

Research Article

Development of Enhanced Composite Climate Change Indicators and Its Nexus with the Performance of the Agricultural Sector in Iran

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Abstract

Climate change significantly affects human life, especially in the Middle East, where harsh climate zones worsen challenges like desertification, water scarcity, and rising sea levels. In Iran, increasing temperatures, reduced precipitation, and persistent water crises make the country highly vulnerable to climate change impacts. Among economic sectors, the agricultural sector has been heavily affected by these changes and is expected to face even more significant impacts in the future. As a result, it is crucial to study the economic impacts of climate change especially on agricultural output. This study aims to introduce two new composite indicators that provide a comprehensive view of the climate change phenomenon for policymakers. Additionally, it seeks to demonstrate the relationship between this index and the agricultural per capita value-added in 23 provinces of Iran from 2000 to 2020, using PVECM models. As a result, composite indices specially in arid regions of the country reveal concerning trends and deteriorate over the period and due to the PVECM results, the value-added and both composite indicators move together in the long run but in the short term, there is no significant causality for index 1; conversely, there is a positive and significant causality from index 2 to value-added. Therefore, climate change will affect agricultural sector adversely more than ever.

Keywords Climate Change . Composite Index . Agricultural Sector . PVECM Model

Introduction

One of the environmental challenges of the current century is climate change, which in various regions of the world has affected environmental quality and sustainable economic growth and every aspect of the human life. Therefore, it made governments adopt policies to reduce its costs

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(Obianyo et al., 2023). Climate change differs from past environmental problems in terms of complexity and difficulty of "solution" detection. This phenomenon imposes economic costs that vary across countries and within them. Today, environmental degradation and climate change put considerable challenges to sustainable development goals. Much of the Middle East is in harsh climate zones, and global warming is worsening desertification, water stress, and rising sea levels. This trend is causing major economic problems, risking food security, and threatening public health. These effects then impact poverty, inequality, displacement, and conflict (Duenwald, et al., 2020).

Iran is located in the arid and semi-arid region in the world, faces severe climate risks, particularly water scarcity and rising temperatures. Water is a major vulnerability in the Middle East and by 2050, water access per capita will be half of current access, worsened by climate change. While in Iran 70% of precipitation is lost to evaporation and over 80% of renewable water is already used but the critical threshold is 60% (Department of Environment, Islamic Republic of Iran, 2015). Among Middle Eastern countries, in the following decades, Iran will face a 2.6 Celsius increase in temperature and a 35% decrease in precipitation (Mansouri Daneshvar et al., 2019).

Climate change significantly affects agriculture sector and is expected to aggravate its impacts through changes in temperature, precipitation, CO₂ levels, climate variability, and surface water runoff. Crop production and productivity are directly influenced by temperature and precipitation, resulting in negative economic and social effects, reducing incomes, and worsening poverty and food insecurity among vulnerable rural populations (Abeysekara et al., 2023; FAO, 2016).

The agriculture sector plays an important role in Iran's economy and food supply. Based on the national statistics, around 20% of the labor force is employed in agriculture, contributing almost 10% to the total GDP, and 11% of Iran's land is dedicated to farming. Climate change could have irreversible effects on this sector, jeopardizing the food supply and leading to a water crisis, as well as potential unemployment due to the negative impacts of it. The impacts on agricultural sector are not just limited to effects on crop yield, while in Iran agritourism or agricultural tourism, is recognized as an economic opportunity, climate change and water scarcity can threaten the sustainability and attractiveness of agritourism activities in the region (Hosseini et al., 2025).

Agriculture and climate change encompass a wide range of topics, and numerous studies are devoted to it. Farajzadeh et al. (2024) use a CGE model to assess climate scenarios up to 2060, showing that while some crops may grow, sectors reliant on specific climatic conditions could experience output declines. Singh et al. (2024) found that minimum temperature consistently reduces rice yields in both the short and long term, while factors such as precipitation and cultivation area may improve yields. Overall, climate change negatively affects rice production in India. Shahpari et al. (2023) examine economic consequences using a CGE model, finding that reductions in agricultural output lower GDP, affect labor markets, household welfare, and sectoral outputs. Rajabalinejad et al. (2023) analyze climate variables from 1971–2020 with FMOLS, showing that extreme temperature and rainfall variations and increased CO₂ emissions reduce agricultural productivity in Iran. Mirjalili & Motaghian Fard (2019), by examining temperature and precipitation impacts on agricultural yield in 14 OIC countries (including Iran), indicate that increasing temperature could harm crop yields.

While most studies in this field focus on analyzing the effects of climate change on the economy using only two variables (temperature and precipitation), this study purpose is to take into account a wide range of climate change variables in order to provide a more comprehensive and precise description of the situation. Due to the development of composite indicators in economics studies, the study develops a composite index for climate change trends in Iran. This composite index can simplify the complexity of this phenomenon, and then we can more easily analyze, compare, and

track the trend of this multi-dimensional concept. The study estimated a composite climate change index for 23 provinces in Iran by using proper methods and 25 climate change core indices. To ensure data consistency over the study period, newly established provinces resulting from recent administrative divisions were excluded and the analysis on 23 provinces covers a broad geographic region and represent diverse climatic conditions across Iran. It's worth mentioning that estimating this composite index can be applied to other countries and regions. The study introduces this indicator for further international and environmental studies. The second objective is to analyze the relationship between this index and the per capita value-added of agriculture in Iran's provinces using the Panel Vector Error Correction Model (PVECM) model. This method enables us to consider both long and short-term causality. Because of the data conditions, the model has been computed from 2000 to 2020.

Methodology

Composite Indicators

In the following, the step-by-step construction of the composite climate change index will be presented.

Indicators Selection

Expert Team on Climate Change Detection and Indices (ETCCDI) introduces climate change standard core indices which can be calculated for any desired year and each of the indices have been computed by the authors using meteorological data from selected provinces and the RCLIMDEX software for the period 2000 to 2020. Since all indices do not have negative impacts as they increase, the study classifies indices into two groups. The first group contains 16 indices, and their increase is expected to be harmful and negatively impact the agricultural sector. On the other hand, the second group contains 9 indices, and their increase is expected to be welcome and have positive impacts. The Table 1 demonstrates the classification of the indices and their details.

Normalization

Normalization is essential before any data aggregation, because the indicators in the data set often have different measuring units. The indicators have been normalized by using the following well-known procedure:

$$\text{Normalization} = \frac{(\text{Actual value} - \text{Minimum value})}{(\text{Maximum value} - \text{Minimum value})} \quad (1)$$

Assignment of Weights

Weighing is the most important step in constructing a composite index. Among various methods, principal component analysis (PCA) is widely used and is applied in this study too. This serves as an effective tool to reveal patterns of similarity and difference within the data and facilitates to reduce the number of dimensions without losing essential information, PCA is suitable when linear relationships among variables are assumed. The functional formulation for PCA is in the equation 2 (Balaganesh et al., 2020; Sendhil et al., 2018).

$$X_t = A_t F_t + e_t \quad (2)$$

Table 1. Climate Change Core Indices

Group one	Group two
1- SU: Number of summer days	1- CWD: Maximum length of wet spell
2- TR: Number of tropical nights	2- PRCPTOT: Annual total precipitation on wet days
3- TX _x : Monthly maximum value of daily maximum temperature	3- GSL: Growing season length
4- TX _n : Monthly minimum value of daily maximum temperature	4- ID: Number of icing days
5- TN90p: Percentage of days when TN>90 th percentile. (TN the daily minimum temperature)	5- FD: Number of frost days
6- TX90p: Percentage of days when TX>90 th percentile. (TX the daily maximum temperature)	6- TN10p: Percentage of days when TN<10 th percentile
7- WSDI: Warm spell duration index	7- TX10p: Percentage of days when TX<10 th percentile
8- CDD: Maximum length of dry spell	8- TN _x : Monthly maximum value of daily minimum temperature
9- R99pTOT: Annual total PRCP when RR>99p	9- TN _n : Monthly minimum value of daily minimum temperature
10-R95pTOT: Annual total PRCP when RR>95p	
11-Rx1day: Monthly maximum 1-day precipitation	
12-Rx5day: Monthly maximum consecutive 5-day precipitation	
13-SDII: Simple precipitation intensity index	
14-R10mm: Annual count of days when PRCP>= 10mm	
15-R20mm: Annual count of days when PRCP>= 20mm	
16-DTR: Daily temperature range	

In which X_i denotes the N-dimensional vector of variables influencing climate change, A_i indicates the $r \times I$ common factor, F_i is the factor loading and e_i is the associated idiosyncratic error term of order $N \times I$. However, the weights were calculated with the following structure:

$$W_i = \sum |L_{ij}| E_j \quad (3)$$

Where W_i is the weights of the i^{th} variable, E_j represents the eigenvalue of the j^{th} factor and L_{ij} indicates the loading value of the i^{th} variable on the j^{th} factor.

Climate Change Composite index

According to our climate change indices and steps of making a composite indicator, our index has followed the below equation:

$$\text{Climate Change Composite Indicator} = \frac{\sum_{i=1}^n X_i W_i}{\sum_{i=1}^n W_i} \quad (4)$$

Where, X_i represents the normalized value of i^{th} variable while W_i is the weight of i^{th} variable. After estimating the two composite indices for the selected provinces, the categorization and status of each province based on the two indices for each year were determined using the classification in Table 2 (Ayyoob et al., 2013). A higher value of the first index is considered harmful, while a higher value of the second index is considered favorable. Given the fact that the main objective of this article is to introduce the composite index and study its relationship with the provincial agricultural value-added, and considering that a detailed trend analysis of the index for all provinces would require extensive tables and charts beyond the scope of this paper, thereafter six provinces with diverse climatic has been chosen to illustrate the general trend of the indices. Figures 1 and 2 illustrate the status of the indices. To better reflect the overall trend in index changes, a three-year moving average has been used. This method, by averaging the values of three consecutive years, allows for the identification of longer-term trends and reduces the impact of short-term volatility.

In this study, the averages have been calculated centrally, meaning that each point on the chart corresponds to the middle year of the three-year period. As indicated in Table 2, it should be noted that for the first index, red indicates a critical and undesirable condition, yellow indicates a moderate level, and green indicates a favorable status. For Figure 2, which corresponds to the second index, green represents a favorable condition, yellow a moderate level, and red a critical situation. In all charts, the horizontal axis represents the year, while the vertical axis shows the value of the index and the three-year moving average

Table 2. Categorization of the Indices

	Condition	Classification	Corresponding Color in Figures
Index 1	Critical: High exposure to harmful indices of climate change	Index 1 > (Mean + 1/2 SD)	Red
	Moderate: Moderate exposure to harmful indices climate change	(Mean – 1/2 SD) < Index 1 < (Mean + 1/2 SD)	Yellow
	Favorable: Low exposure to harmful indices climate change	Index 1 < (Mean – 1/2 SD)	Green
Index 2	High exposure to beneficial indices of climate change	Index 2 > (Mean + 1/2 SD)	Green
	Moderate exposure to beneficial indices climate change	(Mean – 1/2 SD) < Index 2 < (Mean + 1/2 SD)	Yellow
	Low exposure to beneficial indices climate change	Index 2 < (Mean – 1/2 SD)	Green

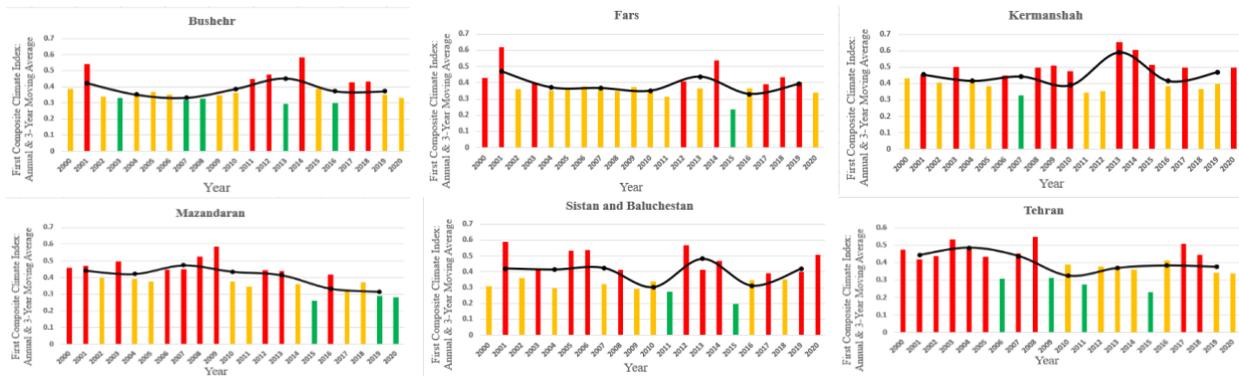


Figure 1. Climate Change Composite Index 1 trends, from 2000 to 2020 in Selected Provinces

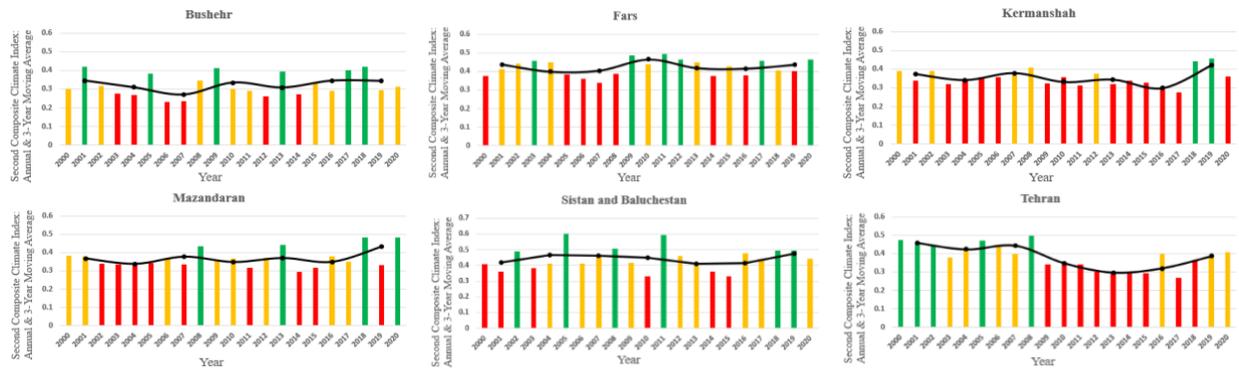


Figure 2. Climate Change Composite Index 1 trends, from 2000 to 2020 in Selected Provinces.

As Figures 1 and 2 illustrate the temporal patterns of the indices in the selected provinces over the study periods, for a better and more comprehensive presentation, Figures 3 and 4 show the spatial distribution of the indices (high, moderate and low) across all 23 provinces for five selected years: 2000, 2005, 2010, 2015, and 2020. The colors indicate the same concepts as in Figures 1 and 2.

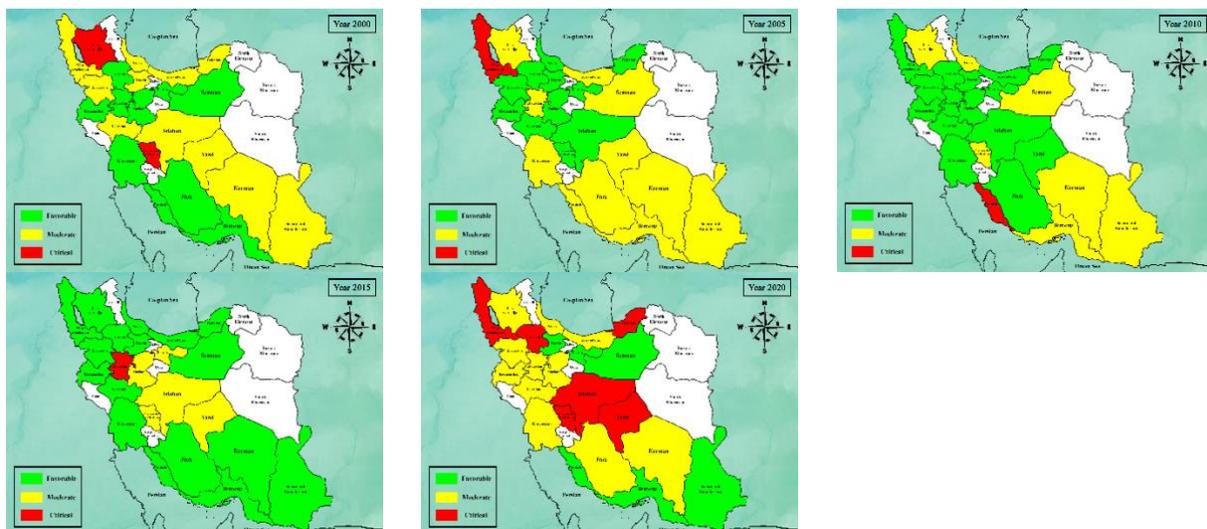


Figure 3. Climate Change Composite Index 1, year 2000, 2005, 2010, 2015 and 2020.

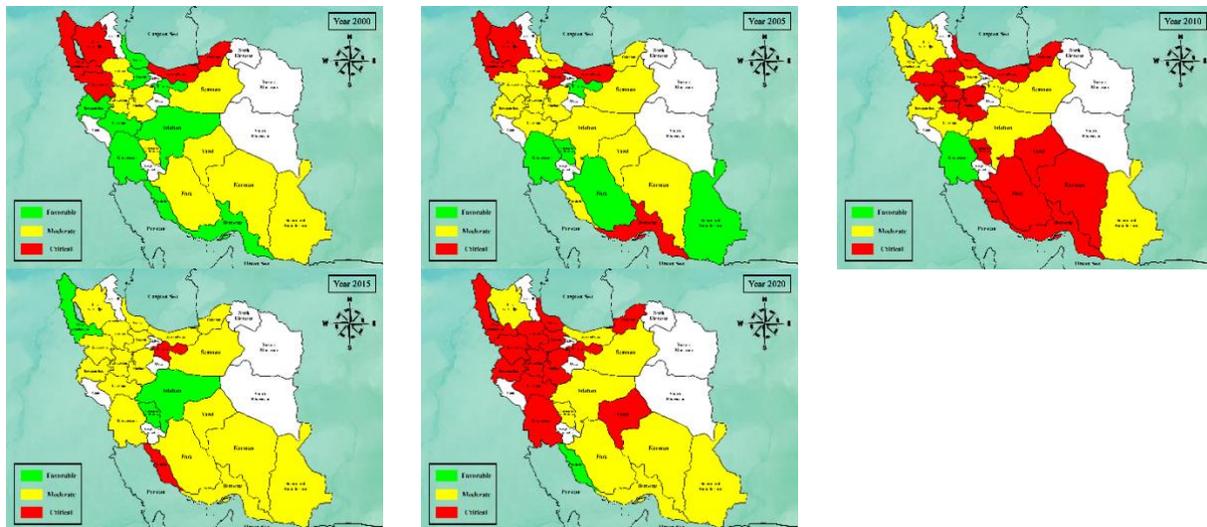


Figure 4. Climate Change Composite Index 2, year 2000, 2005, 2010, 2015 and 2020.

Although the purpose of the study extends beyond regional assessments of indices fluctuations, it is worth to mention that both graphs and maps reveal concerning trends in the indices, particularly in the arid regions of Iran. Despite the indices only covering a 20-year period, the trends provide noteworthy understanding about each province's capability to face climate change. Climate change impacts are not only limited to arid provinces and they can be challenging for all the region. As we have seen in the components of the index 1 (Table 1), provinces which already have experienced extreme weather events are expected to suffer more. Deteriorating the climate change condition can affect different aspects of the economy such as agriculture and it is expected to decrease the agriculture output. Now that we have the measures, we can employ the PVECM model to investigate the nexus between each climate change composite index and per capita agricultural value-added in the selected 23 provinces of Iran.

Model Estimation and Results

Panel Vector Error Correction Model

PVECM is one of the quantitative methods widely used in previous studies (Amaluddin, 2019). Engle and Granger first popularized the VECM method to correct the short-term disequilibrium against the long-term relationship. The main requirement in PVECM that distinguishes it from PVAR or ARDL is that in PVECM, it must be integrate in the same degree or order and also considers the presence of cointegration, which has implications for short-term disequilibrium correction, allowing for equilibrium or long-term relationships. Determining the cointegrated vector shows long-term behavior and captures causality relationships (Leiwakabessy & Payapo, 2022). After estimating the VECM, causality can be inferred by: (1) examining regressors' and Error Correction Term (ECT) t-statistics for short-run and long-run effects, (2) applying the Granger/Wald test on lagged explanatory variables, rejecting the null if $p \leq 0.05$, and (3) using pairwise Granger causality to determine causality direction. The null hypothesis is that there is no Granger causality against the alternative that the null hypothesis is not valid. The null hypothesis is rejected if the probability value of the F-statistic is less than 5% ($p \leq 0.05$) (Mahembe & Odhiambo, 2019).

The study has adopted this method to assess the relationship between the provincial per capita agricultural value-added and the two composite indices of climate change from 2000 to 2020. The PVECM model has been applied because it enables us to look at both short-term and long-term dynamics, which fits well with the climate change nature. This model also allows us to explore potential two-way analysis to consider between agricultural per capita value-added and both climate indices. The descriptive statistics on all the variables are represented in Appendix 1. Those statistics show the behavioral pattern of the variables in the model.

The model was calculated in EViews and the optimal lag structure was specified as one lag in first differences, based on the number of lags used in the estimation procedure within EViews. This specification was chosen to ensure estimation efficiency. There are a few steps for calculating PVECM models as follows.

Panel unit root test

The unit root test is used to determine whether panel data is stationary or not. Data is stationary if its p-value is less than 0.05. All of the variables are stationary at the first difference. The study has used the Levin, Lin and Chu (LLC), ADF-Fisher, and Philips-Perron (PP) tests. The table 3 represents the results of panel unit root tests.

Table 3. Panel Unit Root Tests Results (P-values are in the parenthesis)

Panel unit root test	Variables in level			Variables in the first difference		
	Value-added	Index 1	Index 2	Value-added	Index 1	Index 2
LLC	0.085 (0.5341)	-2.5234 (0.0058)	-2.0514 (0.0201)	-23.3043 (0.0000)	-24.0456 (0.0000)	-28.5665 (0.0000)
ADF-Fisher	21.9660 (0.999)	37.5029 (0.8096)	32.2932 (0.9371)	455.521 (0.0000)	493.581 (0.0000)	513.945 (0.0000)
PP-Fisher	19.1842 (0.9998)	38.9468 (0.7600)	42.8220 (0.6062)	469.640 (0.0000)	444.826 (0.0000)	463.049 (0.0000)

Panel Cointegration Test

Panel cointegration tests assess whether non-stationary variables share a long-run equilibrium relationship, guiding Granger causality test strategy and model choice (Karanfil & Li, 2015). Cointegration indicates that variables move together over time, with short-term deviations corrected in the long run, therefore, causality should be investigated through the panel VECM framework. In contrast, lack of cointegration implies variables move independently, requiring a panel VAR for causality (Mahembe & Odhiambo, 2019). The KAO test was applied and the null hypothesis of no cointegration is rejected at the 5% confidence level. The table 4 illustrates the test results for both composite indices. According to the results, variables are cointegrated in the long-term which is compatible with the nature of the climate change.

Table 4: KAO Cointegration Test

Composite index		T-statistic	P-value
Model with the index 1	ADF	-3.7149	0.0001
Model with the index 2	ADF	-3.7391	0.0001

PVECM Estimation

Table 5 shows the results from panel VECM estimation for the first climate change index and provincial per capita agricultural value-added. First, note that the ECT coefficient indicates the speed of adjustment from the short-term to long-term equilibrium between climate change index 1 and agricultural per capita value-added. As expected, the ECT is negative, so applying the PVECM model is valid. While the value-added is taken as a dependent variable, the ECT is negative but insignificant. This indicates that short-term deviations from the long-term equilibrium have no immediate significant effect on agricultural performance. However, when index 1 is dependent, the ECT is negative and significant with a speed of adjustment of 71.6%. This suggests that the long-term linkage is mainly observed in the way the index 1 adjusts to changes in agricultural performance rather than agriculture sector being directly driven by this index. This table also illustrates short-term causality. Although at the 5% confidence level, there is no statistically significant relationship. This is further confirmed by the Wald test represented in Table 6 with both p-values more than 5%. Therefore, the results suggest that while any deviation from the long-term equilibrium will be corrected over time, short term fluctuations do not have significant immediate impact on agricultural value-added.

Table 5. PVECM Estimation for Index 1 (P-values are in the parenthesis)

Independent Variable	Dependent Variable	
	Value-added	Index 1
ECT	-6.13E-05 (0.8964)	-0.7166 (0.0000)
Value-added (-1)	-0.2228 (0.0000)	0.0042 (0.3704)
Value-added (-2)	-0.2176 (0.0000)	0.0063 (0.1653)
Index 1 (-1)	-0.4011 (0.5473)	-0.132 (0.0432)
Index 1 (-2)	-0.6689 (0.2069)	0.0291 (0.5743)

Table 6. Wald Test Index 1

Dependent Variable	Independent Variable	Chi-sq	Df	P-value
Value-added	Index 1	1.67	2	0.432
Index 1	Added-value	2.32	2	0.312

Table 7 shows the results of the panel VECM estimation for index 2 (beneficial) and provincial per capita agricultural value-added. The ECT coefficient is negative and significant when the value-added is an independent variable which means that about 31.6% of any short-term deviation from the long-run equilibrium will be corrected over time. Conversely, when agricultural value-added is considered as the dependent variable, the ECT is insignificant, indicating that long-term modifications in agricultural sector do not take place in response to the index 2. Testing for short-term causality, shows that agricultural value-added reacts to short-term fluctuations in the index 2. These results are supported by the Wald test in Table 8, with a p-value below 5%. In conclusion, the findings demonstrate that agricultural value-added responds more to short-term fluctuations of

the index 2. This highlights how favorable climate conditions can positively affect agriculture output.

Table 7. PVECM Estimation Index 2 (P-values are in the parenthesis)

Independent Variable	Dependent Variable	
	Value-added	Index 2
ECT	-0.0047 (0.3149)	-0.3165 (0.0000)
Value-added (-1)	-0.2057 (0.0000)	0.0014 (0.6302)
Value-added (-2)	-0.2091 (0.0000)	0.0010 (0.7036)
Index 2 (-1)	1.7925 (0.0545)	-0.4008 (0.0000)
Index 2 (-2)	1.8812 (0.0197)	-0.2017 (0.0000)

Table 8. Wald Test Index 2

Dependent Variable	Independent Variable	Chi-sq	Df	P-value
Value-added	Index 2	6.033	2	0.0489
Index 2	Added-value	0.317	2	0.8533

Discussion and Conclusion:

As climate change increasingly affects our surrounding environment and lives, estimating a climate change composite index is crucial for tracking its trend and guiding policymaking. Despite previous studies that focused only on temperature and precipitation, this study constructs a composite index using 25 core climate change indices. For a better perspective, the indices have been divided into two groups. In the first group, the increasing trend is not desirable, and vice versa in the second. The indicator was computed for 23 selected provinces in Iran from 2000 to 2020. A composite climate change index helps policymakers by combining multiple factors into one index. Results show both indices are deteriorating over time. Even index 2, which could be useful for agriculture, shows no improvement, and index 1 keeps worsening.

The agricultural sector is particularly susceptible to the impacts of climate change. After conducting the index, the linkage between it and the agricultural per capita value-added was examined using the panel VECM model for 2000 to 2020. For the long term, there is a cointegration between variables. As expected from the notable impacts of climate change on agricultural output, the value-added and both composite indicators move together in the long run. However, in the short term, there is no significant causality for index 1; conversely, there is a positive and significant causality from index 2 to value-added, and the Wald test has approved it. As demonstrated in the diminishing trend of the second composite indicator, it is anticipated to decrease the per capita value-added of the sector.

The different behaviors of the two composite climate indices can be due to the nature and timing of their impacts on agricultural performance. Index 1 includes extreme and harmful climate variables such as prolonged heatwaves, drought spells, and excessive temperature shifts. These factors typically produce their effects gradually, damaging the environment like soil conditions, water

availability, and crop productivity over extended periods. Therefore, it is reasonable that this index shows no short-term effect but reflects a significant long-term relationship with agricultural value-added. On the other hand, Index 2 includes more desirable conditions like effective rainfall, extended growing seasons, and balanced precipitation events. These variables are more sensitive in the short term, especially during agricultural periods. This explains why short-term causality is observed for index 2, even though its impacts might not be strong or consistent enough to maintain a long-term equilibrium. These differences indicate that climate risks grow slowly but continually, while short-term climatic variations may provide temporary relief without lasting effects. This insight can be crucial for designing both immediate support policies and long-term adaptation strategies.

Considering the long-term and short-term economic effects observed in the estimated model, the necessity of settling this phenomenon into macroeconomic policies becomes increasingly critical each day. As climate change is inevitable, considering it in policy-making procedure can be helpful to mitigate the negative effects of this phenomenon. On the other hand, in consensus with the studies conducted in Iran, Ahmadi et al. (2021), Sabbaghi et al. (2020), Ghalehsard et al. (2021) agriculture sector is proven to be prone to climate change, and its negative impacts would decrease productivity and production.

There could be lots of reasons for the gained results, but here are some which are more plausible:

- I. Existing long-term causality is entirely consistent with the nature of climate change because it is a phenomenon whose impacts are observed in the long term. However, due to limitations on value-added data for Iran's provinces, estimates were only possible until 2020. "It is likely that the results would be even better over a longer period."
- II. The lack of short-term causality for index 1 and its insignificance may reflect the long-term nature of climate change. However, due to limitation, extending the study period was not feasible; a longer timeframe could yield better results. Including other economic sectors (industry and services) might also improve outcomes. In contrast, index 2 shows a positive and significant short-run from the indicator to the value-added, is consistent with its expected positive impact on agricultural output.

Declarations

Author Contributions All authors participated equally in all stages of the research and manuscript preparation. All authors approved the final manuscript.

Statements and Declarations The authors have no relevant financial or non-financial interests to disclose, also the authors report that there are no competing interests to declare.

Data Availability Statement The meteorological data was obtained from the Iran Meteorological Organization, while the agricultural value-added data were collected from the dataset of the Statistical Center of Iran. Some of these datasets are publicly available, while others may require direct request from the respective organizations. The findings such as measurements of the indices are available from the corresponding author upon reasonable request.

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Appendix 1.
Description of Data

Indicator	Per capita value-added	Index 1	Index 2
Mean	7.154325	0.412115	0.388812
Median	6.779718	0.404967	0.382499
Maximum	16.87369	0.736608	0.674365
Minimum	1.252671	0.124191	0.187249
Standard Deviation	2.591181	0.101457	0.074869
Skewness	0.575076	0.295827	0.540716
Kurtosis	3.936673	3.520746	3.678550
Jarque-Bera	44.27911	12.50227	32.80219
Probability	0.000000	0.001928	0.000000
Sum	3455.539	199.0516	187.7963
Observations	483	483	483