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Mapping socio-environmental vulnerability to assess rural migration in Ghana



^a Martin Luther University Halle-Wittenberg, Institute of Geosciences and Geography, Department of Geoecology, Von-Seckendorff-Platz 4, 06120, Halle (Saale), Germany

^b Martin Luther University Halle-Wittenberg, Institute of Geosciences and Geography, Department of Sustainable Landscape Development, Von-Seckendorff-Platz 4, 06120, Halle (Saale), Germany

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ABSTRACT

Rural communities in Ghana, dependent on agriculture and lacking resources and infrastructure, are highly vulnerable to climate and environmental change. Internal migration is often considered as a strategy to mitigate local livelihood constraints. Understanding the challenges of rural communities requires knowledge of local conditions. As only few studies have mapped vulnerable areas in the context of migration in Ghana at a spatially explicit and nationwide level, this study provides a geodata-based examination of how rural areas in Ghana are vulnerable to multiple, co-occurring socio-economic and environmental factors influencing migration. A multifactorial and expert-based weighted overlay analysis was applied, integrating diverse data sources including climate, remote sensing, and recent census data from Ghana. Bivariate maps visualize vulnerable areas where a high impact of the factors coincides with a high rural population density. High levels of factor impact are observed in the northern regions and coastal areas of Ghana. Relatively low impact is found in more central parts of the country. The results align with current net migration rates, confirming the applicability of our method for assessing rural internal migration. This method enhances the understanding of migration dynamics in Ghana and emphasizes the role of spatial data in migration studies.

1. Introduction

Rural communities in Ghana are highly vulnerable to the impacts of climate and environmental changes due to their reliance on agriculture and lack of financial resources, social facilities and infrastructure (Asare-Nuamah, 2021; Baffoe & Matsuda, 2018; Dumenu & Obeng, 2016). Unfavorable environmental conditions like changes in rainfall patterns as well as poor or degrading soil fertility, especially in the savannah zones, are negatively affecting crop yields (Kanton et al., 2016; Owusu et al., 2021). This disruption of agricultural activities (Azumah & Ahmed, 2023; Schraven & Rademacher-Schulz, 2016), the main source of livelihoods for many rural communities (GSS, 2021a), can be exacerbated by increasing rural population densities, leading to scarcity of natural resources and land (Bonye et al., 2021; van der Geest, 2011).

Internal migration is often a strategy to mitigate local livelihood constraints and to diversify income sources. In addition, remittances

play a central role to improve the household income (Teye & Nikoi, 2022). In Ghana, individuals or households tend to move from rural to urban areas (Antwi-Agyei et al., 2014; GSS, 2023) in particular from northern to southern regions (Arthur-Holmes & Abrefa Busia, 2022; Teye and Nikoi, 2022) or to less populated rural areas where arable land is still available (Ghana Statistical Service, 2023; van der Geest, 2011). Urban areas like Accra and Kumasi are often perceived to offer greater possibilities due to the lack of employment opportunities and educational facilities in rural areas (Awumbila et al., 2014; Baffoe et al., 2021). At the same time, the high population density in urban areas can intensify competition for jobs and resources (Anarfi et al., 2020; Poku-Boansi et al., 2020). This shows that although migration can bring individual benefits, it can also create potential trade-offs and challenges, as pointed out by Szaboova et al. (2023). The social and environmental vulnerability of urban migrants often extends beyond their place of destination and contribute to their precarious situation (Aboagye, 2021; Szaboova et al., 2022).

* Corresponding author.

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E-mail addresses: alina.schuermann@geo.uni-halle.de (A. Schürmann), janina.kleemann@geo.uni-halle.de (J. Kleemann), mike.teucher@geo.uni-halle.de (M. Teucher), christopher.conrad@geo.uni-halle.de (C. Conrad).

Despite the growing risks posed by climate change, it is rarely cited as the main reason for migration decisions (Abu et al., 2014; Adger et al., 2021; Bukari et al., 2020). In addition, the ways how and the extent to which environmental variability affects migration is an ongoing debate (Kaczan & Orgill-Meyer, 2020). Rapid-onset events often result in (involuntary) displacement (Teye & Nikoi, 2022) whereas gradual climatic processes tend to induce rather internal voluntary migration (Rigaud et al., 2021; Zickgraf, 2021). Individual aspiration, financial resources, and social support are widely recognized as key determinants of human mobility (Flahaux & Haas, 2016; Haas, 2021). These are interrelated with external factors such as environmental degradation, infrastructure development, access to markets or job opportunities as they can shape people's motivation to leave their place of origin (Adger et al., 2024; Black et al., 2011; Czaika & Reinprecht, 2022). Given that individual decisions are too diverse to be captured in sustainable development and planning (Adger et al., 2024), it seems necessary to identify and map migration on the basis of underlying factors. A key question is therefore, whether and how the factors influencing internal rural migration in Ghana can be analyzed and weighted to reflect their impact on migration patterns. Another question is whether this approach is sufficient to understand actual migration movements.

Assessing potential migration requires an analysis of the specific challenges faced by the rural population in the areas of origin. While multiple studies have used spatial data to map the vulnerability of populations to environmental variability in combination with socioeconomic factors globally (Carrão et al., 2016; Marzi et al., 2021; Wang & Sun, 2023), for Africa (Busby et al., 2014; Paul et al., 2022) and explicitly for West Africa (Dada et al., 2024; Sherbinin et al., 2015), few have placed this in the context of migration. Spatially explicit research that mapped migration has mainly considered environmental and demographic factors to find hotspots of in- and out-migration (Hermans-Neumann et al., 2017; Neumann et al., 2015; Rigaud et al., 2021) or has analyzed multiple factors on coarser spatial resolution without examining the population in more detail (Mijani et al., 2022). Some previous studies have combined historical district-level net migration rates with environmental or socio-economic data to study migration (Tsegai & Le, 2011; van der Geest, 2011; van der Geest et al., 2010). However, the recent official migration dataset for Ghana (GSS, 2023) has not yet been combined with high-resolution environmental and socio-economic data, nor with spatially explicit population data. Most recent studies have mainly used qualitative methods, such as region-specific surveys (Abu et al., 2014; Antwi-Agyei et al., 2018; Kumasi et al., 2019) or have focused primarily on rainfall data (Issifu et al., 2022; Rademacher-Schulz et al., 2014) to investigate the underlying causes of rural out-migration in Ghana.

There is currently a lack of nationwide and spatially explicit analyses that systematically identifies areas where environmental degradation, unfavorable socio-economic factors, and population pressure overlap. This presents a novel opportunity for further research to address this gap by analyzing multiple expert-weighted environmental and socioeconomic factors to map vulnerability and thus assess rural outmigration in Ghana.

The aim of this study is to determine to which extent spatial data can be used to map vulnerable rural areas in Ghana where the likelihood of migration is expected to be high, thereby pinpointing where policies could be implemented to improve rural livelihoods. We use bivariate maps to illustrate the intensity of the examined factors on rural populations in order to locate vulnerable populations, particularly those dependent on agriculture. This mixed-methods approach is situated at the intersection of environmental and social sciences as it involves expert knowledge and enhances the application of spatial data analysis to study human mobility in Ghana. The resulting maps identify geographic regions with specific opportunities that could influence migration decisions and provide a basis for future studies that seek to explore personal motivations for migration. By addressing places of origin, the study enables policy makers to develop more inclusive and effective strategies that respond to the challenges faced by rural households and support the sustainable development of their home areas.

2. Methodology

2.1. Study area

Ghana is located on the Gulf of Guinea and is bordered by Cote d'Ivoire, Burkina Faso, and Togo. It has a land area of 238,533 square kilometers and a population of approx. 31 million people, making it one of the most densely populated countries in West Africa (GSS, 2021b; World Bank, 2020). The population is made up of different ethnic groups such as the Akan (45.7 %), Mole-Dagbani (18.5 %) and Ewe (12.8 %) (GSS, 2021c). The capital city is Accra, and other major cities include Kumasi, Tamale, Sekondi-Takoradi and Tema. Ghana's economy is mainly driven by the agricultural sector, which employs 33 % of the workforce (62.9 % when referred to rural population), followed by the wholesale and retail trade sector (18.7 %), the manufacturing sector (6.7 %) and the education sector (5.9 %) (GSS, 2021a).

The main staple crops grown in Ghana include maize, cassava, yam and plantain (MoFA, 2021). There are significant rural-urban differences in livelihoods and incomes in Ghana. Rural areas, which are predominant in the northern regions of Ghana, are more heavily dependent on agriculture, while urban areas offer a wider range of job opportunities in manufacturing and services (GSS, 2021a). Ghana consists of six agro-ecological zones (Fig. 1), that represent different potentials for agriculture. The zones are characterized by a precipitation gradient that ranges from more semi-arid areas in the north to humid areas in the south, with the coastal savannah being drier than the adjacent zones.

2.2. Methods

The study employs a methodological approach, designed to identify and map vulnerable areas with a high likelihood of migration using spatial data as its core component. Out-migration is defined as the voluntary movement from rural to urban or other rural areas, investigated at the pixel level (100 m cells). Within Ghana, about 8.2 million inhabitants (27 % of the population) are internal migrants (GSS, 2023). The approach is structured into five integral parts, each contributing to its overall functionality and effectiveness (Fig. 2).

- 1) Literature review: A comprehensive review of the relevant literature was conducted to identify the main factors influencing migration decisions. Upon the findings of previous studies on migration patterns, including the underlying drivers and the impact of various socio-economic, political, and environmental factors (see Black et al., 2011; Neumann et al., 2015; Schürmann et al., 2022), specific factors for expert interviews were identified and used for proxy identification.
- 2) Expert interviews: The factors identified in the literature review were assessed by interviewing experts of migration research. These experts provided insights into the relevance and importance of the identified factors (see Section 2.2.1).
- 3) Preprocessing of spatial data: Proxy indicators representing the factors addressed in the expert interviews were identified. This was done by analyzing the available data sources and selecting the most appropriate indicators for each factor. Environmental factors needed extensive preprocessing (see Section 2.2.2).
- 4) Geographically weighted overlay analysis (WOA): The proxy indicators were included in a WOA. This method enables the factors to be overlaid and weighted according to the perceived importance by the experts. The results of the analysis were then combined with the population density using bivariate maps. This approach facilitated the representation of the vulnerable population and illustrates the



Fig. 1. Ghana with population density (WorldPop & Bondarenko, 2020) and the agro-ecological zones represented by average annual precipitation (in mm) in order to reflect the suitability for farming.

likelihood of migration, considering the adverse factors that influence migration decisions (see Section 2.2.3).

5) Comparative analysis: Current net migration rates from the Ghana Population and Housing Census (PHC) (GSS, 2023), were compared with our results to evaluate the plausibility and to address the applicability of geodata for assessing migration (see Section 2.2.4).

2.2.1. Expert interviews

Fifteen expert interviews (Appendix A) were conducted in Ghana in March and April 2022 to obtain a comprehensive understanding of the key factors that influence migration decisions and to rank the importance of the factors identified. The factors evaluated during the expert interviews are displayed in Table 1. The participants for these interviews were selected from non-/governmental institutions and research institutes that have a focus on human migration or related fields. Each expert had a minimum of three years of experience in migration research. The maximum years of experience were more than 30 years. The interviews were conducted using a questionnaire that combined closed questions related to the impact of individual characteristics on migration decisions, open-ended questions related to migration routes, and Likert scale ratings related to the importance of factors on the migration decision. The latter ones were used for ranking the factors in this study. The questionnaire contained 22 factors, of which 16 were selected for this study given data availability constraints. The Relative Importance Index (RII) was selected to compute a weighting based on the Likert scale, which is calculated as follows:

$$RII = \sum W / (A^*N)$$



Fig. 2. Analytical approach to address applicability of spatial data to map likelihood of migration, n = number of factors.

Where W is the weighting given to each factor by the experts; ranging from 1 (low importance) to 5 (high importance) for migration in Ghana, A is the highest weight, and N is the total number of respondents. The greater the value of RII, the higher the importance of a factor. For its use in the WOA, the RII has been multiplied by 100. Adjacent to the respective RII, the percentage influence for the WOA and its rounded values are given in Table 1.

2.2.2. Compilation and preprocessing of spatial data

The factors under consideration were categorized into "environmental factors" and "socio-economic factors". Environmental proxy indicators were available at the pixel level, while most of the socioeconomic proxy indicators are based on the PHC data and thus available at the district level. A comprehensive list of the proxy indicators can be found in Table 1.

Long-term environmental degradation in migrants' areas of origin tends to induce rather voluntary and internal migration (see Section 1). Therefore, the Sen's slope trend test (Sen, 1968), was utilized to determine the magnitude of the trend for datasets with multiple time steps available using the "trend" package in the R programming language (Pohlert, 2023).

Some proxy indicators required extensive preprocessing, which is explained in the following. Rainfall indices were derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015). The CHIRPS dataset covers the African continent and spans the period from 1981 to the near present. It combines satellite imagery at $0.05^{\circ} \times 0.05^{\circ}$ resolution and in-situ station data to produce gridded precipitation time series suitable for trend analysis and seasonal drought monitoring (Hubertus et al., 2023; Sacré Regis M. et al., 2020). Rainfall indices were computed to explore regional climate effects on agriculture conditions. The onset and cessation dates of the rainy seasons were calculated pixel-wise for each year from 1991 to 2021 using an adapted approach of the method described in Dunning et al. (2016), which extends the methodology of Liebmann et al. (2012). The rainy seasons are determined by calculating the climatological mean rainfall for each day of the year and identifying minima/maxima in the smoothed cumulative daily rainfall anomaly. The onset and cessation of the rainy season correspond to the global

minima and maxima of the daily cumulative rainfall anomaly, calculated for 30-day subsets before and after the identified minima and maxima. The accuracy of the method was evaluated by the proportion of precipitation outside the calculated mean rainy seasons (Appendix B). As consecutive rainy days during the rainy season could not be accurately determined in the transition area from the biannual to the annual rainy season, we included the annual number of consecutive dry days in our analysis.

The Normalized Difference Vegetation Index (NDVI) is used to assess vegetation vitality, productivity, and thus an indicator for evaluating land degradation (Mechiche-Alami & Abdi, 2020; Nyamekye et al., 2021). NDVI is a measure of the reflectance in the near-infrared spectrum (wavelength from 0.841 to 0.876 nm) of green vegetation in a specific area. The resulting value ranges from -1 to 1, with higher values indicating higher vegetation vitality. A low NDVI value shows a low level of vital vegetation or no photosynthetic activity. The MODIS products AQUA (MYD13Q1 - Didan, 2021a) and TERRA (MOD13Q1 -Didan, 2021b) were combined, yielding a total of 46 layers per year for the period from 2011 to 2021. Three-month median composites of June, July, and August were created to account for missing pixels due to heavy cloud cover. These months corresponds to the growing season of major food crops (FAO, 2023) and are expected to capture high annual NDVI values. Pixels without information due to cloud cover were eliminated using the pixel reliability layer of the MODIS products. Subsequently, a 5x5 moving window median was applied to fill in missing values in the data. Sen's slope estimator was used to detect the magnitude of the trend and again, a 5x5 moving window was applied to reduce the number with missing information. Finally, merely only about 2 % of the pixels were classified as "no data" (Appendix B).

For "Agricultural production", the average yield of the ten major food crops, i.e. maize, millet, rice, sorghum, cassava, plantain, yam, soya bean, groundnut and cowpea (MoFA, 2021), was calculated using the dataset provided by IFPRI (2020). Information on the number of "Armed conflicts" from 2011 to 2021 was obtained from the Armed Conflict Location and Event Data project (ACLED) (Raleigh et al., 2010). The frequency of conflicts with fatilities was then aggregated to the district level. For the indicator "Access to farmland", the hectares of cropland (based on ESA CCI-LC (Defourny et al., 2023)) per person active in the

Table 1

Factors that were addressed in expert interviews and their proxy indicators. Adm. Level = Administrative level, RII= Relative Importance Index, WOA= Weighted overlay analysis.

	Factors addressed in expert	Proxy indicator	Temporal	Spatial	RII	Source	% of influence in	
	interview		resolution	resolution/Adm. Level			WOA a	WOA b
Environmental factors	Consecutive dry days in the rainy season	Maximum length of consecutive dry days	1991–2021	5 km	76	Funk et al. (2015)	18	7
	Environmental conditions for agriculture	Later onset of rainy season	1991–2021	5 km	75	Funk et al. (2015)	17	7
	Permanent degradation of land/soils	NDVI in June, July and August	2011-2021	250 m	73	Didan (2021a,b)	17	7
	Fertile soils	Soil organic carbon in 0–20 m	2017	30 m	73	Hengl et al. (2021)	17	7
	Persistent droughts	Annual dry days	1991-2021	5 km	71	Funk et al. (2015)	16	6
	Extreme rainfall events in rainy season	Heavy rainfall events (days with >20 mm) in rainy season	1991–2021	5 km	64	Funk et al. (2015)	15	6
				\sum	432		100	
Socio-economic	Job opportunities	Unemployment rate in %	2021	district	93	GSS (2021a)	13	8
factors	Opportunity for trading	Distance to cities (travel time)	2015	2 km	84	Weiss et al. (2018)	12	7
1401010	Agricultural production	Mean yield of ten major food crops	2017	10 km	71	IFPRI (2020)	10	6
	Food security	Prevalence of severe and moderate food insecurity in the population	2020	district	71	MoFA et al. (2020)	10	6
	Poor infrastructure	Nighttime lights in 2021	2021	500 m	68	Elvidge et al. (2017)	10	6
	Access to education	Number of junior high schools per 1000 inhabitants	2021	district	67	GSS (2021d)	10	6
	Access to water	Distance to main source of drinking water	2021	region	65	GSS (2022)	9	6
	Regular armed conflicts	Frequency of armed conflicts with fatalities	2011-2021	district	61	Raleigh et al. (2010)	9	5
	Safety	Number of police stations per 100,000 inhabitants	2021	district	60	GSS (2021d)	9	5
	Access to farmland	Cropland per farmer	2020/2021	district	59	Defourny et al. (2023); GSS (2021a)	8	5
				\sum_{Σ}	699 1131		100	100
Affected population	Population density (inhabitants/km ²)		2020	1 km		WorldPop and Bondarenko (2020)		
Fobration	Population count (number of inhabitants per 100 m cell)		2020	100 m		Schiavina et al. (2023)		

^a % of influence in WOA for Impact map 1 and Impact map 2 respectively.

^b % of influence in WOA for Impact map 3.

agricultural sector (GSS, 2021a) was calculated.

All datasets have been reclassified to create a common scale. This process is illustrated in Fig. 3. As the WOA only allows for raster format, the PHC data was first reclassified into five classes using the natural breaks method (Jenks, 1967), which creates class boundaries that optimize the grouping of similar values while maximizing differences between classes. Subsequently, the PHC data was aggregated to 10 m raster cells using the "Polygon to Raster" tool in ESRI ArcGIS Pro 2.9. The "Raster Calculator" tool in ArcGIS Pro was used to create a new indicator for proxy indicators with available trend estimates. The process involved combining the trend and respective mean layers, which were reclassified into three classes (Appendix C) and then summed, resulting in the creation of five new classes (Fig. 3). This approach considers areas where the factor is already unfavorable on average and has deteriorated over the last years. Other proxy indicators in pixel format were also reclassified into five classes. The class boundaries are shown in Appendix D. The reclassified raster datasets are provided in Appendix E.

To explore the relationships between different indicators, a correlation matrix was generated at the district level (see Fig. 4), whereby the correlation was derived from the "Band Collection Statistics" tool in ArcGIS Pro. For this purpose, the mean values of the pixel-based data were aggregated to the district level using the "Zonal Statistics" tool in ArcGIS Pro and then reclassified into 5 classes using the natural breaks method. For new proxy indicators, the median values were aggregated to the district level as these have already been reclassified. The correlation matrix shows a stronger positive correlation for "Soil organic carbon" and "Consecutive dry days" which can be explained by the fact that organic matter is related to climatic conditions. In addition, "Soil organic carbon" shows a strong correlation with "Distance to main source of drinking water". However, we included all factors in our analysis as we assume that there is no causal relationship between the time taken to reach the main water source and organic carbon content. The integration of all data sets is described in the following section.

2.2.3. Weighted overlay analysis

The WOA is integrated as a tool in ArcGIS Pro for evaluating and ranking multiple factors within a given geographical area (ESRI, 2023). The tool assigns a weight to each raster layer in the analysis, reflecting its relative importance to the final output layer. The RII has been normalized to a value of 100 (see Table 1) to meet the technical requirements of the WOA. The higher the weight, the higher the influence of the layer on the final output layer.

For the WOA, the highest spatial resolution of each of the proxies was used. Feature classes were scaled from 1 to 5 within the weighted overlay tool, with 5 being the highest score. "No data" was assigned a value of 0. The resulting cell size was defined as 1 km for visual presentation and 100 m for the comparative analysis.



Fig. 3. Schematic workflow of spatial data reclassification and data integration into the weighted overlay analysis, PHC = Population and Housing Census, unfav. = unfavorable.

The output of a weighted overlay is a new raster in which each cell value represents the combined influence of the input rasters. The WOA was conducted separately for three distinct sets of factors: environmental factors, socio-economic factors, and a combination of both. The results were classified on a scale of 1 to 5, with values of 1 and 2 indicating a low impact, 3 representing a moderate impact and 4 and 5 reflecting a high impact of factors (see Fig. 3).

Bivariate maps (Brown, 2020) were utilized to combine the outcomes of the WOA with population density data. This integration allows to identify areas where a high impact of the factors coincides with a high rural population density. These impact maps demonstrate the influence of various socio-economic and environmental factors and highlight areas where these factors are most pronounced and thus the likelihood of migration is assumed to be more likely. For this approach, the population density (WorldPop & Bondarenko, 2020) was reclassified to three classes, which is shown in Fig. 1.

This study focused on the rural population as the main migratory and most vulnerable group. Therefore, settlements with more than 5,000 inhabitants (CIESIN, 2021), which represent the urban areas (GSS, 2014), were blacked out to avoid misinterpretation of the data.



Fig. 4. Correlation matrix of proxy indicators.

2.2.4. Comparative analysis

Although validation of the results is not possible, a comparative analysis of net migration rates and affected population is suitable to verify whether the identified vulnerable areas are associated with the current net migration rates. Vulnerable areas are defined as areas with moderate to high impact of factors. If a region has a negative net migration and a high proportion of its rural population lives in vulnerable areas, it is reasonable to assume that the unfavorable conditions have led to out-migration. However, it is important to note that these two phenomena could also be independent of each other.

Net migration rates for the period 2010 – 2021 based on GSS (2023) were calculated at the regional level to verify if the impact maps accurately depict current migration patterns in Ghana. In this context, migrants are defined as individuals who have resided outside their place of birth for at least twelve months (GSS, 2023).

A population dataset (count of population in 100 m grid cells) developed by Schiavina et al. (2023) was used to compute, first, the proportion of the total population residing in areas with moderate to high impacts of adverse factors and, second, the proportion of the rural population. For this purpose, the extents of urban settlements were subtracted from the gridded population layer. The results were then plotted against the net migration rate (Fig. 6). Plausible results are expected when either more than one third of the rural population lives in vulnerable areas (areas with moderate to high impact of factors) and the region has a negative net migration rate, or less than one third lives in vulnerable areas and the region has a positive net migration rate. To better explain the results, we extracted the main migration flows for each region from the census (GSS, 2023), which are displayed in Appendix F.

3. Results

3.1. Weighted overlay analysis

The results of the WOA combined with the population density are visualized in Fig. 5. These impact maps show areas where unfavorable

conditions coincide with densely populated non-urban areas, highlighting areas of high resource pressure and indicating a higher likelihood of migration.

The analysis revealed that the coast of Ghana, particularly the densely populated rural areas around the capital Accra, is moderately to severely affected by negative environmental factors (Fig. 5.1). The Upper West Region in northern Ghana experiences moderate to severe environmental pressures. Some of these areas are sparsely populated. However, in other parts of the north, particularly in the north-west, high levels of adverse environmental factors coincide with densely populated rural areas. A similar pattern is observed in the Northern, Northern East and Upper East regions, where the impact of environmental degradation ranges from moderate to high. In these regions, the results of the analyses show a high pressure of adverse environmental conditions that suggests a higher likelihood of migration. The Oti Region shows moderate impact combined with medium population density.

The Ahafo, Ashanti, Bono and Western North regions, all located in the semi-deciduous forest or rainforest zone, show the lowest impact of environmental factors. Although there are locations where there is a medium impact on populated areas, the majority of the population experience a rather low level of negative environmental conditions. Furthermore, these regions are the least constrained by socio-economic factors (Fig. 5.2), suggesting a low likelihood of migration driven by socio-economic and environmental factors. In the Western, Central, Eastern and Volta regions, there are certain areas where socio-economic factors have a medium impact and population density is high. On the other hand, the Upper East, Northern East and Northern regions exhibit a high level of negative socio-economic factors combined with a high population density, indicating a high likelihood of migration induced by adverse socio-economic conditions. This pattern is also evident in the western part of the Upper West Region. The Savannah and Bono East regions have a high impact score but mainly a low population density.

Taking into account all the factors analyzed (Fig. 5.3), certain areas stand out where the combination of these factors has a moderate to high influence, coupled with a high population density. Upper West, Upper East, Northern East, and Northern regions are most likely to experience



Fig. 5. Impact maps: Combination of rural population densities with 1) environmental factors, 2) socio-economic factors and 3) environmental and socio-economic factors. The dashed box in the legend highlights the colors that suggest a higher likelihood of migration.



Fig. 6. Comparative analysis of the proportion of total and rural population living in areas with moderate to high impact of factors with the net migration rate for each of the 16 administrative regions. Filled squares represent total population and empty squares represent rural population. Related squares are connected by dashed line.

migration due to the unfavorable interaction of several factors. These regions show at least a moderate impact across a wide geographical area, affecting many inhabitants living in rural communities. Impacts are moderate in coastal areas, but affect large numbers of people in nonurban areas, mainly due to environmental factors. Conversely, Ashanti, Ahafo, Bono, Western North, and Eastern regions appear to be the least impacted by negative external influences, suggesting a lower likelihood of migration related to the factors studied.

3.2. Evaluation of plausibility

The proportion of the population living in vulnerable areas, based on the WOA with combined factors (Fig. 5.3), was compared with the net migration rate per region. The proportion of the rural population and the total population were indicated by the number of inhabitants per 100 m raster cell. The purpose of this comparison was to evaluate whether the produced maps reflect the migration rates described in GSS (2023). This comparative analysis is also a means to evaluate whether geodata can be used to assess spatial migration patterns.

Regions in northern Ghana have a negative net migration rate, meaning that more people leave the region than arrive. In these regions, 100 % of the rural population lives in areas that are moderately to severely affected (see Fig. 6). Furthermore, in Volta, Oti, and the Central Region, over a third of the population resides in areas that are moderately to highly affected by adverse factors. Notably, all these regions recorded a negative net migration rate. In contrast, in Ashanti, Ahafo and Western North, the proportion of the rural population affected by negative factors is relatively low (less than one-third). At the same time, a positive net migration rate was reported for these regions. It is worth noting that the results were somewhat contradictory in some regions. For instance, the Eastern Region had a rather high net migration rate, but a relatively small proportion of the rural population is exposed to unfavorable factors. Western, Bono East and especially Greater Accra Region showed a high impact of factors but a positive net migration rate. i.e. in-migration. Greater Accra Region attracts a large number of internal migrants, although the region is affected by negative factors to a moderate level and the majority of population is living in vulnerable areas. Looking at the main migration flows from GSS (2023) (Appendix F), Volta, Central and Eastern recorded an outflow of more than 100,000 people to the neighboring Greater Accra Region. Ashanti, which is less impacted by external factors, is the primary destination for migrants from the northern regions and Bono. In general, Fig. 6 shows that the majority of regions (12) display plausible results and that the proportion of the rural population affected corresponds to the respective net migration rate, suggesting that adverse external factors have an impact on migration.

4. Discussion

4.1. Vulnerable areas in Ghana with high or low likelihood of migration

The results show that vulnerable areas with a high likelihood of rural migration can be mapped using spatial data. Furthermore, we demonstrated that it is possible to effectively analyze and weight environmental and socio-economic factors influencing internal rural migration in Ghana. The study's reproducibility and transferability have been maximized to facilitate its use in similar contexts. These results can be linked to existing migration research, which suggests that migration decisions are influenced by, among others, macro-level factors (Adger et al., 2024). Furthermore, the study complements the aspirations-capabilities framework (Haas, 2021), by identifying local geographical opportunities, i.e. where socio-economic and environmental factors may shape the decisions of individuals in rural Ghana to migrate.

The results in regards to environmental factors are in line with the analysis conducted by Rigaud et al. (2021) on environmental-induced migration hotspots. However, some studies suggest that long-term environmental degradation influences migration decisions (Bohra-Mi-shra et al., 2014; Mueller et al., 2014) while others highlight more pronounced effects from short-term environmental shocks (Gray & Mueller, 2012). Given the diversity of individual decisions (Adger et al., 2024), it is to be expected that decisions can be triggered by shocks, but are favored by long-term developments. Most of our environmental indicators combine trends with the average condition, which thus indicate areas of increased variability and therefore a greater likelihood of shocks.

The WOA revealed that unfavorable conditions in environmental factors, i.e. high amount of dry days and land degradation, strongly impact the coastal region. At the same time, the Greater Accra Region is attracting the majority of migrants despite having a relatively high total population that is exposed to external factors. This can be attributed to the concentration of industries in Accra and Tema, which serve as economic hubs that offer employment opportunities and better living standards (GSS, 2023). However, this trend has serious implications for the future of the region. The perceived attractiveness of the Accra

Metropolitan Region and surrounding urban areas imply that more and more people will move to these locations (Yeboah, 2021), while agricultural conditions around the city deteriorate (Akubia et al., 2020). This development poses a significant problem in terms of the supply of food and livelihoods for people in the peri-urban areas of Accra (Ashiagbor et al., 2019). In general, approximately one million people live in rural areas in the coastal region in Ghana. These communities often depend on agriculture and fishing for their livelihoods, making them particularly vulnerable to the effects of climate change and other environmental challenges (Addo, 2013; Yang et al., 2019). In addition, sea level rise, which is expected to increase in the coming years, is also a concern for these regions. Coastal cities such as Keta, Ada, Accra, Shama and Sekondi-Takoradi are already facing significant losses of settlements due to coastal erosion, which is expected to worsen in the future (Boateng, 2012; Rigaud et al., 2021). Nevertheless, the attractiveness of cities is superior to prevailing environmental conditions. In other words, the pulling factors may be more important than the driving factors, as already observed in Schürmann et al. (2022).

The vulnerability of the rural population in northern Ghana to a range of negative socio-economic impacts is exacerbated by adverse environmental conditions. The results are consistent with recent literature highlighting the search for better livelihoods and employment opportunities as the main drivers of migration (Arthur-Holmes & Abrefa Busia, 2022), but also acknowledges that environmental factors indirectly influence economic conditions e.g. through effects on the agricultural productivity (Black et al., 2011; Falco et al., 2019). Regions such as Savannah, Oti, or the Northern East Region show high proportions of vulnerable populations but relatively low negative net migration rates. This may be explained by individuals' attachment to their place of origin (Amoako et al., 2023; Balgah & Kimengsi, 2022) or by financial constraints that prevent migration (Schewel, 2020; Warner & Afifi, 2014).

The Ashanti Region is a major destination for internal migrants. Its favorable environmental conditions for agriculture and the presence of Kumasi, Ghana's second largest city, encourage people from rural areas to seek better economic prospects and access to services (Adu-Gyamfi et al., 2022; Oduro-Ofori et al., 2023). This is likewise true for the Western, Western North, and Ahafo Region, which are all located in the more developed and resourceful central part of the country. These regions attract many migrants due to industry, mining, and agriculture (GSS, 2023). Our findings underscore the region's low exposure to adverse environmental and socio-economic factors. As Fig. 6 showed, in Eastern and Bono Region the external pressure was not estimated to be high, yet the regions have a high negative net migration rate. This could likewise be explained by the appeal and proximity of urban areas (Accra and Kumasi respectively). In case of Eastern Region this observation could also be linked to a decline in cocoa production and diamond mining, as well as the closure of factories, which have contributed to the adverse economic situation in the region (GSS, 2023).

The GSS (2023) underscores the importance of upgrading and modernizing the agricultural sector in order to attract young people to pursue careers in agriculture and to generate more employment opportunities. Another approach is to promote agro-based industries, which create a stable market for agricultural products and provide job opportunities for the younger generation at the same time. To realize these objectives, the government of Ghana has implemented the "One District One Factory" policy (Ghana Government, 2017), which seeks to transform the country from an agrarian economy to an industrialized one. However, according to Mensah et al. (2021), the success of this policy depends on the country's ability to attract cleaner industries, enforce stringent environmental regulations, and increase environmentally-related taxes.

Policy makers should engage with local communities and organizations to identify people's adaptation needs and formulate tailored responses (Cobbinah, 2021). This approach is particularly important for promoting rural development. Although migration can offer people

better living conditions and higher incomes, it is crucial to consider the potential negative impacts, especially in relation to migration governance. Strategic interventions to mitigate these impacts, such as managing urbanization, may be necessary (Sietchiping & Omwamba, 2020). Efforts to improve migration conditions should include initiatives to address land degradation (Hoffmann et al., 2022), investment in infrastructure and education (Somanje et al., 2020), and the strengthening of translocal networks that are important for the resilience of migrant communities (Sakdapolrak et al., 2024). It is also crucial to secure remittances as they are a significant source of income for many households (Steinbrink & Niedenführ, 2020). When designing safe and resilient cities, it is important to consider the needs of migrants. This is because their perception of risk, attachment to place, and aspirations can significantly impact their subjective well-being (Szaboova et al., 2022). These measures would not only address immediate challenges, but also contribute to the long-term well-being and resilience of both urban and rural populations. Understanding the challenges in places of origin can help formulate effective strategies to address the aforementioned issues at the source.

4.2. Limitations

Although this study provides important insights into the socioenvironmental vulnerabilities that influence internal migration in Ghana, it has limitations in providing a comprehensive understanding of migration patterns. Migration decisions are not fully captured due to the inability to quantify key factors such as social networks, personal motivations, and aspirations. Vulnerability mapping, however, is influenced by data availability and the selection of indicators (Sherbinin et al., 2015). The study relies on an expert-based approach, which can be subject to certain biases. For instance, the perspectives of experts may not always reflect those of the broader population. Yet, the expert opinions on the external factors influencing migration captured in this study were broadly in line with the current literature (e.g. (Adger et al., 2021; Azumah & Ahmed, 2023; Schürmann et al., 2022) and provided a more nuanced understanding of the issue beyond the simple average weighting of proxy indicators. For example, the search for better economic opportunities, often cited as the main driver of migration, was consistent with the expert weighting. Nevertheless, there is a discrepancy between the high RII values assigned to environmental factors and the comparatively lower rankings given to certain socio-economic factors. This is particularly evident in regard to land availability. Although experts have ranked it as having a lower impact, it is often cited in migration studies as a significant factor affecting agriculture-dependent households in Ghana, particularly in the northern regions (Bonye et al., 2021; Sward, 2017; Nyantakyi-Frimpong & Kerr, 2017). The relatively high weighting of environmental factors is, however, consistent with studies that argue that environmental variability can have a significant impact on vulnerable populations, especially those dependent on agriculture (Asare-Nuamah, 2021; Dumenu & Obeng, 2016; Teye & Nikoi, 2022). Nevertheless, there is a continuing debate about the extent to which environmental factors influence migration decisions (Kaczan & Orgill-Meyer, 2020).

Uncertainties remain due to the fact that 4 out of 16 regions did not show plausible results in the comparative analysis. This finding could hint towards weaknesses in available data or data processing. While environmental data are not restricted to artificial borders, most of the socio-economic data used in this study are only available at the district level. This results in clear boundaries of different feature classes. Aggregating socio-economic data to the raster level is challenging, because it may not be evenly distributed within each district, potentially leading to bias in the aggregated data. However, Ghana is divided into 261 districts, which allows for spatially differentiated analysis. In order to disaggregate the information from the census data to actual population data, population density was overlaid with the WOA outputs. Using the "natural breaks" method (Jenks, 1967), each factor was reclassified to achieve a common scale and to accurately assess the magnitude of the proxy indicators. This approach ensures reproducible results and increases their reliability. Other reclassification strategies may produce different results. Some factors show a stronger positive correlation, in particular "Soil organic carbon" and "Distance to a main source of drinking water". These factors are also more strongly correlated with precipitation indices. However, we include all factors in our analysis because we argue that some correlations are not necessarily causal and that migration is influenced by a variety of interacting factors. The preprocessing of precipitation indices and NDVI values introduced a degree of inaccuracy, as shown in Appendix B. The biannual rainfall in southern Ghana cannot be fully captured by the cumulative rainfall anomaly method we used. In addition, heavy cloud cover during the rainy season results in missing values for the land degradation proxy.

The weighted overlay analysis demonstrates the relative importance of different factors. This means that in some areas, the high impact of one factor, such as the number of dry days in the Upper East region, may be offset by the minor impact of other factors, such as the occurrence of relatively few heavy rainfall events. Overall, the complex decisionmaking process for migration is influenced by a variety of factors, and the WOA allows these factors to be considered simultaneously. A comparative analysis of the net migration rates, and the impact maps may help to evaluate the plausibility of the results. However, an exclusive overlay is not sufficient for validation as both phenomena can coexist without influencing each other.

5. Conclusion

In this paper, a novel mixed-method approach using different spatial data sources was developed to map vulnerable areas with a high likelihood of migration in Ghana. The combination between proxy indicators that reflect unfavorable environmental and socio-economic conditions and incorporating spatially explicit population data provided a differentiated picture of the vulnerable rural population in Ghana. Comparison with net migration data from the most recent PHC emphasizes the plausibility of the results, suggesting that spatial data can be used to identify areas with a high likelihood of internal rural migration. In particular, the research highlights the vulnerability of rural areas in the northern regions of Ghana to adverse socio-economic impacts in combination with environmental degradation, which is reflected in their negative net migration rate. People living in the coastal zone are exposed to environmental impacts that could potentially worsen in the future and contribute to a decline in livelihood quality. A further exacerbation through increasing urbanization by in-migration and thus declining socio-economic conditions is expected. Personal aspirations, place attachment and perceived opportunities may explain results that are not immediately apparent. These include the high attractiveness of urban areas, despite the fact that they are potentially as vulnerable or even more susceptible to environmental or economic risks than rural areas of origin.

The study is subject to some limitations, such as the reliance on an expert-based approach, potential errors in the aggregation of socioeconomic data in raster format, and the lack of individual-level data. However, the results suggest the applicability of spatial data combined with expert opinion to identify areas with high (or low) likelihood of migration for the case of Ghana. The proposed analytical framework can be applied to other West African countries with similar migration contexts and data availability. By identifying vulnerable rural areas that may lead to migration, particularly to urban areas, regional policies can be designed and implemented to mitigate the impact of adverse environmental and/or socio-economic conditions and support off-farm adaptation strategies as well as sustainable rural development. The findings can be placed in the broader context of existing migration frameworks, as they provide insight into the macro-level influences that shape migration decisions and identify geographical opportunities. As such, the results can contribute to improving migration analysis and management strategies for regional planning authorities in the future.

CRediT authorship contribution statement

Alina Schürmann: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. Janina Kleemann: Methodology, Supervision, Writing – review & editing. Mike Teucher: Writing – review & editing, Methodology. Christopher Conrad: Conceptualization, Resources, Supervision, Writing – review & editing.

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We express our sincere gratitude to all the interviewed experts for their valuable time and for sharing their experiences.

Appendix A. List of experts

List of experts. The years of experience refer to the respective interviewee.

Organization/Institution	Main topic of work	Years of experience
Adventist Development and Relief Agency (ADRA)	Returnees, potential migrants, sustainable livelihoods, education	10
CARITAS Ghana	Rural refugees/migration	>20
Catholic Action for Street children (CAS)	Street children/child migration	30
Centre for Popular Education and Human Rights (CEPEHRG)	Human right/health	>20
Challenging Heights	Internal migration, human trafficking, climate change impacts	8
Environmental Justice Foundation (EJF)	Climate change and modern slavery	4
Emperiks Research	Ensure sustainable livelihood and environment	3
Friedrich-Ebert-Stiftung Ghana (FES)	Social democracy, gender issues, climate change	>5
General Agricultural Workers' Union of Ghana (GAWU)	Agricultural issues	19
Green Africa Youth Organization (GAYO)	Climate change, environmental issues, empowerment of women	3
Ghana Refugee Board	Refugees	>20
Immigration Office Kumasi	Immigration issues	>10
International Organization for Migration (IOM)	Managing migration in Ghana	>30
Peasant Farmers Association Ghana	Proper agriculture policies, credit for farmers, land grabbing issues	16
School for Development Studies (SDS)	Migration from the Sahel to Ghana and internal migration	15

Appendix B. a) Uncertainties of rainy season calculation, b) missing pixels in the Normalized Difference Vegetation Index (NDVI) data



Appendix C. Reclassification of the proxy indicators that were combined to new indicator (Fig. 3), before integrating into the weighted overlay analysis. The trend layer was classified manually, the mean layer was classified using natural breaks (according to Jenks (1967))

		Class boundary		
Factor addressed in expert interview	Proxy indicator	Trend (Sen's Slope Estimator)	Mean	Rank
Increase of consecutive dry days (CDD) in rainy	Maximum length of consecutive dry days	-1 0.001	<38.34	1
season		-0.001 - 0.001	49.96	2
		0.001-0.65	67.19	3
Permanent degradation of land/soils	NDVI in June, July and August	-0.079 0.001	< 0.58	3
		-0.001 - 0.001	0.72	2
		0.001-0.062	0.91	1
		no data	no data	0
Persistent droughts	Annual dry days	-0.999 - 0.001	<247.97	1
		-0.001 - 0.001	264.2	2
		0.001-0.44	295.48	3
Extreme rainfall events/flooding in the rainy	Heavy rainfall events within the rainy season (days with precipitation	-0.33 0.001	< 12.01	1
season	>20 mm)	-0.001 - 0.001	15.88	2
		0.001-0.25	27.35	3

Appendix D. Reclassification of the proxy indicators used in the weighted overlay analysis based on natural breaks classification (according to Jenks (1967))

Job opportunities Unemployment rate (%) <9.2	1
12.8	2
16.6	3
21.9	4
45.9	5
Opportunities for trading Distance to cities (travel time in minutes) <153	1
276	2
433	3
673	4
1301	5
Environmental conditions for agriculture Later onset of rainy season in days (Sen's Slope Estimator) 1.55	5
0,7	4
0.37	3
0.1	2
-0	-
Fertile soils Soil organic Carbon (g/kg) in 0–20 m no data	0
	1
	2
9	3
7.2	4
-56	5
Agricultural production Mean yield of 10 major food group (amount of production per harvested area in k_0/h_2) 11.814.1	1
Agricultural production mean yield of 10 major rood crops (amount of production per narvested area, in kg/ma) 11 514.1	2
500.4	3
307.3 2474 7	4
-1853)	5
Each insecurity Dravalance of savare and moderate food insecurity in the population [04] no data	0
rood insecurity in the population [76] no data	1
<0 16.4	1
10.7 27 Q	2
27.0 A6.A	3
40.4 70 0	4
Deer infractructure development Nichttime lights in 2001 (guarge redience) 70.0	1
Pool initati ucture development Nignitume ngins in 2021 (average radiance) /3	1
41.5	2
24.4	3
-2.2	-
Assess to advestion	1
Access to education Number of Junior right schools per 1,000 initialitants 39	1
27	2
22	3
-12	4
Assess to water (Victoria to main source of drinking water (minuter)	1
Access to watch Distance to main source of unifiling water (minutes) <10	1
19	∠
24	3
20	4
Baseles sum ed conflicts	5
Regular armed connects requency of armed connects with fatalities 0	1
2	2

(continued on next page)

(continued) Class boundary Factor addressed in expert interview Proxy indicator Rank 5 3 11 4 5 1 2 3 4 5 1 2 3 12 Safety Number of police stations per 100,000 inhabitants 29 20 15 10 <6 Access to farmland Cropland per farmer (ha) 11.7 5.5 3.7 4 2.6 <1.2 5

Appendix E. Proxy indicators as input for the weighted overlay analysis, sorted by percentage of influence

Unemployment rate	Distance to cities	Maximum length of	Estimates of food insecurity	Nighttime lights	Number of junior high schools
		Consecutive up to yes			
Later onset of rainy season	NDVI in June, July and August	Soil organic carbon	Distance to main source of water	Armed conflicts (frequency)	Number of police stations
Annual dry days	Heavy rainfall events	Mean yield of major food crops	Cropland per farmer	°	impact of factors impact of fa

Appendix F. The table shows the input data for Fig. 6, which includes the net migration rate and the proportion of people living in moderate to highly affected areas (vulnerable areas) based on Fig. 5.3. In addition, respective main out- and in-migration flow based on GSS (2023) are provided

Regions	Net migration rate	Total population in vulnerable areas [%]	Rural population in vulnerable areas [%]	Main out- migration flow	Main in- migration flow
Ahafo	4.3	2.0	4.4	Ashanti	Ashanti
Ashanti	4.5	8.3	1.8	Greater Accra	Upper East
Bono	-2	18.8	36.1	Ashanti	Upper West
Bono East	6.7	61.3	69.8	Ashanti	Upper West
Central	-2.2	48.4	35.5	Greater Accra	Greater Accra
Eastern	-9.3	23.2	23.5	Greater Accra	Greater Accra
Greater Accra	28	95.3	84.5	Central	Eastern
Northern	-12.6	99.3	100.0	Greater Accra	Savannah
Northern East	-8	100.0	100.0	Ashanti	Upper East
Oti	-5	73.9	64.8	Greater Accra	Volta
Savannah	-5.2	100.0	100.0	Ashanti	Upper West
Upper East	-22.9	100.0	100.0	Ashanti	Ashanti
Upper West	-21.7	100.0	100.0	Ashanti	Ashanti
Volta	-27.6	52.9	45.7	Greater Accra	Greater Accra
Western	6.5	73.4	49.7	Greater Accra	Central
Western North	7.6	24.0	24.1	Ashanti	Ashanti

Number of I	migrants
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> 100,000

10 000 - 50 000

< 10,000

References

- Aboagye, D. (2021). Inequalities and realities in migration: Key urban challenges faced by internal migrants in Ghana. Soc Network, 1(8).
- Abu, M., Codjoe, S. N. A., & Sward, J. (2014). Climate change and internal migration intentions in the forest-savannah transition zone of Ghana. *Population and Environment*, 35(4), 341–364.
- Addo, K. A. (2013). Assessing coastal vulnerability Index to climate change: The case of Accra – Ghana. Journal of Coastal Research, 165, 1892–1897.
- Adger, W. N., Campos, R. S. de, Codjoe, S. N. A., Siddiqui, T., Hazra, S., Das, S., Adams, H., Gavonel, M. F., Mortreux, C., & Abu, M. (2021). Perceived environmental
- risks and insecurity reduce future migration intentions in hazardous migration source areas. *One Earth, 4*(1), 146–157. Adger, W. N., Fransen, S., Safra de Campos, R., & Clark, W. C. (2024). Migration and
- sustainable development. Proceedings of the National Academy of Sciences of the United States of America, 121(3), Article e2206193121.
- Adu-Gyamfi, A., Owusu-Addo, E., Inkoom, D. K. B., & Asibey, M. O. (2022). Peri-urban interface: An alternative residential location of low-income migrants in Kumasi, Ghana. *Cities*, 123, Article 103570.
- Akubia, J. E. K., Ahmed, A., & Bruns, A. (2020). Assessing how land-cover change associated with urbanisation affects ecological sustainability in the greater Accra metropolitan area, Ghana. *Land*, 9(6), 182.
- Amoako, C., Doe, B., & Adamtey, R. (2023). Flood responses and attachment to place within low-income neigbourhoods in Kumasi, Ghana. Soc Network, 42(1), 1–13. Anarfi, K., Hill, R. A., & Shiel, C. (2020). Highlighting the sustainability implications of
- urbanisation: A comparative analysis of two urban areas in Ghana. *Land*, 9(9), 300. Antwi-Agyei, P., Dougill, A. J., Stringer, L. C., & Codjoe, S. N. A. (2018). Adaptation
- opportunities and maladaptive outcomes in climate vulnerability hotspots of northern Ghana. Adv Clim Change Res. 19, 83–93.
- Antwi-Agyei, P., Stringer, L. C., & Dougill, A. J. (2014). Livelihood adaptations to climate variability: Insights from farming households in Ghana. *Regional Environmental Change*, 14(4), 1615–1626.
- Arthur-Holmes, F., & Abrefa Busia, K. (2022). Women, North-South migration and artisanal and small-scale mining in Ghana: Motivations, drivers and socio-economic implications. *The Extractive Industries and Society*, 10, Article 101076.
- Asare-Nuamah, P. (2021). Climate variability, subsistence agriculture and household food security in rural Ghana. *Heliyon*, 7(4), Article e06928.

- Ashiagbor, G., Amoako, C., Asabere, S. B., & Quaye-Ballard, J. A. (2019). Landscape transformations in rapidly developing peri-urban areas of Accra, Ghana: Results of 30 years. Open Geosciences, 11(1), 172–182.
- Awumbila, M., Owusu, G., & Teye, J. K. (2014). Can rural-urban migration into slums reduce poverty? Evidence from Ghana.: Migrating out of poverty RPC working paper 13. Migrating out of poverty consortium.
- Azumah, S. B., & Ahmed, A. (2023). Climate-induced migration among maize farmers in Ghana: A reality or an illusion? *Dev Environ Model*, 45, Article 100808.
- Baffoe, G., & Matsuda, H. (2018). An empirical assessment of households livelihood vulnerability: The case of rural Ghana. *Social Indicators Research*, 140(3), 1225–1257.
- Baffoe, G., Zhou, X., Moinuddin, M., Somanje, A. N., Kuriyama, A., Mohan, G., Saito, O., & Takeuchi, K. (2021). Urban-rural linkages: Effective solutions for achieving sustainable development in Ghana from an SDG interlinkage perspective. *Sustainability Science*. 16(4), 1341–1362.
- Balgah, R. A., & Kimengsi, J. N. (2022). A review of drivers of environmental nonmigration decisions in Africa. Regional Environmental Change, 22(4), 1–17.
- Black, R., Adger, W. N., Arnell, N. W., Dercon, S., Geddes, A., & Thomas, D. (2011). The effect of environmental change on human migration. *Global Environmental Change*, 21, S3–S11.
- Boateng, I. (2012). An application of GIS and coastal geomorphology for large scale assessment of coastal erosion and management: A case study of Ghana. *Journal of Coastal Conservation*, 16(3), 383–397.
- Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences of the United States of America*, 111 (27), 9780–9785.
- Bonye, S. Z., Aasoglenang, T. A., & Yiridomoh, G. Y. (2021). Urbanization, agricultural land use change and livelihood adaptation strategies in peri-urban Wa, Ghana. Soc Network, 1(1).
- Brown, S. (2020). bivarRasterPlot. R. https://gist.github.com/scbrown86/2779137a937 8df7b60afd23e0c45c188.
- Bukari, K. N., Bukari, S., Sow, P., & Scheffran, J. (2020). Diversity and multiple drivers of pastoral fulani migration to Ghana. *Nomadic Peoples*, 24(1), 4–31.
- Busby, J. W., Smith, T. G., & Krishnan, N. (2014). Climate security vulnerability in Africa mapping 3.0. Political Geography, 43, 51–67.

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

Center for International Earth Science Information Network (CIESIN). GRID3 Ghana Settlement Extents, Version 01.01. https://data.grid3.org/datasets.

Cobbinah, P. B. (2021). Urban resilience as an option for achieving urban sustainability in Africa. Land issues for urban governance in sub-saharan Africa.

Czaika, M., & Reinprecht, C. (2022). Migration drivers: Why do people migrate?. In Introduction to migration studies (pp. 49–82). Cham: Springer.

Dada, O. A., Almar, R., & Morand, P. (2024). Coastal vulnerability assessment of the West African coast to flooding and erosion. *Scientific Reports*, 14(1), 890.

Defourny, P., Lamarche, C., Brockmann, C., Boettcher, M., Bontemps, S., Maet, T. de, Duveiller, G. L., Harper, K., Hartley, A., Kirches, G., Moreau, I., Peylin, P., Ottlé, C., Radoux, J., van Bogaert, E., Ramoino, F., Albergel, C., & Arino, O. (2023). Observed annual global land-use change from 1992 to 2020 three times more dynamic than reported by inventory-based statistics (in preparation).

Didan, K. (2021a). MODIS/Aqua vegetation indices 16-day L3 global 250m SIN grid V061. Didan, K., 2021b. MODIS/Terra vegetation indices 16-day L3 global 250m SIN grid V061.

Dumenu, W. K., & Obeng, E. A. (2016). Climate change and rural communities in Ghana: Social vulnerability, impacts, adaptations and policy implications. *Environmental Science & Policy*, 55, 208–217.

Dunning, C. M., Black, E. C. L., & Allan, R. P. (2016). The onset and cessation of seasonal rainfall over Africa. Journal of Geophysical Research: Atmospheres, 121(19).

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., Ghosh, T. (2017): VIIRS night-time lights. In: International Journal of Remote Sensing 38 (21), S. 5860–5879.

ESRI. (2023). How weighted overlay works. https://pro.arcgis.com/en/pro-app/late st/tool-reference/spatial-analyst/how-weighted-overlay-works.htm.

Falco, C., Galeotti, M., & Olper, A. (2019). Climate change and migration: Is agriculture the main channel? *Global Environmental Change*, 59, Article 101995.

Flahaux, M.-L., & Haas, H. de (2016). African migration: Trends, patterns, drivers. Dev Environ Model, 4(1).

Food and Agriculture Organization of the United Nations (FAO). (2023). *GIEWS Country Brief: The Republic of Ghana*. https://www.fao.org/giews/country-analysis/coun try-briefs/country.jsp?code=GHA.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations-a new environmental record for monitoring extremes. *Scientific Data*, 2(1), Article 150066.

Ghana Government. (2017). One district one factory – 1D1F. https://ld1f.gov.gh/. Ghana Statistical Service (GSS). (2021c). 2021 population and housing census: General

report volume 3C - Background characteristics. Ghana Statistical Service, Accra. Ghana Statistical Service (GSS). (2014). 2010 population & housing census report: Urbanisation. Ghana Statistical Service, Accra.

Ghana Statistical Service (GSS). (2021b). 2021 population and housing census. Preliminary report. Accra: Ghana Statistical Service.

Ghana Statistical Service (GSS). (2021a). 2021 population and housing census: General report volume 3E -Economic activity. Ghana Statistical Service, Accra.

Ghana Statistical Service (GSS). (2021d). 2021 population and housing census. Proximity of residential structures to essential service facilities. Accra: Ghana Statistical Service.

Ghana Statistical Service (GSS). (2022). 2021 population and housing census: General report volume 3M - Water and sanitation. Ghana Statistical Service, Accra.
Ghana Statistical Service (GSS). (2023). 2021 Population and housing census: Thematic

report - Migration. Ghana Statistical Service, Accra.

Gray, C., & Mueller, V. (2012). Drought and population mobility in rural Ethiopia. World Development, 40(1), 134–145.

Haas, H. de (2021). A theory of migration: The aspirations-capabilities framework. Dev Environ Model, 9(1), 8.

Hengl, T., Miller, M. A. E., Križan, J., Shepherd, K. D., Sila, A., Kilibarda, M., Antonijević, O., Glušica, L., Dobermann, A., Haefele, S. M., McGrath, S. P., Acquah, G. E., Collinson, J., Parente, L., Sheykhmousa, M., Saito, K., Johnson, J.-M., Chamberlin, J., Silatsa, F. B. T., & Crouch, J. (2021). African soil properties and nutrients mapped at 30 m spatial resolution using two-scale ensemble machine learning. *Scientific Reports*, 11(1), 6130.

Hermans-Neumann, K., Priess, J., & Herold, M. (2017). Human migration, climate variability, and land degradation: Hotspots of socio-ecological pressure in Ethiopia. *Regional Environmental Change*, 17(5), 1479–1492.

Hoffmann, R., Wiederkehr, C., Dimitrova, A., & Hermans, K. (2022). Agricultural livelihoods, adaptation, and environmental migration in sub-saharan drylands: A meta-analytical review. *Environmental Research Letters*, 17(8), Article 83003.

Hubertus, L., Groth, J., Teucher, M., & Hermans, K. (2023). Rainfall changes perceived by farmers and captured by meteorological data: Two sides to every story. *Regional Environmental Change*, 23(2).

International Food Policy Research Institute (IFPRI). (2020). Spatially-disaggregated crop production statistics data in Africa south of the sahara for 2017.

Issifu, A. K., Darko, F. D., & Paalo, S. A. (2022). Climate change, migration and farmer-herder conflict in Ghana. *Conflict Resolution Quarterly*, 39(4), 421–439. Jenks, G. F. (1967). *The data model concept in statistical mapping*.

Kaczan, D. J., & Orgill-Meyer, J. (2020). The impact of climate change on migration: A synthesis of recent empirical insights. *Climatic Change*, 158(3–4), 281–300.

Kanton, R. A. L., Prasad, P. V. V., Mohammed, A. M., Bidzakin, J. K., Ansoba, E. Y., Asungre, P. A., Lamini, S., Mahama, G., Kusi, F., & Sugri, I. (2016). Organic and inorganic fertilizer effects on the growth and yield of maize in a dry agro-ecology in northern Ghana. *Journal of Crop Improvement*, 30(1), 1–16. Kumasi, T. C., Antwi-Agyei, P., & Obiri-Danso, K. (2019). Small-holder farmers' climate change adaptation practices in the Upper East Region of Ghana. *Environment, Development and Sustainability*, 21(2), 745–762.

Liebmann, B., Bladé, I., Kiladis, G. N., Carvalho, L. M. V., Senay, G. B., Allured, D., Leroux, S., & Funk, C. (2012). Seasonality of african precipitation from 1996 to 2009. *Journal of Climate*, 25(12), 4304–4322.

Marzi, S., Mysiak, J., Essenfelder, A. H., Pal, J. S., Vernaccini, L., Mistry, M. N., Alfieri, L., Poljansek, K., Marin-Ferrer, M., & Vousdoukas, M. (2021). Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework. *Global Environmental Change*, 71, Article 102393.

Mechiche-Alami, A., & Abdi, A. M. (2020). Agricultural productivity in relation to climate and cropland management in West Africa. Scientific Reports, 10(1), 3393.

Mensah, C. N., Dauda, L., Boamah, K. B., & Salman, M. (2021). One district one factory policy of Ghana, a transition to a low-carbon habitable economy? *Environment, Development and Sustainability*, 23(1), 703–721.

Mijani, N., Shahpari Sani, D., Dastaran, M., Karimi Firozjaei, H., Argany, M., & Mahmoudian, H. (2022). Spatial modeling of migration using GIS-based multicriteria decision analysis: A case study of Iran. *Transactions in GIS*, 26(2), 645–668.

MoFA, GSS, WFP, FAO. (2020). Comprehensive Food Security and Vulnerability Analysis (CFSVA) Ghana. https://ghana.un.org/sites/default/files/2022-03/WFP-0000 137744_%20Comprehensive%20Food%20Security%20and%20Vulnerability% 202020.pdf.

Ministry of Food and Agriculture (MoFA). (2021). Agriculture in Ghana: Facts and figures. Mueller, V., Gray, C., & Kosec, K. (2014). Heat stress increases long-term human

migration in rural Pakistan. Nature Climate Change, 4(3), 182–185.

Neumann, K., Sietz, D., Hilderink, H., Janssen, P., Kok, M., & van Dijk, H. (2015). Environmental drivers of human migration in drylands – a spatial picture. *Applied Geography*, 56, 116–126.

Nyamekye, C., Schönbrodt-Stitt, S., Amekudzi, L. K., Zoungrana, B. J.-B., & Thiel, M. (2021). Usage of MODIS NDVI to evaluate the effect of soil and water conservation measures on vegetation in Burkina Faso. Land Degradation & Development, 32(1), 7–19.

Nyantakyi-Frimpong, H., & Kerr, R. B. (2017). Land grabbing, social differentiation, intensified migration and food security in northern Ghana. *The Journal of Peasant Studies*, 44(2), 421–444.

Oduro-Ofori, E., Amissah, M., Ocloo, K. A., Amaka-Otchere, A. B. K., Dankyi, S. K., & Doe, B. (2023). Livelihood security in urban slums in Ghana: Evidence from the Kumasi metropolis. *Geojournal*, 1–14.

Owusu, V., Ma, W., Emuah, D., & Renwick, A. (2021). Perceptions and vulnerability of farming households to climate change in three agro-ecological zones of Ghana. *Journal of Cleaner Production*, 293, Article 126154.

Paul, N., Silva, V., & Amo-Oduro, D. (2022). Development of a uniform exposure model for the African continent for use in disaster risk assessment. *International Journal of Disaster Risk Reduction*, 71, Article 102823.

Pohlert, T. (2023). trend: Non-Parametric trend tests and change-point detection. *R package version* 1.1.5. https://CRAN.R-project.org/package=trend.

Poku-Boansi, M., Amoako, C., Owusu-Ansah, J. K., & Cobbinah, P. B. (2020). The geography of urban poverty in Kumasi, Ghana. *Habitat International*, 103, Article 102220.

Rademacher-Schulz, C., Schraven, B., Mahama, E.S. (2014). Time matters: shifting seasonal migration in Northern Ghana in response to rainfall variability and food insecurity, Climate and Development, 6:1, 46-52.

Raleigh, C., Linke, r., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An armed conflict location and event dataset. *Journal of Peace Research*, 47(5), 651–660.

Rigaud, K. K., Sherbinin, A. de, Jones, B., Adamo, S., & Maleki, D. (2021). Groundswell Africa: Internal climate migration in West African countries. Washington, DC: The World Bank.

Sacré Regis, M. D., Mouhamed, L., Kouakou, K., Adeline, B., Arona, D., Houebagnon Saint, J. C., Koffi Claude, A. K., Talnan Jean, H. C., Salomon, O., & Issiaka, S. (2020). Using the CHIRPS dataset to investigate historical changes in precipitation extremes in West Africa. *Climate*, 8(7), 84.

Sakdapolrak, P., Sterly, H., Borderon, M., Bunchuay-Peth, S., Naruchaikusol, S., Ober, K., Porst, L., & Rockenbauch, T. (2024). Translocal social resilience dimensions of migration as adaptation to environmental change. *Proceedings of the National Academy of Sciences of the United States of America*, 121(3), Article e2206185120.

Schürmann, A., Kleemann, J., Teucher, M., Fürst, C., & Conrad, C. (2022). Migration in West Africa: A visual analysis of motivation, causes, and routes. *Ecology and Society*, 27(3).

Schewel, K. (2020). Understanding immobility: Moving beyond the mobility bias in migration studies. *International Migration Review*, 54(2), 328–355.

Schiavina, M., Freire, S., & MacManus, K. (2023). GHS-POP R2023A - GHS population grid multitemporal (1975-2030). European Commission, Joint Research Centre (JRC).

Schraven, B., & Rademacher-Schulz, C. (2016). Shifting rainfalls, shifting livelihoods: Seasonal migration, food security and social inequality in northern Ghana. In R. McLeman, J. Schade, & T. Faist (Eds.), *Environmental migration and social inequality* (Vol. 61, pp. 43–56). Cham: Springer International Publishing.

Sen, P. K. (1968). Estimates of the regression coefficient based on kendall's tau. Journal of the American Statistical Association, 63(324), 1379–1389.

Sherbinin, A. de, Chai-Onn, T., Jaiteh, M., Mara, V., Pistolesi, L., Schnarr, E., & Trzaska, S. (2015). Data integration for climate vulnerability mapping in West Africa. *ISPRS International Journal of Geo-Information*, 4(4), 2561–2582.

Sietchiping, R., & Omwamba, J. (2020). The future of urban policy in Africa. Localization of SDG 11 and the new urban agenda. *Local Govern*, 275–291.

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Somanje, A. N., Mohan, G., Lopes, J., Mensah, A., Gordon, C., Zhou, X., Moinuddin, M., Saito, O., & Takeuchi, K. (2020). Challenges and potential solutions for sustainable urban-rural linkages in a Ghanaian context. *Sustainability*, 12(2), 507.

Steinbrink, M., & Niedenführ, H. (2020). Effects of translocal livelihoods on rural change. Africa on the move.

- Sward, J. (2017). In-migration, customary land tenure, and complexity: exploring the relationship between changing land tenure norms and differentiated migrant livelihoods in Brong Ahafo, Ghana. *Population and Environment*, 39(1), 87–106.
- Szaboova, L., Adger, W. N., Safra de Campos, R., Maharjan, A., Sakdapolrak, P., Sterly, H., Conway, D., Codjoe, S. N. A., & Abu, M. (2023). Evaluating migration as successful adaptation to climate change: Trade-offs in well-being, equity, and sustainability. One Earth, 6(6), 620–631.
- Szaboova, L., Safra de Campos, R., Adger, W. N., Abu, M., Codjoe, S. N. A., Franco Gavonel, M., Das, S., Siddiqui, T., Rocky, M. H., & Hazra, S. (2022). Urban sustainability and the subjective well-being of migrants: The role of risks, place attachment, and aspirations. *Population, Space and Place, 28*(1).
- Teye, J. K., & Nikoi, E. G. A. (2022). Climate-induced migration in West Africa. In J. K. Teye (Ed.), *Migration in West Africa. IMISCOE regional reader* (1st ed. 2022 ed., pp. 79–105). Cham: Springer International Publishing; Imprint Springer.
- Tsegai, D., & Le, Q. B. (2011). District-level spatial analysis of migration flows in Ghana: Determinants and implications for policy. Reg Sci Ing, 3(2), 87-100.
- van der Geest, K. (2011). North-south migration in Ghana: What role for the environment? International Migration, 49, e69–e94.
- van der Geest, K., Vrieling, A., & Dietz, T. (2010). Migration and environment in Ghana: A cross-district analysis of human mobility and vegetation dynamics. *Environment* and Urbanization, 22(1), 107–123.

- Wang, T., & Sun, F. (2023). Integrated drought vulnerability and risk assessment for future scenarios: An indicator based analysis. *The Science of the Total Environment*, 900, Article 165591.
- Warner, K., & Afifi, T. (2014). Where the rain falls: Evidence from 8 countries on how vulnerable households use migration to manage the risk of rainfall variability and food insecurity. *Climate and Development*, 6(1), 1–16.
- Weiss, D. J., Nelson, A., Gibson, H. S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T. C. D., Howes, R. E., Tusting, L. S., Kang, S. Y., Cameron, E., Bisanzio, D., & Gething, P. W. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. *Nature*, 553(7688), 333–336.
- World Bank. (2020). World Development Indicators: Population density (people per sq. km of land area). https://data.worldbank.org/indicator/EN.POP.DNST Accessed 22 March 2024.
- WorldPop, & Bondarenko, M. (2020). Individual countries 1km population density (2000-2020).
- Yang, J., Owusu, V., Andriesse, E., & Dziwornu Ablo, A. (2019). In-situ adaptation and coastal vulnerabilities in Ghana and Tanzania. *The Journal of Environment & Development*, 28(3), 282–308.
- Yeboah, T. (2021). Future aspirations of rural-urban young migrants in Accra, Ghana. *Children's Geographies*, 19(1), 45–58.
- Zickgraf, C. (2021). Climate change, slow onset events and human mobility: Reviewing the evidence. Current Opinion in Environmental Sustainability, 50, 21–30.