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Environmental and climate variability in Senegal over the last two decades: A remote sensing approach to assessing climate vulnerability in a Sahelian country

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ABSTRACT

This study examines how environmental, and climate variability has evolved in Senegal over the past two decades, using a remote sensing framework focused on vegetation dynamics, surface temperature, and hydrological change. By integrating MODIS and ERA5-Land datasets within the Google Earth Engine platform, we assessed spatial and temporal trends in NDVI, NDWI, LST, temperature, and precipitation from 2001 to 2023. Our approach employs linear regression, coefficient of variation (CV), and geospatial mapping to detect climate-driven patterns and ecosystem responses at the regional scale. The results reveal increasing climate pressure in central and northern Senegal, evidenced by declining vegetation indices, rising surface temperatures, and rainfall variability exceeding 160 %. In contrast, southern Senegal retains more vegetation and climate stability. Our findings emphasize strong positive correlations between vegetation and precipitation ($r = 0.81$ for NDVI), and a negative correlation between vegetation and LST ($r = -0.79$), suggesting the cooling effect of healthy ecosystems. This research advances regional-scale climate vulnerability mapping and supports targeted land management strategies. The methodology demonstrates the value of cloud-based remote sensing for climate monitoring in data-scarce regions, with practical applications for policymakers, environmental planners, and resilience initiatives.

1. Introduction

1.1. Motivation

Climate change poses a profound global challenge, impacting ecosystems and human communities around the world. It has been shown to worsen recent natural disasters, including major hurricanes, prolonged droughts, and wildfires (Dablander et al., 2024). In Africa, these effects are particularly evident, with changing environmental and climate conditions leading to over 100,000 deaths from natural disasters between 2013 and 2022, affecting 131 million people (African Development Bank Group, 2024). Senegal, situated in the Sahel region, exemplifies this vulnerability due to its reliance on rain-fed agriculture (Collier and Dercon, 2014) and the variability

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of its climatic conditions (Emediegwu et al., 2022). Monitoring and responding to these changes are important for supporting people's livelihoods and strengthening their ability to adapt. A key part of this effort involves identifying the area's most at risk, which helps guide decisions related to public health, water management, agriculture, and environmental conservation (Fonjong et al., 2024; Omotoso et al., 2023). With the growing availability of open data and user-friendly tools such as remote sensing platforms and climate models, it has become possible to monitor climate-related changes even in regions with limited historical records (Eggleton and Winfield, 2020). The motivation for this study lies in using these accessible resources to develop a methodology that can be applied in other countries with similar data constraints. This approach allows us to better understand how environmental and climate conditions have evolved over the last two decades (Hemati et al., 2021) and supports the development of evidence-based decisions in places where such studies are still limited (Radočaj et al., 2020).

1.2. Literature survey

Previous studies underscore the utility of remote sensing in monitoring environmental (Wang, 2023) and climatic dynamics (Lenton et al., 2024). For instance, Brandt et al. (2014) analyzed vegetation trends in the Sahel, while Matas-Granados et al. (2022) highlighted the long-term monitoring of vegetation changes using NDVI. Studies focusing on droughts (Almalki et al., 2022) and floods in Senegal, such as Sseguya and Jun, 2024, reveal critical insights into the country's vulnerability but often overlook the integration of remote sensing data with climate reanalysis. Additionally, some studies use the coefficient of variation (CV) to analyze environmental variable trends and gain insights into the spatio-temporal dynamics of regional sectors through remote sensing (Zhang et al., 2023). Other research has examined how remote sensing data can be used alongside climate variables to assess responses to climate change in Africa. These studies often apply linear regression and the coefficient of variation (CV) to identify the most vulnerable areas and sectors that need targeted action and resilience planning (Ghebrezgabher et al., 2020). Within this body of work, the combination of remote sensing and climate reanalysis models stands out as a valuable approach for understanding climate-related dynamics (Zhao et al., 2023). Moreover, access to more than two decades of consistent satellite and climate reanalysis data allows researchers to evaluate long-term environmental trends. This not only improves our understanding of how ecosystems are changing but also supports the development of mitigation, adaptation, and resilience strategies that are closely aligned with on-the-ground realities (Wang et al., 2022).

1.3. Contribution

This study proposes an integrated approach that combines MODIS-derived NDVI, NDWI, and land surface temperature data with ERA5 Land reanalysis products, specifically temperature and precipitation, to assess climate variability and environmental change in Senegal between 2001 and 2023. The analysis is performed using the Google Earth Engine platform, which enables efficient processing of large-scale geospatial datasets and allows reproducibility in countries where historical environmental data are limited (Amani et al., 2020).

Unlike previous studies that focused on national or continental patterns, this research provides a more detailed assessment of environmental variability at the regional level. This spatial resolution helps identify areas in Senegal that are more vulnerable to climate-related pressures, such as declining vegetation, reduced water availability, and rising surface temperatures. The methodology includes the use of linear regressions between environmental and climate variables, coefficient of variation to explore spatial and temporal patterns, and geovisualization techniques to make these findings accessible and actionable.

One of the main contributions of this work is the combination of remote sensing indices and climate reanalysis data to monitor environmental change over an extended period. This approach not only improves our understanding of the environmental impacts of climate change but also offers a protocol that can be replicated in other countries with similar ecological and data contexts. The study contributes to practical decision-making by highlighting regions that require urgent attention in terms of land management, adaptation strategies, and policy planning. Additionally, it reinforces findings from other regions, confirming that vegetation dynamics are strongly linked to variations in climate conditions (Gao et al., 2022; Mehmood et al., 2024). Similar approaches using remote sensing platforms like Google Earth Engine have been successfully applied in other regions, demonstrating their capacity to monitor environmental variability at large scales and support early-stage climate assessments (Liu et al., 2024). The availability of these data in an open and cloud-based platform such as Google Earth Engine allows researchers and policymakers to track long-term environmental trends and develop locally relevant solutions for climate adaptation and sustainability.

1.4. Organization of the study

The project is organized into five sections. The first section outlines the materials and methods, detailing the study area, the data utilized, and the methodology employed to analyze the data over the past few decades, focused on linear regression between variables and trend changes. Section 3 presents the results, emphasizing key trends and correlations. The discussion section explores the findings' implications and suggests future research directions. Finally, the conclusion summarizes the significance of the study and its main findings.

2. Materials and methods

2.1. Study area description

Senegal, located in the Sahel region of Africa (14° 33′ 0″ N, 14° 0′ 0″ W), consists of 14 administrative regions (Fig. 1). The country has a flat landscape and a tropical climate, with average annual temperatures between 25 °C and 30 °C. Recently, Senegal has faced significant climate fluctuations, including rising temperatures and altered precipitation patterns. This has resulted in severe dry seasons with prolonged droughts and unpredictable wet seasons with significant flooding. Yearly precipitation levels have ranged from 600 to 1200 mm, diverging from historical norms. These changes have adversely affected agriculture and the ecosystem, creating challenges for food security and water availability (Ilboudo Nébié et al., 2021).

2.2. Remote sensing data

We used Remote Sensing data from Moderate-Resolution Imaging Spectroradiometer (MODIS) products through the Google Earth Engine (GEE) geospatial platform between 2001 and 2023. The data was extracted using the EE Python library in a Google Colab Notebook. The remote sensing data included the NDVI (Equation (1)), the NDWI (Equation (2)), and the LST, as described in Table 1. We focused on these data sets due to their significance in monitoring vegetation, hydrology, and surface temperature dynamics (Shah et al., 2024).

The NDVI is one of the most widely used metrics in remote sensing. It helps us assess vegetation health and coverage on a scale from −1 to 1, where higher values indicate healthier or denser vegetation and lower values represent areas with no vegetation or vegetation in poor health. This index provides consistent data over time, enabling the evaluation of large areas to monitor issues such as deforestation, droughts, and other changes in vegetation patterns (Ghebrezgabher et al., 2020).

On the other hand, the NDWI allows us to monitor water-related ecosystem dynamics, including variations in soil moisture. By analyzing NDWI trends, we can detect changes in water availability and signs of vegetation stress over time, providing important parameters for studying climate change (Laonamsai et al., 2023).

With LST data, we can analyze how the land surface reflects energy. LST helps us assess the impacts of deforestation and land-use changes on regional climates, as vegetated areas typically have lower temperatures than built-up land (Frimpong et al., 2023).

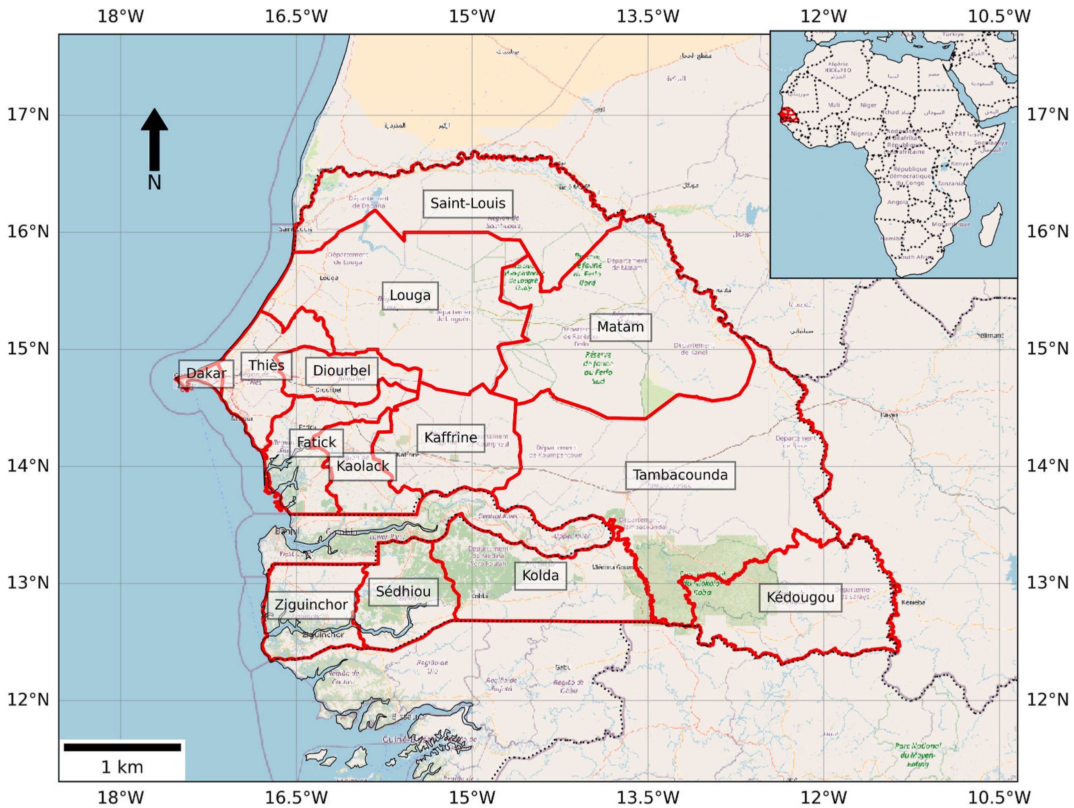

Fig. 1. Senegal's boundary regions in the red contour.

Table 1
GEE Remote Sensing variable used in the analysis.

Spectral Indices	GEE Product	Equation	Spatial Resolution (m)
Normalized Difference Vegetation Index (NDVI) (Tucker, 1979)	MOD13Q1.061 Terra Vegetation Indices 16-Day Global 250m	$NDVI = \frac{NIR - R}{NIR + R}$ (1)	250
Normalized Difference Water Index (NDWI) (Gao, 1996)	MODIS Combined 16-Day NDWI	$\mathrm{NDWI} = \frac{NIR - \mathrm{SWIR}}{NIR + \mathrm{SWIR}}$ (2)	463
Land Surface Temperature (LST) (Wan, 1996)	MOD11A1.061 Terra Land Surface Temperature and Emissivity Daily Global 1 km	MODIS Land Surface Temperature Algorithm	1000

2.3. Climate surface data

To thoroughly understand the relationship between environmental and meteorological parameters in Senegal, we utilized the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) Land data available on the GEE cloud platform. The ERA5-Land simulation offers hourly information on surface variables, with records from 1950 to five days before the current date. This simulation is based on the ERA5 climate reanalysis, which integrates model data with global observations to create a complete and consistent dataset grounded in the laws of physics (Muñoz Sabater, 2019). For our study, we worked on monthly aggregated data from the simulation, specifically extracting temperature and precipitation parameters (refer to Table 2).

ERA5-Land provides superior estimates of regional climatic dynamics compared to other climate reanalysis models in regional studies (Khettouch et al., 2023). It incorporates modeling techniques that are compared with in-situ data, making it a valuable option when field meteorological data is unavailable (Kaissi et al., 2024).

2.4. Comparison and trends in environmental and climate variables

The first step in analyzing the data involved extracting median values for each month and year from 2001 to 2023 using remote sensing and climate data. We employed a Google Colab notebook and the GEE, Pandas, Matplotlib, and Rasterio libraries, saving our results to Google Drive. Once we constructed the dataset, we cleaned it to enable the generation of trend graphs, correlations, linear regressions, and geovisualizations through maps (Alvarez et al., 2024). This process enabled us to analyze the correlations between environmental and climate variables effectively. We harmonized the different spatial resolutions of each dataset using spatial aggregation techniques, which ensured a consistent analysis across various indices and climate model rasters. Specifically, we aggregated the higher-resolution data (NDVI at 250m) using area-weighted averaging to align it with the coarser resolutions of other indices (LST at 1 km). This approach minimizes discrepancies in spatial representation and facilitates the seamless integration of multi-resolution datasets. We validated these methods by cross-referencing the aggregated outputs with established benchmarks from prior studies, ensuring reliability in our comparative analysis (Zheng et al., 2023).

2.4.1. Regression analysis

We analyzed the correlation among various extracted variables to identify patterns. In this context, we employed the Pearson correlation coefficient (r) to evaluate the strength and direction of the linear relationship between two continuous variables. The coefficient ranges from -1 to 1: $+1$ indicates a positive linear relationship, -1 indicates a negative linear relationship, and 0 signifies no correlation between the variables. Additionally, we used the coefficient of determination (R^2) to establish linear regression between the variables, allowing us to fit a simple linear equation to the observed data for two environmental or climate variables. The goal is to identify potential relationships between the variables based on their trends (Ashok et al., 2021).

2.4.2. Coefficient of variation

The coefficient of variation (CV) is a statistical metric used to assess the reproducibility and precision of measurement methods. It is defined as the ratio of the standard deviation to the mean, expressed as a percentage (see Equation (3)). The CV offers insight into the degree of variability relative to the average value. A higher CV indicates greater variability and less consistency, while a lower CV reflects greater precision and reliability in measurements (Zhang et al., 2023). In this study, we generate a CV map for each variable to examine the spatio-temporal stability or fluctuation of the time series between 2001 and 2023.

Table 2
GEE Climate surface data used in the analysis.

Climate data	GEE Product	Bands	Spatial Resolution (m)
European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) Land	ERA5-Land Monthly Aggregated - ECMWF Climate Reanalysis	temperature_2m temperature_2m_max temperature_2m_min total_precipitation_sum	11132

$$CV = \frac{\sigma}{\mu} * 100\% \quad (3)$$

Fig. 2 shows the project workflow, highlighting the cloud computing processing through Google Earth Engine (GEE), Google Colab, and Google Drive.

3. Results

3.1. Monthly environmental and climate variable trend analysis by year

After constructing the dataset using the median values of each raster pixel, we created trend plots for each environmental variable (NDVI, NDWI, LST) and climate variable (median temperature, maximum temperature, minimum temperature, and precipitation) for each month over the years (see Fig. 3). Each variable in our analysis produced consistent results. We used a separate line for each year, which allows for clearer visualization and comparison between years. The graphs highlight specific years when significant increases or decreases in environmental and climate variables occurred, reflecting the dynamic impacts of climate variability on Senegal.

Compared to 2001, NDVI increased in August and September of 2010 2020, and 2022, suggesting higher precipitation during these months in those years. Additionally, there was a decrease in NDVI for most of 2015 and during the first six months of 2020.

Regarding the NDWI, 2001 recorded the lowest value for this hydrological index throughout the year. In contrast, the highest peaks were observed in 2010 and 2022, marked by higher water content.

When examining LST, we noted peaks in March, April, and November 2020. The median temperature through 2020 showed the highest upward trend during the year's first half. Finally, the rainfall data showed a similar trend to the NDVI, with increased rainfall between August and September in 2010 and 2020. However, most of 2015 exhibited the lowest values across most months.

3.2. Correlation and linear regression between variables

The scatterplot matrix illustrates the intricate relationships between environmental indices, temperature, and precipitation in Senegal from 2001 to 2023 (Fig. 4). One of the key findings is the strong positive correlation between the NDVI and the NDWI, with a Pearson correlation coefficient of $r = 0.94$ and an R^2 value of 0.88. This strong relationship may stem from using the near-infrared (NIR) band to calculate both indices. Another significant relationship observed is between NDVI and LST, demonstrating a negative correlation ($r = -0.79$, $R^2 = 0.63$). This suggests that areas with more vegetation correspond to lower surface temperatures and vice versa, suggesting vegetation moderates surface temperature. Furthermore, maximum temperature correlates positively with LST, with a Pearson correlation value of 0.85. These high correlations are anticipated due to the variation in land temperature compared to air temperature.

Regarding precipitation, there is a substantial positive correlation between rainfall and NDVI ($r = 0.81$, $R^2 = 0.66$) and a similar positive trend between rainfall and NDWI ($r = 0.86$, $R^2 = 0.74$). This indicates that higher vegetation or increased soil moisture is associated with greater rainfall. Therefore, it is possible to estimate rainfall effectively using linear regression with either NDVI or NDWI.

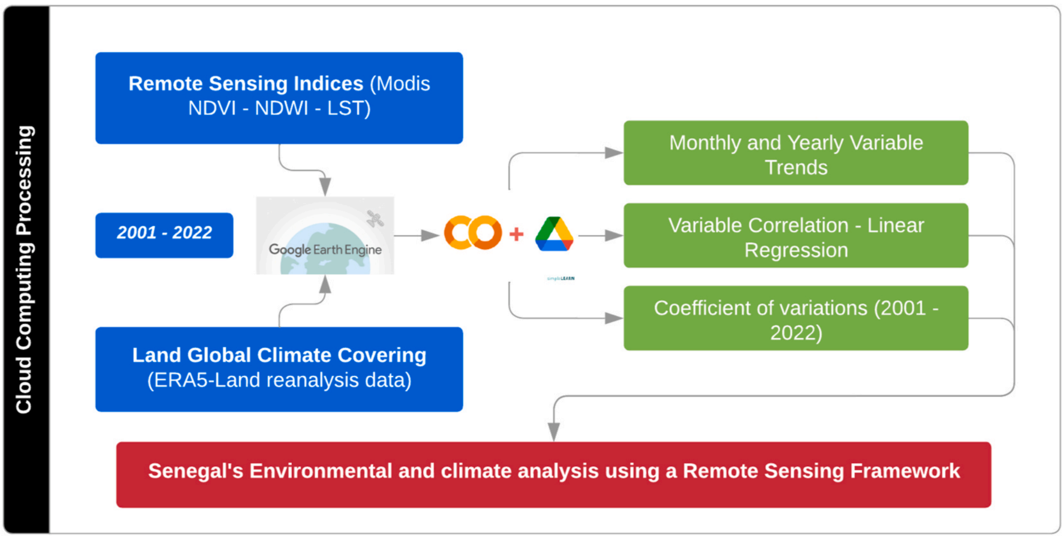

Fig. 2. Project workflow focused on the Remote Sensing cloud computing processing.

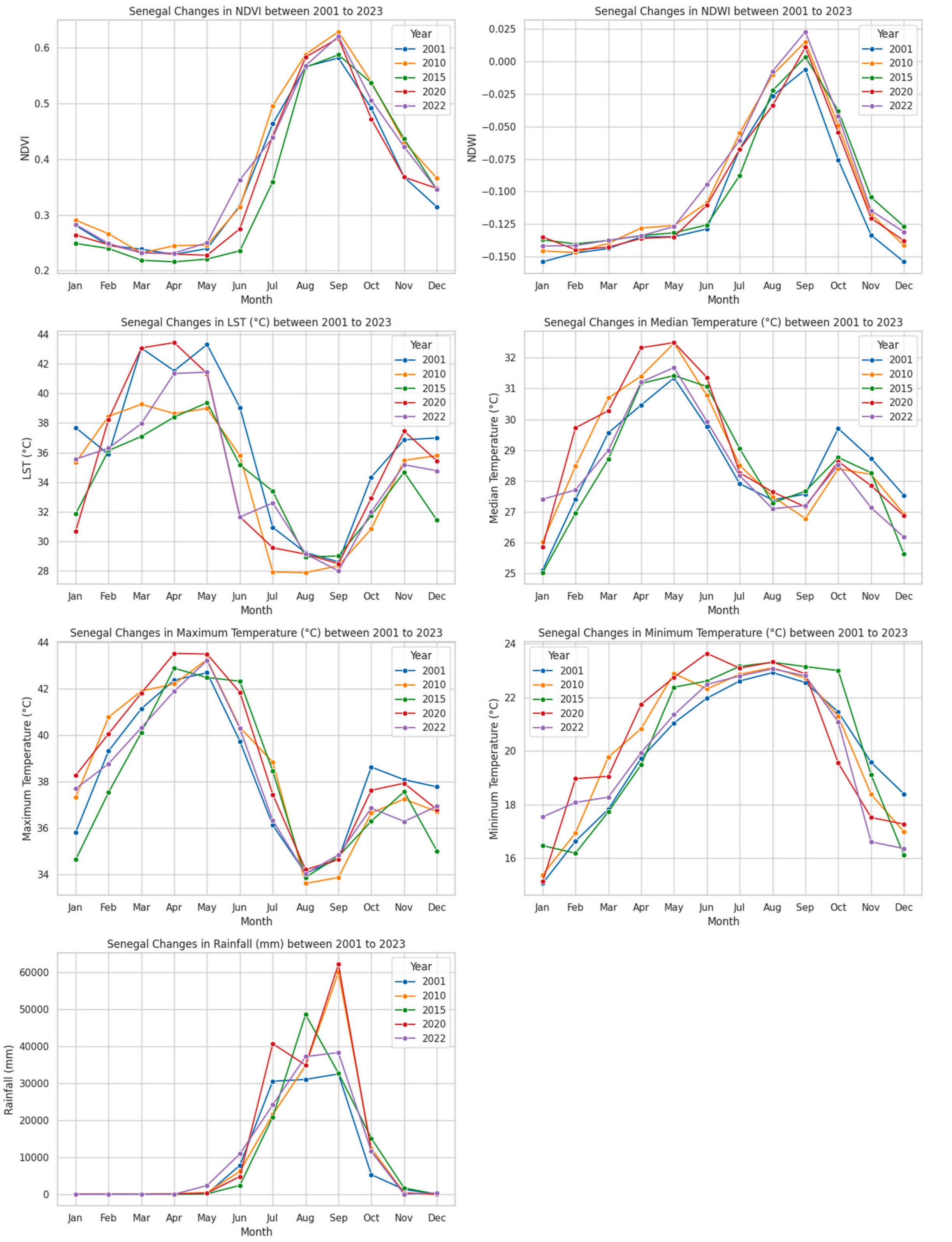

Fig. 3. Monthly trends of environmental and climate variables in Senegal. Each colored line represents a different year, with points marking the monthly median value for the variable.

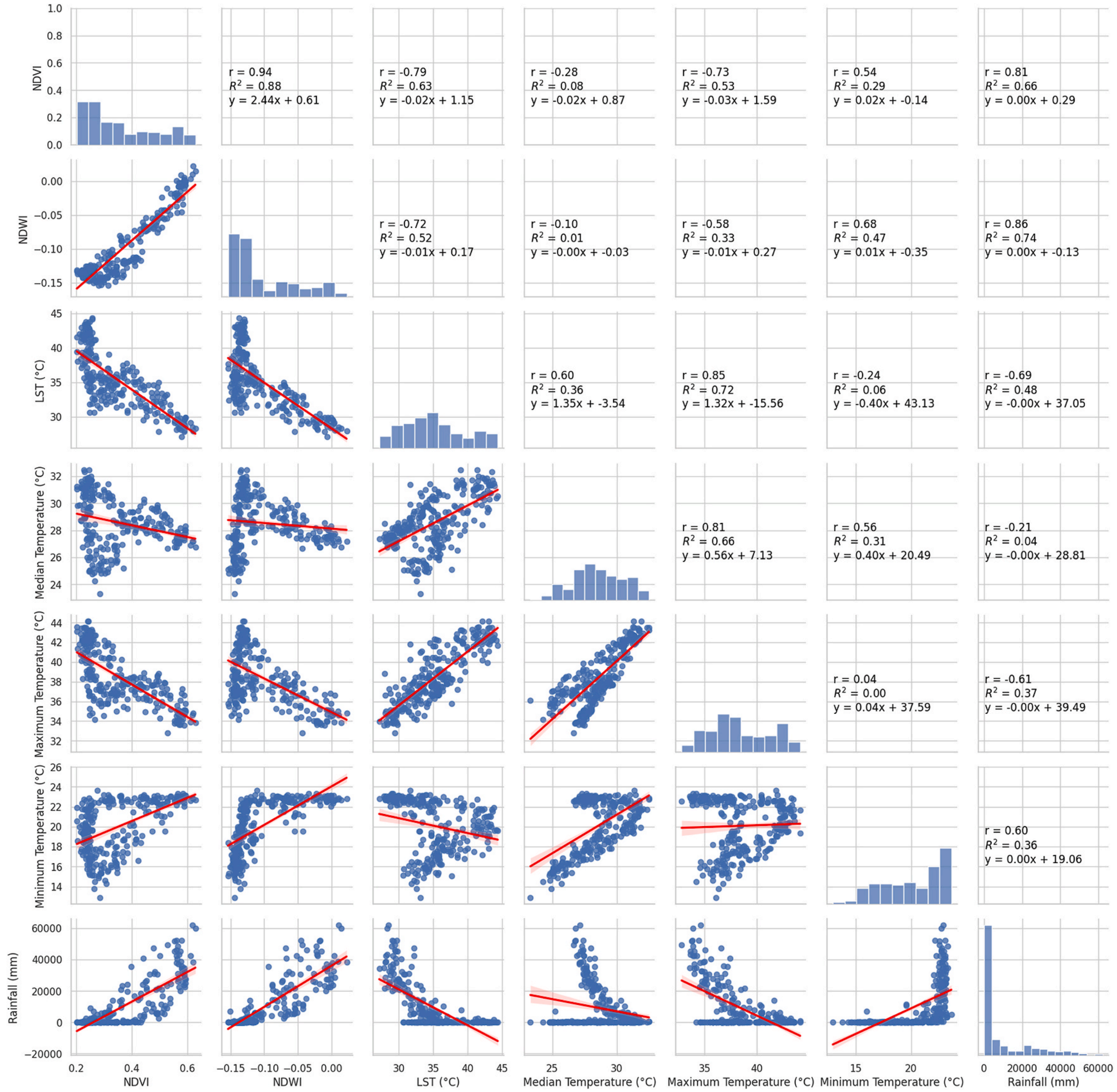

Fig. 4. Correlation and linear regression between variables. The blue dots represent the scatterplot, and the red line shows the linear regression.

3.3. Senegal changes during the last two decades through geovisualization and the CV map

The geovisualization of maps from 2001 to 2023 provides valuable insights into the spatio-temporal changes in various environmental and climate variables in Senegal. Additionally, we have created coefficient of variation (CV) maps that highlight the percentage increase in these changes when comparing the base year (2001) to the final year (2023). This analysis covers the transformations that have occurred in this African country over the last two decades.

Regarding the NDVI, significant findings have emerged about changes in vegetation cover. The NDVI maps for Senegal (Fig. 5), spanning from 2001 to 2023, indicate that in 2001, the NDVI values were moderate, with northern Senegal characterized as arid or semi-arid, displaying lower NDVI values (ranging from 0 to 0.5), while southern regions had more abundant green vegetation (values ranging from 0.5 to 1).

By 2005, NDVI values had increased compared to 2001, particularly in the central and southern regions. However, the 2010 maps revealed a decrease in NDVI in parts of central Senegal compared to 2005. In 2015, a further reduction of NDVI was observed in the northern areas, while there was a slight increase in the central and southern regions.

In 2020, there was a significant uptick in greening across the country, like in 2005; however, by 2023, most of the northern region experienced a decrease in NDVI. These trends are summarized in the CV map, showing variability in NDVI ranging from 30 % to 50 % in central and northern Senegal. The coastal areas maintained their greenery over the past two decades, displaying changes between 0 % and 20 %.

The NDWI geovisualizations (Fig. 6) reveal surface water availability and soil moisture patterns in Senegal over the past twenty years. Particularly, the map from 2001 shows moderate to high NDWI values (greater than 0.5) in the southern and southeastern regions. However, the maps from 2005 to 2010 indicate a decline in NDWI across the central and northern parts of Senegal. In 2015, there was a slight recovery in NDWI in the western regions compared to the previous year analyzed. For the years 2020 and 2023, a recovery is observed in some sections of the southern and central regions.

In terms of the CV map, fluctuations from 2001 to 2023 show variations in NDWI in the southern and central regions, with changes exceeding 60 %. This contrasts with the CV NDVI map, which exhibits greater fluctuations in both regions, with some areas experiencing up to 100 % variation. On the other hand, the northern and western regions display lower CV values, suggesting that these areas maintained more stable water levels and experienced less variation in precipitation and temperature due to their drier climate.

In the analysis of LTS maps from Fig. 7, we observe that in 2001, Senegal exhibited relatively high LST values, with median temperatures exceeding 35 °C in the central and eastern regions. By 2005, there was an increase in LST across most areas, although the western coastal regions remained slightly cooler than the inland areas, likely due to maritime influences. This trend of elevated LST persisted through 2010, 2015, and 2020, with inland areas consistently recording the highest temperatures, sometimes surpassing 40 °C, particularly in the northeastern part of the country. By 2023, LST values remained high throughout most of Senegal, with a notable intensification of heat in the eastern and northeastern regions, indicating a trend of warming that has been especially pronounced in these areas due to the dry climate. In contrast, the CV map shows greater stability compared to other environmental and climate variables. The highest CV is close to 5 %, indicating some variability in LST; however, most of the changes occur in the northern and central regions.

The median temperature geovisualizations (Fig. 8) indicate a warming trend across Senegal, with temperatures rising from 2001 to 2023, particularly in the northeastern and central regions of the country. In 2001, temperatures ranged from approximately 22 °C in the southern areas to around 32 °C in the northern regions, with cooler temperatures mainly found along the south and coastal zones. By 2005, there was a slight increase in temperatures in the areas of the north. The pattern observed in 2010, 2015, and 2020 was like that observed in 2005, showing more significant increases in the northern and northeastern areas. In 2023, these regions experienced a notable peak, with temperatures exceeding 34 °C. These findings contrast with the LST maps (Fig. 7) and the CV temperature map, which reveal that the semi-arid conditions in the northeast and central regions resulted in a temperature fluctuation of 12 percent over the past twenty years.

The maps of rainfall depicted in Fig. 9 illustrate how precipitation variability changed from 2001 to 2023. The most significant changes in rainfall occurred in southern Senegal, where precipitation amounts reached approximately 20 mm or more. In contrast, the central and northern regions experienced lower rainfall levels, typically below 10 mm. In 2001, there was a significant concentration of rainfall in the southwest, which continued into 2005, with increased precipitation observed in that area. However, by 2010, median rainfall decreased across much of the country. Rainfall began to rise again during 2015 and 2020, particularly in the central and southern regions. Notably, in 2023, there was a general decline in rainfall throughout the country. The CV map displays the percentage fluctuation in precipitation, showing a variation between 170 % and 200 % across Senegal. The most substantial fluctuations occurred in the northern and central areas, while the southern region experienced the least variation. We observe a significant contrast when comparing precipitation with other variables like NDWI and NDVI. In the case of NDVI, higher values are noted in the central and southern regions of Senegal, correlating with increased rainfall. Also, the NDWI exhibited greater fluctuation in these areas than rainfall levels.

4. Discussion

This study brings together environmental and climate data to better understand patterns of change in Senegal. The combined use of satellite-based indicators and climate variables offers a way to explore how different regions of the country have experienced environmental shifts in recent decades. These insights can help support local efforts to respond to ongoing changes. In countries like Senegal, where climate adaptation plans are still developing (Epule et al., 2017), there is a growing need for studies that look at

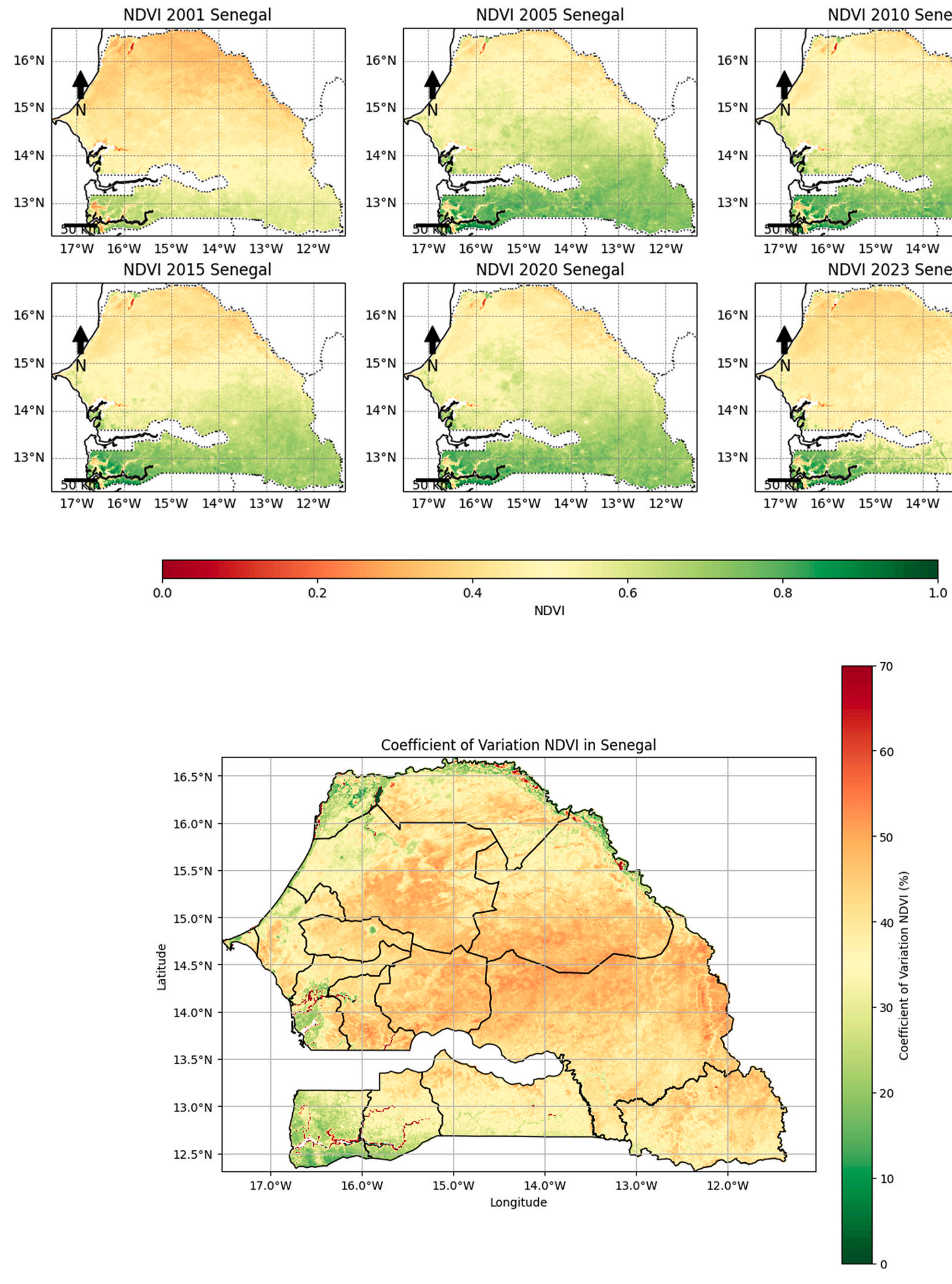

Fig. 5. NDVI Geovisualizations and CV map from 2001 to 2023.

environmental conditions in more detail and over longer time periods.

Our research includes a combination of vegetation and climate indicators, including the Normalized Difference Vegetation Index, Normalized Difference Water Index, land surface temperature, air temperature, and precipitation. These variables were examined from 2001 to 2023 using remote sensing tools available through Google Earth Engine (Alvarez and Govind, 2024). This process makes it possible to identify regions that have experienced the most change and where additional support, or environmental protection efforts may be needed. Many of these areas face challenges related to poor land-use practices, unequal access to agricultural resources, and deforestation (Magalhães et al., 2024; Maisonnave and Mamboundou, 2022).

Shifts in temperature and rainfall have affected vegetation cover in different parts of the country. These changes are connected to more frequent weather events such as droughts, intense rainfall, or changes in seasonal patterns linked to the monsoon and global

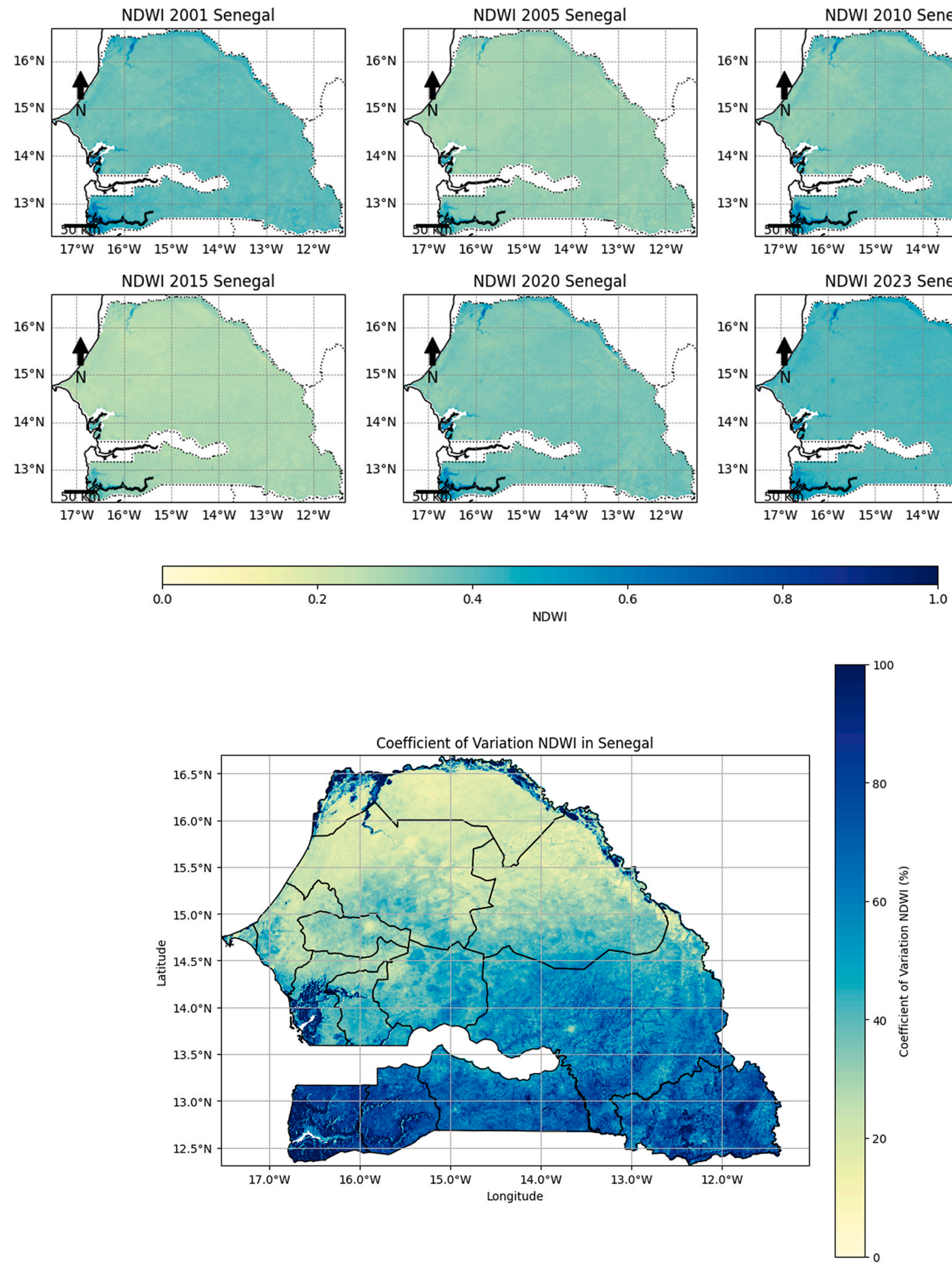

Fig. 6. NDWI Geovisualizations and CV map from 2001 to 2023.

climate systems like El Niño (Dieng et al., 2021; Pausata et al., 2020).

Our analysis shows that the relationship between vegetation and rainfall is strong. Areas in the south of Senegal, where rainfall is generally higher, also show more vegetation, as reflected in the NDVI and NDWI maps. These findings are supported by a strong correlation between rainfall and vegetation indicators, with NDVI showing R squared equal to 0.81 and NDWI showing R equal to 0.86. Years like 2005 and 2015, which had more rainfall, also showed higher vegetation density, especially in the southern and central regions (Özdoğan and Govind, 2022). These patterns are like findings from other studies in West Africa, although there are differences depending on the local environmental context (Makinde et al., 2024). During drier years such as 2001 and 2023, both NDVI and NDWI values decreased, particularly in the north, where vegetation is more sensitive to changes in water availability.

In addition, our results show that temperature and rainfall have become more variable over time. Some areas in the central and

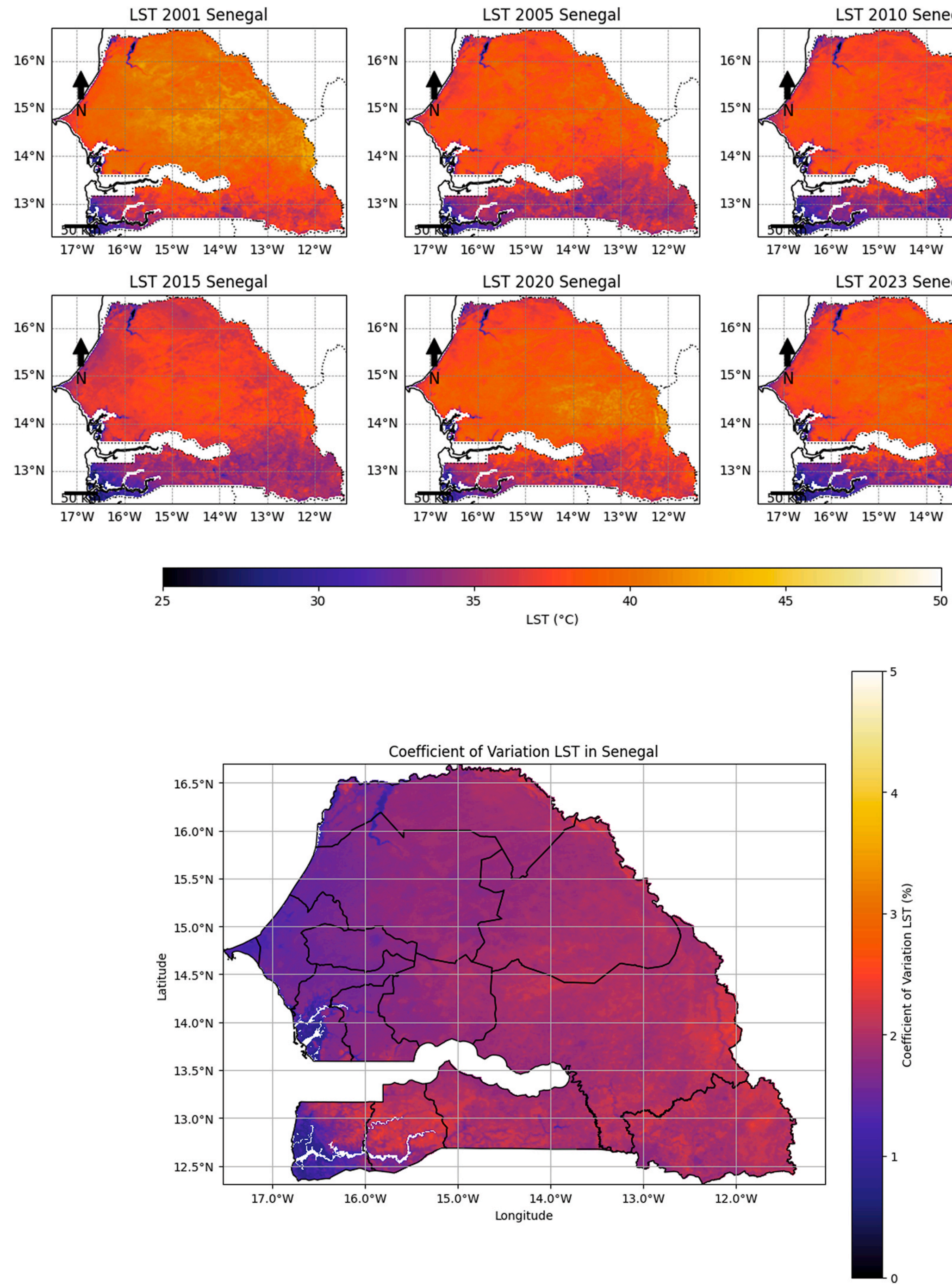

Fig. 7. LST Geovisualizations and CV map from 2001 to 2023.

northern regions of Senegal have seen a temperature increase of nearly twelve percent. Precipitation in these same areas fluctuated by nearly two hundred percent. This level of variability can make it harder for people and ecosystems to adjust and can increase the risk of drought and water stress (Nouaceur and Murarescu, 2020; Balcázar et al., 2022). These findings are consistent with other recent work, such as Nakalembe et al. (2025), who found similar trends using climate data alone.

We also observed that areas with less vegetation tend to have higher land surface temperatures. This pattern, most visible in northern Senegal, highlights how vegetation can help cool the environment through shade and moisture release (Alademomi et al., 2022). In contrast, southern regions with more vegetation showed lower temperature values.

Regions in the north and center of Senegal experienced the highest variability in vegetation, rainfall, and temperature. These areas may be more affected by climate shifts and could benefit from strategies that support long-term land management. Examples include

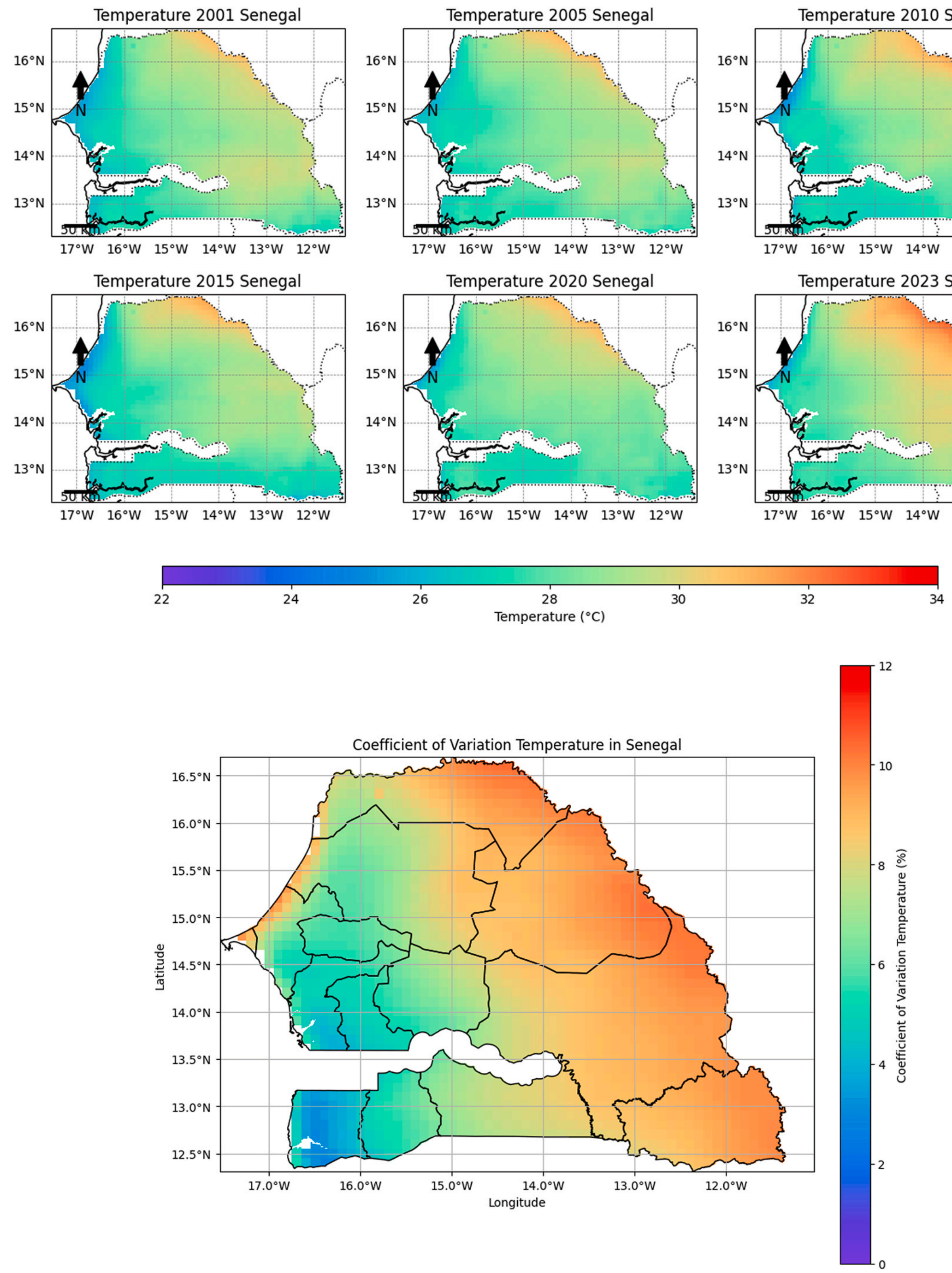

Fig. 8. Median Temperature Geovisualizations and CV map from 2001 to 2023.

the use of drought-tolerant crops, improved irrigation systems, and soil protection techniques (Dieng et al., 2023). On the other hand, the southern part of the country showed more stable environmental patterns. These areas may be in a better position to adopt sustainable agricultural practices that make the most of the current conditions.

Planning for the future also means recognizing how conditions may continue to change. In regions where warmer temperatures and lower vegetation are creating new arid zones, farmers may want to explore crop varieties that are better suited to these conditions (Porcuna-Ferrer et al., 2024). At the same time, monitoring changes in soil moisture—reflected in NDWI—can help improve decisions about water use (Sall et al., 2020).

Finally, areas with higher vegetation cover and biodiversity should be considered a national priority. These places can support both local food security and a more stable climate (Leroux et al., 2022; Dagnachew et al., 2020). Protecting them may offer long-term

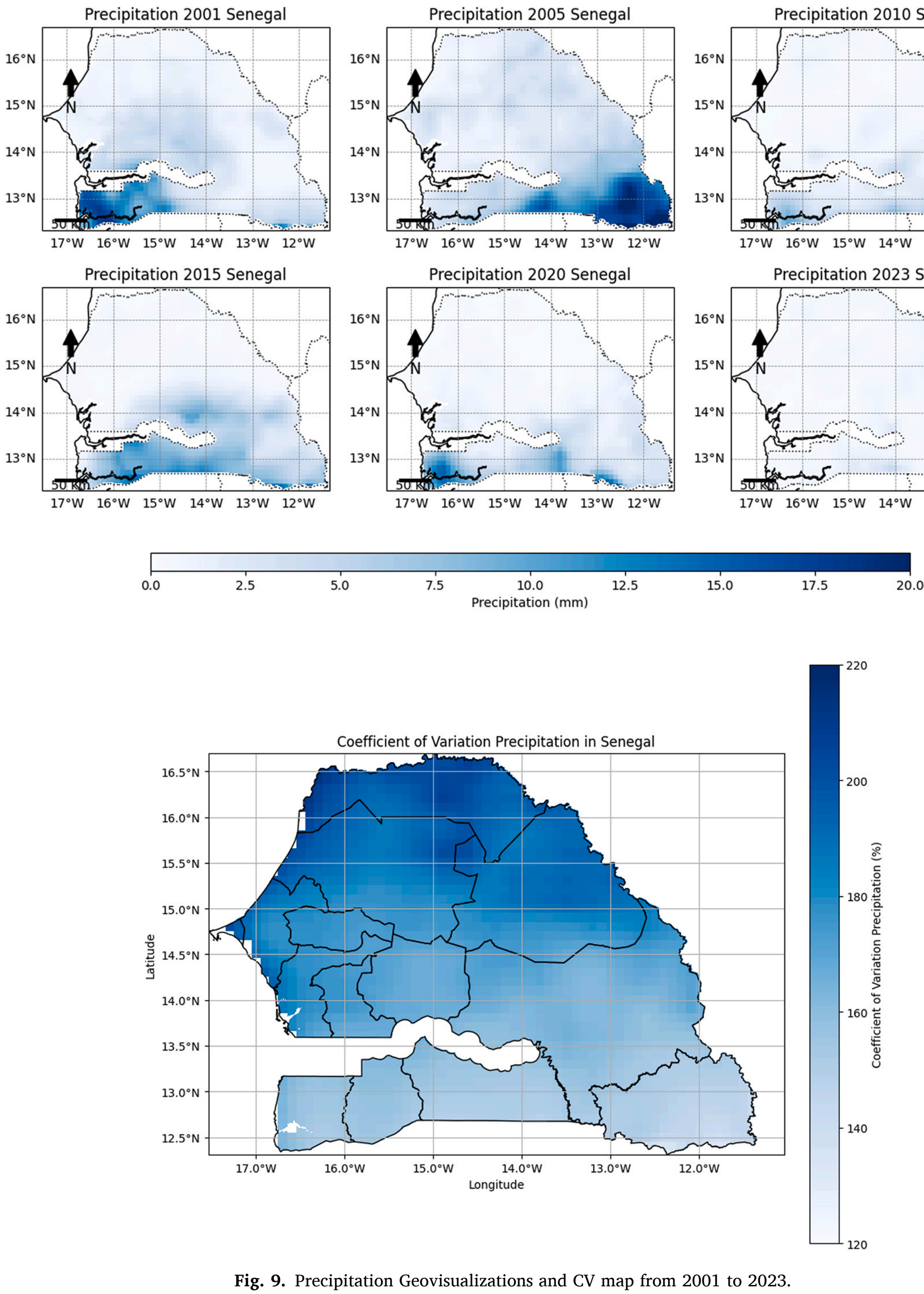

Fig. 9. Precipitation Geovisualizations and CV map from 2001 to 2023.

benefits for both people and ecosystems.

4.1. Social applicability and policy relevance

This study offers insights that can support efforts to strengthen farming systems, manage water resources, and improve land-use planning. The patterns we observed in vegetation and rainfall can help identify areas that are facing challenges and where conservation or adaptation strategies could have a meaningful impact.

While the study provides useful results, there are also some limitations to consider. First, we did not include data collected in the field, which could improve confidence in the satellite-based observations (Shami et al., 2022). Second, we relied on ERA5 Land data for climate conditions and did not include information on local social or economic conditions. In addition, although the data from MODIS were adjusted to allow for comparison, differences in resolution could still affect some results. Using higher-resolution satellite data would allow future studies to focus more closely on small areas or specific communities.

Future research could also use ground-based weather station data for validation and explore drought indices such as the Standardized Precipitation Index or the Standardized Evapotranspiration Index. Including socio-economic data would give a fuller picture of how climate changes affect people and communities. It would also be helpful to examine events such as floods or heatwaves that are becoming more common and could threaten local livelihoods.

The results of this study may be useful to decision-makers working on climate adaptation plans, water and land policy, and sustainable farming. The maps and climate-vegetation patterns presented here can help prioritize where action is most needed. The approach also supports national and regional goals, including the Sustainable Development Goals focused on food, water, and climate resilience.

Remote sensing platforms like Google Earth Engine offer a practical way to monitor environmental change across wide areas, even where access to on-the-ground data is limited (Fall et al., 2021). This method can also be applied in other African countries with similar challenges, helping to identify climate-sensitive zones and shape adaptation plans (Hermans and McLeman, 2021). By combining different types of environmental information, this study adds to our understanding of how people and nature are affected by climate changes and what kinds of responses might be most helpful going forward.

5. Conclusion

In this study, we used remote sensing to analyze the variability of environmental and climate conditions in Senegal over the past two decades. By integrating vegetation indices such as the Normalized Difference Vegetation Index and the Normalized Difference Water Index with land surface temperature, air temperature, and precipitation data, we identified spatial and temporal patterns that reflect the country's exposure to climate change. The southern region, where we found a strong positive correlation between vegetation and rainfall ($r = 0.81$), shows that vegetation growth closely follows precipitation trends. This reinforces the importance of protecting and conserving these greener zones. We also observed an inverse correlation between the vegetation index and land surface temperature ($r = -0.79$), highlighting the cooling effect of vegetation cover. In contrast, the central and northern regions are more exposed to variability and extremes, with vegetation index values fluctuating between thirty and fifty percent, temperature increasing by six to twelve percent, and precipitation varying by more than one hundred sixty percent. These patterns point to increasing environmental stress in already dry and semi-dry areas. Based on these findings, we suggest that region-specific adaptation strategies are needed. These strategies could include improving irrigation practices, preserving vegetation, and creating protected zones. The approach presented in this study demonstrates how satellite data can be used to monitor long-term environmental trends and support informed decision-making in other African countries facing similar climate challenges.

CRediT authorship contribution statement

Cesar Ivan Alvarez: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Ajit Govind:** Supervision, Funding acquisition.

Availability of data and material

The remotely sensed and field sampling data used in this study is available from the corresponding author upon reasonable request.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Cesar Ivan Alvarez reports financial support was provided by CGIAR. Ajit Govind reports a relationship with CGIAR that includes: consulting or advisory, employment, and funding grants. 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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Data availability

Data will be made available on request.

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