Assessing Climate Extremes in Colombia: Development and Analysis of the Actuarial Climate Index (ICA)

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ABSTRACT

This study analyzes climatic variables such as temperature, precipitation, drought, and wind speed to understand past climate behavior in Colombia. The research covers the entire continental area of Colombia, with a specific focus on the regions of Cundinamarca and Bogotá, Valle del Cauca, and Antioquia.

The results reveal a significant increase in extreme high-temperature anomalies, with drought emerging as the second most influential factor. Wind speed also exhibits an upward trend. Based on these findings, an Actuarial Climate Index (ACI) was developed, integrating the behavior of multiple climate variables into a composite metric. The results indicate that Antioquia has the highest values in the ACI, highlighting its increased exposure to climate extremes.

Continuous monitoring of these variables is essential to assess potential climate impacts and support risk management strategies in vulnerable regions.

Keywords: Actuarial Climate Index, Climate Anomalies, Colombia, Antioquia, Cundinamarca, Valle del Cauca

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RESUMEN

Este estudio analiza variables climáticas como la temperatura, precipitación, sequía y velocidad del viento para comprender el comportamiento climático pasado en Colombia. La investigación abarca toda el área continental del país, con un enfoque específico en las regiones de Cundinamarca y Bogotá, Valle del Cauca y Antioquia.

Los resultados revelan un incremento significativo en las anomalías de temperaturas extremas altas, con la sequía como el segundo factor más influyente. Además, la velocidad del viento muestra una tendencia al alza. A partir de estos hallazgos, se desarrolló un Índice Climático Actuarial (ICA), que integra el comportamiento de múltiples variables climáticas en una métrica compuesta. Los resultados indican que Antioquia presenta los valores más altos en el ICA, lo que resalta su mayor exposición a eventos climáticos extremos.

El monitoreo continuo de estas variables es fundamental para evaluar los posibles impactos climáticos y respaldar estrategias de gestión de riesgos en las regiones más vulnerables.

Palabras clave: Índice Climático Actuarial, Anomalías Climáticas, Colombia, Antioquia, Cundinamarca, Valle del Cauca

1. INTRODUCTION

Extreme events have impacted various industries, and many of these events have been increasing in frequency and intensity (Seneviratne et al., 2021). One way to adapt to these changes is by sharing the risk through insurance, which helps distribute potential losses (Thomalla et al., 2006).

Climate change has transformed the insurance landscape, as it is altering the way we interact with and assess environmental risks. One of the most important aspects of this shift is how we calculate risk levels. Given that we operate in a highly variable environment, it is crucial to analyze past events to better understand and anticipate future risks (Berkes 2007). For this reason based on the articles of Zhou et al., (2023) and AAC (2016) we decided to construct this index for Colombia with the intention of understand what had been the behaviour of the climate in Colombia to offer this information to different entities to take decisions.

2. METODOLOGY

To conduct the climatology study and develop a climate index, we first reviewed the available data sources. The dataset that provided the best temporal and spatial resolution for Colombia was The ERA5 Global Reanalysis (Hersbach et al., 2020), which offers a 32-kilometer resolution for the country. The oldest data retrieved spans from 1961 to 2024, covering a study area between latitude 13.0 and -4.6 and longitude -83.0 and -66.0.

The ERA5 dataset consists of reanalysis data, and the downloaded variables include 2-meter temperature, precipitation, U-component, and V-component of wind, all of which are available at an hourly resolution, as shown in Table 1.

For the definition of the Actuarial Climate Index (ACI), we followed the parameters established for the United States and Spain (see Table 1).

Component	Abbreviation	Definition
High Temperatures	T90	Frequency of temperatures above the 90th percentile
Low Temperatures	T10	Frequency of temperatures below the 10th percentile
Precipitation	P	Maximum precipitation over five consecutive days per month
Drought	D	Maximum number of consecutive dry days
Wind Speed	S	Frequency of wind speed above the 90th percentile

Table 1. Definition of the Index Components

The reference period from 1961 to 1990 was used as the baseline to measure changes. The data within this period is utilized to calculate the standardized anomalies and the averages for each component.

Temperature Components: T90 and T10

The temperature components T90 and T10 are defined as the frequency of temperatures above the 90th percentile (T90) and below the 10th percentile (T10) relative to the 1961–1990 reference period.

To calculate T90, the number of days per month with temperatures exceeding the 90th percentile was counted over the entire 1961–1990 period.

For the calculation of $\mu_{ref}T90$,the monthly average of the number of values exceeding the 90th percentile between 1961 and 1990 was computed. In contrast, for $\sigma_{ref}T90$ (standard deviation version), the same dataset was used, but instead of the average, the standard deviation was calculated.

Notation	Explanation
TX90	Percentage of maximum temperature values exceeding the 90th percentile of the reference period
TX10	Percentage of maximum temperature values falling below the 10th percentile of the reference period
TN90	Percentage of minimum temperature values exceeding the 90th percentile of the reference period
TN10	Percentage of minimum temperature values falling below the 10th percentile of the reference period

$$T90(j,k) = \frac{1}{2}(TN90(j,k) + TX90(j,k))$$

Where j represents the months (January, February, ..., December) and k represents the years (1961, 1962, ..., 2024).

$$T10(j,k) = \frac{1}{2}(TN10(j,k) + TX10(j,k))$$

Where j represents the months (January, February, ..., December) and k represents the years (1961, 1962, ..., 2024).

The values for low temperatures are calculated using a similar process to determine frequency, counting the number of times the temperature falls below the 10th percentile, for both maximum and minimum temperatures.

Subsequently, the standardized anomalies were calculated using the mean and standard deviation from the reference period as a baseline.

$$T90_{std}(j,k) = \frac{T90(j,k) - \mu_{ref}T90(j)}{\sigma_{ref}T90(j)},$$

$$T10_{std}(j,k) = \frac{T10(j,k) - \mu_{ref}T10(j)}{\sigma_{ref}T10(j)}$$

Where j represents the months (January, February, ..., December) and k represents the years (1961, 1962, ..., 2024).

Precipitation Component

The precipitation component focuses on extreme rainfall events rather than average precipitation, using the maximum accumulated rainfall over any consecutive 5-day period in a month, denoted as $Rx5day(j,k)$. The percentage anomaly of 5-day rainfall in a given month, relative to the reference period, is calculated as:

$$P_{std}(j,k) = \frac{Rx5day(j,k) - \mu_{ref}Rx5day(j)}{\sigma_{ref}Rx5day(j)}$$

Where j represents the months (January, February, ..., December) and k represents the years (1961, 1962, ..., 2024).

The term $\mu_{ref}Rx5day(j)$ corresponds to the average of all months during the reference period, while $\sigma_{ref}Rx5day(j)$ also denotes the standard deviation during the reference period.

Drought Component

Drought is measured as the maximum number of consecutive dry days (CDD) in each year, where daily precipitation is less than 1 millimeter, denoted as CDD(k). Monthly values are obtained through linear interpolation.

$$CDD(j,k) = \begin{cases} \frac{12-j}{12}CDD(k-1) + \frac{j}{12}CDD(k) & , j = 1,2,\ldots,11 \\ CDD(k) & , j = 12 \end{cases}$$

The calculation of standardized anomalies for CDD follows the same methodology as for Rx5day, using the mean and standard deviation from the reference period to assess deviations from historical conditions.

Wind Power

Wind speed values are converted into wind power (WP) using the relationship $WP(i,j) = \frac{\rho w^3}{2}$ where w is the average wind speed, and ρ is the air density, taken as 1.23 kg/m³. Wind power is used instead of mere wind speed because it better represents the destructive potential of strong winds.

To determine extreme wind events, an upper threshold is applied to define the right-tail cutoff of the wind power distribution. The critical value of 1.28 is used, corresponding to a significance level of 0.10, meaning that only the top 10% of wind power values are considered as extreme.

$$WP_u(i,j) = \mu_{ref}WP(i,j) + 1.28\sigma_{ref}WP(i,j))$$

The number of days in which the average wind speed exceeded the threshold is then expressed as a percentage of the total days in the month, providing a monthly exceedance frequency for each year throughout the entire study period.

$$I(i,j,k) = \begin{cases} 1 & , WP(i,j,k) > WP90(i,j) \\ 0 & , \text{otherwise} \end{cases}$$

$$WP90(i,j) = \frac{\sum_{i=1}^{n(j)} I(i,j,k)}{n(j)}$$

Where j represents the months (January, February, ..., December), k represents the years (1961, 1962, ..., 2024), and i represents the individual days.

The standard deviation is calculated in the same manner as previously described.

$$W_{std}(j,k) = \frac{WP90(j,k) - \mu_{ref}WP90(j)}{\sigma_{ref}W(j)}$$

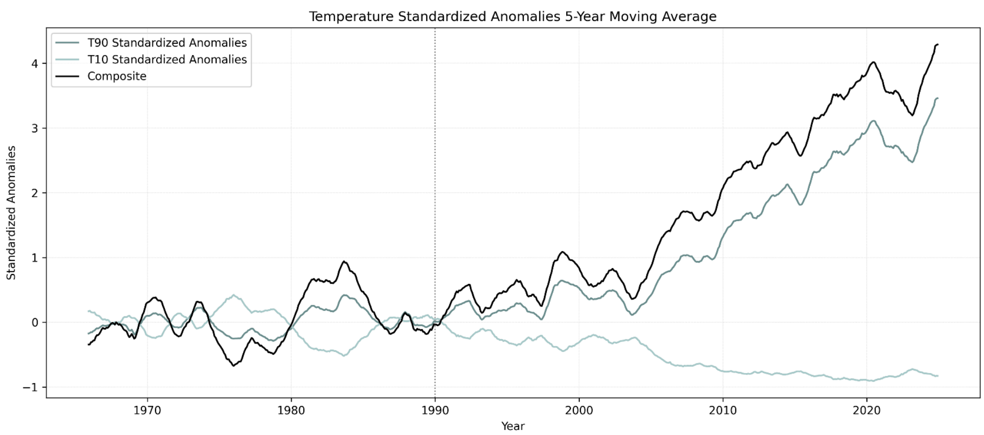
Composite Actuarial Climate Index (ACI)

The standardized values of the six components are averaged to create the Actuarial Climate Index (ACI). However, the values for low temperatures (T10) are subtracted because the probability distribution shifts to the right, meaning that a decrease in extreme cold events contributes to an increase in overall climate risk.

$$ACI = \frac{1}{6}(T90_{std} - T10_{std} - D_{std} - P_{std} - W_{std} - S_{std})$$

3. RESULTS AND DISCUSSION

Temperature



Using the 1960–1990 reference period, it is evident that extreme temperature events—both high and low—have increased in frequency in the years that followed. The black line in the graph represents the sum of T90 and T10, where T10 values are inverted to reflect the decline in extreme cold events and to incorporate them into the composite index in a comparable manner.

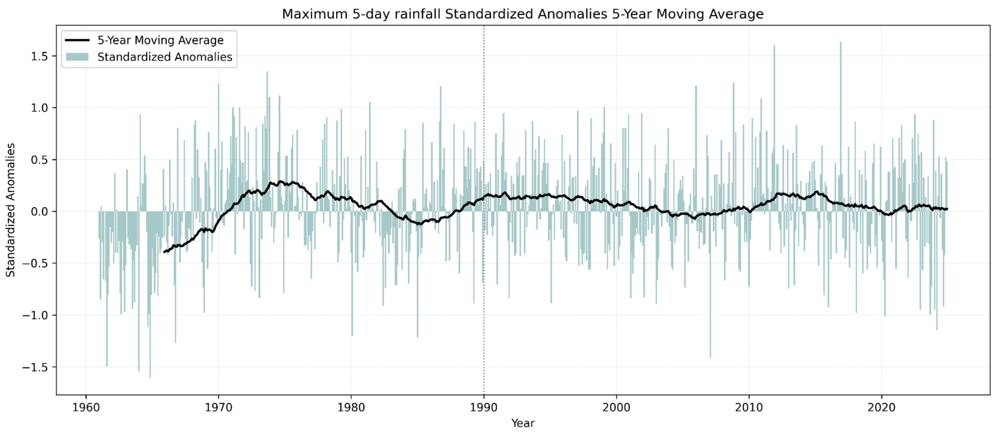
Interpreting this graph, a value of 2, for instance, indicates that the frequency of extreme warm temperatures has increased by two standard deviations relative to the historical average. This signifies a substantial rise in extreme temperature events.

In terms of trends, T90 exhibits a sustained increase until 2004, with a significant upward slope, reflecting a progressive rise in extreme warm temperatures. However, after 2004, the increase becomes even more pronounced, suggesting an intensification of warming. In contrast, T10 follows a downward trend, indicating a decline in extreme cold events, meaning that extremely cold days and nights have become less frequent over time. After 2008, this decline appears to stabilize, suggesting that the frequency of extreme cold temperatures has reached a relatively constant level in recent years.

This pattern aligns with climate change studies, such as Torres (2020), which examined the case of Colombia and found that the frequency of low temperatures has been decreasing, while high-temperature events have increased. This indicates that global warming has shifted temperature distributions toward higher values, reducing the occurrence of extreme cold events while increasing the frequency of extreme heat events.

Additionally, the increase in extreme high-temperature events after 2000 has been corroborated by other research, including Perkins-Kirkpatrick & Lewis (2020), AAC (2016), and Zhou et al. (2023), all of which have observed similar trends.

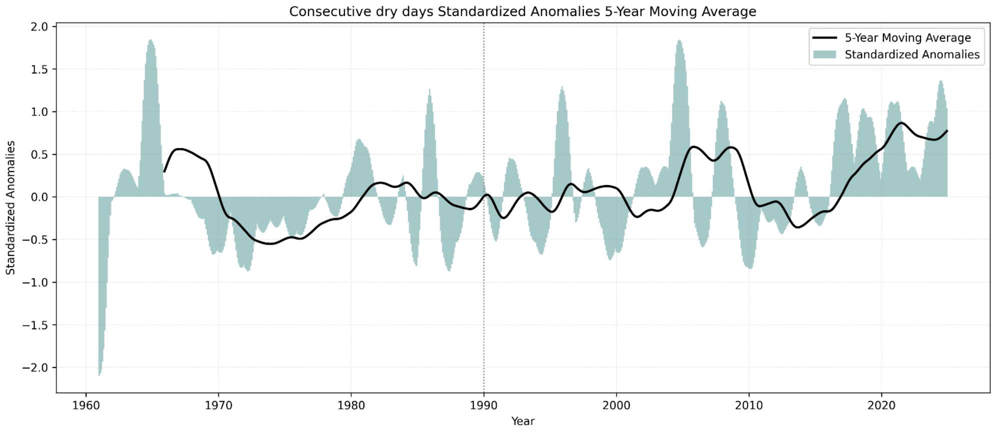
Precipitation



During the reference period, extreme precipitation values exhibited high variability. However, starting in 1990, the trend shows a stabilization, as reflected by the black moving average line. Overall, no significant long-term trend is observed, as average values remain close to zero, indicating no sustained increase in the magnitude of extreme precipitation events.

Nevertheless, rainfall peaks continue to occur, suggesting that while the total precipitation volume has not changed significantly, the frequency of extreme events persists. This aligns with expectations related to climate change, where total precipitation may not necessarily increase, but its distribution and intensity may shift, as noted by Trenberth (2011). Such changes could lead to more pronounced periods of intense rainfall followed by prolonged droughts, increasing climate variability and posing greater challenges for water resource management.

Droughness

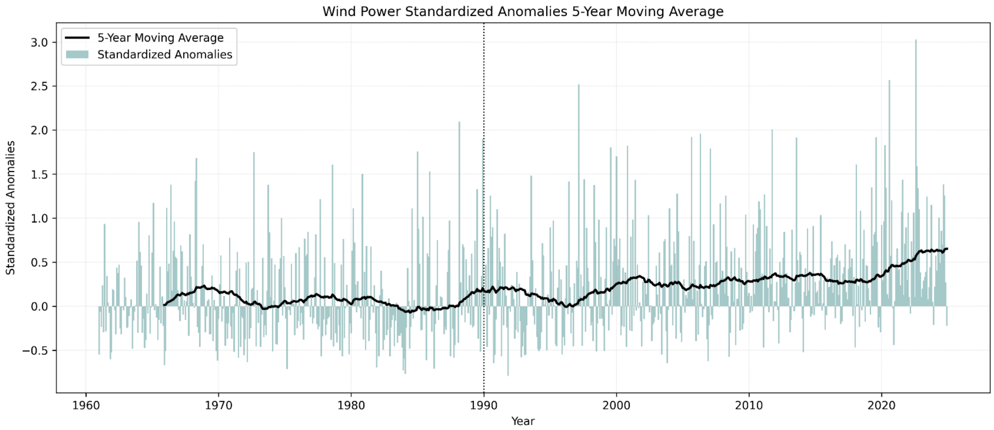


During the reference period, there were significant peaks in drought anomalies, indicating prolonged dry periods. However, after 1980, these fluctuations temporarily stabilized, showing less pronounced variability. From 1990 onward, the trend appears more stable, though periodic variations persist. Nevertheless, since the early 2000s, there has been a sustained increase in the duration of dry periods, indicating a higher frequency of prolonged droughts.

A particularly notable peak occurred in 2016, coinciding with a strong El Niño event. This climate phenomenon is well known for triggering severe droughts across much of Colombia (Marshland 2016), leading to a significant reduction in reservoir levels. This had a severe impact on hydroelectric power generation, which accounts for approximately 60% of the country’s electricity supply.

From a risk and insurance perspective, the increase in prolonged droughts could lead to higher economic losses in key sectors such as agriculture, potable water supply, and energy production (Fernández et al., 2023). This underscores the need for adaptive strategies to mitigate the socioeconomic impacts of prolonged dry spells and to enhance resilience in critical infrastructure and resource management.

Wind speed



Although significant peaks in wind speed have been observed throughout the study period, a sustained increase in average values has been evident since 1998. This trend becomes even more pronounced after 2018, followed by an apparent stabilization in recent years.

This pattern suggests an increase in wind power, with certain months exhibiting particularly anomalous values, indicating greater variability in wind intensity. Such behavior may be linked to changes in atmospheric circulation associated with climate change, potentially leading to stronger and more frequent winds in specific regions (Torralba et al., 2017). Zheng et al. (2019) also found an increase in potential wind energy since 2010, which supports the idea of an increase and in adition could be beneficial for many wind energy projects.

It is crucial to continue monitoring this variable to better understand its evolution and future trends. This will enable a more accurate assessment of its potential impacts on key sectors, such as wind energy production, climate risk management, and infrastructure resilience to extreme wind events.

Climate Actuarial Index

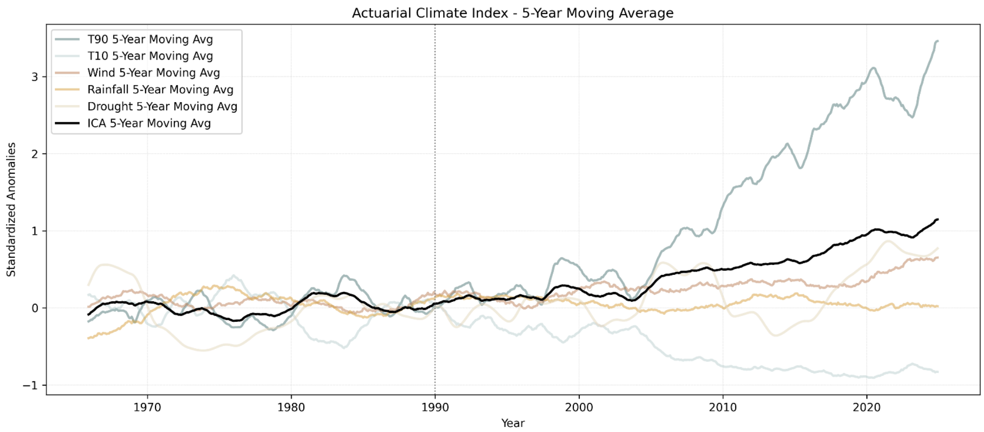


Figure. Figure of the ICA for Colombia

The Actuarial Climate Index (ICA) is a metric designed to assess the variability and evolution of extreme climate events based on various meteorological variables. Under stable climatic conditions, the index values would be expected to fluctuate around zero, reflecting a balance in the occurrence of extreme events. However, since 2004, a significant and sustained increase in the ICA has been observed, suggesting a shift in climate dynamics and an intensification of extreme weather events.

The analysis of the variables that constitute the ICA reveals an upward trend in most components, indicating that multiple factors contribute to the rising index values. Among these variables, temperature changes play a dominant role, specifically the increase in the frequency of extreme high temperatures (T90) and the decline in extreme low temperatures (T10). These changes align with the characteristic pattern of global warming, where heatwaves and extreme high-temperature events become more frequent, while cold extremes become increasingly rare.

Figure X illustrates the evolution of the ICA using a 5-year moving average, demonstrating a consistent upward trend since 2000, with an even more pronounced acceleration in the last decade. This pattern indicates that extreme climate events have not only become more frequent but also more intense, reflecting a structural shift in climatic conditions compared to the reference period. The persistence of this trend reinforces the evidence that climate change is producing increasingly noticeable impacts, leading to greater climate variability and a higher recurrence of extreme weather events.

The rising ICA has significant implications across multiple sectors. The insurance industry, in particular, faces a growing challenge in assessing and covering climate-related risks. Similarly, infrastructure planning and natural resource management must adapt to an environment where severe climate events are becoming more intense and frequent. In this context, continued monitoring and analysis of these variables are essential to strengthen adaptation and mitigation strategies aimed at reducing vulnerability to climate change impacts.

In conclusion, the persistent increase in the Actuarial Climate Index (ICA) suggests a profound shift in climate dynamics, largely driven by the rise in extreme temperatures. This trend underscores the urgent need for adaptation and risk management strategies to reduce vulnerability to climate-related hazards and enhance the resilience of communities and economic sectors most exposed to these phenomena.

The Actuarial Climate Index (ICA) for Colombia shows a clear increasing trend over time, particularly since the early 2000s. Compared to the indices for the Iberian Peninsula (IP) and the United States (USC), Colombia's ICA exhibits a steadier and more gradual increase, whereas the Iberian Peninsula and USC show a more pronounced rise in recent decades, particularly in extreme temperature-related components.

One of the most noticeable differences is the T90 component (extreme high temperatures), which has increased substantially in all three cases. However, in the Colombian graph, T90 rises at a more moderate pace compared to the Iberian Peninsula, where it experiences a sharp acceleration after 2000. In contrast, the USC graph displays a more fluctuating trend in T90 but still follows an overall upward trajectory.

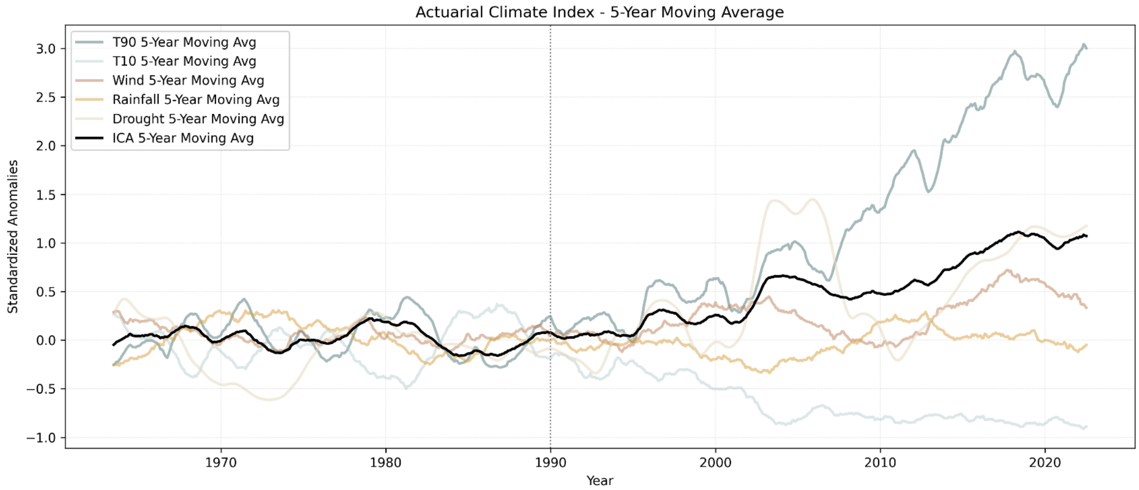
Similarly, T10 has consistently decreased, reinforcing the global warming pattern in all three cases. The drop is particularly evident in the Iberian Peninsula and USC, where the decline accelerates more sharply than in Colombia. This suggests that while warming is evident in all three regions, the reduction in cold extremes may be more pronounced in temperate climates than in tropical ones.

The ICA trends in the three graphs highlight the role of different climatic drivers. In Colombia, wind speed and drought indices show a moderate increase, while in the Iberian Peninsula and USC, precipitation and wind speed fluctuations seem to have a stronger impact on the ICA evolution. The black ICA line in Colombia remains relatively stable compared to the Iberian Peninsula, where it increases rapidly after 2000, and USC, where the trend is more variable but still upward.

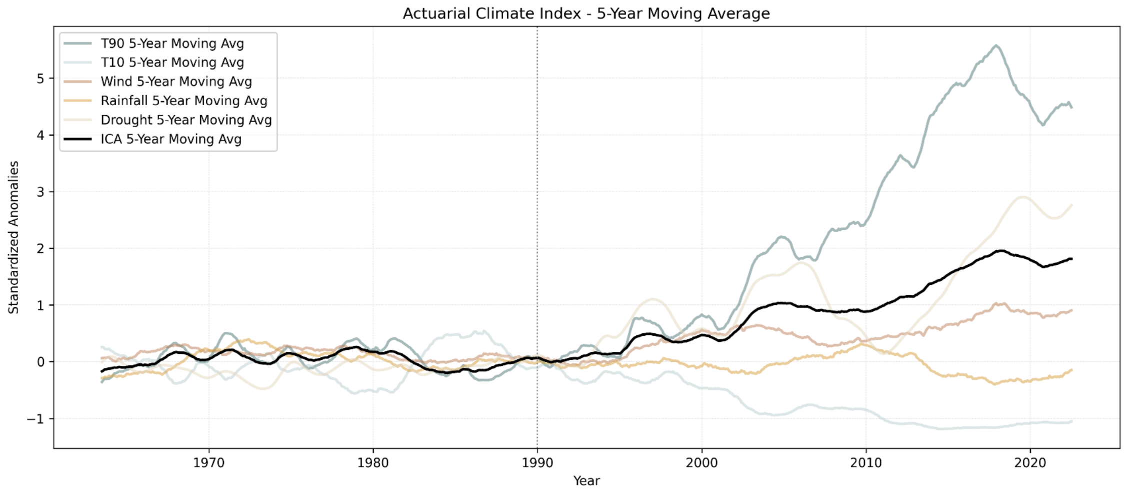
Overall, while all three regions show a strong signal of climate change impacts, the Iberian Peninsula and USC appear to be experiencing more rapid climate shifts, likely due to their exposure to heatwaves and changing precipitation patterns. In contrast, Colombia's ICA suggests a more progressive and steady climate shift, with significant but less abrupt increases in extreme climate variables. This highlights the importance of regional climate variability in understanding and managing climate risks.

ICA for specific regions in Colombia

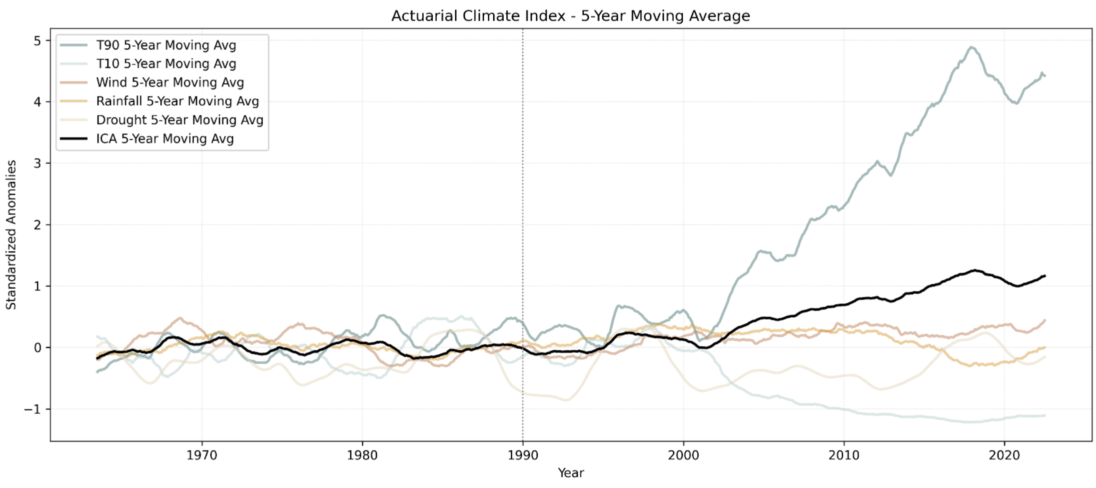
Índice climático actuarial - Región Cundinamarca y Bogotá D.C



Índice climático actuarial - Región Antioquia



Índice climático actuarial - Región Valle del Cauca



The regional analysis of the Actuarial Climate Index (ICA) focused on key areas of the country where the majority of insurance sector clients are concentrated, specifically in the regions of Cundinamarca-Bogotá, Antioquia, and Valle del Cauca. During the 1960–1990 reference period, the index remained within expected values, indicating stable climatic conditions. However, since the 2000s, there has been a sustained increase in extreme climate events, with a notable upward trend in the frequency of extreme high temperatures (T90) across all three regions.

A particularly significant peak in drought frequency is observed in Cundinamarca-Bogotá, likely linked to one of the strongest El Niño events recorded in the country. The consequences of this phenomenon have been well-documented, with widespread effects on water resources and agriculture. However, this event appears to have had a less pronounced impact on the Valle del Cauca region, where drought conditions were comparatively milder.

The ICA values also exhibit notable regional differences. While the index remains slightly above 1 in Cundinamarca-Bogotá and Valle del Cauca, it reaches values close to 2 in Antioquia, indicating a higher intensity of extreme climate events in this region. In particular, drought plays a crucial role in driving the ICA increase in Antioquia, with values reaching as high as 3, making it one of the most affected regions in the analysis. The last major drought event in Antioquia occurred in 2011, further consolidating the region as one of the most vulnerable to hydrological deficits and prolonged dry periods.

These findings underscore the importance of distinguishing climate impacts at the regional level, as each area experiences unique climatic conditions influenced by geographical and meteorological factors. From a risk management and insurance planning perspective, the results suggest the need to adjust adaptation and mitigation strategies, particularly in Antioquia, where drought conditions and extreme temperatures have significantly worsened over the last decade. Continuous monitoring of the Actuarial Climate Index (ICA) in these regions will allow for more accurate climate risk assessments, enabling better-informed decision-making to minimize the impact of climate change on vulnerable sectors.

In comparison of the three regions and the index for the indexes from the Ibenian Peninsula and USA from Zhou et al., (2023), we can see that Antioquia has higher values because the values are in 2, which is one of the higest values in this study.

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4. CONCLUSIONS AND RECOMMENDATIONS

Among the contributing factors, the increase in temperature is the most significant, as it has the greatest impact on the index. Drought emerges as the second most influential variable, playing a crucial role in shaping the index's behavior. This finding is particularly important as it provides insights into the economic sectors most at risk, especially agriculture and energy production. Understanding this relationship can help policymakers and stakeholders develop more effective risk management strategies.

Given the increasing impact of extreme climate events, it is crucial to maintain ongoing monitoring to identify which variables are undergoing significant changes. Additionally, we recommend sharing this data with insurance companies to explore correlations between climate variables and claims. This could help identify areas where expanded coverage is needed to ensure risk-sharing under fair conditions for affected communities.

Antioquia exhibits one of the highest index values, surpassing other regions in the study. This highlights its increased vulnerability to climate extremes and underscores the need for targeted adaptation strategies. The index shows a significant upward trend, reinforcing the importance of continuous monitoring to track changes and assess the potential risks associated with climate variability.

For future research recommendations we propose evaluating the impact of different reference periods to analyze how the choice of baseline influences the index's behavior.

Enhancing the precipitation index methodology by developing a metric that does not merely count extreme rainfall days but instead quantifies the severity of rainfall events. A possible approach could involve counting standard deviation exceedances, providing a more precise representation of precipitation intensity and variability.

These improvements would allow for a more accurate assessment of climate risks, contributing to better-informed decision-making in climate adaptation and insurance coverage strategies.

5. BIBLIOGRAPHY

AAC (2016). Development and Design. American Academy of Actuaries, Canadian Institute of Actuaries, Casualty Actuarial Society, Society of Actuaries.

Berkes, F. (2007). Understanding uncertainty and reducing vulnerability: lessons from resilience thinking. Natural Hazards, 41, 283-295.

Fernández, F. J., Vásquez-Lavín, F., Ponce, R. D., Garreaud, R., Hernández, F., Link, O., ... & Hanemann, M. (2023). The economic impacts of long-run droughts: Challenges, gaps, and way forward. Journal of Environmental Management, 344, 118726.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz‐Sabater, J., ... & Thépaut, J. N. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999-2049.

Marsland, N. (2016). 2015-2016 El Niño Early Action and Response for Agriculture, Food Security and Nutrition.

Perkins-Kirkpatrick, S. E., & Lewis, S. C. (2020). Increasing trends in regional heatwaves. Nature Communications, 11(1), 3357.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. D., ... & Allan, R. (2021). Weather and climate extreme events in a changing climate.

Thomalla, F., Downing, T., Spanger-Siegfried, E., Han, G., & Rockström, J. (2006). Reducing hazard vulnerability: towards a common approach between disaster risk reduction and climate adaptation. Disasters, 30(1), 39-48.

Torralba, V., Doblas-Reyes, F. J., & Gonzalez-Reviriego, N. (2017). Uncertainty in recent near-surface wind speed trends: a global reanalysis intercomparison. Environmental Research Letters, 12(11), 114019.

Torres Moya, E. (2020). Caracterización de las temperaturas extremas del aire para el cultivo de papa en la Sabana de Bogotá.

Trenberth, K. E. (2011). Changes in precipitation with climate change. Climate Research, 47(1-2), 123-138.

Zeng, Z., Ziegler, A. D., Searchinger, T., Yang, L., Chen, A., Ju, K., Piao, S., Li, L. Z., Ciais, P., Chen, D., Liu, J., Chappell, A., Medvigy, D., & Wood, E. F. (2019). A reversal in global terrestrial stilling and its implications for wind energy production. Nature Climate Change, 9(12), 979-985. https://doi.org/10.1038/s41558-019-0622-6

Zhou, N., Vilar-Zanón, J. L., Garrido, J., & Martínez, A. J. H. (2023, December). On the definition of an actuarial climate index for the Iberian Peninsula. Anales del Instituto de Actuarios Españoles, 29, 37-59.