CLIMATE INDEX

ACTUARIAL SOCIETY OF SOUTH AFRICA

Technical Documentation

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1 Introduction

The frequency and severity of insurance losses caused by extreme weather events have increased over the past decade. This trend is consistent with the growing evidence of global warming and increased climate variability. The Actuarial Society of South Africa (ASSA) Climate Index is an industry initiative to develop straightforward and consistent metrics for tracking and quantifying the frequency of climate extremes across South Africa. Its development was informed by leading international efforts including the European Extreme Events Climate Index (E3CI), the Actuaries Climate Index (ACI) for the United States and Canada, and the Australian Actuaries Climate Index (AACI), and was led by Prof Rendani Mbuvha and Dr Nadine van der Walt with expert input from Prof Willem Landman from the University of Pretoria. The index serves actuaries, policymakers, and researchers by providing a transparent measure of how often and how intensely extreme conditions occur, with a focus on temperature extremes, heavy precipitation, and drought. It supports risk assessment, pricing and capital modeling work, climate scenario planning, and disclosures across sectors sensitive to weather and climate variability.

The ASSA Climate Index comprises component indices for extreme maximum temperature, extreme minimum temperature, extreme precipitation, and drought, as well as a composite measure that integrates these signals. Each component is produced as a time series derived from historical observations and expressed as standardized departures from a long-term baseline, facilitating clear interpretation and comparison over time and across regions. Updated on a seasonal cycle, the index enables users to monitor emerging patterns, detect shifts relative to historical norms, and assess implications for environmental and economic stability in the South African context.

The index is built from two gridded, observation-based datasets that provide consistent national coverage: CHIRPS (4, 9) satellite-derived precipitation ($\approx$ 4 km grid cells) and AgERA5 (5) agro-meteorological fields derived from reanalysis ($\approx$ 11 km grid cells). All component calculations are performed at the native grid-cell level, including the construction of baselines and standardized departures, to preserve local climatology and extremes before any aggregation. This bottom-up approach ensures that regional signals are not dominated by stations with uneven coverage (this would require spatial interpolation, leading to further model risk) and that spatial variability is retained in the intermediate results.

Spatial and temporal aggregations are then applied in a transparent, averaging framework. Regional values are computed as the arithmetic mean of the index values for all grid cells whose centroids fall within the region. Time aggregation follows the same principle: monthly component values are first computed, and seasonal indices are formed by averaging the constituent months of the climatological seasons (DJF, MAM, JJA, SON); other user-specified periods are treated analogously. Planned enhancements include expanding the set of components and refining spatial aggregation methods (for example, alternative weighting schemes) to better reflect exposure patterns and sectoral use cases.

2 Data Sources

To ensure spatially complete, reproducible, and regularly updated coverage over South Africa, the index draws on two widely used gridded products. Precipitation is taken from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a quasi-global rainfall dataset at 0.05° resolution (about 4–6 km across South Africa) that blends infrared satellite estimates with in situ gauge observations and extends from 1981 to near-real time. Temperature and precipitation are sourced from AgERA5, which include a suite of indicators derived from the ERA5 reanalysis and curated for agricultural applications by the European Centre for Medium-Range Weather Forecasts, distributed via the Copernicus Climate Data Store (CDS) at 0.1° resolution (about 10–11 km) from 1979 to present. CHIRPS was downloaded from the Climate

Hazards Center, while AgERA5 was obtained from the CDS. Both datasets offer stable, long historical records, consistent national coverage, and routine updates aligned with our seasonal production cycle.

2.1 Rationale for gridded data over national station networks

While South African Weather Service (SAWS) station observations are fundamental, using them directly as the backbone of a national index raises practical and methodological challenges common to many station networks and particularly salient in South Africa: uneven station density (especially in sparsely populated regions), intermittent outages and periods of missing data, station relocations and instrumentation changes that introduce inhomogeneities, variable and sometimes limited metadata and homogenization, and lags or restrictions in access and redistribution. Licensing and cost barriers can also complicate transparent, reproducible, and open publication of national-scale indices.

By contrast, CHIRPS and AgERA5 provide spatially complete fields with consistent processing across the country, long and regularly updated records and clear, open terms that facilitate reproducibility and broad industry use. CHIRPS's gauge-satellite blending improves performance in data-sparse areas and complex terrain, while AgERA5 supplies internally consistent indicators on a uniform grid, both well suited to component-wise calculations at grid level and aggregation to regions and seasons.

2.2 Applicability of CHIRPS and AgERA5 to South Africa

Evaluations over southern Africa consistently support using ERA5-based reanalyses for temperature, with AgERA5 offering a practical balance of accuracy and spatial coverage for impacts work. Regional and subcontinental studies show good consistency between reference observations and ERA5-derived datasets for seasonal means and the frequency of hot and cold extremes, while noting that event magnitudes can be less precise in some settings, hence the value of higher-resolution ERA5 variants for impact analyses (14). A focused assessment across the Northern Cape further demonstrates that AgERA5 reproduces seasonal means and interannual variability well at station sites, and therefore provides a suitable foundation for temperature components of the index although certain regions such as the Kalahari Desert should be treated with caution due to model limitations (11).

For precipitation, multiple South African evaluations point to strong spatial heterogeneity in dataset accuracy, motivating a dual-source approach. CHIRPS is expected to perform well over interior and mountainous regions. In the Enkangala Escarpment / Drakensberg, CHIRPS showed the best overall statistics versus gauges and resolved orographic gradients more effectively than TerraClimate or TAMSAT, which have been found to over- and under-estimate precipitation, respectively (1). A national assessment found high correlations with monthly raingauge totals in the north and parts of the Western / Central catchments, but weaker correlations along the eastern seaboard (8), although CHIRPS have been found to be useful in assessing drought conditions in the Eastern Cape region (12). Complementary evidence from neighboring Eswatini indicates CHIRPS tracks monthly and seasonal variability well but tends to underestimate totals and exhibits lower correlations in complex topography and transition zones, which are patterns relevant to South Africa's eastern highlands and coastal escarpment (7).

Performance challenges are most pronounced in the winter-rainfall southwest regions of South Africa. A catchment-scale comparison reported that CHIRPS underestimated mean annual precipitation in the Western Cape and recommended product recalibration for the winter rainfall zone, even as it performed reasonably elsewhere and within Kruger National Park (13). Independent assessments over the Western Cape likewise show that satellite and reanalysis products exhibit mixed skill and are sensitive to station representativeness and spatial aggregation, underscoring the need for local validation (6).

ERA5-derived precipitation adds value by providing spatially and temporally consistent fields and capturing large-scale seasonal signals, but South African analyses highlight biases and timing discrepancies for convective rainfall and heterogeneous local events, reinforcing the case for combining sources (15). Continental and regional comparisons further emphasize that accuracy varies by regime and application. CHIRPS is often recommended for drought monitoring and climatology, while no single product dominates across all conditions. Site-specific validation and, where appropriate, bias correction are recommended (3).

Methodological work based on Southern Africa also shows that observational choices matter. CHIRPS better captures light-to-moderate events relative to some gauge products, yet higher extremes remain challenging even after bias correction, which has implications for how drought and heavy-rain components are constructed (2). Collectively, these findings justify using AgERA5 for temperature, and combining CHIRPS with ERA5-based precipitation for a more robust and regionally responsive precipitation signal across South Africa.

2.3 Terms of use

CHIRPS is openly available from the Climate Hazards Center for research and operational use with required attribution to the Climate Hazards Group / CHIRPS and the relevant citation; data are provided "as is" without warranty, and users should consult and comply with the Climate Hazards Center data-use policy when redistributing or using the data in derived products[1].

AgERA5 obtained from the Copernicus Climate Data Store is provided under the Copernicus data license, which permits free and open use for any purpose (including commercial), with mandatory acknowledgment of the Copernicus Climate Change Service (C3S)/JRC and no warranty or endorsement; users must retain licence and attribution notices when sharing or adapting the data[2].

3 Component calculations

3.1 Extreme Precipitation

The precipitation component is based on daily gridded values based on the AgERA5 reanalysis product and CHIRPS data. Since each dataset has its own strengths and weaknesses, which results in regional differences in accuracy between the two datasets, the precipitation is provided for both datasets separately. It is imperative that users familiarise themselves with the appropriate dataset to be used based on the region that is of interest. The calculations below are done for each grid cell independently, and this approach is consistent over all climate components.

1. **Reference Climatology:** Let $p(d)$ denote the rolling 5-day total precipitation amount[3] in mm for calendar day d in the year (ignoring leap years, which is dealt with below). Consider a rolling 31-day window centered around $p(d)$ i.e. the window includes the 15 days before and after day d, as well as day d itself). A 31-day window is wide enough to increase sample size, and narrow enough to avoid problems with rainfall seasonality.

   For each d, the precipitation data for all 31-day windows over all years in the base period[4] (1991–2020) are combined. Note that for calendar dates corresponding to early January and late December, this dataset will contain some observations outside of the base period. This yields a dataset of 930 observations (30 years' 31-day observations) per value of d. The climatological threshold $p_{95}(d)$ is then defined as the 95^{th} percentile of this set. To

[1] https://www.chc.ucsb.edu
[2] https://cds.climate.copernicus.eu/api/licence/
[3] Precipitation values less than 1mm are rounded to 0mm before calculating the rolling sum.
[4] https://wmo.int/media/news/updated-30-year-reference-period-reflects-changing-climate

account for leap years, the 29^{th} of February is assigned the average of $p_{95}(59)$ and $p_{95}(60)$ (10).

2. **Frequency calculation:** For each month m and year k in the timeseries, we then determine $P_{m,k}$, the percentage of days for which the 5-day rolling sum exceeds its corresponding percentile. Let μ_m^{base} denote the mean of this number for calendar month m, where the mean is taken over all years in the base period. By definition, μ_m^{base} is typically close to 5%, although some variation is expected for regions and months with low typical rainfall. Similarly, let σ_m^{base} denote the standard deviation of the exceedance percentages for month m and taken over all years in the base period.

3. **Standardised Anomalies:** The standardised anomaly for month m in year k is then given by
$$\delta_{m,k}^P = \frac{P_{m,k} - \mu_m^{base}}{\sigma_m^{base}}.$$

4. **Dry grid cells:** Note that some grid cells over South Africa have few wet days during the base period for some calendar months. It is therefore possible that for some grid cells and months, $\sigma_m^{base} = 0$ because $P_{m,k} = 0$ for years k in the base period. In these cases, to avoid undefined anomalies for such months the above calculations are performed on a seasonal level instead of monthly. The undefined months then receive the seasonal anomaly instead. Since these cases are rare and both the seasonal and monthly anomalies are standardised, this should not lead to biased results and is preferred over incomplete Index timeseries.

3.2 Drought

The calculation of the Drought component is designed on the same principles as the Extreme Precipitation component. The component is calculated on both AgERA5 and CHIRPS data, and both sets of results are provided for users of the ASSA Climate Index. Similar to the Extreme Precipitation component, users should select the most appropriate dataset based on their requirements.

1. **Reference Climatology:** Let $q(d)$ denote the rolling 365-day total precipitation amount[5] in mm for calendar day d in the year (leap years are handled in the same way as for the Extreme Precipitation component).

   A full annual accumulation is used to reflect the way drought conditions develop and are experienced in practice: as multi-seasonal deficits in rainfall that affect water availability, crop yields, ecosystems, and infrastructure. From the perspective of users such as insurers, reinsurers, and policymakers, an annual horizon provides a more stable and decision-relevant signal than shorter windows, which may be dominated by transient anomalies.

   Consider a rolling 31-day window centered around q_d as above. For each d, the precipitation data for all 31-day windows over all years in the base period (1991–2020) are combined similar to the Extreme Precipitation component, yielding a dataset of 930 observations (30 years' 31-day observations) per value of d. The climatological threshold $Q_{05}(d)$ is then defined as the 5^{th} percentile of this set, and here we are interested in observations below this threshold.

2. **Frequency calculation:** For each month m and year k in the timeseries, $Q_{m,k}$ denotes the percentage of days for which the 365-day rolling sum is below its corresponding percentile. Let μ_m^{base} denote the mean of this number for calendar month m, where the mean is taken over all years in the base period. By definition, $\bar{\mu}_m^{base}$ is typically close to 5%. Similarly, let σ_m^{base} denote the standard deviation of the exceedance percentages for month m and taken over all years in the base period.

[5] Precipitation values less than 1mm are rounded to 0mm before calculating the rolling sum.

3. **Standardised Anomalies:** The standardised anomaly for month m in year k is then given by

$$\delta^{D}_{m,k} = \frac{Q_{m,k} - \mu^{base}_{m}}{\sigma^{base}_{m}}.$$

3.3 Extreme Maximum Temperature

The Extreme Maximum Temperature component is based on the frequency of *hot spells*. We define *hot spells* as periods of three (3) consecutive days during which the maximum daily air temperature at 2 m height exceeds a climatological percentile threshold. We use daily maximum temperature data ($T_{\max}$) from the AgERA5 reanalysis product.

1. **Reference Climatology:** For each calendar day d of the year, a climatological threshold $T_{95}(d)$ is computed as the 95^{th} percentile of $T_{\max}$ over a baseline reference period (1991–2020). To increase sample size and smooth inter-day variability, a ± 2 day moving window centered on each day of the year is used, giving a total window width of 5 days and 150 days for each percentile estimate.

2. **Frequency Calculation:** For each day of the year d in year k, we define an exceedance mask $M_{d,k}$ as:

$$M_{d,k} = \begin{cases} 1, & \text{if } T_{\max}(d,k) > T_{95}(d), \\ 0, & \text{otherwise,} \end{cases}$$

   For each month m in year k, let $T^{Max}_{m,k}$ denote the hot spell frequency, where a hot spell is defined as a sequence of at least three consecutive days with $M_{d,k} = 1$. That is, $T^{Max}_{m,k}$ counts the number of runs of length ≥ 3 in the series of exceedance masks $M_{d,k}$ within the month m. For each calendar month, let μ^{base}_{m} and σ^{base}_{m} denote the reference period mean and standard deviation of $T^{Max}_{m,k}$.

3. **Standardised Anomalies:** The standardised anomaly for month m in year k is then given by

$$\delta^{T_{Max}}_{m,k} = \frac{T^{Max}_{m,k} - \mu^{base}_{m}}{\sigma^{base}_{m}}.$$

3.4 Extreme Minimum Temperatures

The Extreme Minimum Temperature is based on the frequency of *cold spells*. We *cold spells* define as periods of three (3) consecutive days during which the minimum daily air temperature at 2 m height falls below a climatological percentile threshold. We use daily minimum temperature data ($T_{\min}$) from AgERA5 and proceed as follows:

1. **Reference Climatology:** For each calendar day d, compute the 5^{th} percentile threshold $T_5(d)$ of $T_{\min}$ over the baseline period (1991–2020). Similarly to the extreme maximum temperature module, a ± 2 day moving window (width 5) is applied around d to increase the sample size and smooth interday variability.

2. **Frequency Calculation:** For each day of the year d in year k, we define a (negative) exceedance mask $M_{d,k}$ as: as:

$$M_{d,k} = \begin{cases} 1, & \text{if } T_{\min}(d,k) < T_5(d), \\ 0, & \text{otherwise,} \end{cases}$$

   For each month m in year k, let $T^{Min}_{m,k}$ denote the cold spell frequency, where a cold spell is defined as a sequence of at least three consecutive days with $M_{d,k} = 1$. That is, $T^{Min}_{m,k}$ counts the number of runs of length ≥ 3 in the series of exceedance masks $M_{d,k}$ within the month m. For each calendar month, let μ_m^{base} and σ_m^{base} denote the reference period mean and standard deviation of $T_{m,k}^{Min}$.

3. **Standardised Anomalies:** The standardised anomaly for month m in year k is then given by

$$\delta_{m,k}^{T_{Min}} = \frac{T_{m,k}^{Min} - \mu_m^{base}}{\sigma_m^{base}}.$$

3.5 Composite Index

The final expression for the composite index in month m and year k is then calculated as an arithmetic mean:

$$\delta_{m,k}^{C} = \frac{\delta_{m,k}^{P} + \delta_{m,k}^{D} + \delta_{m,k}^{T_{Min}} + \delta_{m,k}^{T_{Max}}}{4}$$

It is important to note that CHIRPS provides only precipitation data; therefore, CHIRPS-based composites are calculated by combining CHIRPS rainfall related components with temperature components derived from AgERA5.

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