Energy for Sustainable Development 86 (2025) 101709

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Prioritisation of clean energy interventions in Sub-Saharan Africa: A geospatial multi-criteria decision support tool

Magda Moner-Girona [b,c], Luca Battistella [a,*], Irene Angeluccetti [a], Paola Casati [a,d], James Davy [e], Andreea Tanasa [f], Marco Pittalis [a], Sándor Szabó [a], Natàlia Caldés [g]

[a] *European Commission, Joint Research Centre (JRC), Ispra, Italy*
[b] *Renewable and Appropriate Energy Laboratory, UC Berkeley, USA*
[c] *MonEner - consultant at JRC, Ispra, Italy*
[d] *Jonian Department in Legal and Economic Systems of the Mediterranean, University of Bari, Taranto, Italy*
[e] *Piksel - consultant at JRC, Ispra, Italy*
[f] *Delegation of the European Union in Cotonou, Benin*
[g] *European Commission, Directorate General on International Partnership, Brussels, Belgium*

ARTICLE INFO

Keywords:
SDG7
Web-GIS
Clean Energy
Energy access
Planning
Sub-Saharan Africa

ABSTRACT

Over 570 million people across Sub-Saharan Africa in 2022 lack access to clean energy, a stark contradiction given the continent's considerable untapped potential for renewable resources. This discrepancy results from historical underinvestment in the energy sector. In response to this challenge, this paper contributes to the advancement of sustainable energy in Sub-Saharan Africa, aiding the shift toward a low-carbon transition future. We introduce the Clean Energy Access Prioritiser, an open-source tool designed to guide decision-making for clean energy interventions and investments. The tool, which operates as a web-based, multi-criteria platform, facilitates the identification of feasible areas by integrating environmental, climate-related, and socio-economic factors. The Clean Energy Access Prioritiser allows stakeholders to identify priority areas for clean energy projects through an integrated spatial planning approach. It combines a suite of 25 variables to evaluate areas most and least suitable for investment—hot and cold spots—based on user-defined priorities, using a 5 km grid. As an instrument for strategic planning, the Clean Energy Access Prioritiser holds value for a range of actors involved in energy development. Institutional and private entities, including policymakers, international donors, government agencies, and philanthropic investors, stand to benefit from its data-driven insights. By leveraging this tool, stakeholders can make informed decisions that align with sustainable energy goals and promote the equitable distribution of clean energy resources across Sub-Saharan Africa.

Introduction

It is forecasted that Africa's need for electricity will experience a twofold increase by the year 2030 and an eightfold surge by 2050 (International Energy Agency (IEA), 2022). Fortunately, the continent boasts a vast potential of renewable energy sources. Africa has immense solar energy capabilities estimated at 10 terawatts, along with significant hydropower (350 gigawatts), wind (110 gigawatts), and geothermal energy (15 gigawatts) (Sustainable Energy forAll (SEforALL) and the Climate Policy Initiative (CPI), 2019). However, the continent faces significant challenges in harnessing this potential due to limited resources, infrastructure, and investment, with 570 million people lacking access to electricity and 970 million without clean cooking fuels across Sub-Saharan Africa (IEA et al., 2024; International Energy Agency (IEA), 2022). This situation presents a critical paradox that is rooted in historical underinvestment and necessitates immediate action to pivot Africa toward a sustainable and energy-secure future.

The subject of clean energy access in Sub-Saharan Africa is important now more than ever due to the global urgency to combat climate change and achieve sustainable development. The continent's growing population and economic potential links to the achievement of SDG7, which aims to provide universal access to affordable, reliable, and modern energy services. The current global emphasis on low-carbon transitions and the increasing viability of renewable technologies make this a

* Corresponding author.
E-mail address: Luca.BATTISTELLA@ec.europa.eu (L. Battistella).

https://doi.org/10.1016/j.esd.2025.101709
Received 18 December 2024; Received in revised form 6 March 2025; Accepted 13 March 2025
Available online 30 March 2025

favourable time to address clean energy opportunities (International Energy Agency (IEA), 2023). Achieving energy policy priorities requires huge financial commitments to bridge the energy access gap in Sub-Saharan Africa (International Energy Agency (IEA), 2022). Translating these policy priorities into concrete projects necessitates decision-making tools that effectively integrate environmental, social, and economic domains, enabling access to clean energy.

When strategic planning for energy access interventions, it is crucial to consider a multi-sectoral approach, such as the Water-Energy-Food (WEF) nexus (Botai et al., 2021). This approach provides a vital framework for integrating these challenges and ensuring sustainable progress toward the Sustainable Development Goals (SDGs). Energy production requires water; water supply needs energy; and food production depends on both water and energy. This interconnectedness underlines the necessity for integrated planning and policy-making that considers the potential synergies and trade-offs. By adopting a nexus approach, we can ensure that interventions in one sector do not inadvertently compromise sustainability in another, thus promoting coherence across these critical domains (Nhamo et al., 2020).

Multi-Criteria Analysis (MCA) has emerged as a valuable tool for evaluating and selecting clean energy projects (Estévez et al., 2021; He et al., 2018; Shiraishi et al., 2019). In the context of prioritising clean energy projects, MCA can help policymakers, investors, and other stakeholders evaluate interventions based on diverse factors beyond simple cost metrics, including environmental and social factors. This comprehensive analysis is particularly crucial in Africa, where the energy landscape is complex and multifaceted. For instance, a report by the African Development Bank used MCA to evaluate renewable energy projects in sub-Saharan Africa and identified solar, wind, and hydroelectric power as the most promising sources of clean energy (AfDB, 2022). Another study by the World Bank used MCA to assess the feasibility of wind energy projects in South Africa and identified several projects with high potential for electricity generation(The World Bank Group, 2014).

Decision support tools for prioritising areas for energy investment traditionally vary from web-based data catalogues and mapping platforms, like the European Commission's Africa Knowledge Platform, Energy Access Explorer, IEA- Africa GIS Catalogue for Energy Planning, IRENA Global Atlas, VIDA, Prospect, Powerhive to specific energy planning or optimization software such as OnSSET, Reference Electrification Model (REM), World Bank Global Electrification Platform(GEP), OffgridPlanner, and HOMER, MicroGridsPy (Stevanato et al., 2023, Dimovski et al., 2023, 2024 or Juanpera et al., 2022). Effective decision support tools that utilize MCA can bridge the gap between both approaches, making them accessible to a broader range of stakeholders and facilitating the implementation of clean energy projects. If web-based platforms are more accessible to non-specialists, these usually lack the functionality to integrate and weight different input layers. By contrast, systematic energy planning models are designed to consider multiple input criteria, but they can be confusing to non-experts (Moner-Girona et al., 2018; Morrissey, 2019). The balance between simple, but generic, decision support tools and those that are tailored, yet complex, can affect whether spatial energy planning ultimately leads to implementation at a needed scale. For instance, rural electrification plans that emphasise social infrastructure tend to adopt a more collaborative approach by engaging non-academic stakeholders, from governments to NGOs. Moreover, implementation-focused plans are less likely to rely solely on computer-based analyses but also include equal contributions from expert knowledge. This suggests that planning that involves diverse inputs from non-technical stakeholders may improve implementation because it embeds the planning process into existing socio-economic systems.

As countries and regions mature through the energy planning process, they generally start with plans derived from larger planning units at the national scale, and then subsequently progress to high resolution sub-national plans during later iterations. This natural evolution emphasizes the need for decision support tools that can help fill the gap in functionality between basic web-based visualization platforms and sophisticated systematic planning software, especially for African countries in the early stages of their spatial electrification planning process. Such tools would ideally include many of the same datasets as web-based platforms, while allowing users to integrate and weigh these data based on stakeholders needs.

Our article introduces the Clean Energy Access Prioritiser (CEAP), a tool that embodies the MCA approach in guiding clean energy interventions in Sub-Saharan Africa (SSA). The CEAP integrates 25 geospatially referenced indicators, enabling stakeholders to identify areas of high priority. It does not aim to replace advanced energy planning approaches that optimise the least-cost technology, but rather to provide users a user-friendly tool to identify areas of importance based on criteria that they select and weigh themselves. This tool facilitates the alignment of energy development initiatives with broader sustainable goals, by addressing as well other sector such as water, environmental, and food security and social factors. By adopting a holistic approach to sustainable development, it facilitates the prioritisation and scaling up of clean energy projects across Sub-Saharan Africa.

Future work on the CEAP will involve expanding its capabilities to include more detailed datasets, such as specific technology costs, financing options, and policy analysis. This will enhance the tool's precision and relevance, enabling stakeholders to make even more nuanced decisions regarding clean energy investments. Ultimately, the CEAP aims to support a transition to a sustainable energy future in Africa by facilitating informed and strategic planning across the continent's diverse energy landscape.

In the following sections, we first describe the steps for the construction of the Clean Energy Access Index and the datasets included in *Clean Energy Access Prioritiser*. Next, we present the IT architecture underlying *CEAP* and how different datasets are integrated mathematically during analyses. Third, we showcase *CEAP's* functionality using a case study of Benin, a country with several existing electrification plans that can be used for validation. Lastly, we propose future *CEAP* developments.

Material and methods

The development of the CEAP Index involved four steps (Fig. 1). First, we proceed with a comprehensive collection of granular spatial data to effectively support the identification of planning priorities in the energy access domain. Second, we construct and assess the structure of the Clean Energy Access Prioritiser Index. Third, the selected spatial data undergoes a normalisation process and is transformed into readily accessible Vector Tile services. Fourth, we combine these multiple spatial variables into single index at planning unit level after allowing users to weigh the relative importance of datasets in their prioritisation process. Finally, dedicated algorithms are developed to create a user-friendly online tool to rank planning units based on the prioritisation criteria selected by the user (Battistella et al., 2024).

Structure of the Clean Energy Access Prioritiser Index

The construction of the CEAP index was based on a shift away from average country-level indicators and away from an existing dominant focus on cost analysis or alternative mono-dimensional qualitative measures, while also drawing inspiration from Amartya Sen's insights into addressing deprivations and capabilities essential for living a basic human life (Sen, 2006).

To assess clean energy interventions according to stakeholder priorities, it is essential to concurrently evaluate multiple dimensions not only at the national or sub-national levels, but also at higher geographical resolution. The composite indicator was designed to measure the multidimensional factors that cannot be adequately represented by a single indicator alone. These multidimensional factors

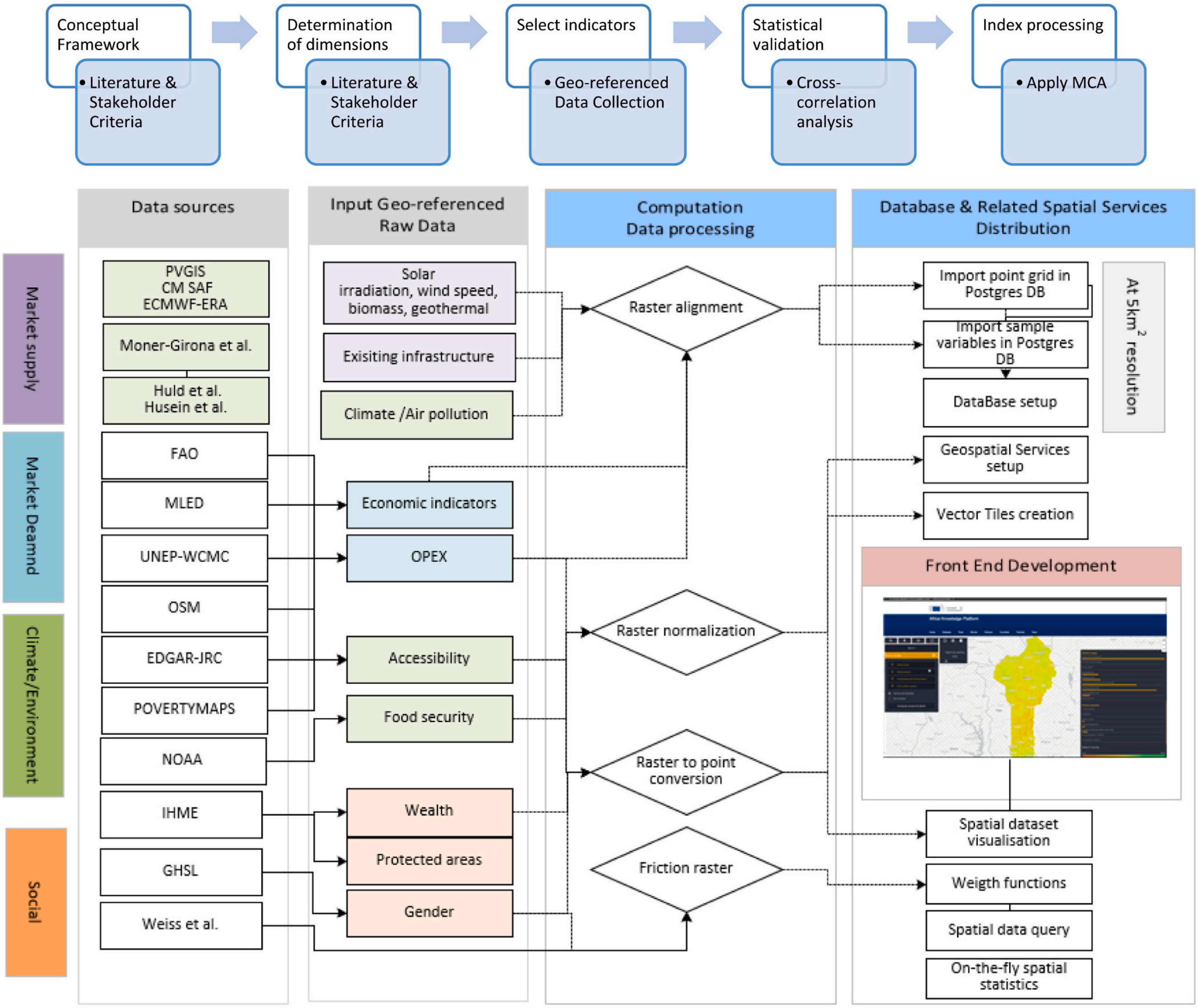


Fig. 1. Steps for the construction of the Clean Energy Access Prioritiser Index.

primarily include market supply/demand, social, climate, and environmental considerations, which constitute the four pillars of the CEAP index (Fig. 2). In order to accurately reconcile these multiple dimensions within a composite indicator that goes down to higher geographical resolution, the holistic structure of the CEAP index was informed by an extensive review of the existing literature, including whitepaper reports, academic papers and press releases which focused on specific sets of thematic indicators. The grouping of indicators within the pillars was informed by an expertise consultation involved in the clean energy sector in Africa and continued review of the literature (Table 1).

Once the structure had been built in alignment with the existing literature and stakeholder expertise, and populated with indicators, the validation and robustness assessment of this structure was followed using correlational assessments (detailed below). The approach employed in crafting the Clean Energy Access Index draws upon the JRC-COIN methodology, developed by the Joint Research Centre's Competence Centre on Composite Indicators and Scoreboards (Joint Research Centre-European Commission, 2020).

Data selection

The CEAP initially employed datasets selected based on the PV-DEI (Bender et al., 2021; Joint Research Centre-European Commission, 2021; Moner-Girona, Bender, et al., 2021) and the Social CEA indicators (Casati, Moner-Girona, Khaleel, et al., 2023; Casati, Moner-Girona, Shehu, et al., 2023) structure as a foundational framework for developing the *CEAP index*. However, given the extensive nature of the indicator list, which primarily concentrated on private investments in decentralised energy, adjustments were required. An important enhancement is that the previous indices were tailored to assess energy access at national level, relying on secondary information and thus lacking in geo-referenced datasets, particularly in areas where socio-environmental conditions are different from other areas. Data selection and availability played a critical role in determining the overall quality of the CEAP. A combination of literature review and expert consultations including 3 experts from the Global Technical Assistance Facility for Sustainable Energy, the Delegation of the European Union to Benin – Energy Sector, and Directorate-General for International Partnerships - Climate Change and Sustainable Energy unit informed the construction of its hierarchical structure. The quality of the geo-referenced datasets was evaluated based on various criteria, including the reliability and accessibility of the data source, methodological soundness in data collection and processing, data accuracy and reliability, and frequency of updates (International Monetary Fund, 2019).

For the indicator data itself, quality assessment relied on criteria outlined by the OECD/JRC European Commission in the 'Handbook on

Fig. 2. Structure of the Clean Energy Access Prioritiser Index determined per planning unit (depending on user weights).

Constructing Composite Indicators' (OECD/JRC, 2005). Following these guidelines ensured that datasets were relevant to the overall purpose of the CEAP, measured within an appropriate timeframe, sensitive to changes in the phenomenon of interest, interpretable, complete with clear definitions, coherent across Sub-Saharan African countries, accurate, and reliable. The variables included in the CEAP are reported in Table 1, together with the source dataset used for computing the average values per planning unit.

Data treatment: projection, resampling, and normalisation

The methodologies employed in constructing the CEAP index and in the manipulation of the spatial datasets indicators had the potential to distort the results derived (Becker et al., 2019). Consequently, meticulous attention was devoted to examining the implications of the decisions regarding normalisation techniques, the handling of missing data, and the procedures to weighting and combining raster data. Initially we ensured indicators were comparable across SSA countries with diverse population sizes, land areas, and natural resources.

The completed data sets were normalised to ensure comparability between indicators that existed at different scales and ranges, and were measured in disparate units. Using the rescaling technique and min-max method for normalisation, all indicators had the same range and can be spatially compared. For example, raw data on total number of health centres without access to electricity in a specific country was intensified by dividing it by the total number of facilities, to make this indicator comparable across countries. After the intensification, we transformed each of the input datasets so that the minimum value was 0 and the maximum value was 1 for continuous data, keeping the shape of the original data distribution.

Automatization of spatial data processing

A custom script was designed to automate the data processing, enabling a standardised procedure of the spatial datasets and in a later step enabling the unified integration into the website's interface (steps summarised in Fig. A.2). The Python script consists of 5 main blocks:

- Creation of a baseline raster layer with a resolution of 5 km × 5 km per pixel at the equator for the analysis at SSA level. This resolution is fine enough for intra-country spatial prioritisations, yet coarse enough to avoid computation performance issues or errors of commission (false-positives) for the datasets.
- All inputs datasets were reprojected from their original projection to the same Coordinate Reference System projection (EPSG: 54009), a computationally efficient variant of the Mercator projection, commonly used for web mapping.
- The original raster datasets were resampled to conform to the baseline grid, selecting resampling technique based on the characteristics of each original raster including resolution, i.e. whether upscale or downscale was needed. For most of the continuous rasters, we used the Average Resampling method, which calculates resampled pixel values based on the average value of overlapping pixels. For discrete rasters, we used the Nearest Neighbour method to calculate the resampled pixel value using the nearest input pixel.
- Each of the input datasets was normalised on a country-by-country basis within the 0–1 range.
- To perform spatial queries, data was transformed into a point vector layer, by using the baseline layer at 5 km grid, obtaining point features for the centre of each individual pixel. Each point included the values of the input datasets as values in its attribute table, as well as country ISO 3 code obtained from a spatial join with the Global Administrative Unit Layers (GAUL).

Structural assessments

To identify the underlying structure of the CEAP, correlations of georeferenced variables were conducted. Initial correlational investigations were conducted using Pearson correlation. This analysis helps to understand how the values of one indicator relate to the values of another indicator across the same geographic extent. Fig. 3 shows the correlation matrix plot (Pearson correlations) which highlights the absence of strong correlations between independent variables within the same Pillar (Market Supply, Market Demand, Socio-Political Aspects, Environment and Climate). The histograms of each indicator are displayed

Table 1
Raw datasets, resolution and source.

	Dataset	Description	Unit	Spatial resolution	Source: methodology and dataset platform
Market supply	Solar potential	The solar potential is measured by the long term yearly average of global horizontal irradiation in the selected area.	Wh/m^2	1 km^2	(Huld et al., 2012) https://ec.europa.eu/jrc/en/pvgis
	Wind potential	Mean wind power density at 10 m height. Higher wind power densities indicate better wind resources.	W/m^2	250 m	(Davis et al., 2023) https://globalwindatlas.info/en/
	Hydropower potential	Annual hydropower potential. It corresponds to the modelled hydropower potential of each location, based on slope and discharge of each river.	GWh/year	250 m	(Hoes et al., 2017) TU-Delft (https://data.4tu.nl)
	Geothermal potential	Total Enhanced Geothermal Systems technical potential with 20 % recovery.	MWe/km^2	18 km	IRENA (https://irena-ga.azurewebsites.net/geoserver/ows/)
	Bioenergy resources	Total biomass production expresses the total amount of dry matter produced over the year.	Kg/ha	300 m	FAO (https://gismgr.fao.org/DATA/WAPOR-3)
	Accessibility	Average time from selected area to nearest city of more than 50,000 people using land (road/off road) or water (navigable river, lake and ocean).	Hours	1 km	(Nelson, 2008; Weiss et al., 2018) Accessibility| Africa Knowledge Platform
	Electricity grid	Existing or planned electric grid lines (LV; MV; HV).	km	vector	(Moner-Girona, Kakoulaki, et al., 2021) https://data.jrc.ec.europa.eu
	Least-cost electricity	Optimal electrification per cluster of population is determined by calculating the levelised cost of electricity (LCOE) of mini-gird, PV stand-alone system (PV/battery or diesel generator) and grid extension		100 m	(Husein et al., 2024)
	Power plants	Geolocation of power plants with installed capacities	MWp	vector	(Gonzalez Sanchez et al., 2021; Gonzalez Sanchez et al., 2020) https://africa-knowledge-platform.ec.europa.eu/energy_tool
Market demand	Productive use	Proportion of surface in the planning unit not covered by built-up non-residential surface. Used for prioritising areas with higher presence of industrial activity, data centres, mining activity.	MWp	10 m	(Pesaresi et al., 2024) Global Human Settlement - GHS-BUILT-C_GLOBE_R2023A)
	Agriculture	Area equipped for irrigation, groundwater irrigation, livestock density. Proportion of surface in the planning unit covered by irrigated areas. Proportion of surface in the planning unit covered by groundwater irrigation. Portion of areas of livestock density.	km^2	10 km	(Siebert et al., 2013) AQUASTAT - FAO's Global Information System on Water and Agriculture, (Robinson et al., 2014) https://wad.jrc.ec.europa.eu/geoportal
	Residential demand	Annual electricity demand per cluster of population.	MWh/year	vector	(Husein et al., 2024; Falchetta et al., 2021) M-LED platform
	Social demand (education and health)	Geolocation and electricity demand of healthcare and education facilities	Number social facilities	vector	(Moner-Girona, Kakoulaki, et al., 2021; Moner-Girona et al., 2025) JRC Data Catalogue| Healthcare facilities JRC Data Catalogue| Educational facilities
Environment and climate	Protected and Conserved Areas	Surface covered by Protected and Conserved Areas.	km^2	300 m	(UNEP-WCMC, 2023) Protected areas| Africa Platform (europa.eu), www.protectedplanet.net
	Temperature anomalies and Drought risk	Variation of average global temperatures. Degree of risk that the area is affected by droughts. Higher risk means that the areas affected will be the most likely to report impacts due to droughts.	degree index	25 km	(Vose et al., 2021) Temperature Anomaly: Yearly (NOAA) (Carrão et al., 2016) Drought risk| Africa Platform (europa.eu)
	Emissions	Annual gridmap for greenhouse gas emissions.	GHG/year	0.1 degree	https://edgar.jrc.ec.europa.eu/dataset_ghg80#p2 (Crippa et al., 2023)
	Air pollution	Annual gridmap for air pollutant emission data CO and PM2.5 - IPCC TOTALS - All sectors.	kg/m^2/s	0.1 degree	https://edgar.jrc.ec.europa.eu/dataset_ap61 (Crippa et al., 2023)
	Access Clean Drinking Water	People with access to clean drinking water o	Percentage	5 km	(Deshpande et al., 2020) https://ghdx.healthdata.org/, https://vizhub.healthdata.org/lbd/wash
Socio-political	Food security	Child growth failure-Severe Wasting	Percentage	5 km	(Kinyoki et al., 2020) https://cloud.ihme.washington.edu, https://vizhub.healthdata.org/lbd/cgf
	Gender balance	Proportion of men/women with less than primary education.	Percentage	5 kmx	(Graetz et al., 2020) https://vizhub.healthdata.org/lbd/education
	Wealth	Relative Wealth Index: predicts the relative standard of living within countries using de-identified connectivity data, satellite imagery and other non-traditional data sources.	0–1	vector	(Chi et al., 2022) http://www.povertymaps.net/#3.76/-12.98/35.1/-15.2/60
	Armed-conflicts	Number of political violence and protest events.		vector	Armed Conflict Location & Event Data (ACLED) https://www.protectedplanet.net/region/AF
	Refugee settlements	Number of refugee settlements derived from Refugee Settlements Electricity Access database		vector	(Baldi et al., 2022) JRC Data Catalogue - Refugee Settlements Electricity Access
	Connectivity	Geolocation of existing cell towers		vector	Open Database of Cell Towers (OpenCellid) https://opencellid.org/downloads
	Development corridors	The georeferenced interlinked tabular and spatial database includes 22 attributes with sources provided for each observation.		vector	(Thorn et al., 2022), https://datadryad.org https://africa-knowledge-platform.ec.europa.eu/dataset/african-development-corridors-database-2022

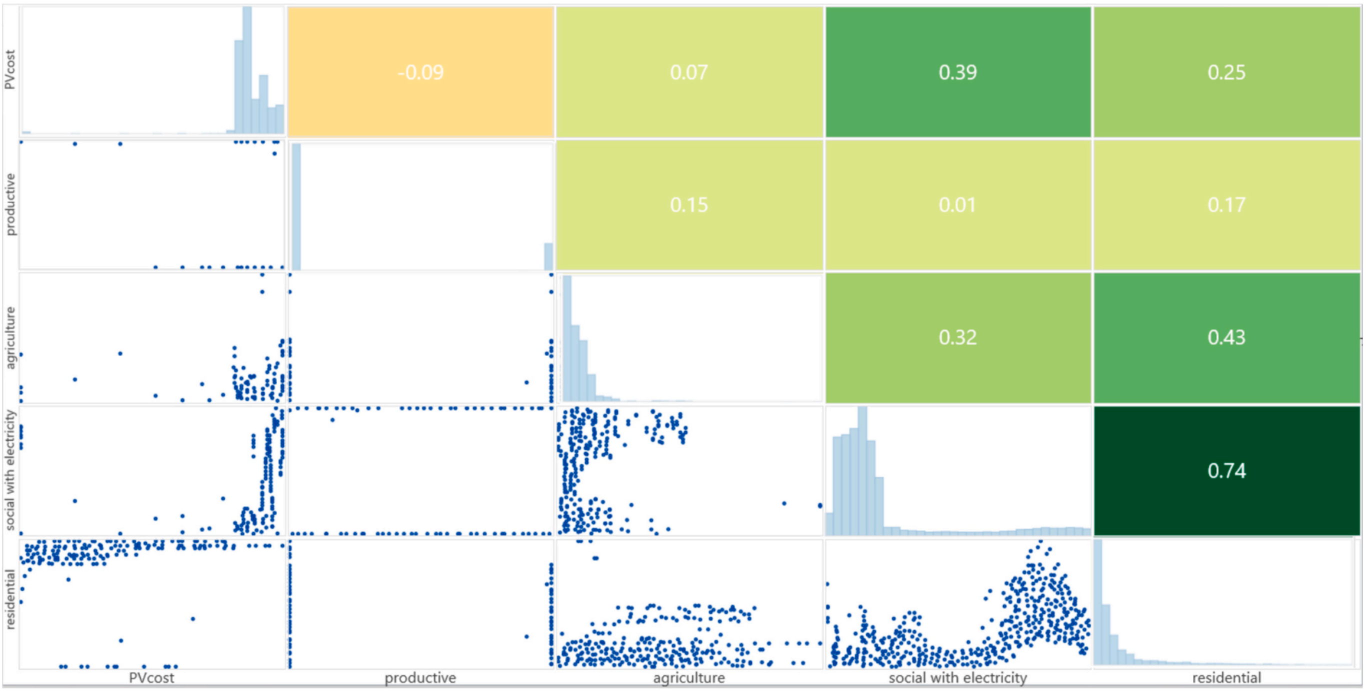


Fig. 3. Correlation matrix plot (Pearson correlations) showing a lack of correlation between independent variables in the same pillars (Market Supply, Market demand, socio-political aspects, environment and climate). The histograms of each indicator are allocated in diagonal of each pillar matrix.

along the diagonal of the matrix for each Pillar. These correlational assessments were undertaken to ensure that indicators within the same sub-pillar were not highly correlated, based on a threshold of $+/-0.7$ for severe collinearity (Dormann et al., 2013), which could render the use of one of them redundant. Cases of strong positive or negative correlations within the same pillar were further investigated to determine whether a theoretical rationale existed for retaining both indicators. For example, in Fig. 3, an examination of the correlation within the market demand indicators reveals a significant collinearity ($+0.74$) between residential and social infrastructure demand, such as schools and healthcare facilities, where a higher population density is typically associated with an increased number of such institutions.

Analyses using Pearson correlation also provided insights into relationships across sectoral variables. For instance, Fig. 4 illustrates potential linkages between solar resources and wealth index, access to clean drinking water and hydropower potential, or food security and gender balance. However, while Pearson correlation is effective for identifying global relationships between variables, it does not account for spatial variability. This limitation is particularly important when working with geographically distributed data, as relationships between variables may vary across different locations (Fotheringham et al., 2006; Fotheringham & Rogerson, 2009).

To address this and strengthen our methodology, we first assessed spatial variability using Global Moran's I (Appendix A) to determine whether the variables exhibited significant spatial autocorrelation. Following this, we employed Geographically Weighted Regressions (GWR) to further explore spatial patterns, Eq. (A1) I in Appendix A. GWR detects spatial variability by allowing relationships between variables to vary across areas (Fotheringham et al., 2006). Building on Pearson correlation, GWR reveals localized patterns and spatial heterogeneity, providing a more nuanced understanding of interactions and identifying areas with stronger or weaker relationships (Fotheringham & Rogerson, 2009). Fig. 5 (A) examines the interaction between the food security dimension and gender balance. Fig. 5 (B) highlights areas where the relationship between these two variables is spatially significant. Regions marked in red indicate areas where higher levels of severe wasting among children are strongly associated with a smaller proportion of men over women with less than primary education. This suggests that in areas with worse child malnutrition, women are disproportionately less educated compared to men, reflecting how severe food insecurity exacerbates existing gender inequalities in educational attainment. Hence, this spatial delineation not only refines the global relationships identified before but also provides critical insights into localized dynamics.

Baseline scenario weights and user-defined weights

The *Clean Energy Access Prioritiser* ranks and prioritises point-based planning units based on the Clean Energy Access Index, CEAP, calculated as:

$$CEAP = \frac{1}{N}\sum^{j}\sum^{i} w_i f_{i,j}$$

where, $f_{i,j}$ is the standardised value of the indicator i in planning unit j,

w_i is the user-assigned weight for the indicator i,
N is the total number of planning units

In the baseline scenario all CEAP indicators are equally-weighted (set to $w_i = 1$), which means that each CEAP indicator is equally important in the analysis. Users can choose to exclude an indicator from the analysis, setting $w_i = 0$, or increase the weight up to 10 (which suggests that the selected indicator is 10 times more important in the prioritisation). The number of planning units, N, varies depending on the user-selected geographic area being analysed.

Developing the web application

In order to provide a widely available and customisable tool with a transparent source code, we exclusively used open-source approaches. Not only do these tools allow for customisable web-mapping applications, but they also form part of a mature and proactive user-community. This makes it easier to build advanced solutions in a knowledge-sharing domain.

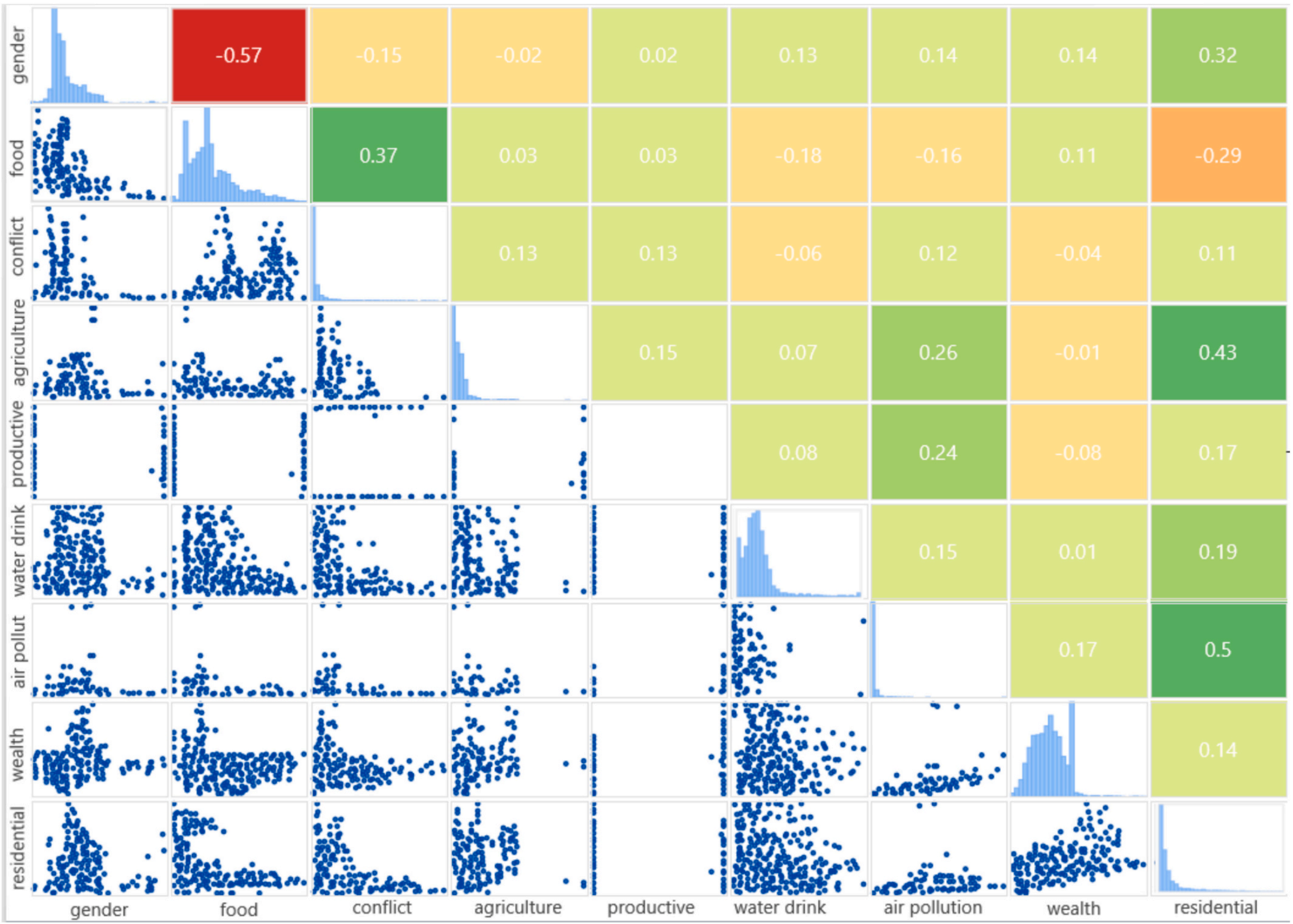


Fig. 4. Cross-correlation matrix for indicators between pillars. Scatterplots (lower left in the matrix), histogram of indicators (diagonal graphs), Pearson r correlation (upper right of in the matrix).

Web database and spatial services

We published the point grid as a Vector Tile geospatial service (.pbf). This service is made available through GeoServer Fig. 6, which is an advanced open-source server designed for sharing geospatial data over the web. The original point grid was stored in a Postgres database, with a PostGIS extension as an indexed materialised view that stores pre-computed query results to optimise performance.

Usually, vector layers that need to be queried on a web map are served as Web Features Services (WFS), though the GeoJSON format (Dorman, 2020). However, Vector Tiles respond faster than WFS, because it uses an integrated cache system called GeoWebCache, a tiling server running as a proxy between a map client and map server. GeoWebCache stores tiles as they are requested, eliminating redundant request processing and thus saving large amounts of processing time.

Front-end development

The front-end includes four main components Fig. 7. The first component provides the geospatial visualization of *Clean Energy Prioritiser's* mapping functionality, both globally and at a national level once a country is selected. The second component shows the weight functions section, which visualises the energy features across the planning domain and allows users to weigh the features. The third and fourth components are analytical components, which allow users to analyse a subset of the planning domain using a regular rectangle or a self-drawn polygon, respectively. These components are based on JavaScript frameworks - Mapbox GL, JQuery, and ChartsJS - to produce the dynamic web application. Mapbox GL allows for data-driven styling capabilities within property functions, which render features based on user-determined properties or zoom level.

User-based spatial selection

To enable user-defined spatial queries, we used TurfJS, a lightweight open-source JavaScript toolkit for conducting spatial operations directly in a browser. It works by taking geometry inputs as GeoJSON from the Vector Tile features and mapping these with Mapbox GL. Users can perform spatial queries by drawing rectangles or irregular polygons on the map and *CEAP* computes statistics on-the-fly. Outputs are presented as a radar plot that compares the energy features from inside the selected area with the average values across the whole country.

Results and discussion

The CEAP is an open-source decision-support tool designed to assist in the identification of priority areas for clean energy interventions and investments. It incorporates a multi-sectoral approach, including environmental and socio-economic factors, to guide policymakers and stakeholders in making informed decisions about where to allocate resources effectively. The tool's functionality and the significance of its results are demonstrated through the application to Benin, which serves as a case study to explore the potential of the CEAP under various policy scenarios.

To ensure the consistency and robustness of the CEAP index, we ran Pearson correlation within each pillar (i.e., Market Supply, Market Demand, Environment and Socio-Political), which confirmed the absence

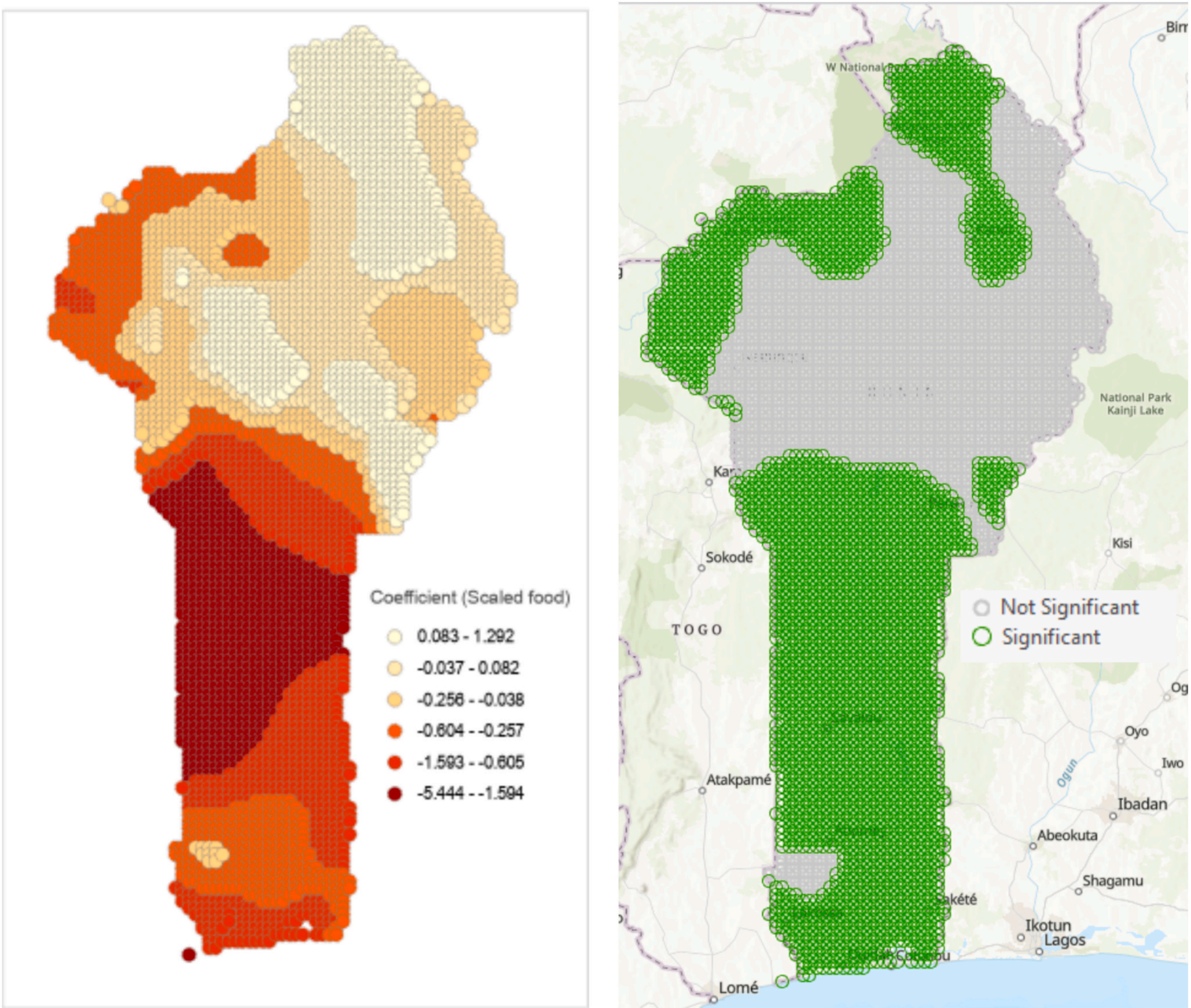


Fig. 5. (A) Significant GWR coefficients gender empowerment and food security (dark red strong positive significance, yellow fades low GWR coefficient (B) Significant (green), not significant (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of strong multicollinearity among the indicators. Expanding the analysis to explore relationships across different sectoral indicators, Pearson correlation revealed meaningful connections. Notably, a significant association was identified between gender balance (proportion of men over women with less than primary education) and food security, particularly severe wasting among children. This underscores the interplay between educational disparities and malnutrition, suggesting that addressing these interconnected challenges requires integrated actions. To further explore the spatial variability in these relationships, we employed Geographically Weighted Regression (GWR) as a supplementary analysis. This approach revealed that the negative relationship between severe wasting and lower educational attainment among women is not uniform across regions. In some areas, the correlation is strong, highlighting a significant and negative link between malnutrition and educational disparities, while in few territories, the connection is weaker or not significant. This underscores the importance of tailoring clean energy interventions to the different social conditions, ensuring that strategies are responsive to local needs and address the unique challenges faced by specific communities.

The CEAP provides a quantitative framework for prioritising areas for intervention. High CEAP scores denote areas with more significant priorities for energy access interventions, based on the user-selected criteria and weights. In our analysis, the CEAP was used to evaluate the baseline scenario and four policy scenarios reflecting the current European Union-African Union (EU-AU) strategies. Upon the selection of a country from the African map within the *CEAP* interface, the nation-specific scores are automatically presented. The baseline scenario established a default setting that assigned equal weight to all indicators ($w_i = 1$ for each indicator), giving each factor the same level of influence in determining priority areas. This comprehensive approach ensures that no single factor is undervalued in the decision-making process.

One of the features of the CEAP is the ability to exclude protected areas from analysis. This is crucial when the goal is to pinpoint the top-ranked sites for clean energy projects while respecting environmental conservation efforts.

Hotspot analysis

The CEAP concentrates on conducting hotspot analysis (CEAP index per planning unit) to identify areas with significantly high (green unit Fig. 8A) or low values (red unit Fig. 8A), thereby revealing areas that are most appropriate for targeted interventions based on the intensity and

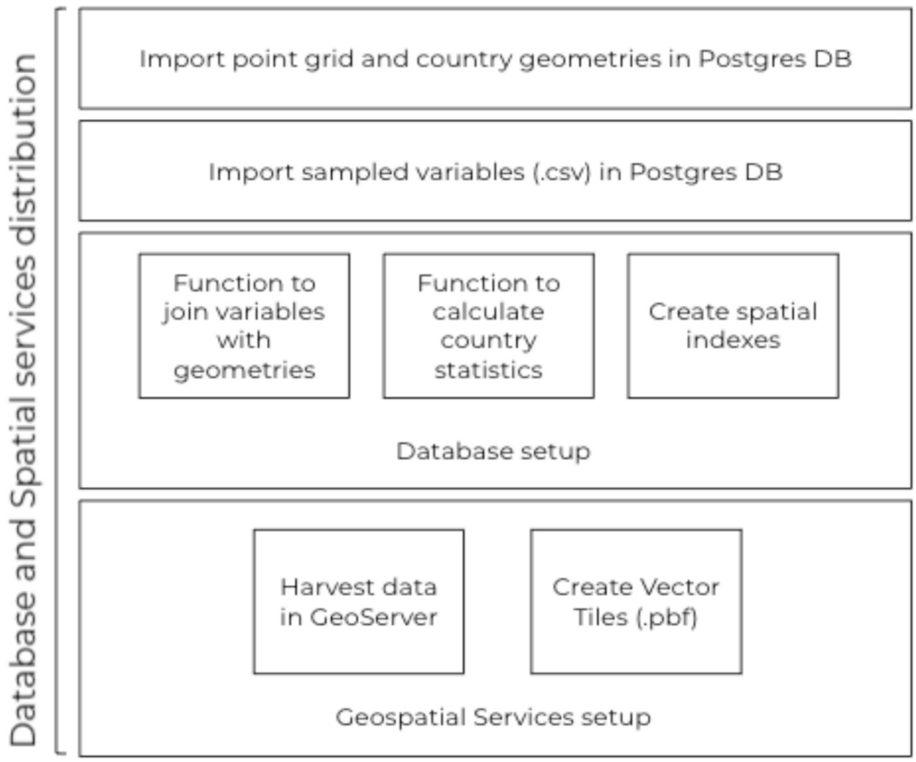


Fig. 6. The workflow used to set up the underpinning database and related spatial services that underlie Clean Energy Prioritiser.

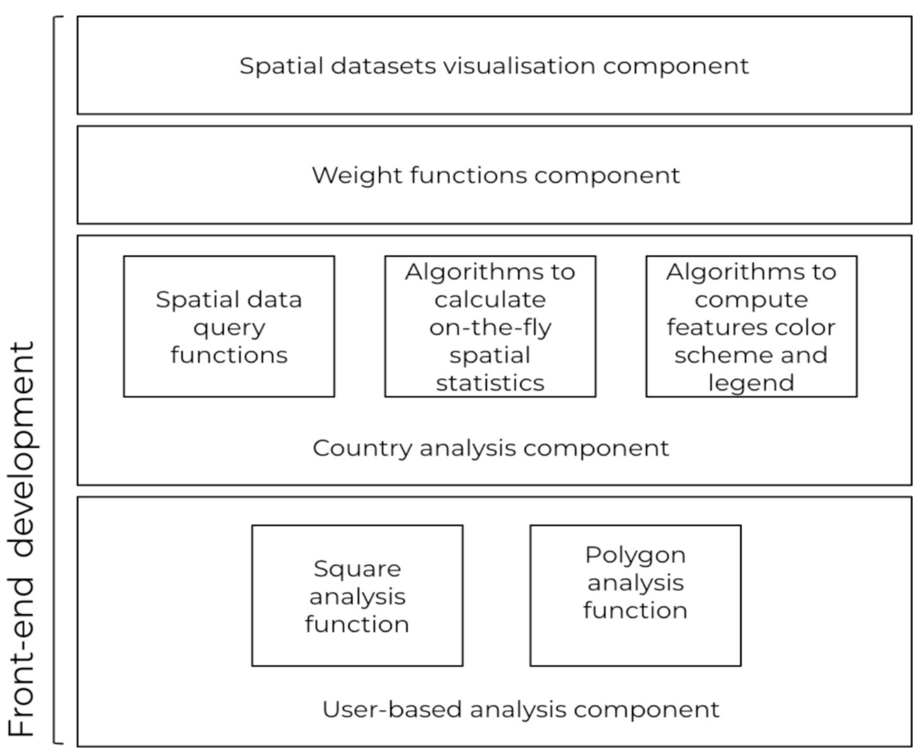


Fig. 7. The workflow for front-end development for Clean Energy Access Prioritiser

clustering of the concerning combination of indicators.

The CEAP also allows to identifying the highest scoring planning units under the user-selected criteria, these are areas with the greatest potential for intervention based on the selected criteria and are represented as a percentage of the country's total area, typically between 0 % and 30 % (In blue in Fig. 8B). Therefore, the tool efficiently pinpoints the top hotspots for clean energy access within the national landscape.

For a more granular analysis, the CEAP offers the functionality to draw a custom-shaped polygon over a subset of planning units, thereby allowing users to examine into specific regions of interest. A radar plot is

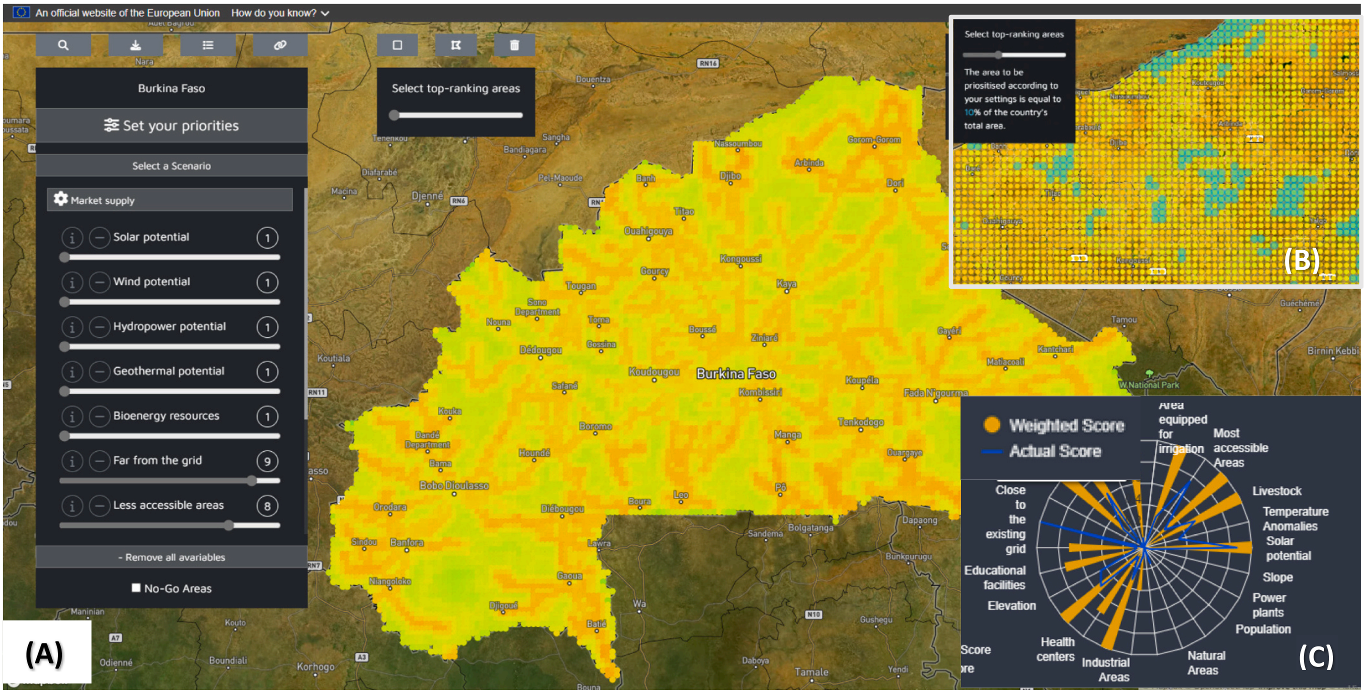


Fig. 8. (A) The Clean Energy Access Prioritiser for Burkina Faso. (B) Selection of the 10 % top ranking area of the country's total area. (C) Summary radar plot for the selected area relative to the whole country and the existing protected area network.

then generated to summarize and compare the features of the outlined area against the national landscape as a whole. This comparative visualization aids in comprehending how different weightings of the indicators affect the ranking of the selected area, providing insights into the strengths and weaknesses of a particular area.

Fig. 8A-C depicts the CEAP interface for Burkina Faso, the selection process using a customized polygon, and the summary radar plot, respectively. These tools are instrumental in visualizing and interpreting the results of the prioritisation process.

The CEAP tool emphasizes the importance of identifying hotspot areas where to prioritize interventions in clean energy access that might otherwise be overlooked if decisions were solely driven by market mechanisms. This clearly indicates how policy incentives could influence investment flows compared to the cases when investors would follow an exclusive profit-oriented investment profile (based on the market/community segments with high ability to pay). This approach provides valuable insights for policymakers, helping them determine where interventions and incentives should be targeted, whether at the regional, national, or local level. Additionally, it offers a framework to compare the potential impacts of different policy scenarios, underscoring the tool's value in supporting clean energy access across diverse contexts.

Policy scenario analysis

To demonstrate the adaptability of the CEAP to various policy frameworks, we explored four distinct policy scenarios, each emphasizing different EU-AU strategic criteria (Africa-EU Energy Partnership (AEEP), 2024):

1. Global Gateway Investment Agenda

   It is being implemented through Team Europe initiatives identifying priority areas for investments (European Union, 2022). Aims to support Africa for a strong, inclusive, green and digital recovery and transformation by:
   - Accelerating the green and digital transition
   - Accelerating sustainable growth and decent job creation

2. Human Development, Peace & Security

   Strengthen resilience in fragile contexts and address the root causes of humanitarian challenge (NDICI – Global Europe, 2021; OECD, 2022). The foundations of peace and security can also be undermined by the acceleration of climate change and environmental degradation, the unintended consequences of energy transition, struggles for control over strategic areas, critical infrastructure, resources and technology.

3. Enabling environment - 360-degree approach: high social, environmental and governance standards
   - Enhances respect for human rights, the rule of law, non-discrimination
   - Strengthens health systems and improves education and training
   - Promotes decent work, gender, youth, social rights and reduction of inequalities

4. Africa-EU Green Energy Initiative

   Connects the two continents to facilitate the achievement of universal access to affordable, sustainable and modern energy in Africa (African Union & European Union, 2024). It does this by supporting and informing relevant political processes and initiatives across the two continents, by mapping, monitoring and convening relevant actions and stakeholders, and by enhancing data and knowledge for decision-making.

Each scenario was tailored with the CEAP to reflect the specific priorities of the respective policy. Different weights were assigned to the CEAP variables, with certain factors assigned higher values to align with the strategic objectives (see Tables SI1–SI4). Four distinct energy projects were assessed through a series of scenarios, each located in a specific geographical location and featuring different energy technologies and purposes. Please note that these are examples with locations and technologies may vary depending on the specific project goals and requirements. These projects reflect a range of drivers, from market-led initiatives to those designed to accelerate the green energy transition:

Project 1: Photovoltaic power plant

- o Location: Illoulofin, Pobè, Plateau Department, South East Benin, close to the border with Nigeria.
- o Energy Technology: Solar PV Power.
- o Purpose: To generate electricity and serve as a model for renewable energy development in the region. To generate electricity from abundant solar resources, reducing reliance on fossil fuels and promoting energy self-sufficiency in the region.
- o Result of a cooperation with the French Development Agency and the European Union, alongside the Benin government to expand the total capacity to from 25 MW 75 MW (Sonon et al., 2022).

Project 2: Interconnection between Benin and Nigeria

- o Location: from Parakou (Benin) to Shiroro-Kainji (Nigeria).
- o Energy Technology: 330 kV Median backbone interconnection reinforcement project
- o Purpose: It is a West Africa Power Pool key priority to ensure stable integration of the national electricity networks in the ECOWAS Region and to facilitate optimal power exchanges and trading between the Member States (Tractebel Engineering and GDF Suez International Power, 2011; West African Power Pool (WAPP), 2019)

Project 2: Hydroelectric Power Plant

- o Location: on the border of Kouffo Department, Benin and Plateaux Region, Togo
- o Energy Technology: Adjarala Hydropower (147 MW).
- o Purpose: Its objective is to increase power supply and reduce the cost of supply in Togo and Benin. Paradoxically, climate change may alter the availability of these natural resources such as water for hydropower, adversely affecting the financial viability of both existing and planned infrastructures (Batablinlè et al., 2024). The WAPP Project (Phase 3) is co-financed by African Development Bank (AfDB) and the World Bank.

Project 4: Thermal-Gas power plant

- o Location: Godomey, Atlantique Department, South Benin.
- o Energy Technology: Maria-Gléta (450 MW) natural gas and heavy fuel oil power plant
- o Purpose: to augment the power generation capacity of the sub-region (West African Power Pool (WAPP), 2012). The project is sponsored by the Government of Ghana/Volta River Authority (VRA), Ghana's national utility for generation and supply.

This enabled to obtain a first level evaluation of how the "most geographically favourable" areas for energy projects change in response to different policy emphases. The results obtained vary significantly for each scenario, emphasizing the critical role that policy frameworks play in the prioritisation of geographical areas and related energy projects.

In the first scenario of the "Global Gateway Investment Agenda" and

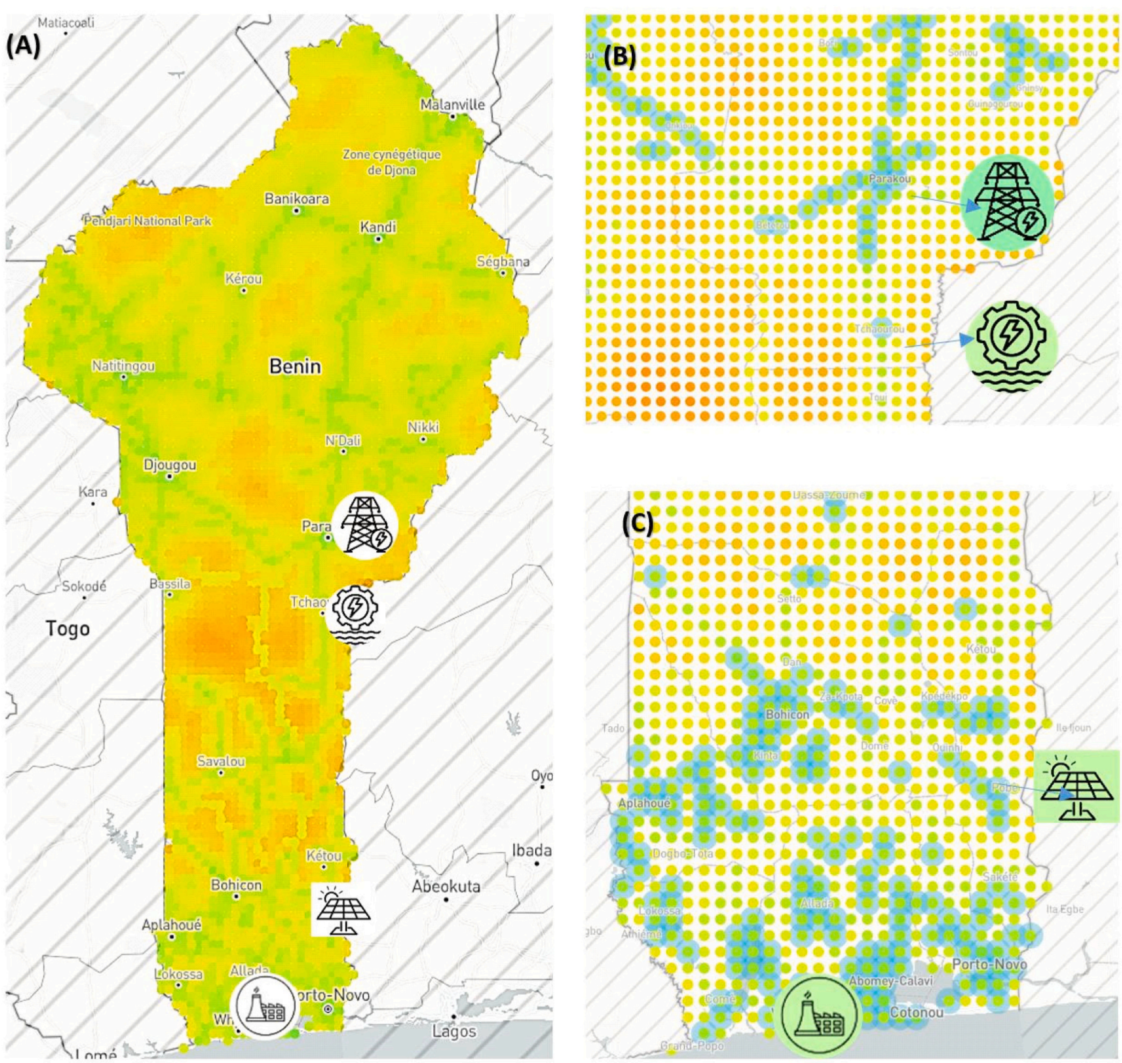


Fig. 9. Representation of the CEAP outputs pertaining to the scenario" Global Gateway Investment Agenda" in Benin. (A) Locations of the four exampled energy projects (B) Area to be prioritised according to the user-defined criteria (highlighted in blue), covering 10 % total area of the country. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

based on the weights assigned to the CEAP variables (see Table SI.1), areas that already had an established electrical grid, power generation facilities, and renewable energy sources obtained a higher level of favourability. Consequently, the four selected projects result situated in location that the CEAP indicates as favourable for this policy scenario, as depicted by the green spots within the blue buffer on Fig. 9B-C.

In the "Human Development, Peace & Security" scenario, the CEAP's assigned weights prioritize geographic regions characterized by fragility, conflict, and limited development. Consequently, all four projects selected under this scenario are situated in areas that do not correspond to the CEAP's high-priority zones, as denoted by the red icons in Fig. 10A. This placement reflects the scenario's prioritisation criteria, which focus on areas far from the electricity grid, regions with displaced populations or refugee settlements, conflict zones, and locations with low accessibility.

The "Enabling Environment" scenario, as depicted in Fig. 11, considers a comprehensive strategy (the 360-degree approach) that takes into account an array of factors, including social, environmental, gender issues, educational opportunities, and capacity development. In this context, the greatest importance was placed on number of schools and health centres, gender and food security as well conserving natural areas and forests, while renewable energy sources were assigned a moderate weight. In this scenario, all the four projects are located in areas with a medium CEAP ranking. Fig. 11 B shows the selection of areas to be given priority, which, according to the user's defined settings, represent an expanded 12 % of the total land area of the country, rather than the intended 10 %.

Lastly, the "Africa-EU Green Energy Initiative" scenario is focused on advancing renewable energy, improving energy access, and increasing energy efficiency. To reflect this, the CEAP variables target areas with industrial activity, existing power plants, and higher concentration of education and health facilities. The ranking of geographical areas obtained with the CEAP for this scenario indicates that three of the selected projects are in locations categorized as "priority area" (green icons in Fig. 12), while the hydropower plant is in an area with a moderate ranking.

These examples demonstrate the adaptability of the CEAP tool, showcasing its ability to convert the policy objectives and criteria of a given scenario into an assessment of how suitable a particular geographic area is for the goals of that scenario.

The socio-economic implications of the prioritised areas under each scenario offer valuable insights for decision-makers, highlighting the importance of aligning clean energy projects with strategic policy objectives to maximize their impact and efficacy.

The analysis of these findings highlights the CEAP's value in directing strategic clean energy planning efforts. With its capacity to integrate various indicators and adapt variables to fit specific policy scenarios, the CEAP proves to be a flexible and useful instrument for pinpointing geographic regions that align closely with the objectives of a particular policy scenario, thereby identifying areas most appropriate for focused investment

Conclusions and future developments

The *Clean Energy Access Prioritiser* is designed and developed to provide a user-friendly and flexible web-based tool that supports the prioritisation of clean energy access initiatives in alignment with global objectives such as Sustainable Development Goal 7 (SDG7). Its architecture enables end-users to conduct spatial analyses online without the requirement for extensive computational resources.

Our case study on Benin showcased the CEAP's versatility, illustrating its capacity to accommodate diverse policy goals and strategic planning objectives. Importantly, the CEAP is not intended to generate a single spatial prioritisation representing the 'perfect sustainable energy planning'. As shown in Fig. 9 to Fig. 12 prioritisation can vary considerably depending on the objectives of policy strategic planning,

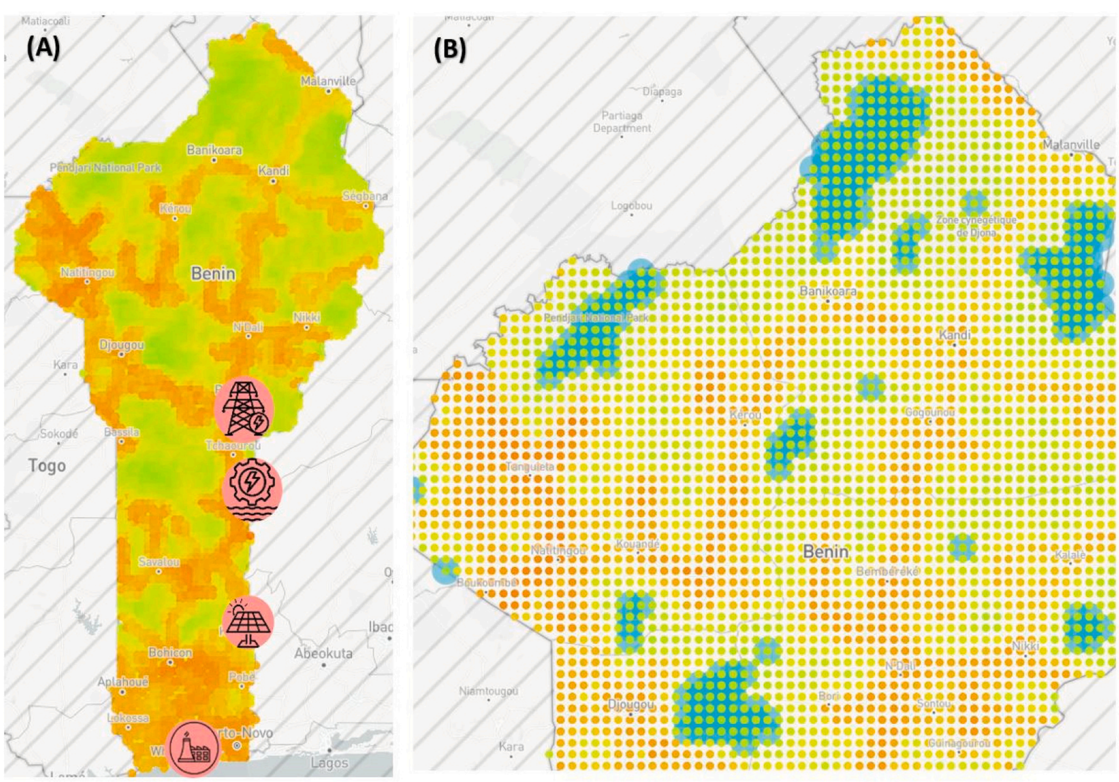


Fig. 10. (A) CEAP outputs for Human Development, Peace & Security. (B) Zoom-in into area (northen region of Benin) to be prioritised according to the user-defined criteria (highlighted in blue), covering 10 % total area of the country. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

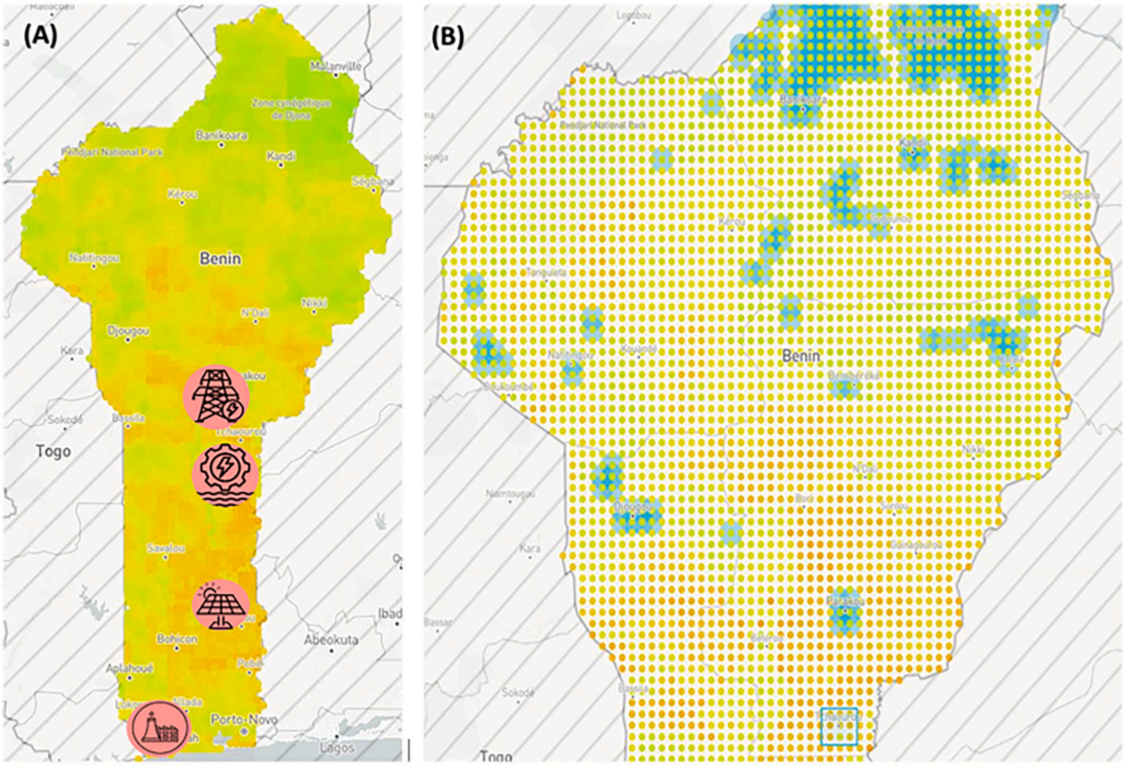


Fig. 11. (A) CEAP outputs for "Enabling Environment" - 360-degree scenario indicating the orange status for the location of the four selected projects. (B) A closer look at the area designated for priority as per user-defined criteria (outlined in blue), encompassing 10 % of the country's total area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

therefore the relative weights assigned to input features. This tool is not meant to replace electrification planning tools or optimization tools. Instead, it offers a platform that exposes and displays underlying assumptions and value judgments explicitly. This transparency is crucial as it fosters stakeholder engagement and consensus, which are vital for successful implementation of clean energy projects.

Our evaluation also highlighted CEAP's limitations, particularly its non-optimization algorithm, and the lack of critical information on opportunity costs. These data will ultimately need to be integrated into subsequent implementation processes at the local and regional levels. While acknowledging these limitations are important, they do not diminish the tool's considerable value, especially in contexts where data availability is limited. In such data-poor regions, the CEAP fills a critical gap by leveraging available continental and country-based datasets to identify priority areas for intervention, thereby accelerating the progress toward achieving SDG7. This may assist African countries in optimizing the allocation of scarce resources toward acquiring relevant energy data. Further, the tool addresses the interconnected challenges of clean energy planning by considering aspects of the Water-Energy-Food (WEF) nexus, recognizing the critical interdependencies between these sectors in ensuring sustainable development.

Moreover, the CEAP has the potential to play a pivotal role in stakeholder engagement within both low- and high-income contexts. Its user-friendly design and capacity for customized analysis make it particularly beneficial in workshop settings, enabling diverse stakeholders to collaboratively examine the trade-offs inherent in energy planning. By making value judgments explicit and transparent, the CEAP fosters informed decision-making and facilitates their integration into more sophisticated and data-intensive energy planning tools.

The use of MCA in prioritising clean energy interventions in SSA offers several benefits. Firstly, it equips decision-makers with the ability to evaluate and compare clean energy projects based on a range of criteria, ensuring that the most beneficial and sustainable projects are prioritised for implementation. Secondly, it enables policymakers to consider the trade-offs between different criteria, balancing factors such as the cost of electricity generation, environmental impacts and social benefits. It could also inform communities as well as investors and project developers about the impacts of adopting various policy frameworks in specific constituencies enabling them to take initiatives, influence and interact with policy making. Finally, MCA can help to identify areas where further research and development are required to enhance the feasibility of clean energy projects.

Looking to the future, plans are underway to expand the CEAP's utility beyond SSA to encompass the entire African continent. The system lays the basis for future enhancements that will take into account a broader range of factors, including providing further updating of the costs of various technologies per country, financing mechanisms, and policy contexts to stimulate cost-effective decision for expanding clean energy access. Further integration of the WEF nexus into these developments will enable the CEAP to address multi-sectoral challenges more effectively. This will ensure clean energy solutions contribute not only to SDG7, but also to other SDGs, fostering inclusive and sustainable development across interconnected sectors. These integrations aim to transform the CEAP into an even more effective tool for multi-sectoral decision-making, thereby facilitating cost-effective and impactful clean energy access initiatives that contribute to sustainable development and poverty alleviation.

In conclusion, the CEAP stands as a bridge between basic web-mapping applications and complex, expert-driven energy project implementation tools. By increasing transparency in the prioritisation process, it plays an essential role in the strategic planning necessary to meet the ambitious targets set by the SDGs. Future developments of the CEAP will focus on enhancing its analytical capabilities, incorporating more comprehensive data, and providing a platform for richer stakeholder engagement, all of which are critical steps toward a sustainable and energy-secure future for Africa.

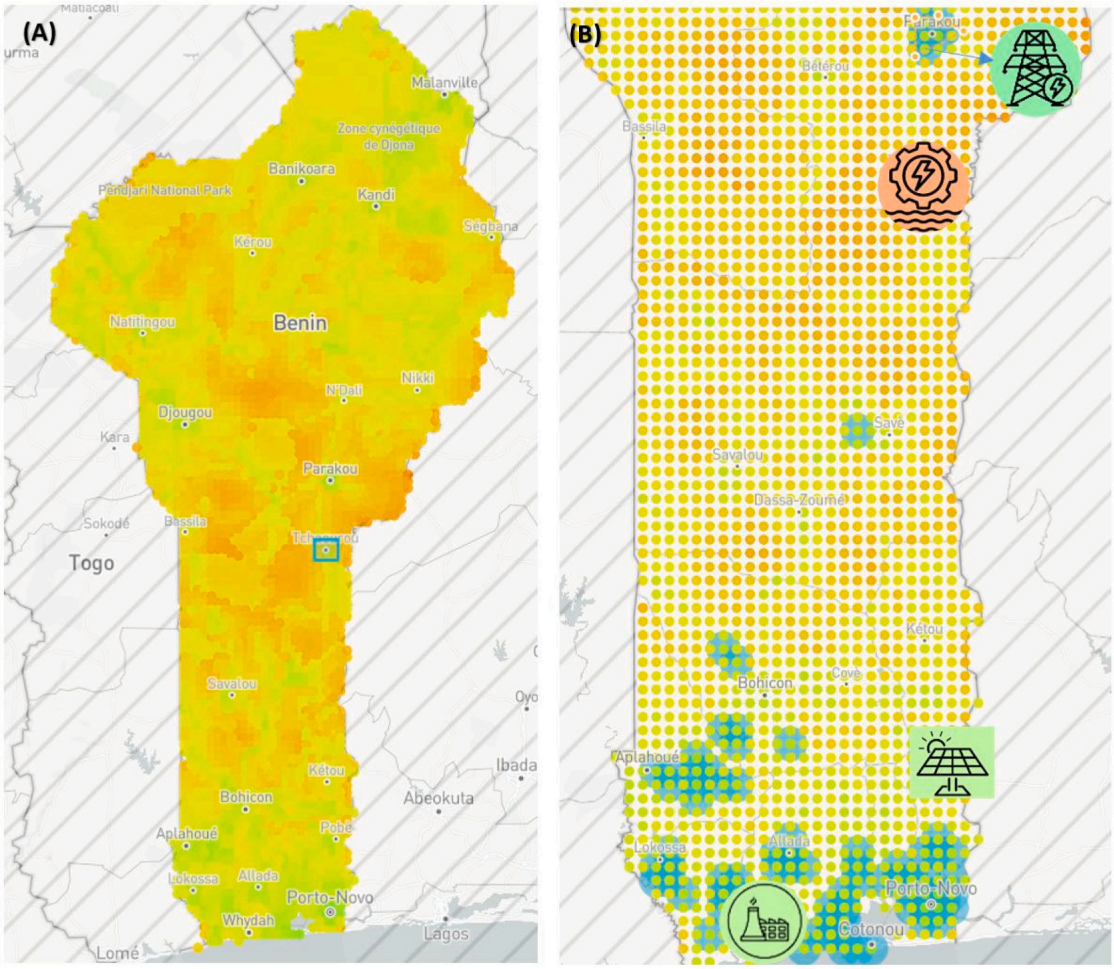


Fig. 12. CEAP outputs for Africa-EU Energy Partnership. Selected 10 % prioritised areas: The area to be prioritised according to your settings is equal to 12 % of the country's total area.

CRediT authorship contribution statement

Magda Moner-Girona: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luca Battistella:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Irene Angeluccetti:** Writing – review & editing, Validation, Methodology, Data curation. **Paola Casati:** Writing – review & editing, Formal analysis, Data curation. **James Davy:** Visualization, Software. **Andreea Tanasa:** Validation. **Marco Pittalis:** Writing – review & editing. **Sándor Szabó:** Writing – review & editing. **Natàlia Caldés:** Writing – review & editing, Conceptualization.

Disclaimer

The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission

Declaration of competing interest

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

Acknowledgments

The development and maintenance of this tool is supported mainly by the institutional activities of the Directorate for Sustainable Resources at the Joint Research Centre (JRC) of the European Commission as well as by the Directorate General on International Partnership (DG INTPA). J.D. and M.M.G serve as consultants for Joint Research Centre—European Commission. The authors would like to acknowledge Javier Baranda (EC.DG INTPA) for his significant contributions in shaping the EU-AU policy strategy scenarios for this study.

Appendix A

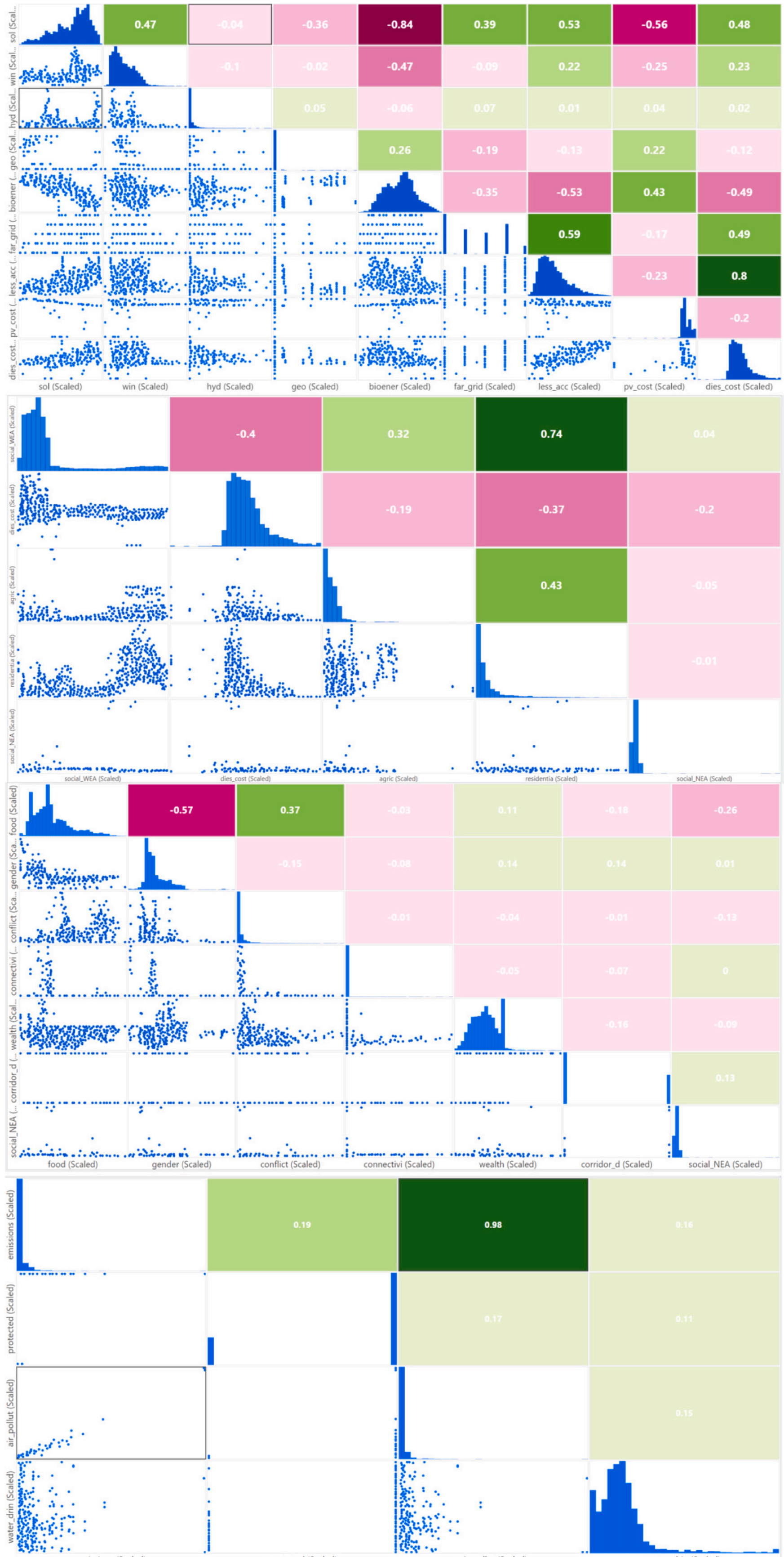


Fig. A.1. Correlation matrix plot (Pearson correlations) showing a lack of correlation between independent variables in the same Pillars (Market Supply, Market demand, socio-political aspects, environment and climate). The histogram of each indicator are allocated in diagonal of each pillar matrix.

Autocorrelation analysis

Autocorrelation assessment was applied to test whether the indicators were spatially dependent across the domain. The Moran's I coefficient of spatial autocorrelation was calculated using:

$$\text{Moran's } I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{A1}$$

where:

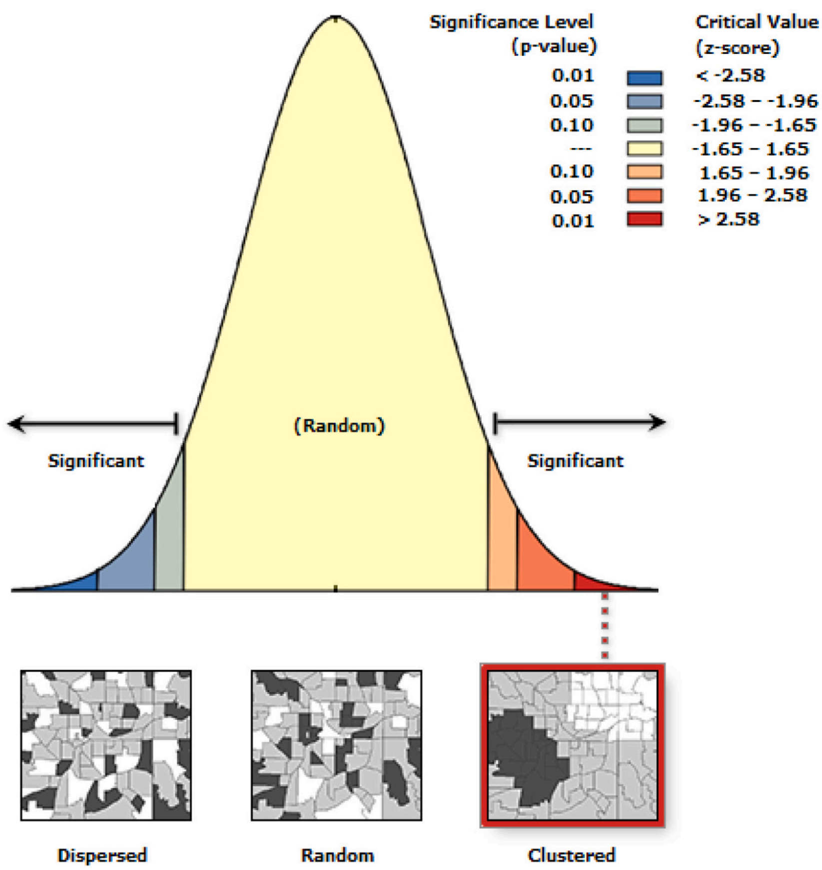
n is the total number of features
w_{ij} is the spatial weight between feature i and j
z_j is the deviation of an attribute for feature i from its mean $x_i - \overline{x}$
S_0 is the sum of all spatial weights.

The $z_I - score$ for the static is computed as

$$z_I = \frac{I - \frac{-1}{(n-1)}}{E[I^2] - E[I]^2} \tag{A2}$$

Table A.1
Summary for Spatial Autocorrelation Statistics: I Morgan with the number of neighbours (8) included in the analysis. (A) Given the z-score of 117.2 for the gender indicator, there is a less than 1 % likelihood that this clustered pattern could be the result of random chance. (B) Given the z-score of 134.9 for food indicator, there is a less than 1 % likelihood that this clustered pattern could be the result of random chance.

Global Moran's I	Gender	Food
Moran's Index	0.841336	0.968853
Expected Index	−0.000209	−0.000209
Variance	0.000052	0.000052
z-Score	117.21	134.9
p-Value	0.000000	0.000000



Geographically weighted regression

GWR is described in detail by (Fotheringham & Rogerson, 2009) as follows:

$$y_i = \sum_{j=0}^{m} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \tag{A3}$$

where y_j is the response variable, $\beta_j(u_i, v_i)$ is the *j* coefficient, (u_i, v_i) is the center location of the feature in coordinates, x_{ij} is the *j* predictor and ε_{ij} is the error term. The parameters (β_j) are calculated using matrix algebra, which incorporates a weight matrix (W_j).

GWR allows coefficients to vary continuously across the study area, enabling the estimation of a unique set of coefficients for any given location. These coefficients are typically calculated on a grid, allowing for the visualization of coefficient surfaces and the exploration of spatial heterogeneity in relationships. The method uses a localized calibration process, where observations closer to the regression point have greater influence on the estimation of the coefficients than those farther away (Fotheringham et al., 1998). Basically, GWR captures the localized relationships around each regression point, with the coefficients being estimated through weighted least squares.

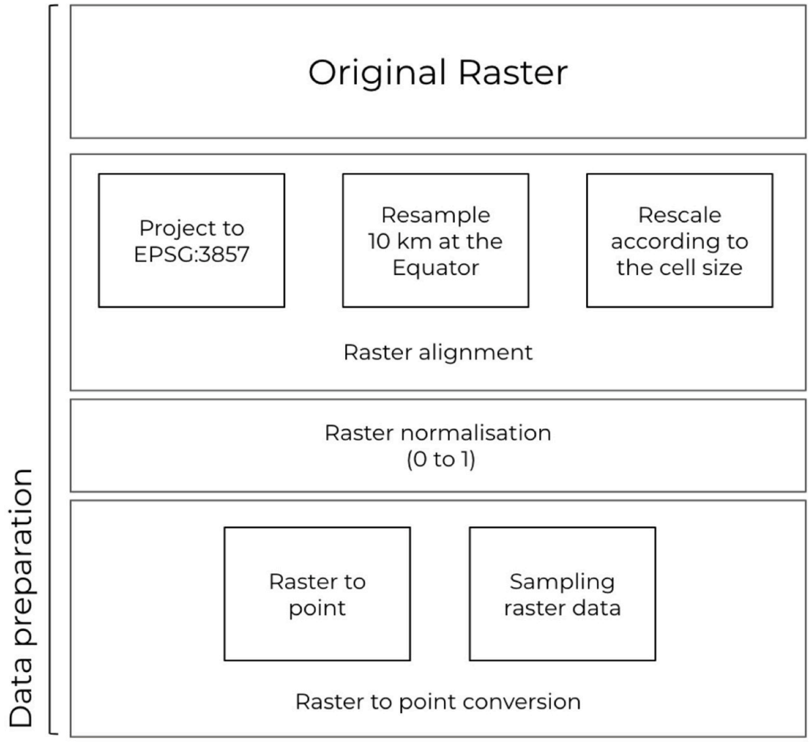


Fig. A.2. Data preparation workflow used for input raster dataset in the Clean Energy Access Prioritiser.

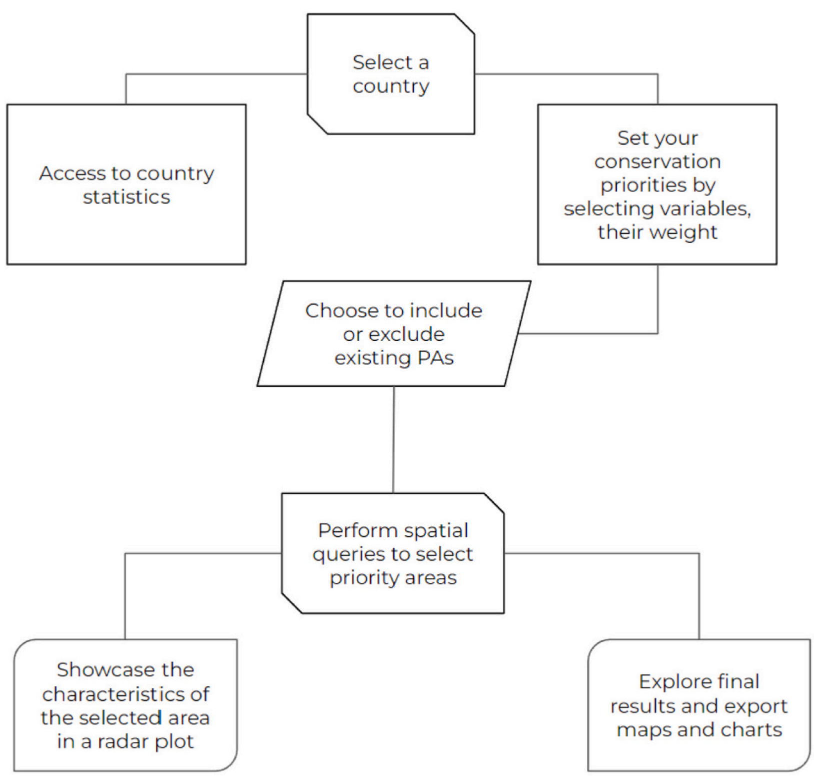


Fig. A.3. Workflow presenting the different functionalities of the Clean Energy Prioritiser tool (select a country, access to country statistics, show how country statistics change if you remove areas already protected, select a high priority area, showcase the characteristics of the selected area in a radar plot, set your energy access priorities by selecting variables, their weight, and whether PAs should be excluded or not).

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esd.2025.101709.

Data availability

To ensure full reproducibility and transparency of our research, we provide all of the scripts used in our analysis. Codes used for this application (i.e. JavaScript scripts) are permanently and publicly available on a Zenodo repository. The repository will be made available before publication

A handbook is available to guide the users through the steps needed to perform a spatial analysis with the Clean Energy Access Prioritiser. It provides also insights on the data in use by the tool. Additionally, the handbook provides a case study starting with variables selection to export of the user selected area map and its related statistics. This document is available https://africa-knowledge-platform.ec.europa.eu/node/34949

A video tutorial is also available to provide further guidance in the usage of the CEAP tool. The video tutorial is available https://africa-knowledge-platform.ec.europa.eu/tutorials

To illustrate the potential impact of energy-related tools and datasets within the AKP on the decision-making process, a comprehensive user story has been developed and made available in the AKP. This user story is readily accessible at https://africa-knowledge-platform.ec.europa.eu/node/34968.

References

AfDB. (2022). *Evaluation of the AfDB's support for renewable energy (2012–2021)*. Abidjan, Côte d'Ivoire: IDEV.

Africa-EU Energy Partnership (AEEP). (2024). Africa-EU strategic partnership [WWW Document]. URL. Africa-EU Strateg. Partnersh. Improv. access to Secur. Afford. clean energy to both Cont. https://energy.ec.europa.eu/topics/international-cooperation/key-partner-countries-and-regions/sub-saharan-africa_en (accessed 12.1.24).

African Union & European Union. (2024). Africa-EU energy partnership [WWW Document]. URL https://africa-eu-energy-partnership.org/about-the-aeep/ (accessed 1.1.24).

Baldi, D., Moner-Girona, M., Fumagalli, E., & Fahl, F. (2022). Planning sustainable electricity solutions for refugee settlements in sub-Saharan Africa. *Nature Energy, 7*, 369–379. https://doi.org/10.1038/s41560-022-01006-9

Batablinlè, L., Bazyomo, S. D., Badou, F. D., Jean, H., Hodabalo, K., Zakari, D., … Lawin, A. E. (2024). Climate, water, hydropower, wind speed and wind energy potential resources assessments using weather time series data, downscaled regional circulation models: A case study for Mono River Basin in the Gulf of Guinea region. *Renewable Energy, 224*, Article 120099. https://doi.org/10.1016/J.RENENE.2024.120099

Battistella, L., Bertelli, A., Moner-Girona, M., & Szabo, S. (2024). *Clean energy access prioritiser - Handbook*. Ispra. https://doi.org/10.13140/RG.2.2.18096.33286

Becker, W., Benavente, D., Dominguez Torreiro, M., Moura, C., Neves, A., Saisana, M., & Vertesy, D. (2019). *COIN tool user guide, EUR 29899 EN*. Publications Office of the European Union. https://doi.org/10.2760/523877

Bender, A., Moner-Girona, M., Becker, W., Bódis, K., Szabó, S., Kararach, A. G., & Anadon, L. D. (2021). Dataset for multidimensional assessment to incentivise decentralised energy investments in Sub-Saharan Africa. *Data in Brief, 37*. https://doi.org/10.1016/j.dib.2021.107265

Botai, J. O., Botai, C. M., Ncongwane, K. P., Mpandeli, S., Nhamo, L., Masinde, M., Adeola, A. M., Mengistu, M. G., Tazvinga, H., Murambadoro, M. D., Lottering, S., Motochi, I., Hayombe, P., Zwane, N. N., Wamiti, E. K., & Mabhaudhi, T. (2021). A review of the water–energy–food nexus research in Africa. *Sustainability, 13*, 1762. https://doi.org/10.3390/SU13041762

Carrão, H., Naumann, G., & Barbosa, P. (2016). Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. *Global Environmental Change, 39*, 108–124. https://doi.org/10.1016/J.GLOENVCHA.2016.04.012

Casati, P., Moner-Girona, M., Khaleel, S. I., Szabo, S., & Nhamo, G. (2023). Clean energy access as an enabler for social development: A multidimensional analysis for Sub-Saharan Africa. *Energy for Sustainable Development, 72*, 114–126. https://doi.org/10.1016/J.ESD.2022.12.003

Casati, P., Moner-Girona, M., Shehu, I. K., Szabó, S., & Nhamo, G. (2023). Datasets for a multidimensional analysis connecting clean energy access and social development in sub-Saharan Africa. *Data in Brief, 47*, Article 108948. https://doi.org/10.1016/J.DIB.2023.108948

Chi, G., Fang, H., Chatterjee, S., & Blumenstock, J. E. (2022). Microestimates of wealth for all low- and middle-income countries. *Proceedings of the National Academy of Sciences of the United States of America, 119*, Article e2113658119. https://doi.org/10.1073/pnas.2113658119

Crippa, M., Guizzardi, D., Solazzo, E., Muntean, M., Schaaf, E., Monforti-Ferrario, F., Banja, M., Olivier, J. G. J., Grassi, G., Rossi, S., & Vignati, E. (2023). *GHG emissions of all world*. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/953322

Davis, N. N., Badger, J., Hahmann, A. N., Hansen, B. O., Mortensen, N. G., Kelly, M., Larsén, X. G., Olsen, B. T., Floors, R., Lizcano, G., Casso, Pau, Lacave, O., Bosch, A., Bauwens, I., James Knight, O., Potter van Loon, A., Fox, R., Parvanyan, T., Hansen, S. B. K., Heathfield, D., Onninen, M., & Drummond, R. (2023). The Global Wind Atlas: A high-resolution dataset of climatologies and associated web-based application. *Bulletin of the American Meteorological Society, 104*(8), E1507–E1525. https://doi.org/10.1175/BAMS-D-21-0075.1

Deshpande, A., Miller-Petrie, M. K., Lindstedt, P. A., Baumann, M. M., Johnson, K. B., Blacker, B. F., Abbastabar, H., Abd-Allah, F., Abdelalim, A., Abdollahpour, I., Abegaz, K. H., Abejie, A. N., Abreu, L. G., Abrigo, M. R. M., Abualhasan, A., Accrombessi, M. M. K., Adamu, A. A., Adebayo, O. M., Adedeji, I. A., … Reiner, R. C. (2020). Mapping geographical inequalities in access to drinking water and sanitation facilities in low-income and middle-income countries, 2000-17. *The Lancet Global Health, 8*, e1162–e1185. https://doi.org/10.1016/S2214-109X(20)30278-3/ATTACHMENT/9F3BA169-DA20-4A6E-ABF0-C4BB9522F942/MMC1.PDF

Dimovski, A., Corigliano, S., Edeme, D., & Merlo, M. (2023). Holistic MILP-based approach for rural electrification planning. *Energy Strategy Reviews, 49*, Article 101171. https://doi.org/10.1016/J.ESR.2023.101171

Dimovski, A., Pezham, Z., Ahmadi, M., Albertini, L. M. F., Edeme, D. I., & Merlo, M. (2024). GIS-facilitated procedure for optimal rural electrification planning: A case study in Naeder, Ethiopia. *Energy for Sustainable Development, 82*, Article 101520. https://doi.org/10.1016/J.ESD.2024.101520

Dorman, M. (2020). Introduction to web mapping. In *Introduction to web mapping* (1st ed.). New York, US: Chapman and Hall/CRC. https://doi.org/10.1201/9780429352874.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., … Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*, 27–46. https://doi.org/10.1111/J.1600-0587.2012.07348.X

Estévez, R. A., Espinoza, V., Ponce Oliva, R. D., Vásquez-Lavín, F., & Gelcich, S. (2021). Multi-criteria decision analysis for renewable energies: Research trends, gaps and the challenge of improving participation. *Sustainability, 13*, 3515. https://doi.org/10.3390/SU13063515

European Union. (2022). *EU-Africa: Global gateway investment package*. https://doi.org/10.2775/080188

Falchetta, G., Stevanato, N., Moner-Girona, M., Mazzoni, D., Colombo, E., & Hafner, M. (2021). The M-LED platform: Advancing electricity demand assessment for communities living in energy poverty. *Environmental Research Letters, 16*. https://doi.org/10.1088/1748-9326/ac0cab

Fotheringham, A., & Rogerson, P. (2009). Geographically weighted regression. In *The SAGE handbook of spatial analysis* (pp. 243–254). SAGE Publications Ltd. https://doi.org/10.4135/9780857020130.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2006). *Geographically weighted regression: The analysis of spatially varying relationships*. Wiley.

Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). *Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis* (Vol. 30, pp. 1905–1927). https://doi.org/10.1068/A301905

Gonzalez Sanchez, R., Kougias, I., Moner-Girona, M., Fahl, F., & Jäger-Waldau, A. (2021). Assessment of floating solar photovoltaics potential in existing hydropower reservoirs in Africa. *Renewable Energy, 169*, 687–699. https://doi.org/10.1016/j.renene.2021.01.041

Gonzalez Sanchez, R., Seliger, R., Fahl, F., De Felice, L., Ouarda, T. B. M. J., & Farinosi, F. (2020). Freshwater use of the energy sector in Africa. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2020.115171

Graetz, N., Woyczynski, L., Wilson, K. F., Hall, J. B., Abate, K. H., Abd-Allah, F., Adebayo, O. M., Adekanmbi, V., Afshari, M., Ajumobi, O., Akinyemiju, T., Alahdab, F., Al-Aly, Z., Rabanal, J. E. A., Alijanzadeh, M., Alipour, V., Altirkawi, K., Amiresmaili, M., Anber, N. H., … Hay, S. I. (2020). Mapping disparities in education across low- and middle-income countries. *Nature, 577*, 235–238. https://doi.org/10.1038/S41586-019-1872-1

He, Y. X., Jiao, Z., & Yang, J. (2018). Comprehensive evaluation of global clean energy development index based on the improved entropy method. *Ecological Indicators, 88*, 305–321. https://doi.org/10.1016/J.ECOLIND.2017.12.013

Hoes, O. A. C., Meijer, L. J. J., Van Der Ent, R. J., & Van De Giesen, N. C. (2017). Systematic high-resolution assessment of global hydropower potential. *PLoS One, 12*, Article e0171844. https://doi.org/10.1371/JOURNAL.PONE.0171844

Huld, T., Müller, R., & Gambardella, A. (2012). A new solar radiation database for estimating PV performance in Europe and Africa. *Solar Energy, 86*, 1803–1815. https://doi.org/10.1016/j.solener.2012.03.006

Husein, M., Moner-Girona, M., Falchetta, G., Stevanato, N., Fahl, F., & Szabó, S. (2024). The impacts of incentive policies on improving private investment for rural electrification in Nigeria – A geospatial study. *Heliyon, 10*, Article e27440. https://doi.org/10.1016/J.HELIYON.2024.E27440

IEA, IRENA, UNSD, World Bank, & WHO. (2024). *Tracking SDG 7: The energy progress report 2024*.
International Energy Agency (IEA). (2022). *World energy outlook special report Africa energy outlook 2022*.
International Energy Agency (IEA). (2023). *Financing clean energy in Africa*.
International Monetary Fund. (2019). International Financial Statistics and data [WWW Document]. URL https://www.imf.org/en/Data.
Joint Research Centre-European Commission. (2020). Competence centre on composite indicators and scoreboards [WWW Document]. URL https://composite-indicators.jrc.ec.europa.eu/ (accessed 1.21.20).
Joint Research Centre-European Commission. (2021). PV decentralised energy investment index (PV-DEI) tool [WWW Document]. URL https://africa-knowledge-platform.ec.europa.eu/pvdei (accessed 10.1.24).
Juanpera, M., Ferrer-Martí, L., & Pastor, R. (2022). Multi-stage optimization of rural electrification planning at regional level considering multiple criteria. Case study in Nigeria. *Applied Energy, 314*, Article 118926. https://doi.org/10.1016/J.APENERGY.2022.118926
Kinyoki, D. K., Osgood-Zimmerman, A. E., Pickering, B. V., Schaeffer, L. E., Marczak, L. B., Lazzar-Atwood, A., … Hay, S. I. (2020). Mapping child growth failure across low- and middle-income countries. *Nature, 577*(7789), 231–234. https://doi.org/10.1038/s41586-019-1878-8
Moner-Girona, M., Fahl, F., Kakoulaki, G., Kim, D.-H., Maduako, I., Szabó, S., Nhamo, G., Sovacool, B. K., & Weiss, D. J. (2025). Empowering quality education through sustainable and equitable electricity access in African schools. *Joule, 9*(2), Article 101804. https://doi.org/10.1016/j.joule.2024.12.005
Moner-Girona, M., Bender, A., Becker, W., Bódis, K., Szabó, S., Kararach, A. G. G., … Diaz Anadon, L. (2021). A multidimensional high-resolution assessment approach to boost decentralised energy investments in Sub-Saharan Africa. *Renewable and Sustainable Energy Reviews, 148*, Article 111282. https://doi.org/10.1016/j.rser.2021.111282
Moner-Girona, M., Kakoulaki, G., Weiss, D. J., Falchetta, G., Taylor, N., Falchetta, G., Weiss, D. J., & Taylor, N. (2021). Achieving universal electrification of rural healthcare facilities in sub-Saharan Africa with decentralized renewable energy technologies. *Joule, 5*, 2687–2714. https://doi.org/10.1016/j.joule.2021.09.010
Moner-Girona, M., Puig, D., Mulugetta, Y., Kougias, I., AbdulRahman, J., & Szabó, S. (2018). Next generation interactive tool as a backbone for universal access to electricity. *Wiley Interdisciplinary Reviews: Energy and Environment, 7*. https://doi.org/10.1002/wene.305
Morrissey, J. (2019). Achieving universal electricity access at the lowest cost: A comparison of published model results. *Energy for Sustainable Development, 53*. https://doi.org/10.1016/j.esd.2019.09.005
NDICI – Global Europe. (2021). *Thematic programme on peace, stability and conflict prevention. 2021–2027* (Luxembourg).
Nelson, A. (2008). *Travel time to major cities: A global map of accessibility [WWW Document]*. Ispra Italy: Glob. Environ. Monit. Unit - Jt. Res. Cent. Eur. Comm.
Nhamo, L., Ndlela, B., Mpandeli, S., & Mabhaudhi, T. (2020). The water-energy-food nexus as an adaptation strategy for achieving sustainable livelihoods at a local level. *Sustainability, 12*, 8582. https://doi.org/10.3390/SU12208582
OECD. (2022). *The Humanitarian-Development-Peace Nexus, The Humanitarian-Development-Peace Nexus Interim Progress Review*. Paris, France: OECD. https://doi.org/10.1787/2F620CA5-EN
OECD/JRC. (2005). Handbook on constructing composite indicators. In *OECD statistics working papers*. https://doi.org/10.1787/533411815016
Pesaresi, M., Schiavina, M., Politis, P., Freire, S., Krasnodębska, K., … Uhl, J. H. Kemper (2024). Advances on the Global Human Settlement Layer by joint assessment of Earth Observation and population survey data. *International Journal of Digital Earth, 17*(1). https://doi.org/10.1080/17538947.2024.2390454
Robinson, T. P., William Wint, G. R., Conchedda, G., Van Boeckel, T. P., Ercoli, V., Palamara, E., … Gilbert, M. (2014). Mapping the global distribution of livestock. *PLoS One, 9*, Article e96084. https://doi.org/10.1371/JOURNAL.PONE.0096084
Sen, A. (2006). Human rights and capabilities. *Journal of Human Development, 6*, 151–166. https://doi.org/10.1080/14649880500120491
Shiraishi, K., Shirley, R. G., & Kammen, D. M. (2019). Geospatial multi-criteria analysis for identifying high priority clean energy investment opportunities: A case study on land-use conflict in Bangladesh. *Applied Energy, 235*, 1457–1467. https://doi.org/10.1016/J.APENERGY.2018.10.123
Siebert, S., Henrich, V., Frenken, K., & Burke, J. (2013). *Update of the digital global map of irrigation areas to version 5* (Rome, Italy).
Sonon, K. E., Zogbochi, V., Chetangny, P. K., Barbier, G., Houndedako, S., Vianou, A., Aredjodoun, J., & Chamagne, D. (2022). Optimization of photovoltaic plant capacity with battery storage for injection into main network: Case of Illoulofin solar plant in Benin. In *8th Int. Conf. Eng. Emerg. Technol. ICEET 2022*. https://doi.org/10.1109/ICEET56468.2022.10007307
Stevanato, N., Pellecchia, G., Sangiorgio, I., Shendrikova, D., Soares, C. A., Mereu, R., & Colombo, E. (2023). Planning third generation minigrids: Multi-objective optimization and brownfield investment approaches in modelling village-scale on-grid and off-grid energy systems. *Renewable and Sustainable Energy Transition, 3*, Article 100053. https://doi.org/10.1016/J.RSET.2023.100053
Sustainable Energy forAll (SEforALL) and the Climate Policy Initiative (CPI). (2019). *Energy finance: Understanding the landscape 2019* (Vienna, Austria).
The World Bank Group. (2014). *Republic of South Africa review of the South Africa renewable energy* (Washington DC, US).
Thorn, J. P. R., Bignoli, D. J., Mwangi, B., & Marchant, R. A. (2022). The African Development Corridors Database: A new tool to assess the impacts of infrastructure investments. *Scientific Data, 9*. https://doi.org/10.1038/S41597-022-01771-Y
Tractebel Engineering, & GDF Suez International Power. (2011). *Update of the ECOWAS revised master plan for the generation and transmission of electrical energy optimal development plan and analysis of transmission network performance and stability*. Brussels, Belgium: WEST AFRICAN POWER POOL (WAPP).
UNEP-WCMC. (2023). *The World Database on Protected Areas (WDPA)*. Cambridge, UK: UNEP-WCMC. www.protectedplanet.net. Accessed through Resource Watch, (July 2023). www.resourcewatch.org.
Vose, R. S., Huang, B., Yin, X., Arndt, D., Easterling, D. R., Lawrimore, J. H., … Zhang, H. M. (2021). Implementing full spatial coverage in NOAA's global temperature analysis. *Geophysical Research Letters, 48*, Article e2020GL090873. https://doi.org/10.1029/2020GL090873
Weiss, D. J., Nelson, A., Gibson, H. S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T. C. D., Howes, R. E., Tusting, L. S., Kang, S. Y., Cameron, E., Bisanzio, D., … Gething, P. W. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. *Nature, 553*, 333–336. https://doi.org/10.1038/nature25181
West African Power Pool (WAPP). (2012). *West African power pool. Business plan 2012/13*.
West African Power Pool (WAPP). (2019). 330 kV Double circuit median interconnection project terms of reference for line route. In *Environmental and social impact assessment*.