

Trends and Climate Drivers of Extreme Precipitation Variability in Senegal: A Century-Long *In-Situ* Rainfall Analysis

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Abstract

In this study, we focused on describing the trends of Extreme Precipitation Indices (EPI) in Senegal and analyzing the significant links between their variability and key climatic factors such as the El Niño-Southern Oscillation Index (ONI), the Land-Ocean Temperature Index (LOTI), and the Land Surface Temperature Index (LST). Based on a century of daily rainfall data from various Senegalese stations, this study utilized twelve (12) EPIs calculated according to the definitions of the Expert Team on Climate Change Detection and Indices (ETCCDI). To analyze the temporal variation characteristics of extreme precipitation, the Mann-Kendall (MK) test was employed to perform a uniformity test on the precipitation data series. A dependence method through differentiation was used to remove data trends and observe correlations between the climate change indices ONI, LOTI, LST, and EPIs. An approach based on lagged correlations between the ONI index and the EPIs was applied to evaluate the predictability of extreme precipitation patterns in Senegal. Trend analysis indicates a significant decrease in total precipitation and frequency and intensity indices in most stations, while duration indices show no clear trend. Regarding their interannual variability, the analysis shows negative correlations between ONI and total precipitation, consistent with the known influence of ENSO on Sahel precipitation. Correlations with LOTI and LST indices, on the other hand, suggest that the Clausius-Clapeyron theory does not hold at Senegal's latitudes, but that adjacent Atlantic ocean warming influence is crucial in modulating extreme precipitation patterns. Finally, on

the predictability of extreme precipitation, the study shows a significant signal up to three months in advance with ENSO for 58% of the EPIs and up to two months in advance for 90% of the EPIs.

Keywords

Senegal, Extreme Precipitation, Trends and Climate Variability, El Niño-Southern Oscillation (ENSO)

1. Introduction

The severe drought in the Sahel region, which began in 1968, marked a turning point in water management and agricultural development [1]. Senegal, like other Sahelian countries, is grappling with an ongoing environmental and climatic “crisis,” which has significantly impeded economic activities [2]-[6]. This crisis is further aggravated by the intensifying effects of global warming [7]. The analysis of the variability and trends of extreme precipitation indices serves a dual purpose: first, it highlights the significant environmental impacts of precipitation, such as floods, flash floods, and droughts, which are all consequences of extreme precipitation events; second, it is essential for monitoring the effects of climate change.

Since the democratization of access to daily satellite precipitation data in the 2010s, numerous studies have begun to document the intra-seasonal characteristics of precipitation, such as their frequencies of occurrence, intensities, and durations [8]-[13]. However, it should be noted that most of these studies rely on the CHIPRS (Climate Hazards Group InfraRed Precipitation Stations) satellite data, whose time series began in 1981 [14] [15]. Although these studies have provided valuable insights, they are not based on long-term time series, which are necessary for a meaningful analysis of associated climatological trends.

In the present paper, we have the opportunity to explore the longest daily rainfall time series available in Senegal, covering the entire 20th century. To our knowledge, the only existing study that exploited extreme precipitation patterns using this dataset is [16], and it focused on decadal variability rather than trends and interannual variability. Thus, the present study represents the first analysis of trends and interannual variability of extreme rainfall patterns in Senegal based on in-situ observations covering a century. This work is part of the statistical modeling of precipitation, using a century-long record of daily rainfall data collected across various stations in Senegal to statistically characterize spatiotemporal variability and identify the key meteorological factors driving extreme precipitation. The paper is structured as follows: Section 2 begins with a presentation of the study area, followed by the methods and statistical tools used in this study. Section 3 is devoted to the analysis and discussion of the results, and finally, the conclusion and perspectives are addressed in Section 4.

2. Data and Methods

2.1. Study Area Description

Located at the westernmost edge of the African continent, Senegal covers an area of 196,722 km² (Figure 1). Senegal is bordered to the northeast by Mauritania, to the east by Mali, to the west by the Atlantic Ocean, and to the south by Guinea and Guinea-Bissau. The Gambia forms an enclave of 10,300 km² within Senegalese territory. Senegal is a flat country with elevations not exceeding 130 meters, except in the southeastern region where the terrain reaches 581 meters at the highest point of the Fouta Djallon foothills. The climate is influenced by both geographical factors, due to the presence of a maritime façade of over 700 km and the location at the extreme west of the African continent, as well as atmospheric influences under the effects of the maritime trade winds, the harmattan, and the monsoon. These air masses determine two seasons distinguished by highly contrasting rainfall (République du Sénégal,

<https://www.ciesin.columbia.edu/decentralization/French/CaseStudies/senegal.html>, accessed on February 18, 2024):

- From November to May, it is the dry season characterized by the predominance of northern trade winds.
- From June to October, it is the rainy season, during which the monsoon, a warm and humid wind, prevails. Rainfall is highly variable in both time and space. There is also a significant hydroclimatic disparity between the humid south (with annual rainfall exceeding 1000 mm) and the dry north (receiving less than 500 mm of rain per year).

Regarding temporal evolution, there is a high interannual variability in precipitation [17], highlighting a succession of more or less marked periods of dry and wet years.

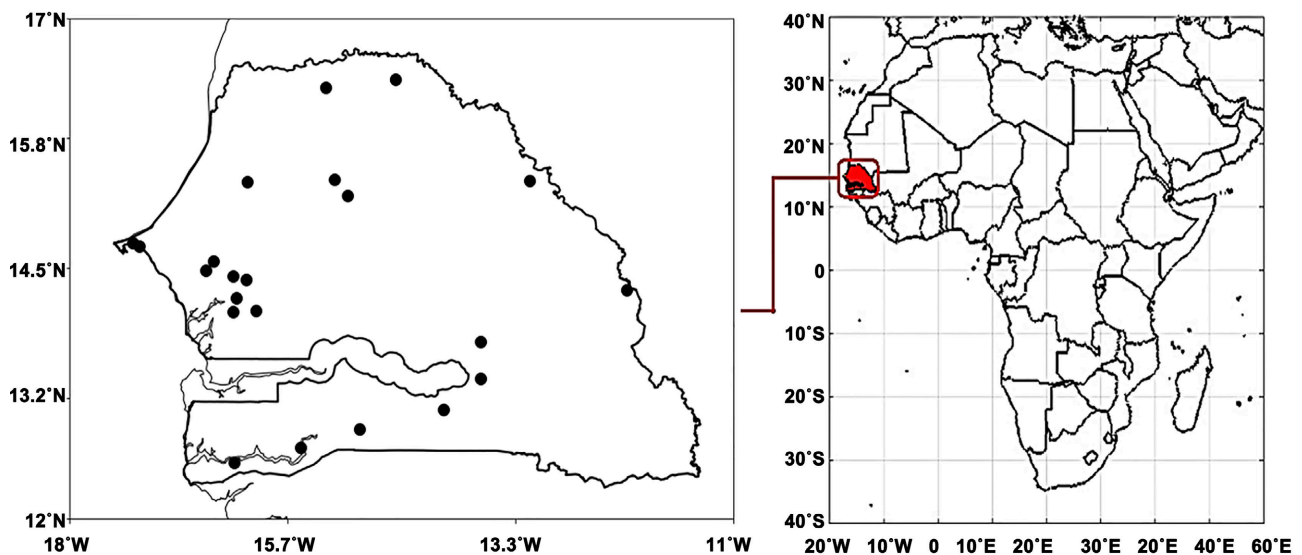


Figure 1. Map of Senegal showing the location of the stations used in this study (left). Senegal is located on the westernmost edge of the African continent (right) and spans latitudes 12°N to 17°N and longitudes 18°W to 11°W.

2.2. Data Sources

2.2.1. Observed Precipitation Data

This study is based on a century-long dataset of daily precipitation collected from various stations across Senegal. These records consist of daily precipitation data from the network of the former National Meteorological Agency in Senegal [now the National Agency for Civil Aviation and Meteorology of Senegal (ANACIM)] and other rain gauges managed by the Senegalese Institute of Agricultural Research (ISRA). The data were collected from 143 stations in Senegal over the period 1900-2014. However, not all data are complete for the entire period. A description and preprocessing of this database are presented by [16]. For validation purposes, gridded monthly precipitation data from the Climatic Research Unit (CRU) TS version 4.04 were used [16]. The CRUTS4.04 dataset covers the period from 1901 to 2019 with a spatial resolution of $0.5^\circ \times 0.5^\circ$. A CRU subset corresponding to CRU monthly precipitation at the CRUTS4.04 grid points closest to the stations was defined by the work of [16] [18].

2.2.2. Climate Change Index Data

This study identifies the Ocean Niño Index (ONI), the Land-Ocean Temperature Index (LOTI), and the Land Surface Temperature (LST) index as crucial indicators for quantifying the influence of climate variability and change on extreme precipitation events (EPE) in Senegal.

The ONI is calculated from the three-month running mean of sea surface temperature (SST) anomalies (ERSST.v5 data) in the Niño 3.4 region ($5^\circ\text{N} - 5^\circ\text{S}$; $120^\circ\text{W} - 170^\circ\text{W}$). A positive ONI indicates warmer-than-average SSTs, signaling an El Niño event, while a negative ONI indicates cooler SSTs, suggesting a La Niña event. ONI is pivotal in forecasting short- to medium-term climate patterns and understanding the global impacts of ENSO on precipitation and temperature, aiding in agricultural planning, water resource management, and preparation for extreme weather events.

LOTI tracks global temperature variations by combining terrestrial and oceanic surface temperature data, collected from meteorological stations and ocean buoys. This index is vital for assessing long-term climate change trends and their impacts on ecosystems, human populations, and economies, by identifying extreme temperature events such as heatwaves or cold spells.

The LST index measures terrestrial surface temperature, which is distinct from the combined land-ocean data of LOTI. LST is essential for understanding environmental changes like urbanization and deforestation, particularly in studying urban heat islands. ERA5 monthly 2-meter temperature data, with a high spatial resolution (31 km), is used to calculate LST. ERA5 provides high-quality, hourly data from the European Centre for Medium-Range Weather Forecasts (ECMWF), which is crucial for precise meteorological analysis and climatology studies [19].

2.3. Methods

The specific technical process is illustrated in **Figure 2**. First, Extreme Precipitation

Indices (EPI) were calculated for each of the 22 selected stations. Second, the spatial variation in the trends of each EPI was documented. Third, three commonly used climate variability and change indicators ONI, LOTI, and LST were selected to determine the impact of climate change on EPI variability in Senegal.

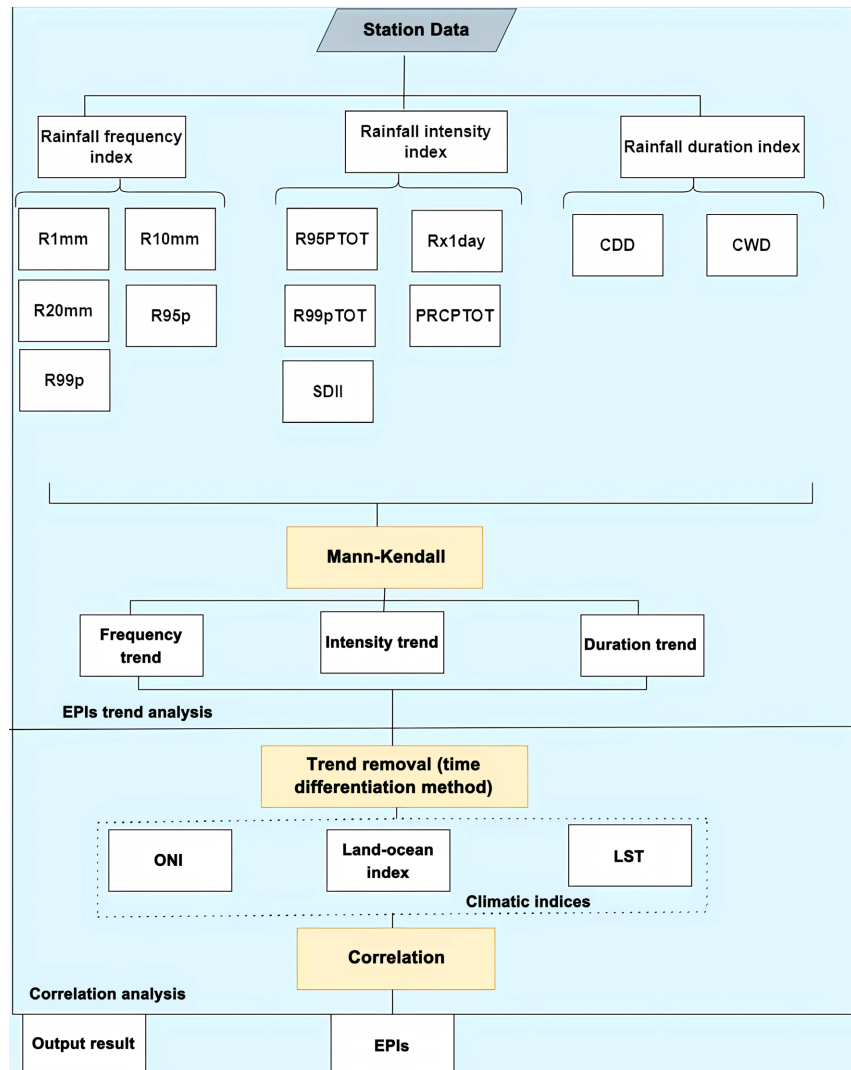


Figure 2. Our research flow chart.

2.3.1. EPIs Calculations

We utilized a set of twelve (12) precipitation indices to analyze the temporal variability of extreme precipitation characteristics in Senegal. These indices were calculated according to the definitions provided by the Expert Team on Climate Change Detection and Indices (ETCCDI), under the guidance of the World Meteorological Organization (WMO) Commission for Climatology. As highlighted in **Figure 2**, the analysis of these extreme precipitation indices (EPIs) encompasses various dimensions, including intensity, duration, and frequency [20] [21]:

- Intensity indices include PRCPTOT, which represents the annual accumulated precipitation measured in millimeters (mm), and SDII, which is the ratio of

the total amount of precipitation (≥ 1 mm) to the number of days, expressed in millimeters per day (mm/d). Additionally, the Rx1day index captures the annual maximum daily precipitation in millimeters, while R95pTOT and R99pTOT account for the annual accumulated precipitation on days when daily precipitation exceeds the 95th and 99th percentiles, respectively, also measured in millimeters.

- In terms of duration, the CDD index measures the longest duration of consecutive dry days (daily precipitation < 1 mm), while the CWD index assesses the longest stretch of consecutive wet days (daily precipitation ≥ 1 mm), both measured in days.
- Regarding frequency, several indices track the number of days with specific precipitation thresholds. The R1mm, R10mm, and R20mm indices capture the total number of days with precipitation amounts exceeding 1 mm, 10 mm, and 20 mm, respectively. The R95p and R99p indices, on the other hand, count the total number of days where daily precipitation surpasses the 95th and 99th percentiles, measured in days.

2.3.2. Non-Uniformity Test Method

To analyze the temporal variation characteristics of extreme precipitation in Senegal, we used the Mann-Kendall test to perform a homogeneity test on the precipitation data series. The Mann-Kendall test [22] is widely used to assess the significance of trends in long-term time series data [23]. The objective of the Mann-Kendall test is to statistically evaluate whether there is a monotonic upward (indicating that the variable increases consistently over time) or downward (indicating that the variable decreases consistently over time) trend in the variable of interest over time.

The Mann-Kendall statistic is defined as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_i - x_j) \quad (1)$$

where n is the length of the series, x_i and x_j are two generic sequential data values, and the sign function $\text{sign}(x_i - x_j)$ is defined by the following equation:

$$\text{sign}(x_i - x_j) = \begin{cases} 1 & \text{if } (x_i - x_j) > 0, \\ 0 & \text{if } (x_i - x_j) = 0, \\ -1 & \text{if } (x_i - x_j) < 0. \end{cases} \quad (2)$$

The statistic S therefore represents the number of positive differences minus the number of negative differences found in the analyzed time series.

The standardized test statistic Z is expressed in the form of the following equation:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}} & \text{if } S > 0, \\ 0 & \text{if } S = 0, \\ \frac{S+1}{\sqrt{\text{var}(S)}} & \text{if } S < 0. \end{cases} \quad (3)$$

With $\text{var}(S) = \frac{1}{18}[n(n-1)(2n+5)]$.

From this observation, it can be deduced:

$$\begin{cases} Z > 0; \text{ upward trend} \\ Z < 0; \text{ downward trend} \end{cases} \quad (4)$$

The presence of a statistically significant trend is evaluated by examining the value of Z . The null hypothesis (H_0) indicates the absence of a trend, while the alternative hypothesis (H_a) indicates the presence of a trend in the series. When $|Z|$ is greater than $Z_{\alpha/2}$, Z is considered consistent with the hypothesis of a trend's existence. Another way to perform the test is by calculating the p-value of the Z statistic, which corresponds to the probability of obtaining a Z statistic value less than or equal to that observed in the series. The smaller the p-value, the more confidently one can conclude the existence of a long-term trend. If the monotonic trend increases beyond a significance threshold p , the null hypothesis (H_0) is rejected. The trend is considered significant according to a given risk threshold α (corresponding to the risk of incorrectly concluding the existence of a trend). In this work, a significance threshold of 0.05 was applied, and a p-value was obtained for each analyzed series.

2.3.3. Drivers Correlation Analysis

In this study, the Pearson product-moment correlation coefficient was applied to examine the relationship between ENSO, LOTI, and LST variations and EPIs sequences, aiming to uncover their interconnections. Specifically, the influence of global climate change on extreme precipitation was quantified using the global land-ocean temperature index [24] [25]. Since the EPIs are annual time series data, the global land-ocean temperature index, the El Niño index, and local temperature were also treated as annual time series for the analysis. These three indicators were averaged on an annual basis to ensure consistency across the time series.

3. Results and Discussion

3.1. Characterization of the Temporal Variation of EPIs

The temporal variation characteristics of the spatially averaged EPI indices across Senegal are first addressed (Figure 3). For each index, the associated trend is superimposed, and using the Mann-Kendall test, the significance level of the trend is analyzed to ensure that the observed results are not merely due to chance.

We find that, with the exception of the CWD index, all wet-related indices show significant negative trends. The evolution of the CWD shows two phases: a first increasing phase from the early 20th century to the 1950s, and a second decreasing phase from the 1960s to the early 2000s. The absence of a trend for the CWD index in Senegal may be due to the fact that the persistence of precipitation did not change uniformly throughout the study period: it increased during the first phase (before the 1950s) and then decreased in the second phase (after the 1950s). The

CDD or dry-related index shows a significant upward trend throughout the 20th century. This is consistent with the evolution of wet-related indices, as an increase in dry days is accompanied by a decrease in precipitation trends.

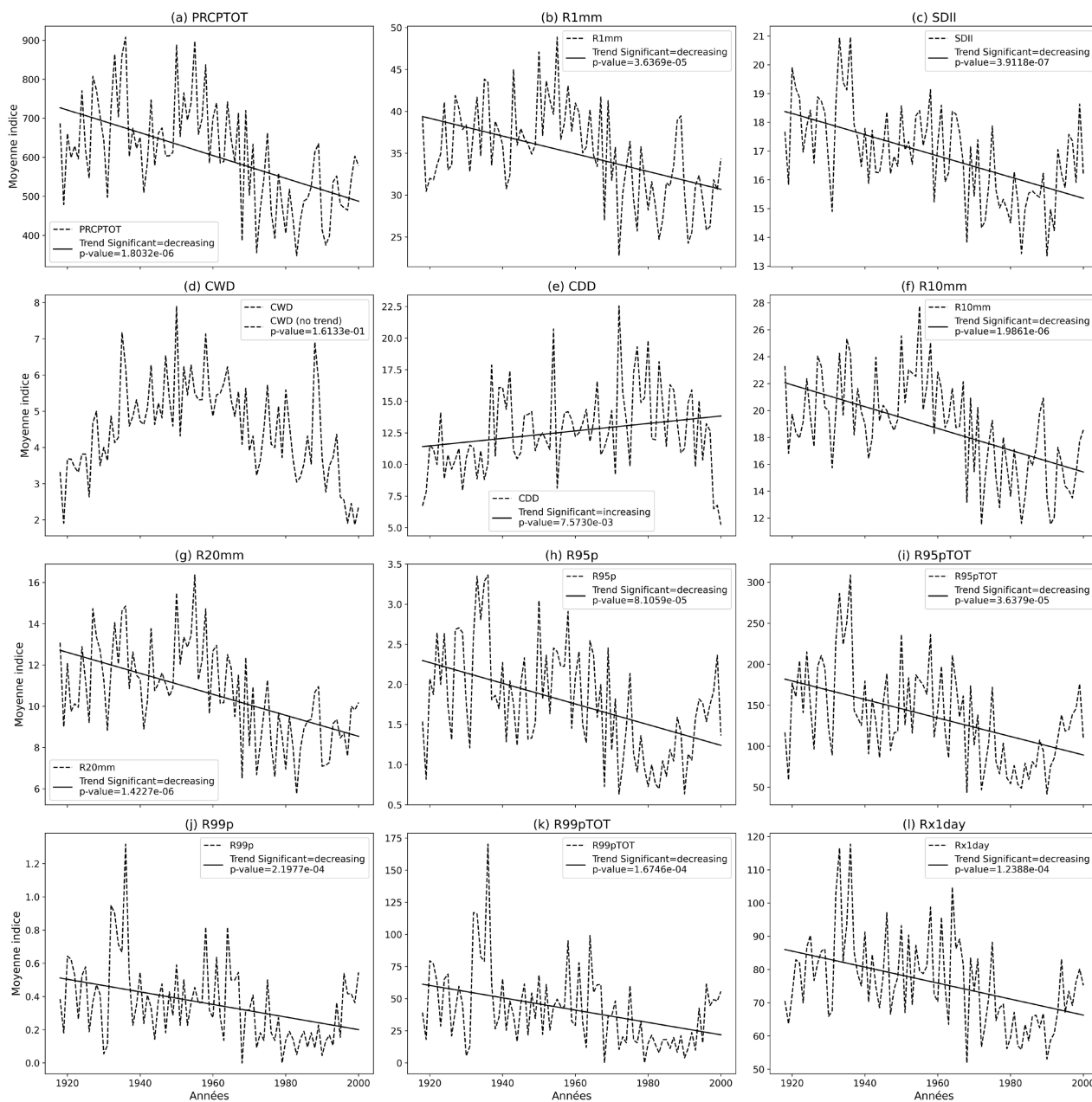


Figure 3. Temporal evolutions (dotted curves) of the mean IPE (spatial average over the 22 stations) and their associated trends (straight line). Only trends that are statistically significant at the 95% level according to the Mann-Kendall test are displayed.

Looking by category, these results show that the intensity and frequency of extreme precipitation events in Senegal have decreased throughout the 20th century. However, for duration indices, while a significant increasing trend is noted with dry spells (CDD), this is not the case for wet spells (CWD). The sustained decrease in the intensity and frequency of extreme precipitation events has had negative

impacts on agriculture, food security, and water resources. The increase in the number of dry days has also heightened the risk of droughts and wildfires.

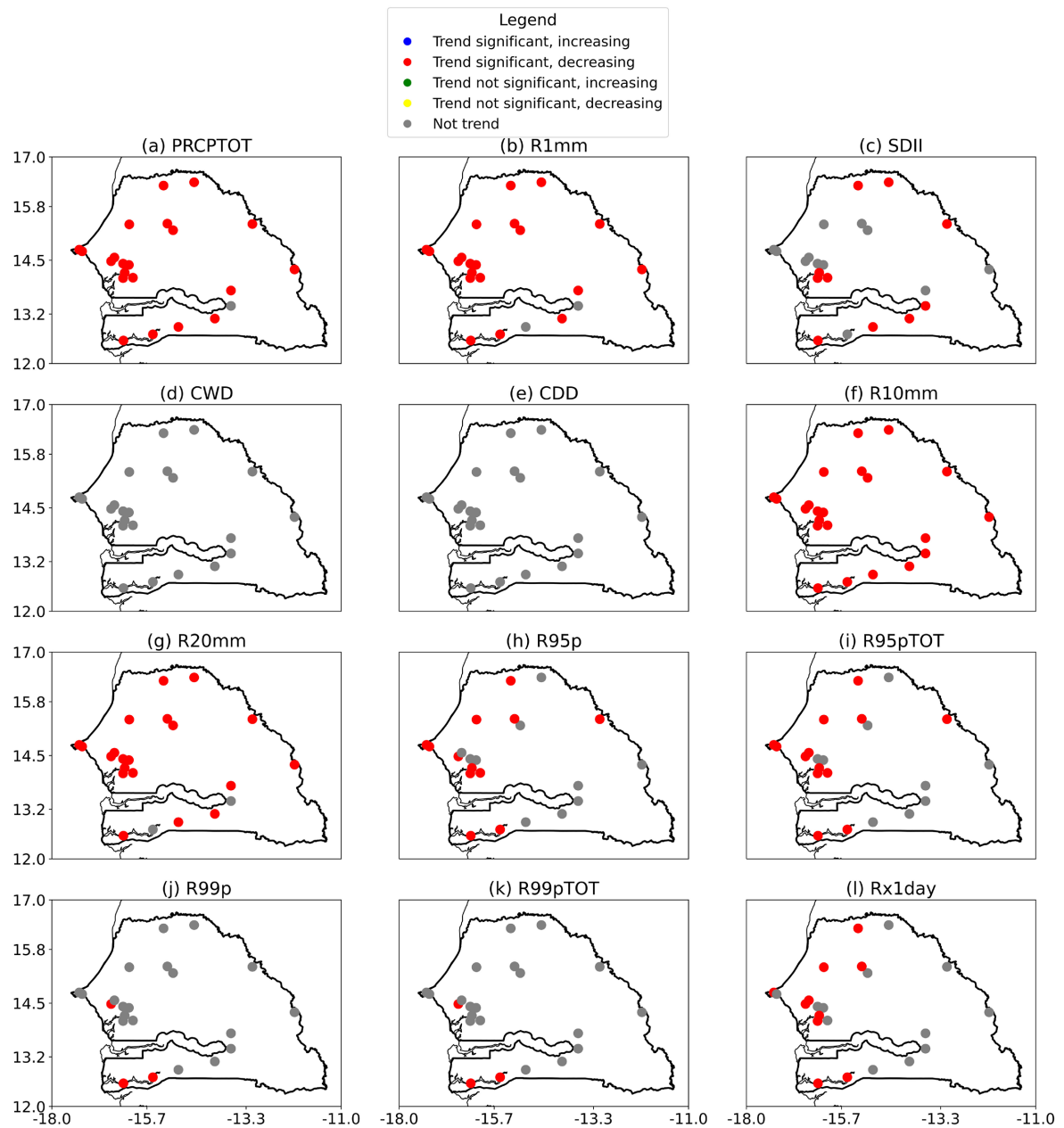


Figure 4. Results on the trends (1918 - 2000) associated with EPIs (each panel representing one index) after applying the Mann-Kendall test at each of our 22 rainfall stations.

This initial phase of the study provided a global overview of the temporal evolution of these indices over Senegal. However, we considered it worthwhile to re-analyze at the scale of each station to conduct an in-depth diagnostic of spatial variability. To do this, we examined the trend associated with each EPI index at each of our twenty-two (22) stations. Rather than representing 22 time series with superimposed trends for each index, we aimed to simplify the analysis at each

station by indicating the trend analysis result using a five-level color code. The levels correspond to significant decreasing, non-significant decreasing, significant increasing, non-significant increasing, or no trend.

Overall, we identified three possible scenarios across all indices and stations considered: a significant decreasing trend, a non-significant decreasing trend, or no trend at all. For total precipitation, 95% of the stations exhibit a significant decreasing trend (**Figure 4(a)**). For the frequency indices, two patterns emerge: either a significant decreasing trend or no trend at all. Specifically, 90% of the stations show a significant decreasing trend for R1mm and R20mm (**Figure 4(b)**, **Figure 4(g)**), and 100% for R10mm (**Figure 4(f)**). Meanwhile, 59% of stations show a decreasing trend for R95p (**Figure 4(h)**), while 41% show no trend. For R99p, only 13% exhibit a decreasing trend, with 87% showing no trend (**Figure 4(j)**). Concerning the duration indices (CWD and CDD), no significant trends were detected across any station (**Figure 4(d)**, **Figure 4(e)**). In contrast to the time series analysis of the CDD index averaged over all stations (Section 4.1), no individual station displays a significant trend, underscoring the importance of conducting station-level trend analysis.

For intensity indices, the results are more variable (**Figure 4(c)**, **Figure 4(i)**, **Figure 4(k)**, **Figure 4(l)**). Only 10% to 50% of the stations exhibit significant decreasing trends, while the remaining stations show no trend. It is also noteworthy that indices like Rx1day, R99pTOT, and R95pTOT show a more pronounced absence of trends compared to other intensity indices like SDII. This indicates that the more extreme the rainfall intensity, the less visible the decreasing trend becomes. These findings are consistent with those of [26] and align with the conclusions of the Intergovernmental Panel on Climate Change (IPCC) concerning the increasing occurrence of extreme rainfall events in the Sahel, exacerbated by the ongoing context of climate change.

In summary, the results indicate that most stations exhibit significant downward trends for total precipitation and frequency indices, while duration indices show no discernible trend. The intensity analysis reveals a mixed situation, with some stations showing significant decreasing trends, especially for indices of lower intensity. These findings underscore the importance of considering spatial variations when evaluating climate trends, and they support previous conclusions on the impact of climate change in Senegal, particularly concerning extreme rainfall events.

3.2. Impact of Climatic Factors on Extreme Precipitation

In this section, we examine the impact of climatic factors on extreme precipitation in Senegal. We focus specifically on analyzing correlations between EPIs and several key climatic parameters, including the ONI, LST, and LOTI indices. It is important to note that the correlations are performed on detrended time series to better capture temporal variability, particularly interannual variability. Understanding these relationships is essential for shedding light on the climatic mechanisms that influence the occurrence, duration, and intensity of extreme rainfall

events in Senegal. This analysis will provide a better understanding of the observed trends in EPIs and their connection to climatic variations at different spatial and temporal scales.

3.2.1. Correlation with the ONI Index

Figure 5 illustrates the correlation between the ONI index and the EPIs. For the total precipitation index, we observe that 95% of the correlations are negative, aligning with previous studies on the relationship between ENSO and precipitation in the Sahel region [11]. However, it is noteworthy that only 50% of the stations

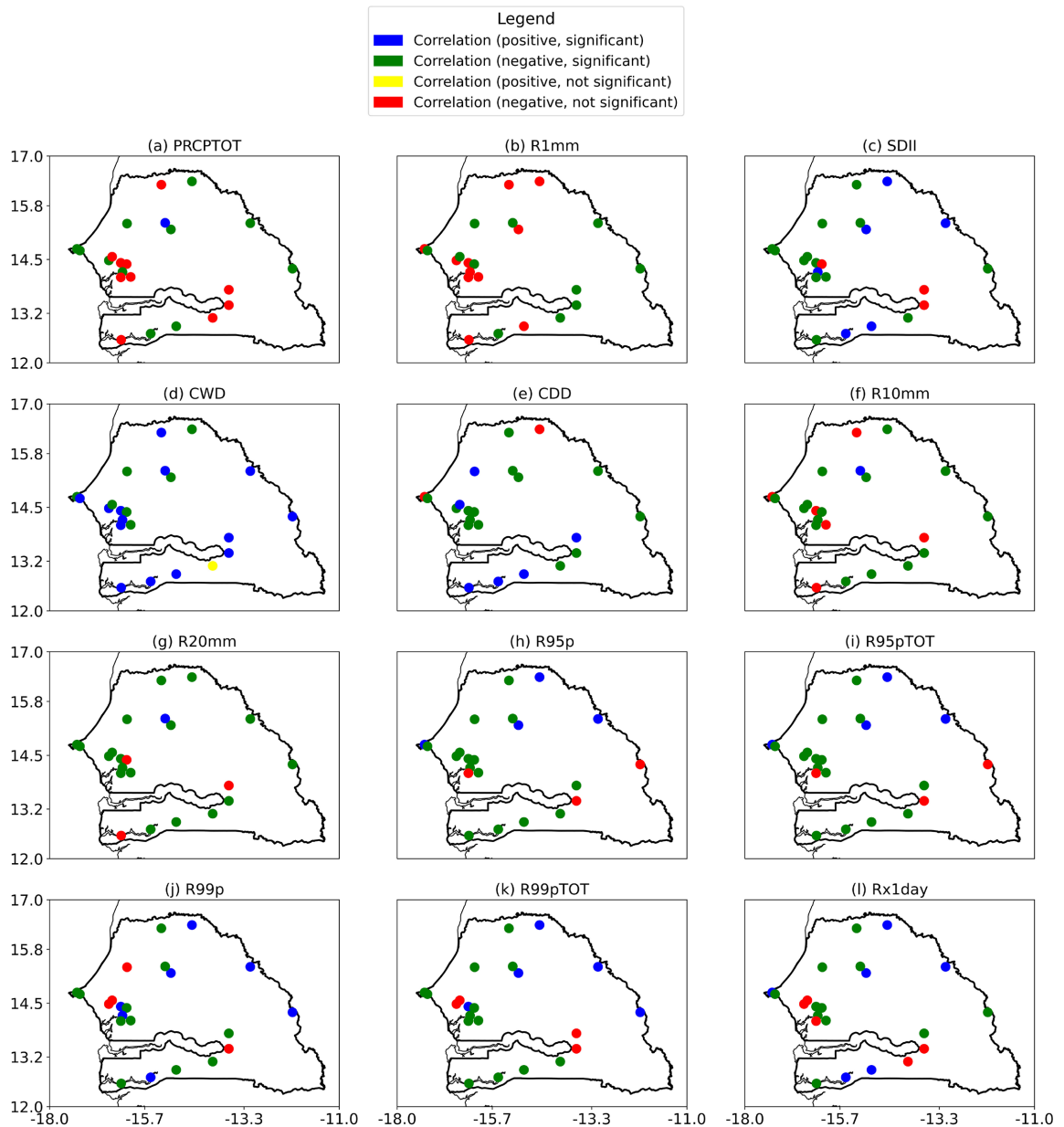


Figure 5. Results from the correlation analysis between the detrended annual (JJAS average) ONI index and the EPIs (1950-2000). A color scheme has been defined (see legend) to indicate whether the correlation is positive, negative, significant, or not.

exhibit significant correlations (**Figure 5(a)**), emphasizing the need for station-scale studies to challenge hypotheses derived from large-scale analyses.

For the frequency indices, the percentage of stations showing significant correlations is 50% for R1mm, 27% for R10mm, 13% for R20mm, and 96% for both R95p and R99p (**Figure 5(b)**, **Figures 5(f)-(h)**). Notably, these significant correlations are predominantly negative (100% for R1mm, 86% for R10mm, 75% for R20mm, 79% for R95p, and 60% for R99p). This trend contrasts with the total precipitation and frequency indices but aligns more closely with findings regarding intensity indices.

For intensity indices, we observe positive correlations at several stations. The significant correlations are mainly positive: 66% for SDII (**Figure 5(c)**), 57% for R95pTOT (**Figure 5(i)**), 56% for R99pTOT (**Figure 5(k)**), and 55% for Rx1day (**Figure 5(l)**). Finally, for duration indices, similar to intensity indices, positive correlations are observed in more than 90% of the stations. These positive correlations represent 100% of significant correlations for the CWD index (**Figure 5(d)**) and 75% for the CDD index (**Figure 5(e)**). Among these significant correlations, 75% are positive for CDD and 100% for CWD.

In summary, the correlations observed between the ONI index and total precipitation are consistent with the literature on the influence of ENSO on precipitation in the Sahel [27]-[29]. In contrast to the correlations with intensity and duration indices, those obtained with frequency indices appear more consistent with the correlations observed with PRCPTOT. This suggests that during El Niño years (positive ENSO phase), the ENSO-induced decrease in total precipitation is manifested through a reduction in the frequency of rainfall events rather than a modulation of the intensity and duration of these events. This result aligns with the conclusions of [30], who hypothesized that El Niño phases could inhibit instability by weakening large-scale trade winds and atmospheric convergence (thus negative correlations between ONI and frequency), while allowing small-scale convective processes, primarily responsible for intense precipitation (positive correlations with intensity), to develop locally, independently of ENSO.

3.2.2. Correlation with the LOTI Index

The LOTI index is a meteorological indicator used to measure changes in the Earth's surface temperature (oceans and continents). As such, it provides insight into the general trend of global temperature rise, making it a crucial tool for studying global warming. The correlation between the EPI indices and the LOTI index reveals a dependency between these phenomena (**Figure 6**).

The positive correlations observed in most stations (80% - 100% of the stations) suggest a relationship between global warming and extreme precipitation patterns. This observation aligns with the Clausius-Clapeyron theory, which posits that global warming increases the amount of water vapor in the atmosphere, potentially raising the likelihood of precipitation [31]. However, it is important to note that not all positive correlations are significant, highlighting the need to account for statistical significance when interpreting results.

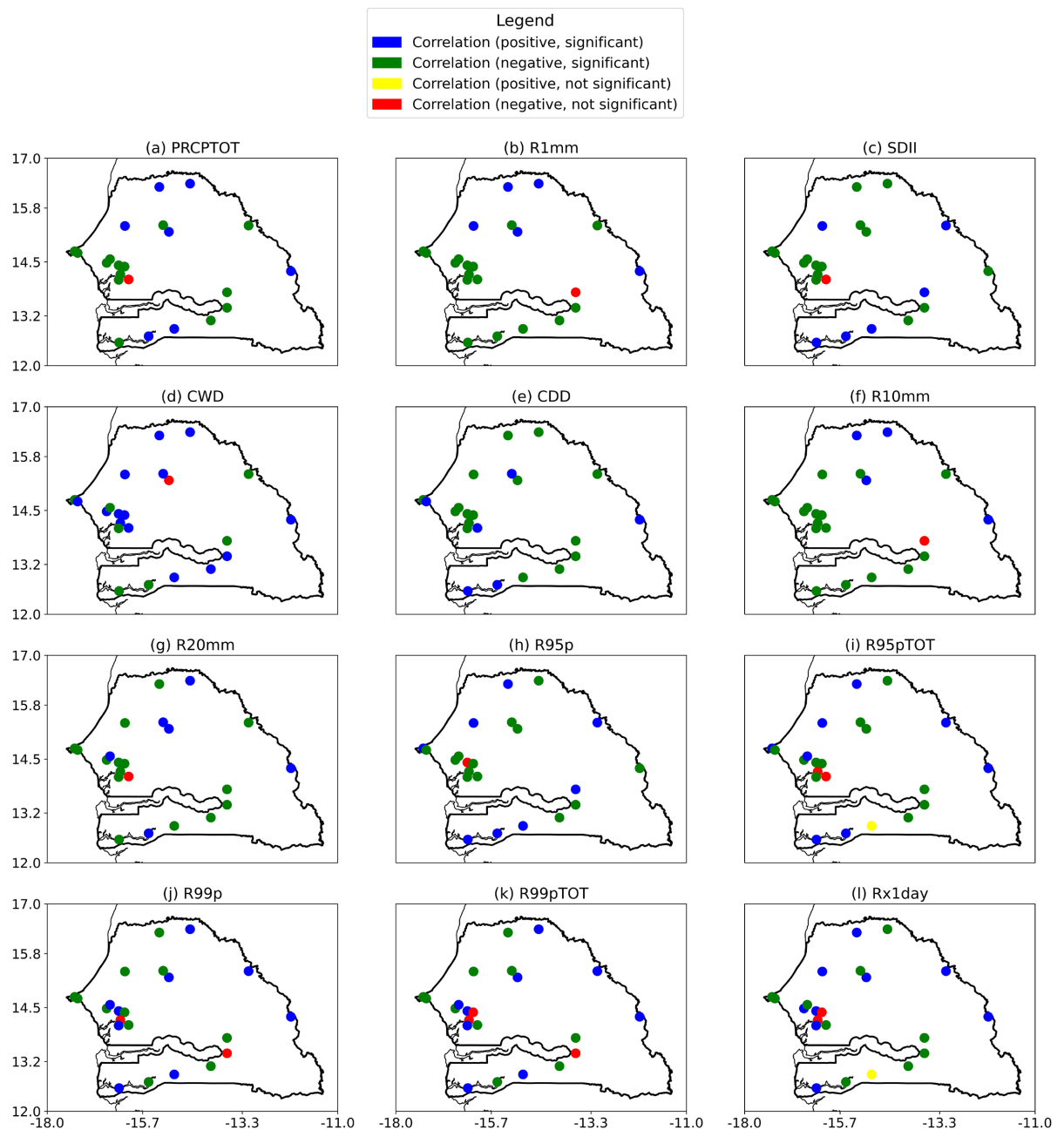


Figure 6. Results from the correlation analysis between the detrended annual (JJAS average) LOTI index and the EPIs (1950-2000). A color scheme has been defined (see legend) to indicate whether the correlation is positive, negative, significant, or not.

Significant correlations are observed in varying proportions depending on the specific EPI index: 33% for PRCPTOT (**Figure 6(a)**), 20% - 25% for the frequency indices (**Figure 6(b)**, **Figure 6(f)**, **Figure 6(g)**, **Figure 6(h)**, **Figure 6(j)**), 29% - 43% for the intensity indices (**Figure 6(i)**, **Figure 6(k)**, **Figure 6(l)**), and 23% - 67% for the duration indices (**Figure 6(d)**, **Figure 6(e)**). This suggests a diverse response of extreme precipitation to global warming. A spatial analysis of the correlations reveals regional variations in the impacts of global warming on extreme

precipitation. In northern Senegal, extreme precipitation indices show positive and significant correlations with the LOTI index, indicating a direct influence of global warming on all components of precipitation: frequency, intensity, and duration. In contrast, in southern Senegal, significant correlations are less frequent for the frequency indices, suggesting regional differences in the response of extreme precipitation to climate change.

In summary, the analysis of correlations between extreme precipitation indices and the LOTI index highlights a complex relationship between global warming and precipitation patterns. Although positive correlations are predominant, their significance varies across different indices and regions of Senegal. These results underscore the importance of a localized and multidimensional approach to better understand the impact of climate change on extreme precipitation in Senegal.

3.2.3. Correlation with the LST Index

The LST (Land Surface Temperature) index is a crucial indicator that reflects the direct impact of local warming on precipitation patterns. Correlations between the LST index and the EPI indices were analyzed, and the results are presented in **Figure 7**. Paradoxically, while significant positive correlations are observed for the duration indices, with 27% of stations showing correlations for CDD and 75% for CWD, only a few stations show significant correlations with intensity indices (PRCPTOT, SDII, R95pTOT, and R99pTOT). In contrast, the majority of frequency indices exhibit predominantly negative correlations. Specifically, 100% of stations show negative correlations for PRCPTOT, R1mm, R10mm, and R95pTOT, while 95% show negative correlations for SDII, R20mm, and R95p. Similarly, over 80% of stations display negative correlations for R99p, R99pTOT, and Rx1day.

This observation contradicts the Clausius-Clapeyron theory, which predicts an increase in the probability of precipitation with local temperature rise. According to this thermodynamic theory, the atmosphere's water vapor storage capacity should increase by 7% per degree Celsius of local temperature rise [32] [33], which should typically lead to a higher probability of local precipitation. Thus, the negative correlations observed between the EPIs and the LST index challenge this theory in the specific context of Senegal.

In summary, the correlations between the LST index and extreme precipitation indices in Senegal exhibit significant complexity, with results that contradict the Clausius-Clapeyron theory. The negative correlations observed challenge this theory in this specific context, while the positive correlations with the LOTI index emphasize the role of oceanic warming in modulating extreme precipitation patterns in the region.

3.2.4. Mechanisms of LOTI and LST Driving

In **Figure 8**, the underlying physical mechanisms behind the correlations identified in **Figure 5** and **Figure 6** are analyzed. **Figure 8(a)** shows that an increase in the LOTI index is associated with anomalous southwesterly low-level winds, which transport moisture from the northern tropical and equatorial Atlantic toward Senegal. This moisture advection enhances the low-level humidity over the

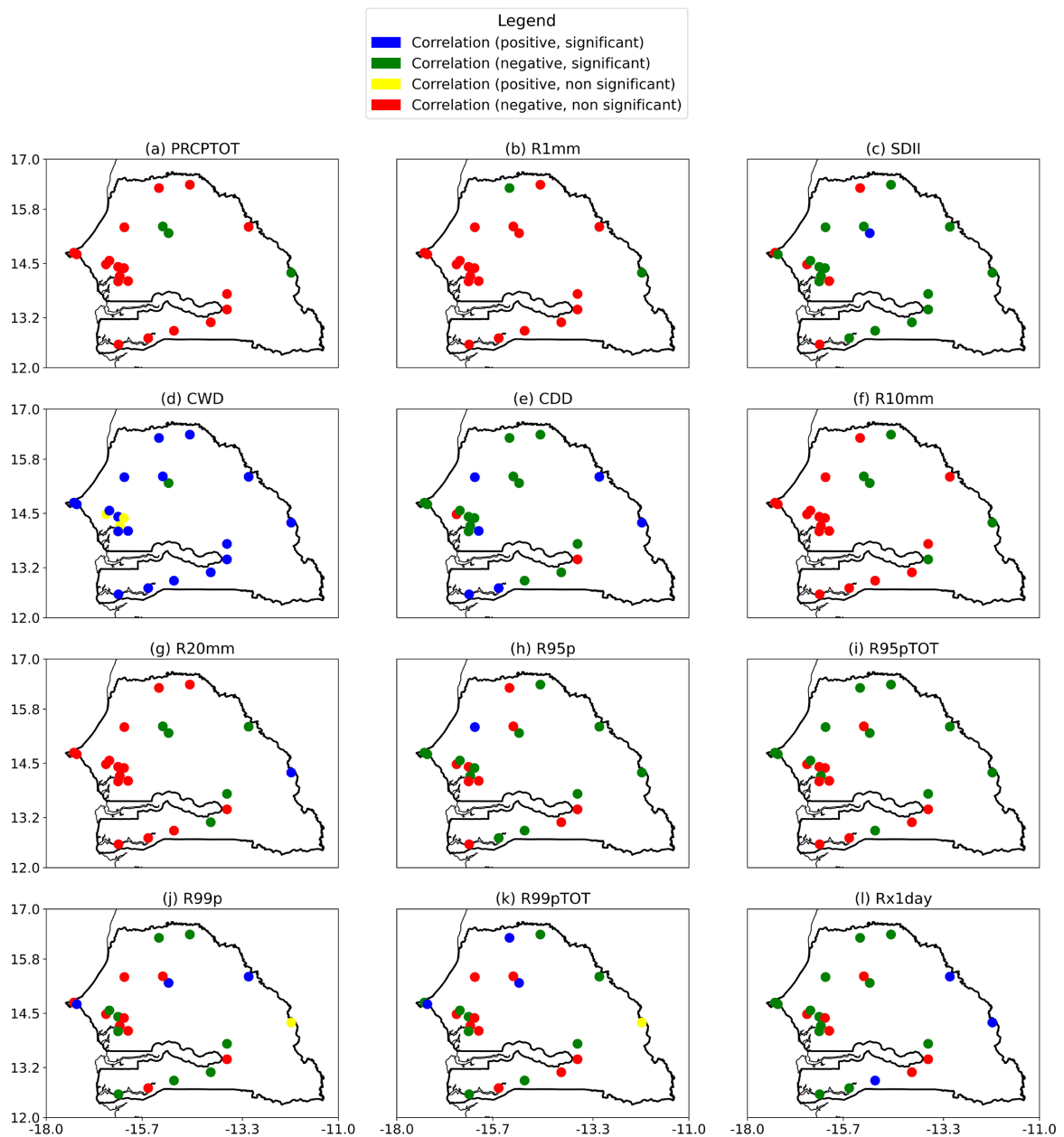


Figure 7. Results from the correlation analysis between the detrended annual (JJAS average) LST index and the EPIs (1950-2000). A color scheme has been defined (see legend) to indicate whether the correlation is positive, negative, significant, or not.

region. In contrast, **Figure 8(b)** shows that an increase in the LST index is associated with anomalous northeasterly low-level winds, which bring dry conditions from North Subtropical Africa (NSA) to Senegal.

A potential explanation for these contradictory results is that the positive correlations between the EPIs and the LOTI index (**Figure 6**) might be driven by oceanic warming (**Figure 8(a)**). As Senegal is a coastal country, the warming of the nearby ocean, along with potential oceanic advection towards the continent, could enhance moisture content in the continental air, increasing the likelihood

of extreme precipitation events. This finding is consistent with recent results from [34], which demonstrated that low-level moisture transport from the ocean to the continent is a primary source of moisture for seasonal rainfall in the western Sahel, including Senegal.

The negative correlation between the LST index and most moisture-related indices (Figure 7) may be explained by local warming over Senegal, which induces a local depression, creating a pressure gradient between the NSA region and Senegalese latitudes. This gradient could direct surface flow from the NSA towards Senegal, transporting dry conditions into the region (Figure 8(b)).

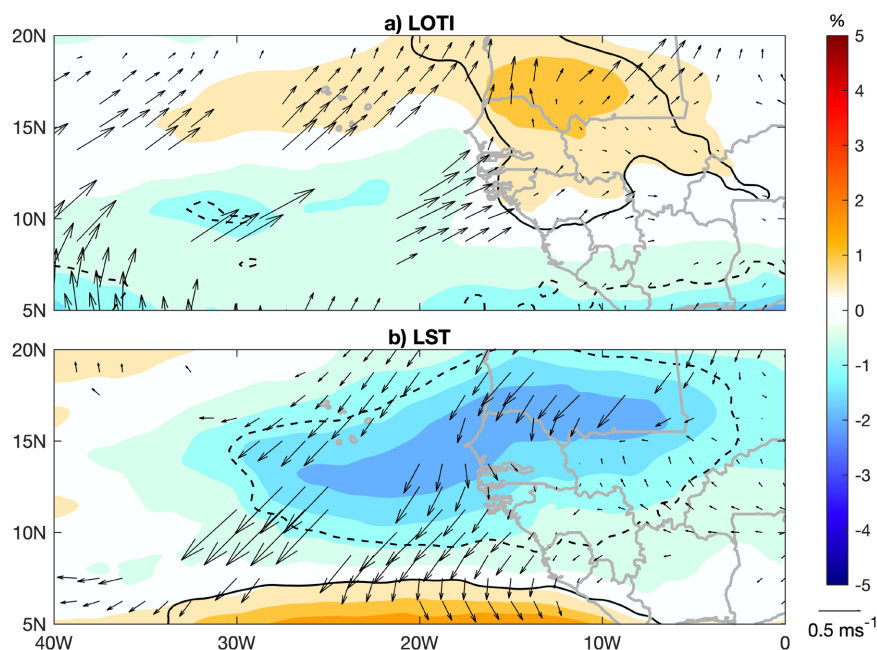


Figure 8. Regression maps of JJAS (1950-2000) anomalies of relative humidity at 850 hPa (colors; %) and horizontal wind at 850 hPa (arrows; m/s) onto (a) LOTI and (b) LST indices. Bold contours indicate the 95% confidence interval using a student's *t*-test, and only significant wind anomaly values are plotted based on the same statistical test.

Moreover, the positive correlations between the LST index and the duration indices suggest that while local warming may not be sufficient to trigger extreme precipitation events, it could prolong the duration of such events (Figure 7(d)). As a result, rising local temperatures may intensify both droughts and floods. This paradox warrants further investigation in future studies.

3.2.5. Predictability of EPIs Based on the ONI Index

To evaluate the predictability of extreme precipitation patterns in Senegal, an approach based on lagged correlations between the ONI index and the EPIs was applied (Figure 9). The LST and LOTI indices were excluded from this analysis due to their localized nature, as well as the fact that the ONI index is recognized as a potential source of predictability for total and extreme precipitation in the Sahel region [28].

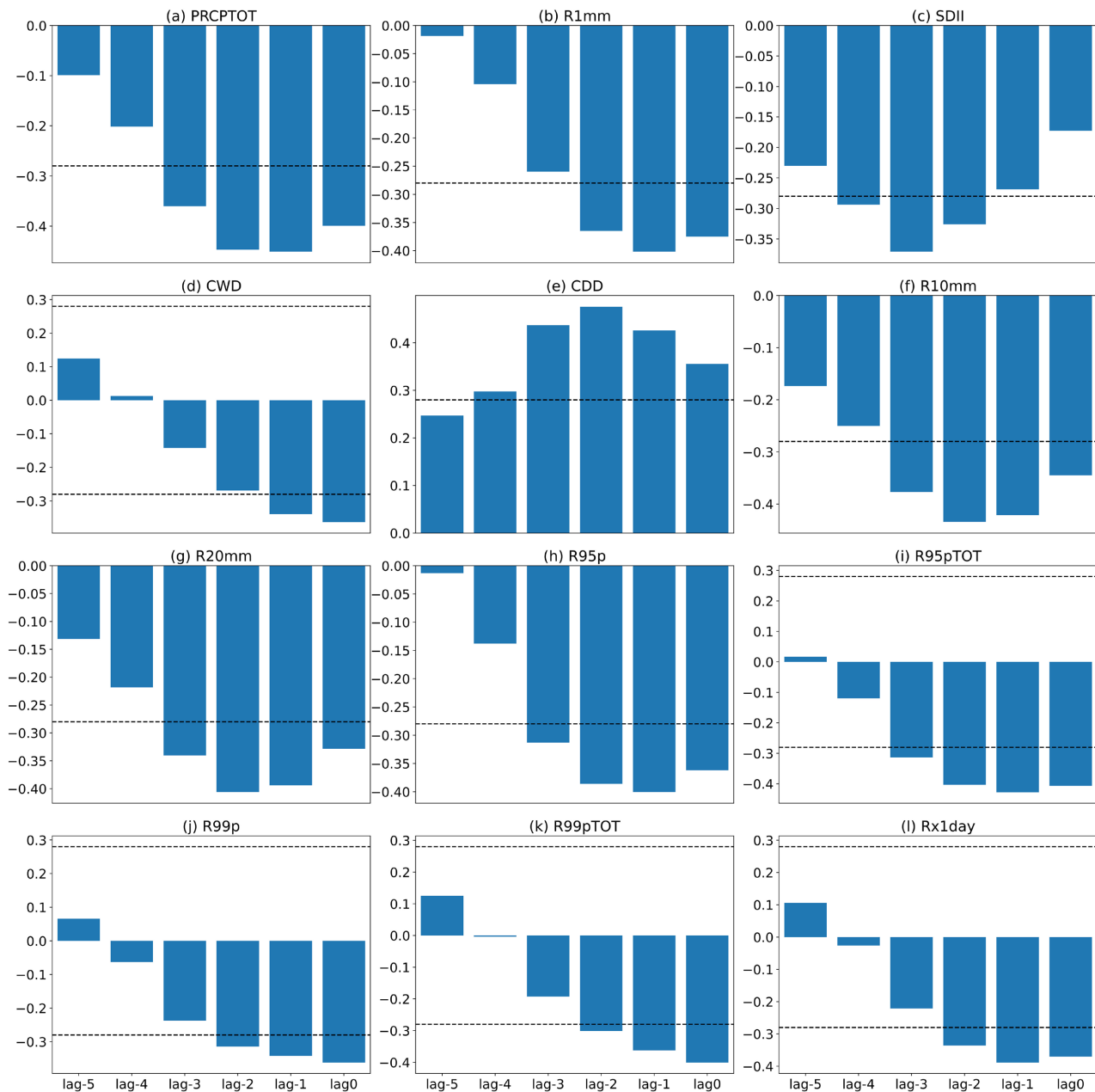


Figure 9. Lagged correlations between the ONI index and the precipitation indices. The lag unit is one (1) month, and the ONI index leads for negative lags.

Specifically, the lagged correlations involve calculating the correlation between the ONI index and each EPI for the June-September (JJAS) period. The result obtained is referred to as the correlation at lag0. The same process is then repeated between the ONI index for May-August (MJJJA) and each EPI for JJAS, defining the correlation at lag-1. This procedure is repeated until lag-5, where the ONI index from January-April (JFMA) is correlated with each EPI for JJAS. Each lag represents a one-month shift, allowing for the analysis of the response of extreme precipitation patterns to ENSO forcing. The statistical significance of the correlations was assessed using a student's t-test at a 95% confidence level.

The results of this analysis are presented in **Figure 9**. The lagged correlations are significant up to lag-2 for most EPIs, except for CWD. For this particular index, predictability appears to be limited to one month in advance, as the signal becomes non-significant beyond this point. Several indices, including PRCPTOT, SDII, CDD, R10mm, R20mm, R95p, and R95pTOT, exhibit predictability up to three months in advance.

In summary, this analysis demonstrates that the predictability of extreme precipitation patterns varies depending on the EPIs and the temporal lags considered. There is no clear trend according to the category (intensity, duration, or frequency) of the EPIs. However, it is notable that more than 90% of the EPIs show at least one month of lead-time predictability, while 58% are predictable up to three months in advance. These results underscore the importance of understanding both short- and long-term dynamics of ENSO-extreme precipitation interactions to further improve forecasting capabilities in Senegal.

4. Conclusions

This study provides an in-depth characterization of trends and the spatiotemporal variability of extreme rainfall in Senegal and its relationships with key climate drivers, including the El Niño Oscillation Index (ONI), the Land-Ocean Temperature Index (LOTI), and the Land Surface Temperature Index (LST). The findings offer valuable insights into extreme precipitation patterns in the country and their implications for water resource management, agriculture, and food security.

The study is based on a century-long dataset of daily rainfall collected from various stations across Senegal. These records were obtained from the former National Meteorological Agency of Senegal [now the National Civil Aviation and Meteorology Agency (ANACIM)] and additional rain gauges managed by the Senegalese Institute of Agricultural Research (ISRA). Twenty-two (22) stations covering the period from 1900 to 2014 were selected based on the findings of [16]. A set of twelve (12) extreme precipitation indices (EPIs) was computed for each station, following the definitions of the Expert Team on Climate Change Detection and Indices (ETCCDI). The Mann-Kendall (MK) test was applied to detect trends in the time series of EPIs, and Pearson correlation analyses were conducted to assess the relationships between ONI, LOTI, LST, and EPIs. The correlations were performed on detrended time series to better capture interannual variability. Finally, we assessed the predictability of EPIs using a lagged correlation approach between the ONI and EPIs.

The main results of this study can be summarized as follows:

- First, most stations show significant decreasing trends for total precipitation and frequency indices, while duration indices exhibit no discernible trends. The intensity analysis presents mixed results, with some stations showing significant decreases, particularly for lower-intensity indices. These findings underscore the importance of considering spatial variations when assessing climate trends and support previous conclusions regarding the impact of climate

change on extreme rainfall events in Senegal [26].

- Second, the correlation analysis between EPIs and climate indices highlights the importance of station-level studies to test hypotheses from large-scale research. The results reveal negative correlations between the ONI and total rainfall, consistent with previous studies on the influence of ENSO on Sahelian precipitation [28] [29] [35]. The correlations with intensity and duration indices are more varied, suggesting different modulations during El Niño years. Regarding the LOTI, positive correlations indicate a relationship between global warming and extreme precipitation patterns, although significance varies. Spatial analysis reveals regional differences in the impact of global warming. Finally, correlations with the LST index present contradictory results with the Clausius-Clapeyron theory, questioning its applicability in the specific context of Senegal. Meanwhile, positive correlations with the LOTI underscore the role of oceanic warming in modulating extreme precipitation patterns.
- Third, regarding the predictability of extreme precipitation patterns, no clear trend was identified based on the intensity, duration, or frequency categories of the EPIs. However, more than 90% of EPIs exhibit predictability at least one month in advance, and 58% are predictable with a lead time of at least three months. These results emphasize the need to better understand the short- and long-term dynamics between ENSO and extreme precipitation patterns to improve forecasting capabilities in Senegal.

For future research, several avenues can be explored to deepen our understanding of extreme rainfall events in Senegal and their climate drivers. First, the analysis could be repeated for the onset, peak, and end of the monsoon season to document sub-seasonal variability. Additionally, further investigation is needed into the physical mechanisms governing the relationships between LST, and extreme precipitation patterns (such as the duration indices) in Senegal.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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