The role of environmental and climate factors on migration: the case of Ghana from 1985 to 2014

ABSTRACT (250 words)

A common perception exists that West-African migration is predominately driven by environmental stress, conflict, and economic factors. For instance, scholars have argued that precipitations and droughts in the Ghanian northern regions are important factors in the out-flows to the southern parts of the country. However, few empirical analyses have been directly tied large-scale migration with slow onset climatic processes.

To fill these gaps, our research focuses on the temporal and spatial changes of migration and contextual factors. Net-migration estimates, temperature, precipitation, conflict, and artisanal (small-scale-company) gold-mining datasets were harmonized at high-resolution, to model environmental migration drivers in Ghana, by 5-year interval, from 1985 to 2014.

We adopt a three-step approach. First, we apply the geographic-weighted-regression (GWR) to explore how factors interact as spatial system; second, we adopt the multiscale-geographic-weighted-regression (MGWR) to investigate the local incidence of each variable. Finally, we validate results using the machine learning approach (geographically-weighted-random-forest, GWRF).

Results reveal the variables that play a relevant role in the interplay with migration. From 2000 to 2014, changes in net migration are associated with changes in maximum-temperatures, mean length of consecutive dry-days, and artisanal gold-mining activities; yet the models capture high spatial variability across Ghanian territories.

Our contribution to the literature on environmental and climate migration is twofold. First, from a methodological perspective, we determine the complementary of the three geo-spatial methods.

Second, our analysis gives empirical evidence on how environmental-climate conditions, acting in combination with other political and socio-economic factors, alter local-systems and in-turn influence migration behaviors over time.

INTRODUCTION

Scholarly research on the direct and indirect contribution of environmental and climate factors to migration has expanded greatly in the past three decades. Studies have well documented that droughts and precipitation anomalies as having the potential to lead to a range of short- and long-term migration outcomes, with the direction, duration of migration and demographic characteristics of migrants, being highly context specific (Gray and Wise, 2016). There is also research suggesting that environmental factors can have an indirect influence on migration through the creation or exacerbation of violent and/or non-violent conflict over access to land or natural resources (UN-Habitat, 2022). As Ferris (2020) notes, beside scholars and humanitarian actors mostly interested in the consequences of displacements linked to sudden-onset, an increasing number of development researchers recognize the assessment of long-term consequences of slow-onset events as a crucial strand to elucidate linkages between climate, conflict, and migration. For instance, environmental and climate factors are believed by scholars to play a causal role in migration patterns over time, within Ghana, between Ghana and neighbouring countries in West Africa and, possibly, from Ghana to more distant destinations in Europe. Previous studies – reviewed in greater detail below – suggest that precipitation patterns and periodic droughts in the drier, northern parts of the country have been important factors in the out-migration of people to more southerly parts of the country, especially younger residents of working age. The most common migration destinations for out-migrants include urban centres, or rural areas, with commercial agricultural production, and artisanal (small scale) gold mining areas. Additionally, research suggests that migration in some areas of dryland Ghana may mostly relate to non-violent resource-based conflict, through the movement of pastoralists and their livestock into farming areas when their usual grazing areas are impacted by droughts (Issifu et al., 2022).

Our study takes advantage of newly available net migration datasets that provide estimates of migration changes at very fine spatial resolution, to explore and map in greater detail how precipitation patterns, extreme temperatures, artisanal (small-scale-company) gold mining, and conflicts have influenced migration patterns in Ghana. Using emergent techniques in geospatial regression and machine learning models, we cover from 1985 to 2014, dividing the 30-year period by 5-year interval. Our methods reveal statistically significant relationships at local level, between environmental factors and changes in net migration patterns, from 2000 to 2014. Specifically results show the association between the changes in net migration and the maximum temperature, mean length of consecutive dry days, and artisanal gold-mining effects; yet these effects vary consistently across Ghanian territories. For instance, in 2005-2009, artisanal gold mining activities are positively associated with migration in the Western region, attracting workers in the areas, and negatively associated with migration in the North-East areas, pushing people to leave.

Our contribution to the literature on climate migration is twofold. First, from a methodological perspective, our approach founds the complementary of the three geo-spatial methods. While the geospatial regression quantifies the spatial variability of the system (places that are closer have potentially higher interactions), the multiscale geospatial regression measures, though the bandwidth indicators, how each factor (as explanatory variable of the system) is differently associated with migration across space. Then, we use the machine learning approach to validate the predictive ability of the spatial system in terms local goodness. Second, our analysis gives empirical evidence on how environmental and climate conditions, acting in combination with other political and socio-economic factors, alter local systems and in turn influence migration behaviors over time. These insights into the complex relationship between slow-onset climate conditions and migration at local level would support the definition of tailored-design public actions and enhance the coordination of political decision-makers at international, national, and local levels.

ENVIRONMENTAL AND CLIMATE MIGRATION IN GHANA

Environmental and climate factors have been identified in multiple previous studies as having effects on migration patterns in Ghana. It has been widely documented that members of households that depend on subsistence agriculture in the rural north have high rates of migration to urban and rural areas in the comparatively wetter central and southern parts of the country (Kuuire et al 2016, Luginaah et al 2009, Teye et al. 2015, Schraven and Rademacher-Schulz 2016, Sow et al 2014, van der Geest et al 2010, van der Geest 2011). Districts that have relatively high levels of outmigration tend to be those with the least vegetation cover and/or suffer from land degradation, with out-migrants from these areas often destined for regions to the southwest where cocoa plantations offer employment or to artisanal gold fields in the west of the country (van der Geest et al 2010, Nyame and Grant 2014). Such moves are increasingly being initiated during in the rainy season, which differentiates them from circular patterns of remittance-seeking out-migration during the dry season and subsequent return that has been practiced in the north for generations to maintain household food security (Rademacher-Schulz et al 2014, Schraven and Rademacher-Schulz 2016). In recent decades, Northern Ghanaian farmers report being motivated to relocate indefinitely to more productive areas of the country because of poor soil conditions, growing climate issues, and a scarcity of good quality land in their home region (van der Geest 2011). Rural population growth rates in northern Ghana have been relatively high in recent decades which, coupled with highly variable rainfall patterns, contributes to the growing pressure on productive land and consequent land degradation (Sow et al 2013). Environmental factors acting in combination with economic and social factors have been identified as contributing to household migration decisions in other parts of Ghana as well. For example, past studies have identified flood hazards as being an important driver of displacement and migration in the Volta River delta (Codjoe et al 2017); shifting precipitation patterns, deforestation and land degradation a factor in out-migration from rural villages in southern Ghana (Carr 2008); and, changing maritime conditions and the health of fish stocks have created growing populations of migrant fishers in coastal Ghana (Asiedu et al 2022).

In the case of slow-onset environmental conditions, there is usually a set of overlapping political and socioeconomic factors at play that shape changes in migration behaviours (Olaniyan et al., 2015). For instance, conflicts emerging from land tenure disputes have a history of displacing people and leading to migration in Ghana. Studies suggest that conflict often ensues between pastoralists (such as Fulani herders) and various farming communities, arising from crop destruction caused by stray cattle (Baidoo, 2014; Issifu et al. 2022). Various hotspots of farmer-herder conflict are observed throughout Ghana, with violence in Agogo in the Ashanti Region (Appiah-Boateng and Kendie, 2022), as well as tensions and movements in northern Ghana and the Volta basin (Tonah 2000, Tonah 2006) as herders seek viable lands for cattle. Nevertheless, in 1992 the established democratic assessment helped the achievement of a political stability characterized by limited protest and conflict events. In addition to conflict, economic factors are considered as drivers of migration in the Western-African region (Flahaux and De Haas, 2016). As one of prevalent and long-established sectors, gold mining activities have served livelihoods and profits for Ghanian families and governments (Chuhan-Pole et al. 2015; Hilson 2002). Since 1987, Ghana experienced its fourth gold era (Amankwah and Suglo, 2003), benefiting from improved exploration and processing techniques that revolutionized the gold mining industry. Yet, the drop of gold prices on the global market in 2000s determined the closure of several mines in Ghana, reducing the number of large-scale companies mainly concentrated in the areas of Ashanti (Gbireh et al. 2009). Since 2005, Ghana has experienced a resurgence of gold rush, with an increasing number of small mining companies that operate in the sector and attract internal and international workers (Botchwey et al. 2019). This new gold rush has been associated with the increase of international migrants to undertake artisanal and small-scale mining, largely reserved for Ghanaian citizens (Minerals and Mining Act 2006), with most of them moving from China (Teschner, 2012; Hilson et al., 2014; Crawford and Botchwey, 2017). These Chinese immigrants in Ghana have been engaged in artisanal (small scale company) gold mining, by introducing new machinery and technologies that have significantly increased gold production while their activities have stimulated the local markets (Botchwey et al. 2019). This new wave of artisanal mining has also resulted in the movements of people from surrounding communities to work, directly or indirectly, in the mining sector. Nonetheless, the presence of foreign miners has frequently resulted in conflict with the local artisanal ones (Botchwey et al. 2019): foreign miners were accused of displacing and outcompeting local alluvial gold miners, contributing to pervasive corruption, and stealing Ghanaian mineral resources through gold smuggling (Abid et al., 2013). The expansion of artisanal mining has resulted in major environmental deterioration, such as the contamination of large water bodies, which are the primary source of livelihood for local communities, and the increase of outmigration for those who can afford to move (Hilson et al. 2014; Botchwey et al. 2019).

DATA

To carry out the analysis, we collect the following datasets: i) net migration estimates; ii) environmental and climate conditions; iii) conflict events; iv) artisanal gold mining activities. Each variable is harmonized at 25km2, covering the period from 1985 to 2014.

i) The net migration estimate dataset (Alessandrini, Ghio, Migali, 2020) is overlaid across Ghana. The spatial grid includes cells that are centered within the country of Ghana and do not overlap with cells centered within neighboring countries; grid cells located along coastal areas are inspected for completeness, and the total number of grid cells centred along the coast are adjusted to include areas that when harmonized, allow capturing of non-zero values of both dependent and independent variables. National geographical regional boundaries of Ghana are used to identify and describe areas in addition to harmonized data; although, regional boundaries were changed in 2018, hence our analysis and visualizations refer to the previously established 10 regional borders from 2013-2017 (Ghana Statistical Service, 2010).

ii) Ghana exhibits unique environmental conditions, which include both arid zones and tropical rainforests, enabling the study of different climate variables in relation to net migration (Dinerstein et al., 2017). Using the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) (Funk et al., 2015) and the Climate Hazards Group Daily Temperature (CHIRTS) (Funk et al., 2019), we derive the following climate change indicators**:** a) Precipitation, meaning 5-year mean annual precipitation (PREC); b) Maximum length of consecutive dry days in one year, where rain is less then 1 mm, calculated from CHIRPS total gridded rainfall, and averaged over five years (MLDS); c) Maximum length of consecutive wet days in one year, where rain is greater than or equal to 1 mm, calculated from gridded rainfall, averaged over five years (MLWS); d) Average daily maximum temperatures, averaged to 5-year intervals (TMAX); e) Average daily minimum temperatures, averaged to 5-year intervals (TMIN).

iii) We analyze data on significant conflict events and related fatalities recorded at geo-point locations (CONFL) by the Armed Conflict Location and Event Data Project (Raleigh et al., 2010) and Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (Sundberg et al., 2013).

iv) For the period 2005-2014, we rely on the database provided by the College of Earth Sciences, Chengdu University of Technology and the School of Geography, Earth and Atmospheric Sciences, Faculty of Science, University of Melbourne (Tang & Werner, 2023). The datasets are derived from the high-resolution satellite imagery for the years, 2008, 2013), which identifies the areas of artisanal small scale gold mining activities in Ghana (MINING).

Table A-1 in Appendix summarizes the selected variables.

METHODS

We model the changes in the dependent and independent variables over each 5-year interval, from 1985 to 2014, as follows:

$$x_{(i,t+1,t)} = \frac{x_{i,t+1} - x_{i,t}}{x_{i,t}}$$

$x_{(i,t+1)}$ is the value of the variable x for the grid (i) at the time (t+1); $x_{i,t}$is the value of the variable x for the grid (i) at the time (t)

A three-step approach is applied to develop the analysis. First, the Geographically Weighted Regression (GWR) is used to assess the spatial variations by the estimates of local parameter effects by geographical unit, as follows:

$$y_i = \beta o(u_i + v_i) + \sum \beta j\,(u_i + v_i)\ \ x_{ij} + \epsilon_i$$

y_i is the change in the net migration for the grid i, whose centroid has the coordinates $(u_i + v_i)$, βo is the local estimated intercept and βj represents the effects of the variable at local level.
The Gaussian weighting function is used to account for the spatial influence of the neighbouring territories (grids).
Second, we adopt the Multiscale Geographically Weighted Regression (MGWR), proposed by Oshan and colleagues (Oshan et al. 2019). The method has been recently adopted in different fields of social science research due to its flexibility to process spatial heterogeneity at different scales (Fotheringham 2017). Indeed, the main advantage of using MGWR consists of removing the spatial non-stationary condition and differentiating the local effects by each dependent variable. This means that a covariate-specific bandwidth is estimated (Yu and Fortheringham, 2020), as formally explained by the following equation:

$$y_i = \sum \beta_{bwj}\,(u_i + v_i)\ \ x_{ij} + \epsilon_i$$

β_{bwj} corresponds to the bandwidth resulting from the application of a spatial weighting kernel for estimating x_{ij} , namely the predictor j of the variable x_i . The bandwidths are selected through a back-fitting algorithm to optimize the expected log likelihood (Oshan et al., 2019). We apply an adaptive Gaussian function to deal with the spatial distribution of observations. A Monte Carlo approach is used to check the nonstationary conditions for each variable (Fotheringham, Brunsdon, and Charlton, 2002).

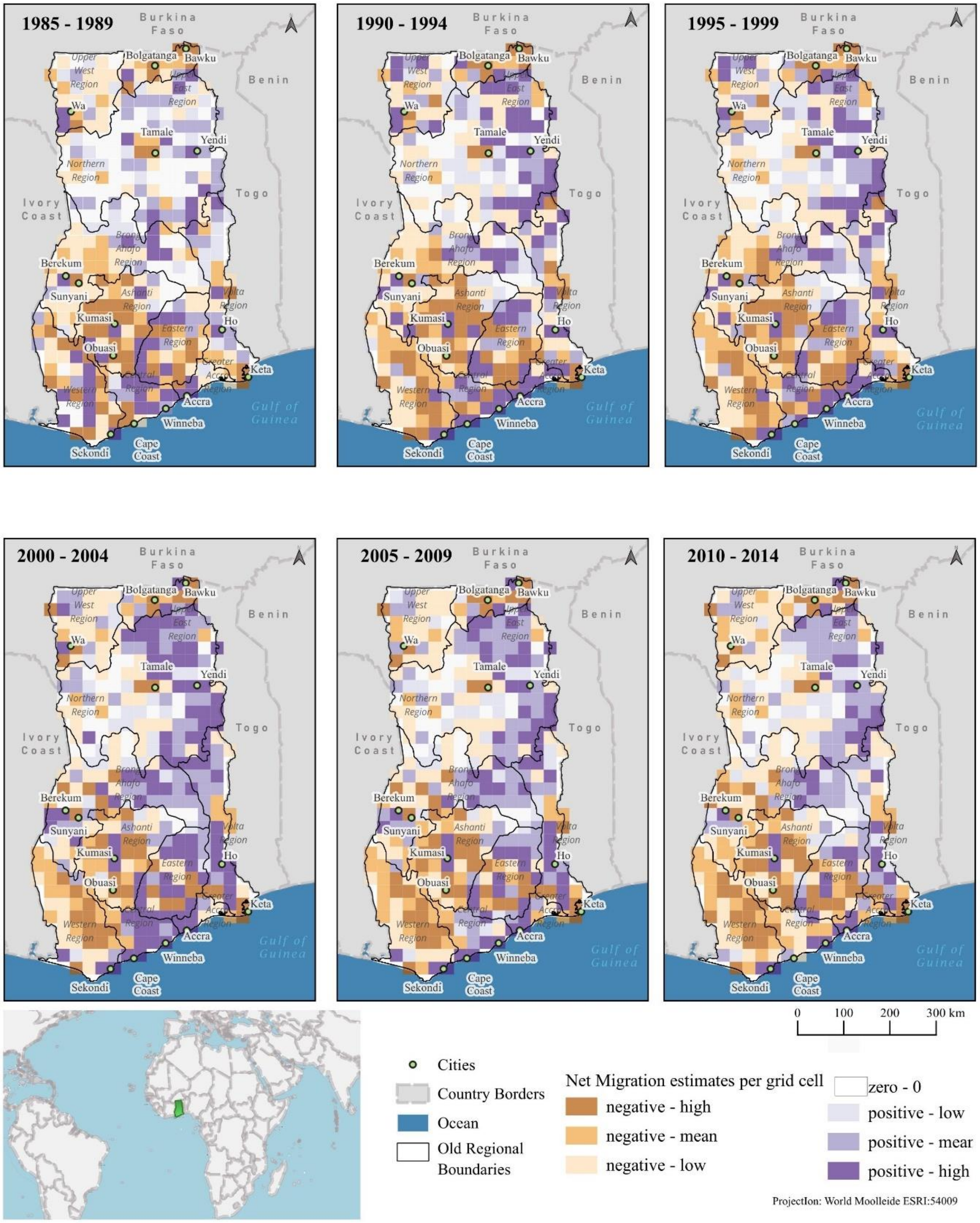
Finally, we adopt a recent variation of forest model (Georganos et al., 2021, Georganos and Kalogirou, 2022), the Geographically Weighted Random Forest Regression (GWRF). The GWRF disaggregates the traditional forest model (Breiman, 2001) into multiple local models to highlighting important local variations and enables studies on the spatial heterogeneity of the data (Nduwayezu et al., 2023). Random Grid Search (RGS) is used to find the optimal hyperparameter, and the optimal bandwidth is determined by minimizing the Out of Bag (OOB) error and the mean-squared error (RMSE) to check and rank the endogenous explanatory factors underlying migration (Schutte et al., 2021). The relevance of each variable describes the associated increase in RMSE: high importance denotes high explanatory power in the model, while negative importance indicates that the variable weakens the model's prediction power. The relative importance (RI) indicates the rank of how well a given factor predicts net migration in relation to the highest one (which corresponds to a RI=1).
To compare the models and assess their complementary to depict the spatial variation of the relationship among the selected variables (Fotheringham, Brunsdon, and Charlton, 2002), we use the Akaike Information Criterion (AIC) (Akaike, 1974) and the goodness-of-fit measures (R2).

NET MIGRATION PATTERNS ACROSS GHANAIAN TERRITORIES

Examining 5-year periods for net migration in Ghana from 1985 to 2014 (Figure 1), we identify three main patterns: i) urban pathways in the south coastal areas; ii) persistence of the north-south regional differential over time; iii) changes in migration dynamics in the Western and Volta regions over 2000-2014 interval.

Figure 1

Net migration, 1985-2014


1985 - 1989
1990 - 1994
1995 - 1999
2000 - 2004
2005 - 2009
2010 - 2014
Burkina Faso
Benin
Togo
Ivory Coast
Gulf of Guinea
Upper West Region
Upper East Region
Northern Region
Brong Ahafo Region
Ashanti Region
Eastern Region
Volta Region
Western Region
Central Region
Greater Accra Region
Bolgatanga
Bawku
Wa
Tamale
Yendi
Berekum
Sunyani
Kumasi
Obuasi
Ho
Keta
Accra
Winneba
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negative - high
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i) urban pathways in the south coastal areas

Over almost all intervals, the coastal cities of Sekondi, Cape Coast, Winneba, and Accra (the capital) recorded a growth of net migration. This tendency is present for the main cities in the southern area of Ghana, including Ho, located in the Volta region. Looking at other regions, the city of Kumasi, which hosts a large domestic airport, stands out for being one of the rare areas in the region of Ashanti recording positive trends of net migration. Despite the city recording the largest deficit of net migration in the early 1980s, since the year 2000 it has reported the highest positive net migration values in the country - in contrast with migration losses in the municipal district of Obuasi, located in the same Ashanti region. This district located south-west of Kumasi, is also the centre of a large-scale gold mining company. On the contrary, several cities in the Northern region record different patterns of migration. For instance, Tamale, a large city in the north, exhibits net-negative migration estimates across all 30 years of study. Its neighbouring district to the east, the municipal district of Yendi, which is closer to the international border with Togo, has net-positive migration even in a smaller population setting. As a result, Tamal hosts a higher intensity of movement while surrounding areas, though positive, may not play as substantial a role in the larger north-to-south patterns. This net migration trend is seen in both the regional differential and urban pathways. These dynamics depict a general increase of net migration into coastal Ghanaian cities over the period 1985-2014, as confirmed by qualitative studies: for instance, younger siblings can emigrate to urban areas, while older ones are compelled to stay in the parents' rural households and continue agriculture activities (Yeboah 2018).

ii*) persistence of north-south regional differentials*

Where it concerns the northern regions (Brong Ahafo, Northern, Upper West, and Upper East), trends seem to split. While the Brong Ahafo and Northern regions maintain a core of negative net migration near major cities, the intensity of net-positive migration surrounding these urban areas varies over time. Qualitative studies looking at female internal migration denote out-migration from the Upper East, Upper West, Northern, Volta, and Central Regions, with no significant in-migration between 2000 to 2010 (Lattof et al., 2018). Migration pathways, though gendered, persist as northern regional differentials. The net migration estimates in the outer edges of these northern regions, near the border between the Upper West region and the Northern Region, encompassing Mole National Park, are not recognized until the early 2000s. Other conservation reserves are scattered around Ghana but are much larger in the more northern regions. The two outermost regions near the Burkina-Faso border, Upper West, and Upper East, have a trend of negative net migration which is dominant over time. The capital of the Upper West region, Wa, is persistently negative, with a trend of regional loss increasing over time - especially in the 2000s. The further north the regions are located, the closer they are to the arid climate of the Sahara, with the Upper East, Upper West, and Northern regions classified as savannas and shrublands. Differences between the northern and southern regions have deep colonial roots, with the colonial era being a time when migrants moved from the poorer regions in the north to the more resource rich south where capitalist exploitation and economic exports began to flourish (Songsore, 2011). Ghana's plethora of gold and mineral extracts enhance these differentials particularly in the Western region.

iii) changes in migration dynamics in the Western Region and Volta Regions

The Western and Volta regions present unique migration dynamics. With the exception of urban areas, the largest swathes of out migration (negative net migration) are reported in the *Western region*, from 1985 to 2000, as recorded in the neighbouring regions of Ashanti, where in 2002 few large-scale gold mining companies remained active (AngloGold Ashanti, with mines at Obuasi; Iduapriem, with mines in the areas of Tarkwa and Bibiani; Bogoso Gold, located in zone of Bogoso; Gold Fields Ghana Ltd, with mines at Tarkwa and Abosso; Sian Gold Mines, in Nkawkaw; Resolute Amansie in Amansie; Bonte Gold Mines in Nkawie-Toase and Prestea Sankofa Gold in Prestea). A trend of net-negative migration is also exhibited in the Eastern Region. A qualitative study of the 2010 Ghanaian Census reported from the year 2000 – 2010, approximately 17% of Ghana's total female out-migrants were emigrating from the Eastern Region, followed by the Northern and Volta Regions (Lattof et al., 2018). The Eastern region net migration estimates consistently show losses throughout the decades with only a dwindling area reporting growth on its border with Ashanti. These activities highlight a series of regional pathways more unique than just the rural-urban or north-to-south dynamics. Rural-urban pathways can still be seen within the Western and Eastern regions as there is high negative migration in local rural areas and high positive migration shown in the neighbouring coastal urban cities, such as Sekondi, Cape Coast in the Western Region and Accra, being located south of the Eastern region.

Another unique regional pattern is that the Volta as one of the regions experiencing the highest loss of migration. The *Volta region*, depicted by the pre-2016 regional boundaries, starts at the south Gulf of Guinea and extends north along the east Lake Volta coast reaching the Oti River. Variations of net migration trends exist when examining the region from north to south; with the north near the Oti River having net-negative migration over different time periods, a similar negative trend moving southward towards the centre of the region until reaching the city of Ho which depicts more positive migration patterns. Lastly the most southern point of the region is home to the coastal towns, namely the city of Keta. According to the previous studies, the city of Keta has been experiencing severe environmental changes for several decades now, i.e. coastal erosion and flood, originating the emigration of the Ewe population (Hillmann et al., 2019). Policies have supported large-scale industrial development throughout the region (Akeampong, 2001) with significant consequences in terms of land degradation due to deforestation and disappearance of clam fishing and other traditional agricultural activities, often accompanied by the increase of out-migration flows, highlighting the Volta as a pathway of migration. The decrease of net migration reported in latest period of the analysis would be explained by the Ebola infection limiting mobility within and between countries.

ENVIRONMENTAL AND CLIMATE FACTORS

We explore the environmental and climate conditions related to the net migration patterns identified by the descriptive analysis, as follows:

i) *urban south coastal areas*

Cities with a prevalence of positive net migration report a decrease in mean precipitation and the length of consecutive wet days, and an increase in the length of consecutive dry days, minimum and maximum temperature, apart from Ho, which records a drop of the max temperature (Table 1). Among cities with a prevalence of net migration, changes in the environmental conditions from 1985-1999 to 2010-2014 are less uniform. Although the mean precipitation declines, the changes (in %) is lower than for the cities with a positive net migration, while the changes in the length of the consecutive wet days is higher, ranging from -52% in Bolgatanga to 22% in Obuasi. This higher variability is also depicted for the other variables. For instance, Tamale records a decrease in the length of consecutive dry days (-12% comparing the period 2010-2014 with the period 1985-1999) accompanied by an increase (2%) of both minimum and maximum temperatures. By contrast, Sunyani records an increase in length of consecutive dry days (21% comparing the period 2010-2014 with the period 1985-1999) and a decrease in all other variables, the length of consecutive dry days, minimum and maximum temperatures (-1%, and -4% respectively).

Table 1

Net migration and climate conditions in selected Ghanian cities, 1985-2014

Net migration	Main cities	Period	Mean precipitation (mm)	Wet days (count)	Dry days (count)	Max temperature (C)	Min temperature (C)
Positive	Accra	1985-89	791.6	5.4	28.6	34.43	19.24
		2010-14	725.2	4	35.4	35.47	21.56
	Sekondi	1985-89	1428.2	9.6	24.6	33.40	20.91
		2010-14	1209.2	4.4	36	34.70	21.87
	Cape Coast	1985-89	1017.8	7	28.2	33.56	20.49
		2010-14	878.4	4.4	31.6	35.02	21.66
	Winneba	1985-89	947.6	6.6	28.4	34.07	18.27
		2010-14	870.8	4.8	32.6	35.10	20.35
	Ho	1985-89	1406.8	9.6	25.4	39.06	20.64
		2010-14	1223.6	5.2	26.8	38.32	21.83
Negative	Bolgatanga	1985-89	989.2	8.4	64.2	43.16	15.71
		2010-14	960.8	4	66.2	43.01	15.96
	Wa	1985-89	1003.4	7	55	41.51	15.14
		2010-14	966.2	5	57	40.92	15.14
	Tamale	1985-89	1177.6	7.2	58.6	41.16	17.29
		2010-14	1072.8	5.8	51.6	42.07	17.69
	Sunyani	1985-89	1250.6	6.8	31.6	38.59	16.46
		2010-14	1117.4	8.2	31.4	38.12	15.85
	Keta	1985-89	1084.2	6.2	34.6	35.89	21.12
		2010-14	998.2	3.6	38.6	36.99	22.58
	Obuasi	1985-89	1358.4	9	29.8	37.77	16.23
		2010-2014	1279.8	11	39.4	37.81	17.68

ii) northern regions

Differences in environmental patterns persist across the northern and southern regions when comparing 1985-1999 and 2010-2014 periods. Northern regions are classified as tropical and sub-humid zones, with high reported levels of land degradation. Over both periods, within the country, the mean of annual rainfall increases traveling southward from the northern Upper West and East regions to the Western coastal regions. The scarcity of precipitation in the north, may be considered as one the prime drivers of environmental degradation, when associated with the high maximum temperature and prolonged periods of dryness.

Higher variability of precipitations can be observed in the Upper East region. For instance, the area of Bolgatanga, is influenced by the convergence of two air masses: the continental and dry air mass, which extends over the Sahara and generates the Trade Winds of harmattan; and the tropical air mass, originating from the South-Atlantic anticyclone and which is associated with the south easterly winds, which accentuate the rainy seasons in Ghana. The convergence of these two air masses can explain the differences in the rainfall trends of the area (Dietz et al. 2004).

Figure 2

Climate conditions in Ghanian Upper West, Upper East and Northern Regions, 1985-1989, 2010-2014

<table>
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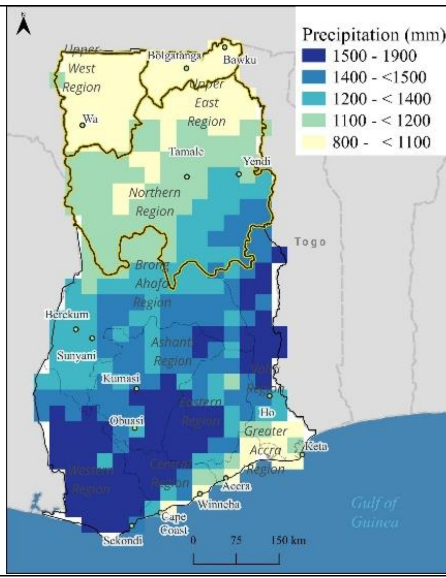
<tr><th colspan="2">Precipitation (mm)</th></tr>
<tr><td>


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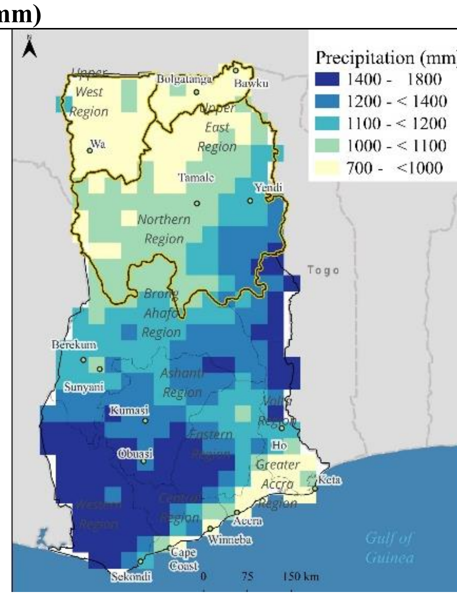

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<tr><th colspan="2">Length of consecutive dry days (count)</th></tr>
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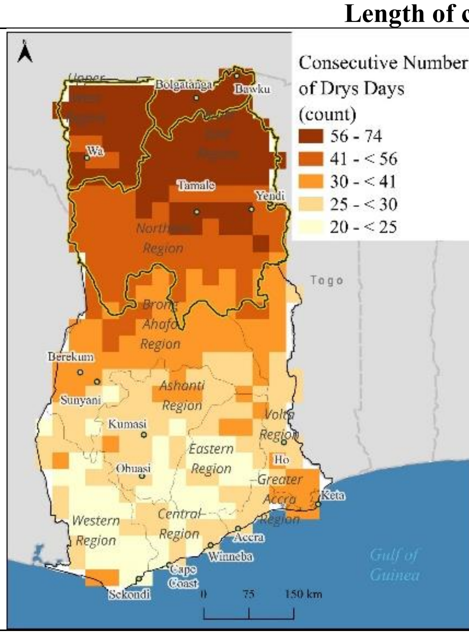

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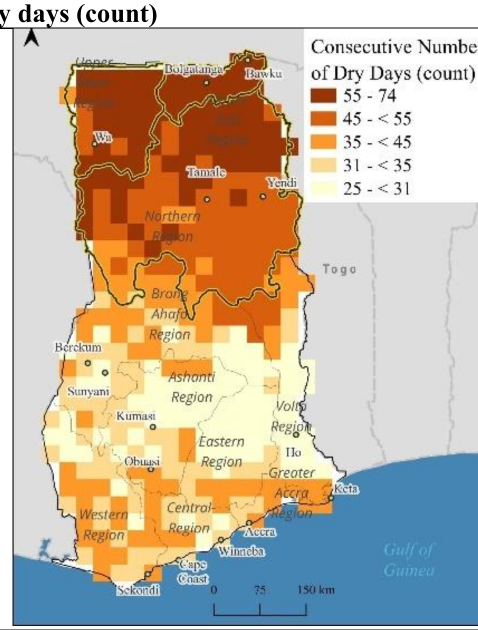

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<tr><th colspan="2">Maximum temperature (°C)</th></tr>
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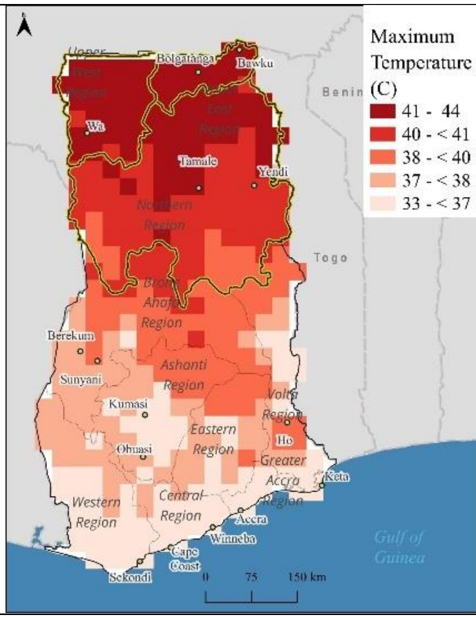
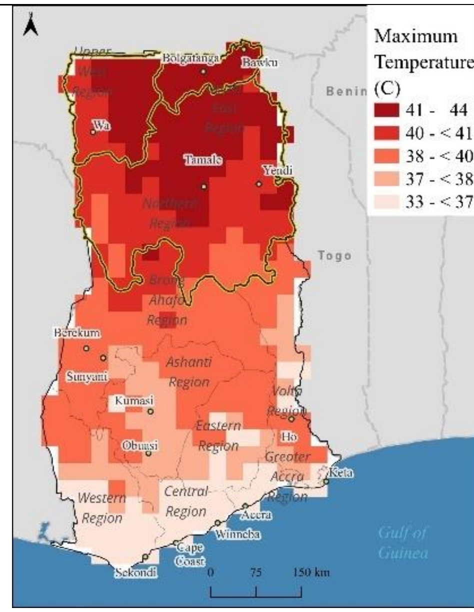




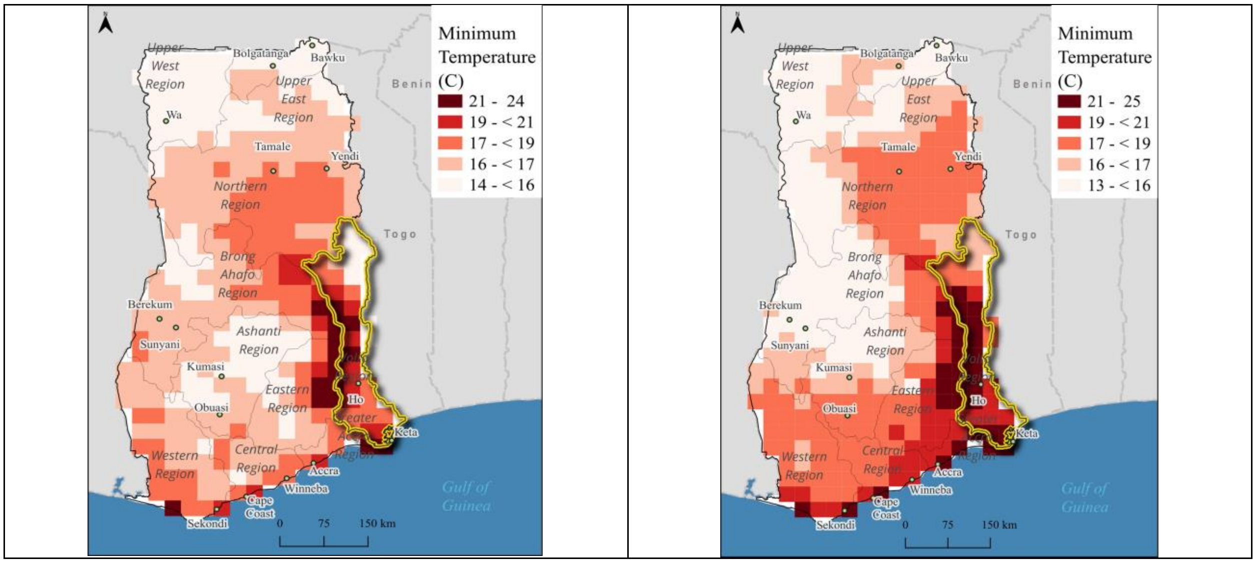
iii) Western and Volta Regions

For the Volta basin, the increase of temperatures in combination with the decrease of rainfall have generated detrimental effects of land erosion. Several anthropogenic environmental hazards have occurred in the area, including the Keta coastal regions (Torvikey, 2014). Authors have stressed impacts of the dams' construction in the region (i.e. Akosombo Dam), contributing to deforestation and loss of arable lands. Furthermore, the slowing down of the river and high temperatures may have facilitated the spreading up of infectious diseases (such as malaria), as documented by Ewe and Ada fishermen who emigrated from the endemic areas of the Volta (Akyeampong 2001; Tsikata 2006).

Figure 3

Climate conditions in Ghanian Western and Volta Regions, 1985-1989, 2010-2014

1985-1989	**2010-2014**
Minimum temperature	



INTERPLAYS BETWEEN NET MIGRATION AND ENVIRONMENTAL FACTORS

The GWR models reveal no significant association between the changes in net migration and environmental variables in the periods 1990-1999 (Table A-2 in Appendix). In 2000-2004, the GWR model shows that the mean of annual maximum temperatures is significantly associated with the changes in net migration (Table A-3 in Appendix), but coefficients vary across territories. When mapping the significant coefficients of co-variants over the period 2000-2014 (Figure 4), the variability across Ghanaian territories can be appreciated. It is worth to note that, rather than in terms of causality, the coefficients presented here should be interpreted as signals of the positive and negative relationships between the dependent and independent variables. In line with the scope of the analysis, the estimated coefficients offer indicative assessments of the role played by each factor on the changes of net migration at local level, in the context of the defined models.

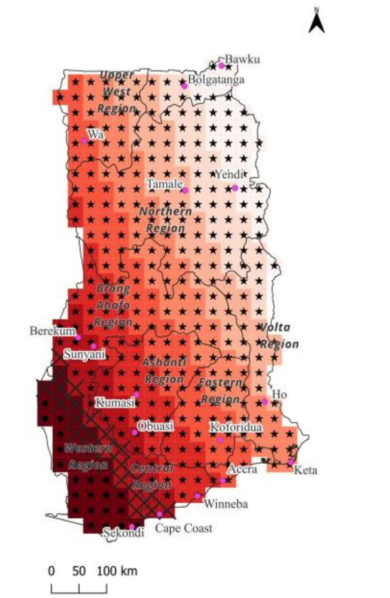
Over the period, in the Upper East and Northern-East regions, variability in the mean of annual maximum temperatures is positively associated with net migration, meaning that the increase of maximum temperatures is related to the increase of net migration. It should be noted that the positive effects on the net migration may consist of a raise of the positive net migration, when influx exceeds out-movements, or a narrowing of the negative net migration, when out-movements exceed influx. Contrarily, in Southern-Western regions, changes in the maximum temperatures are negatively related to changes in net migration: when the mean of maximum temperature increase, the net migration decrease, which may correspond to a decrease of the positive net migration or an increase of migration deficit, when out-movements exceed influx.

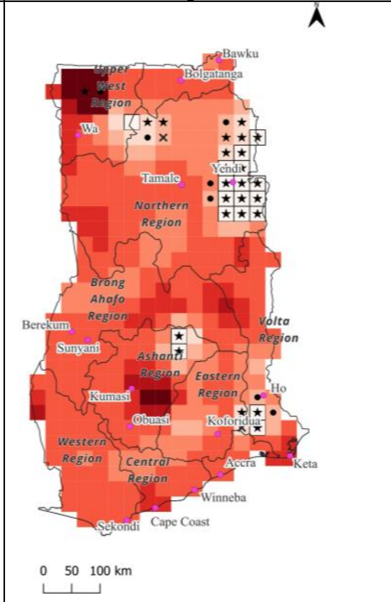
The model MGWR confirms the significance of the maximum temperatures when limited to the areas of Ho, in the Southern East, Sekyare Afram Plains, in the Ashanti area, the Mamprugu Moagdari district, and Yendi in the Northern-East region (Table A-4 and A-5 in Appendix). In this latter, changes in the length of consecutive wet days are also significant, but negatively associated with the changes in net migration.

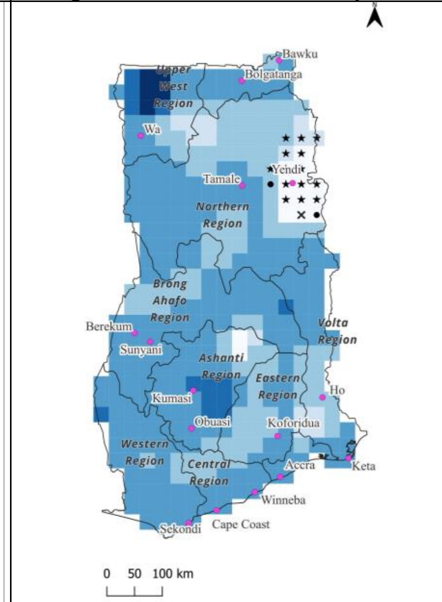
Figure 4

GWR and MGWR model significant results, period 2000-2004

GWR	**MGWR**	**MGWR**
Maximum temperature	**Maximum temperature**	**Length of consecutive wet days**







p-values
• 0.05
× 0.01
★ 0.005

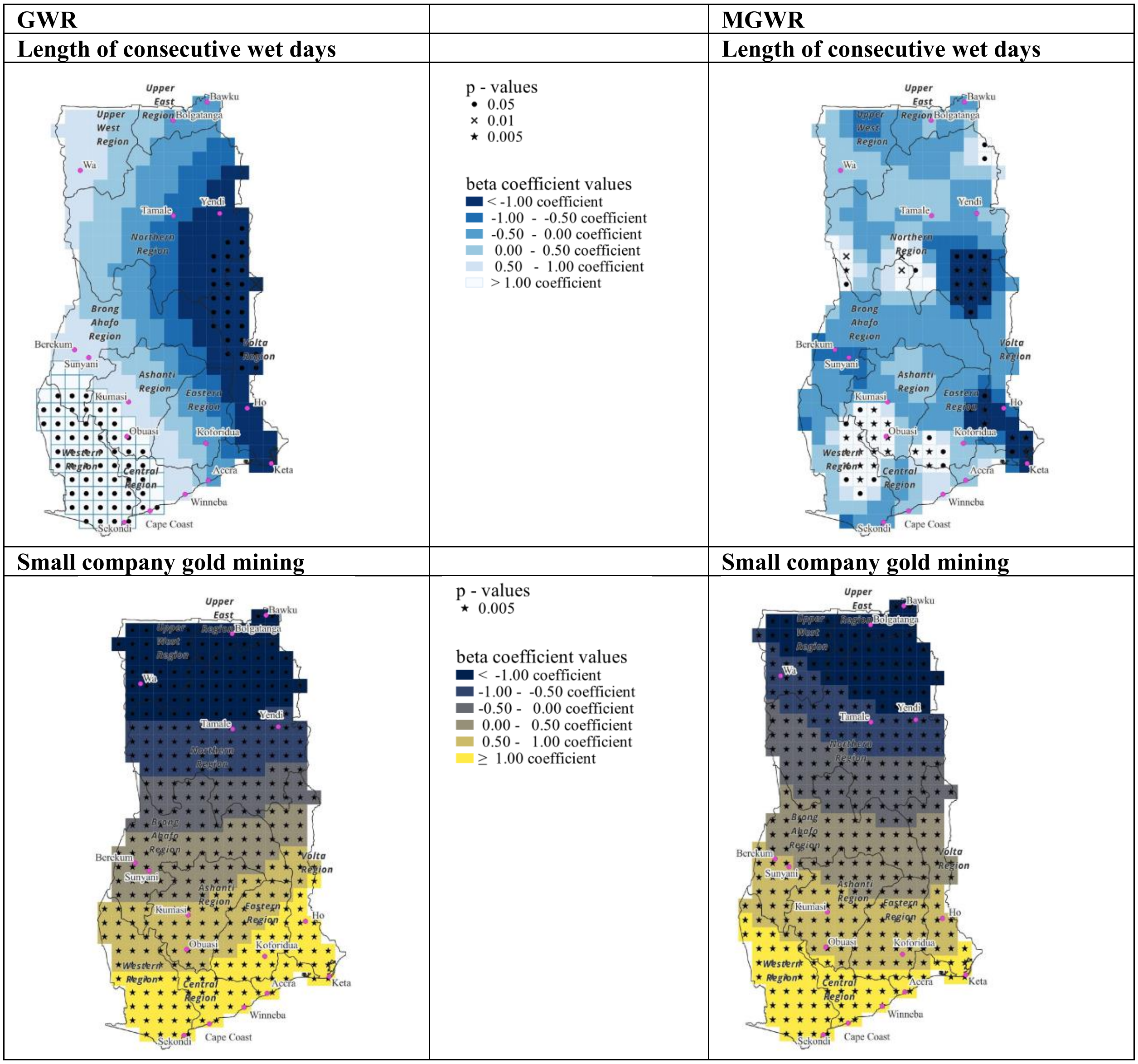
beta coefficient values
<-1.50 coefficient
-1.50 - -1.00 coefficient
-1.00 - -0.50 coefficient
-0.50 - 0.00 coefficient
0.00 - 0.50 coefficient
0.50 - 1.00 coefficient
1.00 - 1.50 coefficient
> 1.50 coefficient

beta coefficient values
< -2.00 coefficient
-2.00 - -1.00 coefficient
-1.00 - 0.00 coefficient
0.00 - 1.00 coefficient
1.00 - 2.00 coefficient
≥ 2.00 coefficient

In 2005-2009, both GWR and MGWR models attest the relevance of the small company gold mining activities in the interplays between environmental conditions, conflict fatalities and net migration. Nevertheless, results from the two models differ when examining the spatial variability. Based on the MGWR model results (Table A-5 in Appendix), in the Upper East region, the small company gold mining effects are negatively related to the change of net migration, whereas in the Western and Central regions the effects are positive, while the GWR model extends the area of incidence to the Greater Accra and Eastern coastal areas (Figure 5). Similarly, when examining the environmental variables, the GWR results present a significant and positive incidence of the length of consecutive wet days in the Western region, while the MGWR limits the effects to Dunkwa, Obuasi, Akim and Oda, main spots of the small company gold mining activities. Following the MGWR results, the negative association with the changes of net migration is restricted to the Krachi West district, rather than the whole Eastern area of the Northern region (Togo's borders) identified by the GWR. Furthermore, in the Western areas of the Northern region (Ivory coast's borders, around the Bui National Park), the GWR model results reveal significant relationships between the changes in net migration and the 5-year mean of precipitation.

Figure 5

GWR and MGWR model significant results, period 2005-2009

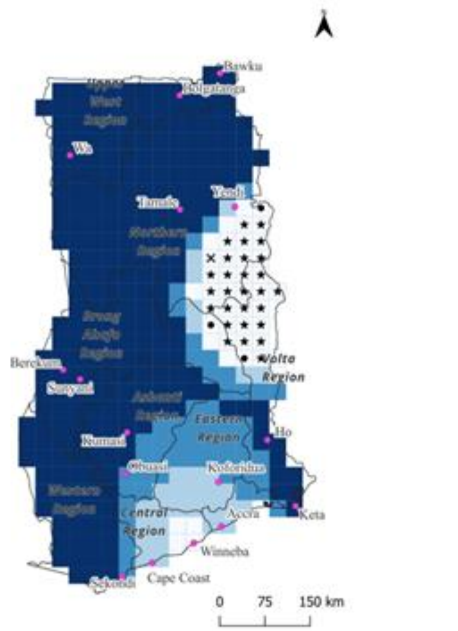


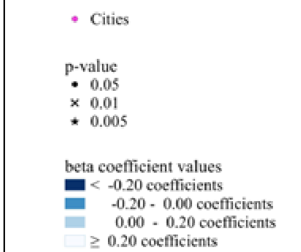
Finally, when examining the latest period 2010-2014, both GWR and MGWR models identify a significant correlation between the length of consecutive wet days with the changes in net migration. As for the previous periods, the spatial variability of MGWR is much more restricted. The MGWR model identifies the significant and positive association in the area of the Oti river, and Winneba and Akim Oda in the south-coastal region, whereas the GWR model also finds significant the south-eastern areas of the Northern region (Figure 6).

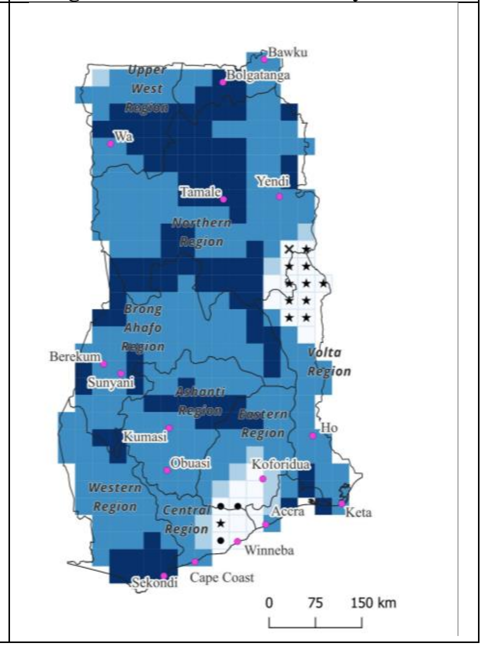
Figure 6

GWR and MGWR model significant results, period 2010-2014

GWR		MGWR
Length of consecutive wet days		**Length of consecutive wet days**







ROBUSTNESS CHECKS

As final step, we apply the Geographically Weighted Random Forest (GWRF) using Gaussian model fitting and fixed kernel bandwidth estimations. To check results from previous models, the GWRF are separately performed for the time intervals 1990-1999 and the time intervals of the 2000-2014. The estimated model fits for 1990-1999 have very small explanatory power, in line with results achieved using GWR and MGWR models (Table A-6 in Appendix). GWRF models are trained again with data for the 5-year intervals 2000-2004, 2005-2009 and 2010-2014.GWRF models delineate the importance of each variable within a single model. Table A-7 in Appendix shows the dependent variables ranked by importance. Importance values are displayed as percent totals, with higher importance indicating total percent of the model estimations explained by which variable. In the 2000-2004 interval, maximum temperature (TMAX) had the highest importance. In 2005, gold mining held the highest importance, but all variables had relatively low distributed values of importance. The maximum number of wet days held the highest importance in 2010-2014 with length of consecutive wet days (MLWD) having almost 50% relative importance compared to other variables. Measures of conflict held the lowest importance throughout all years, close to zero, from 2000 to 2014.

In addition to the relative importance of the explanatory variables, each variable has geographic distributions characterized within each model. Local R-squared values were mapped for each GWRF model calculated for each time interval in the 2000's. The local estimations for each variable with high levels of importance, within each time interval are also mapped. In 2000-2004, maximum temperature achieves the highest importance. Spatially, estimates of importance are spread and variable throughout Ghana. The estimations of small-artisanal gold mining activities that achieve a higher importance in 2005-2009, shown a clearer pattern with negative correlations in the north and positive estimations in the south, particularly in the Western and Central Regions.

The maximum length of consecutive wet days similarly to maximum temperature do not hold a clear pattern of importance but reach a high level of importance in the model in 2010-2014.

Spatial incidence and models' complementary

From a spatial perspective, the bandwidth is an indication of the spatial scale of incidence. Both GWR and MGWR attest the spatial no stationary of the local coefficients, but while the GWR presents a general model variability, the MGWR gives estimates of variability in the scale (bandwidth) by regression coefficient. When the adaptive kernel is adopted, the bandwidth offers the estimated number of the nearest places (the neighbours) from the regression point *i,* which receives a non-zero weight in the local regressions (the ones which are considered as neighbours to *i*) (Oshan et al., 2019). Yet, in our study, Gaussian weighting function is selected to also include neighbours that may be located far from the regression point. We argue that the dependent variable results from the combination between internal and international mobility; thus, no place may be excluded a priori from the analysis. The selection of the optimal bandwidth parameters is based on statistical optimization criteria (Akaike Information Criteria, Yu et al. 2020).
In the period 2000-2004, the lowest bandwidth values are reported by the maximum temperature and length of consecutive wet days, both recording a significant association with the change of net migration, meaning that the spatial scale where the effects of the variables operate on the dependent variable is local or limited to selected areas that are geographically smaller than the whole country. Similarly, it occurs in the period 2005-2009 for the small company gold mining, whereas in 2010-2014 this is exclusively for the length of consecutive wet days. Spatial estimations from the GWR had a global model fit with local significance as global models provide less distinction between the influence of each variable spatially. The MGWR provides greater distinction of each variable spatially as it estimates bandwidths per variable. GWR and GWRF both only provide one bandwidth per model. GWRF provides validation of both GWR and MGWR as it relaxes Gaussian assumptions and splits data to training sets that are used for analysis.

TABLE 2
Models' indicators, 2000-2014

Time Interval	Geographic Weighted Regression **GWR**		Multiscale Geographic Weighted Regression **MGWR**		Geographically Weighted Random Forest Regression **GWRF**	
	R-square	AIC	R-square	AIC	R-square	AIC
2000 - 2004	0.056	1085	**0.718**	870	0.138	1829
2005 - 2009	0.152	1068	0.432	1006	0.124	2230
2010 - 2014	0.492	998	**0.677**	815	0.200	1503

The MGWR outperforms the other models in terms of R-square and AICs values. The period 2000-2004 records the highest R-square values, followed by the period 2010-2014, implying that the model has a god explanatory power (71% and 68% respectively).

The machine learning GWRF applied using the global model, establishes predictions of the data and then decides the optimal parameters needed to describe the model. This approach works best with larger datasets and the low number of values used in this analysis restricted the GWRF. Both GWR and MGWR provide standardization of values which could not be established in the GWRF to predict and estimate values of the explanatory variables. When comparing the outputs of all models, the machine learning GWRF, estimated the relative importance of each variable while GWR and MGWR provided local measures of significance of each variable. Statistically these are not comparable outputs, but these measures show the relevance of each variable within their respective models. Maximum temperature consistently showed relevance throughout each model for the time interval 2000-2004. The multiscale geographic weighted regression was the only model in 2000-2004 that showed local significance for consecutive wet days. The artisanal gold mining showed relevance in all models for 2005-2009. The length of consecutive wet days shows significance in both local and global regression models but no importance in the estimates from the GWRF. Precipitations are significance in the global geographic weighted regression but not enough power to be significant in the local MGWR model or the GWRF. None of the models predict the length of consecutive dry days, minimum temperature, and conflict variables as relevant.

Finally, we examine the standardized residuals, which provide clearer spatial patterns as they are measures of the strength of the difference between observed and expected values. Residuals were mapped per model, by period (Figure A-1 in Appendix). The local residuals for each model that are also mapped and isolated by period, with each model showing slight differences in the outliers identified however some grid cells remain consistent in the GWR, MGWR and GWRF. Spatial patterns are more evident per period even with differing models. In 2000-2004, the residuals remain more consistent in pockets in the north with a cluster near the city of Yendi and specific grid cells in the south such as near the city of Ho, in the Volta. The 2005-2009 interval has the most scattered pattern of residuals however the highlighted cells remain consistent for all three models. The 2010–2014 interval has the most distinct pattern for the GWR and MGWR, with residuals in three places, the most northern point of the Volta region, one grid cell in the Eastern Region and another in the Central region while the GWRF also highlights these areas in addition to more scattered outliers such as in the coastal cities of Winneba and Keta.

CONCLUSIONS (preliminary)

The analysis reveals the relevance of environmental and climate conditions in the spatial patterns of migration across the Ghanian territories, from 2000 to 2014. Using three spatial models, we map the links between migration and contextual factors, developing and testing a new analytical approach that explain the interplay among migration drivers. Findings would contribute to refining the conceptualisations of environmental and climate conditions as drivers of migration and population changes across territories, giving new insights for rethinking mobility in the frame of a more complex, nuanced processes influencing (in)voluntarily trapped populations.

Although the combination of three spatial models provides cross-validation of results, the approach is not exempt from limitations, mainly due to data availability. For instance, the lack of distinction between internal and international migration flows; the periodicity (by 5-year interval) of the analysis and the absence of disaggregation by age and sex.

To fill these gaps, the study would be the basis for designing qualitative surveys in the regions, as part of the Complex Migration Flows and Multiple Drivers in Comparative Perspective (MEMO), a project funded by the Social Sciences and Humanities Research Council of Canada. Combining quantitative and qualitative analyses, MEMO aims to support the development of more adequate and efficient policies and practices to help individuals' decision to improve their ability to move, as well as to remain, despite the impacts of harsh environmental conditions.

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APPENDIX

Table A-1

Selected variables, definition, temporal and spatial coverages

Name	Descriptions - Method	Spatial Coverage	Temporal Coverage	Source
Net Migration Estimates	Gridded indirect estimation of five-year net migration, derived from JRC Global Human Settlement population layer with applied degrees of urbanization coefficients	25x25 km²	1975 to 2015	Joint Research Centre (JRC) – Knowledge Centre on Migration and Demography (KCMD) 2020 JRC Publications Repository - Estimating net migration at high spatial resolution (europa.eu)
PREC *Precipitation - Average of 5 years*	Gridded rainfall, total amount of precipitation, over one point coordinate location summed for one year; then averaged over five years.	0.05° degrees, approx. 5x5km²	1981 - to near present	Climate Hazards Group InfraRed Precipitation with Station Data Version 2.0 (Chirps) CHIRPS: Rainfall Estimates from Rain Gauge and Satellite Observations | Climate Hazards Center - UC Santa Barbara (ucsb.edu)
MLDS (Maximum Length of Dry Days)	The maximum length of consecutive dry days in one year, where rain is less then 1 mm, calculated from CHIRPS total gridded rainfall, averaged over five years.	0.05° degrees, approx. 5x5km²	1981 - to near present	CHIRPS API Compute precipitation indices over a time series. — precip_indices • chirps (ropensci.org)
MLWS (Maximum length of Wet Days)	The maximum length of consecutive wet days in one year, where rain is greater then or equal to 1 mm, calculated from gridded rainfall, averaged over five years.	0.05° degrees, approx. 5x5km²	1981 - to near present	CHIRPS API Compute precipitation indices over a time series. — precip_indices • chirps (ropensci.org)
TMAX *Average Tmax (Temperature Max)*	High-resolution (0.05° x 0.05°, approx. 5km) data set of daily maximum temperatures. At each point location, the daily maximum temperatures collected and the highest value of the year, was used, then averaged to 5-year intervals.	0.05° degrees, approx. 5x5km²	1983 - 2016	Climate Hazards Group Daily Temperature data set. Utilizing Version 1.0 Africa CHIRTSdaily | Climate Hazards Center - UC Santa Barbara (ucsb.edu)
TMIN	High-resolution (0.05° x 0.05°, approx. 5km) data set of daily minimum temperatures. At each point location, the daily maximum temperatures collected and	0.05° degrees, approx. 5x5km²	1983 - 2016	Climate Hazards Group Daily Temperature data set. Utilizing Version 1.0 Africa CHIRTSdaily |

Average Tmin (Temperature Minimum)	the highest value of the year, was used, then averaged to 5-year intervals.			[Climate Hazards Center - UC Santa Barbara (ucsb.edu)]
CONFL *Conflict Fatalities*	Significant conflict events were recorded as geo-point locations for each dataset. The highest recorded fatality estimate per event was used. Events were intersected with AOI ~25 km grid and the sum of fatalities per event was used, when multiple events were recorded per grid cell across multiple years, within each 5-year interval.	georeferenced event coordinates	1989 to 2015	Armed Conflict Location & Event Data Project (ACED) and Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED) ACED: [ACLED | Bringing Clarity to Crisis (acleddata.com)] GED: [UCDP - Department of Peace and Conflict Research - Uppsala University, Sweden (uu.se)]
MINING *Gold - Artisanal mining activities in Ghana per km2*	Database of polygons delineated from high resolution satellite imagery was used to identify areas of artisanal small scale gold mining activities in Ghana. Dataset contains 74,548 polygons, covering ~66,000 total square kilometers globally derived from multiple years (2008, 2013, 2021) of imagery. 1,787 polygons were intersected with the 25x25 km grid over Ghana. The total area of all mines that intersected with one grid cell, was divided by the total area of each cell, to identify gold mining activities per cell	764.71 km^2 area	2008, 2013, 2021	College of Earth Sciences, Chengdu University of Technology (Liang Tang) & School of Geography, Earth and Atmospheric Sciences, Faculty of Science, The University of Melbourne (Tim T. Werner) [Global mining footprint mapped from high-resolution satellite imagery | Communications Earth & Environment (nature.com)]

Using a spatial sampling approach, we integrate observations from the selected datasets, resulting in 383 unique locations for exploratory analysis. A gridded framework is used to calculate observations. As the dependent variable, net migration estimates were mapped using a World Mollweide projection along 25 x 25 km grid cells and reprojected to World Geodetic System version 84 (WGS84) for available five-year intervals. CHIRPS 5 x 5 km raster precipitation values were overlaid as coordinate points. CHIRPS and CHIRTS values were extracted based on the geographic location within the closest range to the centroid of the net migration estimates, with 383 coordinate point locations in total. Subsequent precipitation indices and temperature values were sampled accordingly. Climate variables were then joined to projected vector grid cells to use the sampled values as estimates for the full area covered by its respective grid cell. This direct sampling technique, rather than resampling calculations of variables, allows for more elicit comparisons of observed field data. For point-based observations, such as georeferenced conflict events, point coordinates are joined to the cell of intersection. This allows for harmonization of climate, conflict, and mining data and, socio-economic variables as well as flexibility of modeling. All maps presented utilizing QGIS 3.30.2-'s-Hertogenbosch (QGIS 2023).

TABLE A-2

GWR model results by 5-year period, Ghana 1990 -1999

	1990-1994			**1995-1999**		
Variable	Min	Mean	Max	Min	Mean	Max
Intercept	-0.001	-0.000	0.001	-0.016	-0.002	0.008
MLDS	-0.016	-0.015	-0.015	-0.023	0.005	0.017
MLWS	-0.061	-0.060	-0.059	-0.034	-0.035	-0.005
PREC	0.016	0.018	0.020	-0.059	-0.050	-0.045
TMAX	0.087	0.087	0.087	0.127	0.188	0.252
TMIN	-0.022	-0.021	-0.020	-0.016	0.016	0.032
R^2			0.016			0.056
R^2 adj			-0.000			0.035
RSS			376.971			361.586
AIC			1092.938			1082.459
Bandwidth			12.910			2.800

TABLE A-3

GWR model results by 5-year period, Ghana 2000-2014

	2000 -2004			**2005-2009**			**2010-2014**		
Variable	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Intercept	-0.014	-0.002	0.007	-0.276	-0.005	0.090	-1.980	0.001	0.286
MLDS	-0.023	0.004	0.016	-0.114	-0.031	0.008	-0.098	0.021	1.493
MLWS	-0.072	-0.034	-0.004	-0.184	0.017	0.196	-0.102	0.101	2.901
PREC	-0.062	-0.053	-0.047	0.015	0.081	0.192	-0.716	0.003	0.806
TMAX	0.132	0.190	0.251	-0.059	0.009	0.085	-0.317	0.048	1.276
TMIN	-0.014	0.016	0.033	-0.078	-0.018	0.141	-0.257	-0.039	0.319
CONFL	-0.024	-0.022	-0.019	-0.020	0.033	0.148	-0.100	-0.005	0.151
MINING				-0.456	-0.348	-0.218			

R2	0.056	0.152	0.492
R2 adj.	0.032	0.102	0.348
RSS	361.630	324.969	194.455
AIC	1085.464	1068.178	997.965
Bandwidth	2.860	1.330	0.460

TABLE A-4

MGWR model results by 5-year period, Ghana 1990-1999

	1990 - 1994					**1995 - 1999**				
Variable	BW	alpha95%	Min	Mean	Max	BW	alpha95%	Min	Mean	Max
Intercept	12.910	0.998	-0.002	-0.001	0.000	12.910	0.998	-0.002	-0.001	0.000
MLDS	12.910	0.998	-0.015	-0.015	-0.014	12.910	0.997	0.057	0.058	0.060
MLWS	12.910	0.997	-0.060	-0.060	-0.059	12.910	0.997	0.046	0.047	0.049
PREC	12.910	0.996	0.016	0.018	0.020	12.910	0.997	-0.010	-0.009	-0.008
TMAX	12.910	0.997	0.086	0.087	0.088	12.910	0.997	-0.080	-0.079	-0.078
TMIN	12.910	0.998	-0.022	-0.021	-0.020	12.910	0.997	0.049	0.051	0.052
R^2	0.016					0.015				
R^2 adj	-0.000					-0.001				
RSS	376.972					377.180				
AIC	1095.032					1095.251				

TABLE A-5

MGWR model results by 5-year period, Ghana 2000 - 2014

	2000-2004					**2005-2009**					**2010-2014**				
Variable	**BW**	**alpha95%**	**Min**	**Mean**	**Max**	**BW**	**alpha 95%**	**Min**	**Mean**	**Max**	**BW**	**alpha95 %**	**Min**	**Mean**	**Max**
Intercept	12.910	0.999	-0.051	-0.051	-0.051	12.910	0.998	0.011	0.012	0.013	12.910	1.970	0.063	0.064	0.064
MLDS	12.910	0.999	-0.042	-0.041	-0.041	12.910	0.998	-0.031	-0.031	-0.030	12.910	1.972	0 .032	0.033	0.033
MLWS	0.210	0.324	-4.988	-0.073	0.384	0.220	0.312	-2.270	0.042	1.686	0.200	3.425	- 0.245	0.103	7.095
PREC	12.910	0.999	-0.050	-0.049	-0.049	12.910	0.998	0.076	0.077	0.078	12.910	1.972	0.073	0.074	0.075

TMAX	0.180	0.281	-1.557	0.080	2.778	9.280	0.994	-0.009	-0.006	-0.003	12.910	1.971	0.001	0.002	0.003
TMIN	4.640	0.986	-0.089	-0.079	-0.069	12.910	0.997	-0.023	-0.022	-0.022	12.910	1.971	-0.064	-0.064	-0.063
CONFL	12.890	1.000	0.002	0.002	0.002	12.910	0.997	0.031	0.032	0032	12.910	1.976	-0.009	-0.009	-0.008
MINING						1.910	0.990	-0.0464	-0.405	-0.375					
R^2					0.718					0.432					0.677
R^2 adj					0.567					0.310					0.592
RSS					108.183					217.699					123.663
AIC					870.515					1006.926					814.963

TABLE A-6

GWRF model results, Ghana 1990-1999

Parameter	**1990-1994**		**1995-1999**	
	OOB	Not OOB	OOB	Not OOB
R^2	-0.1388	74.742	-0.1401	69.887
MSE	300.20	66.585	314.56	74.492
AIC	2198.805	1622.016	2012.389	1303.482
AICc	2199.104	1622.315	2012.934	1304.018
mtry	5	5	6	6
ntree	800	800	800	800
bw	18.1	18.1	17.4	17.4

TABLE A-7

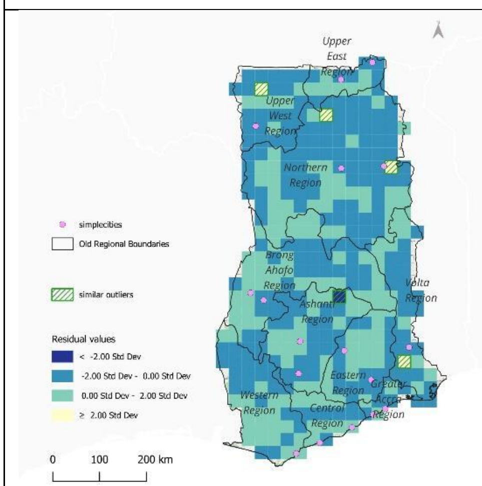
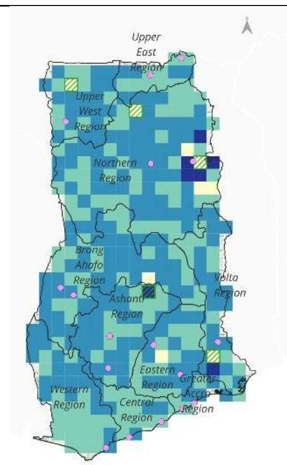
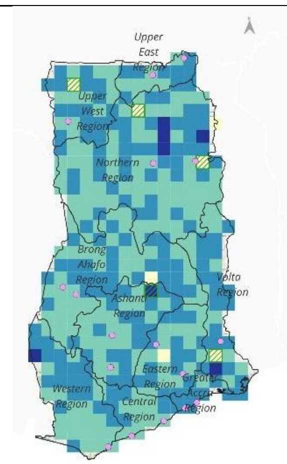
GWRF model results, Ghana 2000-2014

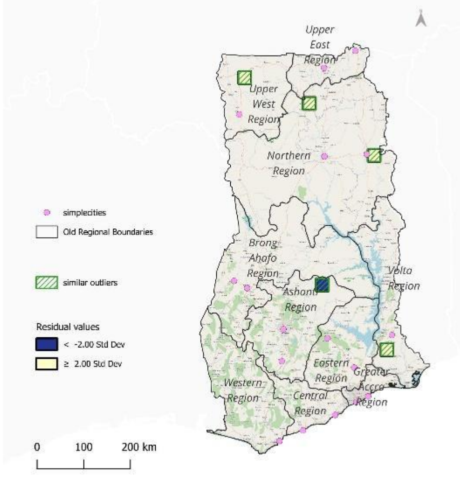
	2000 - 2004		**2005 -2009**		**2010 - 2014**	
Parameter	OOB	Not OOB	OOB	Not OOB	OOB	Not OOB
R^2	0.1381	0.7183	0.1239	0.7022	0.2004	0.7392
MSE	145.814	72.124	158.173	70.393	128.095	66.193

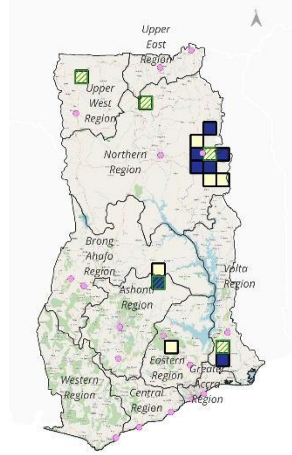
AIC	1829.284	1627.377	2230.223	1790.07	1502.592	979.712
AICc	1829.729	1627.921	2230.196	1790.634	1503.006	980.223
mtry	3	3	5	5	3	3
ntree	500	500	750	750	500	500
bw	15.3	15.3	15.5	15.5	13.2	13.2

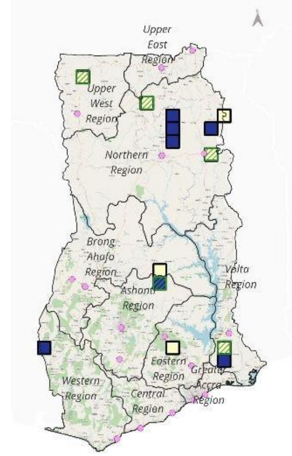
Figure A-1

Standardized residuals for GWR, MGWR, GWRF

2000-2004		
GWR	MGWR	GWRF
		
GWR - outliers	MGWR - outliers	GWRF - outliers

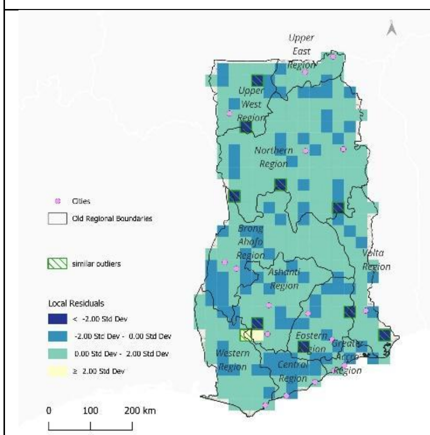


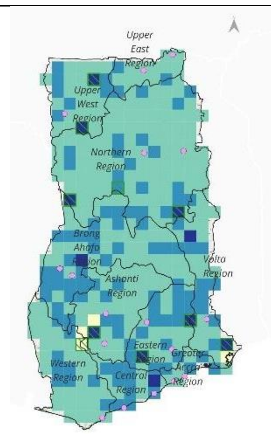


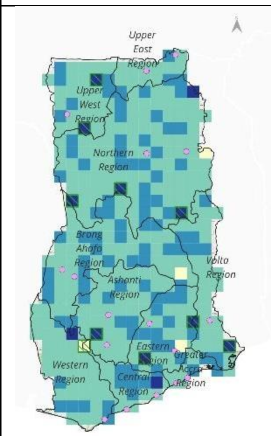


2005 - 2009

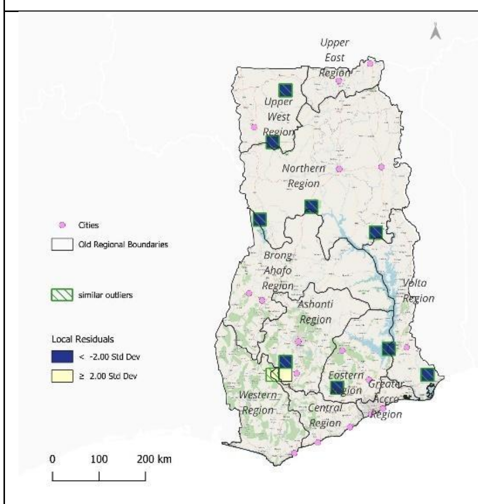
GWR	MGWR	GWRF

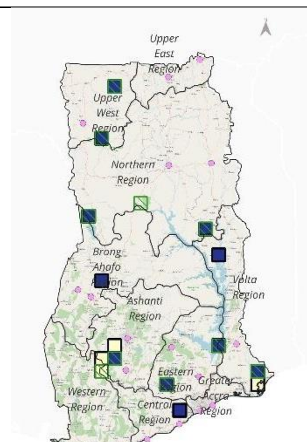


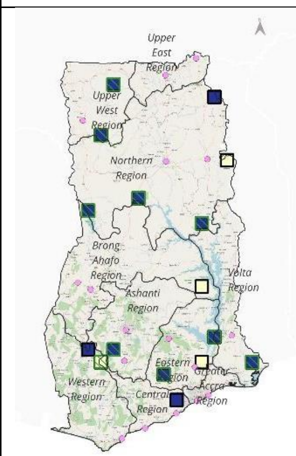




GWR residual outliers	MGWR residual outliers	GWRF residual outliers







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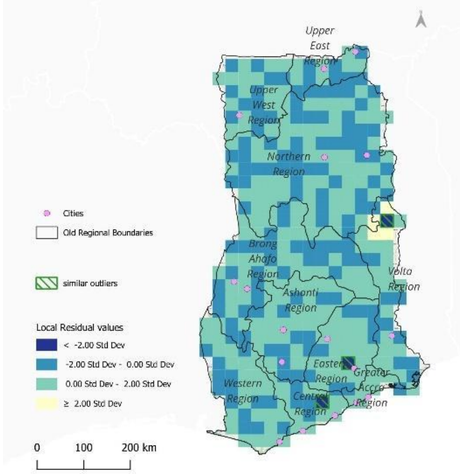
<td>
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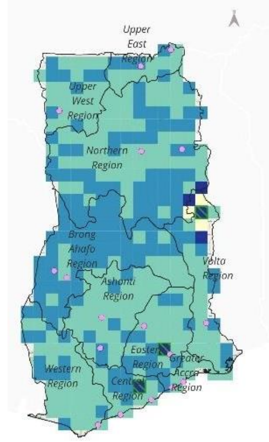
<td>
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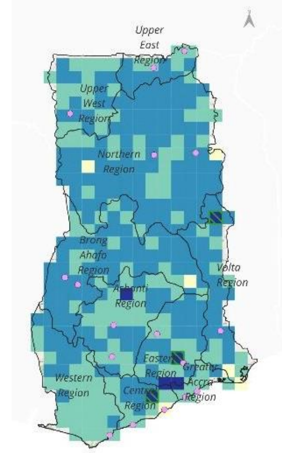
<td>
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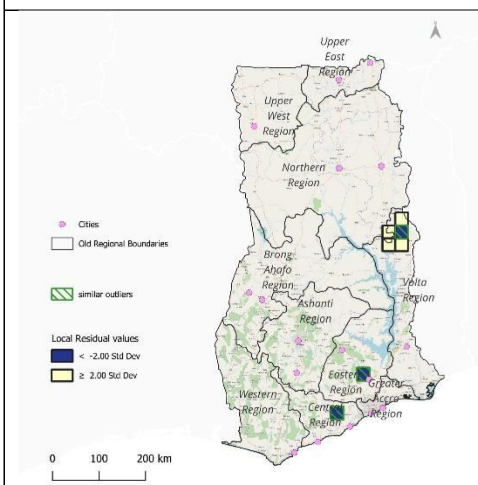
<td>
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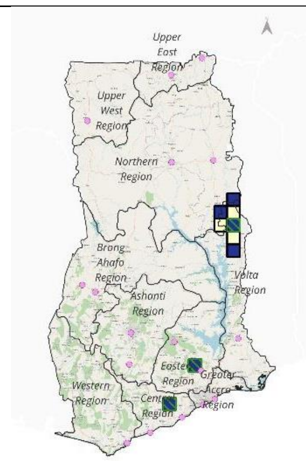
<td>
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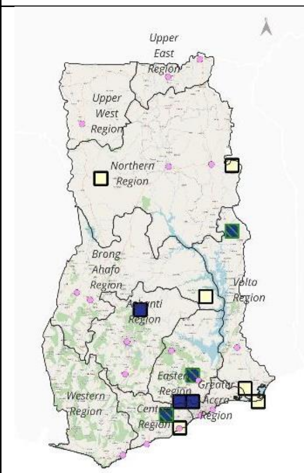
<td>
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