İstatistik Araştırma Dergisi
Journal of Statistical Research
ISSN: 2791-7614

(2022), 12 (2)
Başvuru/Received: 30/10/2022
Kabul/Accepted: 30/11/2022

https://journal.tuik.gov.tr/

ARAŞTIRMA MAKALESİ RESEARCH ARTICLE

Actuaries Climate Index: An Application for Turkey

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Abstract

The aim of this paper is to propose a Turkish application of the Actuaries Climate Index (ACI), which is a measure of changes in extreme weather and sea levels. The index periodically provides data and information to scientists, practitioners and policy makers working with the risks caused by climate change in order to help them analyze the financial effects of these risks. For this aim, we calculate ACI for Ankara province using data obtained from standard databases. When the application suggested in this article is extended to the entire country, the recommended calculation will help the involvement of Turkey in addition to all European countries included in the European ACI, which is the continuation of the ACIs developed primarily in Canada and the USA.

Keywords: Climate Change, Extreme Weather Risks, Threshold, Reference Period, Standardized Anomaly, Sustainability

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Citation / Atıf: Nevruz E., ATICI R.Y., YILDIRAK K. (2022). Actuaries Climate Index: An Application for Turkey. İstatistik Araştırma Dergisi, 12 (2), 14-25.

Citation / Atıf: Nevruz E., ATICI R.Y., YILDIRAK K. (2022). Actuaries Climate Index: An Application for Turkey. İstatistik Araştırma Dergisi, 12 (2), 14-25.

Aktüerler İklim Endeksi: Türkiye için Bir Uygulama

Özet

Bu makalenin amacı, ekstrem hava ve deniz seviyesi değişikliklerinin bir ölçüsü olan Aktüerler İklim İndeksinin (AİE) için bir Türkiye uygulamasını önermektir. Endeks, iklim değişikliğinin neden olduğu risklerle çalışan bilim insanlarına, uygulayıcılara ve politika yapıcılara, bu risklerin finansal etkilerini analiz etmelerinde yardımcı olmak için periyodik olarak veri ve bilgi sağlamaktadır. Bu amaçla, standart veri tabanlarından elde edilen verileri kullanarak Ankara ili için AİE hesaplanmıştır. Bu makalede önerilen uygulama tüm ülke kapsamına genişletildiğinde, önerilen hesaplama ilk olarak Kanada'da ve ABD'de geliştirilen AİE'lerinin devamı olan Avrupa AİE'de yer alan tüm Avrupa ülkelerine ek olarak Türkiye'nin de dahil olmasına yardımcı olacaktır.

Anahtar Sözcükler: Ekstrem Hava Riskleri, Eşik Değer, İklim Değişikliği, Referans Periyodu, Standartlaştırılmış Anomali, Sürdürülebilirlik

1. Introduction

Global climate change has emerged in recent years as one of the most challenging issues confronting human society. The "Climate Action" target, one of Sustainable Development Goals (SDGs), adopted by United Nations, aims to strengthen resilience and ability for adaptation to hazards and natural disasters caused by climate change. As the amount of greenhouse gases produced by human activity rises, they accumulate in the atmosphere, warm the climate, and cause various changes in the atmosphere, on land, and in the oceans. According to the Greenhouse Gas Emission Statistics of the Turkish Statistical Institute; energy-related emissions has the largest share in total greenhouse gas emissions as CO2 equivalent with 72%, followed by agriculture with 13.4%, industrial processes and product use with 11.2%, and waste sector with 3.4% in 2019 in Turkey. Energy sector emissions increased by 161% in 2019 compared to 1990 and amounted to 364.4 Mt CO2 eq. whereas industrial processes and product use emissions increased by 147.1%. In addition, agricultural sector emissions increased by 47.7% and waste emissions by 55.7% in 2019 compared to 1990. The change in the pattern and severity of weather events negatively affects sustainable production conditions, and numerous business lines lose their attractiveness and have negative effects on the supply-demand balance. New risk management and insurance solutions are therefore required in consideration of this reality.

Various climate factors that represent extreme weather are used to generate the ACI. The Turkish Actuaries Climate Index (TrACI) seeks to offer data and information to insurance products that provide coverage against risks caused by climate change and to develop a benchmark that examines the financial consequences of these risks. This paper has a significant impact on economic and national energy security in addition to the strategic importance of climate change in actuarial operations such as risk management, product development, pricing, reserving, and investment decisions in the insurance sector. In this regard, developing a climate index unique to Turkey will fill a gap in the Turkish insurance market, especially for actuarial work based on environmental risks. Sustaining this index and providing regular updates will also contribute to the insurance industry.

As in many other disciplines, indices, which are functions that combine multiple indicators, are very useful in actuarial sciences. Indices are efficient since they are statistically robust and easy to understand. In this paper, it is aimed to develop ACI for Ankara by using standardized data sets in existing data sources. The ACI investigates changes in the frequency and length (i.e. severity) of extreme temperatures (high and low temperatures, separately), as well as the changes in heavy precipitation, drought, strong winds, and sea level.

2. Literature

The ACI was launched after a joint research project funded by four North American actuarial organizations that are the American Academy of Actuaries (AAA), the Canadian Institute of Actuaries (CIA), the Casualty Actuarial Society (CAS), and the Society of Actuaries (SOA) in 12 sub-regions in the US and Canada. Actuaries develop models to examine the consequences of uncertain climatic events on the financial losses of various businesses, just as climatologists, environmentalists, and agricultural scientists do in order to assess potential climate changes and their impacts on the environment and agriculture. As a result, the ACI might offer actuaries trustworthy data on "extreme" weather events, which is crucial for calculating and simulating insurance and financial risks associated with climate change (Pan et al., 2022).

Curry (2015) evaluates the ACI, which was initially developed over Canada and the United States, in light of the possibility of expanding it to include the United Kingdom and Europe. Reviewing the definition and underlying methodology of the ACI, it is concluded that no modifications are required for the UK-European ACI to be applied to the new domain. In 2018, the North American ACI was served as a model for the Australian ACI (AACI), as well (AACI, 2018). Kotnala et al. (2018) prepare a plan for creating a climate index for actuarial practice in India, which is called Indian ACI (IACI), after following the discussion of the efforts made by other groups, such as actuarial associations. Although these indices are developed with a similar goal, different underlying components of these ACI indices prevent direct comparison.

The insurance business has acknowledged that human health, mortality, and morbidity are also tied to climate change, in addition to property losses caused by natural disasters. Miljkovic et al. (2018) econometrically show the causality between property damages and mortality rates once the relationship between property damages and climate variables is established. Although there is a close relationship between index insurance and probabilistic seasonal predictions, Carriquiry and Osgood (2012) proposes to formalize this relationship for the first time in the literature by addressing interactions between insurance, climate forecast, and input decisions.

Moreover, Jiang and Weng (2019) focuses on the subject of climate change risk in the stock market by employing the ACI as a proxy for climate change risk. It is obtained that the ACI trends as a type of production risk have an adverse influence on agricultural productivity and corporate profitability of businesses involved in agriculture whereas a considerable forecasting power of climate change is discovered on company revenues.

Pan et al. (2022) investigate the effectiveness of the ACI and suggest a method that combines linear regression and probit regression models to evaluate and forecast agricultural losses for crop insurance and reinsurance applications.

3. The ACI Model

Advanced global climate models are utilized to predict how these indicators may change over time. The trend in public and structured data focuses on “average” changes over a given period. Instead of average climate change, the data sets used to develop the ACI are considered to assess the “risk” posed by climate change, which denotes the “frequency of severe climate changes”.

The assessment of climate change using the ACI is retrospective. The United States and Canada ACI measure, on which our study is based, incorporates data from 6 different climate indicators (ACI, 2018) given in Table 1.

Table 1. Definition of the ACI indicators

Indicator	Abbreviation	Definition
High temperatures	$T90$	Temperature frequencies above the 90th percentile
Low temperatures	$T10$	Temperature frequencies below the 10th percentile
Heavy rainfall	P	Maximum monthly rainfall for five consecutive days
Drought	D	Maximum consecutive dry days in a year
High wind	W	Wind speed frequencies above the 90th percentile
Sea level	S	Changes in sea level

3.1. The Calculation of Standardized Anomalies of ACI Components

The difference between a quantity and its average value throughout a reference period, divided by the quantity's standard deviation over the reference period, is the standardized anomaly (Curry, 2015).

The change in the frequency of warmer temperatures above the 90th percentile ($T90$) and colder temperatures below the 10th percentile ($T10$), relative to the reference period, are referred as the extreme temperature components. Since $T10$ is often lower than it was during the reference period due to the recent warming of temperatures, the sign of $T10$ is inverted in the calculation of the ACI in order to reflect its contribution to increased risk in the temperature distribution accurately. The melting of ice, the spread of diseases, and the population of pests and insects that were previously less likely to live at colder temperatures all contribute to a rise in the ACI’s value as a result of the decrease of cold extremes.

In particular, the monthly frequency of daily maximum (i.e., often daytime) and minimum (i.e., typically nighttime) temperatures that fall below the 10th and above the 90th percentiles of the probability density function are used. These components, which are determined for the reference period, are summarized in Table 2 more specifically.

Table 2. Explanation of the frequencies of extreme surface temperatures

Notation	Explanation
$\boldsymbol{TX90}$	The number of days above the 90th percentile of high temperatures
$\boldsymbol{TX10}$	The number of days below the 10th percentile of high temperatures
$\boldsymbol{TN90}$	The number of days above the 90th percentile of low temperatures
$\boldsymbol{TN10}$	The number of days below the 10th percentile of low temperatures

The variations in exceedance frequency, or anomalies, are calculated as the difference between the exceedance frequency ($TX90$) and the mean of the exceedance frequencies of the related component determined across the monthly reference period, $\mu_{\text{ref}}(TX90)$. In addition, the standardized anomaly accurately determines how much of the variation is significant relative to the underlying degree of variability for each quantity, that is calculated by $\sigma_{\text{ref}}(TX90)$.

On the other hand, the correlation between warm/cold days and nights must be taken into consideration. In order to prevent the temperature components of the ACI from being over-weighted, the average of warmer (colder) days and warmer (colder) nights are used. Therefore, the following equations appear to be the standardized anomaly of high and low temperatures, respectively.

$$T90_{\text{std}} = \frac{1}{2}\left(\frac{TX90-\mu_{\text{ref}}(TX90)}{\sigma_{\text{ref}}(TX90)} + \frac{TN90-\mu_{\text{ref}}(TN90)}{\sigma_{\text{ref}}(TN90)}\right) \tag{1}$$

$$T10_{\text{std}} = \frac{1}{2}\left(\frac{TX10-\mu_{\text{ref}}(TX10)}{\sigma_{\text{ref}}(TX10)} + \frac{TN10-\mu_{\text{ref}}(TN10)}{\sigma_{\text{ref}}(TN10)}\right) \tag{2}$$

The highest 5-day rainfall ($Rx5\text{day}$) in the month, which measures flood risk (P), and the highest number of consecutive dry days (CDD) in a year with less than 1mm of daily precipitation, which measures drought (D), are the components of precipitation. Similar to how it is done for each of the other components, differences between the 5-day rainfall maxima and the number of consecutive dry days and their corresponding average values during the reference period are calculated for each month.

As the first component of precipitation, $Rx5\text{day}$ is the maximum of 5 consecutive days of precipitation in the relevant month, i.e. $Rx5\text{day} = \max(R_i)$ where R_i is calculated with the following formula.

$$R_i = \begin{cases} r_i + r_{i+1} + r_{i+2} + r_{i+3} + r_{i+4} & ; i = 1 \\ r_{i-1} + r_i + r_{i+1} + r_{i+2} + r_{i+3} & ; i = 2 \\ r_{i-2} + r_{i-1} + r_i + r_{i+1} + r_{i+2} & ;\ 2 < i \leq n-2 \end{cases} \tag{3}$$

Here, $r_i; i = 1,2,\ldots,n$ is the precipitation amount of the i^{th} day where n is the number of days in the relevant month.

As the second component of precipitation, the maximum number of consecutive dry days in a year, or $CDD(k)$, is used to determine the severity of a drought. Since the number of consecutive dry days per year could only be calculated as one value per year, unlike the temperature and rainfall components of the ACI, monthly values are obtained by a linear interpolation technique. Dry days are defined as those with less than 1 millimeter of precipitation. By using linear interpolation, as shown in the following equation, monthly values are derived for each month j, year k (ACI, 2018).

$$CDD(j,k) = \begin{cases} \frac{(12-j)}{12} CDD(12,k-1) + \frac{j}{12} CDD(12,k) \,;\, j = 1,2,\dots,11 \\ CDD(k) \,;\, j = 12 \end{cases} \tag{4}$$

Hence, the standardized anomaly of the monthly highest 5-day rainfall and monthly highest number of consecutive dry days are given in Equation (5) and (6), respectively.

$$P_{\mathrm{std}} = \frac{Rx5\mathrm{day} - \mu_{\mathrm{ref}}(Rx5\mathrm{day})}{\sigma_{\mathrm{ref}}(Rx5\mathrm{day})} \tag{5}$$

$$D_{\mathrm{std}} = \frac{CDD - \mu_{\mathrm{ref}}(CDD)}{\sigma_{\mathrm{ref}}(CDD)} \tag{6}$$

In addition to the temperature and precipitation components, wind power component is also included in the ACI. Using the formula $WP = \frac{1}{2}\rho w^3$, where w is the daily mean wind speed and ρ is the air density, which is assumed to be constant at $1.23\ \mathrm{kg/m^3}$ for the North American ACI case and is $1.3\ \mathrm{kg/m^3}$ at sea level, the values of the daily wind speed data are converted to wind power (WP). Wind power is chosen because it has been demonstrated that the effects of strong winds, i.e. damages, are proportional to WP rather than to w. The 90th percentile of wind power ($WP90$), across the monthly reference period is determined using the same procedure mentioned above. The following equation represents the standardized anomaly of the wind power.

$$W_{\mathrm{std}} = \frac{WP90 - \mu_{\mathrm{ref}}(WP90)}{\sigma_{\mathrm{ref}}(WP90)} \tag{7}$$

Lastly, it is considered that the sea level (S) component should also be included in the ACI for coastal regions. Tide gauges monitor sea level relative to the land below, but as the land is shifting, they might not accurately reflect the current sea level. The ACI sea level component evaluates the combined influence of the generally rising seas and the rising/dropping land on coastal shorelines. The standardized anomaly of the sea level is given as follows.

$$S_{\mathrm{std}} = \frac{S - \mu_{\mathrm{ref}}(S)}{\sigma_{\mathrm{ref}}(S)} \tag{8}$$

The percentage of coastal grid points relative to all grid points in a region is known as f_S in the gridded representation of the UK-European ACI (Curry, 2015). Due to the fact that the variable $f_S, 0 < f_S \leq 1$ only affects a small portion of the continent's or a specific region's total area, it is included as an adjustment to the sea level contribution to the ACI which is shown in Equation (9).

3.2. The ACI as a Compound Indicator

The complexity of data-based studies prompts researchers to combine many indicators into a single index (Bruggemann and Patil, 2010). Although weighted sums are frequently used to aggregate data, there are certain drawbacks and difficulties of selecting appropriate weights in order to calculate the compound indicator. First of all, the aggregation could lead to the loss of indicator information, i.e. the information collected in a single compound indicator gets interlaced. When multiple indicators have the same characteristics, it may be undesirable for decision-makers to give them more weight than needed.

As a result, compound indicators' ability to offer an efficient metric system of measurement is particularly beneficial (Bruggemann and Patil, 2011). The ACI, a compound index as a function of the components introduced in Section 3.1, is defined as follows.

$$\mathrm{ACI} = \mathrm{mean}(T90_{\mathrm{std}} - T10_{\mathrm{std}} + P_{\mathrm{std}} + D_{\mathrm{std}} + W_{\mathrm{std}} + f_S S_{\mathrm{std}}) \tag{9}$$

There, the usage of standardized anomalies offers a useful method of integrating these indicators in an easy-to-understand and relevant way. The method maintains the accuracy of the component values while allowing the combination of such fundamentally dissimilar numbers in a single index. The standardized anomaly for any given indicator represents how abnormal that month's or season's value is in comparison to that period's mean and standard deviation. As a result, each component uses the same notation of subscript "std", and is expressed in units of the standard deviation of that parameter. This adheres to the approach suggested by Hansen et al. (1998).

4. Application

In this study, the ACI, which is utilized in North America and Australia and being built in Europe and India, has been calculated for Ankara, the capital city, as a pilot application for Turkey. The components of the ACI defined in Section 3.1 are taken from the NASA POWER gridded data set which is available online (https://power.larc.nasa.gov/). We searched data for climatic variables used in the ACI, which are high and low temperature, precipitation, consecutive dry days, wind and sea level, and we used data from 1981 to 2021 in our analyses.

The ACI does not include a sea level component since Ankara lacks an oceanic shoreline, which means we take $f_S = 0$ in Equation (9). The mean of the other components is used to determine the ACI for Ankara as in Midwest (MID) region for North America ACI case, i.e.

$$\mathrm{ACI} = \frac{1}{5}(T90_{\mathrm{std}} - T10_{\mathrm{std}} + P_{\mathrm{std}} + W_{\mathrm{std}} + D_{\mathrm{std}}) \tag{10}$$

Equation (10) is used in order to calculate the ACI for Ankara as an application in our study.

4.1. The Calculation of the ACI

In order to calculate standardized anomalies of the variables, a reference period must be determined first. We decide to use the years 1981 to 2010 as our reference period due to the lack of information, and because of the fact that it is more recent and that Australian ACI and UK-European ACI also use this range. All calculations are made using R programming in this study.

4.1.1. Threshold Determination for Extreme Weather Variables

In order to determine the frequency of extreme weather events, threshold values were computed for the variables in Equation (10). Once the threshold values are determined, it indicates the frequency of extreme weather by the number of days that fall below the 10th threshold value and exceed 90th threshold value of the relevant climate variable.

If we examine each climate variable in Equation (10) individually, the frequency of the extremes (the number of days exceeding 90% threshold values) for the variable $T90_{\mathrm{std}}$ are indicated as $TX90$ and $TN90$ given in Equation (1) whereas the frequency of the extremes (the number of days falling behind 10% threshold values) for the variable $T10_{\mathrm{std}}$ are indicated as $TX10$ and $TN10$ given in Equation (2). Similarly, the frequency of the extremes (the number of days exceeding 90% threshold values) for the variable W_{std} is indicated as $WP90$ given in Equation (7). Apart from these variables, for P_{std} and D_{std}, we calculate $Rx5\mathrm{day}$ using Equation (3) and CDD using Equation (4) instead of threshold determination.

Zhang et al. (2005) propose to use 5CD technique which was utilized to determine the threshold required to identify extreme weather events. According to this method, data from five consecutive days centered on the day of interest are used to estimate thresholds. When a typical 30-year base period is adopted, the daily thresholds are, in fact, percentiles computed from samples of no more than $5 \times 30 = 150$ days of data.

As an illustration, for determining the threshold value to be used to determine whether an extreme weather situation occurs for a variable on January 12, the values on January 10, 11, 12, 13, and 14 are taken for each year over the complete reference period of 30 years. When the values of these 150 days are ordered as $y_1 < y_2 < \cdots < \boldsymbol{y_{15}} < \cdots < \boldsymbol{y_{135}} < \cdots < y_{150}$ where y_i denotes the value of the i^{th} order statistics, the value of the 15th day ($150 \times 0.10 = 15$)

is the 10% threshold value whereas the value of the 135th day ($150 \times 0.90 = 135$) is taken as the 90% threshold value.

4.2. The Analysis of the ACI and Its Components

Extreme weather variables, which are single components of the ACI, and the ACI generated by combining them will be addressed in this section. Before calculating the ACI, we firstly present the descriptive statistics of the raw data of the climatic variables included in the ACI, which are wind speed, wind power, high temperatures, low temperatures, and total precipitation, respectively.

Table 3. Descriptive statistics of raw weather variables

Descriptive Statistics	w (m/s)	WP (W)	$T90$ (°C)	$T10$ (°C)	P (mm)
n	14,976	14,976	14,976	14,976	14,976
Minimum	0.6	0.13284	-10.32	-23.43	0
Maximum	11.23	870.9923	39.83	22.07	49.88
1.Quartile	2.32	7.679608	7.79	-2.03	0
3.Quartile	3.94	37.61524	25.39	10.6	0.67
Mean	3.247715	32.8642	16.53928	4.018337	1.115182
Median	3.03	17.10815	16.77	4.1	0.03
Stdev	1.306309	51.38992	10.2714	7.6323	2.800158
CV	0.402224	1.563705	0.621031	1.899368	2.510943
Skewness	1.147054	5.548769	-0.07774	-0.18279	4.679596
Kurtosis	2.273153	49.59994	-1.06211	-0.74701	33.55473

The temperature anomalies, which are calculated as a combined indicator of high and low temperatures, are two important components of the index. These factors stand apart from the others since they have an integrated effect on the index. For this reason, the graph below shows a composite temperature indicator. The five-year moving average of $T90_{\mathrm{std}}$ and $T10_{\mathrm{std}}$, which are standardized anomalies for high and low temperatures, and the composite indicator of these two ($T90_{\mathrm{std}} - T10_{\mathrm{std}}$) are given in the chart below.

Figure 1. The five-year moving average of standardized anomalies of high and low temperatures and their composite indicator

As seen in Figure 1, Ankara has experienced increasingly extreme temperatures since the start of the reference period. The fact that standardized minimum temperatures, $T10_{\mathrm{std}}$, have been declining under zero since the end of the 1990s indicates that extreme minimum temperature observations have become less frequent than they were during the reference period, while extreme maximum temperature observations have become more frequent than they were during the reference period.

Having calculated the standardized anomalies of the each component in Equation (10), the ACI for Ankara is calculated. The five-year moving average of the ACI is represented as follows.

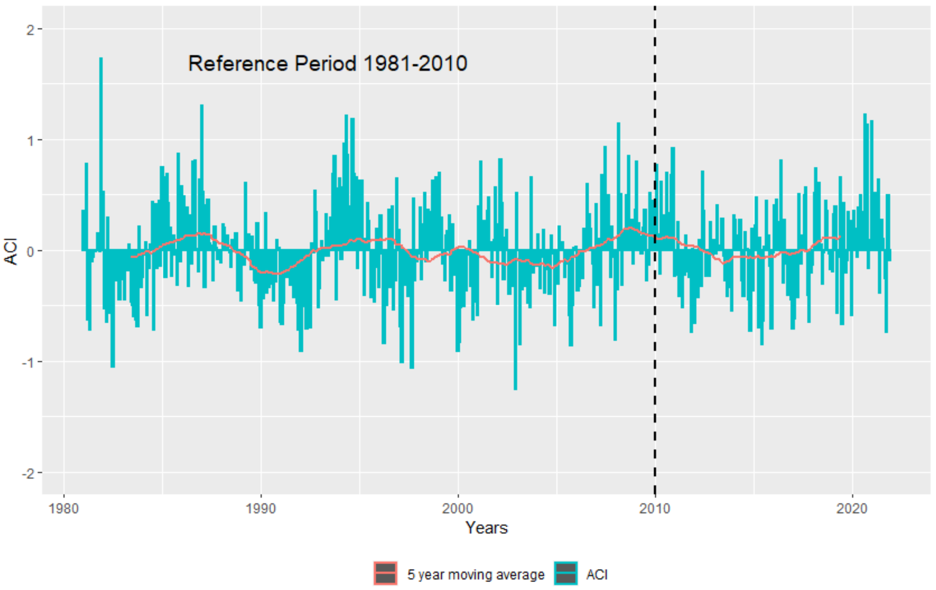

Figure 2. The ACI (the five-year moving average and monthly) for Ankara

Figure 2 shows that the ACI averages zero for the 1981-2010 reference period. The graph demonstrates that the average ACI remains close to zero, indicating that an increase in the frequency of climate extremes is not expected for Ankara in the future.

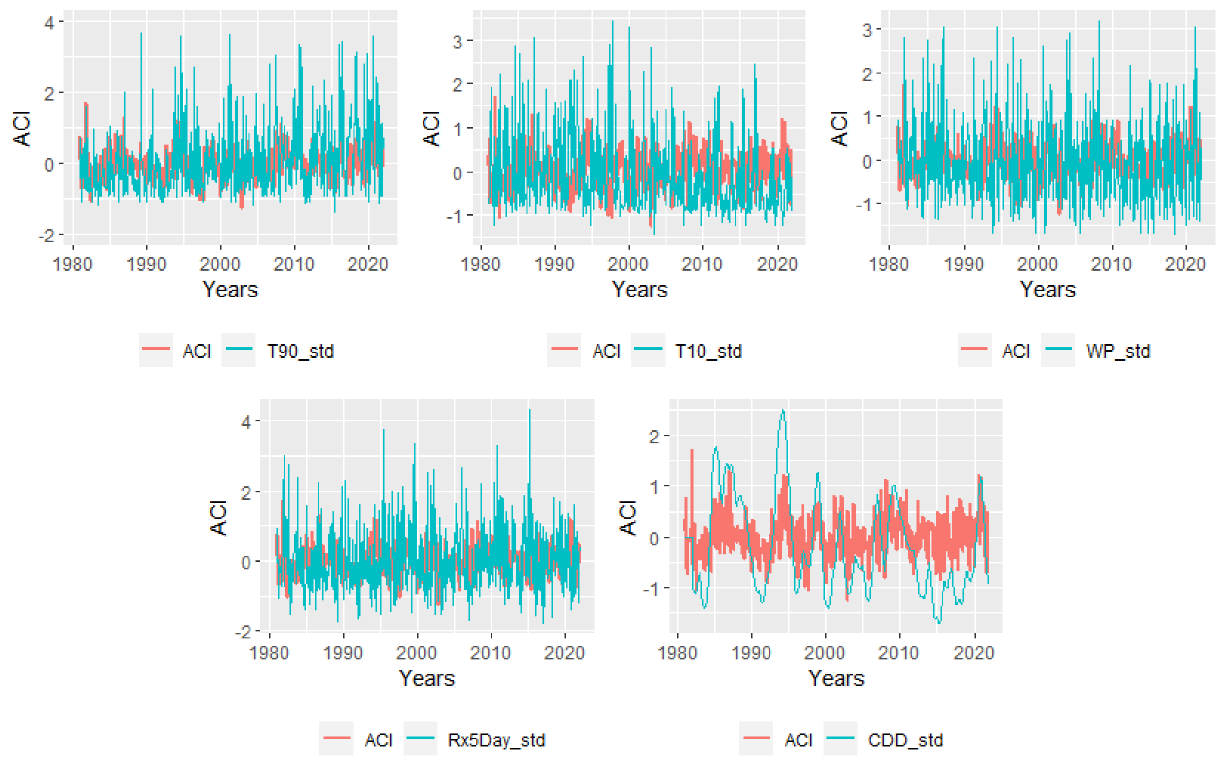

Figure 3. The ACI (monthly) and its components (monthly) for Ankara

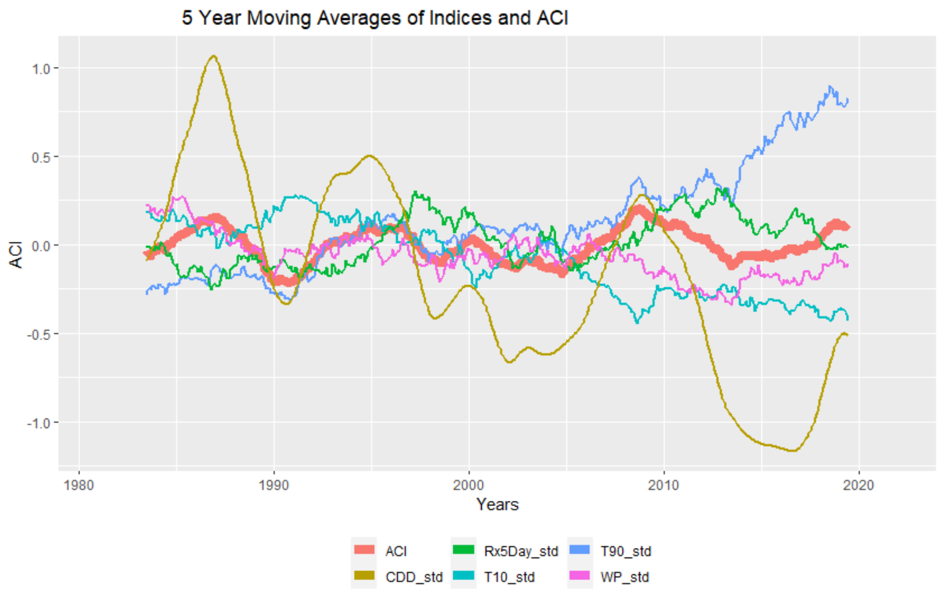

Figure 4. The five-year moving average of the ACI and its components for Ankara

According to Figures 3 and 4, it is seen that all components except $T10_{std}$ move in the same direction as ACI. The symmetry of $T10_{std}$ over the *x*-axis also moves in the same direction as ACI since $T10_{std}$ joins to ACI formula with a negative sign. In this context, it may be concluded that no component has a greater impact on the ACI than the others by examining the ways in which the indicators affect the ACI collectively. This outcome is not unexpected given that the index is determined by taking the arithmetic mean of its components rather than the weighted mean.

In addition to the graphical representation, the descriptive statistics of the monthly ACI are also illustrated in the following table.

Table 4. Descriptive statistics of monthly ACI for Ankara

Descriptive Statistics	***January***	***February***	***March***	***April***	***May***	***June***	***July***	***August***	***September***	***October***	***November***	***December***
Minimum	-0.9117	-0.9075	-1.0136	-0.8369	-0.7231	-0.8472	-1.0530	-0.7209	-1.0649	-0.8566	-0.7440	-1.2551
Maximum	1.2991	0.7972	1.1359	0.9545	1.2091	0.8549	0.9233	0.7914	1.2224	1.1305	0.8636	1.7190
1.Quartile	-0.4606	-0.3194	-0.2630	-0.3566	-0.2703	-0.2755	-0.2919	-0.2743	-0.3267	-0.3291	-0.2746	-0.3246
3.Quartile	0.4147	0.3788	0.4058	0.2495	0.3196	0.1999	0.2609	0.2677	0.3887	0.2274	0.2445	0.1894
Mean	-0.0311	0.0316	0.0795	-0.0309	0.0413	0.0197	-0.0371	0.0265	0.0356	-0.0310	-0.0463	-0.0326
Median	-0.1386	0.0942	0.1285	-0.0569	0.0378	0.0464	-0.0420	0.0602	-0.0158	-0.1595	-0.1271	-0.0974
Stdev	0.5541	0.4519	0.4780	0.4157	0.4173	0.3987	0.3812	0.3537	0.4949	0.4605	0.3845	0.5179
CV	-17.8392	14.3049	6.0162	-13.4437	10.0993	20.2010	-10.2877	13.3490	13.8905	-14.8501	-8.3015	-15.8834
Skewness	0.3813	-0.2768	-0.0762	0.0949	0.3764	0.2013	-0.2567	0.0660	0.4467	0.4553	0.2912	0.7727
Kurtosis	-0.6596	-0.9427	-0.4860	-0.6298	-0.1414	-0.5294	0.1861	-0.6276	-0.1173	-0.4951	-0.5445	1.8387

4.2.1. Time Series Analysis of the ACI

Beside the graphical and statistical analysis of the ACI, time series modeling is considered helpful for future forecasting. Using the values of the ACI from January 1981 to December 2021, we find that the series is stationary based on the Augmented Dickey-Fuller test since $p = 0.01 < 0.05$ where alternative hypothesis represents stationarity. In this situation, it is possible to analyze the series without any differencing.

Table 5. Fit results of time series models

Models	***BIC***	***AIC***	***Log-Likelihood***
$\boldsymbol{ARIMA}(\mathbf{0},\mathbf{0},\mathbf{1})$	577.37	564.77	-279.39
$\boldsymbol{ARIMA}(\mathbf{1},\mathbf{0},\mathbf{0})$	568.31	555.72	-274.86
$\boldsymbol{ARIMA}(\mathbf{1},\mathbf{0},\mathbf{1})$	547.23	530.44	-261.22
$\boldsymbol{ARIMA}(\mathbf{2},\mathbf{0},\mathbf{1})$	552.81	531.82	-260.91
$\boldsymbol{ARIMA}(\mathbf{1},\mathbf{0},\mathbf{2})$	552.67	531.67	-260.84
$\boldsymbol{ARIMA}(\mathbf{3},\mathbf{0},\mathbf{1})$	556.10	530.91	-259.46
$\boldsymbol{ARIMA}(\mathbf{1},\mathbf{1},\mathbf{1})$	564.49	547.71	-269.49
$\boldsymbol{ARIMA}(\mathbf{2},\mathbf{0},\mathbf{1})(\mathbf{1},\mathbf{0},\mathbf{0})_{\mathbf{12}}$	552.79	531.79	-260.90

When we examine the models that can be applied for the ACI series, the ARIMA$(1,0,1)$ model is the best model according to the BIC and AIC information criteria, and ARIMA$(2,0,1)(1,0,0)_{12}$ could be the most suitable model according to the log-likelihood. In addition to these, it is necessary to check whether the errors are white noise processes. The following table represents the results of Ljung-Box Test.

Table 6. Ljung-Box test results

Models	*X-squared*	*p-value*
$\boldsymbol{ARIMA}(\mathbf{1},\mathbf{0},\mathbf{1})$	0.32798	0.5669
$\boldsymbol{ARIMA}(\mathbf{2},\mathbf{0},\mathbf{1})(\mathbf{1},\mathbf{0},\mathbf{0})_{\mathbf{12}}$	0.00444	0.9468

According to the results in Table 5 and Table 6, the most suitable model for the series is the ARIMA(1,0,1) model.

5. Conclusion and Further Study

Insurance companies need to be able to adequately price, pool, and spread risk in order to remain sustainable. However, as climate parameters change, modeled losses become more unpredictable. This makes it more difficult for insurers to recognize their tail risk, or the possibility that significant catastrophic losses could endanger solvency. To determine whether there is an increasing occurrence and risk of weather extremes, insurers must consider the frequency of severe weather. However, the majority of climatic data is presented as averages throughout time, which insurance actuaries do not find useful. The ACI studies appear to be effective to measure the anomalies that could be seen as the indicators of climate-related actuarial risks.

According to the existing studies and the results of this paper, it must be noted that the primary problem of obtaining ACI is choosing the best gridded dataset for the weather extremes rather than altering how the index is formulated. Therefore, our aim for further studies is to extend our application from Ankara to Turkey.

The potential uses of the ACI could be summarized as insurance applications (developing and pricing new insurance products and improving the measurement of tail risk), practices of businesses and financial institutions (developing and pricing new climate-related financial instruments and improving own risk management skills), and government administration (improving preparation and budgeting for disasters and “Climate Action” as a SDG) (Kotnala et al., 2018). Therefore, the ACI can be altered by including components specific to the area of interest for future computations that are more detailed, such as the hail component for car insurance. This suggestion could be handled in the context of Actuaries Climate Risk Index (ACRI).

More specifically, it is thought that in further research, a classification on a regional basis would be made in order to extend this application for Ankara to the entire country. In terms of sales and marketing, it is anticipated that using Turkey’s existing seven geographical regions will be more practical; nonetheless, the Köppen climate classification (see Lohmann et al., 1993 for detail) appears to be one of the most useful techniques for reflecting geographical information.

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