Assessing Large-Scale Healthcare Resource Accessibility Using Remote Sensing and Geospatial Analysis: A Case Study of Wildfire-Exposed Regions in Africa

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Keywords: Wildfire, Healthcare, Mismatch, Remote Sensing, Climate-resilient.

Abstract

Wildfire smoke exposure is an emerging public health challenge across Africa, yet its interaction with healthcare accessibility remains poorly characterised. We developed the Health-Exposure-Resource Mismatch Index (HERMI), combining satellite-derived $PM_{2.5}$, population density, and geocoded health facilities to quantify spatial imbalances between exposure and care. Nearly two-thirds of Africa's population live in areas of mismatch, with severe hotspots in Angola, the Central African Republic, and South Sudan. Urban centres show lower mismatch despite higher exposure, underscoring the role of healthcare capacity in mitigating environmental risks. Although constrained by incomplete facility data and simplified accessibility measures, HERMI provides a scalable framework to identify intervention priorities and delivers actionable evidence for climate-resilient health planning across the continent.

1. Introduction

Wildfires are a recurring and growing concern across Africa, especially in fire-prone ecosystems such as tropical savannahs and dry woodlands (Nyamadzawo et al., 2013; Ouattara et al., 2025). While the environmental and atmospheric impacts of wildfires have been widely studied, their public health implications remain underexplored (Reid et al., 2016; Wimberly et al., 2024). As climate change drives more frequent and intense fire activity, wildfire-related air pollution — particularly fine particulate matter ($PM_{2.5}$) — poses increasing risks to human health, especially in regions where access to medical care is limited (Barros et al., 2025; Xu et al., 2023).

Although many studies have examined the health impacts of air pollution, few have considered how wildfire exposure aligns with the distribution of healthcare services (Barkoski et al., 2024; Hertelendy et al., 2024). In many high-risk areas, large populations face both high exposure to smoke and poor access to medical facilities (D'Evelyn et al., 2022). This spatial mismatch presents a significant challenge for building resilient health systems.

To address this gap, we introduce the HERMI, a geospatial framework that integrates wildfire exposure, population distribution, and healthcare accessibility into a unified indicator. By combining MODIS active fire data, CAMS-modelled $PM_{2.5}$ concentrations, GHS-POP population grids, and health facility datasets from Healthsites.io, HERMI provides a systematic method to identify areas where high wildfire exposure coincides with limited healthcare availability.

This study applies HERMI at the continental scale for Africa, with three key objectives: 1. to develop and operationalize a spatial indicator that captures wildfire-healthcare mismatches; 2. to identify regional hotspots of severe mismatch where vulnerable populations face compounded risks; and 3. to demonstrate how remote sensing and open geospatial data can support climate-resilient health planning. In doing so, this work bridges environmental monitoring and public health analysis, providing actionable insights for researchers, policymakers, and disaster risk managers.

2. Materials and Methods

2.1 Study Area and Data Sources

The study covers the entire African continent (Figure 1). In 2020, MODIS active fire detections revealed clear regional clustering (see Table 1 for the data description.). The largest continuous concentration of wildfires forms a belt stretching from northern Angola through southern Democratic Republic of the Congo to western Zambia, with additional dense clusters in northern Mozambique and Tanzania, and smaller pockets in western Ethiopia. A second major belt follows the southern Sahel, with high densities across northern Nigeria, southern Chad, and South Sudan; outside this zone, a distinct cluster is observed in the Central African Republic. In Southern Africa, prominent

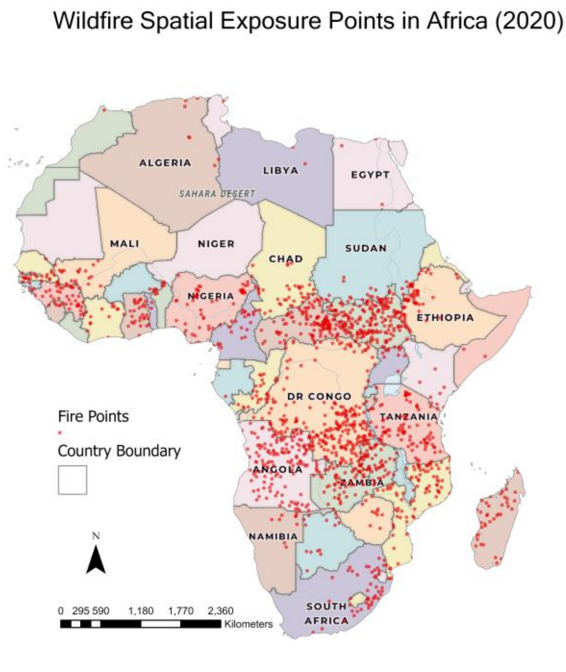

Figure 1. Wildfire Spatial Exposure Points in Africa (2020). Map created using ArcGIS Pro (Esri, Redlands, CA, USA: https://www.esri.com)

concentrations occur in the northeastern to eastern parts of South Africa, while Namibia exhibits only scattered detections. By contrast, the Sahara and much of the Mediterranean coastal fringe show very few fire events. Overall, 1,494 fire events were recorded across Africa in 2020, which serve as the basis for the wildfire-exposure analysis that follows.

To construct the HERMI, we integrated geospatial datasets representing wildfire exposure, population distribution, and healthcare accessibility (Table 1). All datasets were harmonized into a common grid and coordinate reference system (WGS84, EPSG:4326), clipped to the African boundary, and resampled to the spatial resolution of the $PM_{2.5}$ raster to ensure comparability.

Table 1 Description of input datasets (2020) for HERMI.

Data Category	**Data Source[1]**	**Spatial resolution**	**Description**
Wildfire activity	MODIS MCD14A1	1km × 1km	Active fire detections (used for density estimation)
Air pollution ($PM_{2.5}$)	CAMS Reanalysis	10km×10km	Annual mean $PM_{2.5}$ concentration
Population	GHS-POP	250m × 250 m	Gridded population density
Healthcare facilities	Healthsites.io	Point data	Hospitals and clinics data
Boundaries	GADM	-	Continental administrative boundaries

[1]*Data sources: MODIS MCD14A1 (NASA FIRMS, https://earthdata.nasa.gov/firms), CAMS Reanalysis (ECMWF, https://atmosphere.copernicus.eu), GHS-POP (EC-JRC, https://ghsl.jrc.ec.europa.eu/), Healthsites.io (https://healthsites.io), GADM (https://gadm.org).*

2.2 Methodology

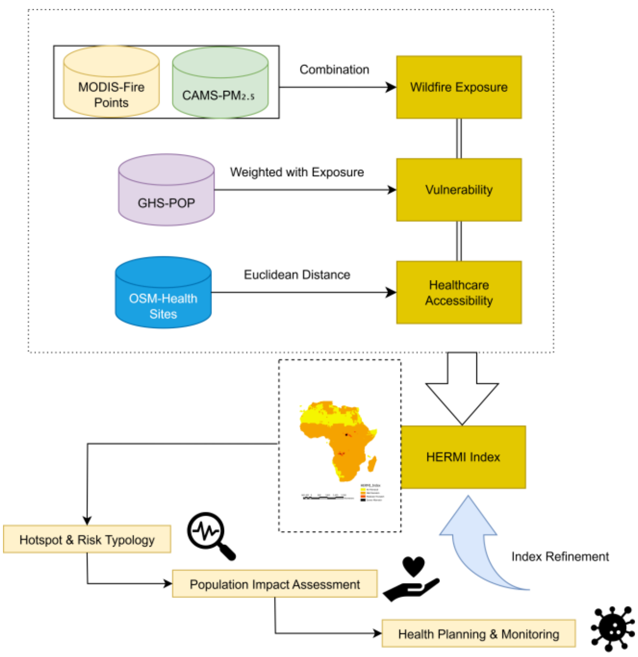

Figure 2. Workflow of the HERMI framework.

We developed a spatial framework to quantify wildfire-related health–resource mismatches across Africa in 2020. The framework integrates three domains — wildfire exposure, population vulnerability, and healthcare accessibility — into a composite HERMI. This design captures not only hazard intensity but also its interaction with population distribution and medical service availability. The overall workflow is illustrated in Figure 2: MODIS active fire detections and CAMS-derived $PM_{2.5}$ were combined to construct wildfire exposure, GHS-POP was used to represent population vulnerability, and healthcare facilities provided healthcare accessibility surfaces. These components were integrated into the HERMI, which in turn supported hotspot identification, population impact assessment, and applications in health planning.

2.2.1 Wildfire Exposure

Wildfire hazards arise both from local fire occurrence and from smoke transported over long distances, typically ranging from hundreds to thousands of kilometres (Barros et al., 2025; Johnston et al., 2012). Using only active fire detections would underestimate exposure in downwind areas, while relying solely on near-surface $PM_{2.5}$ concentrations (~10 m above ground) from the CAMS reanalysis would overlook local ignition intensity. To integrate these complementary dimensions, we averaged a kernel density surface of MODIS active fire detections (F) and CAMS $PM_{2.5}$ concentrations (P), each normalised to [0,1]:

$$Exposure_i = \frac{norm(F_i) + norm(P_i)}{2}, \quad (1)$$

Where F_i denotes the kernel density of MODIS active fire detections at location i, and P_i denotes the annual mean CAMS $PM_{2.5}$ concentration. Both variables were min–max normalised to the range [0,1] prior to integration.

2.2.2 Population Vulnerability

Not all hazards translate into equal risk: the health burden depends on the number of people exposed. To shift from a purely hazard-centric to an impact-centric perspective, we incorporated GHS-POP 2020 population density (D) as a vulnerability factor, normalised to [0,1]:

$$Vulnerability_i = norm(D_i), \quad (2)$$

This approach emphasises densely populated areas, where the same level of hazard translates into disproportionately higher health impacts.

2.2.3 Healthcare Inaccessibility

Exposure only becomes a severe mismatch if it coincides with weak healthcare access. Accessibility was modelled as the Euclidean distance to the nearest hospital or clinic, rescaled to the unit interval [0,1]:

$$Inaccessibility_i = \frac{d_i - dmin}{dmax - dmin}, \quad (3)$$

where d_i is the Euclidean distance from location $_i$ to the closest facility, and $dmax$ and $dmin$ denote the minimum and maximum observed distances across the study region. Although Euclidean distance simplifies travel dynamics, it provides a transparent and continentally consistent proxy in contexts where detailed road-network data are uneven. This choice prioritises reproducibility, while acknowledging that network-based travel times could refine local assessments.

2.2.4 HERMI

The three dimensions were integrated as:

$$HERMI_i = (Exposure_i + Vulnerability_i) \times Inaccessibility_i , \quad (4)$$

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where the additive term ($Exposure_i$ + $Vulnerability_i$) combines hazard intensity with population density, ensuring that areas with both high exposure and concentrated populations are up weighted. Multiplication by Inaccessibility_i then highlights locations where health burdens are most likely to exceed treatment capacity. By design, the index captures the degree of mismatch between environmental hazard and healthcare provision, rather than absolute exposure levels.

2.2.5 Risk Stratification

To enable continent-wide comparison, HERMI values were scaled to [0,1] and classified into four categories. Cells with HERMI = 0 were labelled "No mismatch," while positive values were divided into mild, moderate, and severe mismatch:

HERMI class =

- 0, if HERMI = 0
- 1, if 0 < HERMI ≤ Q30
- 2, if Q30 < HERMI ≤ Q50
- 3, if HERMI > Q50

This scheme reflects relative severity across Africa rather than imposing arbitrary absolute cut-offs. Population counts within each class were then aggregated at national level to quantify affected populations and support regional planning.

3. Results

The HERMI results for 2020 (Figure. 3) reveal distinct spatial gradients across Africa, shaped by the interaction of wildfire exposure, population density, and healthcare accessibility. Large parts of Sub-Saharan Africa are classified as mild mismatch, reflecting widespread but moderate levels of wildfire exposure combined with limited healthcare accessibility in rural areas.

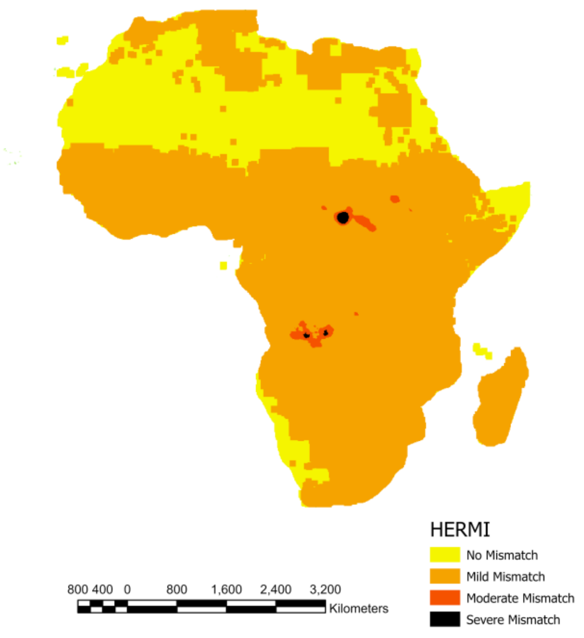

Figure 3. The HERMI results for 2020.

Severe mismatch clusters are most pronounced in northern Angola and western Central African Republic, where recurrent wildfire activity coincides with particularly scarce healthcare facility coverage, leaving already vulnerable populations with minimal access to essential services. Broader Moderate Mismatch zones extend across the central — southern fire belt, notably in northern Angola, southern Democratic Republic of Congo, eastern Central African Republic, southwestern and northern South Sudan, southern Sudan, and northern Namibia — regions where moderate-to-high rural population densities combine with limited healthcare accessibility, further compounding wildfire-related health risks.

By contrast, West African coastal states (e.g., Nigeria, Ghana, Côte d'Ivoire) and major metropolitan areas such as Lagos, Nairobi, and Johannesburg show generally mild mismatch values. Despite dense populations and recurrent fires, the presence of comparatively stronger healthcare networks reduces overall mismatch scores. In North Africa (e.g., Algeria, Libya, Egypt) and in desert regions of southern Africa, mismatch values remain low due to extremely sparse population and limited wildfire activity, even though healthcare accessibility is poor.

A broader regional comparison shows that East Africa exhibits a patchwork of mismatch categories: highland agricultural areas and urbanising corridors (e.g., around Addis Ababa and Nairobi) fall into mild-to-moderate classes, whereas arid pastoral regions remain largely no mismatch due to minimal exposure. In southern Africa, rural dryland mosaics in Angola, Namibia, and Zambia show more pronounced moderate-to-severe mismatches, consistent with well-documented fire belts. These regional contrasts indicate that HERMI is sensitive not only to hazard levels but also to socio-demographic and infrastructural conditions.

Overall, HERMI highlights two critical vulnerability archetypes: (i) peri-urban fringes of fast-growing cities, where expanding populations face increasing wildfire exposure but healthcare expansion lags, and (ii) remote rural fire-prone landscapes, where recurrent burning intersects with weak healthcare coverage. These regions represent priority areas for wildfire-related health adaptation and resilience planning.

The spatial distribution of HERMI categories reveals substantial disparities across Africa. About 34.7% of the population are located in no mismatch areas, where wildfire-related $PM_{2.5}$ exposure and healthcare accessibility are relatively balanced. In contrast, 26.4% fall within mild, 28.6% within moderate, and 10.3% within severe mismatch zones. This distribution highlights that nearly two-thirds of the population experience some degree of healthcare–exposure imbalance, with more than one in ten residing in the most acute high-exposure, low-accessibility contexts. Importantly, these figures underscore not only the scale of the problem but also its heterogeneity: mismatch hotspots are spatially clustered rather than evenly distributed, which has direct implications for prioritising targeted interventions and resource allocation.

4. Discussion

As Scott Weichenthal has emphasized, prolonged exposure to wildfire smoke is of serious concern and may increase cancer risks in affected populations (Weichenthal, 2025). Precisely for this reason, our study highlights where such risks are amplified in Africa by the combined effects of wildfire exposure, population distribution, and healthcare accessibility.

4.1 Wildfire emissions: regional risks, global relevance

Wildfire smoke from Africa is not only a regional concern but also a global phenomenon. Observations from the Amazon Tall Tower Observatory show that up to ~60% of soot over the central Amazon can originate from African fires, underscoring their intercontinental reach (Holanda et al., 2023). Yet, while transboundary plumes illustrate Africa's global atmospheric relevance, the most acute health burden remains within the continent, where populations face direct exposure alongside structural deficits in healthcare systems.

4.2 How HERMI reflects degrees of imbalance

HERMI differs from conventional hazard indices in that it measures misalignment rather than hazard magnitude. In this framework, a value of zero represents balance — either because exposure and vulnerability are negligible, or because healthcare accessibility is sufficient to offset potential risks. Any positive value, however small, already signals that hazard and population needs are not fully matched by available healthcare. For this reason, we applied fixed thresholds (0-0.3 = mild, 0.3-0.5 = moderate, 0.5-1 = severe) to represent degrees of imbalance. This approach contrasts with quantile-based classification, which assigns classes based on relative ranks and may hinder comparability across regions or overtime (Song et al., 2024). By contrast, fixed thresholds ensure that categories correspond to substantive differences in mismatch severity, thereby supporting more consistent interpretation in longitudinal and cross-regional analyses.

4.3 Contrasting vulnerabilities and population burden

Our results reveal two dominant archetypes of mismatch. In peri-urban belts on the fringes of cities such as Kinshasa, Nairobi, and Lagos, expanding populations face increasing smoke exposure while healthcare expansion lags, producing mild-to-moderate mismatch. In contrast, remote fire-belt landscapes in Angola, South Sudan, the Central African Republic, and northern Namibia combine recurrent burning with chronic healthcare scarcity, generating severe mismatch even under modest exposure levels. This duality shows that mismatch is shaped not only by hazard intensity but also by where people live relative to health systems. Population statistics reinforce this picture: while 34.7% of Africa's population reside in balanced zones (no mismatch), 65.3% experience some degree of mismatch, including 10.3% in severe contexts. These proportions underscore that more than one in ten Africans face the highest-risk combination of smoke exposure and inadequate healthcare access (Atuyambe et al., 2024), and that mismatch is spatially clustered rather than evenly distributed, suggesting that targeted interventions are more effective than blanket strategies (Wang et al., 2016).

4.4 Implications, limitations, and broader significance

Reducing wildfire-related health risks requires dual strategies: managing exposure through fire control, land-use practices, and air-quality monitoring, and addressing access deficits through investment in rural facilities, mobile clinics, and surge capacity (Reid et al., 2016). HERMI provides a first-pass tool for governments and NGOs to prioritise such high-risk zones for emergency planning and health-system strengthening. Certain limitations remain. For consistency, the Healthsites database was restricted to hospitals and clinics (Mathers et al., 2002), excluding pharmacies, private practices, and other facility types that do not directly reflect essential treatment capacity; this filtering may lead to conservative estimates of accessibility in some regions. In addition, Euclidean distance offers only a proxy for accessibility and neglects transport networks and economic barriers (Zgonc et al., 2019). Finally, the analysis is static, based on 2020 conditions, and does not capture interannual variability in fire regimes or dynamic changes in health systems. Future refinements should incorporate travel-time models, facility capacity metrics, and seasonal fire dynamics, and ideally validate HERMI against observed outcomes such as hospital admissions or respiratory morbidity. Despite these caveats, HERMI's reliance on open and reproducible geospatial datasets (MODIS, CAMS, GHS-POP, Healthsites) makes the framework transferable and scalable. While Africa's fires have global atmospheric relevance, the most urgent inequities are local, where exposure collides with fragile health systems. By treating wildfire smoke not only as an environmental hazard but also as a stress test for healthcare systems, HERMI connects climate, air quality, and health resilience—transforming a diagnostic map into actionable guidance for national adaptation and resilience strategies.

5. Conclusion

This study aimed to reveal where wildfire smoke exposure in Africa coincides with inadequate healthcare access. Built entirely from open geospatial datasets, HERMI reframes wildfire risk as a systemic imbalance rather than hazard magnitude. Results show two dominant archetypes—peri-urban belts where population growth outpaces healthcare and remote fire-prone landscapes marked by structural scarcity—with 65.3% of the population experiencing some mismatch and 10.3% facing severe conditions. These insights highlight the need for targeted interventions that reduce exposure while strengthening healthcare systems, positioning HERMI as a transferable framework for climate-resilient health planning.

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