A red green and black stripes

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Small Area Estimation of Poverty Mapping in Burkina Faso by Integrating Survey, Geospatial Data and ACLED Data

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(Title, Arial Bold 24pt)

Subtitle (bold 18pt)

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# Abstract

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# Introduction

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# Methodology

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# Data

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## EHCVM data

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The Harmonized Survey on Household Living Conditions (EHCVM) is a joint initiative of the UEMOA Commission and the World Bank. It is conducted as part of the Program for the Harmonization and Modernization of Household Living Conditions Surveys within the UEMOA member states (PHMECV). The survey includes four components: a household component, a community component, a price component, and a component on non-standard units (NSU).

This survey is necessary to generate our poverty estimates (a.k.a direct estimate) for the in-sample areas. Since the survey employs a sampling strategy, we cannot take the values they produce at face value and first must adjust them to make them more representative of the whole sample.

Figure xxx provides an overview of the direct estimate across area level.

*Figure xxx: Estimated poverty rate (direct estimates) in area level (communes)*

A map of the african continent

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The area level where we don’t have any data is out – sample areas, we will use model and geospatial data to estimate poverty in both in-sample and out-sample areas.

## ACLED data

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ACLED collects data for more than 240 countries and territories in near real time. Conflicts differ in intensity, frequency, and form. Drawing on the latest data and patterns, the ACLED Conflict Index assesses levels of conflict according to four key indicators: deadliness, danger to civilians, geographic diffusion of conflict, and armed group fragmentation.

In this report, we consider conflict diffusion indicator because conflicts can be clustered or diffuse, and more or less dangerous due to the exposure of larger civilian populations to insecurity. Geographic variations present unique operational challenges for states, armed groups, and communities under threat

The conflict index sets out to answer three questions: How much conflict is occurring in the world? Where is conflict happening? Is conflict worsening or improving?

The conflict diffusion, which is obtained using the geocoordinates of each political violence event combined with population data from WorldPop. The construction of this indicator involves the following three steps. First, we overlay a 10x10km grid on all the country. Second, to avoid scarcely populated areas having an unduly effect on the final diffusion indicator, we exclude all grid cells with less than one inhabitant. Finally, for each third-level administration unit, we compute the proportion of eligible grid cells with one or more conflict events during the period.

***Spectral indices*** (bold italic 12pt)

Spectral indices, which are derived from remote sensing data, play a crucial role in supporting the Sustainable Development Goals (SDGs) set by the United Nations. These indices provide valuable information for monitoring environmental changes, managing natural resources, and supporting sustainable practices in various sectors.

For each third-level administration unit we compute the minimum, median, maximum and standard deviation using Landsat 9-C2-SR 2022 median composite.

Variable Index for the Landsat 9-C2-SR 2022 georeferenced

|  |  |  |
| --- | --- | --- |
| **Variable Name in the Database** | **Definition** | **SDG** |
| MNDWI | Modified Normalized Difference Water Index | SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action) |
| VARI | Visible Atmospherically Resistant Index | SDG 15 (Life on Land) |
| SAVI | Soil Adjusted Vegetation Index | SDG 13 (Climate Action), SDG 15 (Life on Land) |
| OSAVI | Optimized Soil Adjusted Vegetation Index | SDG 13 (Climate Action), SDG 15 (Life on Land) |
| NDMI | Normalized Difference Moisture Index | SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action), SDG 15 (Life on Land) |
| EVI | Enhanced Vegetation Index | SDG 2 (Zero Hunger), SDG 13 (Climate Action), SDG 15 (Life on Land) |
| NDVI | Normalized Difference Vegetation Index | SDG 2 (Zero Hunger), SDG 13 (Climate Action), SDG 15 (Life on Land) |
| ARVI | Atmospherically Resistant Vegetation Index | SDG 13 (Climate Action), SDG 15 (Life on Land) |
| UI | Urban Index | SDG 11 (Sustainable Cities and Communities) |

Reference: Landsat 9 C2 SR - 2022 (median composite)

* Modified Normalized Difference Water Index

The Modified Normalized Difference Water Index (MNDWI) is a spectral index designed to enhance water feature detection in remote sensing imagery. This spectral index helps identify and assess water spread during flood events; differentiating wetlands from surrounding land cover; detecting water bodies in highly urbanized regions and monitoring lakes and rivers for water availability. We compute MNDWI using this formula:

Where:

* Green refers to the reflectance in the green band.
* SWIR refers to the reflectance in the Shortwave Infrared (SWIR) band.
* Visible Atmospherically Resistant Index

The Visible Atmospherically Resistant Index (VARI) is a spectral index designed to enhance vegetation signals while minimizing atmospheric effects, using only visible bands. It is particularly useful in areas where Near Infrared (NIR) data is unavailable.

Where:

* Green refers to the reflectance in the green band.
* Red refers to the reflectance in the red band.
* Blue refers to the reflectance in the blue band.
* Soil Adjusted Vegetation Index

The Soil Adjusted Vegetation Index (SAVI) is used to correct for soil brightness when assessing vegetation. SAVI helps assess crop health in areas with significant soil exposure, monitoring vegetation loss in dry areas and differentiating between soil and vegetation.

Where:

* NIR refers to the Near Infrared reflectance.
* Red refers to the reflectance in the red band.
* L is the soil brightness correction factor.
* Optimized Soil Adjusted Vegetation Index

The Optimized Soil Adjusted Vegetation Index (OSAVI) is a spectral index used to assess vegetation while minimizing the influence of soil brightness. OSAVI is used in agricultural monitoring (assessing crop conditions in soil-vegetation areas), forestry studies (evaluating vegetation health in mixed soil-vegetation areas) and land degradation assessments.

Where:

* NIR refers to the Near Infrared reflectance.
* Red refers to the reflectance in the red band.
* 0.16 is a soil adjustment factor to reduce soil brightness impact.
* Normalized Difference Moisture Index

The Normalized Difference Moisture Index (NDMI) is used to assess vegetation moisture content and monitor water stress in plants. NDMI is useful for vegetation moisture assessment (detecting water stress in crops and forests), drought monitoring and assessing forest health and fire risk.

Where:

* NIR refers to the Near Infrared reflectance.
* SWIR refers to the reflectance in the Shortwave Infrared (SWIR) band.
* Enhanced Vegetation Index

The Enhanced Vegetation Index (EVI) is designed to improve the sensitivity of vegetation detection while reducing atmospheric influences and soil background effects. It is particularly useful in densely vegetated areas. It works well in areas with dense vegetation, unlike NDVI, which tends to saturate. EVI also helps measuring vegetation-related carbon dynamics.

Where:

* NIR refers to the Near Infrared reflectance.
* Red refers to the reflectance in the red band.
* Blue refers to the reflectance in the blue band.
* g is the grain factor
* C1, C2 are coefficients for atmospheric resistance
* L is canopy background adjustment
* Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indices for vegetation analysis. It helps assess vegetation health, biomass, and land cover classification. NDVI is easy for interpretation, values range from -1 to 1, where higher values indicate dense vegetation, and lower values indicate barren land or built-up areas.

Where:

* NIR refers to the Near Infrared reflectance.
* Red refers to the reflectance in the red band.
* Atmospherically Resistant Vegetation Index

The Atmospherically Resistant Vegetation Index (ARVI) is a spectral index designed to minimize atmospheric effects, particularly the influence of aerosols in vegetation analysis. ARVI is a modified version of the Normalized Difference Vegetation Index (NDVI) that incorporates the blue band to correct for atmospheric scattering. ARVI is useful for agricultural assessments (evaluation crop conditions and productivity), deforestation studies (tracking forest loss) and environmental monitoring (assessing plant stress and health in various areas).

Where:

* NIR refers to the Near Infrared reflectance.
* Red refers to the reflectance in the red band.
* Blue refers to the reflectance in the blue band.
* is a correction factor that accounts for atmospheric influence, typically set to 1.
* Urban Index

The Urban Index (UI) is another spectral index designed to enhance the detection of urban and built-up areas. It provides an alternative to Normalized Difference Built-up Index (NDBI) by incorporating different spectral bands to improve accuracy in urban classification. UI is important for monitoring expansion of cities, distinguishing urban and non-urban features and assessing human impact on the landscape.

Where:

* NIR refers to the Near Infrared reflectance.
* Blue refers to the reflectance in the blue band.

The integration of spectral indices enables a more comprehensive analysis of land cover dynamics, particularly in urban, semi-urban, and vegetated environments. These indices help with water detection, urban expansion monitoring, vegetation health analysis and drought assessment, supporting sustainable land and resource management.

By integrating spectral indices with SDG goals, we can assess and manage resources more effectively to ensure the sustainability of natural systems, manage land cover, monitor agriculture and vegetation health, and track urbanization. These indices support decision-making in fields like climate action, water management, agriculture, biodiversity conservation, and urban planning, directly contributing to the achievement of SDGs.

Reference: Landsat 9 C2 SR - 2022

Earth Resources Observation and Science (EROS) Center. (2020). Landsat 8-9 Operational Land Imager / Thermal Infrared Sensor Level-2, Collection 2 [dataset]. U.S. Geological Survey. https://doi.org/10.5066/P9OGBGM6.

Montero, D., Aybar, C., Mahecha, M. D., Wieneke, S. (2022). spectral: Awesome Spectral Indices deployed via the Google Earth Engine JavaScript API. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W1-2022. Free and Open Source Software for Geospatial (FOSS4G) 2022 Academic Track, 22-28 August 2022, Florence, Italy. doi: 10.5194/isprs-archives-XLVIII-4-W1-2022-301-2022

## Socio-economic data

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* Healthcare Accessibility and Travel Time to Cities

This enumerates land-based travel time (in minutes) to the nearest hospital or clinic for all areas between 85 degrees north and 60 degrees south for a nominal year 2019. It also includes "walking-only" travel time, using non-motorized means of transportation only.

**References:** Healthcare Accessibility

[D.J. Weiss, A. Nelson, C.A. Vargas-Ruiz, K. Gligorić, S. Bavadekar, E. Gabrilovich, A. Bertozzi-Villa, J. Rozier, H.S. Gibson, T. Shekel, C. Kamath, A. Lieber, K. Schulman, Y. Shao, V. Qarkaxhija, A.K. Nandi, S.H. Keddie, S. Rumisha, E. Cameron, K.E. Battle, S. Bhatt, P.W. Gething. Global maps of travel time to healthcare facilities. Nature Medicine (2020).]

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| **Description** | **Spatial Resolution** | **Temporal Resolution** |
| Travel Time to Nearest Healthcare Facility with Access to Motorized Transport (in minutes) | 1km | 2019 |
| Walking-only Travel Time to Nearest Healthcare Facility without Access to Motorized Transport (in minutes) | 1km | 2019 |
| Travel Time to Cities (in minutes) | 1km | 2015 |

The economic and man-made resources that sustain human wellbeing are not distributed evenly across the world but are instead heavily concentrated in cities. Poor access to opportunities and services offered by urban centers (a function of distance, transport infrastructure, and the spatial distribution of cities) is a major barrier to improved livelihoods and overall development. Advancing accessibility worldwide underpins the equity agenda of ‘leaving no one behind’ established by the Sustainable Development Goals of the United Nations1. This has renewed international efforts to accurately measure accessibility and generate a metric that can inform the design and implementation of development policies. The only previous attempt to reliably map accessibility worldwide, which was published nearly a decade ago2, predated the baseline for the Sustainable Development Goals and excluded the recent expansion in infrastructure networks, particularly in lower-resource settings. In parallel, new data sources provided by Open Street Map and Google now capture transportation networks with unprecedented detail and precision. Here we use a map that quantifies travel time to cities for 2015 at a spatial resolution of approximately one by one kilometer by integrating ten global-scale surfaces that characterize factors affecting human movement rates.

**References:** Travel Time to Cities

1. United Nations. *Transforming our World: The 2030 Agenda for Sustainable Development.* (United Nations Department of Economic and Social Affairs, 2015)
2. Nelson, A. Travel time to major cities: a global map of accessibility. <http://forobs.jrc.ec.europa.eu/products/gam/> (Global Environment Monitoring Unit, Joint Research Centre of the European Commission, 2008)

* WorldPop
* State of residence
* Electricity accessibility

Monthly average radiance composite images using nighttime data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB).

As these data are composed monthly, there are many areas of the globe where it is impossible to get good quality data coverage for that month. This can be due to cloud cover, especially in the tropical regions, or due to solar illumination, as happens toward the poles in their respective summer months.

We compute a linear fit over the series of values from 2015-01-01 to 2021-12-31 at each pixel and considering the y-intercept (offset) and slopes (scale)

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| **Indicator** | **Description** | **Spatial Resolution** | **Temporal Extent** |  |  |
| offset | the y-intercept (offset) of monthly average radiance composite images (2015 - 2021) | 5km | 2000-2022 |  |  |
| scale | the slopes (scale) of monthly average radiance composite images (2015 - 2021) | 5km | 2000-2022 |  |  |

* Reference: Electricity accessibility

C. D. Elvidge, K. Baugh, M. Zhizhin, F. C. Hsu, and T. Ghosh, “VIIRS night-time lights,” *International Journal of Remote Sensing*, vol. 38, pp. 5860–5879, 2017.

* Health situation of children (Children 2 to 10 years of age)

|  |  |  |  |
| --- | --- | --- | --- |
| **Description** | **Spatial Resolution** | **Temporal Resolution** | **Temporal Extent** |
| Proportion of Children 2 to 10 years of age showing, on a given year, detectable Plasmodium falciparum parasite | 5km | Annual | 2000-2022 |
| Number of deaths from Plasmodium falciparum per 100,000 population during a defined year 2000-2022 | 5km | Annual | 2000-2022 |

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# Results

## Selection bias test

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## Fay-Herriot

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Fay-Herriot models are the traditional approach for cases where access to microdata is not possible or when the census and survey are not aligned

Fay Herriot models were introduced to estimate mean per capita income in small areas in the USA (Fay and Herriot 1979)

The method consists of modelling poverty rates (or other indicators) at the area level

The resulting estimate is a weighted average between the direct estimates (those derived directly from the survey) and the model-based estimates

The weight given to each estimate in a given area depends on the sample size for that area and the quality of the model

For areas not in the sample we rely solely on the model-based estimates

Covariates are standardized (mean=0, std. dev.=1) before model selection.

Non-significant covariates are removed from the model sequentially, starting with those with the largest p-values.

The model selection stage uses the FH option (Fay Herriot’s moments method) due to lower computational requirements.

Covariates with a Variance Inflator Factor (VIF) above 5 are excluded from the final model.

The final model employs 11 covariates and an intercept to explain poverty across the 210 districts.

The adjusted 𝑅^2 of the model is 0.73, indicating substantial explanatory power.

Assumptions of the model need to be verified, as mentioned in the introduction.

A map of the african continent

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* Checking assumptions

A graph of a normal distribution

AI-generated content may be incorrect.Figure xxx: Fay-Herriot Residual Plots - FHA graph with a line and a curve

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Figure xxx: Direct vs Small Area Estimates (Left, point) (Right, SE) - FH

## A graph with blue dots AI-generated content may be incorrect.A graph with blue dots AI-generated content may be incorrect.

## Figure xxx:

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## Machine Learning

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# Discussion

# Policy implication

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About the Authors

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References

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Endnotes

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1201 Eye Street, NW, Washington, DC 20005 USA | T. +1-202-862-5600 | F. +1-202-862-5606 | Email: [ifpri@cgiar.org](mailto:ifpri@cgiar.org) | [www.ifpri.org](http://www.ifpri.org/) | [www.ifpri.info](http://www.ifpri.info/)

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