

Climate Risk Exposure of Educational Facilities in Kenya: A National Multi-Hazard Spatial Assessment Using the IPCC AR6 Framework

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Research Article

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Abstract

Climate change poses an intensifying threat to educational infrastructure across Sub-Saharan Africa, yet spatially explicit, facility-level risk assessments remain scarce in data-constrained environments. This study operationalizes the IPCC AR6 risk framework ($Risk = Hazard \times Exposure \times Vulnerability$) to evaluate multi-hazard climate risk for 9,451 educational facilities across Kenya at 1 km spatial resolution. Using Earth observation datasets CHIRPS precipitation (1981–2023), MODIS land surface temperature (2018–2023), SRTM topography, and CMIP6 SSP2-4.5 projections (2040–2059) we generated independent hazard layers for drought, flood susceptibility, and heat stress. Institutional exposure was quantified from a validated school location database, while socio-spatial vulnerability was estimated by combining WorldPop population density with inverse VIIRS nightlight radiance. The resulting facility-level risk scores ranged from 0.034 to 0.804, revealing substantial spatial heterogeneity. While 62.2% of schools fell within moderate-to-low risk categories, 14.8% (1,405 facilities) were classified as Very High risk, concentrated predominantly in northeastern arid and semi-arid lands and the Lake Victoria Basin. Three distinct hotspot typologies emerged: coastal flood-heat compound risk (412 schools), ASAL drought-heat syndrome (578 schools), and Lake Victoria Basin flood-exposure amplification (315 schools). Under mid-century CMIP6 projections, an additional 2.3% of schools are projected to shift into the Very High-risk category. The findings demonstrate the utility of scalable geospatial analytics for infrastructure risk assessment in data-limited regions and provide an evidence base for prioritizing climate-resilient educational infrastructure investment in Kenya.

1. Introduction

1.1 The Climate-Education Nexus in Sub-Saharan Africa

Climate change is fundamentally reshaping the operating environment for education systems across Sub-Saharan Africa, where intensifying hydro-climatic extremes increasingly compromise infrastructure integrity, student health, and learning continuity. The IPCC Sixth Assessment Report establishes that Eastern Africa faces critical intensification of droughts, floods, and heat extremes, with regional temperatures already 1.5°C above pre-industrial levels (IPCC 2022; Berihu et al. 2025). These hazards affect educational infrastructure through multiple, often compounding pathways: flooding undermines foundation stability and sanitation systems (Acharya & Silori, 2025); drought-induced soil subsidence accelerates structural degradation; and extreme heat reduces cognitive performance, with each 1°F increase in school-day temperature lowering student achievement by approximately 1% (Park et al. 2020; Graff Zivin et al. 2018). These physical and human capital impacts cascade through education systems, threatening the achievement of Sustainable Development Goal 4 and perpetuating intergenerational cycles of poverty.

1.2 Kenya's Educational Landscape and Climate Vulnerability

In Kenya, this crisis is particularly acute due to the nation's diverse physiography, spanning coastal lowlands, the Lake Victoria Basin, the Central Highlands, and expansive arid and semi-arid lands (ASAL) covering 80% of the territory. This spatial heterogeneity exposes the country's strategic educational network 9,451 registered facilities serving over 12 million learners to regionally differentiated yet compounding climate hazards. Recent trends indicate a worsening trajectory: 2024 was officially Kenya's hottest year on record (Daily Nation 2025), while erratic rainfall produced catastrophic flooding that affected 43 counties and damaged or destroyed at least 62 primary schools (UNICEF 2025). Despite Kenya's leadership in climate policy through the Climate Change Act (2016) and National Adaptation Plan (2015–2030), the education sector still lacks spatially explicit, facility-level analytical tools for prioritizing adaptation investments (World Bank 2023). Existing assessments are limited by administrative aggregation that obscures localized risk heterogeneity and single-hazard approaches that fail to capture compound impacts (Gebre, 2021; Njuguna et al. 2023; Mauti et al. 2025).

1.3 Research Gap and Contribution

Despite growing literature on climate vulnerability in East Africa, assessments of the education sector suffer from “administrative obscuring” aggregation at coarse county or regional scales that masks the granular reality of climate impacts at the institutional level. This leads to sub-optimal adaptation planning, with resources often directed to administrative units rather than the most vulnerable facilities (Imran 2020; Gebre 2021). This study addresses three key questions: (1) what is the high-resolution spatial distribution of multi-hazard climate risk across Kenya's 9,451 educational facilities? (2) How do hazard, exposure, and socio-spatial vulnerability interact multiplicatively to produce differential risk profiles? (3) What regional hotspot typologies emerge, and how can they inform differentiated adaptation responses? By shifting from administrative averages to pixel-based analysis at 1 km resolution, this study provides the first facility-level evidence base for Kenya, with risk scores ranging from 0.034 to 0.804.

1.4 Conceptual Framework and Scientific Justification

This study operationalizes the IPCC AR6 risk framework, which defines risk as the convergence of physical hazards, exposure of assets, and underlying system vulnerability: **Risk = Hazard × Exposure × Vulnerability**, with each component normalized to a 0–1 scale. A multiplicative aggregation model was deliberately chosen over an additive approach. This is scientifically justified because it enforces a non-compensatory relationship: if any component approaches zero, overall risk approaches zero. This prevents overestimation of risk in areas lacking exposure and ensures that “High Risk” is assigned only where all three dimensions intersect. The analytical workflow integrating Earth observation data, hazard modeling, exposure mapping, and vulnerability assessment is visually synthesized in Fig. 1. This framework aligns with recent advances in IPCC AR6 (Birkmann et al., 2022) and infrastructure risk assessment (Koks et al., 2019; Singh et al., 2026).

2. Materials and Methods

2.1 Study Area and Spatial Discretization

Kenya covers 582,646 km² across 47 counties, spanning latitudes 5°N to 5°S and longitudes 34°E to 42°E. The national territory was discretized into a 1 km grid as the primary spatial unit of analysis. The country's diverse physiography includes five main climatic zones: coastal tropical, (ASAL, covering 80% of the territory), Lake Victoria Basin, Central Highlands, and western Kenya. With a population exceeding 50 million, of which 70% reside in rural areas (KNBS, 2019), educational infrastructure stability is closely linked to regional climate dynamics. A validated database of 9,451 school locations was obtained from the Kenya Ministry of Education via the Humanitarian Data Exchange under a Creative Commons Attribution 4.0 license. Figure 2 illustrates the study area, major climatic zones, and the spatial distribution of the 9,451 educational facilities included in this study.

2.2 Data Acquisition and Harmonization

All datasets were processed in Google Earth Engine (Gorelick et al. 2017). Datasets with native resolutions ranging from 30 m to 25 km were harmonized to a common 1 km grid using bilinear interpolation for continuous surfaces and nearest-neighbor resampling for categorical data. This ensured precise spatial alignment for multiplicative integration. Table 1 summarizes the primary data sources, native resolutions, harmonized resolution, and references. Datasets were selected based on peer-reviewed validation, open access, and sufficient temporal coverage for both historical and future analyses.

Table 1
Data acquisition, specifications, and sources

Component	Dataset	Source	Native Resolution	Harmonized Resolution	Reference
Drought (historical)	CHIRPS daily precipitation	UCSB-CHG	5 km	1 km	Funk et al., 2015
Drought (future)	CMIP6 SSP2-4.5 (2040–2059)	NASA GDDP	1° (~ 111 km, downscaled)	1 km	Thrasher et al., 2022
Flood	SRTM DEM + CHIRPS 95th percentile	USGS / UCSB-CHG	30 m / 5 km	1 km	Farr et al., 2007
Heat stress	MODIS MOD11A2 LST (8-day, 1 km)	NASA LP DAAC	1 km	1 km	Wan et al., 2015
Exposure	School locations	KMOE (HDX)	Point data	1 km	KMOE, 2010
Sensitivity	WorldPop population density (2020)	WorldPop	100 m	1 km	Tatem, 2017
Adaptive capacity	VIIRS nightlight (monthly, 2023)	NOAA	500 m	1 km	

2.3 Hazard Construction and Normalization

Each hazard layer was modeled independently at 1 km resolution and normalized to a 0–1 scale using 5th – 95th percentile min-max scaling to reduce outlier influence while preserving spatial variability (Gallina et al. 2016). Drought hazard integrated historical CHIRPS precipitation (1981–2024) and CMIP6 SSP2-4.5 projections (2040–2059) using the index:

DH = [(P_baseline – P_recent) + (P_baseline – P_future)] / 2, where positive values indicate increasing deficits. Flood susceptibility combined SRTM topography (elevation and slope) with extreme precipitation (95th percentile CHIRPS) via the Compound Topographic Index. Heat stress was quantified as the 90th percentile of daytime MODIS LST (2018–2023). The composite hazard index was calculated as the arithmetic mean of the three normalized layers, supported by PCA showing balanced contributions (first component explained 78% of variance). The spatial patterns of individual and composite hazards are presented in Supplementary **Fig. S1** (panels a–d)."

2.4 Exposure Assessment

Exposure was defined as the spatial concentration of educational assets. The 9,451 validated school locations were rasterized at 1 km resolution rather than using kernel density estimation to avoid smoothing artifacts. This layer was combined with resampled WorldPop population density (2020) and

normalized to 0–1, creating a hybrid surface representing both institutional presence and demographic load (Fig. 3).

2.5 Vulnerability Index Construction

Vulnerability combined population sensitivity and limited adaptive capacity (Cutter et al. 2003; Birkmann et al. 2022). Sensitivity used normalized WorldPop population density. Adaptive capacity was proxied by VIIRS nightlight radiance (2023), with inverse values ($1 - \text{Adaptive_norm}$) applied. The Socio-Spatial Vulnerability Index was calculated as:

Vulnerability = (Sensitivity_norm + (1 – Adaptive_norm)) / 2.

Higher values indicate areas with high demographic pressure and low adaptive capacity (Fig. 4).

2.6 Risk Computation, Classification, and Validation

Final risk was computed multiplicatively as **Risk = H × Exposure_norm × Vulnerability_norm**. Risk scores (0.034–0.804) were classified into five categories using equal-interval thresholds: Very Low (0.0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0). Validation involved spatial comparison with independent records (Dartmouth Flood Observatory, Kenya Meteorological Department) and PCA. Although ground-truth data were limited, multiple lines of evidence support model reliability.

3. Results

3.1 National Risk Distribution

The composite risk surface showed substantial spatial heterogeneity across the 9,451 educational facilities. Using five equal-interval risk classes, 37.8% of schools fell into High (23.0%) or Very High (14.8%) categories (Table 2). The 1,405 Very High-risk schools serve approximately 1.2 million learners and represent an immediate adaptation priority. Figure 5 displays the national risk distribution, highlighting three distinct spatial clusters. Disaggregation by school type revealed differential exposure (Table 3), with special needs schools showing the highest proportion in High/Very High categories (45.2%), followed by primary schools (38.9%).

Figure 5. National Special climate risk distribution

Table 2
Distribution of schools by climate risk class (n = 9,451)

Risk Class	Risk Level	Facility Count (n = 9,451)	Percentage (%)	Cumulative %
1	Very Low	1,472	15.5	15.5
2	Low	1,719	18.1	33.6
3	Moderate	2,715	28.6	62.2
4	High	2,184	23.0	85.2
5	Very High	1,405	14.8	100.0
Total		9,451	100%	

Table 3
Risk distribution by school type

School Type	Number	% Very High	% High/Very High
Primary	7,832	15.2	38.9
Secondary	1,512	13.1	34.2
Technical/Vocational	89	11.2	31.5
Special Needs	62	19.4	45.2

3.2 Spatial Distribution of Hazard Components

Drought hazard exhibited a strong east-west gradient, with very high values (0.8–1.0) concentrated in northern and northeastern ASAL counties (Turkana, Marsabit, Wajir, Mandera). Moderate to high drought hazard extended into transitional zones, while low hazard prevailed in western Kenya and the Central Highlands. Flood susceptibility was highest in low-lying, high-rainfall areas, particularly the Lake Victoria Basin, Tana River Delta, and coastal zones. Heat stress was widespread in lowland and arid regions, with very high values dominating northern ASAL and coastal hinterlands, and lower values in elevated areas. The composite multi-hazard index identified "triple-threat" zones in northeastern ASAL and along the Tana River corridor where drought, heat, and flood risks overlap (Supplementary **Fig. S1**, panels a–d).

3.3 Regional Hotspot Typologies

Three distinct hotspot typologies emerged from the interaction of hazard, exposure, and vulnerability (Fig. 6).

Coastal Hotspot (Flood–Heat Compound Risk)

Coastal counties contained 412 Very High-risk schools (29.3% of all Class 5). This zone features alternating flood and extreme heat stress, high asset density, and elevated vulnerability.

Northeastern ASAL Hotspot (Drought–Heat Syndrome)

ASAL counties hosted 578 Very High-risk schools (41.1%). Dominant drivers are chronic drought and extreme heat, compounded by high exposure in pastoralist areas and limited adaptive capacity (73% of ASAL schools lack improved water sources).

Lake Victoria Basin Hotspot (Flood–Exposure Amplification)

This basin accounted for 315 Very High-risk schools (22.4%). Flood hazard is amplified by exceptionally high school density (1,562 facilities), creating systemic risk despite moderate hazard intensity.

3.4 County-Level Risk Rankings and Temporal Dynamics

County rankings confirmed a north–south gradient (Tables 4 and 5). ASAL counties showed the highest percentages of Very High-risk schools (e.g., Mandera 50%, Wajir 48.1%), while coastal and Turkana counties had the largest absolute numbers. Temporal analysis compared historical (1981–2023) and future (2040–2059) scenarios. Incorporating CMIP6 SSP2-4.5 projections shifted an additional 2.3% of schools (≈ 218 facilities) into the Very High-risk category and increased High-risk schools by 2.8% (Table 6). This indicates climate change will expand the footprint of extreme risk across Kenya, consistent with regional projections (IPCC, 2022).

Table 4
Top 10 counties by percentage of schools in Very High risk

Rank	County	Total Schools	Very High Risk	% Very High	Primary Hazard(s)
1	Mandera	312	156	50.0	Drought, Heat
2	Wajir	287	138	48.1	Drought, Heat
3	Garissa	345	162	47.0	Drought, Heat
4	Tana River	189	76	40.2	Flood, Drought
5	Marsabit	218	86	39.4	Drought, Heat
6	Lamu	97	34	35.1	Flood, Heat
7	Turkana	476	162	34.0	Drought, Heat
8	Kilifi	568	182	32.0	Flood, Heat
9	Kwale	327	103	31.5	Flood, Heat
10	Isiolo	134	41	30.6	Drought, Heat

Table 5 Top 10 counties by number of schools in Very High risk (see Supplementary Table S3 for complete data)

Table 6 Projected change in climate risk distribution under mid-century CMIP6 SSP2-4.5 projections (2040–2059) (see Supplementary Table S4 for complete data)

4. Discussion

4.1 Alignment with Existing Literature and Scientific Interpretation

This study confirms and extends previous research on climate vulnerability in East African education systems while providing new facility-level insights through the multiplicative IPCC AR6 framework. The identification of three distinct hotspot typologies coastal flood-heat compound risk, ASAL drought-heat syndrome, and Lake Victoria Basin flood-exposure amplification aligns with documented regional patterns of hydro-climatic stress (Birkmann et al. 2022; Mohamed 2024). However, the quantification of risk scores across a continuous scale (0.034–0.804) advances beyond coarse administrative assessments by revealing localized convergence of hazards, exposure, and vulnerability. This spatial heterogeneity reinforces the growing consensus that climate impacts are increasingly characterized by compound, non-linear hazard interactions rather than isolated climatic extremes (Serdeczny et al. 2017).

In ASAL regions, the drought-heat syndrome is consistent with evidence of increasing drought-related absenteeism and dropout rates (UNESCO 2024; UNICEF 2023). High classroom temperatures frequently exceeding 38°C align with findings that each 1°F rise reduces learning outcomes by approximately 1% (Park et al. 2020). These conditions are amplified by limited water infrastructure and weak adaptive capacity, creating a multi-causal system where environmental stress and infrastructural deficits reinforce one another. Qualitative studies from Kenya's ASAL counties (Chongwo et al. 2025) confirm that caregivers consistently report drought and heat as dominant stressors undermining school attendance and cognitive development. Household-level evidence further demonstrates that droughts reduce access to essential infrastructure while exacerbating structural deterioration and maintenance costs (Njogu 2022), directly supporting our observation that schools in drought-prone areas face compounded infrastructure stress.

Coastal areas exhibit compound flood-heat risk, where seasonal flooding followed by extreme heat exacerbates vulnerability in high-density urban settings (Wing et al. 2019; Roth 2007). Approximately 60% of coastal urban populations in Africa reside in informal settlements with limited adaptive capacity, a context characterizing Mombasa and other coastal cities (Neumann et al. 2015). The Tana River Basin case study (Okoko 2022) reinforces these findings, demonstrating that historical development policies have systematically increased flood vulnerability among communities in floodplain areas, directly aligning with our observed clustering of flood-exposed educational facilities along the Tana River corridor. The Lake Victoria Basin demonstrates "exposure amplification," where moderate flood hazard combines with exceptionally high school density to generate large absolute numbers of at-risk facilities. Lake Victoria's water levels exhibit historical fluctuations of 1.5–2.5 m, with recent record highs inundating critical shoreline infrastructure (Khomba et al. 2020). This "Paradox of Density" underscores

that risk is not driven by hazard intensity alone but by the interaction of all three IPCC components, supporting Birkmann's (2022) theory of dynamic equilibrium where high-load environments exhibit systemic fragility.

4.2 Contribution to IPCC AR6 Framework Application

This study operationalizes the IPCC AR6 risk framework at national scale using entirely open-access Earth observation data. While previous applications of the AR6 framework have been largely conceptual or restricted to localized pilot areas (Birkmann et al. 2022; Ranasinghe et al. 2021), this study integrates multi-hazard modeling, pixel-level exposure mapping, and nightlight-based vulnerability indicators into a unified, scalable assessment tool. The multiplicative formulation ($\text{Risk} = H \times E \times V$) proved effective by enforcing non-compensatory logic: high risk only emerges where hazard, exposure, and vulnerability converge. This approach avoids overestimation common in additive models and produces policy-relevant classifications.

The equal weighting of hazards was supported by PCA (first component explained 78% of variance), confirming balanced contributions across drought, flood, and heat (Gallina et al. 2016). VIIRS nightlight radiance served as a practical proxy for adaptive capacity in data-scarce environments (Elvidge et al. 2017; Ghosh et al. 2021). In Kenya, where systematically collected, geo-referenced data on school infrastructure quality remains scarce, nighttime luminosity provides a valuable alternative. The strong correlation between low radiance and elevated risk scores across the northern frontier validates this approach, providing empirical support for its application in other data-limited contexts. The resulting facility-level risk database provides a scalable template for other Sub-Saharan African countries facing similar data constraints.

4.3 Socio-Spatial Drivers of Vulnerability

The Socio-Spatial Vulnerability Index reveals two contrasting patterns that fundamentally shape the risk distribution across Kenya's educational facilities. In remote ASAL areas, low nighttime luminosity indicates profound infrastructure deficits and isolation, amplifying climate impacts. This condition of "frontier vulnerability" is characterized by extreme geographic distance from administrative centers and limited access to emergency resources. Longitudinal household data from Kenya confirms that rural communities supported by improved physical infrastructure such as all-weather roads and electricity grids are far more resilient to environmental shocks over time (Musyoka et al. 2020). This explains why low VIIRS radiance strongly correlates with severe risk classifications along the Mandera-Wajir-Garissa axis and across the Turkana Basin.

In contrast, major urban centers like Nairobi and Mombasa benefit from higher adaptive capacity that partially buffers high exposure. Strong nighttime luminosity reflects developed infrastructure, economic activity, and institutional resources, functioning as an "infrastructural buffer" (Elvidge et al. 2017). However, peri-urban and basin areas show elevated vulnerability due to rapid population growth outpacing infrastructure development. The highest overall vulnerability scores occur within the rapidly expanding peri-urban fringes of the Lake Victoria Basin, the Central Highlands, and the Nairobi-Kajiado

corridor. In these transitioning areas, high student-to-teacher ratios, overstretched school infrastructure, and unplanned urbanization reduce the ability of local institutions to absorb climate shocks. These findings highlight that vulnerability is shaped as much by adaptive capacity deficits as by hazard exposure itself, requiring geographically differentiated strategies: foundational infrastructure investment in frontier regions, and strengthened institutional capacity in rapidly urbanizing landscapes.

4.4 Policy Implications and Tiered Intervention Framework

The facility-level risk assessment supports a shift from broad administrative planning to targeted intervention, consistent with both the IPCC AR6 recommendations (IPCC 2022) and Kenya's National Adaptation Plan (Government of Kenya 2015). The 1,405 Very High-risk schools (serving ~ 1.2 million learners) and 2,184 High-risk schools should be prioritized for immediate adaptation. A tiered approach is recommended: emergency retrofitting for the 68 highest-risk facilities (risk scores > 0.75) within 12 months; hazard-specific interventions by typology (water/heat resilience in ASAL, flood-proofing in coastal and basin areas); and biennial monitoring of Moderate-risk schools (2,715 facilities) as sentinel sites to track risk migration under accelerating climate change.

This spatially explicit evidence base strengthens applications to international climate finance mechanisms, including the Green Climate Fund and Adaptation Fund, which increasingly require transparent targeting metrics (World Bank 2023). The economic rationale for proactive adaptation is supported by evidence that the costs of inaction measured in disrupted education, damaged infrastructure, and diminished human potential substantially exceed the investment required for climate-resilient schools. Furthermore, combining school-level interventions with broader ecosystem restoration and water-harvesting initiatives can significantly improve local adaptive capacity, as demonstrated in vulnerability assessments of Kenya's drought-prone ASALs (Njoka et al. 2016). Community-based disaster management committees, informed by facility-level risk mapping, can strengthen adaptation by linking satellite-derived evidence with indigenous knowledge and local preparedness strategies (Mohamed 2025).

4.5 Limitations and Scientific Uncertainty

Several limitations should guide future methodological refinement. Key limitations include reliance on a single climate model and emissions pathway (SSP2-4.5), which constrains representation of future uncertainty. Although sensitivity analysis using SSP5-8.5 produced consistent spatial patterns (5–8% increase in high-risk categories), multi-model ensembles would better capture inter-model variability (Thrasher et al. 2022; Hausfather and Peters, 2020). The current framework employs a multiplicative risk formulation ($\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$) consistent with the IPCC AR6 framework. Although this approach captures the interaction among hazard, exposure, and vulnerability, it still simplifies the complex nonlinear and cascading nature of real-world climate impacts. Future research could evaluate alternative risk aggregation approaches, including empirical, machine-learning, or process-based models, to assess whether they improve the representation of cascading and compound climate risks while maintaining consistency with the IPCC AR6 framework.

Terrain-based flood susceptibility identifies relative exposure but does not model inundation depth, flood frequency, or distinguish between fluvial and pluvial processes. While comparison with Dartmouth Flood Observatory records suggests good spatial agreement, hydraulic modeling approaches (e.g., CaMa-Flood, LISFLOOD) would substantially improve site-specific engineering applications (Wing et al., 2019; Sampson et al. 2015). Nightlight-based adaptive capacity proxies have limitations in rural areas with limited electrification or cultural patterns that suppress nighttime activity (Mellander et al. 2015). Incorporating direct, school-level indicators building materials, water access, and emergency equipment would improve model accuracy. The 1 km resolution, while superior to county-level aggregation, may still smooth over micro-scale vulnerabilities in dense informal settlements or complex terrain.

Exposure estimates are static and do not capture seasonal attendance fluctuations, agricultural schedules, or climate-induced migration. Integrating Education Management Information Systems (EMIS) and dynamic enrollment data would significantly improve temporal accuracy (UNESCO 2024). Formal validation was constrained by limited ground-truth data; the absence of a standardized national database of school-level climate damage means risk scores remain model-dependent. Future research should incorporate: (1) multi-model climate ensembles to evaluate risk migration; (2) field-based validation through citizen science and school impact reports; (3) cross-sectoral analysis of cascading water-energy-education interactions; and (4) evaluation of localized adaptation measures, including school greening, passive cooling, rainwater harvesting, and nature-based flood mitigation.

5. Conclusions

This study presents the first nationally consistent, facility-level assessment of multi-hazard climate risk across Kenya's educational system by operationalizing the IPCC AR6 risk framework through the integration of open-access Earth observation datasets, educational exposure, and socio-spatial vulnerability indicators. Moving beyond conventional regional assessments, the study demonstrates that educational climate risk is fundamentally governed by the spatial convergence of hazard intensity, exposure concentration, and adaptive-capacity deficits rather than by hazard magnitude alone. This framework provides a reproducible approach for identifying localized climate-risk hotspots and offers a scalable methodology for climate-risk assessment in data-constrained environments.

Three principal conclusions emerge from the analysis. First, climate risk is highly heterogeneous across Kenya, with nearly two-fifths (37.8%) of the 9,451 assessed schools classified as High or Very High risk. The observed facility-level risk continuum (0.034–0.804) confirms that climate vulnerability is spatially concentrated rather than uniformly distributed. Among these, 1,405 Very High-risk schools, serving approximately 1.2 million learners, require immediate adaptation interventions. Within this group, the 68 schools with risk scores exceeding 0.75 constitute the country's highest climate adaptation priority.

Second, the study identifies three distinct regional climate-risk pathways that require differentiated adaptation strategies rather than a single national response. Educational vulnerability in the ASAL counties is primarily driven by the interaction of prolonged drought, extreme heat, and chronic water

insecurity. Coastal schools experience compound flood–heat stress associated with tropical climate dynamics and rapid urban expansion, whereas schools within the Lake Victoria Basin illustrate a Paradox of Density, where concentrated educational assets substantially amplify systemic risk despite comparatively moderate hazard intensity. These findings demonstrate that effective adaptation depends on understanding the specific mechanisms through which hazard, exposure, and vulnerability interact across contrasting geographical settings. Consequently, adaptation strategies should be context-specific: water security and passive cooling in ASAL counties, integrated flood protection and heat mitigation along the coast, and flood-resilient infrastructure, evacuation planning, and early warning systems in the Lake Victoria Basin.

Third, proactive adaptation is both an educational imperative and a sound long-term investment. Under mid-century CMIP6 SSP2-4.5 projections, approximately 218 additional schools are projected to transition into the Very High-risk category, highlighting the urgency of anticipatory adaptation. The 2,715 schools currently classified as Moderate Risk represent critical "sentinel" institutions where regular monitoring and timely intervention could prevent progression to higher-risk conditions and reduce future infrastructure losses. Although detailed engineering and economic assessments are required to quantify investment needs, the results indicate that proactive adaptation is likely to be more cost-effective than responding to climate-induced disruptions after they occur. The facility-level, spatially explicit risk database developed in this study provides an evidence base to support such assessments and to guide transparent prioritization of adaptation investments.

Beyond its national relevance, this study advances climate-risk science by demonstrating that the IPCC AR6 risk framework can be operationalized using freely available geospatial datasets within data-limited settings. The resulting methodology supports climate-resilient educational planning, transparent allocation of adaptation finance, and systematic monitoring of resilience over time. Future research should build upon this framework by incorporating multi-model climate projections, dynamic educational datasets, field-based validation, and evaluations of localized adaptation measures, including school greening, passive cooling, rainwater harvesting, flood-resilient landscaping, and other nature-based solutions to strengthen institutional resilience under accelerating climate change.

Ultimately, strengthening climate resilience in the education sector extends beyond protecting physical infrastructure; it safeguards learning continuity, human capital development, and long-term national resilience. The analytical framework and facility-level risk database developed in this study provide practical decision-support tools for Kenya while offering a transferable methodology for assessing and managing climate risks across educational systems and other climate-sensitive sectors throughout Sub-Saharan Africa and comparable data-scarce regions worldwide.

Declarations

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Figures

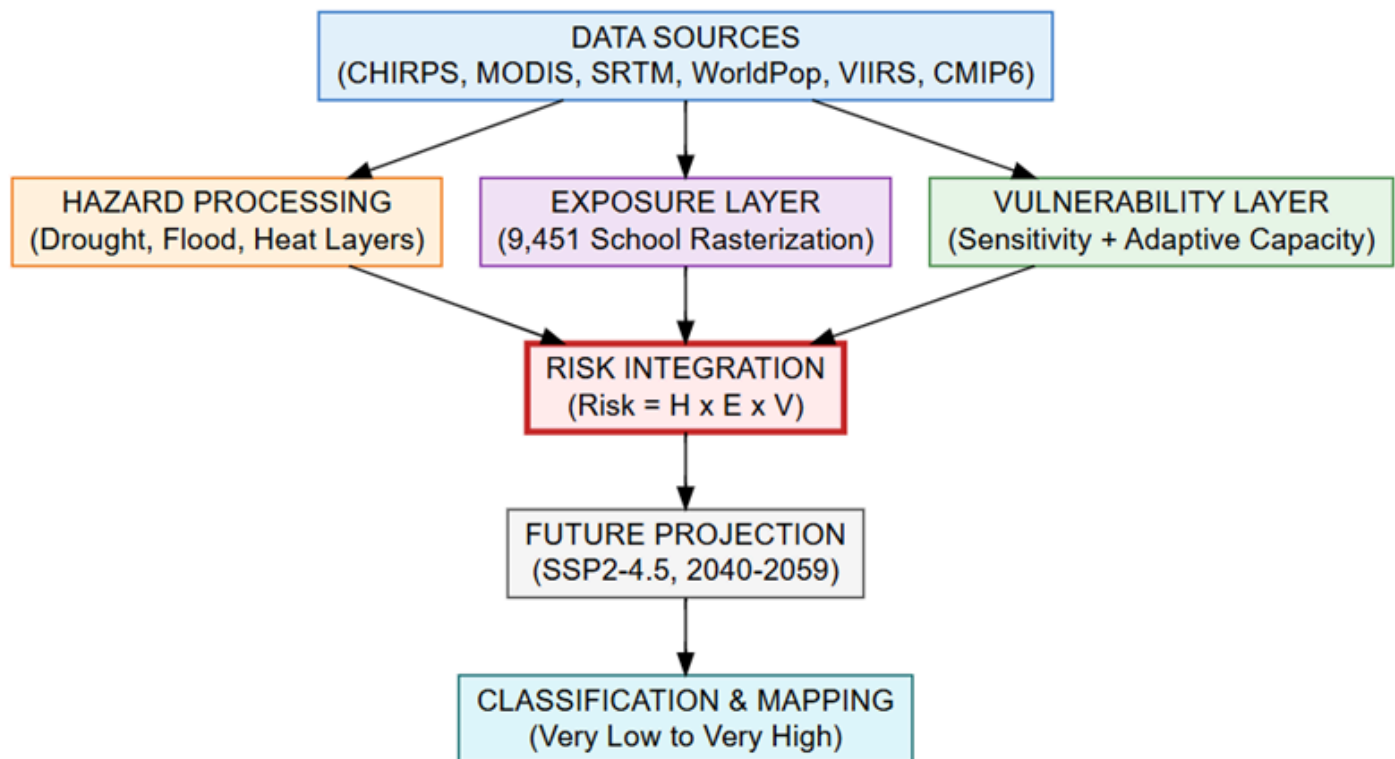


Figure 1

Methodological workflow operationalizing the IPCC AR6 risk framework

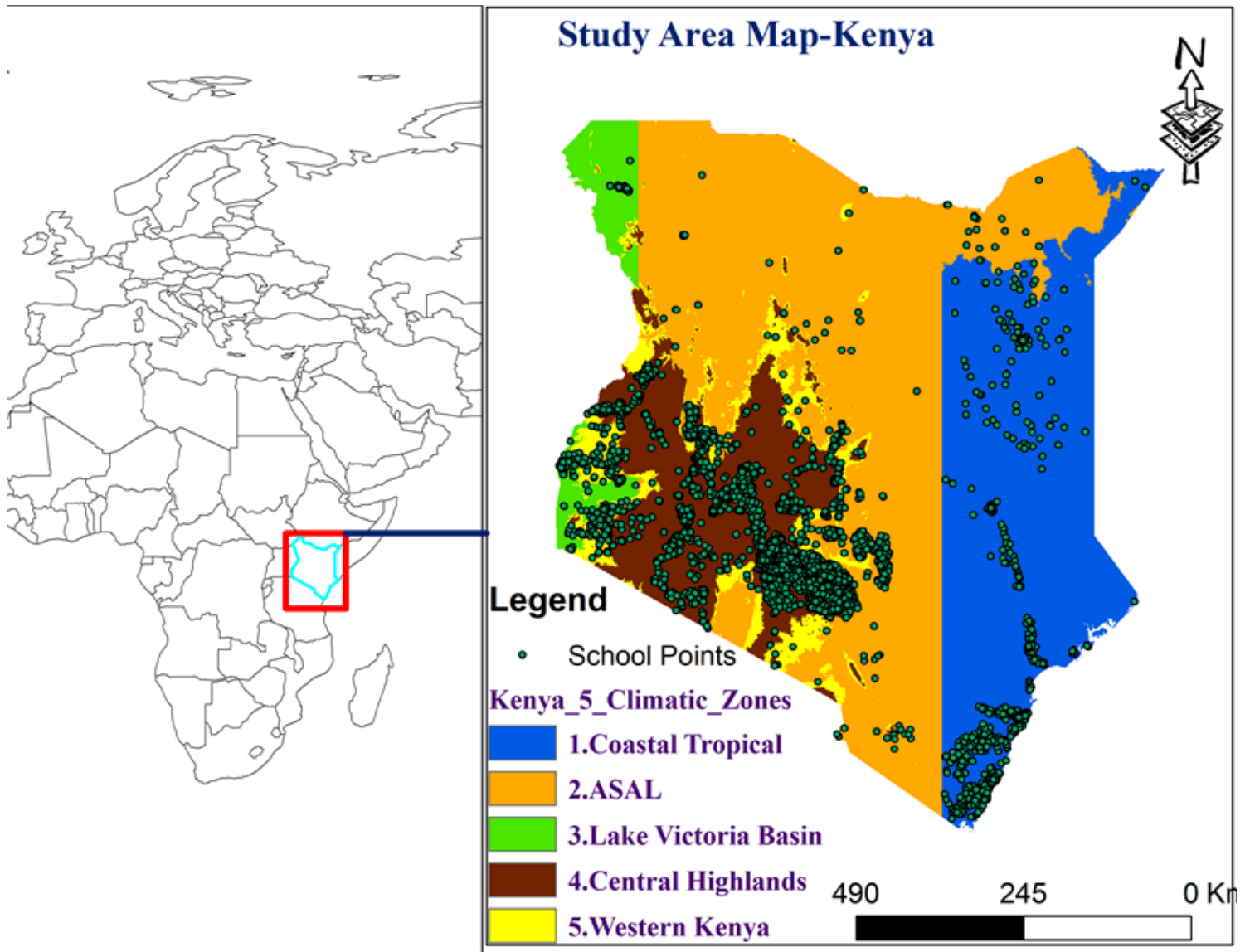


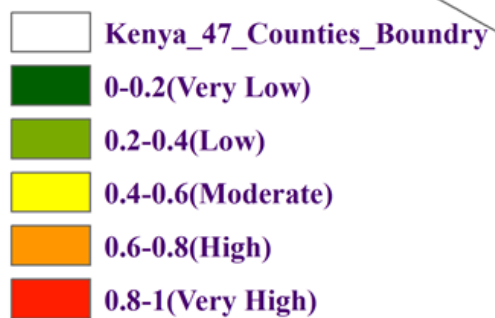
Figure 2

Study Area Map

Spatial Exposure Density of Educational Facilities map (Kenya)



Legend



430 215 0 Km

Figure 3

Spatial exposure density of Educational facilities

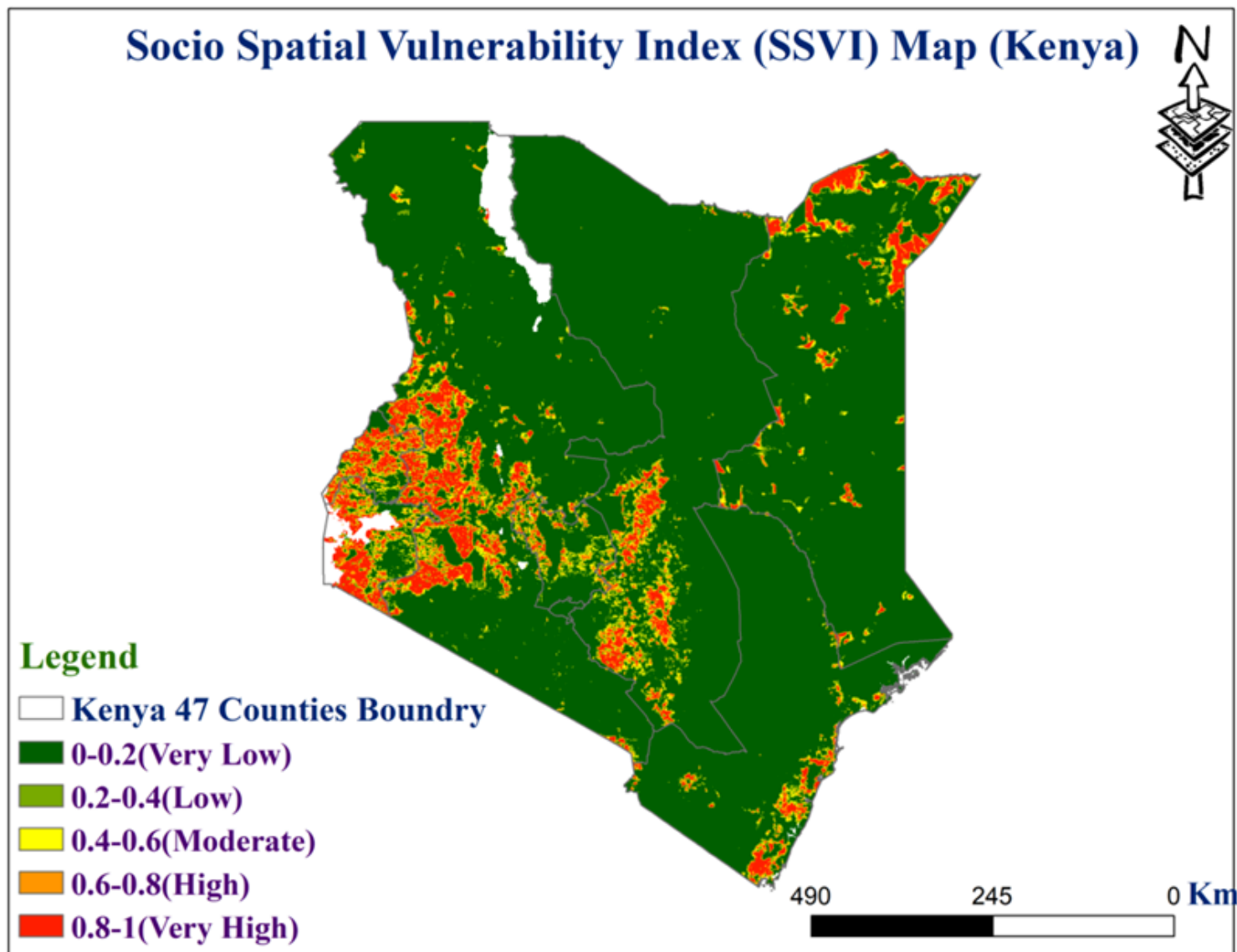


Figure 4

Socio-Spatial Vulnerability Index

Spatial Distribution of Climate Risk to Educational Facilities in Kenya

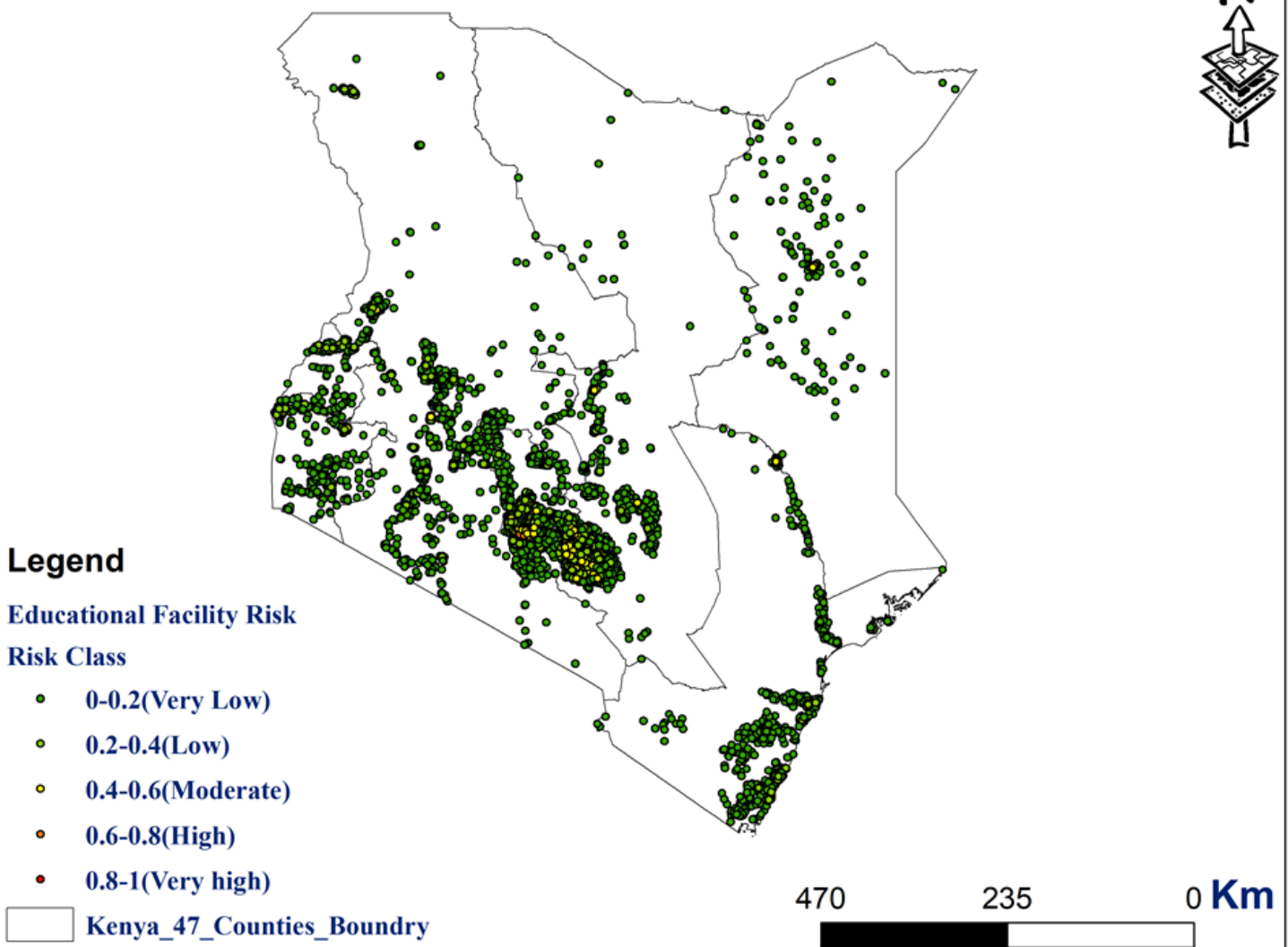


Figure 5

National Special climate risk distribution

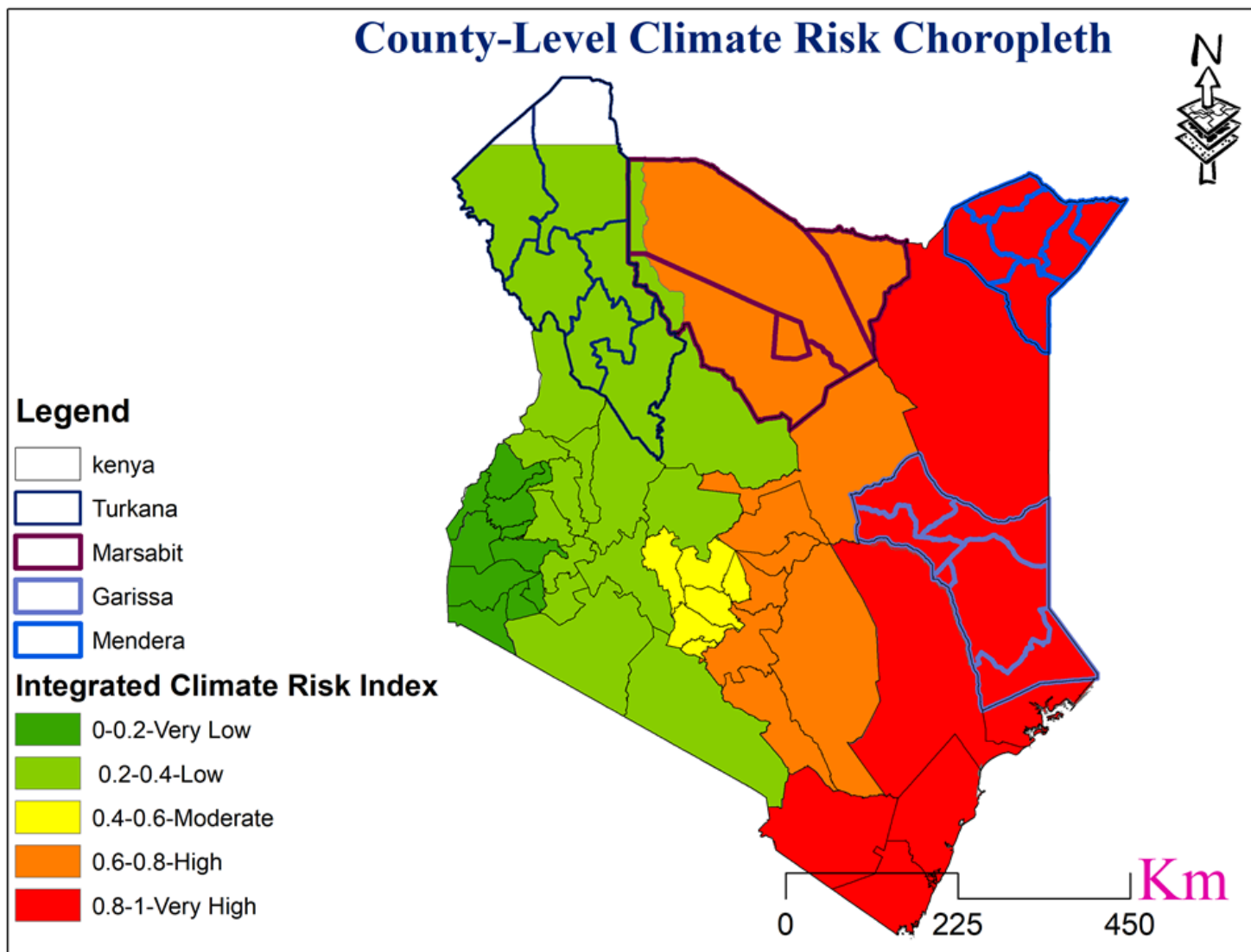


Figure 6

Country level climate risk choropleth showing three hotspot typologies

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