

A Reproducible Open-Data Workflow for Identifying Coastal Electrical Infrastructure Exposure to Flood and Coastal Hazards: A Comparative Application in Jamaica and Mozambique

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Abstract

Coastal power grids in small island developing states (SIDS) and low- and middle-income countries (LMICs) face escalating climate threats, yet analytical tools for assessing infrastructure exposure remain fragmented across disciplines, institutionally siloed, and difficult to transfer between national contexts. This paper presents a reproducible, open-data geospatial workflow implemented entirely in QGIS that identifies the exposure of coastal electrical infrastructure to flood and coastal hazards. The workflow integrates three methods: (1) blue spot detection adapted from road drainage engineering, (2) terrain-derived flood susceptibility classification, and (3) coastal proximity analysis through 1 km and 5 km buffer zones. The workflow is applied to Jamaica and Mozambique as contrasting cases, a Caribbean SIDS with near-universal electrification and an LMIC with approximately 36% electrification, using identical global open-data inputs. Jamaica's island geography concentrates coastal exposure (70% of plants within 5 km of the coast), while Mozambique's deltaic terrain dominates inland flood exposure (83% of transmission lines in high susceptibility zones). The contrasting patterns reflect genuine geographic differences: island geography concentrates generation coastally, while continental deltaic terrain amplifies inland flood exposure. The workflow operates without proprietary GIS software or commercial hazard data, and its outputs are structured as standardised exposure tables suitable for integration with downstream energy planning and investment appraisal tools.

1 Introduction

The electricity systems of coastal developing countries occupy a particularly exposed position in the global climate risk landscape. Hurricane Maria caused a systemwide collapse of Puerto Rico's transmission and distribution system in 2017, producing the longest blackout in United States history and destroying approximately 50,000 utility poles (Kwasinski et al. 2019). Emergency power restoration lasted more than ten months (Kwasinski et al. 2019). Cyclone Idai devastated grid infrastructure across central Mozambique in March 2019, leaving the city of Beira without power for weeks and causing an estimated USD 87 million in energy-sector damage (World Bank/GFDRR 2019). These are not isolated events, they are recurring manifestations of a risk pattern that climate change is deepening through intensified tropical cyclone precipitation, accelerating sea-level rise, and more frequent heavy precipitation (IPCC 2021). Power systems are particularly vulnerable to these phenomena (Panteli and Mancarella 2015).

Yet the analytical tools available to utilities and planning ministries in these countries remain poorly matched to the scale of climate-driven infrastructure risk they face (Nicolas et al. 2019). This mismatch is not primarily technological, the geospatial methods, hazard datasets, and financial planning models needed for climate-resilient power system investment all exist. The problem is institutional fragmentation: hazard analysts produce spatial risk maps that are not designed for energy sector decision-making, energy planners optimise electrification pathways without accounting for spatially differentiated climate exposure, and finance ministries budget for power sector investment without spatially explicit risk information (Hallegatte et al. 2019; Nicolas et al. 2019).

This fragmentation imposes costs that fall disproportionately on the countries least equipped to absorb them. In high-income contexts, specialised consultancies and well-resourced utility planning departments bridge the gaps between geospatial analysis, engineering assessment, and financial planning. In SIDS and LMICs, those intermediaries are either absent or prohibitively expensive (Hallegatte et al. 2019; Nicolas et al. 2019). The result is a capacity asymmetry that mirrors and reinforces the climate vulnerability asymmetry: the countries most exposed to climate-driven infrastructure damage are systematically excluded from the analytical workflows that could identify and prevent it (Hallegatte et al. 2019; Robinson 2020). The World Bank estimates that every USD 1 invested in making infrastructure resilient in low- and middle-income countries saves USD 4 in avoided losses and disruptions (Hallegatte et al. 2019).

Existing approaches to climate risk assessment of power infrastructure in developing countries span a wide range. Post-disaster needs assessments produced after major events provide detailed retrospective damage accounting but are inherently reactive (World Bank/GFDRR 2019). Proprietary platforms such as FATHOM (Sampson et al. 2015) and Climate Central's CoastalDEM (Kulp and Strauss 2019) provide enhanced-accuracy flood and coastal risk screening. However, access to these platforms typically requires commercial licensing or institutional agreements, and their effective use demands specialist expertise in flood modelling that may not be routinely available in all SIDS and LMIC institutional contexts (Hallegatte et al. 2019). The workflow presented here complements such platforms by enabling low-cost open-data screening to identify priority areas where targeted higher-resolution data acquisition (such as local LiDAR or utility-specific surveys) would yield the greatest return.

This paper presents a compound flood and coastal exposure workflow implemented entirely in QGIS that integrates three complementary screening methods, blue spot detection adapted from road drainage engineering (Larsen and Pihl 2010), terrain-derived flood susceptibility via Topographic Convergence Index (TCI), and coastal proximity buffers, to identify exposed electrical infrastructure. The workflow is applied to Jamaica as a Caribbean SIDS with near-universal electrification and to Mozambique as a Southeast African LMIC with lower electrification and recent devastating cyclone experience. The Jamaica-Mozambique pairing tests transferability across maximally different contexts while using identical global open-data foundations.

Several studies have assessed flood exposure of electrical infrastructure using GIS. Sánchez-Muñoz et al. developed a GIS-based flood risk tool for the power distribution grid in Barcelona, integrating failure probability modelling, but relied on synthetic data generated from utility-specific assets not available in open-data contexts (Sánchez-Muñoz et al. 2021). Koks et al. conducted a global multi-hazard risk analysis of transport infrastructure assets using open data but did not extend the analysis to power grid assets (Koks et al. 2019). Qiang mapped flood exposure of critical infrastructure in the United States using FEMA flood maps, but the approach depends on national flood mapping products that, as this paper documents, do not exist for SIDS like Jamaica (Qiang 2019). Blue spot detection originated in the road sector (Larsen and Pihl 2010) and has been applied to road network flood screening (Balstrøm et al.

2024) but has not, to the authors' knowledge, been transferred to power grid infrastructure. This transfer requires adapting the causal logic: whereas a road surface is itself the exposed element, a transmission conductor sits elevated above the terrain. Blue spots on the power network therefore screen for tower and pole foundation saturation, water ingress in ground-mounted substation equipment, and access-road impassability during repair operations, rather than for direct line flooding (Panteli and Mancarella 2015).

Two features distinguish the present work from this body of literature. First, the adaptation of blue spot detection from road drainage engineering to electrical infrastructure represents a novel domain transfer with a distinct causal structure. For road networks, the exposed element is the surface itself, for power grids the mechanism is indirect, shifting the screening question from “where does water pool on the asset” to “where does water pool around the asset and its repair access.” This domain transfer has not, to the authors' knowledge, been systematically screened using open data at national scale. Second, the workflow operates entirely within open-data and open-source constraints, a design requirement driven by institutional reality rather than a budget compromise.

2 Study Areas

2.1 Jamaica

Jamaica is a Caribbean SIDS with a population of approximately 2.83 million people (United Nations 2022) and near-universal electrification (IEA et al. 2025). Jamaica Public Service (JPS) is the country's vertically integrated electric utility, managing approximately 14,000 km of transmission and distribution lines and 52 substations (TrackingStandard 2024). The transmission system operates at 138 kV and 69 kV, with distribution at 24 kV, 13.8 kV, and 12 kV (Office of Utilities Regulation 2016). Coastal generation is concentrated in the Kingston-Old Harbour corridor (south coast) and Montego Bay (north coast). Hurricane exposure is well documented in Jamaica's recent history, with major events including Gilbert (1988), Ivan (2004), Dean (2007), Sandy (2012), and Melissa (2025). Hurricane Ivan alone caused damage equivalent to 8% of GDP, the highest single-event loss in the 2000–2009 decade (Burgess et al. 2015), with detailed sectoral impacts quantified through ECLAC's Damage and Loss Assessment methodology (ECLAC 2004). Hurricane Melissa made landfall on 28 October 2025 as a Category 5 storm, the strongest ever recorded in Jamaica (National Hurricane Center 2026), causing direct physical damage estimated at US\$8.8 billion (41% of 2024 GDP), of which 33% was to infrastructure (World Bank/GFDRR 2025). Jamaica also experiences recurring flooding in the Yallahs River valley, Rio Cobre basin, and Hope River catchment, where major infrastructure is concentrated on floodplains and has sustained significant damage from past events (Glas et al. 2017).

Topographically, the Blue Mountains create steep eastern terrain rising above 2,000 m, the southern coastal plain including the Kingston-Spanish Town corridor is low-lying and infrastructure-dense, and the northern coast is a narrow strip with abrupt elevation transitions (ESA 2024). At 30 m DEM resolution,

landscape-scale depressions in valley bottoms and coastal lowlands are detectable, urban-scale ponding around individual substations is not (ESA 2024; Gesch 2018).

2.2 Mozambique

Mozambique is a Southeast African LMIC with approximately 36% national electrification (IEA et al. 2025). Electricidade de Moçambique (EDM) operates the state-owned utility system (World Bank/GFDRR 2019). Cyclone Idai (March 2019) made landfall near Beira with winds of 180–220 km/h and significant storm surge, causing an estimated USD 87 million in energy-sector damage, with total recovery needs across all affected provinces reaching USD 3.2 billion (World Bank/GFDRR 2019). Kenneth struck northern Mozambique six weeks later, the first time two cyclones of such intensity struck in the same season (Mawren et al. 2020). Freddy (2023) brought record-breaking rainfall to Mozambique (Scoccimarro et al. 2024).

The Sofala Province coastline around Beira is predominantly flat and low-lying, with extensive areas below 5 m elevation (ESA 2024). Mozambique's low electrification rate, approximately 36% nationally (IEA et al. 2025), represents a fundamentally different infrastructure context compared to Jamaica's near-universal grid coverage, a contrast that tests the workflow's applicability across different development stages. The identical workflow was executed for Mozambique using the same global open-data sources, with practical adaptations for the substantially larger DEM documented in Section 4.

2.3 Comparative Summary

Table 1 summarises the comparative context of the two study areas across key dimensions relevant to the workflow application.

Table 1
Comparative context for the two study areas

Dimension	Jamaica	Mozambique
Country type	Caribbean SIDS	Southeast African LMIC
Electrification	~ 100%	~ 36% national
Utility	JPS (vertically integrated)	EDM (state-owned)
Cyclone exposure	Atlantic hurricanes (Cat 1–5)	SW Indian Ocean (Idai, Kenneth, Freddy)
DEM source	Copernicus GLO-30 (ESA 2024)	Copernicus GLO-30 (ESA 2024)
OSM power coverage	121 transmission line segments via Overpass Turbo (OpenStreetMap contributors 2026), 10 generation plants via WRI (Global Energy Observatory et al. 2019)	260 transmission line segments via Overpass Turbo (OpenStreetMap contributors 2026), 26 generation facilities via Overpass Turbo (OpenStreetMap contributors 2026) + WRI Global Energy Observatory et al. 2019)
Blue spot depth threshold	0.3 m	0.3 m
CRS	EPSG:32618 (UTM 18N)	EPSG:32736 (UTM 36S)

3 Data and Sources

The workflow uses exclusively open datasets available globally. This section documents each source, its fitness for purpose, and empirical findings regarding data availability for both Jamaica and Mozambique.

3.1 Terrain and Elevation

The Copernicus Global Digital Elevation Model (GLO-30) at 30 m resolution serves as the primary elevation input for both countries (ESA 2024). GLO-30 provides stated vertical accuracy of < 4 m LE90 globally (ESA 2024). In tropical landscapes, effective vertical accuracy varies substantially with terrain type and vegetation cover, ranging from approximately 2 m in open and low-relief areas to over 4 m in mountainous regions and dense forests (Okolie et al. 2024). A critical limitation is that GLO-30 is a Digital Surface Model (DSM), not a Digital Terrain Model (DTM): vegetation canopy and building tops inflate elevation values (ESA 2024), with the magnitude of inflation correlating positively with tree cover density (Okolie et al. 2024). This affects depression detection in forested areas and urban zones.

FABDEM (Hawker et al. 2022), a Copernicus derivative with machine-learning removal of canopy and buildings, was evaluated as an alternative. However, FABDEM was not used for blue spot detection because its building-removal algorithm may over-smooth urban depressions, precisely the features most relevant to grid infrastructure.

For Jamaica, GLO-30 was accessed via OpenTopography as a single tile (approximately 130 MB) and reprojected to EPSG:32618 (UTM Zone 18N). For Mozambique, the same source was downloaded as three tiles covering the national extent, merged into a single raster (8.7 GB), and reprojected to EPSG:32736 (UTM Zone 36S). The substantially larger DEM size for Mozambique introduced computational constraints documented in Section 4.2. The same DSM limitations apply to both countries, compounded in Mozambique by extensive coastal mangrove and savanna vegetation.

3.2 Power Grid Infrastructure

Generation plant locations were obtained from the WRI Global Power Plant Database v1.3.0 (Global Energy Observatory et al. 2019) for both countries. For Jamaica, filtering by country code yielded 10 plants with coordinates, capacity (MW), and primary fuel attributes. For Mozambique, the same filter yielded only 3 plants, insufficient for a national-scale exposure analysis. To supplement this, generation facilities were extracted from OpenStreetMap via Overpass Turbo (OpenStreetMap contributors 2026) using queries for power=plant and power=substation within the Mozambique administrative area. Polygonal facilities were converted to centroids, yielding 26 generation plants total.

Transmission lines were extracted from OpenStreetMap via Overpass Turbo for both countries, as the standard Geofabrik extract lacked the power infrastructure layer in both cases. For Jamaica, the query produced 121 line segments with attributes including voltage, operator, and OSM identifiers. For Mozambique, the identical query structure produced 260 segments.

Distribution-level infrastructure (LV lines, poles, transformers) was not available in open data for Jamaica, and was not pursued for Mozambique in order to maintain methodological consistency between both case studies. This constrains the analysis to generation and transmission assets only, systematically undercounting total exposed infrastructure in both countries.

3.3 Flood Hazard Data

A key finding of this work is that standard global flood datasets do not cover Jamaica. The JRC Global Flood Hazard maps (Dottori et al. 2016) exclude rivers with upstream drainage area below 5000 km², a threshold imposed by the coarse resolution of the underlying ERA-Interim climatology and the GloFAS hydrological model. None of Jamaica's drainage basins approach this threshold, given that the entire country covers approximately 10,991 km². The FATHOM Global 2.0 dataset distributed by the World Bank (Sampson et al. 2015) applies a less restrictive drainage area threshold than the JRC product but was inaccessible through the standard download portal at the time of analysis. The WRI Aqueduct Coastal layer (Ward et al. 2020) lacked a clear download path. This systematic exclusion of small island states from global flood hazard products is itself a methodological finding of this work, consistent with broader observations that global coastal assessments often lack SIDS-specific focus (Vousdoukas et al. 2023).

In the absence of external flood data, flood susceptibility was derived directly from the GLO-30 DEM using hydrological tools within QGIS (Section 4.2) for both countries. This approach produces a topographic proxy for flood susceptibility rather than a calibrated hydrological model with depth

predictions, a limitation that is documented transparently. For Mozambique, the TCI-based proxy was adopted from the outset for methodological consistency with Jamaica rather than as a response to data unavailability. Mozambique's terrain (characterised by extensive low-lying deltaic plains along the Zambezi, Limpopo, and Save river systems) produces substantially higher TCI values across broader areas than Jamaica's mountainous topography, a difference reflected in the results (Section 5).

3.4 Administrative Boundaries

GADM v4.1 (GADM 2024) provided administrative boundaries for both countries: Jamaica's 14 parishes and Mozambique's 11 provinces. In each case, the coastline was extracted by dissolving administrative polygons into a single national boundary and converting to lines using the QGIS Polygons to Lines tool. Coastal buffers of 1 km and 5 km were generated from this derived coastline. The 1 km buffer captures assets facing immediate coastal hazards including storm surge, coastal flooding, and salinity-related degradation (Hasan and Bhowmik 2016). The 5 km buffer was chosen to extend coverage to a broader nearshore zone capturing assets that may be affected by indirect coastal exposure and longer storm surge inundation. The Low Elevation Coastal Zone (LECZ) framework provides complementary elevation-based context (McGranahan et al. 2007).

3.5 Data Summary

Table 2 summarises the primary data sources used for both countries.

Table 2
Primary data sources for Jamaica and Mozambique

Dataset	Source	Resolution	Format	Key limitation
Copernicus GLO-30 (Jamaica)	ESA / OpenTopography	30 m	GeoTIFF	DSM not DTM, ~ 130 MB
Copernicus GLO-30 (Mozambique)	ESA / OpenTopography	30 m	GeoTIFF	DSM not DTM, 8.7 GB, requires 32 + GB RAM for processing
WRI Power Plants v1.3 (Jamaica)	datasets.wri.org	Point	CSV	10 plants, no distribution assets
WRI Power Plants v1.3 (Mozambique)	datasets.wri.org	Point	CSV	3 plants, supplemented with 23 OSM facilities (26 total)
OSM Transmission Lines (Jamaica)	Overpass Turbo	Vector	GeoJSON	121 segments, Geofabrik power layer absent, voltage partially null
OSM Transmission Lines (Mozambique)	Overpass Turbo	Vector	GeoJSON	260 segments, Geofabrik power layer absent, voltage partially null
GADM v4.1	gadm.org	Level 1	Shapefile	Coastline derived from dissolved boundary

4 Materials and methods

The workflow integrates three complementary exposure screening methods into a single reproducible sequence implemented in QGIS 3.34. All operations use native QGIS tools and the built-in GRASS toolset, no external plugins or proprietary software are required. The workflow is organised into five phases: data preparation, terrain analysis, blue spot detection, coastal buffer generation, and spatial intersection of hazard zones with electrical assets. Figure 1 illustrates the complete workflow.

4.1 Data Preparation (Phase 0)

All source datasets were reprojected to country-specific UTM coordinate reference systems: EPSG:32618 (WGS 84 / UTM Zone 18N) for Jamaica and EPSG:32736 (WGS 84 / UTM Zone 36S) for Mozambique. The Copernicus GLO-30 DEM was reprojected using the GDAL Warp tool for both countries. For Mozambique, the DEM was downloaded as three tiles from OpenTopography and merged using GDAL Merge prior to reprojection.

For Jamaica, WRI Global Power Plant Database v1.3 was imported using latitude/longitude fields with source CRS EPSG:4326, filtered to country code "JAM" (10 plants), then reprojected. These 10 facilities correspond to major generation plants catalogued by WRI, which includes grid-scale facilities of 1 MW and above (Byers et al. 2018), smaller distributed generation, captive industrial plants, and behind-the-meter installations are not captured. Transmission lines (121 segments) were extracted from OpenStreetMap via Overpass Turbo, as the standard Geofabrik extract for Jamaica did not include the power infrastructure layer. Each segment is a geometric feature in the OSM database defined by its digitised nodes, typically representing high-voltage transmission corridors rather than distribution feeders. All vector layers were assembled into a single GeoPackage for reproducibility and portability. For Mozambique, WRI plants (3 facilities) were supplemented with 23 additional generation facilities extracted from OpenStreetMap via Overpass Turbo (OpenStreetMap contributors 2026), including polygonal facilities converted to centroids, yielding 26 plants total. The 26 Mozambican facilities represent a composite dataset combining WRI-catalogued plants (Global Energy Observatory et al. 2019) and OSM-mapped generation sites (OpenStreetMap contributors 2026), with heterogeneous attribute completeness. The Geofabrik extract for Mozambique also lacked the power infrastructure layer, so transmission lines (260 segments) were extracted via Overpass Turbo using the identical query structure as Jamaica. The same definitions apply: segments are OSM geometric features representing high-voltage transmission corridors. All vector layers were assembled into a separate GeoPackage. GADM v4.1 (GADM 2024) provided administrative boundaries for both countries: Jamaica's 14 parishes and Mozambique's 11 provinces.

4.2 Terrain Analysis (Phase 1)

Terrain analysis employed open-source hydrological tools accessed through the QGIS Processing Toolbox. The analytical sequence is identical for both countries, with one tool substitution for Mozambique due to computational constraints.

Hydrological correction. For Jamaica, the GRASS tool `r.fill.dir` was applied to the GLO-30 DEM to produce a hydrologically consistent surface by filling all topographic depressions. An initial attempt to apply the SAGA "Fill Sinks (Wang & Liu)" algorithm, a standard depression-filling method in DEM hydrology (Wang and Liu 2006), was prevented because this tool was unavailable in QGIS 3.34.8. GRASS `r.fill.dir` produces functionally equivalent results. For Mozambique, the substantially larger DEM (8.7 GB versus approximately 130 MB for Jamaica) exceeded the processing capacity of GRASS `r.fill.dir` within available computational resources. The WhiteboxTools (Lindsay 2016) implementation of the Wang and Liu depression-filling algorithm (Wang and Liu 2006) was used instead, producing a functionally equivalent filled DEM in approximately one hour on a workstation with 64 GB RAM. The Wang and Liu algorithm addresses the same objective as GRASS `r.fill.dir`: producing a depressionless DEM suitable for hydrological analysis. This tool substitution demonstrates a practical dimension of open-source workflow reproducibility: when one tool encounters computational limits at national scale, equivalent open-source alternatives exist.

Flow accumulation and drainage. For both countries, GRASS `r.watershed` was applied to the filled DEM with a threshold of 1,000 cells and D8 flow direction, producing flow accumulation and drainage direction rasters.

River network derivation. For both countries, the QGIS Raster Calculator was used to extract cells with flow accumulation $\geq 10,000$, producing a binary river network raster.

Flood susceptibility classification. For both countries, the Topographic Convergence Index (TCI), also known as the Topographic Wetness Index (TWI) (Beven and Kirkby 1979), output from `r.watershed` was reclassified into three classes (Low, Medium, High) using "Reclassify by Table" in the QGIS Processing Toolbox. The TCI reflects the tendency of terrain to accumulate water based on upstream contributing area and local slope, higher values indicate greater flood susceptibility (Beven and Kirkby 1979; Moore et al. 1991). The reclassification thresholds were determined empirically from the statistical distribution of TCI values across each country's terrain.

4.3 Blue Spot Detection (Phase 2)

Blue spot detection adapts a technique pioneered by the Danish Road Directorate for identifying ponding hazards on road networks (Larsen and Pihl 2010) to power grid infrastructure. A blue spot is a local topographic depression where water pools during heavy rainfall. Unlike coastal surge or river flooding, blue spot flooding occurs when rainfall fills a closed depression faster than it can drain. The methodological transfer from roads to power infrastructure is valid because both asset types share the same physical vulnerability mechanism: they occupy fixed locations in the terrain that cannot be relocated when water accumulates. For roads, ponding renders the surface impassable to vehicles (Larsen and Pihl 2010; Balstrøm et al. 2024). For electrical infrastructure, the same ponding damages ground-mounted equipment (switchgear, transformers, cable terminations) through water ingress (Kwasinski et al. 2019), corrodes foundations and earthing systems, and renders access roads to transmission towers impassable during heavy rain extending outage repair times (Panteli and

Mancarella 2015). The detection method (identifying terrain depressions from DEM differencing) is identical because the physical process (rainfall filling a closed topographic depression) is independent of the asset type located within it (Balstrøm and Crawford 2018).

The detection sequence is identical for both countries and proceeds in three steps:

Step 1. Depth computation. The original DEM was subtracted from the filled DEM using the QGIS Raster Calculator to produce a depression depth raster. Positive values indicate depression depth at each cell.

Step 2. Noise filtering. Cells with depth below 0.3 m were discarded via Raster Calculator. The 0.3 m threshold was applied identically in both countries. This threshold reflects the relationship between GLO-30's effective vertical accuracy (3–5 m in tropical contexts) and the minimum detectable depression depth. At 30 m resolution, only depressions spanning multiple pixels are reliably detected (ESA 2024).

Step 3. Vectorisation and area filtering. The filtered raster was converted to polygons using the GDAL Polygonize tool. An area field (m²) was calculated using the Field Calculator. Contiguous depression areas smaller than 1,800 m² (approximately two pixels at 30 m resolution) were removed, eliminating single-pixel noise artefacts. The resulting blue spot polygons were stored in each country's GeoPackage.

4.4 Coastal Buffer Generation (Phase 3)

The procedure is identical for both countries. GADM Level 1 administrative boundaries were dissolved into a single national polygon, then converted to a coastline using the QGIS Polygons to Lines tool. Buffer zones of 1 km and 5 km were generated from this derived coastline. The 1 km buffer represents immediate coastal exposure, while the 5 km buffer represents broader nearshore exposure, following the rationale established in Section 3.4.

For Mozambique, the coastline geometry was simplified using the Douglas-Peucker algorithm with a 100 m tolerance prior to buffer generation, as the high geometric complexity of the unsimplified coastline (approximately 2,500 km with numerous islands and estuarine features) produced processing times exceeding one hour. The 100 m simplification is negligible at the national-scale mapping resolution (1:7,000,000) and does not affect the buffer classification of any electrical asset.

4.5 Spatial Intersection (Phase 4)

Each hazard layer (blue spot polygons, flood susceptibility classes, coastal buffers) was spatially intersected with both asset types (generation plants and transmission lines) using the QGIS "Extract by Location" tool with an "intersects" predicate. This produced exposure layers capturing every combination of hazard zone and asset type. The count of features in each intersection layer, relative to the total asset count, yields the exposure percentages reported in Section 5.

For Jamaica, the flood susceptibility raster was vectorised and clipped to a 500 m buffered GADM boundary to remove ocean artefacts, producing a polygon layer that was used directly in Extract by Location for both plants and transmission lines.

For Mozambique, the flood susceptibility raster (8.37 GB) could not be vectorised within available computational resources. Two alternative approaches were adopted. For generation plants (point features), Sample Raster Values was used to assign the flood susceptibility class directly to each plant location. For transmission lines (line features), a 30 m buffer was applied to each segment to create polygonal features, and Zonal Statistics was used to extract the maximum raster value per feature. Lines with a maximum value of 3 (High) were classified as flood-exposed. These adaptations produce equivalent binary classification (exposed/not exposed to high flood susceptibility) while avoiding the computationally prohibitive vectorisation of the full national raster.

4.6 Use of AI tools

During the preparation of this manuscript, the authors used large language model assistance (Claude, Anthropic) for drafting support, language editing, and verification of bibliographic citations against published literature. All AI-assisted content was reviewed, verified, and edited by the authors, who take full responsibility for the final manuscript. AI tools were not used in the geospatial data analysis, QGIS workflow execution, or methodological design, which were performed exclusively by the authors. AI-generated images were not used in this manuscript.

5 Results

5.1 Jamaica

Table 3 presents the complete exposure results for Jamaica’s electrical infrastructure across the three hazard screening methods.

Table 3

Flood and coastal exposure of Jamaica's electrical infrastructure. Blue spots = depression depth ≥ 0.3 m and area $\geq 1,800$ m². Flood high = TCI-based high susceptibility class. Coast = within buffer distance from GADM-derived coastline

Asset	Total	Blue spots	Flood high (TCI)	Coast 1 km	Coast 5 km	Coast 5 km %
Generation plants	10	0 (0%)	1 (10%)	5 (50%)	7 (70%)	70%
Transmission lines	121	62 (51%)	62 (51%)	38 (31%)	68 (56%)	56%

Seven of ten generation plants (70%) are located within 5 km of the coast, and five (50%) within 1 km. This reflects Jamaica's concentration of generation capacity along low-lying coastal corridors, principally in the Kingston-Old Harbour corridor and Montego Bay. These plants are exposed to storm surge, sea-level rise, and coastal flooding mechanisms that the terrain-derived blue spot analysis does not capture.

Sixty-two of 121 transmission line segments (51%) intersect zones classified as high flood susceptibility by the TCI analysis. The spatial coincidence between transmission corridors and high flood susceptibility

zones is notable: lines tend to follow valley bottoms, river crossings, and coastal plains, precisely the areas where the TCI predicts water accumulation (Ouyang and Dueñas-Osorio 2014).

The same proportion (51%, 62 segments) of transmission lines intersects detected blue spot polygons. While the overlap between flood-susceptible zones and blue spots is substantial, the mechanisms are distinct: TCI identifies zones of general hydrological convergence, while blue spots identify specific closed depressions where ponding occurs. The coincidence suggests that Jamaica's transmission network systematically traverses terrain prone to both fluvial accumulation and local ponding.

No generation plants fall within blue spot polygons detectable at 30 m resolution. This does not mean plants are safe from ponding, it means that at the spatial resolution of this analysis, the depressions where plants are located are either too small or too shallow to detect. Urban-scale ponding around individual plant compounds requires LiDAR at finer resolution than the 30 m GLO-30 DEM used here.

The systematic absence of Jamaica from JRC Global Flood Hazard maps (whose 5000 km² basin threshold excludes the entire country), the inaccessibility of FATHOM Global 2.0 through standard channels, and the absence of WRI Aqueduct downloads collectively demonstrate that small island states are structurally excluded from the global flood hazard data infrastructure. The TCI-based proxy adopted here addresses this gap at the cost of reduced precision: it identifies where terrain characteristics favour flooding, not where flooding of a specific depth will occur at a given return period (Teng et al. 2017).

5.2 Mozambique

Table 4 presents the exposure results for Mozambique's electrical infrastructure using the identical three-hazard screening workflow applied to Jamaica, with CRS EPSG:32736 (UTM Zone 36S).

Table 4
Flood and coastal exposure of Mozambique's electrical infrastructure. Blue spots = depression depth ≥ 0.3 m and area ≥ 1,800 m². Flood high = TCI-based high susceptibility class. Coast = within buffer distance from GADM-derived coastline.

Asset	Total	Blue spots	Flood high (TCI)	Coast 1 km	Coast 5 km	Coast 5 km %
Generation plants	26	1 (4%)	4 (15%)	5 (19%)	7 (27%)	27%
Transmission lines	260	153 (59%)	217 (83%)	20 (8%)	51 (20%)	20%

Only seven of 26 generation plants (27%) are located within 5 km of the coast, compared to 70% in Jamaica. This reflects Mozambique's continental geography, where hydroelectric capacity (notably Cahora Bassa in Tete Province) is sited in the interior along major river systems rather than at coastal shipping terminals (World Bank/GFDRR 2019).

Two hundred seventeen of 260 transmission line segments (83%) traverse zones classified as high flood susceptibility by the TCI analysis. This is substantially higher than Jamaica (51%) and reflects

Mozambique's extensive low-lying deltaic terrain along the Zambezi, Limpopo, and Save river systems, where the TCI registers widespread hydrological convergence (World Bank/GFDRR 2019).

One hundred fifty-three of 260 transmission line segments (59%) intersect detected blue spot depressions, compared to 51% in Jamaica. Combined with the flood susceptibility result, this indicates that the Mozambican transmission network is systematically routed through terrain prone to both diffuse flooding and localised ponding, consistent with broader evidence that infrastructure in developing countries disproportionately occupies flood-exposed terrain (Rentschler and Salhab 2020).

Unlike Jamaica, where no plants fell within blue spots at 30 m resolution, one Mozambican plant intersects a detected depression. This difference may reflect the flatter terrain producing larger detectable depressions, though the same resolution caveats apply.

5.3 Comparative Analysis

Table 5 presents the side-by-side comparison of exposure results across both countries.

Table 5 Comparative flood and coastal exposure of electrical infrastructure in Jamaica and Mozambique. Identical workflow, identical global open-data inputs, contrasting geographic and infrastructure contexts.			
Hazard metric	Jamaica	Mozambique	Interpretation
Plants within 5 km coast	70%	27%	Island vs. continental geography
Lines in flood high zones	51%	83%	Deltaic lowlands amplify flood susceptibility
Lines in blue spots	51%	59%	Flatter terrain produces more detectable depressions
Plants in blue spots	0%	4%	Resolution-dependent, one plant detected in Mozambique

The contrasting patterns confirm that the workflow produces context-sensitive results despite using identical global inputs and methods. Jamaica's island geography concentrates generation capacity coastally but limits inland flood exposure. Mozambique's continental landscape distributes generation inland but exposes the transmission network to extensive flood and ponding hazards across its deltaic coastal plain. These differences are not artefacts of the method, they reflect genuine geographic and infrastructure-planning differences between a SIDS and a continental LMIC.

5.4 Cartographic Results

Six maps were produced, three for Jamaica (Figs. 2–4) and three for Mozambique (Figs. 5–7) using identical symbology to enable direct visual comparison. All maps were produced in QGIS Print Layout and exported at 300 dpi.

Figure 2 presents coastal exposure in Jamaica. Generation capacity is visibly concentrated along the southern coast in the Kingston-Old Harbour corridor and the northern coast at Montego Bay with seven of ten plants falling within the 5 km buffer. The 1 km and 5 km buffers encompass a substantial proportion of the island's area, reflecting Jamaica's narrow geography where most terrain is within coastal influence.

Figure 3 presents blue spot depressions and transmission line exposure in Jamaica. Depression density is highest in the central interior valleys and the Kingston-Spanish Town lowlands. Transmission lines in blue spots (51%, orange) follow valley bottoms and river crossings, consistent with the engineering logic of routing lines through flatter terrain.

Figure 4 presents the integrated flood and coastal exposure view for Jamaica. High flood susceptibility zones (TCI class 3) are concentrated in valley bottoms and coastal plains, the same corridors where transmission lines are routed. The visual overlap between high susceptibility zones, blue spot concentrations, and transmission routes illustrates the compound exposure documented in Tables 3 and 5.

Figure 5 presents coastal exposure of generation plants and transmission lines in Mozambique. In contrast to Jamaica, where generation capacity clusters along the coast, Mozambique's plants are distributed across the interior with coastal concentration limited to the southern Maputo region. The 1 km and 5 km coastal buffers encompass a proportionally smaller share of infrastructure, reflecting the country's continental extent.

Figure 6 presents blue spot depressions and transmission line exposure. The density of detected depressions is visibly higher in southern and central Mozambique, particularly in the low-lying Zambezi and Limpopo deltaic regions. Transmission lines in the Beira-Chimoio corridor and the southern network around Maputo show extensive intersection with blue spot polygons (59% of all segments).

Figure 7 presents the integrated flood and coastal exposure view combining flood susceptibility classification, blue spot depressions, coastal buffers, and electrical assets. High flood susceptibility (TCI class 3) dominates the coastal plain and river valleys, consistent with the quantitative finding that 83% of transmission line segments traverse high-susceptibility zones. The visual contrast with Jamaica's Fig. 4, where high susceptibility is concentrated in valley bottoms rather than across broad plains, illustrates the geographic basis for the differing exposure patterns documented in Table 5.

6 Discussion

6.1 Transferability

The workflow's transferability has been empirically demonstrated through the Jamaica-Mozambique comparative application. The identical analytical sequence, DEM fill, TCI computation, blue spot detection, coastal buffering, and spatial intersection, was applied to both countries using the same

global open-data sources, producing interpretable and contrasting results that reflect genuine geographic and infrastructure differences.

Three practical factors conditioned transferability: (1) computational scale required tool substitution for Mozambique's larger DEM, demonstrating that open-source workflows must accommodate alternative tools when dataset size exceeds the capacity of any single tool, (2) OSM power data quality varies substantially, Jamaica's Geofabrik extract lacked the power layer entirely while Mozambique's OSM coverage, though more extensive, required supplementation with WRI data and (3) the TCI reclassification thresholds may benefit from country-specific calibration based on local terrain statistics, though the same thresholds were applied in both countries for consistency.

The contrasting patterns in results, Jamaica's coastal concentration of generation versus Mozambique's inland distribution, Jamaica's moderate flood exposure versus Mozambique's extensive deltaic susceptibility confirm that the workflow produces context-sensitive screening despite using identical inputs and methods. This supports scalability to other coastal developing countries with comparable open-data coverage.

A natural extension of the workflow is the transition from line intersection to access-corridor exposure. The blue spot intersection with transmission lines reported in Section 5 captures where network corridors pass through terrain prone to ponding, but does not isolate the specific failure mechanism most consequential for outage duration: impassability of the access roads used by repair crews. Overlaying the OSM roads layer with the blue spot polygons and linking each transmission segment to the exposure status of its nearest access road would distinguish segments where the line itself crosses a depression from segments whose repair access is compromised, producing a more causally specific vulnerability metric. The datasets required are already used elsewhere in this workflow, and the analysis is methodologically modest but conceptually important. It is not executed here because the present paper focuses on the comparative application of the three-hazard screen, the access-road overlay is identified as a priority for subsequent work.

6.2 Data Gaps as Findings

The workflow's reliance on open data revealed coverage differences across the two study areas that are informative for practitioners seeking to replicate the approach. For Jamaica, global flood hazard products are not usable: JRC excludes basins below 5000 km², which excludes all of Jamaica, and FATHOM was inaccessible through standard channels, leading to the adoption of the TCI-based proxy. For Mozambique, the WRI Global Power Plant Database yielded only 3 facilities, requiring supplementation with OpenStreetMap records to reach 26. In both countries, the Geofabrik OSM extract did not include the power infrastructure layer, necessitating direct queries via Overpass Turbo.

These coverage differences are not unique to the present study. Open global datasets are continuously improving in spatial and thematic coverage, and their current limitations reflect the stage of development rather than a fundamental constraint. Where open data coverage is insufficient for a specific application,

commercial and institutional datasets (such as utility asset registers, national flood models, or high-resolution commercial DEMs) can complement the open-data baseline. The workflow is designed to accommodate such substitution: any higher-quality local dataset can replace the corresponding global input without altering the analytical sequence.

This complementary framing is important. The value of an open-data workflow is not that it renders commercial data unnecessary, but that it provides a reproducible, low-cost screening layer that identifies where investment in higher-resolution data and analysis would yield the greatest return (Hallegatte et al. 2019).

6.3 Technical Limitations

The most fundamental constraint is DEM resolution. At 30 m, each pixel covers 900 m². Only landscape-scale depressions spanning multiple pixels are detectable, urban-scale ponding around individual substations or pole bases is invisible (ESA 2024). Furthermore, GLO-30 is a DSM: in forested areas, canopy height inflates apparent elevation by 10–30 m, creating false depressions at canopy gaps and masking true ground-level depressions beneath the canopy (Hawker et al. 2022). The substantial vertical errors documented for GLO-30 in tropical landscapes, particularly in mountainous and densely vegetated areas (Okolie et al. 2024), mean that elevation bands below 3 m above mean sea level are unreliable at the individual pixel level.

The TCI-based flood susceptibility classification is a topographic proxy, not a hydrological model. It identifies where terrain characteristics favour water accumulation based on upstream contributing area and local slope, but does not incorporate rainfall intensity, return periods, drainage infrastructure, soil permeability, or land cover. A detected high-susceptibility zone served by adequate storm drains may never flood in practice, a flat area with poor drainage may flood repeatedly despite moderate TCI values. Validation against reported flood locations and local drainage knowledge is essential before the analysis informs capital investment decisions.

Blue spot detection identifies where water can pool topographically but does not model the volume or duration of ponding. The depth values represent the maximum potential depth if the depression were filled to its spill point, an upper bound that may never occur in practice depending on rainfall intensity, infiltration, and drainage. The 0.3 m threshold, while necessary to filter DEM noise, means that depressions shallower than 0.3 m are excluded even though such depths can damage ground-mounted electrical equipment.

The asset overlay depends entirely on open-data completeness. For Jamaica, the 10 WRI generation plants represent only major facilities and the 121 OSM transmission line segments represent the mapped portion of the transmission network. For Mozambique, WRI yielded only 3 plants, necessitating supplementation with 23 OSM facilities to reach 26, a composite dataset with heterogeneous attribute completeness. In both countries, distribution-level infrastructure is absent, creating an asymmetric error

structure: confirmed exposures are reliable (low false positive rate from terrain analysis), but total exposure is systematically underestimated (high false negative rate from incomplete asset data).

A practical limitation specific to Mozambique is computational scale. The 8.7 GB national DEM required tool substitution (WhiteboxTools instead of GRASS r.fill.dir), alternative spatial intersection methods (Zonal Statistics instead of raster vectorisation), and coastline simplification for buffer generation. These adaptations produced equivalent analytical results but required significantly more processing time, disk space, and RAM than the Jamaica workflow. This computational dimension is rarely discussed in methodological papers but has direct implications for the reproducibility of open-source workflows in resource-constrained institutional settings (Singleton et al. 2016).

6.4 Policy and Planning Implications

The exposure results produced by this workflow are not an end product but a decision-support input. Their value is realised when they feed specific planning or financing channels. Five use cases illustrate how the outputs can inform policy.

First, prioritised reinforcement of exposed network segments. The spatial screen identifies which transmission corridors and generation sites justify targeted hardening, including reinforced foundations, stronger poles, shorter spans, or selective undergrounding in the highest-exposure zones. Rather than uniform resilience investment across the network, the screen directs scarce capital to the segments where the marginal return is highest (Hallegatte et al. 2019).

Second, rapid-recovery infrastructure and access planning. Where a flood-exposed transmission segment is also served by a flood-exposed access road, restoration time compounds. The spatial identification of blue spots and high flood susceptibility zones along transmission corridors can inform road upgrading priorities, alternative repair routes, and pre-positioned repair staging areas for post-event restoration (World Bank/GFDRR 2019; Schweikert et al. 2014).

Third, dimensioning of contingent liability and insurance instruments. Finance ministries and utilities must budget for disaster-related capital replacement. Spatial exposure screens quantify the asset base whose replacement cost defines the required coverage for sovereign risk financing instruments. Such instruments include contingent credit lines, parametric insurance, and catastrophe bonds (Clarke and Dercon 2016).

Fourth, siting of future generation and renewable expansion. Low-electrification expansion in Mozambique and renewables rollout in Jamaica both involve siting decisions for new capacity. The exposure screen allows planners to avoid locking in new assets in high-exposure terrain, shifting from diagnosing legacy exposure to preventing future exposure. This is particularly relevant as both countries expand solar and wind generation, which can be sited with more spatial flexibility than legacy thermal plants (Moner-Girona et al. 2016; Shahzad et al. 2024).

Fifth, siting of non-network critical assets. Battery storage systems, control centres, and modernised substations are high-value point assets whose location is not geographically constrained in the way legacy generation is. The screen identifies where these should not be placed. As storage deployment accelerates, placing high-value installations in blue spots or low-elevation coastal zones embeds avoidable vulnerability for decades (Nicolas et al. 2019).

The workflow thus functions as a screening layer that informs multiple downstream planning and financing decisions. Its outputs gain value not in isolation but when integrated into the institutional processes that allocate capital, site infrastructure, and manage risk.

7 Conclusions

This paper has presented a reproducible, open-data workflow implemented in QGIS for identifying the flood and coastal exposure of electrical infrastructure, applied comparatively to Jamaica and Mozambique. The principal findings are:

- (a) The workflow produces context-sensitive results in contrasting geographic contexts: Jamaica's island geography concentrates coastal exposure (70% of plants within 5 km), while Mozambique's deltaic terrain amplifies inland flood exposure (83% of transmission lines). High blue spot exposure in both countries (51% and 59% of transmission lines) reveals a systemic vulnerability of low-lying routing independent of geographic context.
- (b) Standard global flood hazard datasets structurally exclude small island states. The documented absence of Jamaica from JRC and FATHOM products, due to basin area thresholds below 500 km², demonstrates an analytical gap that disproportionately affects countries most exposed to climate-driven flooding. The TCI-based proxy adopted here addresses this gap with documented trade-offs.
- (c) The adaptation of blue spot detection from road drainage engineering to power grid infrastructure represents a novel domain transfer. One generation plant in Mozambique and no plants in Jamaica fall within detected blue spots at 30 m resolution, while over half of transmission lines in both countries intersect blue spot depressions.
- (d) The workflow operates entirely with open data and open-source tools. Tool substitutions such as WhiteboxTools for Mozambique's 8.7 GB DEM and Zonal Statistics for raster overlay demonstrate that equivalent outcomes can be achieved when computational constraints arise, enabling institutional sustainability of the analytical capability.

Three priorities follow. First, targeted LiDAR acquisition in priority corridors identified by the 30 m screening, where higher-resolution data would add the most value (Gesch 2018). Second, the exposure results can directly inform infrastructure planning by identifying which corridors should be prioritised for flood protection, where new grid extensions should avoid high-susceptibility zones, and where existing assets may require hardening (Hallegatte et al. 2019). Third, extension of the blue spot analysis from line

intersection to access-corridor exposure, overlaying the OSM roads layer to identify transmission segments whose repair access is compromised by ponding.

Declarations

Competing interest

All authors except Jairo Quirós Tortós are employed by Climate Lead Group (CLG), a consulting organization that provides advisory services on climate change adaptation, energy transition, and policy development for public and private institutions, including in Latin America and the Caribbean. Jairo Quirós Tortós is affiliated with Loughborough University. The methodology presented in this manuscript relates to areas within CLG's general field of practice. The authors declare no other competing interests relevant to the content of this article.

Ethics approval and consent to participate

Not applicable. This research did not involve human participants, human data, or animal subjects.

Consent for publication

Not applicable.

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Author Contribution

IRA led the conceptualization and methodological design of the workflow, performed the data curation, formal analysis, and visualization, executed the QGIS analysis for Jamaica and the majority of the Mozambique analysis, conducted the bibliographic verification, and wrote the first draft of the manuscript. LVG contributed to the conceptualization, supervised the research, managed project administration, performed a portion of the GIS analysis for Mozambique, and commented on previous versions of the manuscript. AMB, JRP, and JQT contributed to the conceptualization, supervised the research, and commented on all versions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

All input datasets used in this study are openly available: Copernicus GLO-30 DEM via OpenTopography (<https://portal.opentopography.org>), GADM v4.1 (<https://gadm.org>), WRI Global Power Plant Database v1.3 (<https://datasets.wri.org/dataset/globalpowerplantdatabase>), OpenStreetMap power features via Overpass Turbo (<https://overpass-turbo.eu>), and VIIRS VNL v2.2 nighttime lights (<https://eogdata.mines.edu/products/vnl>). The QGIS processing scripts and intermediate GeoPackage files generated during the workflow are available from the corresponding author upon reasonable request.

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Figures

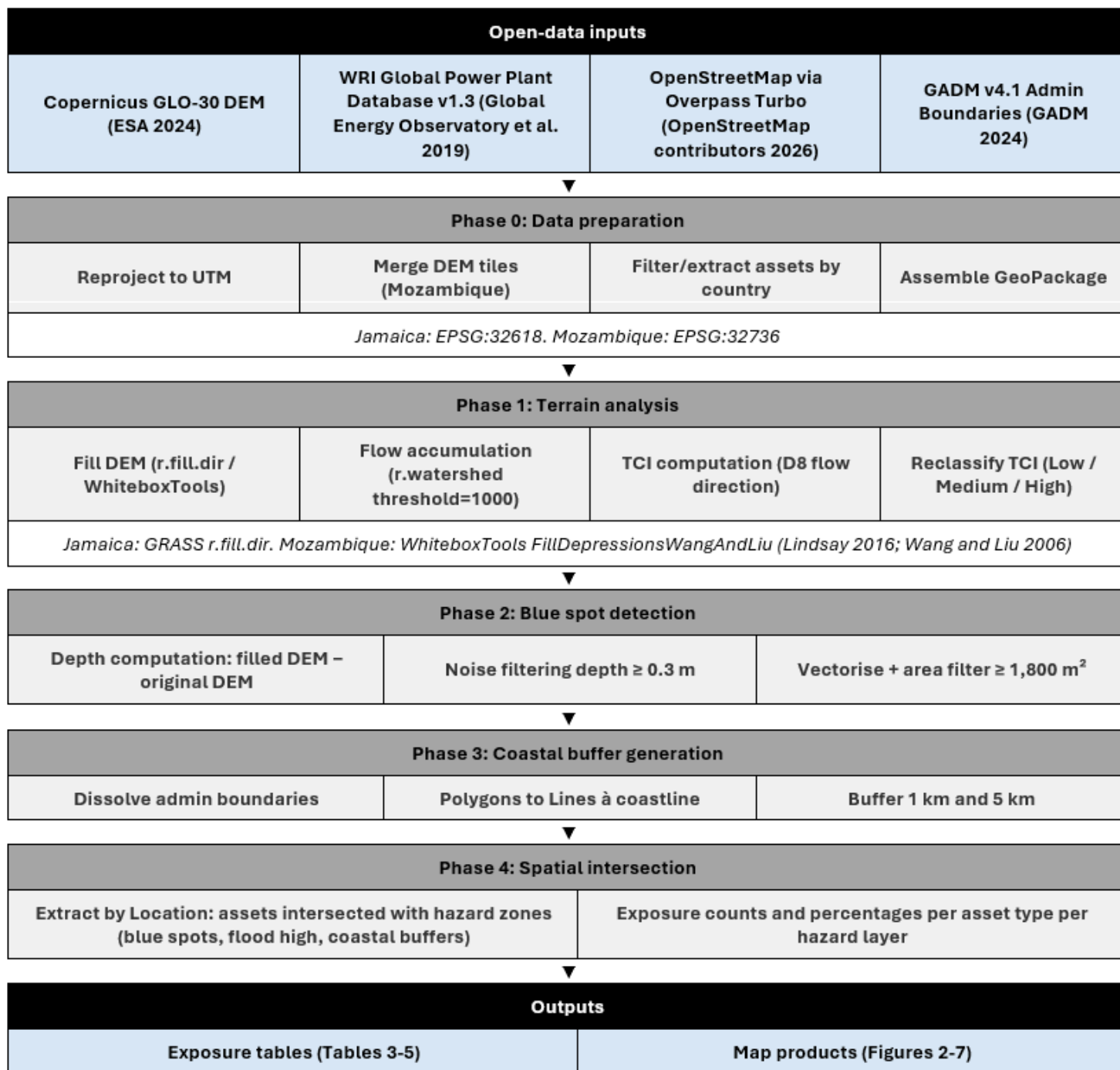
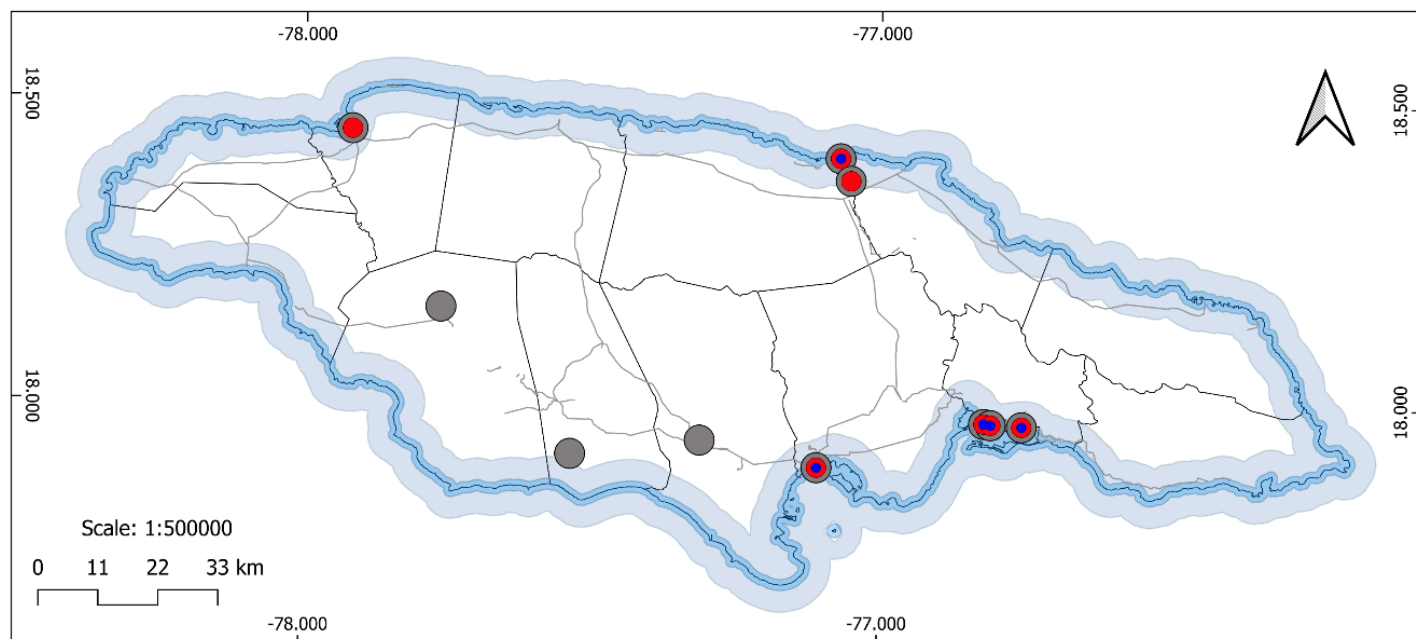


Figure 1

Multi-hazard exposure workflow for Jamaica and Mozambique. The workflow is organised into five phases using QGIS 3.34 and open-data inputs. Tool substitutions for Mozambique are noted in Phase 1.



Legend

- Generation plants (≤ 1 km coast)
- Generation plants (≤ 5 km coast)
- Generation plants
- Power Lines
- Buffer 1km
- Buffer 5km
- Parish boundaries

Study area

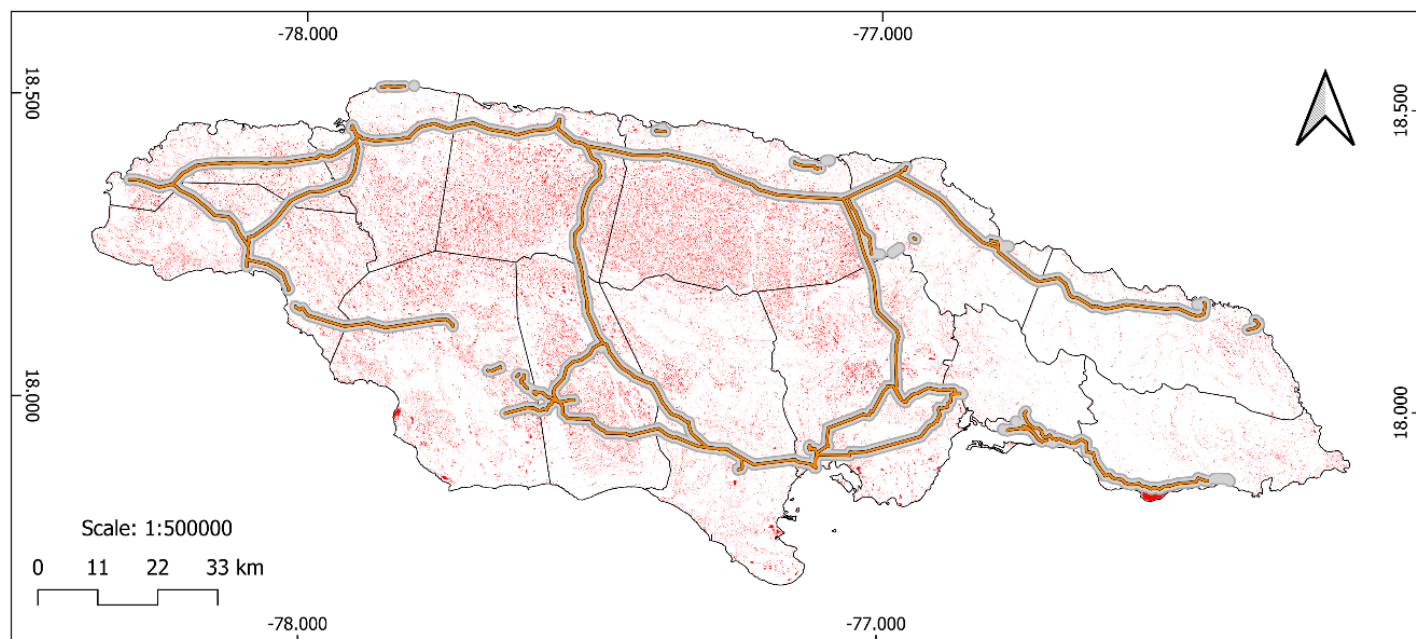


Sources: GADM v4.1 (gadm.org); WRI Global Power Plant Database v1.3 (datasets.wri.org); OpenStreetMap via Overpass Turbo. CRS: WGS 84 / UTM Zone 18N.

Elaboration: Climate Lead Group (CLG), 2026.

Figure 2

Jamaica: coastal exposure of generation plants and transmission lines. CRS: EPSG:32618.



Legend

- Transmission lines in blue spots (51%)
- Transmission lines (all)
- Parish boundaries
- Blue spot depressions (≥ 0.3 m depth)

Study area

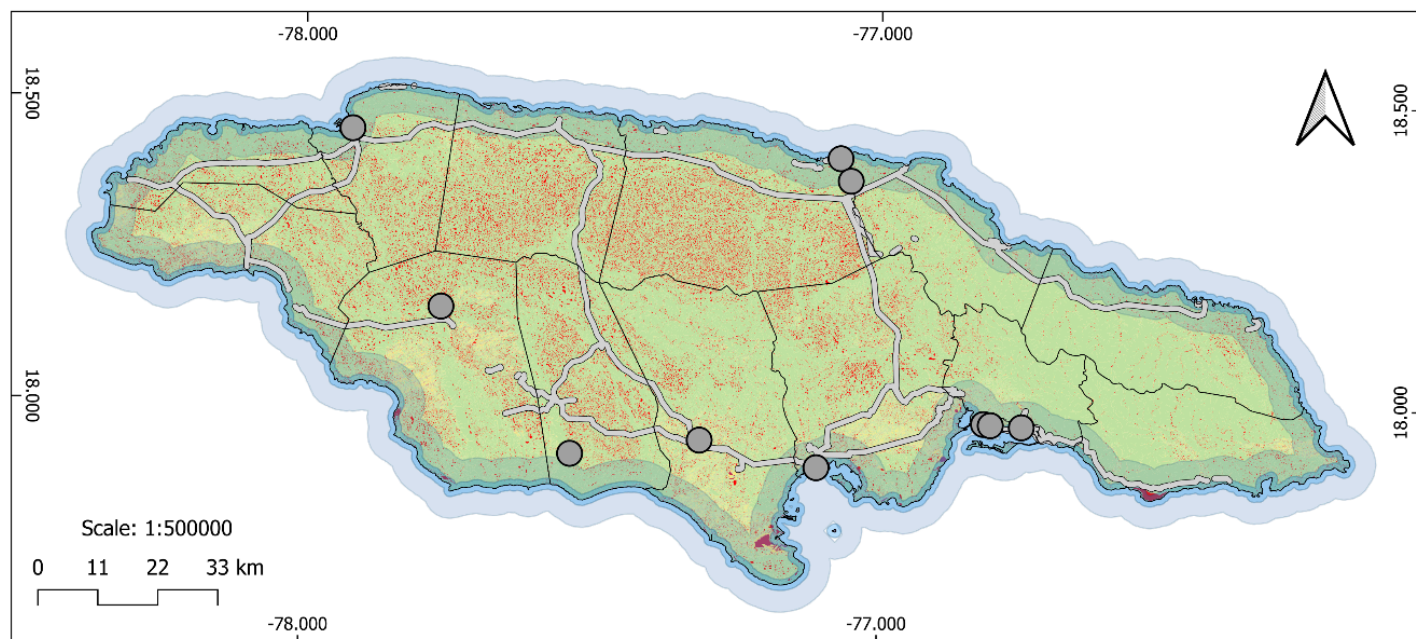


Sources: Copernicus GLO-30 DEM (ESA, 2024); OpenStreetMap via Overpass Turbo; GADM v4.1.

Elaboration: Climate Lead Group (CLG), 2026.

Figure 3

Jamaica: blue spot depressions (≥ 0.3 m depth, $\geq 1,800$ m²) and transmission line exposure (51% of segments). CRS: EPSG:32618.



Legend

- Generation plants
- Parish boundaries
- Transmission lines
- Coastal buffer 1 km
- Coastal buffer 5 km
- Blue spot depressions (≥ 0.3 m depth)
- Flood susceptibility (Low / Medium / High)
 - Low
 - Medium
 - High

Study area

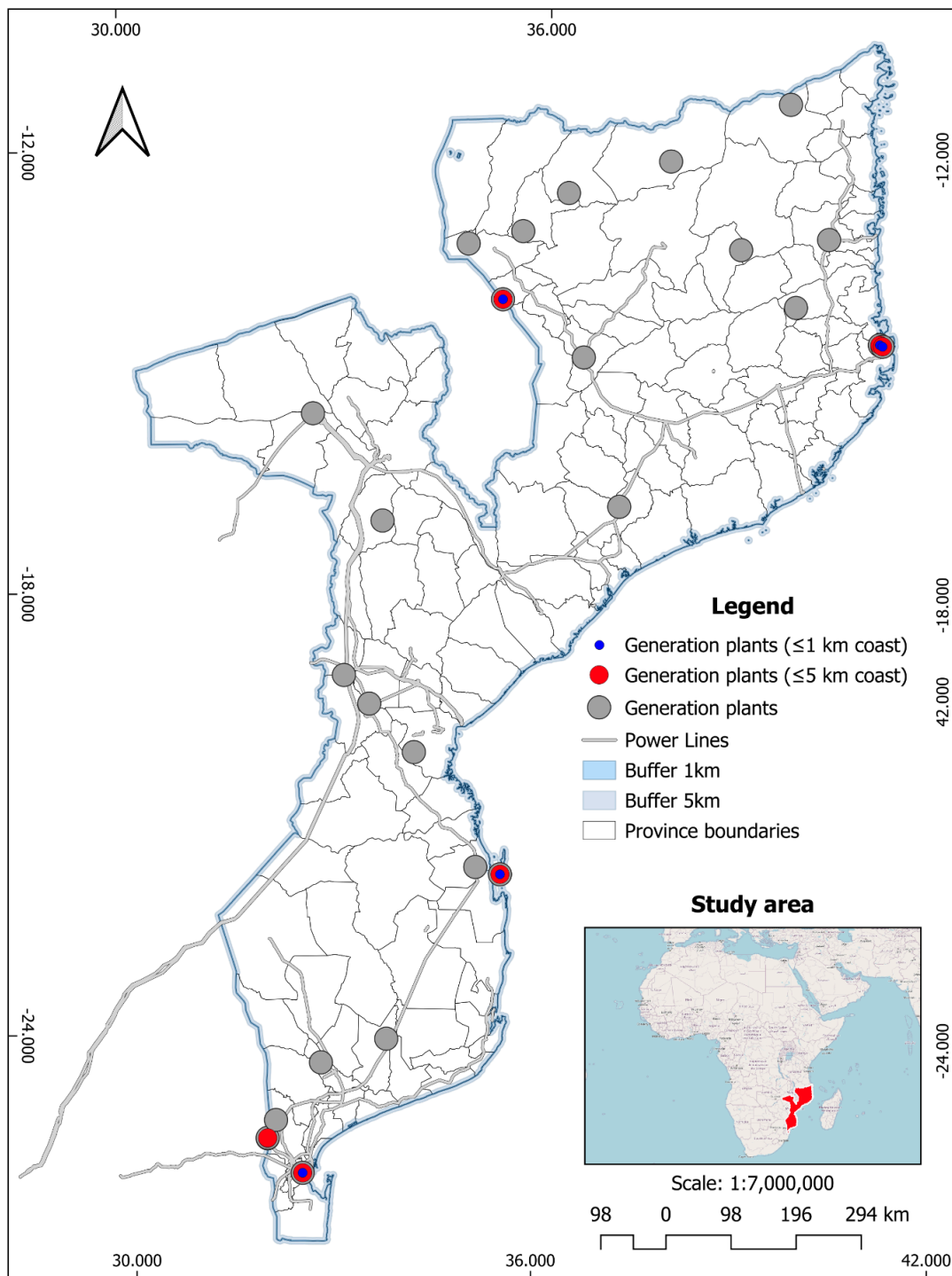


Sources: Copernicus GLO-30 DEM (ESA, 2024); WRI Global Power Plant Database v1.3 (datasets.wri.org); OpenStreetMap via Overpass Turbo; GADM v4.1. CRS: WGS 84 / UTM Zone 18N.

Elaboration: Climate Lead Group (CLG), 2026.

Figure 4

Jamaica: integrated flood and coastal exposure combining flood susceptibility (TCI), blue spot depressions, and coastal buffers with electrical infrastructure. CRS: EPSG:32618.

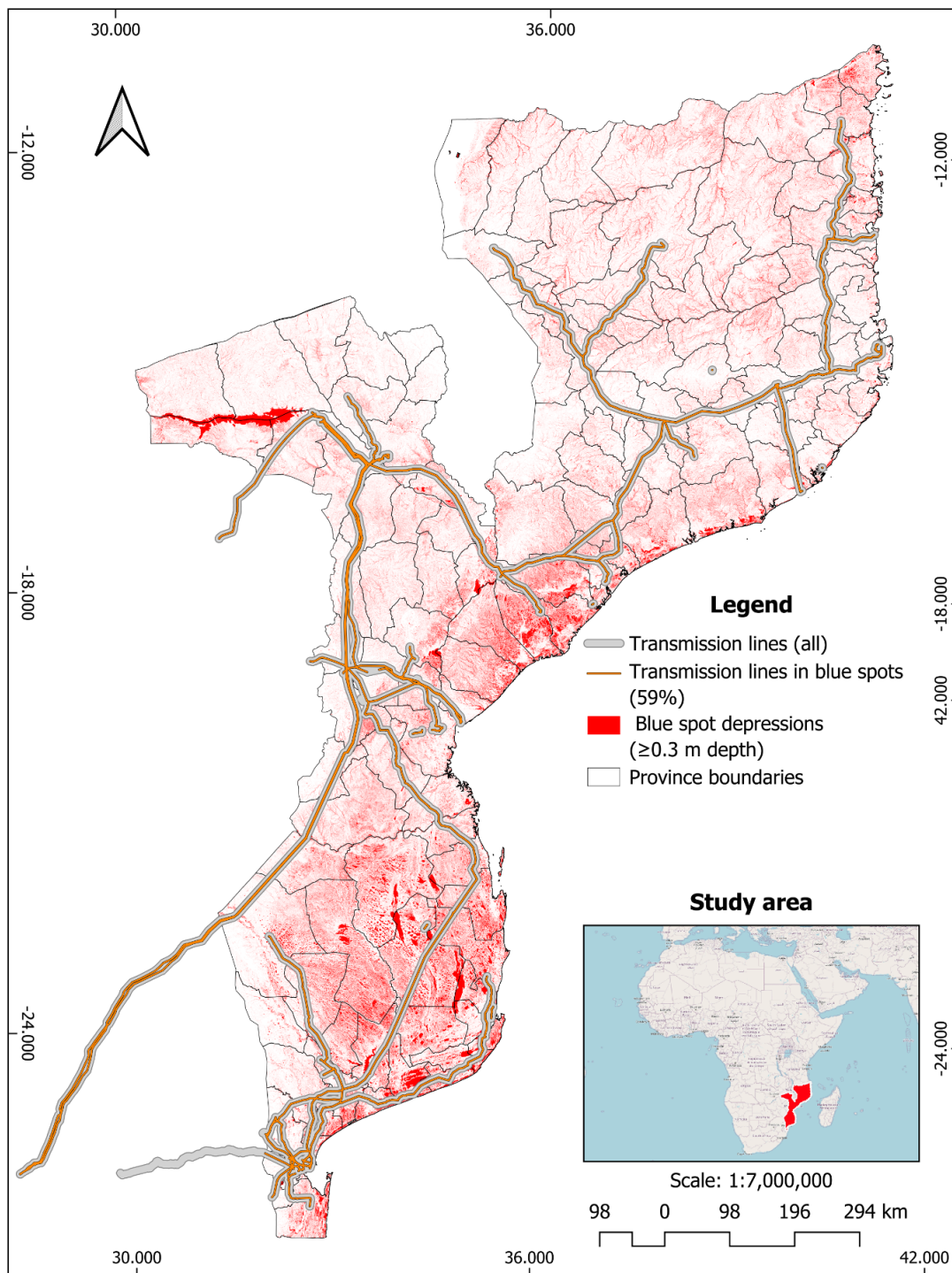


Sources: GADM v4.1 (gadm.org) WRI Global Power Plant Database v1.3 (datasets.wri.org); OpenStreetMap via Overpass Turbo. CRS: WGS 84 / UTM Zone 36S.

Elaboration: Climate Lead Group (CLG), 2026.

Figure 5

Mozambique: coastal exposure of generation plants and transmission lines. Buffers of 1 km and 5 km from GADM-derived coastline. CRS: EPSG:32736.

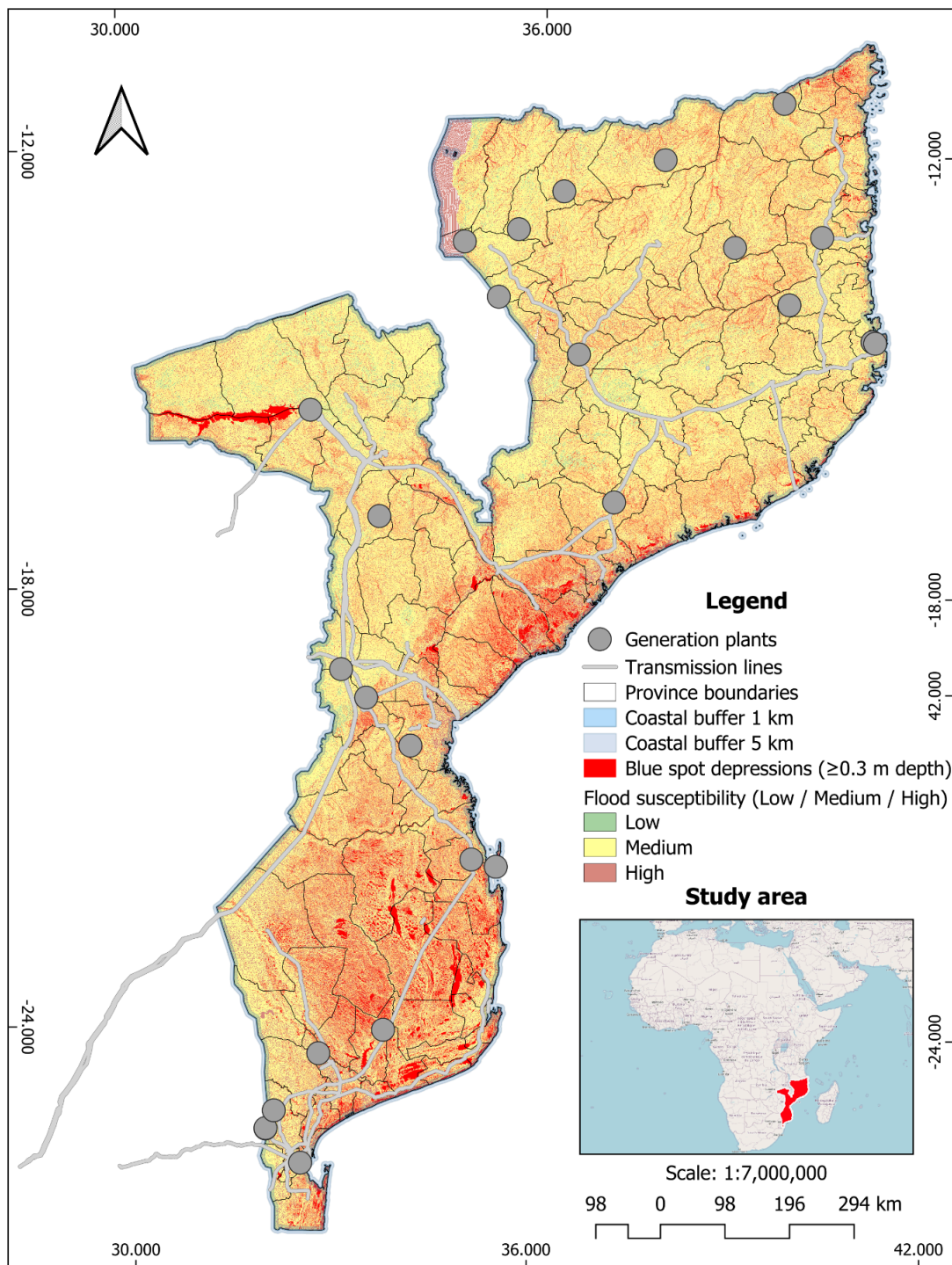


Sources: Copernicus GLO-30 DEM (ESA, 2024); OpenStreetMap via Overpass Turbo; GADM v4.1. CRS: WGS 84 / UTM Zone 36S

Elaboration: Climate Lead Group (CLG), 2026.

Figure 6

Mozambique: blue spot depressions (≥ 0.3 m depth, $\geq 1,800$ m²) and transmission line exposure (59% of segments). CRS: EPSG:32736.



Sources: Copernicus GLO-30 DEM (ESA, 2024); WRI Global Power Plant Database v1.3 (datasets.wri.org); OpenStreetMap via Overpass Turbo; GADM v4.1. CRS: WGS 84 / UTM Zone 36S.

Elaboration: Climate Lead Group (CLG), 2026.

Figure 7

Mozambique: integrated flood and coastal exposure combining flood susceptibility (TCI), blue spot depressions, and coastal buffers with electrical infrastructure. CRS: EPSG:32736.