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Aissatou Ndiaye, Dahirou Wane, Cheikh Dione, Amadou Thierno Gaye

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Assessing solar energy production in senegal under future climate scenarios using regional climate models

Aissatou Ndiaye [a,b,*], Dahirou Wane [b], Cheikh Dione [c], Amadou Thierno Gaye [b]

[a] *Chair for Regional Climate and Hydrology, Institute of Geography, University of Augsburg, Augsburg 86135, Germany*
[b] *Laboratoire de Physique de l'Atmosphère et de l'Océan Siméon Fongang, Université Cheikh Anta Diop, Dakar-Fann BP 5085, Dakar, Sénégal*
[c] *Institut Pierre Simon Laplace, CNRS, Ecole Polytechnique de Paris, Institut Polytechnique de Paris, Paris, Palaiseau 91128, Cedex, France*

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ABSTRACT

The transition to renewable energy is pivotal for climate change mitigation, yet it entails a greater reliance on weather and climate conditions, impacting energy production from solar plants. Senegal's energy sector is increasingly reliant on solar power, making it essential to assess its long-term viability under changing climate conditions. This study evaluates future solar energy production in Senegal up to 2050, focusing on eight operational solar plants: Bokhol, Sakal, Malicounda, Kahone, Ten Merina, Mekhe, Ndiass, and Kael. The regional climate model (RegCM4) driven by three Global Climate Models (GCMs) from CORDEX-CORE simulations is used and the analysis is conducted under the RCP8.5 scenario. The shortwave solar radiation and ambient air temperature at 2 m from the ERA5 re-analysis provided by the ECMWF are used to evaluate the RegCM4 simulations. Bias correction is applied to enhance the model's accuracy. The validation shows that ERA5 captured the temporal pattern of solar energy production. For the intensity, a minor relative bias averaging 5.6 % over the considered period is noted. Without correction, the model exhibits a relative bias of 10.4 %, which improves to 0.11 % after correction. Additionally, the results show a general decreasing trend in solar energy production over the country. The solar plants are projected to have a decrease in production ranging from -0.43 to -1.14 kWh/year. Policymakers should diversify energy sources, invest in storage solutions, and adopt climate-resilient solar technologies. This study provides insights into the potential impacts of climate change on solar energy generation in Senegal, informing policymakers and stakeholders to optimize power generation and ensure a sustainable energy future.

1. Introduction

The impact of human-induced climate change is driven by over a century of accumulated greenhouse gas (GHG) emissions from activities like energy use, land-use change, and production and consumption patterns (IPCC-AR6, 2023). The primary goal of any mitigation strategy to avoid climate change risks is to reduce GHG emissions [1]. The 2021 Glasgow Climate Pact reiterated the commitment of national governments to limit the global average temperature increase to 1.5 °C, recent climate policies are increasingly focusing on reducing fossil fuel use in the years ahead [2]. The energy sector is responsible for around 80 % of human-caused CO_2 emissions and has a central role in reducing carbon emissions. Over 90 % of the solutions in 2050 involve renewable energy through direct supply, electrification, energy efficiency, and green hydrogen and bioenergy with carbon capture and storage (IRENA, 2021).

The transition from fossil to renewable energy is crucial to ensure a complete transition to a low-carbon economy and effectively mitigate climate change [3]. Renewable energy is expanding faster during the last decade due to its status as a clean and sustainable energy source. According to the International Energy Agency [4], global annual renewable capacity additions increased by almost 50 % in 2023, and almost 3700 GW of new renewable capacity is expected over the period 2023–2028, driven by supportive policies. Solar photovoltaics (PV) and wind energy will account for 95 % of global renewable expansion [4]. Solar energy has gained significant importance due to the need to reduce the use of fossil fuels and public acceptability is the main driver for creating meaningful energy change ([5,6] Renewable energy targets are consistently raised in many countries primarily for climate change mitigation. In Senegal, the country is set to achieve an additional

* Corresponding author.
E-mail address: aissatou.ndiaye@uni-a.de (A. Ndiaye).

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installed capacity of 100 MW of solar, 100 MW of wind, 50 MW of biomass, and 50 MW of Concentrated Solar Power (CSP) by 2030 [7]. The country's renewable energy capacity has increased with the construction of nine solar plants at Ten Merina, Mekhe, Sakal, Kahone I and II, Malicounda, Bokhol, Kael, Ndias and one wind farm at Taiba Ndiaye. These solar plants are on-grid, meaning they contribute directly to Senegal's national electricity network, which is a mix of fossil fuel, wind, hydro, and solar energy. Solar energy alone cannot ensure a stable and continuous power supply, especially under fluctuating weather conditions (El-Khozondar et al., 2023; [8])

The transition to renewable energy involves a more dependent energy sector on weather and climate conditions. Weather and climate variability have a substantial impact on the energy sector, given that both energy demand and supply depend on atmospheric conditions across various time scales [9]. Seasonal or multiannual climate oscillations, along with long-term trends, significantly impact the generation of renewable energy from solar and wind power installations [10]. To successfully shift to more renewable energy sources, it is crucial to gain a comprehensive understanding of this variability and its impacts on the power system [11].

Several studies have demonstrated the influence of climate change on energy at a broad level [12–14], and renewable energy in particular (e.g., [15–21]; Ogunjobi et al., 2022; [22,23]). Research conducted across West Africa using various climate models to evaluate future solar resources indicates a general decline in solar PV potential with varying degrees of magnitude [17,20,22,23]. Over Senegal, studies about the same topic aren't demonstrated in our knowledge while renewable energy sources are becoming more important as the country strives to achieve its goals of energy security and access. One reason for the lack of studies is that Senegal only began expanding its renewable energy capacity in 2016. The first solar power plant, Bokhol, was inaugurated in 2016. Before this, the electricity sector relied heavily on fossil fuels, which were imported and placed a significant burden on the economy (CDN Senegal, 2020; Ba et al, 2021). For example, in 2017, Senegal's oil imports cost around 1.3 billion euros, equivalent to 60 % of export revenue (Ba et al., 2021). Another reason could be data accessibility. Conducting in-depth research on solar power plants requires access to detailed operational and climate data. In many cases, such data is not readily available to researchers in Africa [24].

Studies over the country mainly focused on other aspects of solar energy ([25]; Niang et al., 2023; [26]). Sarr et al. [25] used Global Horizontal Irradiance estimates (GHI) obtained from satellite imagery to evaluate the solar resources in the country and their daily, seasonal, and interannual variability for a mini-grid solar system. They found that Senegal experiences significant variability in solar resources over time and across different locations, depending on the year and specific site conditions. Niang et al. (2023) evaluated the seasonal performance of six solar power plants in Senegal, namely Bokhol, Sakal, Malicounda, Kahone, Ten Merina, and Mekhe. The results of their study showed that energy production varies significantly with the seasons, reaching its highest levels from March to May (dry season) and dropping to its lowest in September (wet season). Although these studies characterized solar energy production across the country, projections of future solar energy production under climate scenarios are missing, leaving a gap in understanding how long-term changes might affect solar energy generation in Senegal.

Different from the study of Niang et al. (2023) who used three models (RETScreen, PVGIS, and PVsyst) to simulate the seasonal production of the solar plants in Senegal, this study uses a mathematical equation to simulate (reproduce) the monthly production of Ten Merina solar plant and projects the future production of eight solar plants in Senegal (Bokhol, Sakal, Malicounda, Kahone, Ten Merina, Mekhe, Ndiass and Kael). Hence, the objective of this study is to investigate the potential changes in solar energy production capacity at existing solar plants in the country by 2050 under the high emission scenario (RCP 8.5). The analysis uses the latest CORDEX-CORE data with a 25 km horizontal resolution, along with the regional climate model version 4 (RegCM4), which is driven by three GCMs. The focus of the analysis is on eight solar plants: Bokhol, Sakal, Malicounda, Kahone, Ten Merina, Mekhe, Ndiass, and Kael.

The subsequent section describes the data and methodology used, while Section 3 delves into the evaluation of the model and the anticipated changes in solar energy production. The last section presents the conclusion of the study.

2. Data and methods

2.1. Study area and data

This study focuses on eight (8) solar plants, mainly located in western Senegal (Bokhol, Sakal, Malicounda, Kahone, Ten Merina, Mekhe, Ndiass, and Kael), with particular emphasis on Ten Merina, where the observation data used were collected. Ten Merina is located in the department of Tivaoune, the region of Thies (the second most populated region). The location of the Ten Merina plant, as well as the other solar plants considered in this study, are shown in Fig. 1. The plant is an on-grid independent power producer with an installed capacity of 30 MW but delivering 20 MW to the national electricity company (SENELEC). The plant comprises 92,160 polycrystalline panels over an area of 44 ha. All remaining seven plants also utilize polycrystalline panels and are connected to the grid with varying capacities: 30 MW for Mekhe, and 20 MW for Bokhol, Sakal, Malicounda, Kahone, and Kael, while Ndiass has a capacity of 23 MW.

The plants have meteorological stations that measure solar irradiance, cell and ambient air temperature, humidity, wind speed, etc. One-year hourly data (2020) on solar irradiance, cell, and ambient air temperature from Ten Merina were collected. Daily production data for the plant for 2020 and yearly for 2018, 2019, and 2021 were also collected. The monthly and yearly mean used in this study are calculated from the hourly and daily data.

CORDEX-CORE simulation data with 25 km of horizontal resolution from the Word Climate Research Program (WCRP) is used in this study for the projection of solar energy production. The regional climate model (RCM) RegCM4, driven by three GCMs (NorESM1-M, MPI-ESM-MR, and HadGEM2-ES) from the Coupled Model Intercomparison Project 5 (CMIP5) is used. Ndiaye et al. [23] found that RegCM4 is an effective model for simulating solar irradiance in West Africa and it is also able to accurately predict ambient air temperature. Therefore,

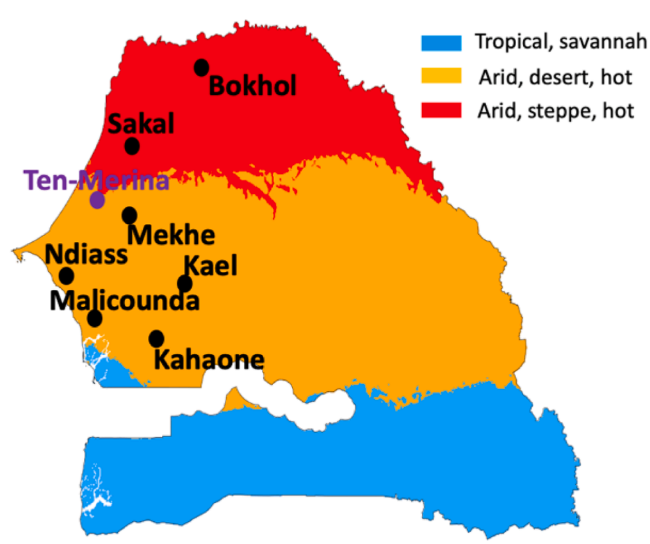

Fig. 1. Study area showing the solar plants considered in this study (in red dots). Most of the plants are located in the western part of the country (Senegal).

RegCM4 is chosen for this study. RegCM4 is the fourth-generation version of the RegCM regional modelling system [27] developed at the Abdus Salam International Centre for Theoretical Physics (ICTP). Monthly simulated shortwave solar radiation and ambient air temperature are used. More details about the parametrization of the models can be found in Giorgi et al. [28] and Ndiaye et al. [23]. The simulation period ranges from 1975 to 2050, from which the period 1975–2004 is taken as a reference and 2005–2050 for the future under the high emission scenario (RCP8.5).

ERA5 reanalysis data from the ECMWF are used in this study to validate the performance of the RegCM4 model to simulate solar radiation and ambient air temperature during the period from 1979 to 2004. ERA5 dataset is the fifth generation ECMWF reanalysis for the global climate and weather produced by the Copernicus Climate Change Service at ECMWF [29]. The ERA5 dataset offers estimates of atmospheric variables with a horizontal resolution of about 25 km. We used daily solar radiation and ambient air temperature data to compute the monthly and yearly averages.

In this study, the yearly mean is calculated from the monthly and daily data respectively for CORDEX and ERA5.

2.2. Methods

2.2.1. Solar production estimation

To estimate the monthly production (P) of the Ten Merina solar plant, the formula of Mavromatakis et al. [30] is used. It is a method for estimating solar plant production based on the performance of the PV cells in real-world environmental conditions (actual operating environment in which a solar plant functions). The production can be expressed by using Eq. 1:

$$P = Pp * Pr\frac{G}{Gstc} \tag{1}$$

Where Pp is the nominal power of the PV module, given by the manufacturer under Standard Test Conditions (STC). G is the solar irradiance at the plane of the module, G_{STC} is the solar irradiance of 1000 W/m^2, and Pr is the performance ratio of a PV system and takes into account environmental factors. Pr is designed to account for variations in PV cell efficiency caused by temperature changes.

To have the energy produced by the plant in kWh, we multiply P by the time (t).

$$P(kWh) = Pp * Pr\frac{G}{Gstc} * t \tag{2}$$

2.2.1.1. Estimation of the performance ratio. The performance ratio Pr is estimated following Jerez et al. [31] formula given in Eq. 3:

$$Pr = 1 + \gamma(Tcell - Tstc) \tag{3}$$

where Tcell is the PV cell temperature and Tstc is the temperature of the cell under STC (25 °C). γ is the temperature coefficient of the maximum power and is equal to 0.0035 $^\circ C^{-1}$ for poly-crystalline silicon cells [32].

2.2.1.2. Estimation of the cell temperature. According to Skoplaki et al. [33] and Sun et al. [34], Tcell is computed based on the Nominal Operating Cell Temperature coefficient (NOCT):

$$Tcell = Ta + \left(\frac{NOCT - 20}{800}\right) * G \tag{4}$$

The NOCT is generally provided by the manufacturer and is approximately 45 ± 2 °C for monocrystalline and polycrystalline PVs [34]. The NOCT is defined by the temperature of the PV cell or module, which can be ascertained under typical conditions: solar irradiance of 800 W/m2, ambient temperature of 20 °C, and without any load conditions [34]. Ta is the ambient air temperature.

2.2.2. Bias correction

Bias correction is used to improve model accuracy by adjusting estimated parameters to account for biases. This adjustment can be done by using a variety of statistical and machine learning methods [35]. Some statistical methods include but are not limited to linear and variance scaling, quantile mapping, delta change method, power transformation, etc. [35–37]. The method by Hawkins et al. [38], which adjusts both the mean and variability of model outputs to match observations, provides a good approach to improve bias correction for data sensitive to temporal variability. Compared to the delta change approach, for example, which only adjusts the mean and not the variability. Also, in contrast to quantile mapping, which adjusts the entire distribution and can correct extremes, Hawkins' method is computationally simpler. Therefore, in this study, to reduce the overestimation of the energy production computed from the CORDEX-CORE data, the statistical method of Hawkins et al. [38] is used which adjusts not just the average values but also the temporal variability of the model output to align with the observations. It is an empirical bias correction, a variance scaling method that adjusts the model using observed statistics.

$$P_{BC}(t) = \overline{O}_{ref} + \frac{\sigma_{Oref}}{\sigma_{Mref}}\left(\mathrm{Mraw(t)} - \overline{M}_{ref}\right) \tag{5}$$

Where P_{BC} (t) is the bias-corrected production calculated with CORDEX-CORE data, O_{ref} and M_{ref} are ERA5 and CORDEX energy production in the historical reference period (1975–2004), respectively. M_{raw} is raw CORDEX-CORE energy production for the historical or future period; σ_{Mref} and σ_{oref} represent the standard deviation in the reference period of the CORDEX-CORE and ERA5 energy production, respectively.

2.2.3. Analysis

In this study, the reference evaluation is done with data from the Ten Merina solar plant which serves to validate ERA5 and CORDEX-CORE data. The projection of the energy production of the other solar plants is calculated by extracting the data from CORDEX-CORE at the nearest grid point of the location of the plants. To assess the significance of the projected changes in solar energy production, we also used the Mann-Kendall test, a non-parametric test widely used for detecting trends in climate data [39,40]. The analysis was performed on the significance of the trends at a 90 % confidence level. For each solar plant, we calculated the P-value and the H statistic, which indicate the presence and direction of a trend. In this study all trends with P-value less than 0.5 and H equal to 1 (H=1) are significant.

All the plants, including Ten Merina, are polycrystalline PV. Therefore, the same γ is used. Note that, due to a lack of plant specifications data, the nominal power Pp of Ten Merina is used and is considered constant for all the other plants.

3. Results and discussion

3.1. Validation of the estimated energy production

Fig. 2 shows the monthly mean of the observed and reconstructed energy production of the Ten Merina solar plant along with the solar radiation for the year 2020. It indicates that the production is bimodal with a first maximum in March, during the very dry season (January-May), and the second in October, the transition between the wet and dry seasons. During the rainy season (June-September) the production is low (less than 1.310^5 kWh).

The highest production is recorded in March (~1.5510^5 kWh) and April (~1.5210^5 kWh) when the country receives abundant irradiation. While lowest production during the rainy season can be explained by the cloud's effects on solar radiation and indirectly in the production. Neher et al. [41] indicated that the seasonal variation in the GHI across West Africa is dominated by high cloudiness caused by the moist monsoon winds from the southwest during the wet season and the dry Harmattan

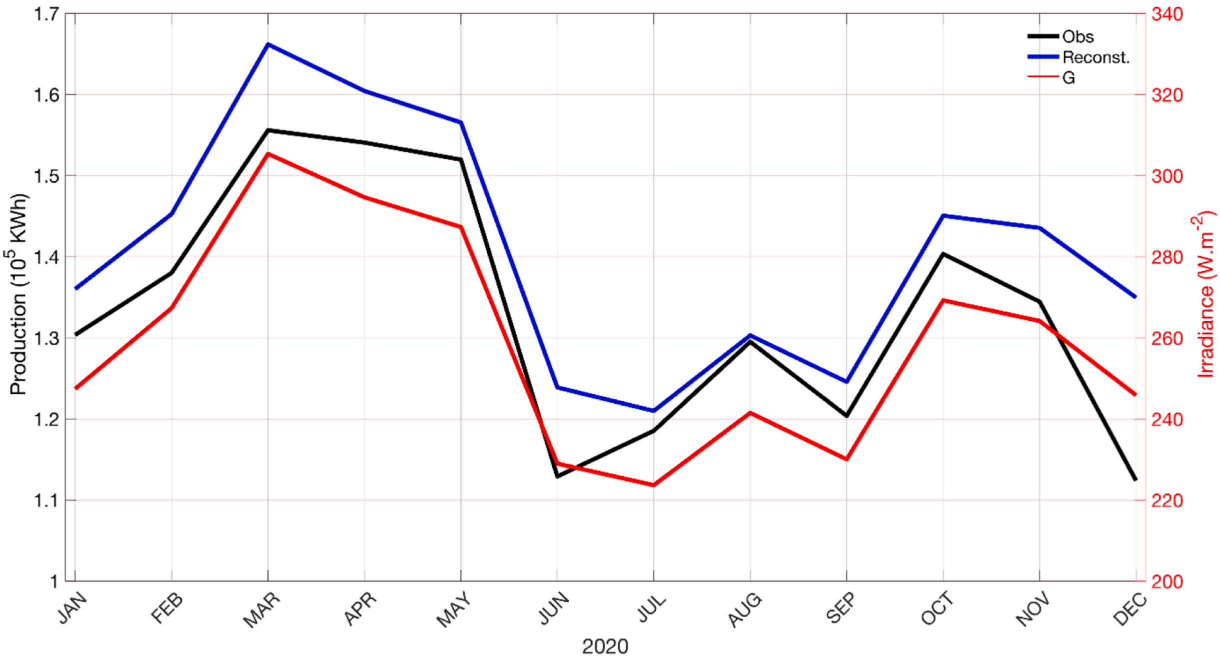

Fig. 2. Evolution of the monthly solar energy production and solar radiation of the Ten Merina plant for the year 2020. The observed energy production is depicted by the black curve, while the blue curve shows the calculated (reconstructed) production using Eq. 2. The red line indicates the solar irradiance.

winds from the northeast during the dry season. A similar pattern in energy generation is observed in the study conducted by Niang et al. (2023), which analyzed monthly production data from six solar plants in Senegal in 2019. This indicated the dependence of solar energy on weather conditions. Besides, the figure shows that the seasonal cycle of observed production is well represented by the reconstructed one. This indicates that the formula is accurate and can be used to predict the energy production of the plants considered in this study.

3.2. Evaluation and validation of ERA5

To use ERA5 for the validation of CORDEX data, its capability to estimate the yearly energy production of Ten Merina is assessed. Therefore, ERA5′s production is validated by comparing it with observed production data available for the years 2018–2021 (see Table 1). This comparison helps determine the accuracy of ERA5 in estimating the climate variables such as temperature and solar radiation used to calculate the production. Table 1 shows the reconstruction of the solar energy production of Ten Merina using ERA5 data from 2018 to 2021. ERA5 captures the temporal pattern and the intensity of the production during the considered period with a slight overestimation ranging from 5847 to 10,403 kWh/year, averaging 7561 kWh/year. This is associated with a mean relative bias of 5.6 %, which indicates a consistent yet minor overestimation in the data. The ERA5-estimated mean production is slightly higher than the observed mean production with a low bias. In general, ERA5 demonstrates the ability to capture the temporal pattern and intensity of observed production from 2018 to 2021 with minor biases and can be used to validate CORDEX-CORE simulations.

Table 1
ERA5 mean production vs observed mean production of Ten Merina for the years 2018–2021. The bias between the two productions as well as the relative bias are calculated.

Year	2018	2019	2020	2021
Observed production (kWh)	136,444	139,357	133,626	132,267
ERA5 (modelled production, kWh)	143,047	145,204	141,017	142,670
Bias (kWh)	6603	5847	7391	10,403
Mean Bias (kWh)	7561			
Relative Bias (%)	4.8	4.2	5.5	7.8
Mean Relative Bias (%)	5.6			

3.3. Model evaluation

For the validation of the models, a comparison of the model outputs and ERA5 is shown in Figs. 3 and 4. Fig. 3 shows the estimated spatial distribution of the annual mean solar production over Senegal from CORDEX-CORE and ERA5 data. The simulations show the same pattern as ERA5 even though the intensity of the production is overestimated over the whole country. In the northern part, production ranges between 140 kWh and 160 kWh, whereas in the southern part, it is between 120 kWh and 140 kWh (Fig. 4a). This result is in line with the study of Sarr et al. [25] who used satellite data to map the spatial and temporal characteristics of the solar resource in Senegal and found that GHI is more important in the northern part of the country. The GCMs demonstrate satisfactory accuracy in their spatial representation. They generally provide a relatively good representation of the mean production. However, the accuracy of the GCMs varies across different zones of the country. The central and northern parts of Senegal are better represented as compared to the southern part where the production is more overestimated by all the models. This could be due to the challenges faced by GCMs in simulating microclimate. Microclimate conditions are influenced by two primary factors: the local weather patterns and the characteristics of the urban fabric at the specific location [42]. The southern part of Senegal is characterized by a more humid and tropical microclimate, with higher rainfall and more vegetation, as compared, for example, to the northern part, which belongs to the Sahel zone and has a drier, semi-arid microclimate. The coarse spatial resolution, along with the significant bias and uncertainty in GCMs, limits their effectiveness for local-scale climate studies, which are crucial for impact assessments [43].

Fig. 4 indicates the evolution of the solar production at the Ten Merina grid point extracted from the model simulations and ERA5 over the reference period. It indicates an overestimation of the production even though the annual variability is captured (Fig. 4a). An overestimation of about 10,000 kWh by the models and the ensemble mean

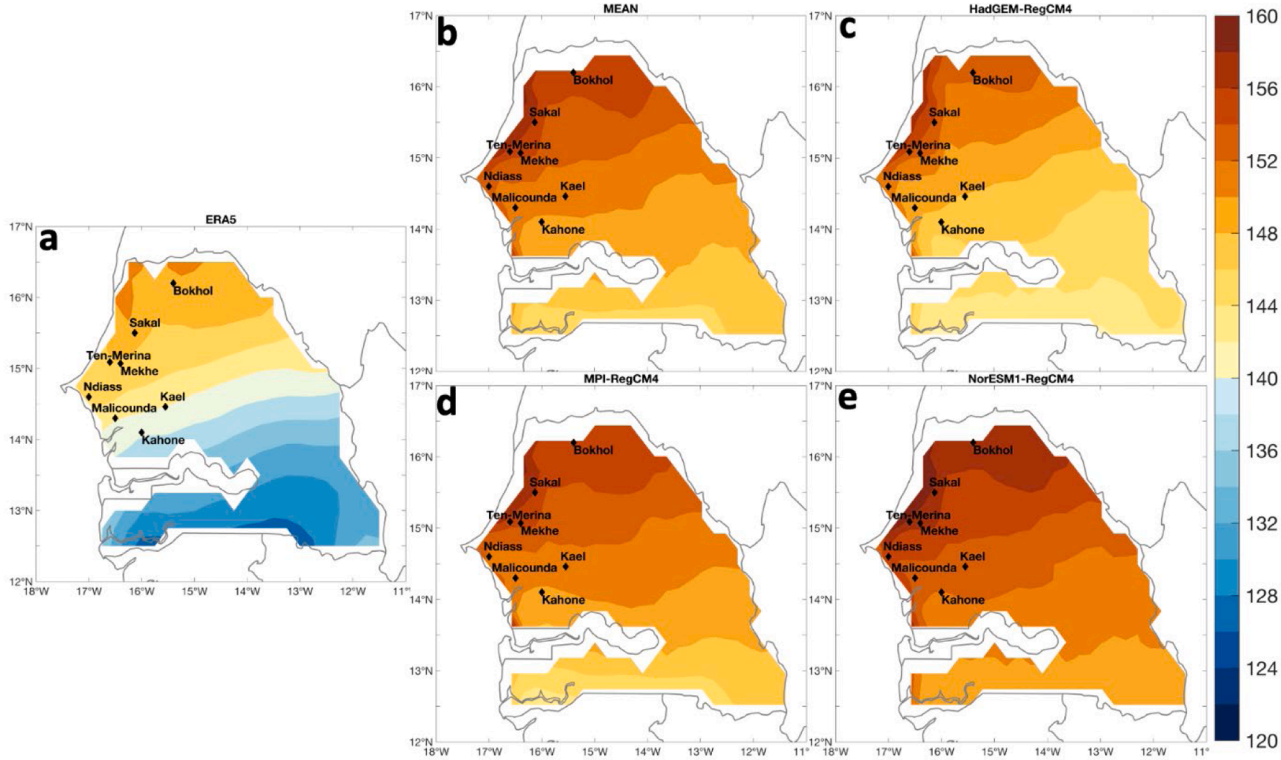

Fig. 3. Spatial distribution of the annual mean solar production using RegCM4 of CORDEX-CORE and ERA5: (a) mean solar production estimated with ERA5 data; (c, d, e) mean solar production estimated with RegCM4 driven by HadGEM2-ES, MPI-ESM-MR and NorESM1; (b) mean of the three GCMs. The black dots show the solar plant's location.

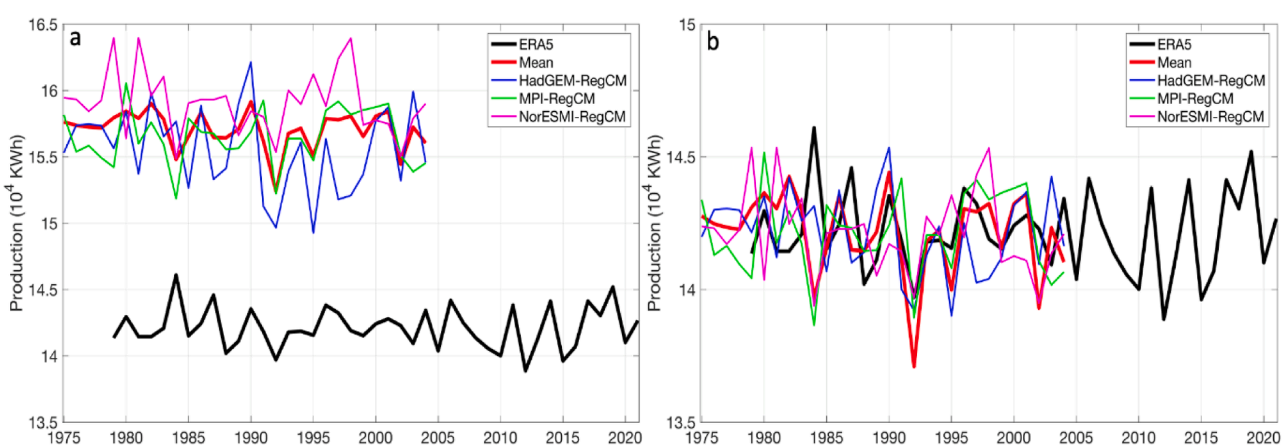

Fig. 4. Time series of the annual mean solar production of the Ten Merina plant using different simulations of RegCM4 from CORDEX-CORE (1975–2004) and ERA5 (1979–2021): (a) annual mean production from CORDEX-CORE and ERA5 without bias correction; (b) bias-corrected annual mean production from CORDEX-CORE and ERA5 using Eq. 5.

(mean) is noticed. This could be caused by various reasons such as the resolution, changes in the local climate, parametrization of the model, etc. The GCMs are often unable to capture local-scale effects such as topography, land-use changes, and aerosol effects [44]. The models may also be subject to biases in their assumptions and parameterizations. The observed biases could originate from both the driving GCMs and the RCM. RCMs are dynamic models that use local information such as topography to generate high-resolution climate data (e.g. CORDEX) from GCMs. However, RCMs are prone to significant biases, errors, and sensitivity to the boundary conditions of the driving GCMs [44]. However, as noted by Moemken et al. [45], disparities among the GCMs typically outweigh those among the RCMs. Despite the higher resolution and detailed regional climate information provided by the CORDEX-CORE datasets, biases are noticed. These results suggest a bias correction to better estimate the future changes in solar energy production in Senegal.

A bias correction is performed using the method described in Eq. 5 (Fig. 4b). The bias of about 10,000 kWh is corrected and the simulated production by CORDEX-CORE is more accurate (Fig. 4b). Following the application of bias correction methods, all the CORDEX-CORE simulations including the mean exhibit a decrease in bias. The corrected mean of the models has a correlation coefficient of 0.82 with the ERA5 production. This correction helps have a better projection of future production and provides a more reliable estimation of the production. The results suggest that the model can accurately predict the annual mean production of Ten Merina with bias correction.

3.4. *Projected production in Ten Merina and other solar plants*

The projection of Ten Merina production at horizon 2050 as well as the future production of other solar plants in Senegal are shown in Fig. 5. For a more accurate projection by the models, a bias correction was applied using ERA5 production data from 2005 to 2021, where available, resulting in the corrected projected production. Only the corrected trend of the GCMs was considered, as it provides a more accurate estimation.

Fig. 5 shows a spatial distribution of the solar energy production trend over the country. All the models and their mean project a decreasing trend. HadGEM-RegCM4 expects the highest decrease ranging from -3 to -7 kWh/year, followed by NorESM1-RegCM4. MPI-ESM-RegCM4 expects the lowest decrease over the country from -0.6 to -2 kWh/year. The reduction in production is more pronounced in the southern and eastern parts of the country. The southern part of the country is expected to have on average an annual reduction of about -2 kWh/year while the highest decrease in the production of about -3 kWh/year will prevail in the southeastern part. This decrease in solar energy potential aligns with projections across most sunbelt regions, where similar trends of decline have been observed. In North Africa, productivity is expected to decrease by up to 7 % [16], while in East Africa, a reduction of 6 % has been reported [46]. Over Southern Africa, median changes in GHI have been projected by 2050 [15]. Similar trends are anticipated in West Africa, where studies found a similar decline in solar energy potential [23,47,48]. Beyond Africa, projections in other sunbelt regions reveal different patterns. In Australia, future PV potential is expected to decline across most of the continent due to reduced insolation and rising temperatures [49] while in Brazil, solar resources are projected to increase by 3.6 % by the end of the century [50].

The reduction in solar energy production can present significant challenges for Senegal's energy and socioeconomic development. Solar energy is central to Senegal's goal of universal electricity access by 2025, especially for rural communities. As solar production decreases, energy poverty could increase, and this could leave rural populations without reliable electricity for socio-economic activities. The country's nationally determined contributions outline two main goals relating to the energy transition: increasing the share of renewable energy in the national energy mix to 40 % by 2035 and increasing the use of natural gas to replace fossil fuel power plants (CDN Senegal, 2020). The decrease would also delay Senegal's ambitions to meet its renewable energy targets. To mitigate these impacts, the country must diversify its renewable energy sources beyond solar. Furthermore, improving energy storage, such as battery systems, could help manage fluctuations in solar

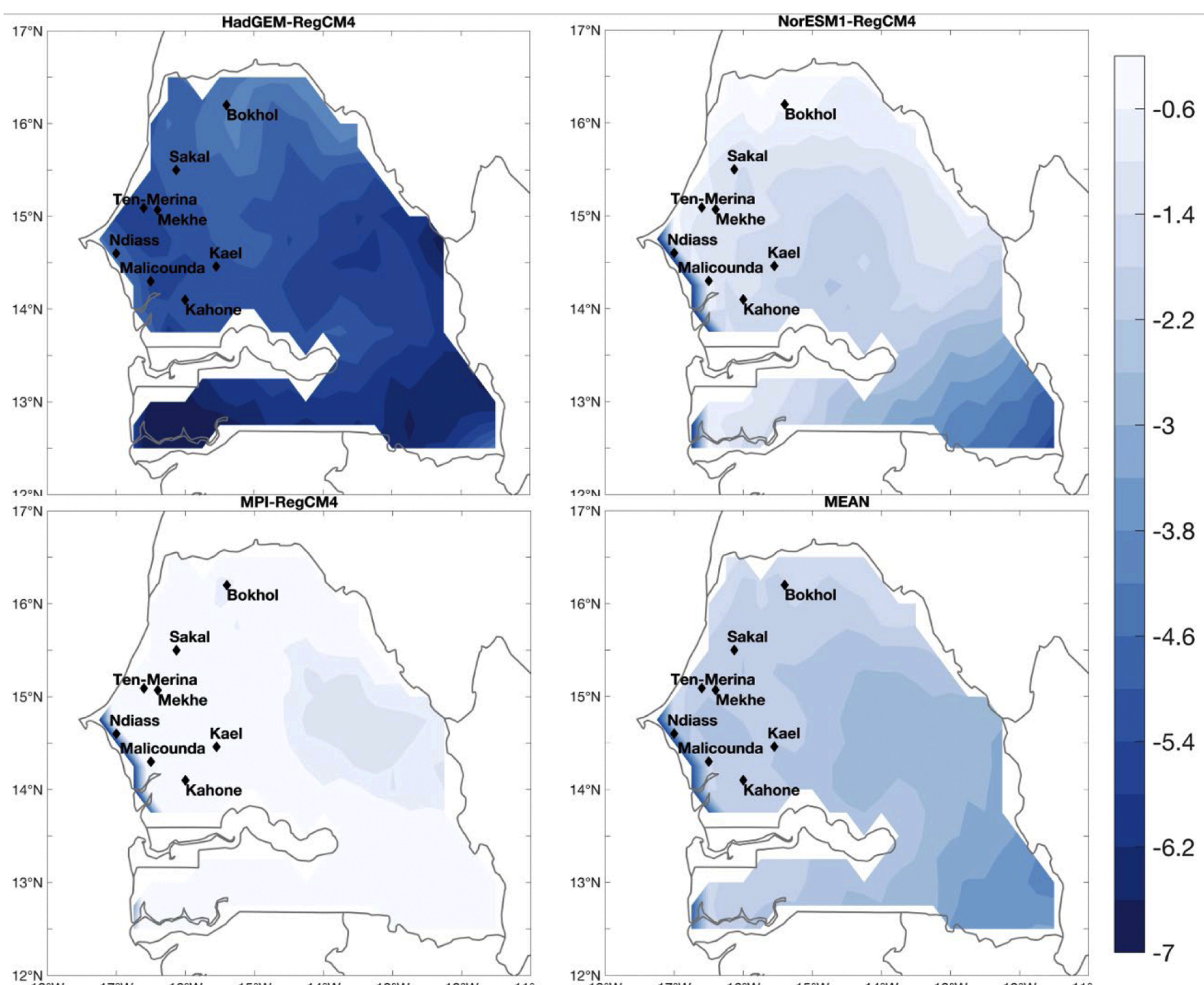

Fig. 5. Spatial plot of the projected production trend over Senegal using RegCM4 of **CORDEX-CORE** (2005–2050): (a) projected trend simulated with HadGEM2-ES; (b)projected trend simulated with NorESM1; (c) projected trend simulated with MPI-ESM-MR; (d) mean of the three GCMs.

production. Another approach is to adopt mitigation strategies used in other regions. For instance, in India, where environmental factors affect solar panel efficiency, measures such as advanced cooling techniques to prevent overheating and regular cleaning systems to maintain optimal performance have been implemented.

For the projection of the other specific solar plants, the closest grid points are extracted from the mean (Fig. 6). Fig. 6a shows a slight decrease in the solar production for the plants in the future period (2006–2050). However, the magnitude of the decrease in kWh presents a spatial variability. The plants experiencing the greatest decrease in production are Malicounda and Sakal, followed by Mekhe (Fig. 6a). The remaining plants, including Ten Merina, exhibit decreases of less than or equal to 1 kWh/ year. The figure displays the overall trend divided into two distinct periods, along with their significance at the 90 % confidence level. The period from 2006 to 2025 reflects an increasing trend in all plant productions, while the period from 2025 to 2050 shows a decline. As an illustration, in the case of Ten Merina for example, the production trend shifts from 4.62 kWh/year to 2.61 kWh/year, indicating that the overall decrease in production between 2006 and 2050 can be attributed to the decline observed specifically from 2025 to 2050. And this is the

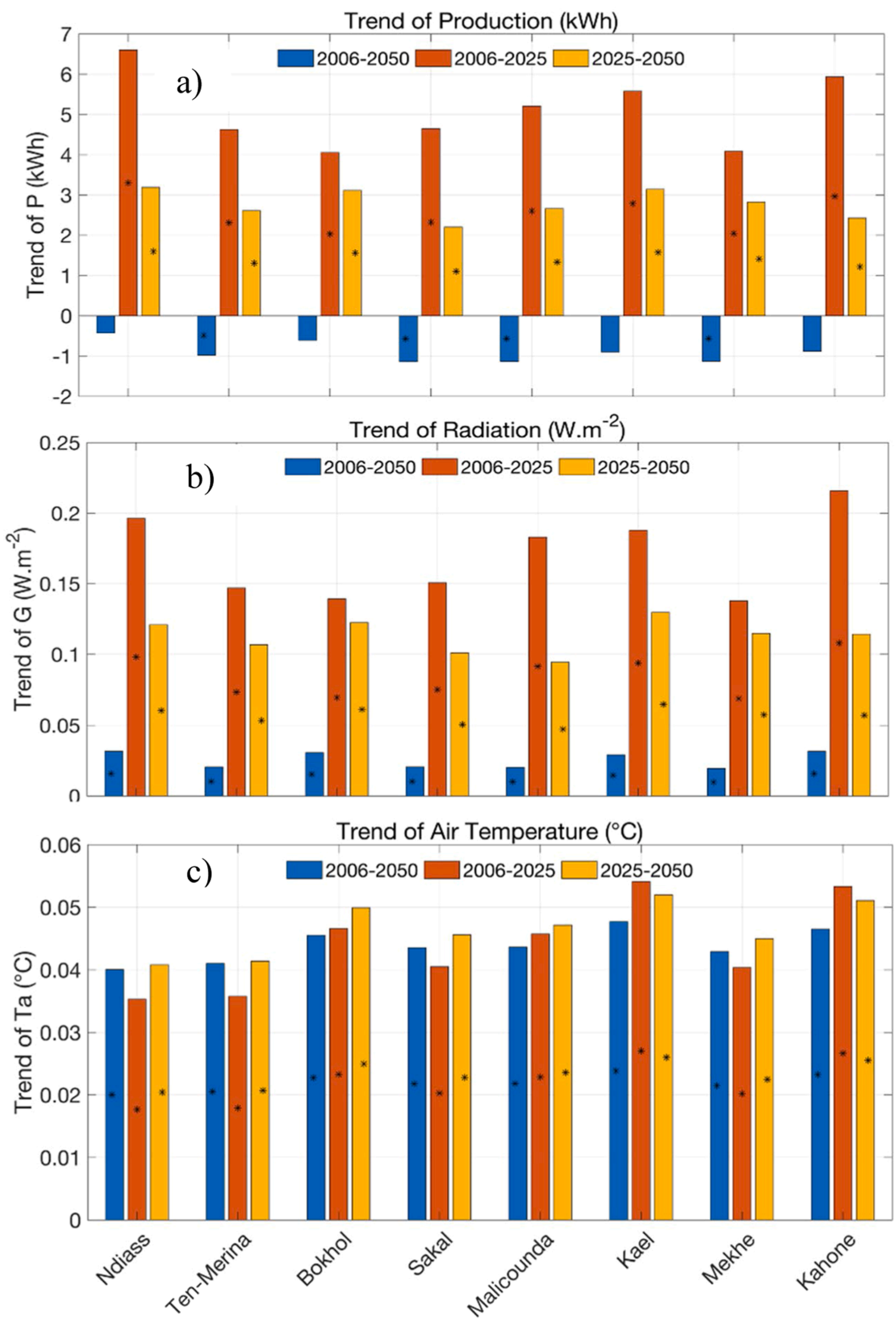

Fig. 6. Projected trend of the variables for all the solar plants considered in this study for the periods 2005–2050 (blue), 2006–2025 (orange), and 2025–2050 (yellow): (a) for the energy production (kWh), (b) for the solar radiation (W.m-2) and (c) for the air temperature (°C). The stars indicate the period where the trend is significant at 90 % using the Mann-Kendall test.

same for all the plants. The projected trend is significant for four solar plants, which exhibit the highest decrease: Malicounda, Sakal, Mekhe, and Ten Merina (Fig. 6a). This observation suggests that Malicounda and Sakal are most affected by factors contributing to the decline in production, resulting in a more significant decrease compared to the other plants. Nevertheless, these plants, along with the other plants that are less affected, are all located in the west, where a smaller decrease has been observed. This suggests a lesser decline in future production in that region as compared to the southeast region. The southern, southeastern, and central parts of the country will experience more decline as compared to the western part when considering the projection of the ensemble mean of the GCMs (Fig. 5d).

The projected decrease in production can be attributed to various factors. Fig. 6b, and c display the projected trends in solar radiation and air temperature for the solar plants, respectively. A decreasing trend in solar radiation is observed for all the plants, which is significant across all stations. Additionally, a significant increase in air temperature is noted for almost all solar plants. This aligns with the projected reduction in solar irradiance and the anticipated rise in temperature across West Africa, as illustrated by Ndiaye et al. [23], which could contribute to the decline in production. Many studies investigated the relationship between meteorological factors and PV performance and found a strong relationship between solar radiation, temperature, and PV performance [30,51,52]. In addition, Jong Yoo et al. [53] found a positive correlation between plant power generation and solar radiation and temperature and concluded that solar radiation influences solar power generation more than temperature, but both must be considered for an accurate prediction of solar power generation. This finding is consistent with the results at the Kahone station, where a decrease in temperature is observed, yet the sharp decrease in solar radiation led to a decline in solar power production.

However, in practice, another potential reason for the decrease could be the aging or degradation of solar panels over time. Factors such as exposure to harsh weather conditions, accumulation of dust, and material degradation can adversely affect the performance of solar panels [54–56]. However, in this study, we only looked at the meteorological factors.

4. Conclusion

This study investigates the future production of solar PV plants production over Senegal. This study provides the first attempt to assess the future solar production in Senegal. RegCM4 driven by three GCMs (NorESM1-M, MPI-ESM-MR, and HadGEM2-ES) from CMIP5 was used. Observed production of the Ten Merina solar plant was used to validate the reconstructed (modelled) production, demonstrating a successful reconstruction of solar production at this plant. Then, this method was used to analyze the future trend of solar energy production across Senegal.

The estimated solar energy production with ERA5 shows a good representation of the temporal variability of the observed production with some minor relative biases (<10 %). The seasonal cycle of solar production over Senegal (Ten Merina) is largely influenced by solar radiation, with peak production occurring in March-April and the lowest production during the rainy season (July-September). This demonstrates the dependence of solar production on climatic conditions. For the future, the projected production of Ten Merina and other solar plants indicates a decreasing trend over the period 2006 – 2050. Malicounda, Sakal, and Mekhe are projected to experience the highest decrease.

It's worth noting that the trend of solar production across the country is initially characterized by an increase from 2006 to 2025. However, the models project a decline in production across all solar plants from 2025 to 2050. This decline could be explained by the variation in the solar irradiance and ambient air temperature. The decreasing trend in solar production is associated with a decreasing trend in solar irradiance and an increase in air temperature. To mitigate the projected decline in solar energy production, policymakers should prioritize diversifying the renewable energy portfolio by investing in complementary sources such as wind and hydropower. Additionally, enhancing the efficiency of future solar PV projects by using cooling systems technologies to mitigate the effect of rising temperatures, can help optimize output under a changing climate.

This is the first attempt to see the future of the solar plant's production in Senegal. Further analysis and investigation are necessary to identify the specific factors causing the production decline in each plant and develop suitable mitigation strategies. In this study, only meteorological factors are considered. Other factors that could contribute to a decrease in the production of these plants are not covered. While meteorological factors are important, a more comprehensive analysis with specific data on each plant that considers a broader range of factors would help to fully understand the reduction in production. Future research should integrate non-meteorological factors such as dust accumulation, the aging of the panels (material fatigue), etc. This approach would provide more insights, and appropriate measures can be implemented to address the issues and optimize power generation. The method used in this study can be applied to other countries, as it depends on site-specific data. With access to these parameters, the approach can be adapted to estimate solar energy production in any location, including across West African countries.

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CRediT authorship contribution statement

Aissatou Ndiaye: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Dahirou Wane:** Writing – review & editing, Visualization, Methodology. **Cheikh Dione:** Writing – review & editing, Supervision. **Amadou Thierno Gaye:** Writing – review & editing, Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could influence the work reported in this paper.

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Data availability

The observed data from the solar plant used in this study are not publicly available. The CORDEX-CORE and the ERA5 data can be downloaded respectively from https://cordex.org/data-access/esgf/ and https://www.ecmwf.int//en/forecasts/datasets/reanalysis-datasets/era5.

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