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SPATIOTEMPORAL DYNAMICS OF ACUTE GASTROENTERITIS (AGE) IN DOUALA, CAMEROON: A GEOSPATIAL ANALYSIS OF GROUNDWATER QUALITY AND ENVIRONMENTAL DETERMINANTS

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ABSTRACT

This study investigates the spatiotemporal dynamics of Acute Gastroenteritis (AGE) in Douala, Cameroon, from 2010 to 2013, focusing on the influence of groundwater quality and environmental factors on disease incidence. By integrating detailed physicochemical and microbiological assessments of well water with advanced geospatial modeling techniques namely Geographically Weighted Regression (GWR) and Maximum Entropy (MaxEnt) the analysis reveals significant seasonal fluctuations and spatial clusters of AGE, particularly during the rainy season. The findings indicate that areas with shallow groundwater tables, such as Akwa Nord, Bépanda, and Omnisport, experience higher AGE incidences, likely due to increased vulnerability to contamination from urban runoff, agricultural inputs, and inadequate waste disposal. The study underscores the urgent need for targeted water and sanitation interventions, enhanced monitoring, and community-focused public health strategies to mitigate the impact of groundwater contamination on public health in Douala's informal settlements. The results highlight the critical role of environmental factors in shaping disease dynamics and emphasize the importance of integrating environmental and health data to inform evidence-based policy decisions.

Keywords: Acute Gastroenteritis (AGE), groundwater quality, spatial analysis, waterborne diseases, seasonal variations, fecal coliforms, MaxEnt, Geographically Weighted Regression (GWR), Douala, Cameroon, water sanitation, public health.

1. INTRODUCTION

Acute Gastroenteritis (AGE) remains a significant public health challenge, particularly in low- and middle-income countries where it is a leading cause of morbidity and mortality among children under five (WHO, 2020). In Cameroon, AGE is recognized as one of the most prevalent waterborne diseases. National reports indicate that AGE ranks among the critical health issues, especially in urban areas such as Douala, where rapid population growth, inadequate infrastructure, and water scarcity exacerbate the situation. In Douala's informal settlements, access to potable water is limited, and residents frequently rely on contaminated groundwater from hand-dug wells (Zephania & Fombutio, 2010).

Numerous studies across Africa have underscored the close relationship between water quality and AGE outbreaks. For instance, earlier research (Katte et al., 2003) attributed approximately 15% of child mortality in Cameroon to AGE, primarily due to poor water quality and inadequate sanitation. More recent investigations (Ngwa et al., 2021; Fokou et al., 2022) have reinforced these findings by demonstrating a high incidence of AGE in urban slums, where groundwater contamination is common due to poor waste management and heavy rainfall. Similar patterns have been observed in other African countries, such as Nigeria (Dipeolu et al., 2019), highlighting the global challenge posed by inadequate water and sanitation in peri-urban and informal settlements.

The quality of groundwater in Douala is of particular concern. Limited access to treated water compels many residents to use hand-dug wells that often exhibit poor bacteriological and physicochemical quality. Studies in Kenya (Ochieng et al., 2018), Nigeria (Akinyemi et al., 2020), and South Africa (Igbinosa et al., 2017) have documented that groundwater in informal settlements frequently fails to meet basic quality standards, increasing the risk of waterborne diseases like AGE.

Recent advances in geospatial modeling, including techniques such as Geographically Weighted Regression (GWR) and Maximum Entropy (MaxEnt), have enabled a more nuanced understanding of the spatial dynamics of disease outbreaks. These methods allow for the exploration of local variations in disease risk by integrating environmental and socio-economic variables (Zhang et al., 2021; Nguyen et al., 2023). By mapping groundwater vulnerability and correlating chemical and microbiological contamination with AGE incidence, these models inform targeted public health interventions.

This study focuses on the northeastern coastal region of Douala-Cameroon, where AGE remains a major public health concern exacerbated by both environmental and socio-economic factors. The central hypothesis is that groundwater contamination particularly from poorly maintained hand-dug wells is a significant determinant of high AGE incidence in Douala’s coastal areas. The objectives of this study are to:

- ✓ Assess the bacteriological and physicochemical quality of well water in the northeastern coastal region of Douala;
- ✓ Map the spatial distribution of AGE incidence and identify environmental risk factors, including water contamination and inadequate sanitation;
- ✓ Evaluate the vulnerability of groundwater to contamination from various sources, such as human waste and environmental pressures;
- ✓ Contribute to the improvement of public health policies by providing data-driven recommendations for water management and disease prevention in Douala's urban informal settlements.

2. LITERATURE REVIEW

2.1 Global Context of AGE and Waterborne Diseases

Acute Gastroenteritis (AGE) is a critical global health issue, particularly in regions with limited access to clean water and proper sanitation. Diarrheal diseases, including AGE, account for over 1.6 million deaths annually (World Health Organization [WHO], 2020). Numerous studies have demonstrated that bacterial contamination from untreated groundwater plays a significant role in triggering AGE outbreaks. For example, research by Kumar et al. (2020) in South Asia has shown that inadequate water treatment infrastructure and poor water quality contribute substantially to the prevalence of AGE. Likewise, Nguyen et al. (2023) have highlighted how environmental factors such as rainfall variability and extreme weather events intensify these outbreaks, underlining the necessity for comprehensive water quality monitoring.

Recent advances in geospatial analysis, particularly through techniques like Geographically Weighted Regression (GWR) and Maximum Entropy (MaxEnt), have greatly enhanced our ability to map and predict disease risk on a local scale (Elith et al., 2011; Zhang et al., 2021). These methods allow researchers to identify contamination hotspots and to design targeted interventions, a crucial step in mitigating the global burden of waterborne diseases.

2.2 The Situation in Cameroon

In Cameroon, Acute Gastroenteritis (AGE) remains a significant public health challenge, especially within urban informal settlements. Updated reports from the Cameroon Ministry of Public Health (2022) indicate that AGE imposes a considerable burden on the population, largely due to widespread reliance on contaminated groundwater sources. In many parts of Douala, where over three million residents live, access to potable water is severely limited, forcing people to depend on hand-dug wells that are often poorly maintained and highly susceptible to contamination.

Field studies conducted by Ngwa et al. (2021) and Akoa et al. (2021) have shown that high population density, inadequate waste disposal systems, and the close proximity of water sources to septic tanks significantly exacerbate AGE outbreaks. For example, Zephania and Fombutio (2010) documented that only a small fraction of Douala's population has access to treated water, which results in heavy reliance on untreated wells. This situation is further compounded by Tatah et al. (2008), who revealed substantial bacterial contamination in the Douala Lagoon a critical water body influenced by the indiscriminate discharge of untreated waste.

Additional research by Nkongho et al. (2019) and Mbah et al. (2020) underscores that rapid urbanization and the lack of robust water management strategies are key contributors to the deterioration of groundwater quality in urban settings. These studies highlight how unregulated urban growth, inefficient waste treatment practices, and insufficient sanitation infrastructure collectively heighten the risk of waterborne diseases like AGE.

Together, these findings emphasize the urgent need for improved water management, enhanced sanitation services, and targeted public health interventions in Douala. Addressing these challenges is crucial to reducing the persistent risk of AGE among the city's vulnerable populations.

2.3 Waterborne Disease Outbreaks and Climate Change

Climate change significantly contributes to the increasing incidence of waterborne diseases, including Acute Gastroenteritis (AGE). Changes in rainfall patterns, temperature fluctuations, and extreme weather events can deteriorate groundwater quality by intensifying contaminant levels. Increased rainfall and flooding events, as demonstrated by González-Suárez et al. (2020), lead to higher pollutant concentrations in shallow aquifers, elevating the risk of disease outbreaks. Similarly, Abdullahi et al. (2023) showed that climate variability in West Africa is directly correlated with a rise in waterborne diseases, highlighting the need for climate-responsive public health strategies.

Research in Africa further elucidates this interplay. Okeke et al. (2019) in Nigeria highlighted that environmental stressors and inadequate sanitation infrastructure significantly increase exposure to waterborne pathogens. In Cameroon, Tchouaket et al. (2022) documented that extreme weather events, such as prolonged droughts and heavy rainfall, exacerbate groundwater contamination and intensify AGE incidence in urban areas like Douala. Ngatchou et al. (2021) found that seasonal fluctuations in rainfall patterns lead to marked variations in water quality, with intense rainfall events causing substantial runoff that transports pollutants into local water sources.

Seydou et al. (2021) in the Sahel region provided evidence that climate-induced changes in hydrological cycles can alter groundwater chemistry, increasing the potential for waterborne disease transmission. These findings underscore the need for advanced spatial modeling techniques, such as Geographically Weighted Regression (GWR) and Maximum Entropy (MaxEnt), which integrate environmental and climatic variables to offer more accurate predictions of disease risk and enable targeted interventions.

Overall, these studies emphasize that addressing waterborne diseases in the context of climate change is critical for safeguarding public health, particularly in vulnerable regions across Africa.

3. MATERIALS AND METHODS

3.1 Study Area

The study was conducted in the northeastern part of Douala, Cameroon, covering an area of approximately 1,026.97 hectares and encompassing the health districts of Douala 1, 3, and 5 (figure 1). This dynamic urban region includes neighborhoods such as Akwa-Nord, New-Deido, Deido, Bépanda TSF, Bépanda Omnisport, and Bessingué, and extends northward to sub-districts like Bépanda-Bonewonda, Bépanda-Yong-Yong, Bépanda Petit-Wouri, Bépanda Voirie, Bépanda-TSF, and Bépanda-Bonamoussongo. Centrally, the area is organized around key landmarks, including the CAMTEL Company and the Omnisports Stadium.

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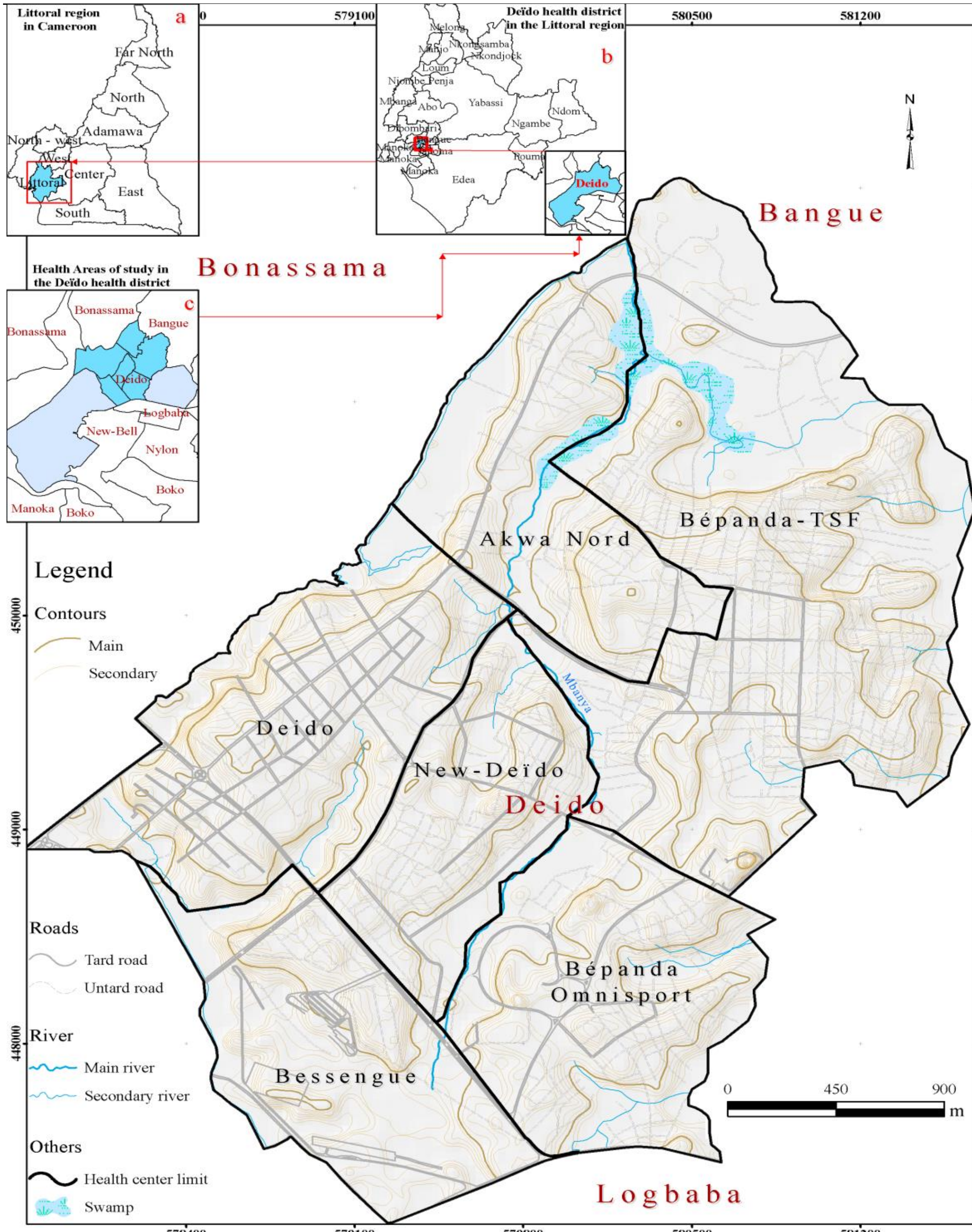

Figure 1: Health areas of study in the Deido health district

Douala is situated within the expansive Cameroon Estuary and is typified by a low-lying topography with sandy clay soils, extensive swamp lands, and numerous streams and drainage ditches. These physical characteristics contribute to a high vulnerability of groundwater resources, making them prone to contamination. Researchers such as Zephania & Fombutio

(2010) have long highlighted that Douala's rapid urbanization has resulted in densely populated informal settlements with severe infrastructural deficiencies, inadequate waste disposal systems, and erratic access to clean water. Tatah et al. (2008) further emphasized that the indiscriminate disposal of untreated waste into water bodies particularly in areas like the Douala Lagoon leads to high levels of bacterial contamination, thereby heightening the risk of waterborne diseases.

In addition, studies by Ndze et al. (2012) and Mbuh et al. (2012) have documented the adverse effects of urban sprawl in Douala, noting that poor water quality and insufficient sanitation infrastructure are strongly associated with the incidence of Acute Gastroenteritis (AGE). These studies underscore that the prevalence of AGE in this region is not only due to environmental factors but also linked to socio-economic challenges, including overcrowding and the limited availability of potable water. More recently, research by Ngwa et al. (2021) and Nkongho et al. (2019) has reinforced these findings by demonstrating that the combined effects of demographic pressures and the region's unique hydrogeological conditions such as low elevation and expansive swampy areas create a susceptible environment for pollution from industrial runoff, inadequate sewage treatment, and improper waste disposal.

The water infrastructure in this part of Douala is notably inadequate. Out of a total population exceeding three million, only about 65,000 people are connected to the public water system, forcing most residents to rely on approximately 70,000 urban wells many of which are shallow (generally not exceeding 1.5 meters in depth) and poorly maintained. Consequently, groundwater in the area often fails to meet basic quality standards, posing a significant public health risk. As documented by Zephania & Fombutio (2010), the combination of poorly maintained sewage systems and direct discharge of latrine and septic tank contents into the environment further exacerbates the contamination of both groundwater and surface water sources. High ambient temperatures and irregular rainfall patterns compound these issues by stressing urban infrastructure and intensifying natural processes that degrade water quality.

Social factors further complicate the scenario. Traditional attitudes toward waste disposal and water use, coupled with limited access to sanitation education and resistance to new hygiene practices, create high-risk behaviors that hinder effective public health interventions. This confluence of environmental, infrastructural, and socio-economic challenges makes the study area a microcosm of the issues facing rapidly urbanizing regions in Cameroon. Overall, the evidence from local researchers including Zephania & Fombutio (2010), Tatah et al. (2008), Ndze et al. (2012), Mbuh et al. (2012), Ngwa et al. (2021), and Nkongho et al. (2019) underscores the urgent need for improved water management, enhanced sanitation, and targeted public health interventions to mitigate the risks associated with contaminated groundwater and the spread of waterborne diseases like AGE.

3.2 Data Collection

- **Clinical Data:**

Clinical data on Acute Gastroenteritis (AGE) were obtained from the Deido Health District Hospital covering the period from 2010 to 2013. Patient records were carefully reviewed, and cases were included if individuals presented with symptoms such as diarrhea, nausea, vomiting, fever, and abdominal pain. Each case was verified against established diagnostic criteria for AGE, ensuring data reliability. The extracted data were entered into Microsoft Excel for initial processing, with subsequent geocoding and spatial analysis conducted in ArcGIS Pro (v2.8). This spatial analysis enabled the mapping of AGE cases across different health zones, facilitating the examination of spatial patterns and potential environmental correlations (Cameroon Ministry of Public Health, 2022).

- **Environmental Data:**

Environmental monitoring focused on 40 privately owned wells (figure 2) distributed throughout the study area. These wells were selected based on criteria such as population served, proximity to potential sources of contamination, and accessibility. Data collection was conducted during both the dry season (February) and the rainy season (August) from 2010 to 2013, capturing seasonal variations in water quality.

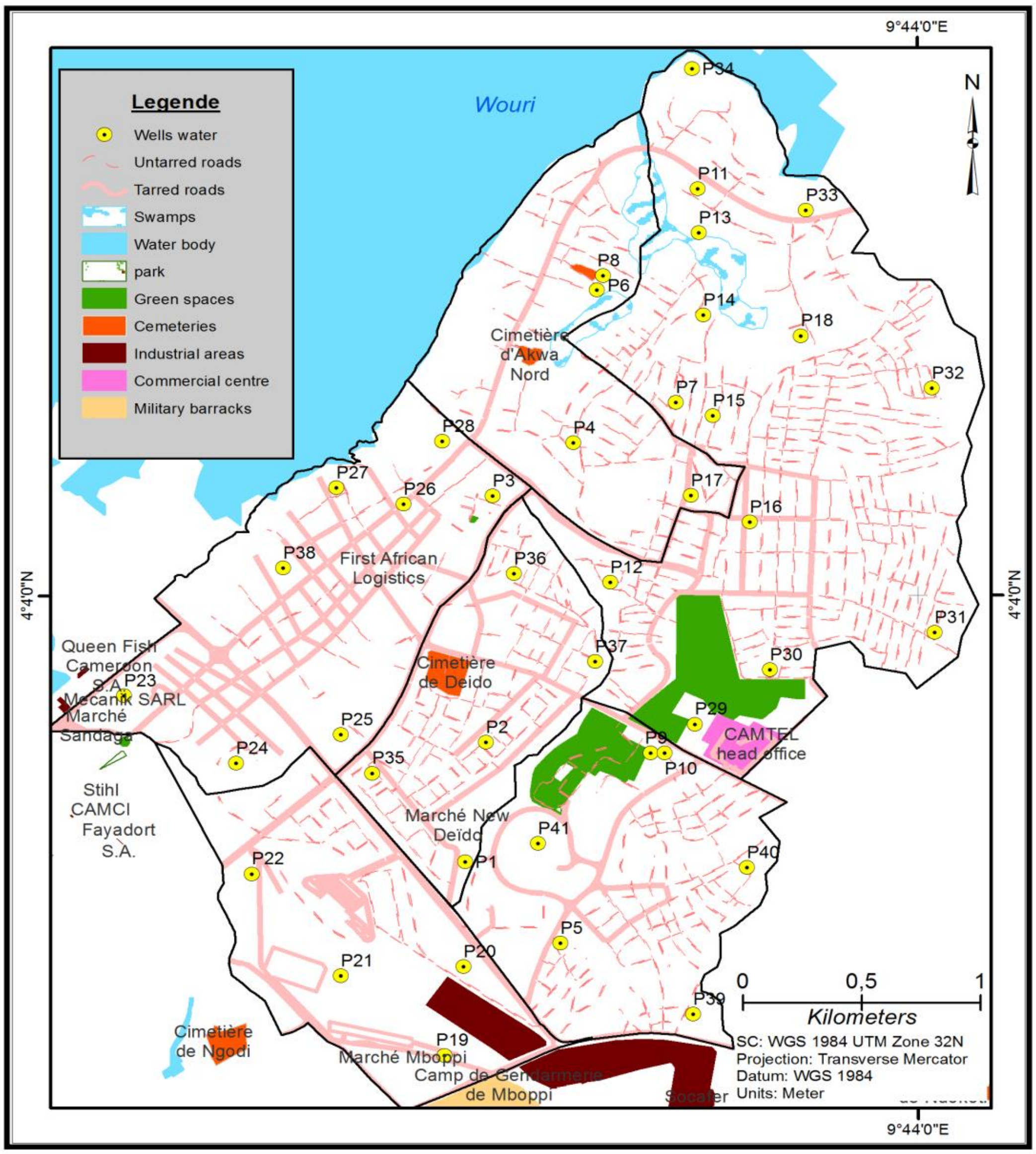

Figure 2: Location of the wells water points in the study area

- **In Situ Measurements:**
- **Physical Parameters:** Temperature was measured using calibrated digital thermometers. pH and electrical conductivity (EC) were recorded on-site with portable devices (e.g.,

Metrohm 826 for pH and HANNA HI 9033 for EC) to obtain immediate assessments of water quality.

- **Chemical Parameters:** Water samples were collected to determine concentrations of suspended matter and key ions, including calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^{+}), chloride (Cl^{-}), sulfate (SO_4^{2-}), and nitrate (NO_3^{-}). These analyses were performed in the Hydrac Laboratory in Douala using standardized techniques such as flame photometry and manual titration. Quality assurance was ensured by following WHO (2022) guidelines and verifying instrument calibration through ion charge balance methods.
- **Microbiological Indicators:** The microbial quality of the water was evaluated by quantifying total coliforms (TC) and fecal coliforms (FC) using the membrane filtration method. Specific culture media, such as MacConkey agar for fecal coliforms and Slanetz & Bartley agar for total coliforms, were employed in accordance with standard microbiological protocols.

The dual-season sampling strategy (dry and rainy seasons) was critical for capturing the influence of seasonal climatic variations on groundwater quality. Data from each sampling campaign were rigorously documented and later integrated with clinical data in ArcGIS Pro to explore spatial correlations between environmental parameters and AGE incidence.

This comprehensive data collection framework, which combines clinical epidemiological data with detailed environmental monitoring, provides a robust basis for subsequent spatial analyses and statistical modeling. It facilitates the identification of hotspots and aids in understanding the complex interplay between water quality and the prevalence of waterborne diseases in Douala.

3.3 Statistical and Spatial Modeling

To understand the relationship between environmental factors and AGE incidence, we employed a combination of descriptive statistics, hydrochemical facies analysis, and advanced spatial modeling techniques.

- **Descriptive Statistics and Temporal Trends**

AGE distribution was analyzed using histograms and cumulative incidence curves to detect temporal variations. Histograms illustrated frequency distributions of AGE cases across different demographic groups, while cumulative incidence curves allowed the identification of seasonal trends and peak infection periods.

- **Piper Diagrams for Hydrochemical Facies Characterization**

To assess groundwater chemistry, we used Piper diagrams, a graphical representation that classifies water types based on the relative concentrations of major cations (Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}) and anions (Cl^{-}, SO_4^{2-}, HCO_3^{-}). The algorithm for constructing a Piper diagram follows these steps:

- **Normalization of Ion Concentrations:**

Convert ion concentrations (meq/L) into percentages of total cations and total anions:

$$Ca^{2+}\% = \frac{Ca^{2+}}{Ca^{2+}+Mg^{2+}+Na^{+}+K^{+}} \quad x\ 100$$

$$Cl^{-}\% = \frac{Cl^{-}}{Cl^{-}+SO_4{}^{2-}+HCO_3{}^{-}} \quad x\ 100$$

- **Triangular Projection:**
- Plot the cation percentages on a ternary diagram.
- Plot the anion percentages on a separate ternary diagram.
- **Projection onto the Diamond Diagram:**
- Transform ternary coordinates into a central diamond-shaped field.
- This field provides an integrated classification of water types, identifying hydrochemical facies such as calcium-bicarbonate (Ca-HCO_3), sodium-chloride (Na-Cl), and sulfate-rich water types (Ca-SO_4).

By analyzing Piper diagrams for different seasons (rainy vs. dry), we identified trends in groundwater mineralization, contamination sources, and hydrogeochemical evolution.

- **Geographically Weighted Regression (GWR) for Spatial Relationships**

GWR was applied to model the relationship between environmental predictors (e.g., water quality parameters, elevation, well locations) and AGE incidence. Unlike traditional regression models, GWR accounts for spatial heterogeneity by allowing regression coefficients to vary across geographic locations.

- **Algorithm for GWR**
- ➢ Select a Set of Explanatory Variables *(X1, X, …Xn)*

The independent variables include groundwater contamination indicators (e.g., NO_3^{-}, SO_4^{2-}, fecal coliforms), elevation, and population density.

- ➢ Kernel Weighting Function for Local Estimaion:

Assign higher weights to nearby observations using a spatial kernel function:

$$\omega_{i\,(u,v)} = e\left(-\frac{d_{ij}^2}{h^2}\right),$$

Where:

- d_i is the distance between observation i and the regression point *(u,v).*
- h is the bandwidth parameter controlling the spatil scale.

- **Estimate Local Regression Coefficients :**

  Fit a separate regression model at each location *(u, v)* using weighted least squares:

  $$Y_{(u,v)} = \beta_0(u,v) + \sum_k \beta_k(u,v) X_k + \epsilon$$

  Where:

  - $Y_{(u,v)}$ is the dependent variable (AGE incidence at location *u, v).*

  - $\beta_k(u, v)$ are the local regression coefficients.
- **Model Validation & Significance Testing:**
- OLS regression diagnostics: Examine global multicollinearity using Variance Inflation Factor (VIF).
- Koenker's test (BP test): Determines whether relationships vary spatially.
- F Join test: Evaluates overall model fit across different geographic areas.
-
- **Maximum Entropy (MaxEnt) Modeling for AGE Risk Prediction**

Since AGE incidence is not normally distributed and has spatially non-stationary relationships, we opted for MaxEnt modeling a machine-learning approach that estimates the probability distribution of AGE cases based on environmental constraints.

- **Algorithm for MaxEnt Modeling**

MaxEnt follows a probability-based approach, predicting areas with high AGE occurrence by maximizing entropy subject to known constraints.

- **Define the study Area & input Data**
- Presence-only AGE case locations *($X_1, X_2, \ldots X_n$)*.
- Environmental predictors (groundwater chemistry, elevation, distance to sanitation facilities).
- **Calculate Environmental Suitability Scores**

MaxEnt constructs a probability distribution *P(x)* that maximizes entropy while satisfying feature constraints:

$$P(x)=\frac{1}{z}exp(\sum_{i=1}^{n}\lambda_i fi(x))$$

Where:

- fi*(x)* are the environmental features (e.g., NO_3^- concentration, distance to contaminated wells).
- λ_i are the weights (parameters) to be estimated,
- z is a normalization constant ensuring the probabilities sum to 1.
- **Iterative Optimization via Regularization**
- Adjust feature weights using a Lagrange multiplier method.
- Constrain the entropy-maximizing distribution to match observed environmental conditions.
- **Generate Predictive Maps Using Ensemble Techniques**
- Bootstrap resampling: Generate multiple models using different random training sets.
- Ensemble averaging: Aggregate outputs to improve reliability.
- **Model Evaluation with ROC Curves**
- Calculate Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC) analysis.
- AUC values close to 1.0 indicate strong predictive power.

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Table 1 : Comparative Summary of Methods

Method	**Strengths**	**Limitations**
Piper Diagrams	Provides detailed water chemistry classification; detects hydrochemical facies	Does not directly link water quality to health outcomes
Geographically Weighted Regression (GWR)	Captures spatial variability in relationships; allows local coefficient estimation	Requires large, spatially continuous datasets; limited by collinearity issues
Maximum Entropy (MaxEnt)	Robust for presence-only data; strong predictive power; accommodates non-linear relationships	Requires extensive environmental data; computationally intensive

4. RESULTS AND DISCUSSION

4.1 Quality Assessment of Well Water

- **Chemical and Microbiological Trends**

The groundwater quality analysis from 2010 to 2013 indicates progressive deterioration, as evidenced by rising concentrations of major cations (Ca^{2+}, Mg^{2+}, Na^{+}) and anions (Cl^{-}, SO_4^{2-}, NO_3^{-}) (Tables 1 and 2; Figures 3–10). This trend suggests increasing contamination, likely resulting from urban runoff, agricultural inputs, and inadequate waste disposal. Notably, potassium (K^{+}) displays contrasting trends, with its maximum concentrations declining while minimum values rise, suggesting natural aquifer variability or inconsistencies in sampling methodology.

These findings align with Dechangue et al. (2021), who observed low mineralization in peri-urban groundwater in Douala, with electrical conductivity ranging between 44.30 and 483 µS/cm. Similarly, Ayimele et al. (2020) reported that groundwater in Buea and Tiko subdivisions exhibited pH values between 4.9 and 8.4, with electrical conductivity reaching 2330 µS/cm, suggesting high vulnerability to microbial pollution.

Figures 3 and 4 illustrate a progressive increase in Ca^{2+}, Mg^{2+}, and Na^{+}, confirming growing mineralization a trend also reported by Djaouda et al. (2018), who recorded conductivity variations from 171.5 to 1910.3 µS/cm in Maroua's groundwater. Furthermore, Figures 5 and 6 reveal a steady rise in nitrate levels, at times exceeding WHO-recommended limits. These results are consistent with Fantong et al. (2013), who linked nitrate pollution in the Mayo Tsanaga River Basin to decreasing groundwater age and depth, indicative of anthropogenic pollution sources such as agricultural fertilizers and domestic waste infiltration.

- *Microbiological Contamination*

The presence of total coliforms and fecal coliforms in well water samples highlights significant microbial contamination, reinforcing the public health risk of waterborne diseases**.** Ayimele et al. (2020) found that 72.41% of borehole water samples in Buea and Tiko exceeded WHO limits for total coliforms, with E. coli detected in 76.47% of samples. Similarly, Djaouda et al. (2018) reported 72.2% of boreholes in Maroua testing positive for E. coli, attributing contamination to the close proximity of wells to latrines and domestic waste sites**.** These findings emphasize the high vulnerability of groundwater in densely populated urban areas due to poor sanitation infrastructure.

The Piper diagrams (Figures 7–10**)** reveal distinct seasonal variations in hydrochemical facies. During the rainy season**,** calcium chloride, calcium bicarbonate, and sodium bicarbonate facies dominate, reflecting dilution effects, urban runoff, and waste discharges**.** Conversely, the dry season shows a shift towards sodium chloride and calcium chloride facies, driven by evaporation and reduced groundwater recharge. These seasonal variations illustrate the combined impact of natural hydrological processes and anthropogenic influences on groundwater quality**.**

4.2 Spatial and Temporal Patterns of AGE Incidence

- *Seasonal Variations*

AGE incidence data from 2010 to 2013 exhibit clear seasonal patterns, with peaks consistently occurring during the rainy season. This correlation suggests that increased rainfall exacerbates groundwater contamination, leading to higher AGE cases. Dechangue et al. (2021) similarly reported seasonal fluctuations in Douala's groundwater chemistry, with potential consequences for waterborne disease transmission. Fantong et al. (2013) further emphasized that seasonal changes amplify groundwater contamination in urban Cameroon**,** reinforcing the critical role of climate in water quality deterioration**.**

- ***Spatial Clusters***

Geospatial analysis identifies Akwa-Nord, New-Deido, Bépanda TSF, Bépanda Omnisport, and Bessingué as AGE hotspots, characterized by:

- High population density**,**
- Limited sanitation infrastructure, and
- Dependence on shallow groundwater sources**.**

These zones are particularly vulnerable due to inadequate waste disposal and the proximity of latrines to wells. The spatial clustering of AGE cases is consistent with Ayimele et al. (2020)**,** who found high bacteriological contamination rates in poorly regulated urban boreholes across Cameroon.

Furthermore, Figure 20 illustrates how topography influences AGE incidence. Upper land areas such as Deido and New-Deido exhibit lower contamination levels and lower AGE incidence, whereas lower-lying areas (Bépanda TSF, Bépanda Omnisport, Akwa Nord) experience higher rates, likely due to shallow groundwater tables and leachate from uncontrolled waste disposal sites**.** Seasonal comparisons confirm that the rainy season exacerbates contamination**,** with significant increases in nitrate, potassium, bicarbonate, chloride, and sulfate levels compared to the dry season.

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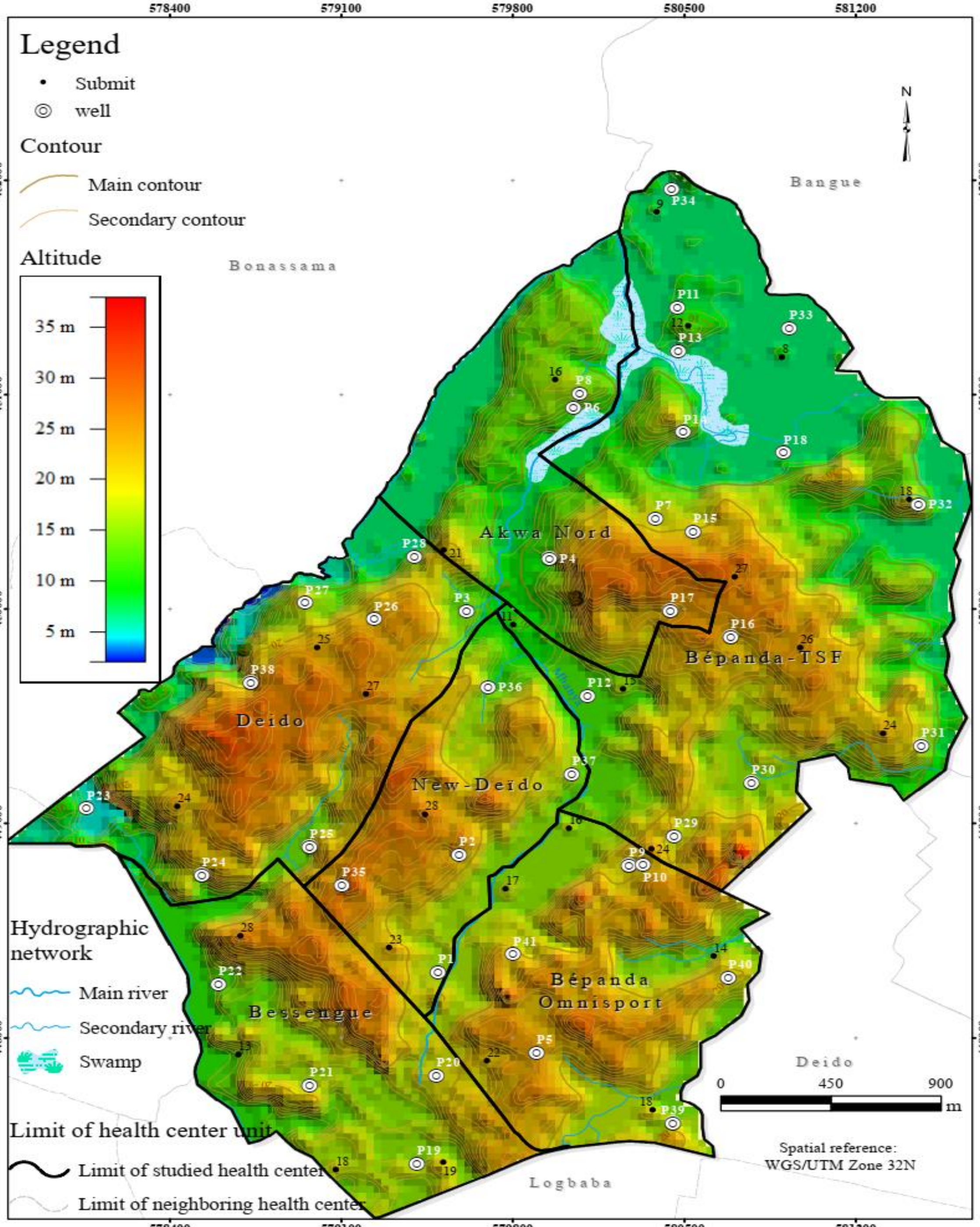

Figure 3: Spatialization of sampled wells points

4.3 Symptomatology and Lethality

Understanding the clinical presentation and fatality rates of Acute Gastroenteritis (AGE) across different geographic locations is crucial for identifying high-risk areas and implementing targeted public health interventions. This section integrates spatial analyses, symptom distribution, and lethality trends to assess the relationship between environmental conditions and AGE outcomes.

- Symptomatology and Spatial Patterns

The primary symptoms of AGE in the study area include:

- Diarrhea (acute, watery, or dysenteric).
- Vomiting (often leading to dehydration).
- Abdominal pain and cramps (indicative of gastrointestinal irritation).
- Fever (suggesting possible bacterial or viral infection).

Spatial analysis (Figure 16) reveals a strong correlation between poor sanitation, contaminated water sources, and higher AGE symptom prevalence. Specific health areas with recurrent AGE symptoms include:

- Akwa Nord, Bessingué, and New-Deido, where well water samples exhibited high concentrations of nitrates, coliform bacteria, and heavy metals.
- Peri-urban zones, characterized by informal settlements with inadequate waste disposal and drainage, show elevated diarrheal and dehydration-related cases.

- Algorithm for Symptom Clustering Analysis

To identify spatial patterns in symptom distribution, a clustering algorithm was applied using **Getis-Ord Gi* (hotspot analysis) **:

- ✓ Define spatial units (health districts) and AGE symptom frequencies *(Xi).*
- ✓ Compute the z-score and p-value to determine statistically significant clusters:

$$G_i^* = \frac{\sum_j \omega_{i,j} X_j}{\Sigma_j x_j}$$

- **Interpretation of clusters:**
  - ✓ Hotspots (high z-score, low p-value) → High AGE symptom prevalence.
  - ✓ Cold spots (low z-score, high p-value) → Low symptom prevalence.

- Akwa Nord and New-Deido are persistent AGE symptom hotspots, aligning with high waterborne contamination levels.
- Outlying districts exhibit lower symptom burdens, possibly due to better infrastructure and access to piped water.

- Lethality Trends and Case-Fatality Rates (CFRs)

The case-fatality rate (CFR) is a key epidemiological metric for assessing AGE severity across different locations. CFR is calculated as:

$$CFR = \frac{\text{Number of AGE deaths}}{\text{Total AGE cases}} \text{ X } 100.$$

- **Geospatial Patterns of Lethality**

Analysis of AGE-related lethality curves (Figures 17 and 19) indicates that Akwa Nord, Bessingué, and New-Deido report higher-than-average CFRs compared to the national benchmark (0.1%–0.3%).

- Algorithm for Lethality Risk Mapping

To identify areas with heightened AGE lethality risks, a spatial autoregressive (SAR) model was employed:

  - Define AGE mortality rates per health district.
  - Apply spatial lag regression to account for neighboring effects:

$$Y = pWY + X\beta + \epsilon$$

where *W* the spatial weight matrix and ρ\rhoρ is the spatial dependence coefficient.

Generate risk-adjusted lethality maps to identify priority intervention areas.

CFR exceeds 0.5% in certain districts, suggesting possible:

- ✓ Healthcare accessibility issues (delayed hospital admissions, insufficient medical supplies).
- ✓ More virulent AGE strains or secondary infections.
- ✓ Severe dehydration due to untreated water sources.
- ✓ Disparities in AGE outcomes correlate with infrastructure gaps (e.g., districts with fewer health centers report higher CFRs).

4.3 Spatial Analysis and Predictive Modeling

- *Geographically Weighted Regression (GWR)*

To spatially correlate AGE incidence with environmental predictors, a GWR model was initially applied using the general equation:

$$Y_j = B_0(U_j, V_j) + \sum_k B_k(U_j, V_j) X_{jk} + \varepsilon_j$$

Where Y_j represents AGE incidence, and (U_j, V_j) denotes geographic coordinates. However, statistical tests including OLS, VIF, Wald Join, and Koenker's tests indicated that most explanatory variables, except Mg^{2+}, were not satistically significant, limiting the robustness of the GWR model.

Despite this initial application, statistical diagnostics indicated weak spatial relationships, with high multicollinearity and insignificant coefficients for several water quality indicators. Given these findings, GWR was abandoned in favor of Maximum Entropy (MaxEnt) modeling, which provided more robust predictive mapping capabilities.

- *Maximum Entropy (MaxEnt) Analysis*

Given the limitations of GWR**,** MaxEnt modeling was used to estimate the spatial distribution of AGE cases**.** MaxEnt, based on the principle of maximum entropy, generates probability distributions constrained by observed environmental conditions. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values assessed model performance, and ensemble predictions averaged multiple outputs.
Figures 20–24 display MaxEnt-generated maps for 2010–2013, showing:

- ✓ High-probability zones aligning with areas of poor sanitation and groundwater contamination**.**
- ✓ Rainy season predictions consistently indicating higher AGE risk**.**
- ✓ The summary ensemble map (Figure 24) revealing AGE occurrence probabilities ranging from 0.23% to 0.46%**,** closely matching national surveillance data**.**

4.4 Public Health and Policy Implications

The strong association between degrading groundwater quality and the incidence of Acute Gastroenteritis (AGE) in Douala underscores the urgent need for comprehensive public health interventions and policy reforms. Addressing the multifaceted challenges requires a strategic blend of infrastructure investment, enhanced monitoring, strengthened healthcare services, and active community engagement. These measures not only aim to curb the current burden of AGE but also to build resilience against future environmental and climatic stresses. Below, we detail the key policy recommendations:

- **Targeted Sanitation Investments:**

Prioritize critical areas such as Akwa Nord, Bessingué, and New-Deido—regions identified as high-risk hotspots—for immediate infrastructural upgrades. This includes expanding access to piped water systems, modernizing sewage and waste disposal networks, and rehabilitating dilapidated sanitation facilities. Improving these systems will reduce the reliance on contaminated hand-dug wells, thereby minimizing exposure to waterborne pathogens. Investing in localized sanitation improvements is consistent with the recommendations by Fantong et al. (2013), who advocate for adaptation strategies that respond to localized environmental risks.

- **Enhanced Monitoring:**

Implement real-time water quality surveillance systems that integrate sensor networks, remote sensing, and GIS-based analysis. These systems should be capable of continuously tracking key physicochemical and microbiological parameters, enabling early detection of contamination events. Timely data can facilitate rapid response measures, thereby mitigating potential outbreaks of AGE. Enhanced monitoring also supports adaptive management practices, allowing policymakers to refine interventions based on emerging trends and climatic variability.

- **Public Health Preparedness:**

Strengthen healthcare services in vulnerable zones by increasing the availability of diagnostic facilities, improving emergency response capabilities, and ensuring that healthcare professionals receive training on waterborne disease management. Investment in local health infrastructure is crucial for reducing AGE morbidity and mortality, especially during periods of seasonal spikes. Establishing emergency protocols and stockpiling essential medical supplies can further enhance the community's capacity to respond to acute health crises.

- **Community Engagement:**

Engage local communities through education and outreach initiatives that emphasize the importance of safe water storage, proper sanitation practices, and personal hygiene. Empowering residents with knowledge about the risks associated with contaminated water and the benefits of behavioral change is vital for sustainable public health improvement. Community-based programs can foster local ownership of water management practices and promote grassroots advocacy for better sanitation infrastructure.

Collectively, these interventions form a holistic strategy to mitigate the adverse impacts of groundwater contamination on public health. They align with the findings of Fantong et al. (2013), who emphasize the need for localized adaptation strategies to address climate-induced groundwater contamination risks. By combining targeted infrastructure investments with advanced monitoring and community-focused initiatives, policymakers can create a resilient urban health system capable of reducing the incidence and severity of AGE in Douala.

Conclusion

This study highlights the significant impact of deteriorating groundwater quality on Acute Gastroenteritis (AGE) incidence in Douala, Cameroon. By integrating hydrochemical assessments, epidemiological data, and geospatial modeling techniques (GWR and MaxEnt), we identified key spatiotemporal dynamics of AGE transmission. Groundwater contamination, driven by urban runoff, agricultural inputs, and poor waste disposal, was found to be a critical determinant of AGE incidence, particularly in areas with high population density and limited sanitation infrastructure. The study revealed distinct hotspots (e.g., Akwa Nord, New-Deido) with significant seasonal fluctuations in contamination levels and AGE cases, especially during the rainy season.

The use of advanced geospatial modeling techniques provided valuable insights into the spatial relationships between environmental factors and AGE incidence. While GWR offered initial insights, the MaxEnt model demonstrated superior predictive capabilities, identifying high-probability zones of AGE occurrence that align closely with areas of poor sanitation and groundwater contamination.

The findings underscore the urgent need for comprehensive public health interventions. Targeted infrastructure investments, enhanced monitoring, and community-focused initiatives are essential to address groundwater contamination and reduce the burden of AGE. Prioritizing sanitation upgrades, implementing real-time water quality surveillance systems, and strengthening healthcare services in vulnerable zones are critical steps. Additionally, community engagement through education and outreach initiatives is vital for fostering sustainable public health improvements and promoting behavioral change.

Addressing groundwater contamination is a pressing public health priority that requires a multifaceted approach. By combining targeted infrastructure investments with advanced monitoring and community-focused initiatives, policymakers can create a resilient urban health system capable of mitigating the adverse impacts of groundwater contamination on public health. Future research should build upon this integrated approach to refine risk prediction models and evaluate the long-term impact of targeted interventions.

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Annexes

A. Tables

Table 2: Maximum Values of Cations and Anions for 2010–2013

Variables	2010	2011	2012	2013
T	25	28	25	28
pH	8	7	8	7
MES	144	9	107	10
CE (µS/cm)	210	625	318	644
Cl^- **	241	67	241	90
Ca^{2+} *	132	75	171	132
Fe^+	3	2	3	2
HCO_3^- **	330	91	330	105
Mg^{2+} *	31	20	140	50
Na^+ *	96	67	189	69
NO_3^- **	28	62	41	77
SO_4^{2-} **	251	51	251	63
K^+ *	121	27	125	37
CF ***	7043	5767	3312	3442
SF ***	1386	1979	1283	2030

Source: Laboratory and Fieldwork

Keys:

- *Cation
- ** Anion
- *** Fecal Coliform and Total Coliform

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Table 3: Minimum Values of Cations and Anions for 2010–2013*)*

Variables	2010	2011	2012	2013
T	23	26	23	26
pH	5	5	5	5
MES	3,5	1	91	3
CE (µS/cm)	54	182	80	193
Cl^- **	5	19	18	23
Ca^{2+} *	22	14	65	21
Fe^+	1	0,076	1,48	0,14
HCO_3^- **	63	20	131	25
Mg^{2+} *	6	2	50	10
Na^+ *	13	25	48	29
NO_3^- **	4	10	12	15
SO_4^{2-} **	6	10	10	14
K^+ *	2	9	9	13
CF ***	26	41	25	38
SF ***	41	32	44	38

Source: Laboratory and Fieldwork

Keys:

- *Cation
- ** Anion
- *** Fecal Coliform and Total Coliform

B. Figures

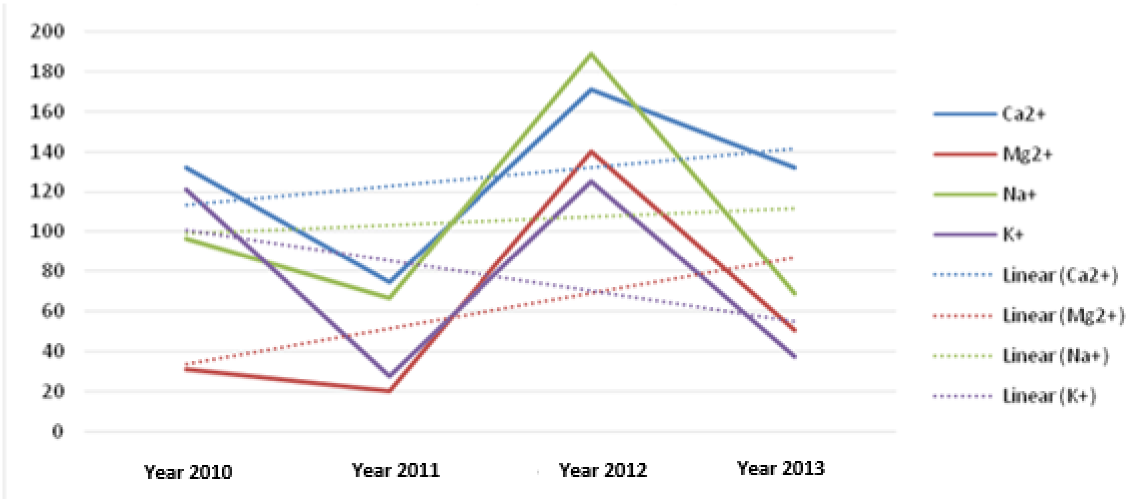

Figure 4: Trends in the proportion of major cations from 2010 to 2013 (maximum values)

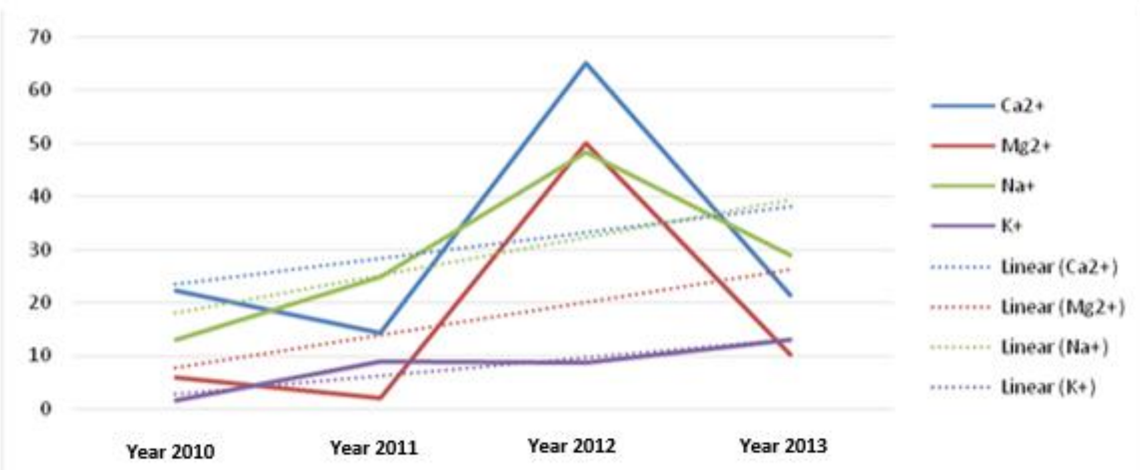

Figure 5: Trends in the proportion of major cations from 2010 to 2013 (minimum values)

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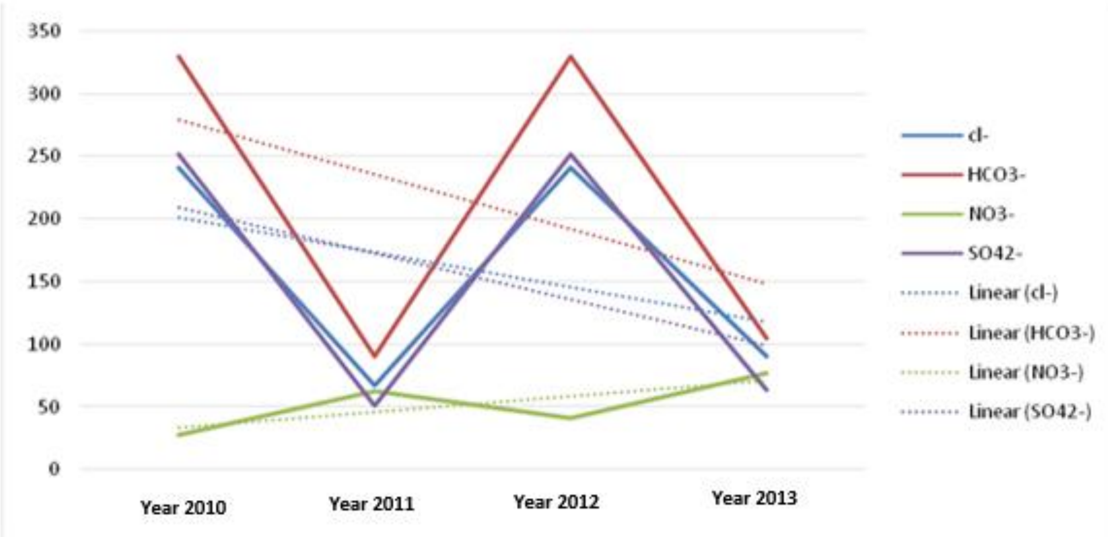

Figure 6: Trends in the proportion of major anions from 2010 to 2013 (maximum values)

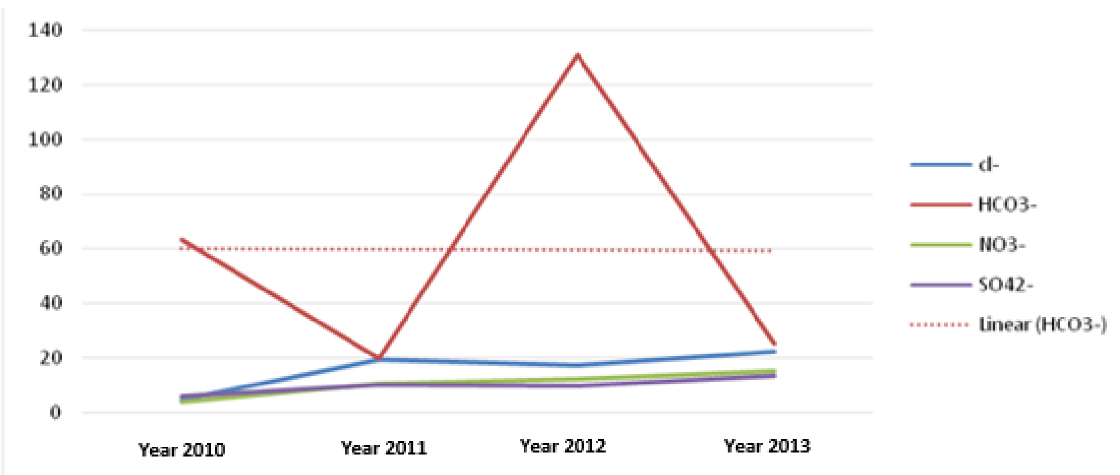

Figure 7: Trends in the proportion of major anions from 2010 to 2013 (minimum values)

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(a) Without mineralization circle; **(b)** with mineralization circle

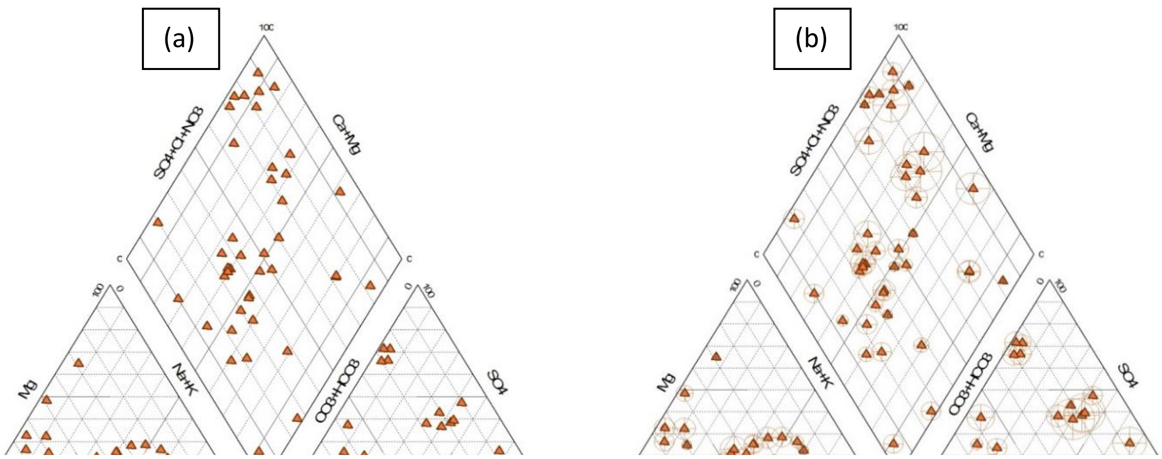

Figure 8: Groundwater facies in the Mbanya watershed, rainy season 2010 (August)

Source: fieldwork and laboratory

(a) without mineralization circle**;** **(b)** with mineralization circle

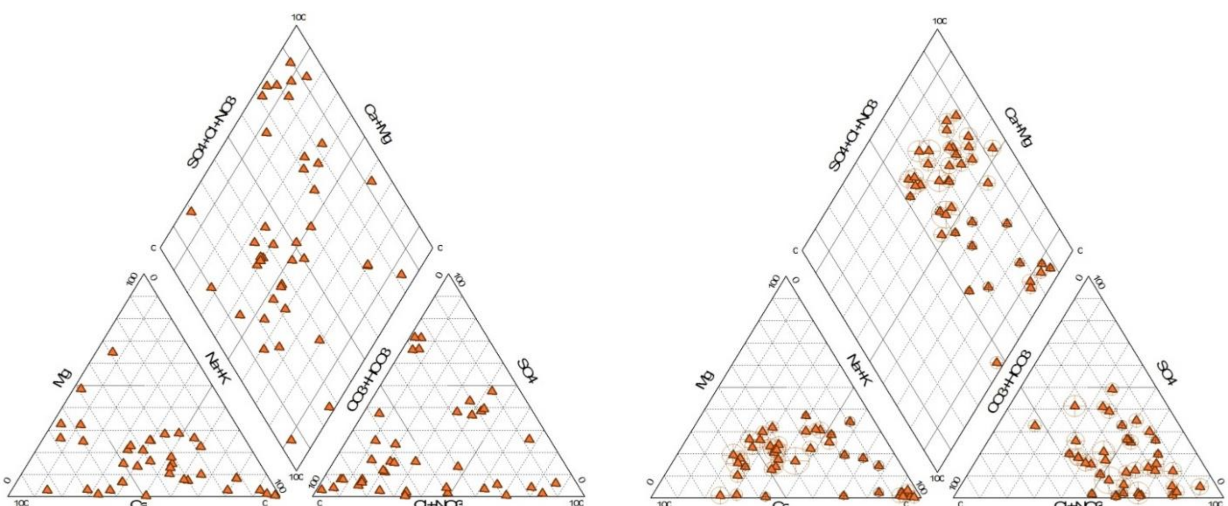

Figure 9: Groundwater facies in the Mbany**(b)** with mineralization circle a watershed, dry season 2011 **(**February**)**

Source: fieldwork and laboratory

(a)without mineralization circle**;** **(b)** with mineralization circle

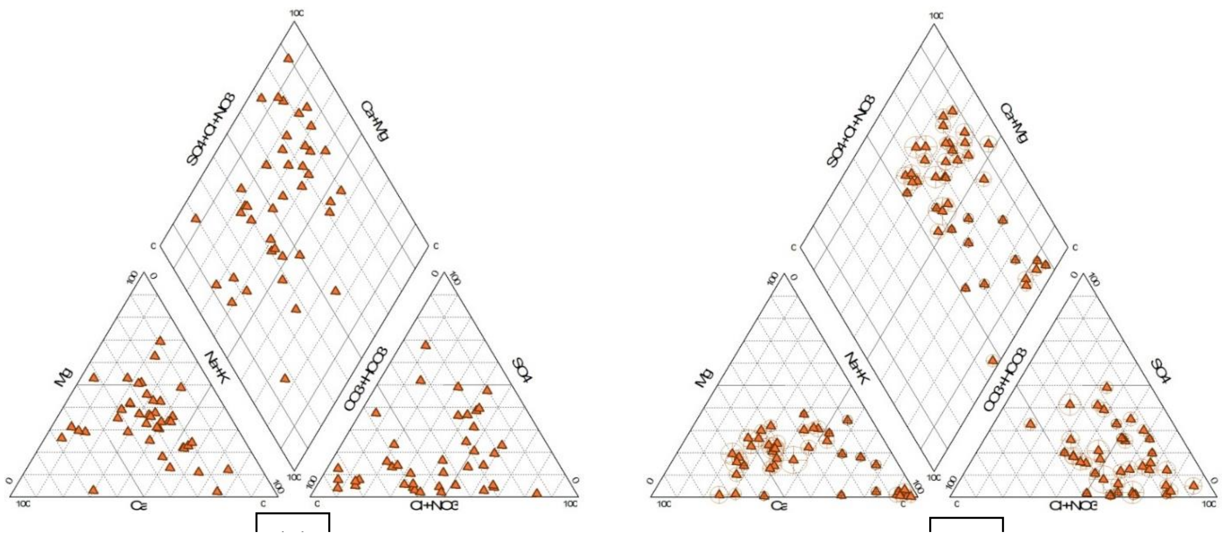

Figure 10 : Groundwater facies in the Mbanya watershed, dry season 2011**,** rainy season 2012 (August)

Source: fieldwork and laboratory

(a)without mineralization circle; **(b)** with mineralization circle

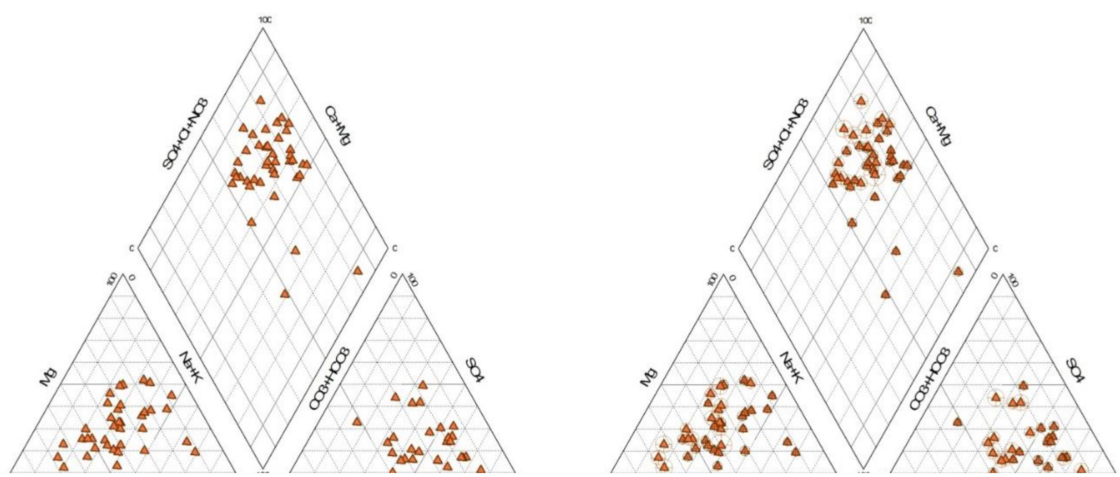

Figure 11: Groundwater facies in the Mbanya watershed, dry season 2013 **(**February**)**

Source: fieldwork and laboratory

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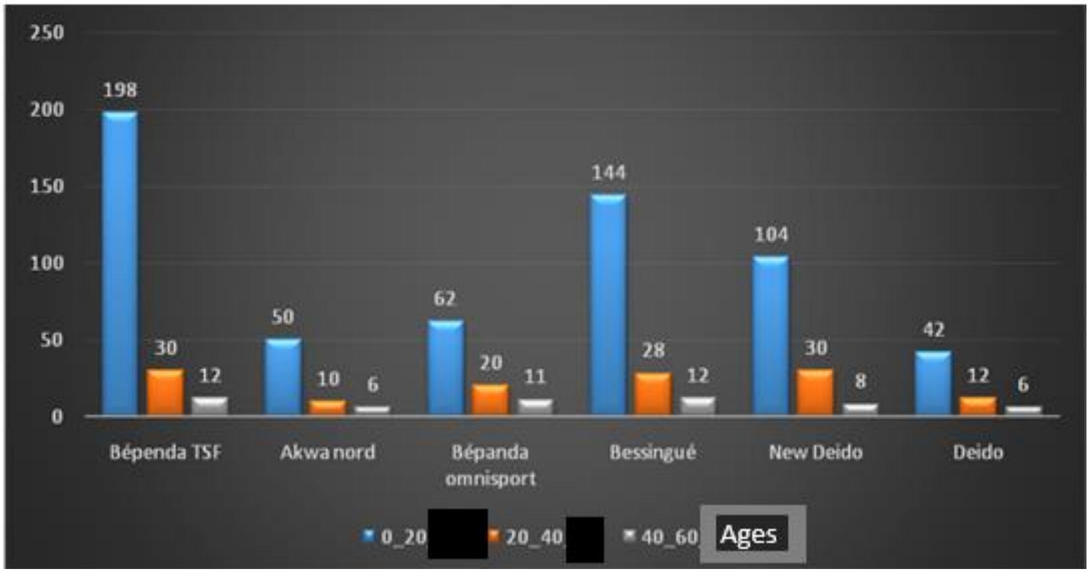

Figure 12: 2010 distribution of patients according to age group

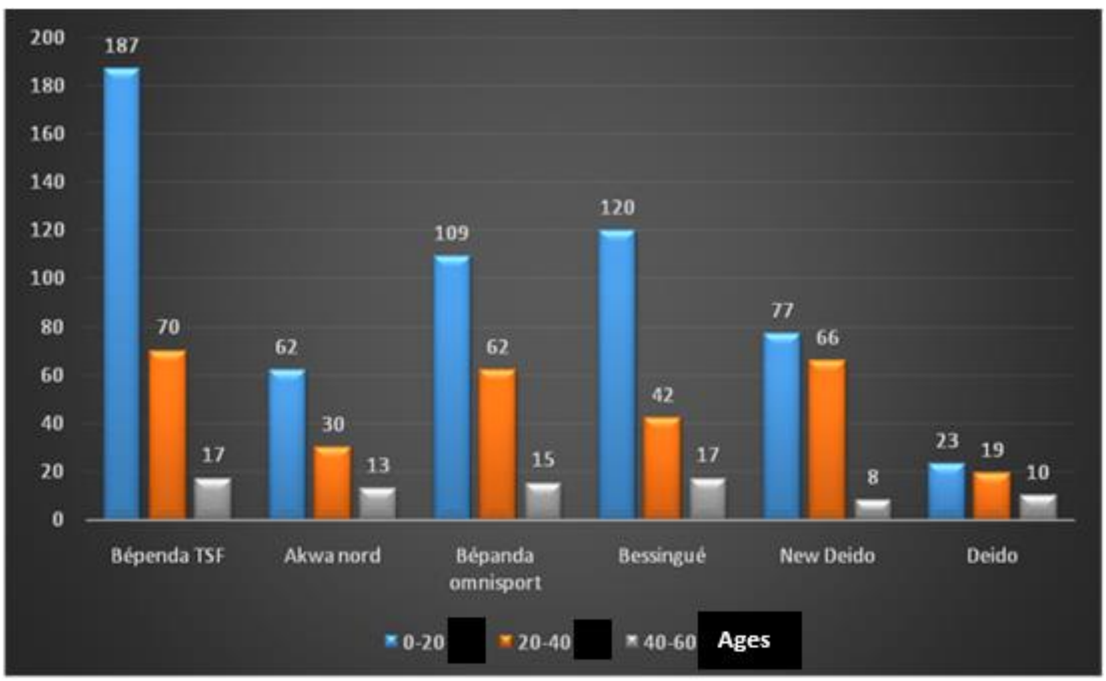

Figure 13: 2011 distribution of patients according to age group

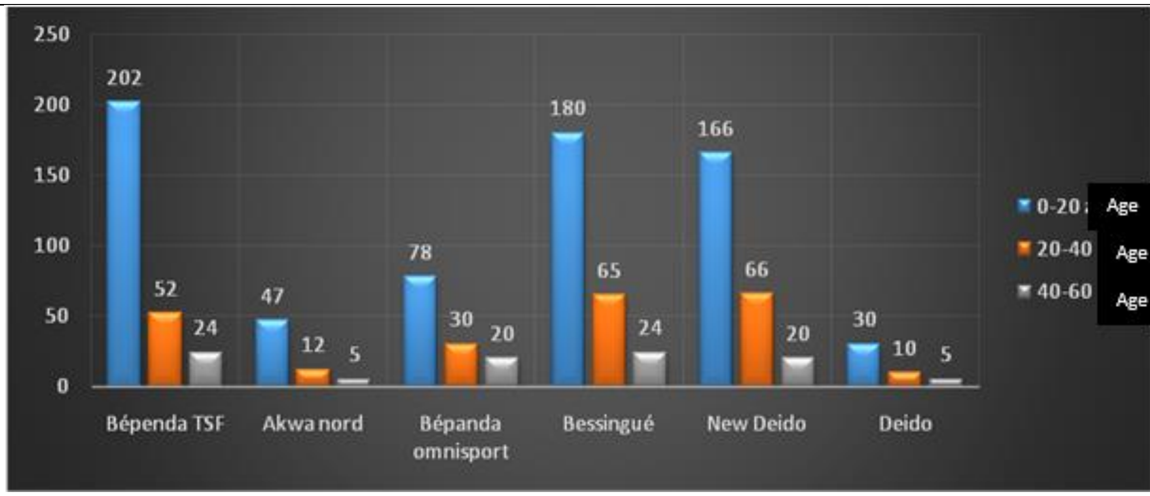

Figure 14: 2012 distribution of patients according to age group

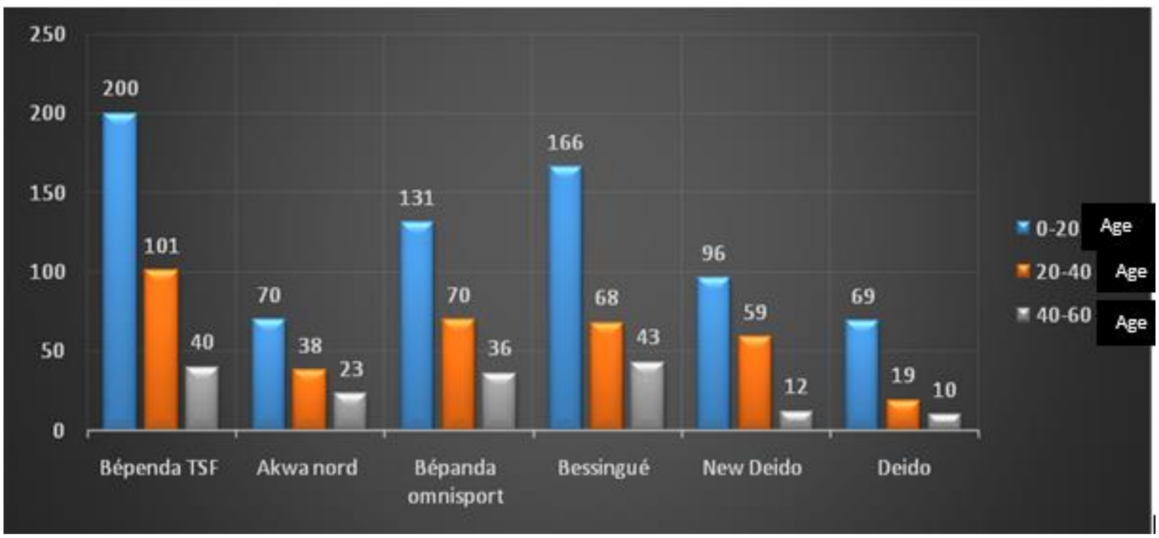

Figure 15: 2013 distribution of patients according to age group

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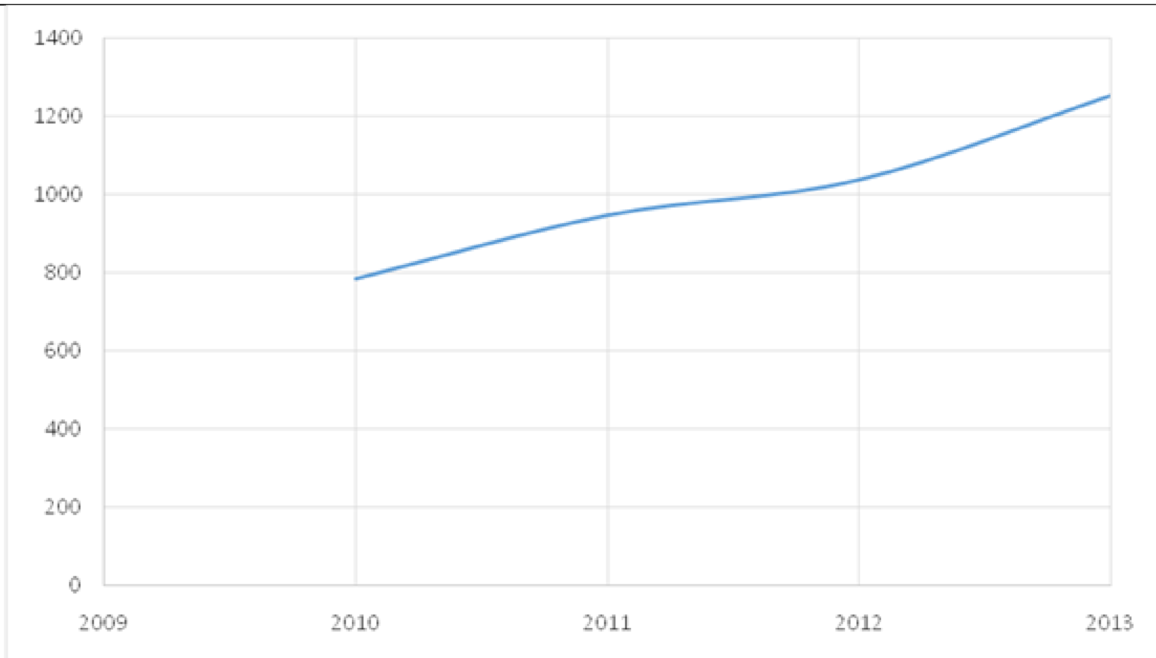

Figure 16: Cumulative incidence of AGE patients from 2010 to 2013

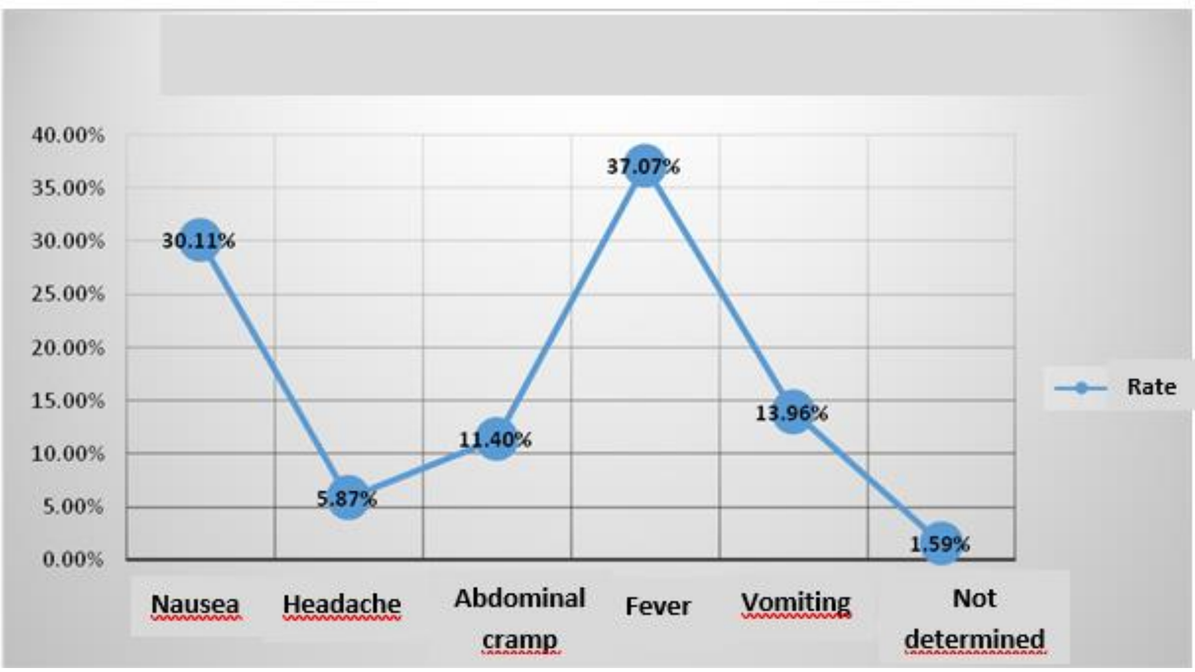

Figure 17: Dynamics symptomatology of AGE, 2010-2013 2010 to 2013)

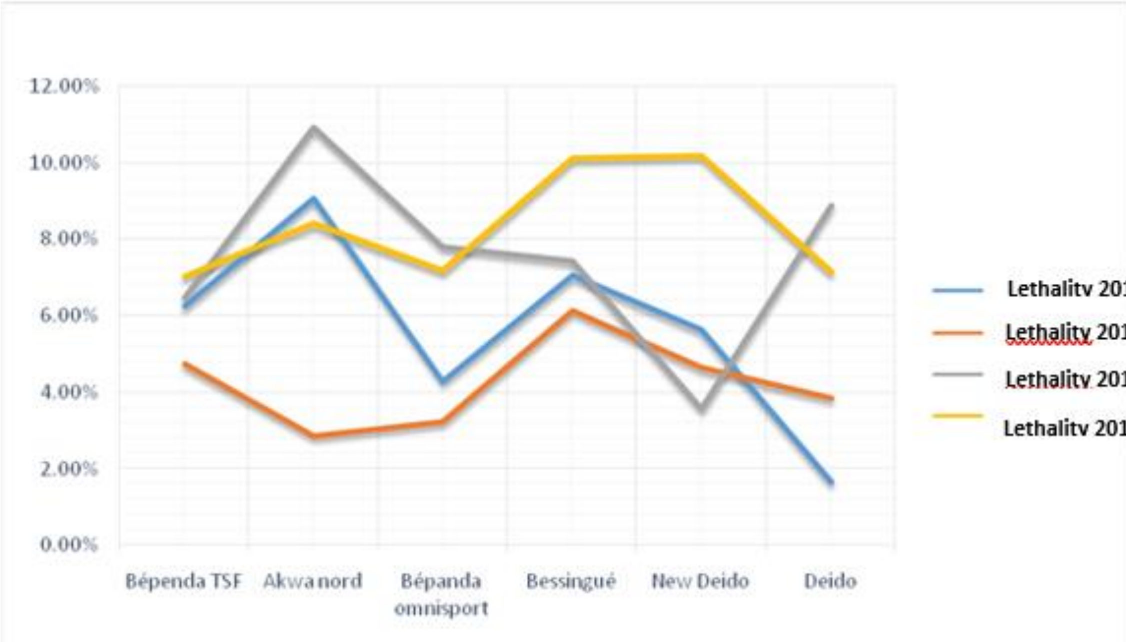

Figure 18: **case fatality rate (CFR)**

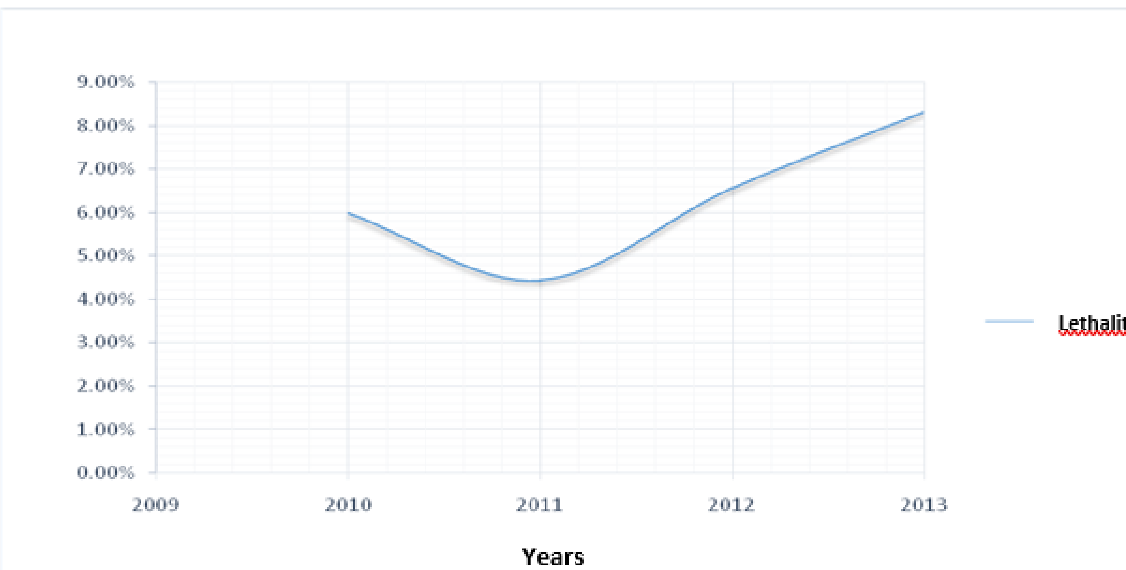

Figure 19: The cumulative trend in the lethality of AGE from 2010-2013

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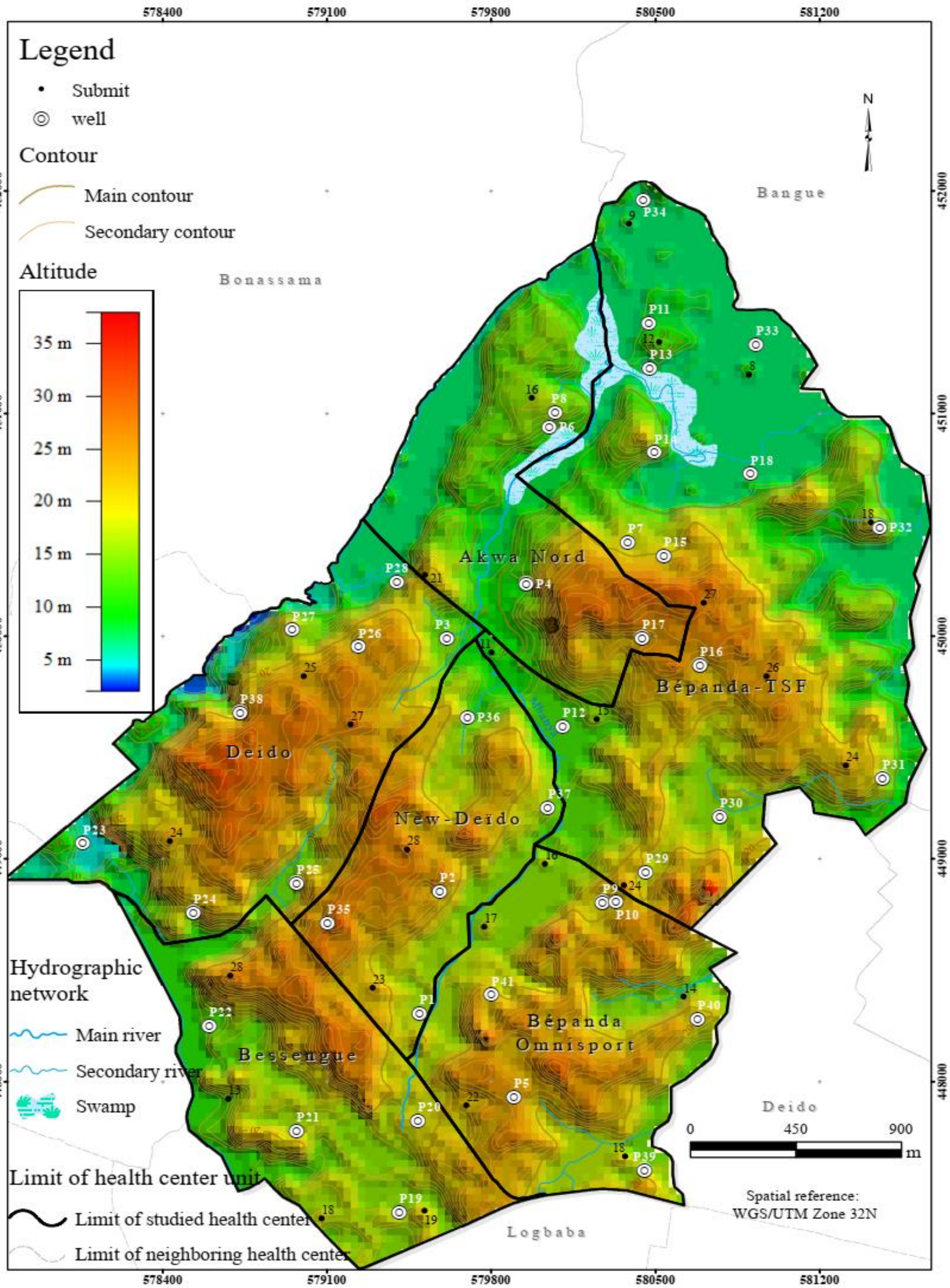
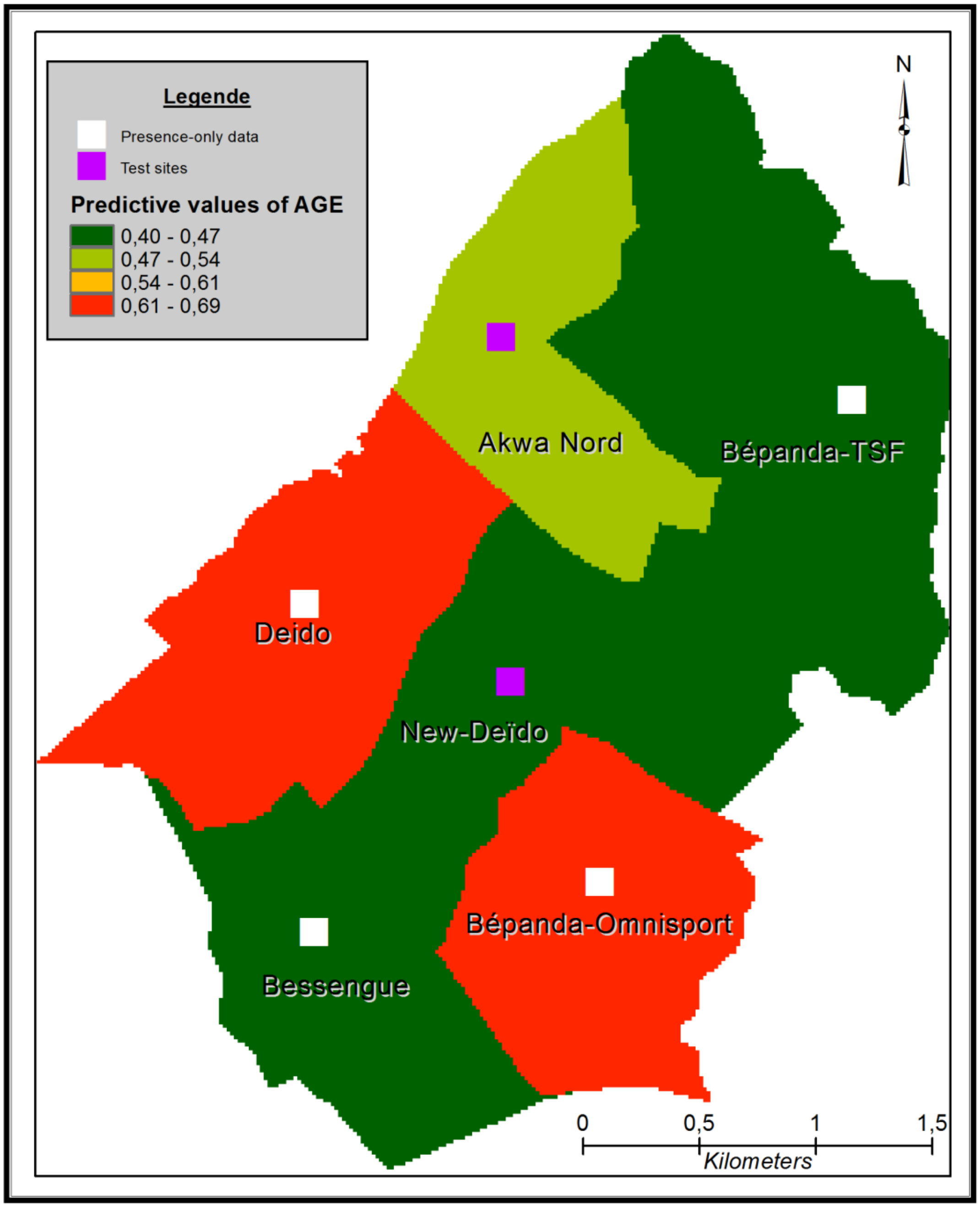


Figure 20: Spatialization of sampled wells points



Fi

gure 21: Probability of occurrence of acute gastroenteritis (AGE) in 2010 from minima. The colour code represents the percentage of presence of AGE. Warm colours

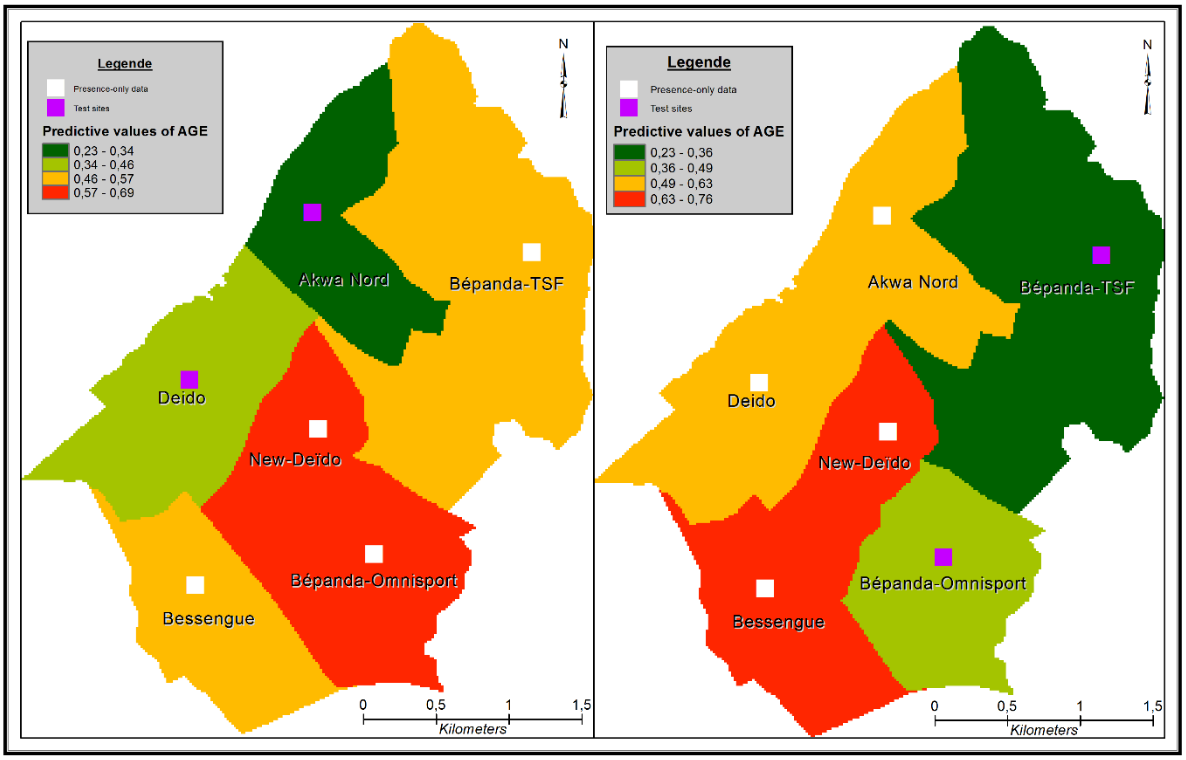


Figure 22: Probability of occurrence of acute gastroenteritis (AGE) in 2011 from minima and maxima

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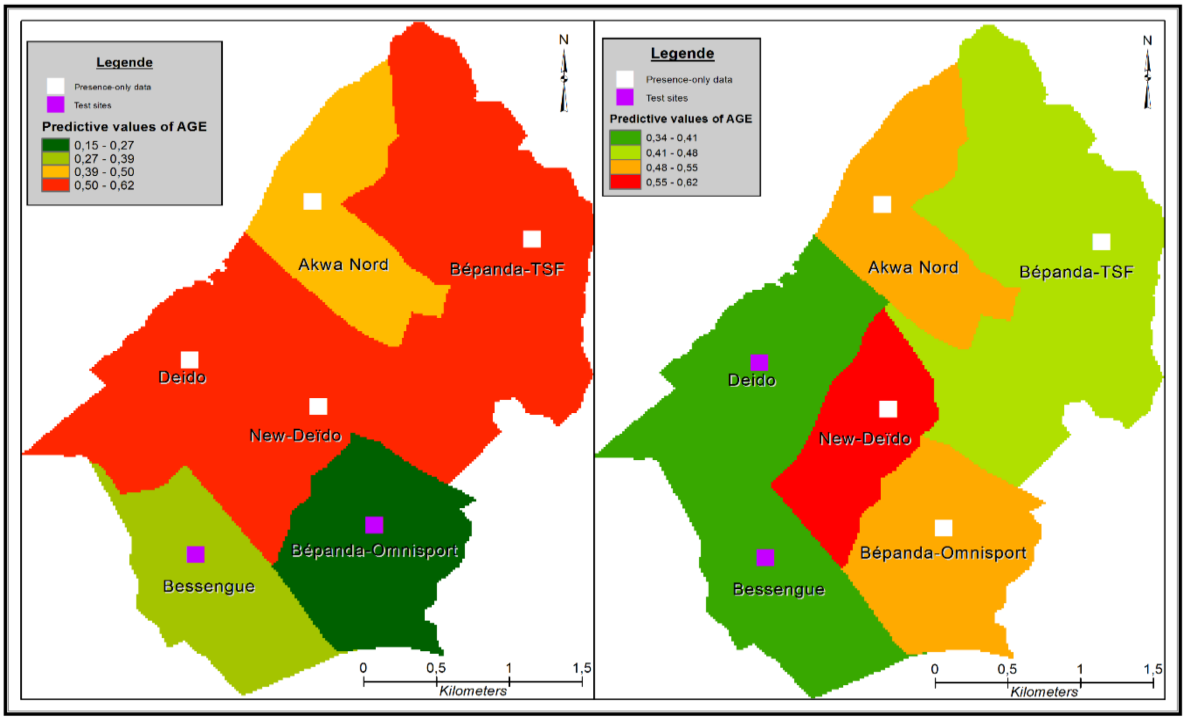

Figure 23: Probability of occurrence of acute gastroenteritis (AGE) in 2012 from

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minima and maxima.

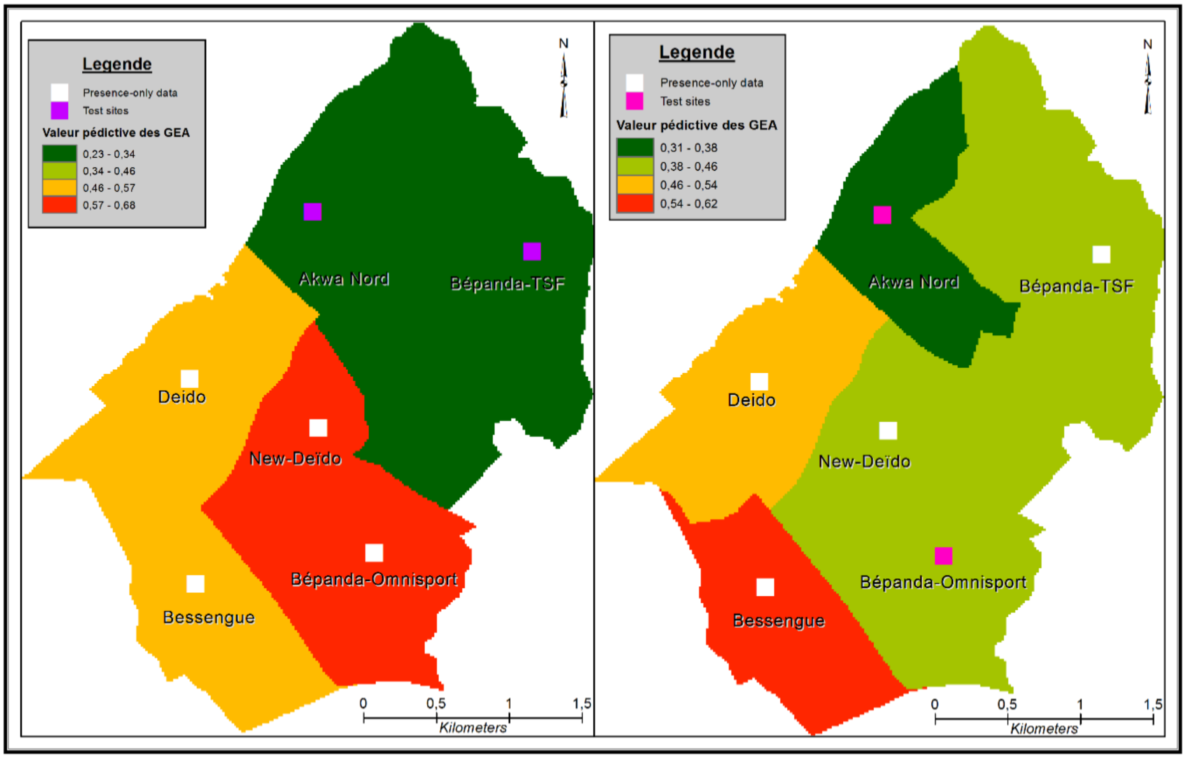

Figure 24: Probability of occurrence of acute gastroenteritis (AGE) in 2013 from minima and maxima.

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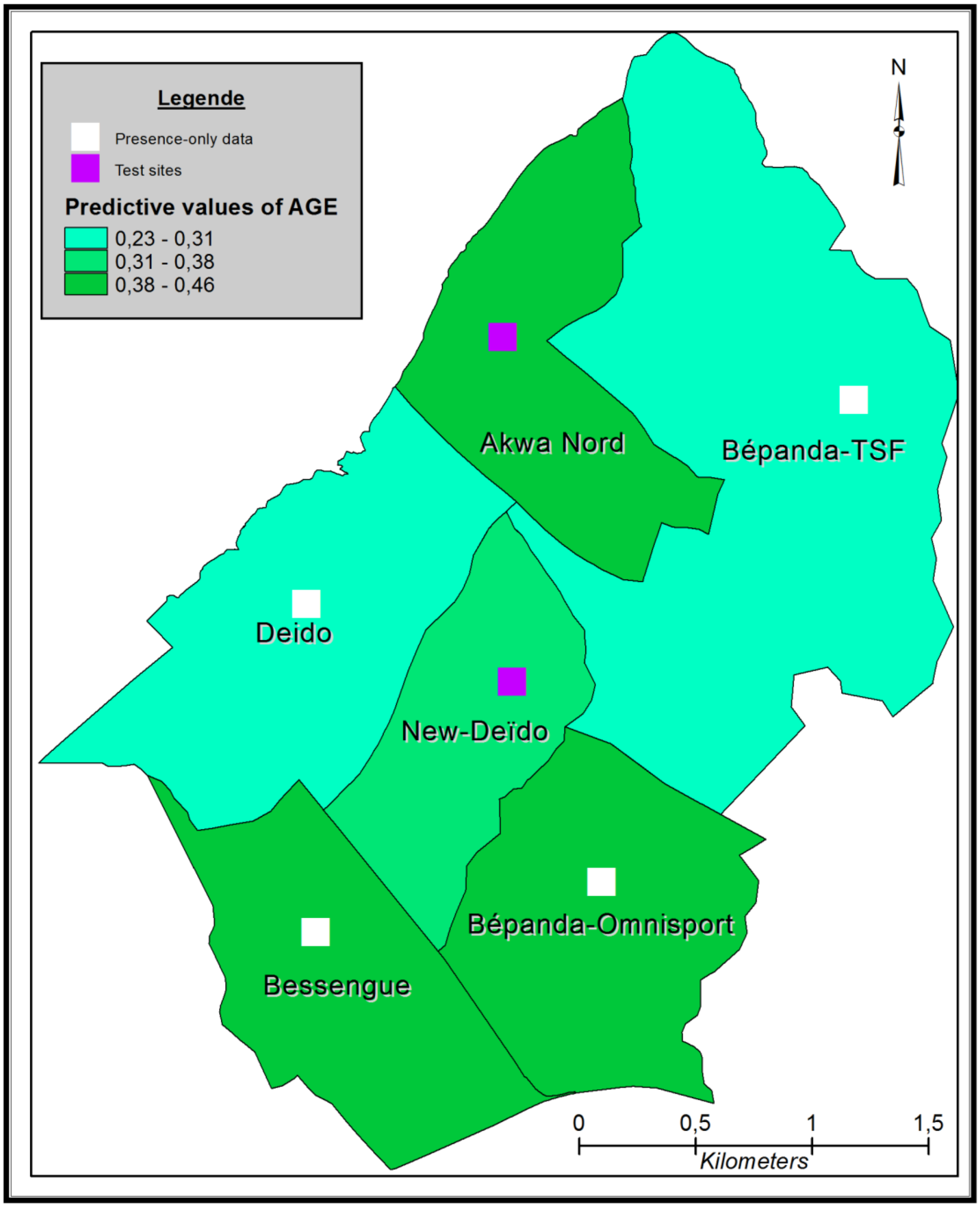

Figure 25: Summary probability of occurrence of acute gastroenteritis from 2010 to 2013