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Unseen but increasing: recent changes in risk of extreme precipitation over Southern Africa and Southeast Asia

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ABSTRACT

There is evidence that rainfall extremes have become more intense and frequent over the last few decades, but it is difficult to assess these changes due to the limitations of our short observational records. We use the UNprecedented Simulated Extreme ENsemble (UNSEEN) approach to (1) assess changes in extreme rainfall over Southern Africa and Southeast Asia over the last 40 years and (2) identify locations that have a high chance of breaking rainfall records. We find that extreme rainfall risk has already increased since 1981 during the rainy season in both regions, including a doubling of risk in some months for many major population centers such as Phnom Penh, Vientiane, Bangkok, Hanoi, Maseru, Johannesburg, Lilongwe, and Lusaka. The pattern of increasing risk of extreme rainfall is projected to increase further in the coming 20 years in the CMIP6 ensemble; yet UNSEEN estimates of changes from the last 20 years are already greater than these future projections in the Philippines, northern Mozambique, and northern Madagascar. Finally, we compare the UNSEEN ensemble to historical records to identify places that have "soft records" and are likely to see record-setting events. These places with increasing risks but no recent extremes are labeled as "sitting ducks" in today's climate. We find that much of Mozambique, the Philippines, and Laos would be considered "sitting ducks" for extreme precipitation in at least one month of the year. Disaster risk managers should use these types of large ensembles when estimating the risk of extremes in today's climate, in order to ensure that society is prepared for record breaking events. This approach can also be used for improving engineering design estimates of rainfall return periods and for stress-testing health system and disaster preparedness.

1. Introduction

In recent decades, there has been an increase in extreme weather in much of the world. In Southeast Asia, heat extremes and heavy precipitation have increased, and in Southern Africa, extreme heat, heavy precipitation, and droughts have all happened more frequently (Gutiérrez et al., 2021; Papalexiou and Koutsoyiannis, 2013; Seneviratne et al., 2021; Rodell and Li, 2023). Extreme precipitation has caused major infrastructure damage and disease outbreaks in both regions of the world, spurring calls for increased disaster preparedness. In Southeast Asia, dengue fever and leptospirosis epidemics are correlated with rainfall, and cyclones have aided the spread of cholera in Mozambique (Sumi et al., 2017; Cambaza et al., 2019).

In this study, we examine historical changes in extreme rainfall in Southern Africa and Southeast Asia, focusing on the Philippines and Mozambique as examples of two coastal countries with a high risk of extreme rainfall. In both countries, concerns about the increasing frequency of extreme rainfall have been raised after recent extreme events, such as the washing out of bridges due to the passage of Tropical Cyclone Idai in March 2019 and again in 2022 due to Severe Tropical Storm Ana (Otto et al., 2022). The bridge in Nampula Province that connected northern and southern Mozambique was washed out due to the passage of Tropical Cyclone Jude in March 2025. In the Philippines, Tropical Cyclone Trami (Kristine) displaced almost 1 million people, causing severe flooding and landslides. Ash fall deposits were remobilized by extreme rainfall into deadly lahars 4 years after the explosive eruption of Taal Volcano (Davies, 2024). However, despite extreme weather events in the last few years, there is little information about underlying trends

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in the observed frequency and intensity of heavy rainfall.

In both Southern Africa and Southeast Asia, there is only low or medium confidence that extreme rainfall has been increasing over (Seneviratne et el. 2021). One key reason for the lack of confidence in historical changes is that both regions have relatively short observed records and few observational weather stations, compared to the North Atlantic, for example. Maps of observed changes in annual maximum rainfall have similar confidence levels for these two regions (e.g. see Gutiérrez et al., 2021), yet the limited data available might obscure differences between and within each region and between seasons. Simulated/modelled weather data offer an alternative way to estimate where and how much risks are changing, such as the UNprecedented Simulated Extreme ENsemble (UNSEEN) approach, which increases sample size to understand risk in these regions. We seek to understand whether the UNSEEN approach can detect changing risks in regions where these changes might not be possible to detect using station-based observations. Both regions receive tropical cyclones, but we have selected the Southern Africa region as representative of a high-latitude region with distinct wet and dry seasons with varied climate zones (dry, temperate, and tropical) to compare to Southeast Asia as a primarily tropical region with high rainfall totals in much of the year. In comparing the two regions, we compare the extent to which change is detectable in two data-scarce regions and the extent to which disaster planning could be underestimating risks in data-scarce regions with different climates. Analyzing both regions using the same methodology allows us to identify which findings are region-specific versus generalizable properties of UNSEEN-based risk assessment.

Many countries in both regions have seen significant policy investments in early warning systems for flooding and tropical cyclones, making research about changing risk particularly salient for decision-making (UNDRR and WMO, 2025). Policymakers and disaster managers in these countries require updated risk information about extreme rainfall in the current and future climate to guide investment decisions that will protect vulnerable communities. Mozambique, for instance, is aiming at strengthening the inclusion of climate science information and risk information in its current effort to develop the Nationally Determined Contribution 3.0 to the United Nations Framework Convention on Climate Change. Both countries are investing in health systems that can manage the risk of water-borne and vector-borne disease during and after extreme rainfall events.

We assess three aspects of risk associated with extreme rainfall:

1. How is the risk of extreme rainfall changing in Southern Africa and Southeast Asia? We compare estimates derived from an extreme value analysis of observational data vs. estimates from a synthetic dataset of weather (UNSEEN).
2. How does current risk compare to future projections?
3. Which locations have the highest chance of breaking a record for extreme rainfall in today's climate?

1.1. *Observational data of extreme weather*

To assess changes in extreme weather, the most logical approach is to examine the historical record to identify trends over time in the probability of extremes. However, there is limited station data in Southern Africa and Southeast Asia, both in terms of spatial coverage and number of years of data available. Many countries in our study area have few gauges reporting to the GPCC dataset, including Mozambique, Madagascar, Zambia, Botswana, Angola, the Philippines, Laos, Cambodia, and Thailand (Shen et al., 2020).

Therefore, in this study, we use Climate Hazards Group InfraRed Precipitation with Station data v2.0 (hereafter simply CHIRPS) as a proxy for observational data. This dataset is generated using both satellite and station data since 1981 (Funk et al., 2015). In our study regions, daily rainfall estimates from CHIRPS were found to have a negative bias in Mozambique, Madagascar, and the Philippines, with a few small regions showing a positive bias (Shen et al., 2020). CHIRPS has been shown to underestimate daily precipitation extremes in Vietnam (Thanh and Son, 2025). A monthly comparison of CHIRPS against gauge-based GPCC (Global Precipitation Climatology Centre) data from 1981 to 2016 found that a generally negative bias of CHIRPS before the year 2000 seems to be reduced in the following years. CHIRPS and other satellite-derived datasets tend to accurately distinguish between days with and without rainfall, yet often underestimated the magnitude of precipitation (Saragih et al., 2022; Toté et al., 2015). In Mozambique, CHIRPS outperformed other observational products during the cyclone season (Toté et al., 2015). In Southeast Asia, a multi-country study of the Lower Mekong Basin found that forcing a hydrological model with CHIRPS data was more accurate than using the sparse station data available (Luo et al., 2019), and another study found that it performed well when used for forcing crop simulations in Vietnam (Gummadi et al., 2022).

1.2. *Risk of extreme rainfall and future projections*

To accurately estimate the risk of extreme rainfall, models need to capture both the thermodynamical (atmospheric capacity) and dynamical (location) changes to storms and extreme weather. When it comes to the thermodynamical changes, a warmer atmosphere can hold more water, and therefore there is greater water vapor in the atmosphere in a warming climate (Seneviratne et el. 2021). Studies have the greatest agreement on this effect, estimating that precipitation rates from tropical cyclones will increase approximately 7% for every 1 °C global warming (Knutson et al., 2020).

Beyond these thermodynamical changes, models need to capture storm dynamics, such as changes to the speed and track of storms with a changing climate. The rate of movement of a storm is its translation speed, and slower speeds can increase rainfall accumulations and therefore have a greater flood risk (Titley et al., 2021). Using dynamical models, studies have found that translation speed is projected to decrease in the extratropics, such as the coast of the United States (Gori et al., 2022; Yamaguchi et al., 2020). Changes to the track of storms can introduce cyclone risk to new areas, and modelling studies have suggested a poleward expansion of tropical cyclones (Studholme et al., 2021) as well as slower decay and migration of storms further inland (Li and Chakraborty, 2020) which can produce higher precipitation totals, for example in Australia (Bruyère et al., 2019) and China (Lai et al., 2024). These dynamical changes can affect the intensity and persistence of extreme rainfall.

As a result of both thermodynamical and dynamical changes, studies of future storms in the Southwest Indian Ocean show likely increases in rainfall rates, as well as changes to the intensity and size of storms (Thompson et al., 2021), with detectable increases in extreme rainfall already in today's climate (Otto et al., 2022). However, there are geographic and seasonal differences; mean precipitation in Mozambique, for example, is projected to increase during the rainy season (Dec-Feb) and decrease during the dry season (Sep-Nov) (Maúre et al., 2018; Mavume et al., 2021). Within-country differences are also expected, with higher variability in precipitation across the country (Mavume et al., 2021).

In the Philippines, tropical cyclones bring the largest contribution to rainfall amounts in the northern part of the country, and this contribution has been increasing over time (Bagtasa, 2017). Extreme rainfall is also associated with non-landfalling tropical cyclones. For example, non-landfalling tropical cyclones that move north and east of the country can enhance southwesterly winds and deliver extreme rainfall in the western part of the archipelago (Lagmay et al., 2015). Of all the recorded high precipitation events between 1958 and 2017, only 15% were associated with landfalling tropical cyclones (Bagtasa, 2019). The maximum precipitation ever recorded in the country was at Baguio station during Tropical Cyclone Utor, which did not make landfall, but was associated with more than 1000 mm of precipitation in 24 h on 4 July 2001 (Nolasco-Javier et al., 2015). Dynamical changes to the paths of these storms will have high consequences for future rainfall risk in the Philippines.

1.3. Breaking records

Given that extreme rainfall is rare by definition, changes to the risk of such record-breaking events can be difficult to estimate or detect from observations. This is exacerbated by sparse observation networks, and operational disruption and physical damage to these observation networks by extreme weather (Mark et al., 2019). In addition to the impact of climate change, experience of extreme storms is one factor which affects risk perception and often preparedness (Shao, 2016; Zhang, 2022; Keul et al., 2018). The southern Philippines island of Mindanao, experiences fewer storms than the northern parts of the country. In places with frequent storms, risk perception and preparedness might be higher than places with infrequent storms.

When Super Typhoon Bopha hit Mindanao on December 4, 2012, heavy rains caused a massive debris flow in the Mayor River watershed, which destroyed much of the village of Andap in the municipality of New Bataan, burying parts under rubble up to 9 m thick and resulting in 566 fatalities. Founded in 1968, New Bataan had never faced super typhoons or debris flows before. This unfamiliarity contributed to the death and damage (Rodolfo et al., 2016).

Scientific advances now enable the identification of regions with a high chance of breaking the observational record. Extreme value distributions fit to observational data can identify regions that have a "low state likelihood" and have a relatively high chance of a record-breaking event in the future, although different observational datasets disagree on hotspots of low state likelihood globally (de Vries et al., 2025 preprint). These places are also referred to as having "soft records", because their observed records are not very extreme relative to the local distribution (Stelleme et al., 2025 preprint).

To identify these soft records, researchers have used large ensembles of simulations of today's climate to have a larger sample size of plausible extreme events, referred to as the UNprecedented Simulated Extreme ENsemble (UNSEEN) approach. The UNSEEN approach has been used in different parts of the world to assess (a) extreme rainfall and temperature risks and (b) changes to those risks in recent decades (e.g. Kelder et al., 2020; Irving et al., 2024). Masukwedza et al. (2025) used both types of UNSEEN results to classify locations as "sitting ducks" if (a) their record-breaking event has a <1-in-100-year return period and (b) such events have become more frequent in the last 40 years (Fig. 1).

In this analysis, we apply the same UNSEEN methods to rainfall data in Southern Africa and Southeast Asia and discuss risk in Mozambique and the Philippines. We estimate how the risk of extreme rainfall has already changed in both regions since the 1980s, and identify the locations with the highest chances of breaking a record for extreme rainfall. We discuss how these two results can combine to create "sitting duck" areas within each region, focusing on the example countries of Mozambique and the Philippines. Finally, we compare UNSEEN results to future climate projections.

2. Methods

To assess the risk of extreme precipitation in each region, we compare two approaches: extreme value analysis of observational datasets and extreme value analysis of a synthetic dataset of modelled weather. Previous studies have used weather generators or single model initial-condition large ensembles (SMILES) to create synthetic datasets of plausible weather, but weather generators do not incorporate physics to generate plausible outliers, and SMILES are computationally intensive to create (Kelder et al., 2020). Therefore, we choose to use the UNSEEN approach for the synthetic dataset, which uses archives of historical seasonal forecasts from SEAS5 as a large ensemble of plausible weather

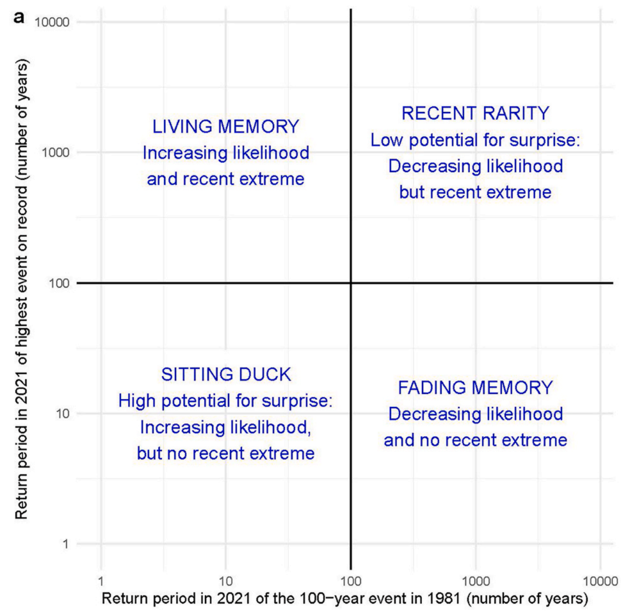

Fig. 1. Matrix characterizing locations by (vertical axis) how likely it is for a record to be broken and (horizontal axis) whether extreme events are becoming more frequent. Reproduced from Masukwedza et al. (2025).

events. This approach consists of three major steps: preprocessing of the large ensemble dataset, evaluation of the dataset for fidelity to observations, and finally extreme value analysis of the synthetic weather data (Kelder et al., 2020). Each of these steps is explained as follows: data preprocessing (section 2.1 and 2.2), comparison of the archived forecasts against observations to assess whether the model is realistic (section 2.3), and analysis of change in the extreme value distribution for the observational dataset and the model dataset for the locations in which the model seems to have fidelity against observations (section 2.4).

2.1. Historical datasets

For observational data over both Southern Africa and Southeast Asia, we useCHIRPS, which combines 0.05° resolution satellite imagery and station data to create a quasi-global precipitation timeseries since 1981 (Funk et al., 2015). We include all land areas within 100E to 128E and 4N to 20N for Southeast Asia and 11E to 50E and −10S to −35S for Southern Africa. We use data from 1981 to 2024, taking maximum daily precipitation for each month of the dataset.

For the UNSEEN large ensemble, we use archived historical forecasts from SEAS5, the ECMWF seasonal forecasting system (Johnson et al., 2019). These forecasts are initialized on the first of every month and run 7 months into the future. In each simulated month, we use the maximum daily precipitation. There are 25 ensemble members from 1981 to 2016 and 51 ensemble members from 2017 to 2024. This large ensemble provides 7 months of data for each ensemble member for each of the 43 years. Therefore, the UNSEEN data preprocessing can be represented in the following equation, with P_{miyl} representing maximum precipitation for any given month (m) and ensemble member (i) and year (y) and lead-time (l). This is the maximum over daily precipitation for this month/ensemble member/year/lead time from day 1 to the last day (d) of that month.

$$P_{miyl} = \bigvee_1^d P_{mily} \tag{1}$$

The UNSEEN method uses large ensembles to estimate the risk of extreme and unusual events, and SEAS5 is widely used for UNSEEN because it is a dynamical model containing both a long time series and a large archive. However, SEAS5 is a low-resolution model that does not contain some of the highest and most extreme precipitation values in the

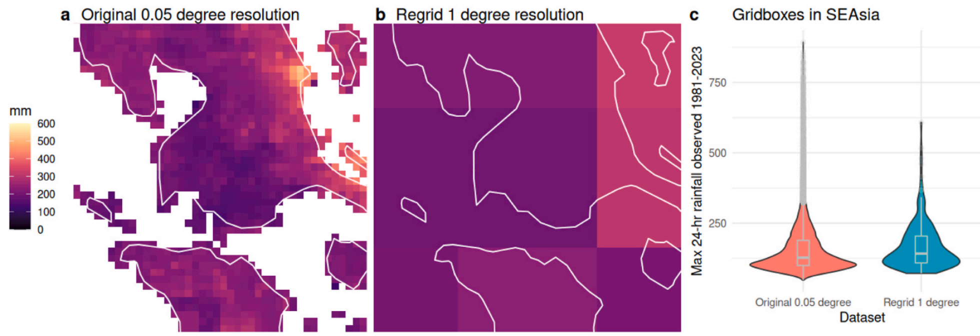

Fig. 2. Consequences of regridding CHIRPs to the 1-degree resolution. (a) CHIRPS data in its original resolution near Manila in the Philippines, (b) the same data regridded to the 1-degree resolution, and (c) maximum precipitation 1981-2024 for all CHIRPS gridboxes in the Southeast Asia domain at the 0.05 and 1° resolution.

CHIRPS dataset. Local-level station precipitation will contain even higher values, due to the potential for small-scale extremes. Large-scale features such as tropical cyclones do appear in the low-resolution data because of their large geographical size; studies about precipitation rates have averaged rainfall over a set radius around the storm, such as 150 km or 500 km radius (Knutson et al., 2020). Results from the UNSEEN analysis should be interpreted as large-scale precipitation events, with the potential for higher extremes and lower values at locations within each gridbox. Rather than using the UNSEEN data to estimate the absolute value of unprecedented extremes, which could never account for small-scale events, we use the results to fit the extreme value distribution in each area and assess for changes in the distribution over time.

To compare SEAAS5 with CHIRPS, we use first-order conservative remapping to re-grid the 0.05° CHIRPS observational data to match the 1° SEAS5 ensemble (Schulzweida et al., 2019). This approach is recommended when going from a fine to a coarse resolution, as it is essentially an averaging function that satisfies any conservation constraints (Jones, 1999). In regridding to the coarser resolution, we lose information about some of the most extreme rainfall events, which happen at small spatial scales (Fig. 2). After regridding, we take the maximum monthly rainfall values.

2.2. Building the UNSEEN ensemble

To build the large ensemble, we treat each of the SEAS5 ensemble member's output for each month as an independent realization of the possible climate for that month, however, we exclude the first month in each run because it is likely that the ensemble members would be too similar and therefore not represent independent simulations of the possible climate in that month. It is possible that the seasonal forecast ensemble might have predictability beyond one month of lead time, so we also assess longer lead times to see whether the ensemble members have enough spread that they are sufficiently independent. To do this, we carry out pairwise Spearman's rank correlations between all ensemble members at all lead times greater than 1. Spearman's rank correlation is appropriate given that the absolute value of extreme rainfall might differ between the ensemble members, but if all the ensemble members are showing a relative extreme, we should be concerned about lack of independence. We exclude lead times in months/locations when the median correlation is greater than 0.25, indicating a lack of independence. In our Southern Africa domain, this resulted in an exclusion of 0.02% of the data, and in Southeast Asia, 15% of data was excluded, demonstrating that the UNSEEN ensemble has higher skill in seasonal forecasting in the Southeast Asia region. Our data exclusion criteria replicates previous studies using seasonal forecasts for an UNSEEN approach (e.g. Kelder et al., 2020). For gridboxes that we find to be sufficiently independent, combining all lead times and ensemble members, each month of each year in the dataset therefore has 150 ensemble realisations for the period 1981-2016, or 306 ensemble realisations between 2017 and 2024.

2.3. Testing the UNSEEN ensemble for appropriateness

Before analyzing the UNSEEN ensemble to assess changes in extreme values, we carry out a fidelity test to identify where and when the SEAS5 model is able to reasonably capture aggregate statistics of the local climate (Kelder et al., 2020; Irving et al., 2024). This fidelity test compares SEAS5 with CHIRPS observational data at each gridbox. First, we carry out a proportional bias-correction to the model data, adjusting each of the ensemble members k at each timestep t by the ratio of the SEAS5 average value to the CHIRPS average value for that month i and location j as in equation (2) (e.g. Kelder et al., 2020, Coughlan de Perez et al., 2023).

$$Model_{ijkt} * \frac{Obs_{ij}}{Model_{ij}} \tag{2}$$

We use the Kolmogorov–Smirnov test (ks.test in the R package "stats") to assess whether the monthly maximum observations and the SEAS5 model results come from the same probability distribution (without needing to specify the distribution itself). While some studies have assessed each of the individual empirical moments of the data (mean, standard deviation, skewness, kurtosis), others have found that the Kolmogorov–Smirnov test returns comparable results in assessing fidelity of the synthetic dataset and avoids issues of multiple tests (Irving et al., 2024). Any data from a month in a location that has a p-value less than 0.05 is excluded from the analysis, because we reject the null hypothesis that the two samples are from the same population (Irving et al., 2024). In Southern Africa, this test excluded 42% of all gridbox-month combinations, and in the Philippines, it excluded only 15% of all gridbox-month combinations, demonstrating that the SEAS5 model produces less realistic weather in much of Southern Africa in the dry season (Fig. 3). Locations that failed the independence test (pairwise correlations of ensemble members >0.25) or the fidelity test (K-S p-value less than 0.05) are depicted in Fig. 3 as black pixels. These locations were excluded from further analysis.2.3 Answering research questions.

2.3.1. How is the risk of extreme rainfall changing in Southern Africa and Southeast Asia?

With the resulting large ensemble of gridbox-months that pass both the independence and fidelity tests, we use the UNSEEN approach to estimate the risk of extremes and how those have changed over the observational record (Irving et al., 2024; Kelder et al., 2020; Coughlan de Perez et al., 2023). For each month at each location, we fit a stationary general extreme value (GEV) distribution to the UNSEEN ensemble data using the fevd function from the R package "extRemes". We then fit a non-stationary GEV distribution using time as a linear

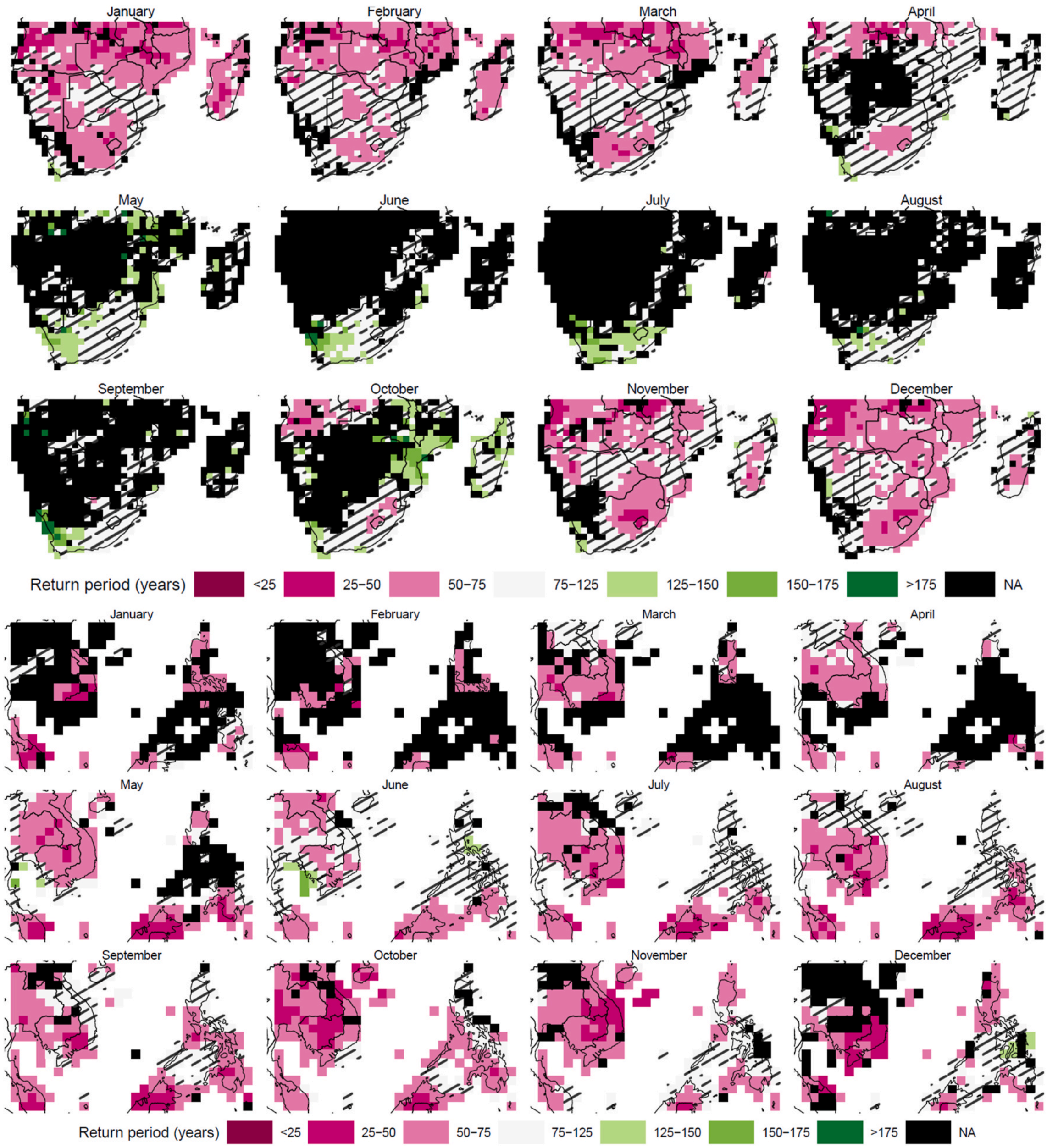

Fig. 3. Return period in 2024 of the event that would have been a 1-in-100-year event in 1981. Top (bottom) rows are Southern Africa (Southeast Asia), each labeled by the month of the year. Areas in red show an increasing risk of extreme precipitation over time, and green regions show a decreasing risk of extreme precipitation. White regions show little change, and hatching indicates regions where any change was not statistically significant. Black pixels failed the model fidelity or independence tests and are excluded from the analysis.

covariate to estimate how the return periods of extremes have changed over time. We use a two-sided likelihood-ratio test to determine whether the non-stationary GEV fit is a better fit for the data, and we use the non-stationary fit if the p-value is < 0.05. Future studies could consider the use of Global Mean Surface Temperature (GMST) as a covariate instead of time, to assess an underlying climate change signal in this data.

For each month at each location, the observed monthly maximum rainfall from the CHIRPS dataset contains only 43 datapoints, one per year from 1981 to 2024. It is difficult to detect trends in extreme values from such a short timeseries, especially because the occurrence of an outlier event near the beginning or the end of the timeseries can have an outsized effect on the estimation of a trend. However, we repeat the same GEV analysis on the observational data, identifying months and locations for which a non-stationary GEV fit is a better fit for the observational data using a likelihood-ratio test.

Based on these GEV models, we then calculate the value of the event that had a 1-in-100-year return period in 1981, and then calculate the return period of the same event in 2024. If the same event has a smaller return period in 2024 than in 1981, for example, we can estimate how much more likely the event is to happen in today's climate. We repeat this calculation for both the UNSEEN method and the observational data.

2.3.2. *How does current risk compare to future projections?*

To compare UNSEEN changes with CMIP6 projections, we use the IPCC Atlas derived variable of monthly maximum 1-day precipitation (RX1day) projected percent change in the near term (2021-2040) relative to a baseline of 1986-2005 (Gutiérrez et al., 2021; Iturbide et al., 2022). We selected SSP3-7.0 as a middle-of-the-road climate scenario. We average results from 28 models; ensemble details are listed in Table S1. To compare with the UNSEEN ensemble, we calculate the

Table 1
Return period in 2024 of the event that would have been a 1-in-100-year event in 1981 for grid boxes containing the capital and other major population centers in the study regions. Values lower than 100 represent an increase in the risk of daily precipitation maximums. Return period Values correspond to October (Southeast Asia) and January (Southern Africa), the representative peak-rainfall months.

Country	City	Return period
Cambodia	Phnom Penh	43.9
Laos	Vientiane	47.9
Philippines	Manila	77.4
Thailand	Bangkok	48
Vietnam	Hanoi	56.5
Eswatini	Mbabane	69.2
Eswatini	Lobamba	69.2
Lesotho	Maseru	47.1
Madagascar	Antananarivo	87.6
Malawi	Lilongwe	46.8
Mozambique	Maputo	100
Mozambique	Beira	70.9
Namibia	Windhoek	100
South Africa	Cape Town	130.7
South Africa	Pretoria	59.2
South Africa	Bloemfontein	56.6
South Africa	Johannesberg	59.2
Zambia	Lusaka	52.8
Zimbabwe	Harare	59.8
Zimbabwe	Mutare	61.9

UNSEEN average percent change in monthly RX1day from the recent past (2006-2024) compared to the same baseline (1986-2005).

2.3.3. Which locations have the highest chance of breaking a record for extreme rainfall in today's climate?

To estimate the risk of breaking a record in each month and location, we use the CHIRPS data to identify the highest rainfall value on record, and then calculate the return period of that event in 2024 using the GEV for the UNSEEN ensemble (e.g. Kelder et al., 2020). Using the UNSEEN simulations, the probability of breaking the CHIRPS record extreme rainfall (RX1day) is calculated for every month at every grid cell. Soft records are identified where this probability is greater than 1% annually (1-in-100 year return period), defined as a 'high chance'. We also plot the percent of UNSEEN simulations for each month that exceeded the all-time observational record.

Finally, we identify "sitting ducks": locations where there is a high potential for surprise, increasing likelihood, but no recent extreme (Masukwedza et al., 2025). To determine the locations within Southern Africa and Southeast Asia where there are 'sitting ducks' we used locations where a) the non stationary model has the best fit, and b) where there is a 'high chance' of exceeding the observed maximum (see Fig. 1). We separate the results by month, since out-of-season extreme rainfall also provides a high potential for surprise even if the overall magnitude is not a record (Heinrich et al., 2024).

3. Results

Our results are presented as answers to the three major questions:

- How is the risk of extreme rainfall changing in Southern Africa and Southeast Asia?
- How does current risk compare to future projections?
- Which locations have the highest chance of breaking a record for extreme rainfall in today's climate?

3.1. How is the risk of extreme rainfall changing in Southern Africa and Southeast Asia?

We find evidence that the risk of extreme rainfall has already changed substantially in Southern Africa and Southeast Asia between 1981 and 2024. In many locations and months, a non-stationary GEV provides a better fit to the UNSEEN data than a stationary GEV, and therefore, the event that used to be a 1-in-100-year event in 1981 has a different return period in 2024 (Fig. 3). In many months and locations, daily rainfall extremes are more likely now than in 1981 (red areas in Fig. 3); any areas where the non-stationary GEV did not provide a better fit to the data are assumed to have a stationary distribution with no change in return periods (white areas in Fig. 3).

When applied to the observational data, we find little evidence of non-stationary trends, and most months at most locations show a better fit for a stationary extreme value distribution than a non-stationary one. This is likely due to the fact that there are so few data points in the observational record. A few months/regions show non-stationary trends, but these seem to be dominated by extreme weather events happening at the beginning or end of the 43-year timeseries (see Supplementary Fig. S1). Therefore, we focus our analysis on the trends detected by the UNSEEN large ensemble, assuming that the model trend is representative of real-world trends even if those trends are not yet discernible in the short observational record. Previous studies have used a single stationary extreme value fit for observational data when comparing to results from different time periods simulated by large ensembles data (Sparks and Toumi, 2025).

In Southern Africa, there is a strong and detectable trend in an increase in extreme precipitation for most of the region between November and March, which is the typical rainy season. In Mozambique, increases are most pronounced in the northern (wetter) part of the country, especially in January and February, when what used to be a 1-in-100-year event is now something that could happen every 75 years or less. January-March is the peak of the cyclone season in that region. Using January as a representative rainy season month for much of the region, we find that extreme rainfall is more likely in most of the major cities and population areas in Southern Africa (Table 1).

During the dry season, however, many parts of Southern Africa show a decrease in the likelihood of extreme precipitation, especially in western South Africa in May-September and Mozambique in May. This reflects IPCC projections for future changes in maximum yearly precipitation RX1day, which also project drying in these months (Gutiérrez et al., 2021). The UNSEEN ensemble does not pass fidelity tests during much of the dry season for most of this region (black mask in Fig. 3).

In the Southeast Asia domain, few locations show a decreasing risk of daily rainfall extremes. For most months in almost all locations, there is an increasing risk of extreme daily rainfall, with the greatest increases in risk of extreme precipitation in June-November for the southern part of

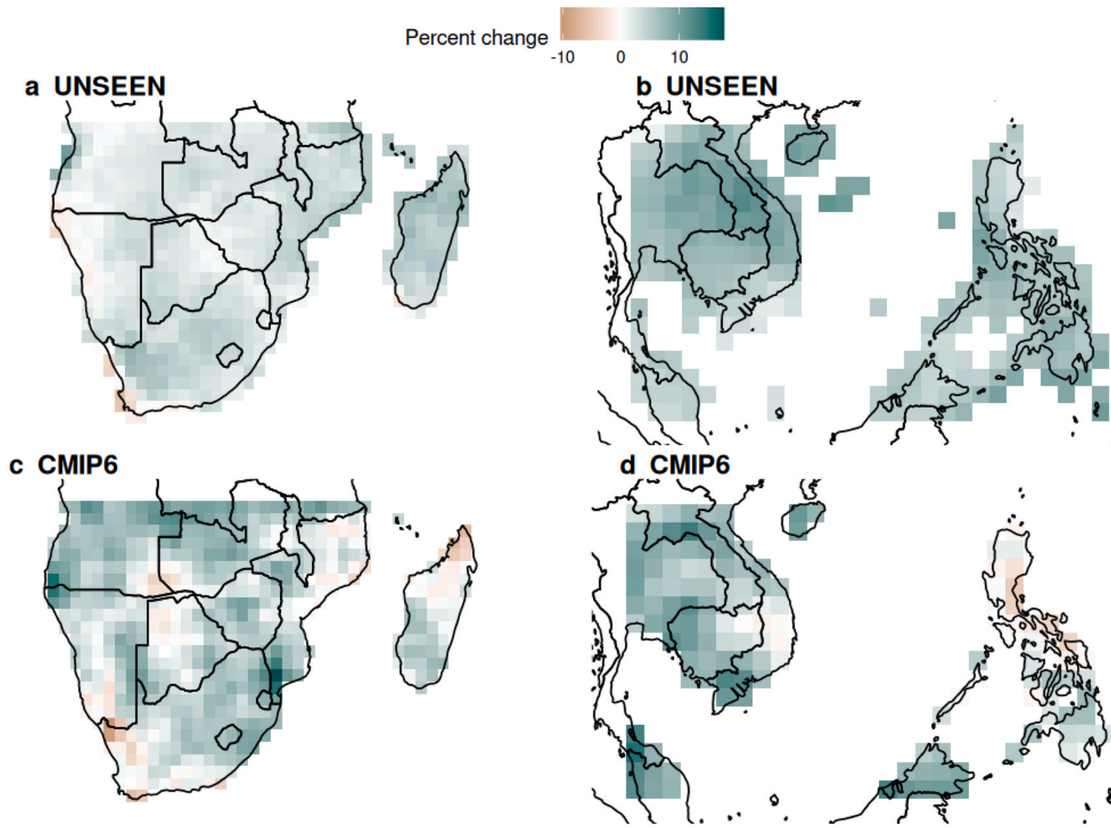

Fig. 4. Average percent change in maximum 1-day precipitation (RX1day) relative to a baseline period of 1986-2005. Change observed 2006-2024 compared to baseline in the UNSEEN ensemble for (a) the month of January in Southern Africa and (b) October in Southeast Asia. Change projected by the CMIP6 ensemble for 2021-2040 compared to baseline for the month of (c) January in Southern Africa and (d) October in Southeast Asia.

the Philippines and November-May in the northern part. In the central part of the Philippines, the model fails to show fidelity to observations in the dry months of Jan-May, but it shows increasing risk of extreme weather in the wetter months, especially in August-October. July-October is the peak of the cyclone season, with the strongest increases in risk in the southern part of the domain during that season. In some major cities, such as Phnom Penh and Bangkok, the risk of an event similar to the 1-in-100-year event in 1981 is now doubled in 2024 (Table 1).

Comparing the results across these two regions, we find that trends in monthly maximums reveal a more complex picture of changing extremes in Southern Africa, and an analysis of simple trends in yearly maximum rainfall could obscure opposing trends in different seasons. In this region, where wet and dry seasons are more pronounced, trends in extreme values are not detectable for most of the shoulder seasons in between the wet and dry seasons. This is not true in Southeast Asia, where detectable trends emerge in almost all months in much of the region.

3.2. How does current risk compare to future projections?

The increasing risk of extreme precipitation that we find in the UNSEEN ensemble generally aligns with the direction of change projected for the future with climate change. In terms of seasonality, CMIP6 precipitation projections for maximum 1-day precipitation (RX1day) in East Southern Africa show an increase during the rainy season (December-April) and a decrease in risk during the dry season, (May-October), which mirrors our findings for historical changes from 1981 to the present (Fig. 3). Similarly, CMIP6 projects an increase in RX1day in all months in their South-East Asia region.

The magnitude of the historical UNSEEN changes over the last 20 years is generally less than what is projected for the coming 20 years. Fig. 4 compares the percent change in RX1day for a heavy rainfall month between the last 20 years in UNSEEN (4a and 4b) and the coming 20 years in CMIP6 (4c and 4d). In most places, there have been increases in the past 20 years in UNSEEN that are projected to further increase in the CMIP6 ensemble, including over most of Southern Madagascar, Southern Mozambique, Eastern South Africa, Zimbabwe, Zambia, Thailand and Cambodia.

However, there are notable areas where changes observed in the UNSEEN ensemble over the last two decades are already greater than what was projected for the coming two decades by CMIP6. These regions include Northern Mozambique and Southern Philippines, for example, where UNSEEN estimates of increased extreme rainfall risk since 2005 exceed CMIP6 average projections for 2021-2040. In the northern parts of the Philippines and Madagascar, the average of the CMIP6 ensemble shows possible decreases in future extreme rainfall in these months, but the UNSEEN ensemble finds a trend for increasing extreme rainfall risk over the last two decades.

Comparing two regions of different climates regimes, we find that CMIP6 has higher spatial variability in future projections than the relative homogeneity of the historical changes estimated by the UNSEEN ensemble. In Southern Africa, the signal-to-noise ratio is higher in future projections than historical estimates of change, while the UNSEEN historical estimates of change are stronger in Southeast Asia. This underscores the need for creative approaches (like UNSEEN) to assess changing risk in regions with little observed data, because the rate of change historically could be larger than might be otherwise expected given similar future projections from global climate models.

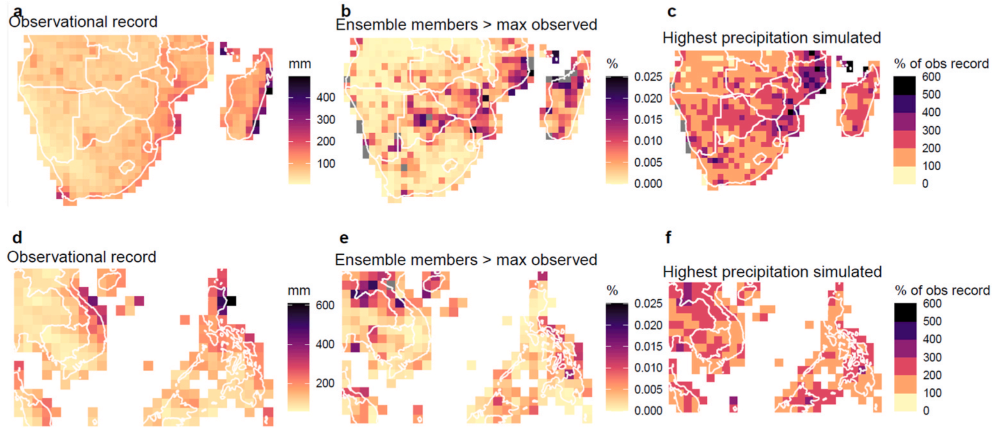

Fig. 5. (a&d) Highest precipitation in the observational reanalysis record. (b&e) Percent ensemble members in the UNSEEN large ensemble that exceed the maximum observed rainfall RX1day from CHIRPS between 1981 and 2024. Lighter colors indicate that there were many UNSEEN simulations that broke historical records. (c&f) Magnitude of the highest simulated RX1day relative to the highest observed RX1day.

3.3. Which locations have the highest chance of breaking a record for extreme rainfall in today's climate?

3.3.1. Record-breaking ensemble members

Given that the UNSEEN ensemble detects a substantial change in risk over the last 4 decades, we analyze which locations have soft records: having the highest chance of breaking a record for extreme rainfall in the current climate. Without using any extreme value distributions, Fig. 5a and c simply depict how many of the UNSEEN ensemble members exceeded the CHIRPS record precipitation in Southern Africa and Southeast Asia. A relatively large percentage of the ensemble exceeded the observed record 24-h precipitation (RX1day) in much of Mozambique, especially near the coast, as well as northern Madagascar, northern Laos, and central Philippines.

Within Southern Africa, the highest simulated precipitation by the UNSEEN ensemble is 6 times larger than the highest precipitation in

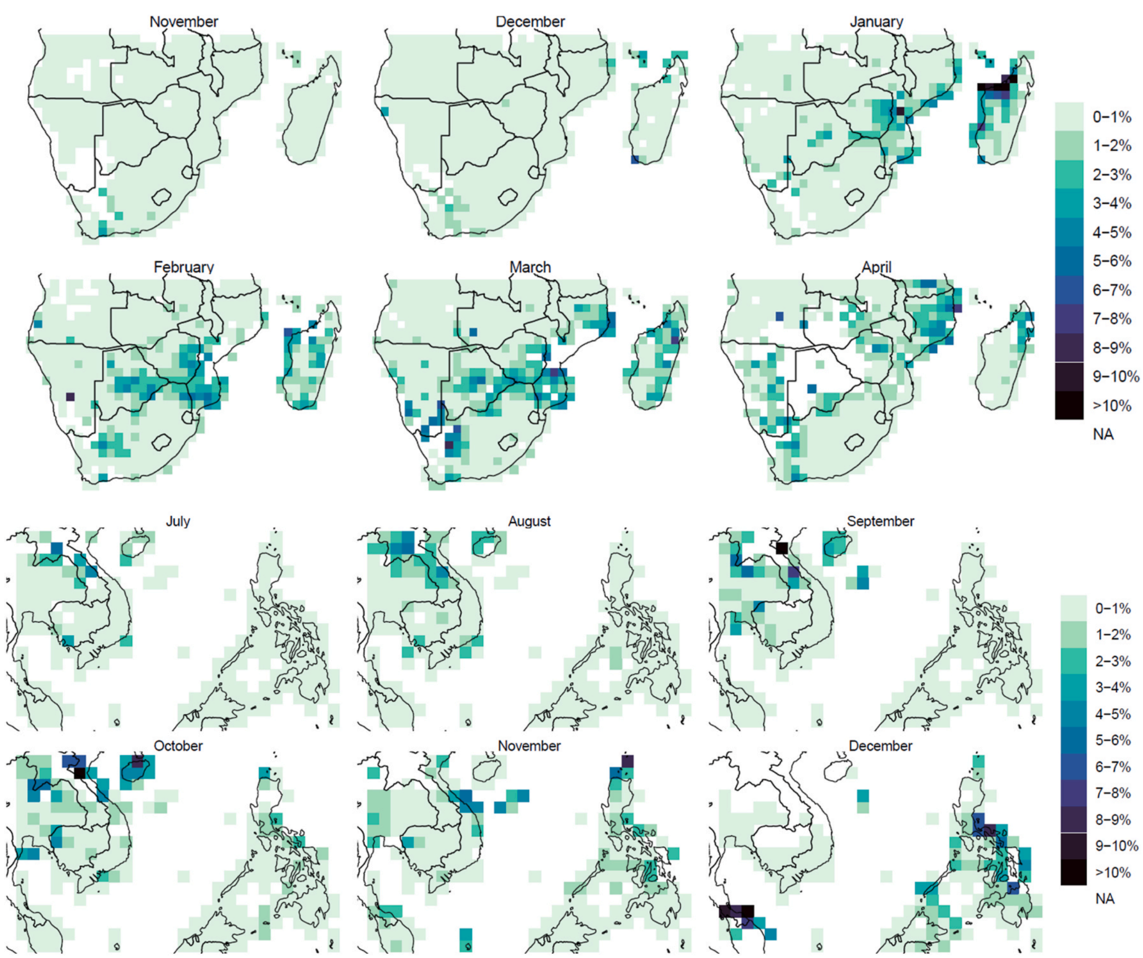

Fig. 6. Probability of breaking a 24-h rainfall (RX1day) record in each month of the rainy season in Southern Africa (top two rows) and Southeast Asia (bottom two rows). Each sub-plot represents one month of the year. Only rainy season months are shown, due to negligible probabilities in other months.

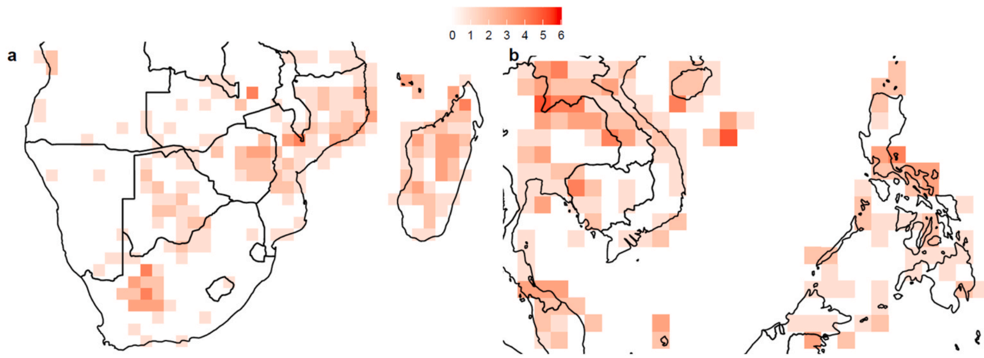

Fig. 7. Number of months in each pixel in (a) Southern Africa and (b) Southeast Asia that would be classified as a "sitting duck" for extreme precipitation in the 2024 climate. These are regions with an observed increasing risk of extreme precipitation and high chance of breaking the observed record (greater than 1% chance of breaking the observed record in any given year).

CHIRPS for that region (Fig. 4b), with many locations in Mozambique having simulated values over 4 times greater than the CHIRPS estimates. This indicates the potential for extreme rainfall well in excess of observed values in these regions. For the Southeast Asia region the highest simulated precipitation is also in excess of the CHIRPS estimates, though to a lesser magnitude (Fig. 4d). This is potentially for two reasons, the first being that the region is more active in terms of tropical cyclones, thereby there is somewhat of a larger sample size of potential extreme rainfall events. In addition, the station data indicates that observed extreme rainfall in the Philippines is generally higher than in Mozambique, and so much so that rainfall many times in excess of the observed values is likely physically implausible.

Comparing a wetter, tropical region of Southeast Asia with the drier region of Southern Africa allows us to assess the relative value of the UNSEEN approach in different climates. In the drier region, we find simulated events that are more dramatic, and we recommend that the UNSEEN approach might be most valuable for identifying extreme scenarios in regions with long tails for extreme rainfall. This can include places with low annual rainfall that have the possibility of landfalling cyclones, such as Mozambique.

In both regions, we find that the regions with the smallest historical extremes, often the driest regions, are also the regions where the highest precipitation simulated is many times larger than the historical record. This is the case in Laos, for example, where simulated events reach 200-300% of the observational record. In other regions, such as northern Mozambique or southern Philippines, the frequency of landfalling cyclones is less than other parts of the country, therefore the distinction between the observational record and the highest precipitation simulated is demonstrating the long tail of the cyclone distribution.

3.3.2. Record-breaking risk derived from GEV distributions

Moving beyond a direct comparison of UNSEEN ensemble members to the observational record, we use the 2024 UNSEEN GEV fits to estimate the chance in any given month of exceeding the CHIRPS all-time record precipitation (Fig. 6). The risk of a record-breaking extreme is not uniform across the year, and therefore we fit extreme value distributions separately in order to analyze each month separately. In Mozambique, there is a high chance of record-breaking precipitation in February in the south, March in the middle part of the country, and April in the northern part of the country. This tracks the movement of the ITCZ north from February to April, following the period of heaviest rainfall for each location. In many places, we find a >10% chance of breaking a precipitation record in these months.

In Southeast Asia, probabilities of breaking precipitation records are higher in some places, especially in Laos (July-October). There is a substantial chance of breaking a record in the northern part of the Philippines in October and November, and the central part in December.

3.3.3. Identification of 'sitting ducks'

Combining results from Fig. 3 (changes to risk over time) and Fig. 6 (probability of breaking a record), we identify locations that would be classified by Masukewedza et al. (2025) as "sitting ducks" (classification in Fig. 1). These locations show increasing frequencies of extreme events in the UNSEEN distribution, yet the observational record has no recent extremes and shows a high probability of a record-breaking event in today's climate. We calculate results for each month of the year, highlighting places that see both increasing risk and soft records for multiple months of the year (Fig. 6).

Much of Mozambique, especially the northern part of the country, has a high chance of breaking a record in several months of the year (Fig. 7). In Southeast Asia, most areas of the Philippines would be considered "sitting ducks" for extreme precipitation in at least one month of the year. The fact that cyclone-affected areas of both regions have at least one month of "sitting duck" risk is surprising, considering that the Philippines sees a much higher frequency of landfalling cyclones than Mozambique or Madagascar, for example. This reinforces the finding that short historical records can be misleading approximations of extreme rainfall risk even in regions that receive frequent storms. We also find high risk over Laos for many months of the year, which is a more consistent signal across much of the year when compared to Zimbabwe, for example, where the signal is limited to only a few months of the year.

4. Discussion

We find that there are many places in Southern Africa and Southeast Asia that would be considered "sitting ducks" for extreme precipitation in today's climate, because risks are increasing in the background but people have not experienced a statistically rare event in recent decades. Indeed, the UNSEEN approach has enabled us to augment the observed record and find robust evidence that the risk of extreme rainfall has already increased across wide swaths of each region, which might not be apparent to people relying on the short observational record to assess risks. In some locations, the historical trends in extreme rainfall exceed what is expected for the coming 20 years in climate projections. Soft records exist across much of northern Mozambique and Madagascar, with high probabilities (>5% chance) of exceeding the observational record in a year with the climate of 2024. We also find soft records in the central Philippines and northern Laos and Vietnam. Given the short observational record of only 43 years of satellite data (combined with station data), we are unable to detect trends in the risk of extreme weather events in most locations across our study regions. Instead, we find only a few locations that register a dramatic non-stationary distribution (e.g. 1-in-100-year events now determined to be 1-in-1 000-year events), which is likely a result of statistical randomness driven by extreme weather at the beginning or the end of the 45 years. Therefore, while we are not able to use observed trends to validate model trends, the fact that model trends exist while observed trends are as-yet undetectable indicates that large ensembles like UNSEEN can help make changing risks visible to decision-makers.

We find that the SEAS5 ensemble produces plausible extreme rainfall events several times larger than the largest event observed since 1981. In the capital cities of Lusaka and Maseru, for example, the risk of extreme rainfall has doubled. In the Philippines, what used to be a 1-in-100-year event in the Metro Manila region, home to 14 million people, is now a 1-in-77 year event. In many parts of Mozambique, simulated daily maximum rainfall was three times larger than the largest event observed since 1981. Such record-shattering events could shock society.

Comparing two regions with limited historical data availability allows us to comment on the usefulness of the UNSEEN approach in characterizing changes in risk. Both Southern Africa and Southeast Asia have regions with risk of tropical cyclone landfall, yet they otherwise have distinct climatologies, ranging from wet tropical climates to temperate and dry regions. In Southern Africa, we find that a month-by-month analysis of change in extreme rainfall risk reveals opposing trends in wet and dry seasons, which otherwise could be obscured by analysis of annual maximums. This is not evident in Southeast Asia, where we find that UNSEEN reveals the potential for record-breaking events even in places with high observed records. We recommend using UNSEEN to help people conceptualize shocking events in places with long tails, like dry regions of Southern Africa, and also using UNSEEN to help people realize that even if they have experienced extreme events in the past, such as high-risk regions of the Philippines, that risks could have already changed without people realizing it. However, we find that the SEAS5 model, when used for UNSEEN simulations, struggles to represent daily rainfall distributions in mid-latitude dry regions, and caution should be used if selecting this model to assess similar climates. The SEAS5 model is also less suited for the UNSEEN approach in regions/months when the model has higher skill in seasonal precipitation forecasting, such as in January in Southeast Asia, because the ensemble members have higher correlations and therefore do not represent the true range of plausible weather.

Beyond the risk of surprised illustrated in this study, there is a potential for even more surprising events due to enormous within-gridbox variability; for example, the Baguio station in the Philippines has recorded rainfall extremes twice as large as its nearest neighbors (Fig. S1). More research is needed on the potential for variation in extreme values within these coarse-resolution gridboxes to provide plausible estimates of what society might need to prepare for. In addition, the CHIRPS dataset has historically underestimated precipitation extremes, therefore it is likely that the observed maximums in this study are biased and appear lower than reality. We recommend that anyone using these results for disaster simulations consult with local authorities to assess what is known about historical records in the region, including using non-conventional data sources, such as newspaper records and local knowledge. These can help contextualize the risk of breaking records that is estimated using CHIRPS and synthetic UNSEEN data.

Our results have implications for long-term risk reduction and preparedness investments across both Southern Africa and Southeast Asia. Places that have not recently experienced a statistically rare extreme event might be more exposed and vulnerable to the event because there has been less motivation to invest in preparedness. Analysis of UNSEEN events can inform preparedness decisions, demonstrating that risks have increased already, even though this increase might seem invisible thus far. Disaster risk reduction investments are critical in places with soft records. For example, just last year in October 2024, Severe Tropical Storm Trami (local name: Kristine) delivered up to 740 mm of rainfall within 24 h in Naga City, Camarines Sur. The highest daily rainfall surpassed the 100-year return period record of the closest PAGASA synoptic station for the region, which stands at merely 507.4 mm within a 24-h timeframe. The lack of anticipation and preparedness for this level of rainfall brought by Trami took many off guard in the city of Naga which resulted in 12 fatalities.

Our findings add to a larger body of research that has documented increases in heavy precipitation in both Southeast Asia and Southern Africa (Gutiérrez et al., 2021; Papalexiou and Koutsoyiannis, 2013; Seneviratne et al., 2021; Rodell and Li, 2023). While it is difficult to discern a trend in observational records of tropical cyclones (Fitchette and Grab, 2014), model simulations of tropical cyclone risk show changes to tracks and intensities (Garner et al., 2024). A study of the oldest weather stations in South Africa finds evidence of increasing likelihoods of extreme rainfall across most of the country (McBride et al., 2022).

Knowing that return periods have changed can have implications across multiple sectors, requiring improved waterborne disease monitoring programs and redesigned drainage systems that accord with updated 1-in-100-year event levels. Traditionally, disaster risk reduction planning has estimated risks using historical information, which is problematic in a climate that has shifting probabilities with time (Lagmay et al., 2023). Disaster managers often refer to the worst-case scenario in the historical record when planning for disaster, and our results suggest this could be a substantial underestimation of a plausible worst case in many regions. In particular, regions that have developed large population centers and major agricultural investments in soft record or "sitting duck" regions where risks are perceived to be low could see large consequences of exposed assets during record-breaking extreme events. For example, the Mindanao region of the Philippines is the breadbasket of the country, historically experiencing fewer severe weather-related disasters than the north. In Mozambique, the northern part of the country is the site of contested resource extraction investments, which might not be adequately preparing for an increasing risk of extreme rainfall because of soft records in that region.

In addition to structural investments in disaster risk reduction, cyclone-prone regions have also invested in early warning systems to alert people and reduce the impacts of extreme rainfall when it is forecasted in the short term. However, our analysis finds a substantial probability of record-breaking events, which might stress existing early warning systems that are not designed for events of such magnitude. Early action plans are often designed based on experience with past extreme events, either locally or in the same region. This means they can underestimate unprecedented severe weather events and fall short in their risk reduction and climate change adaptation plans that can lead to a disaster.

Finally, the sitting duck regions we highlighted in this research could also struggle with disaster response and recovery during and after an unprecedented extreme event. For instance, response contingency plans may not be tested in locations that have not recently experienced a cyclone, these areas may not have warehouses stocked with sufficient first aid kits, and knowledge of adequate evacuation routes may be limited. Unprecedented events may then put additional pressure on recovery efforts, requiring a higher level of resources and a call to build back better rather than back to what was originally there.

The risks of soft-records are relevant to places outside of the Philippines and Mozambique. Indeed, research has shown some level of "social learning" after high-profile disasters; for example, flood insurance increased significantly after Hurricanes Harvey and Irma in the United States, not solely in places that had been affected or nearby (Xu and Box-Couillard, 2024). It is our hope that the results of this study might be able to encourage similar learnings and help elevate the importance of preparing for unseen risks far beyond our study locations.

We recommend further research that compares these results with other methods to assess the risk of extreme weather to identify areas of high agreement and therefore high confidence. This can include methods that apply extreme value statistics to the observational record or pool observations spatially to better assess return periods across a region. Other methods include the development of weather generators, AI models, or Single Model Initial-condition Large Ensembles experiments (SMILES) (Kelder et al., 2020). Biases in large-scale reanalysis datasets limit the ability of the UNSEEN method to assess the potential for synoptic-scale events, therefore bespoke local models that account for local-scale weather processes can also be used to better assess changes to extremes. The results of this study are driven by trends in the overall SEAS5 dataset that was used for the UNSEEN ensemble, therefore we also recommend comparisons against other large ensembles, such as archived decadal forecasts and the Large Ensemble Single Forcing Model Intercomparison Project (LESFMIP) (Stellema et al., 2025; Smith et al., 2022). Such comparisons can also investigate the causal drivers behind modelled changes in risk. Furthermore, we recommend future research into impact modelling using large ensembles, to assess how each of these unprecedented extremes might result in societal consequences.

5. Conclusion

We live in a climate which has already changed and will continue to change, and where the underlying risk of extreme weather has already changed substantially in the past four decades. Because extreme weather is rare by definition, people might not be sufficiently prepared for the unprecedented events that are now more likely, because they do not have recent experience of such an event. We recommend the use of large ensembles of climate simulations, including archived simulations such as SEAS5, to assess the degree to which risks have already changed for rare events. We hope such risk assessments can inform greater investment in preparedness, stress-testing our current disaster management systems to ensure we are ready to anticipate for, respond to, and recover from the types of events that are more likely in today's climate. For example, in Supplementary Fig. S2, we illustrate a single extreme rainfall event in Southern Mozambique of more than 200 mm of rainfall in one day, which could be used for a scenario exercise by disaster managers.

Large ensemble approaches such as UNSEEN provide a powerful means of quantifying plausible extremes and pinpointing regions where risks are already rising. By expanding the sample of possible events beyond the short observational record, these approaches make highly consequential threats visible to decision makers. This is critical in regions like Southern Africa and Southeast Asia, where infrastructure, livelihoods, and disaster management systems are highly sensitive to extreme rainfall. In particular, the health sector grapples with vector-borne and water-borne disease in both regions that is associated with extreme rainfall events. Comparing countries that are geographically far apart allows us to see whether trends are similar in locations with different climatologies. For example, our results show that the percentage increase in the maximum rainfall amounts is very different in the Philippines and Mozambique. We therefore recommend the routine integration of large-ensemble evidence into risk assessments, infrastructure design standards, contingency planning, and Anticipatory Action frameworks. Doing so would allow governments, humanitarian actors, and development partners to move from reactive responses to proactive strategies by stress-testing current systems against extreme weather events that may exceed anything in living memory, and ensuring that health, finance, logistics, and governance mechanisms are in place for record-shattering extremes that are already more likely in today's climate.

CRediT authorship contribution statement

Erin Coughlan de Perez: Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft. **Luis Artur:** Conceptualization, Writing – review & editing. **Dorothy Heinrich:** Conceptualization, Writing – review & editing. **Mahar Lagmay:** Conceptualization, Writing – review & editing. **Gibbon Innocent T. Masukwedza:** Conceptualization, Writing – review & editing. **Bernardino Nhantumbo:** Conceptualization, Data curation, Writing – review & editing. **Elisabeth Stephens:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Erin Coughlan de Perez reports financial support was provided by NASA. Erin Coughlan de Perez reports financial support was provided by National Institutes of Health. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wace.2026.100910.

Data availability

The datasets analysed in the current study are available in the following locations: CHIRPS: https://www.chc.ucsb.edu/data/chirps; SEAS5: https://cds.climate.copernicus.eu/cdsapp#!/dataset/seasonal-original-single-levels?tab=overview. Observational data can be requested from national meteorological societies of the Philippines and Mozambique. The authors can provide the code or materials used in this study upon request, and code is also available on the Github repository: https://github.com/ecn620/UNSEEN.

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