural labor is involved in agricultural activities. It also has an important role in providing foreign exchange revenues. Although there is no exact estimate of CO_2 emission from Iran's agriculture sector, it is estimated to be approximately 2.5% of the country's total CO_2 emission (Yousefi-Sahzabi et al., 2011). Due to the poor soil quality and water shortage in Iran, only 12% of the total lands are being cultivated. Less than one-third of the cultivated areas are irrigated lands, and the rest are under rain-fed farming (Barati et al., 2019a). Physical water crisis (Barati et al. 2019b; Madani, 2010, 2014), land degradation (Bahrami et al., 2010; Barati et al., 2021; Emadodin et al., 2012; Khaledian et al., 2017), and agricultural land conversion (Azadi et al., 2015; Barati et al., 2015) are some of the major challenges facing agriculture sector in Iran. The study area of this research is comprised of all provinces of Iran (31 provinces) that are shown in Fig. 2.

2.2 Materials and methods

This study used secondary data to analyze the impact of AE on CC. Two main kinds of data, including time-series and cross-sectional data, were used to analyze the influence of AE on CC. Time-series data were annual surface temperatures of provinces over 1960–2017. The source of these data was Iran's Meteorological Organization (IMO). These data were used to calculate the average temperatures baseline (anomaly baseline), long-term average surface temperature (1960–2017), and the average distance from anomaly as the climate change index (CCI). They also used these data to depict the CC trend over time. The cross-sectional data were used to depict the AE situation of the study units. The source of these data was the latest database of the Statistical Center of Iran (2017) (SCI). This study integrates socioeconomic and biophysical aspects of AE and shows the mechanism of the impact of AE on CC as well. For this, first, two indices were developed to represent the structural characteristics of AE (AEI) and CC (CCI) in Iran. Then, these indices were

Fig. 2 Study area (Iran)

calculated for all provinces of Iran. In the end, it investigated the impact of AEI on CC using the partial least-square (PLS) method.

To analyze the significant effect of AE on CC, this study used the two following indicators as the most important indicators of CC at the province level: (a) the average long-term surface temperature (AST) and b) the distance between average annual surface temperature and anomaly (DA).

The components of AEI and its calculation method are described in the following sub-sections.

2.2.1 The procedure of developing the agricultural expansion index (AEI)

The agriculture sector in Iran primarily consists of three main sub-sectors: farming (crop cultivation), horticulture, and animal husbandry. These three sub-sectors are also among agricultural components that have the greatest impact on CC (Eggleston et al., 2006). Therefore, those variables which were more related to these three prime sub-sectors were used to construct AEI. Moreover, the availability of data for all provinces was considered in the selection of AEI to make the comparison possible. These variables and their related factors are indicated in Table 1.

Table 1 The components of the structural equation modeling of AEI and CCI

Latent variables		Observed variables (indicators)	
Main index	Sub index	Symbol	Description
AEI	AHI (Animal husbandry index)	BAHI	Big animal husbandry indicator
		SAHI	Small animal husbandry indicator
	ALI (Agricultural land area index)	IFLI	Irrigated farm land indicator
		RFLI	Rain-fed farm land indicator
		IOLI	Irrigated orchard land indicator
		ROLI	Rain-fed orchard land indicator
	DEI (Demographic index)	APPI	Agricultural producer population indicator
		RRPI	Rate of rural population indicator
CCI	–	AST	Average surface temperature (1960–2017)
		DA	Distance of anomaly

To construct an overall index to show the agricultural expansion for each study unit (province), the AE index was developed using the following procedure:

1. Selecting and gathering secondary data about the agricultural expansion, including main agricultural variables such as irrigated and rain-fed farm and orchard land area, number of farms, animal husbandries, small and big livestock, and the ratio of rural population for each province.
2. Calculating an expansion index for each variable using Eq. 1.
3. Normalizing each expansion index using Eq. 2.
4. Calculating an agricultural expansion index for each province using Eq. 3.

$$\mathrm{EI}_{ij} = \frac{V_{ij} / \sum V_{ij}}{A_j / \sum A_j} \tag{1}$$

in which: $i = 1, 2, \ldots, n$, and n is the number of included variables, $j = 1, 2, \ldots, m$, and m is the number of provinces, EI_{ij} is the expansion index of variable i for province j, V_{ij} is the value of variable i for province j, and A_j is the area of province j.

$$\mathrm{NEI}_{ij} = \frac{\mathrm{EI}_{ij} - \min\left(\mathrm{EI}_{i1}, \mathrm{EI}_{i2}, \ldots, \mathrm{EI}_{ij}\right)}{\max\left(\mathrm{EI}_{i1}, \mathrm{EI}_{i2}, \ldots, \mathrm{EI}_{ij}\right) - \min\left(\mathrm{EI}_{i1}, \mathrm{EI}_{i2}, \ldots, \mathrm{EI}_{ij}\right)} \tag{2}$$

in which NEI_{ij} is the normalized expansion index of variable i for province j, and

$$\mathrm{AEI}_j = \frac{\sum \mathrm{NEI}_{ij}}{n} \tag{3}$$

where AEI_j is the agricultural expansion index of province j, and n is the number of variables.

2.2.2 The procedure of developing climate change index (CCI)

To indicate the climate change level for each province, this study used the mean distance between annual and anomaly temperature over 1960–2017. The anomaly temperature was calculated for a 25-year period (1976–2000) (Eq. 4). It was the average annual temperature over 1976–2000. Annual temperature is the average surface temperature of the province over each year. Finally, a climate change index (CCI) was calculated for each province using the following formula (Eq. 5):

$$\mathrm{DA}_{jz} = T_{jz} - \mathrm{AT}_j,\ z(1960,\ 1970, \dots, 2017) \tag{4}$$

in which DA_{jz} is the distance between the annual temperature of province j for year z and the anomaly temperature of province j, T_{jz} is the annual temperature of province j for year z, and AT_j is the anomaly temperature of province j.

$$\mathrm{CCI}_j = \frac{\sum \mathrm{DA}_{jz}}{t} \tag{5}$$

in which CCI_j is the climate change index of province j, and t is the length of the period of time over 1960–2017 (58 years).

Table 2 includes all normalized variables of AEI and CCI.

2.2.3 Investigating the impact of AEI on CCI

To investigate the impact of AEI on CCI, both descriptive and analytical methods have been used. In the descriptive section, descriptive statistics, GIS maps, and integrated charts were utilized. In the analytical section, partial least-square (PLS) structural equation modeling was used (using Smart-PLS software v.3). PLS, as a method of structural equation modeling, allows estimating complex structural or cause–effect relationship models with latent (they are usually displayed by circles) and observed variables (they are usually displayed by rectangles) (Hair Jr et al., 2016; 2017). This study applies a structural equation modeling that allows integrated analysis of socioeconomic and biophysical factors affecting CC in a single framework through the application of latent variables. This method enables examining pathways by which AE affects CC, quantifying the overall effect of AE on CC and its significance, and providing statistical evidence for verifying the hypothesized model. Structural equation modeling has widely been applied in land system science (Xiaoyu et al., 2021), erosive ecological structure (Zhou et al., 2019), and climate-induced vegetation change (Buchwal et al., 2020; Hou et al., 2020). However, this method has seldom been used in analyzing the impacts of AE on CC, indicating the methodological novelty of this paper. PLS is also useful when the sample size is small and the data have high collinearity (Palermo et al., 2009). Each PLS model has two main sub-models: (a) estimation model, representing the relationship between the data observed and the latent variables. As a weighted sum of its observed data, it estimates the latent variables. (b) A structural model, showing the relationship between latent variables (Hair Jr et al., 2016). A structural model applies a single or multiple linear regression to the latent variables to estimate them. Figure 3 prepares the conceptual model of this study.

Table 2 Normalized values of AEI and CCI variables

Province	AST	DA[a]	IOLI	ROLI	IFLI	RFLI	APPI	SAHI	BAHI	RPRI	AEI	Normal AEI
Markazi	13.947	0.445	0.393	0.003	0.344	0.266	0.102	0.416	0.141	0.153	0.190	0.319
Gilan	16.234	0.439	0.333	1.000	0.606	0.040	1.000	0.370	0.825	1.000	0.587	1.000
Mazandaran	16.168	0.404	0.886	0.220	0.478	0.096	0.619	0.551	0.474	0.877	0.440	0.748
East Azerbaijan	11.343	0.386	0.542	0.012	0.186	0.579	0.228	0.757	0.046	0.351	0.372	0.631
West Azerbaijan	11.343	0.386	0.704	0.044	0.380	0.336	0.228	1.000	0.332	0.445	0.370	0.628
Kermanshah	14.797	0.158	0.142	0.009	0.210	0.694	0.220	0.581	0.111	0.274	0.235	0.396
Khuzestan	14.301	0.261	0.112	0.006	1.000	0.303	0.084	0.582	0.158	0.256	0.261	0.440
Fars	12.285	0.175	0.235	0.078	0.340	0.063	0.058	0.347	0.050	0.158	0.135	0.224
Kerman	17.050	0.625	0.506	0.001	0.149	0.001	0.041	0.119	0.024	0.088	0.095	0.156
Razavi Khorasan	14.321	0.278	0.190	0.066	0.400	0.122	0.100	0.396	0.068	0.205	0.160	0.267
Isfahan	16.456	0.161	0.133	0.002	0.156	0.005	0.053	0.086	0.088	0.066	0.062	0.099
Sistan and Baluch	18.819	0.144	0.031	0.002	0.059	0.013	0.010	0.048	0.012	0.100	0.029	0.043
Kurdistan	14.301	0.261	0.144	0.040	0.066	0.900	0.167	0.369	0.121	0.226	0.217	0.366
Hamadan	11.984	0.214	0.373	0.013	0.496	1.000	0.264	0.735	0.170	0.488	0.369	0.627
Chaharmahal Bakhtiari	12.341	0.149	0.403	0.003	0.210	0.093	0.164	0.630	0.119	0.299	0.204	0.342
Lorestan	17.363	0.848	0.189	0.010	0.192	0.621	0.209	0.851	0.138	0.319	0.266	0.448
Ilam	17.027	−0.178	0.008	0.002	0.201	0.327	0.102	0.493	0.047	0.119	0.135	0.225
Kohgiluyeh Boyer	15.043	−0.033	0.294	0.026	0.078	0.334	0.180	0.901	0.067	0.291	0.226	0.380
Bushehr	24.772	0.060	0.170	0.025	0.088	0.317	0.039	0.208	0.028	0.159	0.105	0.173
Zanjan	12.354	0.217	0.575	0.004	0.112	0.662	0.160	0.456	0.154	0.224	0.247	0.417
Semnan	19.206	0.555	0.044	0.000	0.062	0.008	0.000	0.058	0.016	0.000	0.019	0.025
Yazd	19.665	0.435	0.230	0.000	0.000	0.000	0.028	0.000	0.020	0.013	0.029	0.043
Hormozgan	27.231	0.539	0.068	0.014	0.045	0.004	0.004	0.032	0.008	0.153	0.035	0.053
Tehran	17.458	0.059	0.667	0.000	0.890	0.012	0.159	0.719	1.000	0.898	0.438	0.745
Ardabil	9.350	0.393	0.458	0.007	0.472	0.823	0.264	0.047	0.427	0.329	0.406	0.690
Qom	18.416	0.522	0.195	0.000	0.287	0.002	0.018	0.186	0.210	0.061	0.098	0.161
Qazvin	14.377	0.859	1.000	0.012	0.736	0.291	0.217	0.501	0.353	0.297	0.353	0.599

Table 2 (continued)

Province	AST	DA[a]	IOLI	ROLI	IFLI	RFLI	APPI	SAHI	BAHI	RPRI	AEI	Normal AEI
Golestan	17.723	0.501	0.149	0.086	0.562	0.662	0.229	0.727	0.267	0.640	0.353	0.599
North Khorasan	13.214	0.093	0.150	0.047	0.307	0.210	0.106	0.547	0.054	0.183	0.168	0.280
South Khorasan	16.796	0.350	0.000	0.001	0.018	0.004	0.000	0.004	0.000	0.010	0.004	0.000
Alborz	15.817	0.271	0.800	0.001	0.542	0.008	0.266	0.624	0.580	0.581	0.345	0.584

AST Average surface temperature over 1960–2017, *DA* Distance of anomaly, *IOLI* Irrigated orchard land indicator, *ROLI* Rain-fed orchard land indicator, *IFLI* Irrigated farm land indicator, *RFLI* Rain-fed farm land indicator, *RRPI* Rate of rural population indicator, *APPI* Agricultural producer population indicator, *SAHI* Small animal husbandry indicator, *BAHI* Big animal husbandry indicator, *RRPI* Rate of rural population indicator, *AEI* Agricultural expansion index, *Normal AEI* Normalized AEI

[a]The term temperature anomaly means a departure from a long-term average

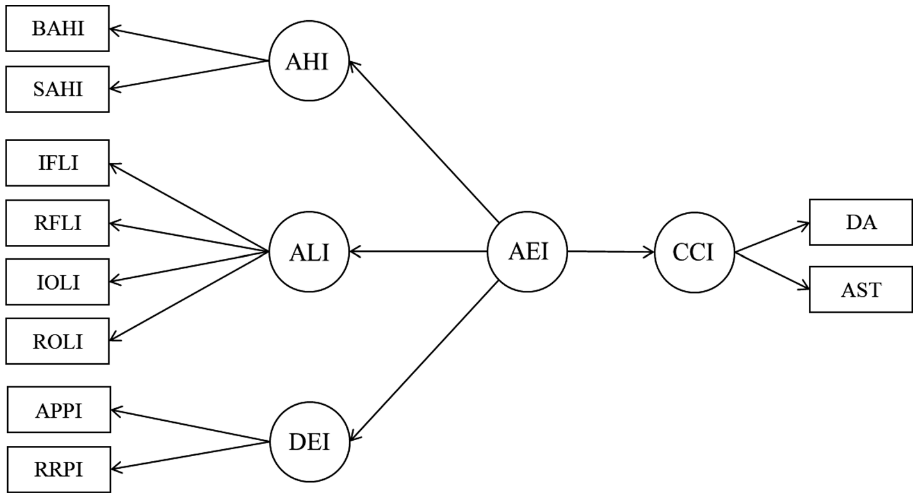


Fig. 3 The conceptual model of the study

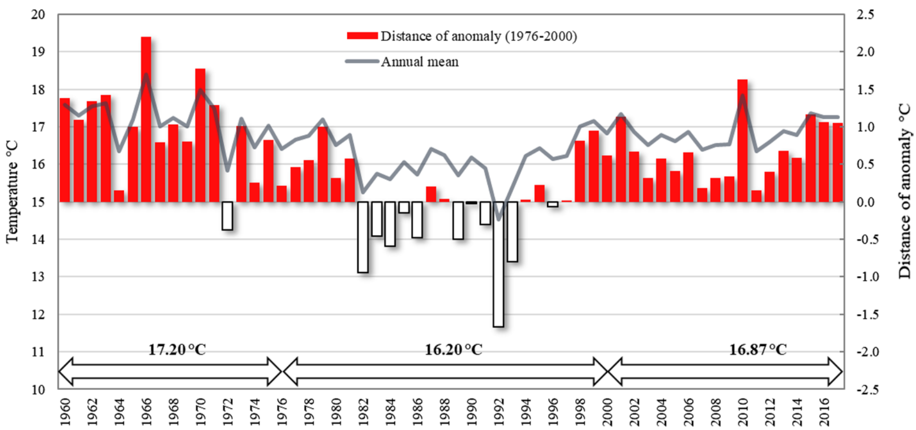


Fig. 4 The trend of Iran's surface temperature change based on annual mean temperature and distance of anomaly (1976–2000)

3 Results and discussion

3.1 Temperature changes as the main indicator of CC in Iran

Figure 4 shows the trend of surface temperature changes in Iran over 1960–2017. Based on this figure, the annual mean temperature and its distance of anomaly (over 1960–2017) did not have a stable trend. The average annual temperature of Iran decreased from 1982 to 1994 and increased again. The main part of this period coincided with the Iran–Iraq war during 1980–1988. During this period and also several

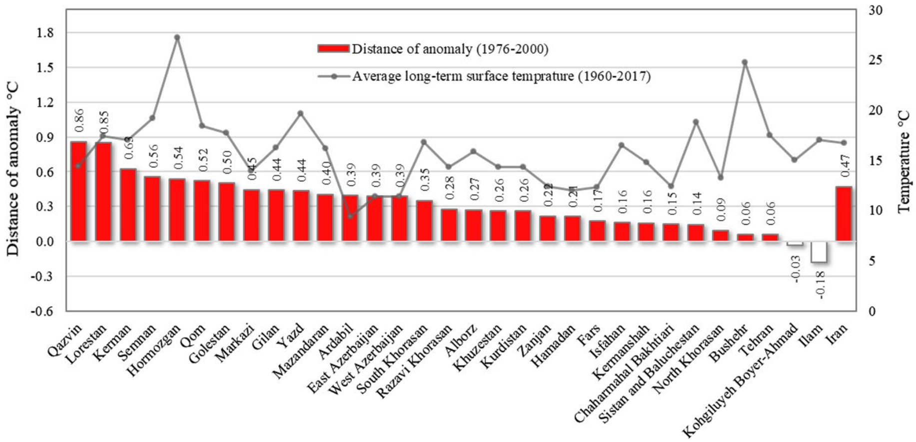


Fig. 5 The surface temperatures of Iran's provinces in the long term (1960–2017) and their average distance of anomaly (1976–2000)

years afterward, many economic activities have been closed down. This can be considered as a possible explanation for such a decline in temperature.

Figure 5 shows the average surface temperatures of Iran's provinces in the long term (1960–2017), as well as their average distance of anomaly (1976–2000). It shows that over 1960–2017, the average annual surface temperatures of most provinces, except Kohgiluye and Ilam, have increased. In general, this increase across Iran has been about 0.47 °C. Soltani et al. (2016), Rahimi et al. (2018), and Tabari and Talaee (2011) also emphasized the increase in the average surface temperature across Iran. The results show that Qazvin and Lorestan had the largest increase in the average annual surface temperature. Hormozgan and Bushehr had the highest average surface temperature in Iran while Ardabil experienced the lowest.

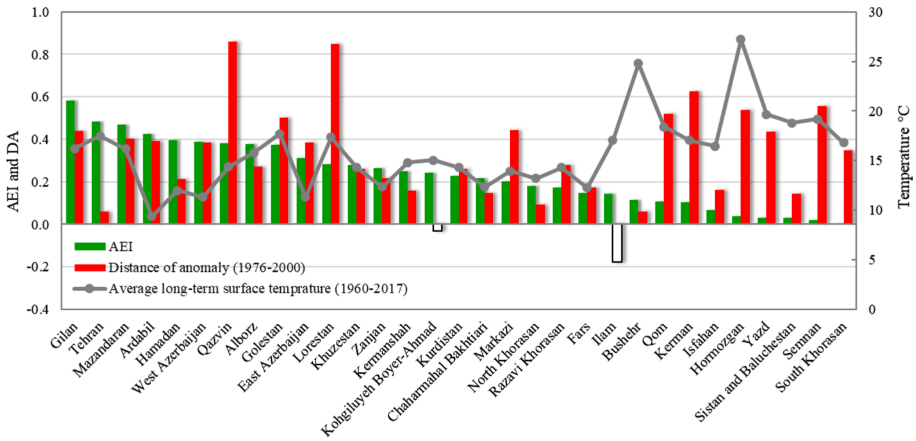


Fig. 6 AEI, DA, and AST indicators of Iran's provinces in comparison with each other

3.2 AE and CC in Iran

Results of comparison among provinces based on their AEI, DA, and AST are presented in Figs. 6 and 7. Seemingly, provinces with less AEI have experienced more changes in CCI (both average long-term surface temperature and average distance of anomaly). However, this is only a hypothesis that is not statistically significant. There are also some observations that provinces such as Qazvin, Golestan, and Lorestan faced a huge change in DA and AST simultaneously.

The provinces located in the north, northwest, and west of Iran have a larger AEI compared with those located in the south, southeast, and east of the country (Fig. 7).

Figure 8 shows the dispersal of the provinces in terms of their AEI (a), AST (b), rural population rate (c), and distance of average annual temperature from anomaly (d). It can be observed that agriculture has expanded more in the north and northeast of the country (Fig. 8a) where the average surface temperature is also lower than that of other areas (Fig. 8b). As shown in Fig. 8c, rural population rates for the south and southeast provinces are higher than those of others, except for a small number of northern provinces. Nonetheless, the former provinces have not scored high based on their AEI (Fig. 8a). Based on Fig. 8d, there is no significant distribution in terms of the DA indicator among the provinces.

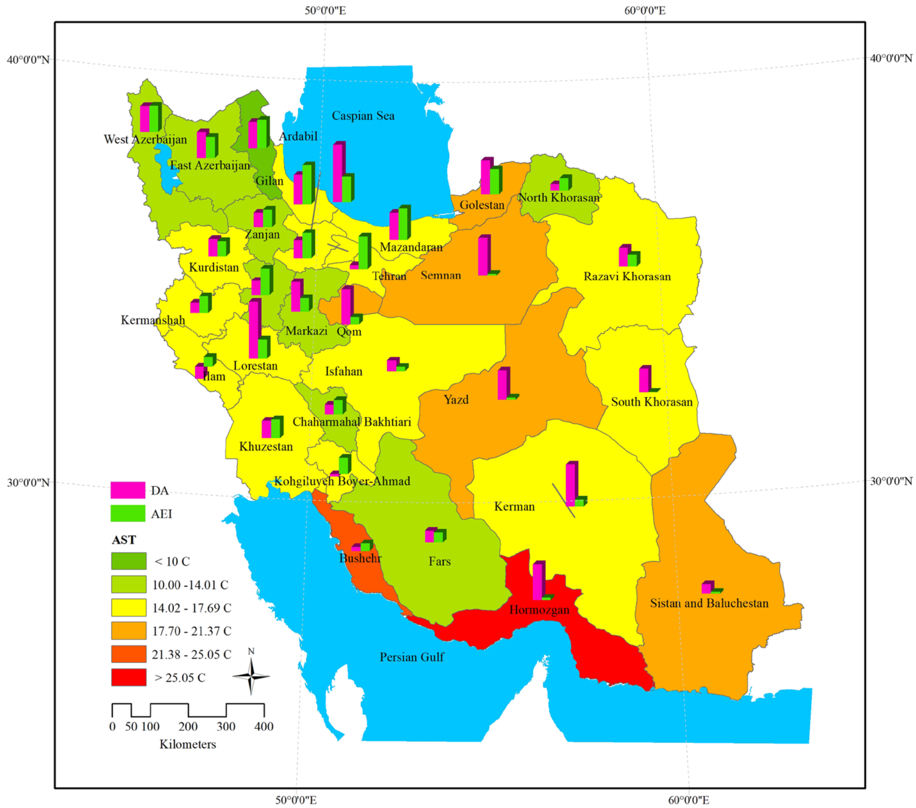
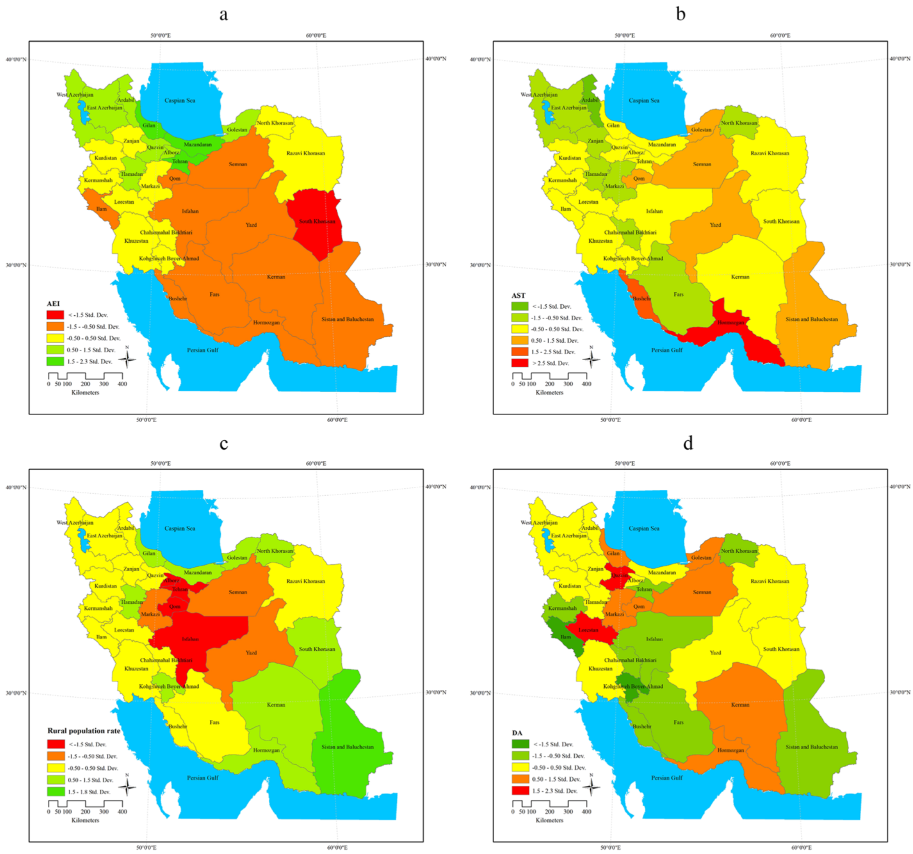


Fig. 7 The geographical distribution of Iran's provinces based on their AEI, DA, and AST indicators



AEI (Agricultural Expansion Index)

AST (Average Surface Temperature in the long run, 1960-2017)

DA (Distance of Anomaly)

Fig. 8 The geographical distribution of Iran's provinces based on their AEI, DA, RPR, and AST indicators. **a** Agricultural expansion index, **b** the average surface temperature in the long run (1960–2017), **c** rural population rate, and **d** the mean distance of anomaly index

3.3 Impacts of AE on CC in Iran

This study developed a conceptual model (Fig. 3) to investigate the impact of AE on CC. Regarding the small size of the statistical population (Iran's provinces), and since the proposed model is a primitive one, the PLS structural equation modeling (using Smart-PLS software v.3) is used to estimate this model. Figure 9 shows the estimated model. Before model interpretation, it is necessary to evaluate both measurement (outer) and structural (inner) parts of the model (model fit evaluation). First, the measurement model should be evaluated and then the structural part (Hair Jr et al., 2016). Standardized loadings, average variance extracted (AVE) (that is commonly used to assess the convergent validity of the shared variance between the latent variables of the model), composite reliability (CR) (i.e., a measure of the overall reliability of a collection of heterogeneous, but similar items), and finally, weights' significance (*P* value) are some of the most important criteria to evaluate

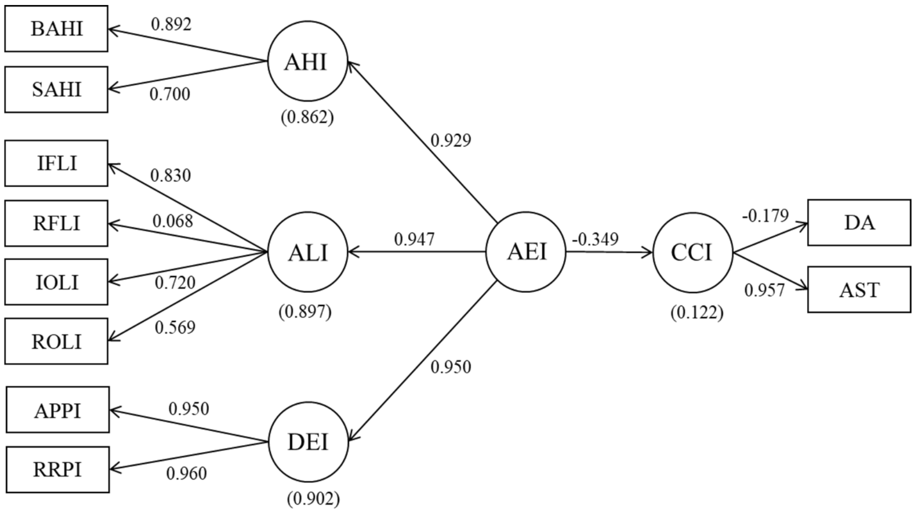


Fig. 9 The estimated factor loadings and adjusted R^2 (numbers in parentheses) of the base model (Fig. 3)

the measurement part of the model (Garson, 2016; Hair Jr et al., 2017). To evaluate the structural or inner part of the model (which consists of the factors and the paths between them), the most popular indicators are structural path coefficients (loadings), path significance (P value), adjusted R square (i.e., a modified version of R square that has been adjusted for the number of predictors in the model), and Q^2 value (the model's predictive power) (Garson, 2016). Based on the results (Fig. 9 which includes the estimated factor loadings of the base model, and Table 3 which consists of the goodness-of-fit criteria), most paths (except the two ALI → RFLI and CCI → DA paths) have a proper loading (a good loading is more than 0.7, and an acceptable loading is more than 0.5). In addition, AVE and CR for some parts of the measurement model are not good either. Therefore, before any interpretation, it needs to be modified. This model was modified by removing two nonsignificant paths (ALI → RFLI and CCI → DA), and it was estimated again.

Figure 10 and Table 4 include the modified model and its measured goodness-of-fit indicators. In the modified model, both measurement (outer) and structural (inner) models have fitted well. Therefore, model interpretation could be done. What does this model tell? Or what is the meaning of this model? The measurement part of the model means that the components of AEI (its indicators) have been proper. In other words, the second-order measurement model (including AEI, AHI, ALI, DEI, and their indicators), which is designed to measure AEI, has played its role well (all paths are significant and have proper loadings and R^2). The weight criteria (Table 3) indicate the relative importance of each variable for each factor. According to the weight criteria, the big animal husbandry indicator (BAHI), the irrigated farmland indicator (IFLI), and the rate of rural population indicator have been the most important indicators for their latent variables (factors). However, in this study, the most important part of the model is the structural one. It is due to the fact that this part implies the impacts of the agricultural expansion on climate change (AEI → CCI). According to this model, AE has a significant impact on average surface temperature. However, this impact has been proved negative (−0.306). It means that provinces with a higher AEI have had a lower long-term surface temperature. However, this effect has not been very strong. In other words, about 6% of surface temperature variances at the province

Table 3 The goodness-of-fit criteria of the base model

Measurement model						Structural model			
Path/variable	Loading (> 0.5 or 0.7)	P value (< 0.05)	Weight	AVE (> 0.5)	CR (> 0.7)	Path/variable	Adjusted R^2	Loading (> 0.5 or 0.7)	P value (< 0.05)
AHI → BAHI	0.892	0.000	0.749	0.643	0.780	AEI → AHI	0.862	0.929	0.000
AHI → SAHI	0.700	0.000	0.474						
ALI → IFLI	0.830	0.000	0.512	0.384	0.660	AEI → ALI	0.897	0.947	0.000
ALI → RFLI	0.068	0.813	0.092						
ALI → IOLI	0.720	0.000	0.454						
ALI → ROLI	0.569	0.005	0.425						
DEI → APPI	0.950	0.000	0.494	0.912	0.954	AEI → DEI	0.902	0.950	0.000
DEI → RRPI	0.960	0.000	0.553						
CCI → AST	0.957	0.004	0.990	0.474	0.336	AEI → CCI	0.112	−0.349	0.087
CCI → DA	−0.179	0.718	−0.291						

Loading is the coefficient of the path in the reflective mod (it is estimated by a single regression where the latent variable represents the independent variable and the indicator is the dependent variable)

Weight is the coefficient of the path in the formative mod (it is estimated by a multiple regression where the latent variable represents a dependent variable and the indicators are the independent variables)

AVE is the average variance extracted

CR is composite reliability

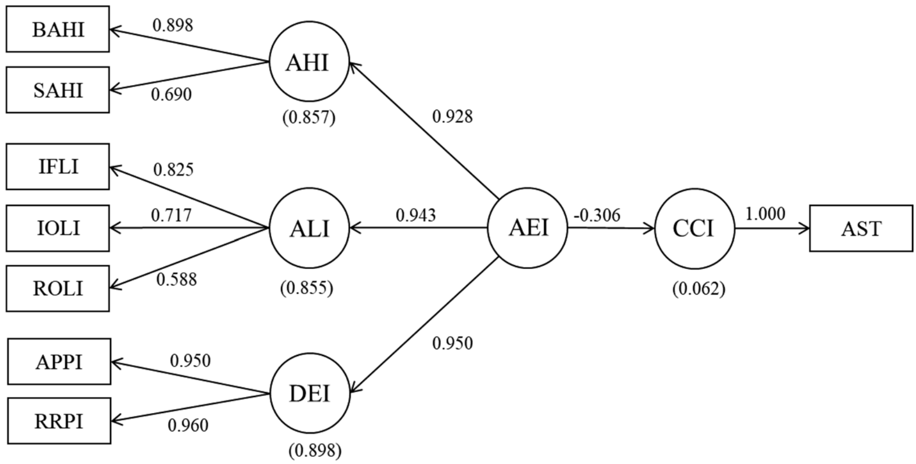


Fig. 10 The estimated factor loadings and adjusted R^2 (numbers in parentheses) of the modified model

level have been defined with the variance of provinces' AEI. Therefore, the effect of AE on long-term surface temperature is not very strong. There is some literature that claimed about the impacts of agriculture on temperature through CO_2 emission and land use change (Alkimim & Clarke, 2018; Anita et al., 2010; EPA, 2019; Füssel et al., 2012).

Mande et al. (2015) believed that AE in southeastern Burkina Faso could spark unforeseen climate change. Liu et al. (2018) claimed that the dramatic exploitation of agriculture has caused some environmental and ecological problems and has affected the stability of northwest China. This study also investigated the impact of AE on CC using the average distance from anomaly temperature over 1960–2017 as the second model (Fig. 11). This model also fitted well (Fig. 11 and Table 5). Based on this model, although most provinces have faced a positive change in surface temperature during recent decades (Figs. 5, 6, 7, and 8), AEI has had no significant impact (P value > 0.05) on DA. Many Iranian policymakers and environmentalists have claimed that agriculture has been responsible for many environmental changes, especially in recent decades. There are many investigations that emphasized the increased trends of temperature in Iran (Rahimi et al., 2018; Soltani et al., 2016; Tabari & Talaee, 2011).

3.4 AE and CC an over view

Since the world's population is estimated to reach 9.8 billion by 2050 (Kaneda & Dupuis, 2017), agricultural activities will play a more important role in providing the required human food (food security) and sustainable development (Pachauri et al., 2014; Zurek et al., 2022). FAO predicts that global arable land use will reach 1.66 billion hectares in 2050 (Roser & Ritchie, 2019) and a major part of this growth will result from developing countries. Iran, like many developing countries, has faced this challenge. Agriculture and climate affect each other seriously. On the one hand, agriculture is strongly related to climate. Therefore, climate and its changes adversely affect agricultural activities (Schmidhuber & Tubiello, 2007). Changes in rainfall and temperature patterns, as a result of CC, will exacerbate droughts and water crisis in Iran which consequently affect farming systems (Azadi et al., 2018). On the other hand, agriculture, as the major form of the

Table 4 The goodness-of-fit criteria of the modified model

Measurement model						Structural model			
Path/variable	Loading (> 0.5 or 0.7)	*P* value (< 0.05)	Weight	AVE (> 0.5)	CR (> 0.7)	Path/variable	Adjusted R^2	Loading (> 0.5 or 0.7)	*P* value (< 0.05)
AHI → BAHI	0.893	0.000	0.759	0.641	0.779	AEI → AHI	0.857	0.928	0.000
AHI → SAHI	0.690	0.000	0.461						
ALI → IFLI	0.825	0.000	0.511	0.514	0.757	AEI → ALI	0.885	0.943	0.000
ALI → IOLI	0.717	0.000	0.453						
ALI → ROLI	0.588	0.007	0.425						
DEI → APPI	0.950	0.000	0.494	0.912	0.954	AEI → DEI	0.898	0.950	0.000
DEI → RRPI	0.960	0.000	0.553						
CCI → AST	1.000	–	1.000	1.000	1.000	AEI → CCI	0.062	−0.306	0.027

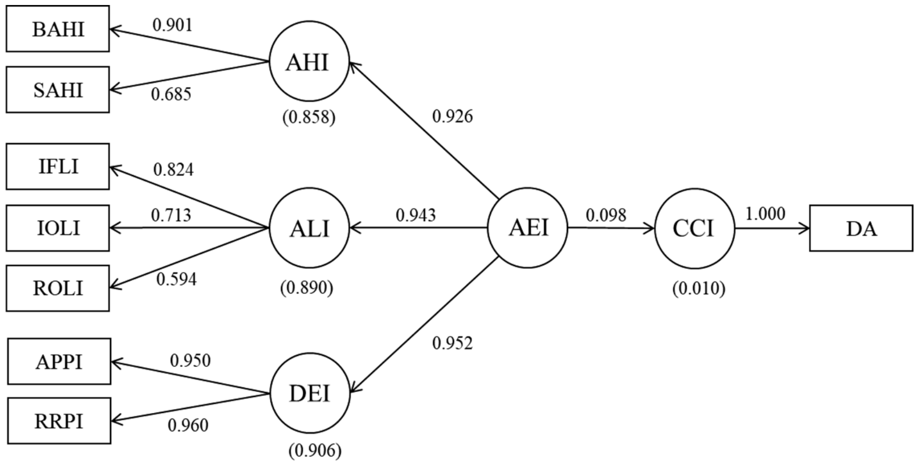


Fig. 11 The estimated factor loadings and adjusted R^2 (numbers in parentheses) of the second model

social–ecological system, affects the global climate (IPCC, 2015, 2018a). Agriculture affects the environment and climate in different ways such as soil erosion (Maeda et al., 2010) and degradation (Baude et al., 2019; Panagos et al., 2018), loss of biodiversity (Lanz et al., 2018), and groundwater pollution (Almasri & Kaluarachchi, 2004; Okumah et al., 2018).

The results of this study showed that the average long-term surface temperature in Iran over 1960–2017 has faced some different variations. Among these variations, for a period of time (1982–1994), it faced a significant decline. This period coincided with the Iran–Iraq war (1980–1988). In addition, several years later, when many economic activities were closed down, this phenomenon was repeated. These fluctuations in mean temperature were also reported by Ghasemi (2015). In addition, the average long-term (1960–2017) distance from anomaly (1976–2000) in Iran has increased by 0.47 °C. Roshan et al. (2011) also reported this increasing temperature trend in Iran, and using a temperature simulation, forecasted a 4.41 °C increase in Iran's mean temperature by 2100. IPCC (2015) reported a similar temperature trend on a global scale (0.85 °C, over the period 1880–2012). IPCC (2018b) also predicted that global warming is likely to reach 1.5 °C between 2030 and 2052.

Although the distance of temperature from anomaly among provinces with low AEI seems to be more than provinces with high AEI, this is not absolutely correct. There are also some provinces with high AEI and DA such as Qazvin and Golestan. This result was foreseeable since AEI is not the only driver of temperature change and CO_2 emission. For example, Qazvin has faced a high rate of agricultural land conversion because of urban and road network expansion (Asadi et al., 2016; Barati et al., 2015). Moreover, Golestan has also experienced a series of significant land-cover and land use changes over 1967–2010 (Zamani et al., 2012). IPCC (2018a) reported that over the past 50 years, human activities have resulted in huge emissions of GHGs to the atmosphere and there is a 95% certainty that human-induced environmental footprints are responsible for the current level of global warming. CO_2 emissions from the combustion of fossil fuels and industrial processes contributed to about 78% of total GHG emissions among various human activities.

Table 5 The goodness-of-fit criteria of the second model

Measurement model						Structural model			
Path/variable	Loading (> 0.5 or 0.7)	*P* value (< 0.05)	Weight	AVE (> 0.5)	CR (> 0.7)	Path/variable	Adjusted R^2	Loading (> 0.5 or 0.7)	*P* value (< 0.05)
AHI → BAHI	0.901	0.000	0.764	0.641	0.778	AEI → AHI	0.858	0.926	0.000
AHI → SAHI	0.685	0.000	0.454						
ALI → IFLI	0.824	0.000	0.509	0.513	0.757	AEI → ALI	0.890	0.943	0.000
ALI → IOLI	0.713	0.000	0.450						
ALI → ROLI	0.595	0.005	0.438						
DEI → APPI	0.950	0.000	0.495	0.912	0.954	AEI → DEI	0.906	0.952	0.000
DEI → RRPI	0.960	0.000	0.552						
CCI → DA	1.000	–	1.000	1.000	1.000	AEI → CCI	0.010	0.098	0.512

This study indicated that although AE has had a negative impact on long-term average surface temperature in Iran, its effect has been much lower than that of other sectors. Putting this more precisely, there are other sectors in the country that have a more significant impact than agricultural expansion. It is noteworthy to mention that the AEI explained approximately 6% of the total variance of long-term surface temperature in Iran. The most important part of surface temperature variance in Iran has been caused by other factors or variables such as CO_2 emissions from liquid fuel consumption. They have been responsible for more than 37% of the total CO_2 emission. Residential buildings and commercial and public services have been responsible for about 22% of CO_2 emissions. Electricity and heat production have also been responsible for about 34% of total CO_2 emissions in Iran in 2014 (Trending Economics, 2019). Iran has been among the 10 biggest emitters of CO_2 in 2018 (EurekAlert & AAAS, 2018).

Avoiding CO_2 emission has been introduced as the main way to limit global warming. Based on the Paris Agreement, to achieve the goal of a 1.5 °C increase in global temperature, CO_2 emissions would need to decline by 50 percent by 2030. It also needs to reach net-zero by around 2050. Therefore, Iran has no way but to decline CO_2 emissions. In this regard, policymakers must pay more attention to the main sources of CO_2 emissions in Iran. For example, CO_2 emissions from cars, lorries, and other transportation systems which have low energy efficiency have raised oil consumption. The efficiency of gas consumption, as the most important source of heating energy in recent decades, should be increased. Iranian government needs to pay much more attention to this issue and try to replace fuel and gas with renewable resources such as wind and sun-based energies.

Food waste is another important source of CO_2 emission in the world. It contributes to about 6.7% of global CO_2 emissions (IPCC, 2007; Zurek et al., 2022). Humans have lost or wasted about one-third of the foods that have been produced for global consumption. Reducing food waste through enhancing waste management, which would lead to more efficient land and water resources management, has not only positive impacts on livelihoods but also positive impacts on climate change (FAO, 2019). Food waste is also another challenge for the Iranian community. About 25 million tons of food are wasted in Iran (Fami et al., 2019). This amount of wasted food has both socioeconomic and environmental consequences. The government, private sector, and civil society should collaborate to raise awareness on the issues. They should develop policies and actions to address the root of the problem.

This study demonstrated that AE has no significant impact on recent changes in surface temperature based on anomaly (DA). Therefore, in addition to the agriculture sector, it seems that policymakers should pay more attention to other sources of CO_2 emissions as the main global warming factor, e.g., energy, transport, industry, food, and water and soil waste (IPCC, 2018b). Toward this end, Iran needs to consider reducing CO_2 emissions from buildings, industries, agriculture, and transport sectors and enhancing the rapid deployment of low-carbon technologies seriously. In the agriculture sector, Iran would need to improve and sustain its agricultural practices and technologies to halt increasing local surface temperature. Therefore, it would be essential to reduce the uncontrolled use of chemical inputs such as pesticides and chemical fertilizers; improve the irrigation and water management systems, tillage, and other soil management operations; reduce plant hormone applications; avoid planting without rotation, etc. (Önder et al., 2011). These policies would alleviate the negative impacts of AE on CC and would enhance the adaptation of the agricultural sector to the increasing destructive weather events in Iran (Karimi et al., 2018). Without any doubt, performing these strategies requires a coherent national policy with great economic and public support. In addition, these policies should improve the public environmental culture, raise public awareness about their environmental actions, and develop climate change awareness systems.

4 Conclusions

Land use and cover changes and climate change are two highly interrelated and major global challenges which are one of the most important environmental problems of today. During current decades, the impacts of CC on agriculture have been properly investigated; however, the impacts of agriculture on CC have received lower attention. This study attempts to bridge the current knowledge gap in analyzing the impact of AE on CC. It applied a wider time frame and a large geographical area to capture both possible spatial and temporal variations in AE–CC interactions based on Iran experiences. Based on the results, (A) the average surface temperatures of Iran's provinces, as the main indicator of CC, has been increased about 0.47 °C during 1960–2017. (B) AE has a significant negative but not strong impact on average surface temperature. Therefore, AE has not played an important role in CC in Iran. (C) Although most provinces have faced a positive change in surface temperature during recent decades and many Iranian policymakers and environmentalists have claimed that agriculture has been responsible for many environmental changes, AEI has had no significant impact on DA. Therefore, there is an incomplete knowledge about the climatic impacts of agriculture and other sectors and factors in Iran. Since there is a lack of accurate information on the climatic impacts of various sectors and sub-sectors in Iran, analyzing different climatic aspects of economic sectors seems a priority. Future studies should consider different forestry, land use, and agricultural sectors and manage their impacts on climate, through monitoring their emissions for instance. Moreover, regulating the local climate while ensuring economic growth in Iran is a serious challenge. The study showed that AE has only a scant share in the country's total GHG emissions in the long run. Iran, similar to many developing countries, has outweighed economic ambitious over environmental sustainability. This means that in every decision that legislators make, the economy proceeds the environment. The higher weight of the economy in decision making is perhaps more obvious in Iran since it has been under severe economic sanctions and thus desperately needs to sustain its economy. In terms of AE, Iran has serious limitations in importing foods and thus plans to pursue a self-sufficiency policy in providing its food. This means more lands would be converted into agriculture in the future, and consequently, the impact of agriculture on changing local climate will continue to rise. In a systemic view, this change in climate would adversely impact the sustainability of human–environment interactions and threaten biological diversity in the country as well. In this situation, policymakers should consider a systemic and balanced vision in their decision making to ensure environment protection, development, and sustainability.

Data availability The data will be available on reasonable request.

Declarations

Conflict of interest The authors have no conflict of interest.

References

Agovino, M., Casaccia, M., Ciommi, M., Ferrara, M., & Marchesano, K. (2018). Agriculture, climate change and sustainability: The case of EU-28. *Ecological Indicators*. https://doi.org/10.1016/j.ecolind.2018.04.064

Alkimim, A., & Clarke, K. C. (2018). Land use change and the carbon debt for sugarcane ethanol production in Brazil. *Land Use Policy, 72*, 65–73. https://doi.org/10.1016/j.landusepol.2017.12.039

Almasri, M. N., & Kaluarachchi, J. J. (2004). Assessment and management of long-term nitrate pollution of ground water in agriculture-dominated watersheds. *Journal of Hydrology, 295*(1), 225–245. https://doi.org/10.1016/j.jhydrol.2004.03.013

Amiri, M., & Eslamian, S. (2010). Investigation of climate change in Iran. *Journal of Environmental Science and Technology, 3*(4), 208–216. https://doi.org/10.3923/jest.2010.208.216

Anita, W., Dominic, M., & Neil, A. (2010). *Climate change and agriculture impacts, adaptation and mitigation: Impacts*. OECD Publishing.

Asadi, A., Barati, A., Kalantari, K., & Odeh, I. (2016). Study of relationship between roads network development and agricultural land conversion in Iran northwest. *International Journal of Environmental Research, 10*(1), 51–58.

Ashraf, M., Sanusi, R., Zulkifli, R., Tohiran, K. A., Moslim, R., Ashton-Butt, A., & Azhar, B. (2019). Alley-cropping system increases vegetation heterogeneity and moderates extreme microclimates in oil palm plantations. *Agricultural and Forest Meteorology, 276*, 107632.

Azadi, H., & Barati, A. A. (2013). *Agricultural Land Conversion Drivers in Northeast Iran* (LDPI Working Papers, Issue. T. L. D. P. Initiative. http://www.plaas.org.za/plaas-publication/ldpi-36

Azadi, H., Barati, A. A., Nazari Nooghabi, S., & Scheffran, J. (2022). Climate-related disasters and agricultural land conversion: Towards prevention policies. *Climate and Development*. https://doi.org/10.1080/17565529.2021.2008291

Azadi, H., Barati, A. A., Rafiaani, P., Raufirad, V., Zarafshani, K., Mamoorian, M., Van Passel, S., & Lebailly, P. (2015). Agricultural land conversion drivers in northeast Iran: Application of structural equation model. *Applied Spatial Analysis and Policy*. https://doi.org/10.1007/s12061-015-9160-4

Azadi, H., Keramati, P., Taheri, F., Rafiaani, P., Teklemariam, D., Gebrehiwot, K., Hosseininia, G., Van Passel, S., Lebailly, P., & Witlox, F. (2018). Agricultural land conversion: Reviewing drought impacts and coping strategies. *International Journal of Disaster Risk Reduction, 31*, 184–195.

Bahrami, A., Emadodin, I., Ranjbar Atashi, M., & Rudolf Bork, H. (2010). Land-use change and soil degradation: A case study, North of Iran. *Agriculture and Biology Journal of North America, 1*(4), 600–605.

Barati, A. A., Asadi, A., Kalantari, K., Azadi, H., & Witlox, F. (2015). Agricultural land conversion in northwest Iran. *International Journal of Environmental Research, 9*(1), 281–290.

Barati, A. A., Azadi, H., Dehghani Pour, M., Lebailly, P., & Qafori, M. (2019). Determining key agricultural strategic factors using AHP-MICMAC. *Sustainability, 11*(14), 3947.

Barati, A. A., Azadi, H., & Scheffran, J. (2019b). A system dynamics model of smart groundwater governance. *Agricultural Water Management, 221*, 502–518. https://doi.org/10.1016/j.agwat.2019.03.047

Barati, A. A., Azadi, H., & Scheffran, J. (2021). Agricultural land fragmentation in Iran: Application of game theory. *Land Use Policy, 100*, 105049. https://doi.org/10.1016/j.landusepol.2020.105049

Baude, M., Meyer, B. C., & Schindewolf, M. (2019). Land use change in an agricultural landscape causing degradation of soil based ecosystem services. *Science of the Total Environment, 659*, 1526–1536. https://doi.org/10.1016/j.scitotenv.2018.12.455

Beillouin, D., Cardinael, R., Berre, D., Boyer, A., Corbeels, M., Fallot, A., Feder, F., & Demenois, J. (2022). A global overview of studies about land management, land-use change, and climate change effects on soil organic carbon. *Global Change Biology, 28*(4), 1690–1702. https://doi.org/10.1111/gcb.15998

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of Environmental Management, 114*, 26–35. https://doi.org/10.1016/j.jenvman.2012.10.036

Buchwal, A., Sullivan, P. F., Macias-Fauria, M., Post, E., Myers-Smith, I. H., Stroeve, J. C., Blok, D., Tape, K. D., Forbes, B. C., & Ropars, P. (2020). Divergence of Arctic shrub growth associated with sea ice decline. *Proceedings of the National Academy of Sciences, 117*(52), 33334–33344.

Central Bank of the Islamic Republic of Iran. (2018). *Annual Review 1395*. https://www.cbi.ir/page/17602.aspx

De Palma, A., Sanchez-Ortiz, K., Martin, P. A., Chadwick, A., Gilbert, G., Bates, A. E., Börger, L., Contu, S., Hill, S. L. L., & Purvis, A. (2018). Chapter four: Challenges with inferring how land-use affects terrestrial biodiversity—Study design, time, space and synthesis. In D. A. Bohan, A.

J. Dumbrell, G. Woodward, & M. Jackson (Eds.), *Advances in ecological research* (Vol. 58, pp. 163–199). Academic Press. https://doi.org/10.1016/bs.aecr.2017.12.004

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). *2006 IPCC guidelines for national greenhouse gas inventories* (Vol. 5). Institute for Global Environmental Strategies Hayama.

Emadodin, I., Narita, D., & Bork, H. R. (2012). Soil degradation and agricultural sustainability: An overview from Iran. *Environment, Development and Sustainability, 14*(5), 611–625.

EPA. (2019). *Global greenhouse gas emissions data*. Retrieved 14 Feb from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#agriculture

EurekAlert, & AAAS. (2018). *Strong growth in global CO2 emissions expected for 2018*. Retrieved Feb 27 from https://www.eurekalert.org/pub_releases/2018-12/uoea-sgi120318.php

Fahrenkamp-Uppenbrink, J. (2013). The effects of land-use change. *Science, 339*(6126), 1360–1360.

Fami, H. S., Aramyan, L. H., Sijtsema, S. J., & Alambaigi, A. (2019). Determinants of household food waste behavior in Tehran city: A structural model. *Resources, Conservation and Recycling, 143*, 154–166. https://doi.org/10.1016/j.resconrec.2018.12.033

FAO. (2018). *State of the world's forests 2016. Forests and agriculture: Land-use challenges and opportunities*. Food and Agriculture Organization of the United Nations. https://books.google.de/books?id=Y-ZVvgAACAAJ

FAO. (2019). *Food loss and food waste*. The Food and Agriculture Organization. Retrieved Feb 27 from http://www.fao.org/food-loss-and-food-waste/en/

Friedrich, J., Ge, M., & Pickens, A. (2017). *This interactive chart explains world's top 10 emitters, and how they've changed*. https://www.wri.org/blog/2017/04/interactive-chart-explains-worlds-top-10-emitters-and-how-theyve-changed

Füssel, H.-M., Jol, A., Kurnik, B., Hemming, D., Hartley, A., Hildén, M., Christiansen, T., Lowe, J., Meiner, A., & Kristensen, P. (2012). Climate change, impacts and vulnerability in Europe 2012: An indicator-based report. *EEA Report*, 12.

Garson, G. D. (2016). *Partial least squares: Regression and structural equation models*. Statistical Associates Publishers.

Ghasemi, A. R. (2015). Changes and trends in maximum, minimum and mean temperature series in Iran. *Atmospheric Science Letters, 16*(3), 366–372. https://doi.org/10.1002/asl2.569

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hair, J. F., Jr., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*. Sage Publications.

Hou, G., Bi, H., Huo, Y., Wei, X., Zhu, Y., Wang, X., & Liao, W. (2020). Determining the optimal vegetation coverage for controlling soil erosion in Cynodon dactylon grassland in North China. *Journal of Cleaner Production, 244*, 118771.

IPCC. (2007). *Climate change 2007: Synthesis report. Summary for Policymakers*.

IPCC. (2015). *Climate change 2014: mitigation of climate change* (Vol. 3). Cambridge University Press.

IPCC. (2018a). *Global warming of* 1.5 °C*: Summary for policy makers*. http://report.ipcc.ch/sr15/pdf/sr15_spm_final.pdf

IPCC. (2018b). Summary for Policymakers. In: V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, Maycock, M. Tignor, & T. Waterfield (Eds.), *Global Warming of 1.5 °C. An IPCC Special Report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. World Meteorological Organization. https://www.ipcc.ch/sr15/chapter/summary-for-policy-makers/

June, T., Meijide, A., Stiegler, C., Kusuma, A. P., & Knohl, A. (2018). The influence of surface roughness and turbulence on heat fluxes from an oil palm plantation in Jambi, Indonesia. IOP Conference Series: Earth and Environmental Science.

Kaneda, T., & Dupuis, G. (2017). *2017 world population data sheet* (p. 2017). Population Reference Bureau.

Karimi, V., Karami, E., & Keshavarz, M. (2018). Climate change and agriculture: Impacts and adaptive responses in Iran. *Journal of Integrative Agriculture, 17*(1), 1–15. https://doi.org/10.1016/S2095-3119(17)61794-5

Kertész, Á., Nagy, L. A., & Balázs, B. (2019). Effect of land use change on ecosystem services in Lake Balaton Catchment. *Land Use Policy, 80*, 430–438. https://doi.org/10.1016/j.landusepol.2018.04.005

Khaledian, Y., Kiani, F., Ebrahimi, S., Brevik, E. C., & Aitkenhead-Peterson, J. (2017). Assessment and monitoring of soil degradation during land use change using multivariate analysis. *Land Degradation & Development, 28*(1), 128–141. https://doi.org/10.1002/ldr.2541

Lanz, B., Dietz, S., & Swanson, T. (2018). The expansion of modern agriculture and global biodiversity decline: An integrated assessment. *Ecological Economics, 144*, 260–277.

Lenka, S., Lenka, N., Sejian, V., & Mohanty, M. (2015). Contribution of agriculture sector to climate change. In *Climate change impact on livestock: Adaptation and mitigation* (pp. 37–48). Springer.

Li, J., Zhou, K., Dong, H., & Xie, B. (2020). Cultivated land change, driving forces and its impact on landscape pattern changes in the Dongting Lake Basin. *International Journal of Environmental Research and Public Health, 17*(21), 7988.

Li, Y., Liu, W., Feng, Q., Zhu, M., Yang, L., Zhang, J., & Yin, X. (2023). The role of land use change in affecting ecosystem services and the ecological security pattern of the Hexi Regions, Northwest China. *Science of The Total Environment, 855*, 158940. https://doi.org/10.1016/j.scitotenv.2022.158940

Liu, Y., Xue, J., Gui, D., Lei, J., Sun, H., Lv, G., & Zhang, Z. (2018). Agricultural oasis expansion and its impact on oasis landscape patterns in the southern margin of Tarim basin, Northwest China. *Sustainability*, *10*(6), 1957. https://doi.org/10.3390/su10061957

Lin, M., & Huang, Q. (2019). Exploring the relationship between agricultural intensification and changes in cropland areas in the US. *Agriculture, Ecosystems & Environment, 274*, 33–40. https://doi.org/10.1016/j.agee.2018.12.019

Madani, K. (2010). Game theory and water resources. *Journal of Hydrology, 381*(3), 225–238. https://doi.org/10.1016/j.jhydrol.2009.11.045

Madani, K. (2014). Water management in Iran: What is causing the looming crisis? *Journal of Environmental Studies and Sciences, 4*(4), 315–328.

Maeda, E. E., Abera, T. A., Siljander, M., Aragão, L. E., de Moura, Y. M., & Heiskanen, J. (2021). Large-scale commodity agriculture exacerbates the climatic impacts of Amazonian deforestation. *Proceedings of the National Academy of Sciences, 118*(7), e2023787118.

Maeda, E. E., Pellikka, P. K., Siljander, M., & Clark, B. J. (2010). Potential impacts of agricultural expansion and climate change on soil erosion in the Eastern Arc Mountains of Kenya. *Geomorphology, 123*(3–4), 279–289. https://doi.org/10.1016/j.geomorph.2010.07.019

Mande, T., Ceperley, N. C., Katul, G. G., Tyler, S. W., Yacouba, H., & Parlange, M. B. (2015). Suppressed convective rainfall by agricultural expansion in southeastern Burkina Faso. *Water Resources Research, 51*(7), 5521–5530. https://doi.org/10.1002/2015WR017144

Mansouri Daneshvar, M. R., Ebrahimi, M., & Nejadsoleymani, H. (2019). An overview of climate change in Iran: Facts and statistics. *Environmental Systems Research, 8*(1), 7. https://doi.org/10.1186/s40068-019-0135-3

Mantyka-Pringle, C. S., Visconti, P., Di Marco, M., Martin, T. G., Rondinini, C., & Rhodes, J. R. (2015). Climate change modifies risk of global biodiversity loss due to land-cover change. *Biological Conservation, 187*, 103–111. https://doi.org/10.1016/j.biocon.2015.04.016

Mohammadi, A., Rafiee, S., Jafari, A., Keyhani, A., Mousavi-Avval, S. H., & Nonhebel, S. (2014). Energy use efficiency and greenhouse gas emissions of farming systems in north Iran. *Renewable and Sustainable Energy Reviews, 30*, 724–733. https://doi.org/10.1016/j.rser.2013.11.012

National Research Council. (2012). *Science for environmental protection: The road ahead*. National Academies Press.

Nelson, G., Cai, Z., Hassan, R., Godfray, C., Santos, M., & Hema, S. (2012). Food security and climate change. A report by the High level panel of experts (HLPE) on food security and nutrition of the committee on world food security (CFS).

Ng, E. L., Honeysett, J., & Scorgie, Y. (2023). Regionalised greenhouse gas emissions from food production in South-Eastern Australia. *Sustainable Production and Consumption, 35*, 116–128. https://doi.org/10.1016/j.spc.2022.10.023

Okumah, M., Chapman, P. J., Martin-Ortega, J., & Novo, P. (2018). Mitigating agricultural diffuse pollution: Uncovering the Evidence base of the awareness–behaviour–water quality pathway. *Water, 11*(1), 29.

Önder, M., Ceyhan, E., & Kahraman, A. (2011). Effects of agricultural practices on environment. *Biol Environ Chem, 24*, 28–32.

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J. A., Clarke, L., Dahe, Q., & Dasgupta, P. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. IPCC.

Palermo, G., Piraino, P., & Zucht, H.-D. (2009). Performance of PLS regression coefficients in selecting variables for each response of a multivariate PLS for omics-type data. *Advances and Applications in Bioinformatics and Chemistry: AABC, 2*, 57–70.

Panagos, P., Standardi, G., Borrelli, P., Lugato, E., Montanarella, L., & Bosello, F. (2018). Cost of agricultural productivity loss due to soil erosion in the European Union: From direct cost evaluation approaches to the use of macroeconomic models. *Land Degradation & Development, 29*(3), 471–484.

Ponpang-Nga, P., & Techamahasaranont, J. (2016). Effects of climate and land use changes on water balance in upstream in the Chao Phraya River basin. *Thailand. Agriculture and Natural Resources, 50*(4), 310–320. https://doi.org/10.1016/j.anres.2016.10.005

Rahimi, M., Mohammadian, N., Vanashi, A. R., & Whan, K. (2018). Trends in indices of extreme temperature and precipitation in Iran over the period 1960–2014. *Open Journal of Ecology, 8*(07), 396. https://doi.org/10.4236/oje.2018.87024

Reisinger, A., Havlik, P., Riahi, K., van Vliet, O., Obersteiner, M., & Herrero, M. (2013). Implications of alternative metrics for global mitigation costs and greenhouse gas emissions from agriculture. *Climatic Change, 117*(4), 677–690. https://doi.org/10.1007/s10584-012-0593-3

Roser, M., & Ritchie, H. (2019). *Yields and land use in agriculture. Published online at OurWorldInData.org*. https://ourworldindata.org/yields-and-land-use-in-agriculture

Roshan, G. R., Azizi, G., & Mohammadi, H. (2011). Simulation of temperature changes in Iran under the atmosphere carbon dioxide duplication condition. *Iranian Journal of Environmental Health, Science and Engineering, 8*(2), 139–152.

Sampaio, G., Nobre, C., Costa, M. H., Satyamurty, P., Soares-Filho, B. S., & Cardoso, M. (2007). Regional climate change over eastern Amazonia caused by pasture and soybean cropland expansion. *Geophysical Research Letters*. https://doi.org/10.1029/2007GL030612

Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences, 104*(50), 19703–19708.

Shahbazian, Z., Faramarzi, M., Rostami, N., & Mahdizadeh, H. (2019). Integrating logistic regression and cellular automata–Markov models with the experts' perceptions for detecting and simulating land use changes and their driving forces. *Environmental Monitoring and Assessment, 191*(7), 1–17.

Shrestha, S., Binod, B., Talchabhadel, R., & Virdis, S. G. P. (2022). Integrated assessment of the landuse change and climate change impacts on the sediment yield in the Songkhram River Basin, Thailand. *Catena, 209*, 105859. https://doi.org/10.1016/j.catena.2021.105859

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N. H., Rice, C. W., Robledo Abad, C., Romanovskaya, A., Sperling, F., & Tubiello, F. (2014). Agricul-ture, forestry and other land use (AFOLU). In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. V. Stechow, T. Zwickel, & J. C. Minx (Eds.), *Climate change 2014 Mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change* (pp. 811–922). Cambridge University Press.

Soltani, M., Laux, P., Kunstmann, H., Stan, K., Sohrabi, M. M., Molanejad, M., Sabziparvar, A. A., Ranjbar SaadatAbadi, A., Ranjbar, F., Rousta, I., Zawar-Reza, P., Khoshakhlagh, F., Soltanzadeh, I., Babu, C. A., Azizi, G. H., & Martin, M. V. (2016). Assessment of climate variations in temperature and precipitation extreme events over Iran [journal article]. *Theoretical and Applied Climatology, 126*(3), 775–795. https://doi.org/10.1007/s00704-015-1609-5

Statistical Center of Iran. (2017). *Iran statistical yearbook 2016–2017 (1395)* (S. C. o. Iran, Ed.). Statistical Center of Iran. https://www.amar.org.ir/english/Iran-Statistical-Yearbook

Tabari, H., & Talaee, P. H. (2011). Analysis of trends in temperature data in arid and semi-arid regions of Iran. *Global and Planetary Change, 79*(1–2), 1–10. https://doi.org/10.1016/j.gloplacha.2011.07.008

Trending Economics. (2019). *Iran: CO2 emissions (kt)* https://tradingeconomics.com/iran/co2-emissions-kt-wb-data.html

Tubiello, F., Salvatore, M., Cóndor Golec, R., Ferrara, A., Rossi, S., Biancalani, R., Federici, S., Jacobs, H., & Flammini, A. (2014). Agriculture, forestry and other land use emissions by sources and removals by sinks. *Statistics Division, Food and Agriculture Organization, Rome*.

Usgcrp. (2017). *Climate Science Special Report: Fourth National Climate Assessment, Volume I.*

Wuebbles, D. J., Fahey, D. W., Hibbard, K. A., DeAngelo, B., Doherty, S., Hayhoe, K., Horton, R., Kossin, J. P., Taylor, P. C., Waple, A. M., & Weaver, C. P. (2017). Executive summary. In D. J. Wuebbles, D. W. Fahey, K. A. Hibbard, D. J. Dokken, B. C. Stewart, & T. K. Maycock (Eds.), *Climate science special report: Fourth national climate assessment.* (Vol. I). U.S. Global Change Research Program.

Xiaoyu, Z., Gang, D., Xiaoping, X., Changliang, S., Dawei, X., Ruirui, Y., Lijun, X., Jing, Z., Chen, M., & Ming, L. (2021). Divergent socioeconomic drivers of land use at various times in the Hulunber grassland area, China. *Ecological Indicators, 132*, 108243. https://doi.org/10.1016/j.ecolind.2021.108243

Yousefi-Sahzabi, A., Sasaki, K., Yousefi, H., & Sugai, Y. (2011). CO2 emission and economic growth of Iran. *Mitigation and Adaptation Strategies for Global Change, 16*(1), 63–82. https://doi.org/10.1007/s11027-010-9252-z

Zamani, M., Sadoddin, A., & Garizi, A. Z. (2012). Assessing land-cover/land-use change and its impacts on surface water quality in the Ziarat Catchment, Golestan Province-Iran.

Zhou, J., Fu, B., Yan, D., Lü, Y., Wang, S., & Gao, G. (2019). Assessing the integrity of soil erosion in different patch covers in semi-arid environment. *Journal of Hydrology, 571*, 71–86.

Zurek, M., Hebinck, A., & Selomane, O. (2022). Climate change and the urgency to transform food systems. *Science, 376*(6600), 1416–1421. https://doi.org/10.1126/science.abo2364

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