Models for Predicting Bulinids Species Habitats in Southwestern Nigeria Using Geographic Information System

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MODELS FOR PREDICTING BULINIDS SPECIES HABITATS IN SOUTHWESTERN NIGERIA USING GEOGRAPHIC INFORMATION SYSTEM

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ABSTRACT

Background: Schistosomiasis prevalence is high in southwestern Nigeria and planorbids of the genus *Bulinus* had been implicated in the transmission of the disease in the area. The knowledge of species distribution in relation to environmental variables will be auspicious in planning control strategies.

Methods: Satellite imagery and geographic information system (GIS) were used to develop models for predicting the habitats suitable for bulinid species. Monthly snail sample collection was done in twenty-three randomly selected water contact sites using standard method for a period of two years. Remotely sensed variables such as Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI) were extracted from Landsat TM, ETM^+; Slope and Elevation were obtained from digital elevation model (DEM) while Rainfall was retrieved from European Meteorology Research Program. These environmental factors and snail species were integrated into GIS to predict the potential habitats of different bulinid species using exploratory regression models.

Results: The following environmental variables: flat-moderate slope (0.01-15.83), LST (21.1ºC-23.4ºC), NDVI (0.19-0.52), spatial rainfall (> 1,569.34 mm) and elevation (1-278 meters) all contributed to the model used in predicting habitat suitable for bulinids snail intermediate hosts. Exploratory regression models showed that LST, NDVI and slope were predictors of *B. globosus* and *B. jousseaumei*; elevation, LST, Rainfall and slope were predictors of *B. camerunensis*; spatial rainfall, NDVI and slope were predictors of *B. senegalensis* while NDVI and slope were predictors of *B. forskalii* in the area. Bulinids in the forskalii group showed clustering in middle belt and south. The predictive risk map of *B. jousseaumei* was similar to the pattern described for *B. globosus*, but with a high R-square value of 81%.

Conclusion: The predictive risk models of bulinid species in this study provided a robust output for the study area which could be used as base-line for other areas in that ecological zone. It will

be useful in appropriate allocation of scares resources in the control of schistosomiasis in that environment.

Keywords: Bulinid species, GIS/RS, Schistosomiasis, Nigeria.

Introduction

Schistosome infection cause debilitating illness in millions of children and adult in different part of the world, especially in tropical countries. Freshwater snails continue to play significant role in in the transmission of the infection. Therefore, this freshwater snails need to be scientifically explored extensively (1-3). They invade freshwater bodies where they serve as intermediate host, transmitting several parasites (4, 5). Different stages of the life cycle of these parasites are completed in the snail species. These intermediate hosts inhabit a wide range of natural and man-made habitats and they are often found in irrigation canals, dams, ponds and ditches (6-8).

Studies in Southwestern Nigeria have shown that prevalence of schistosome infection among the inhabitants and snail intermediate hosts is high (9, 10). The main stay of schistosome treatment in human is paraziquantel-based therapy; while snail control is almost neglected or perhaps they are considered as an accompanying strategy, most especially in high transmission areas (11). It has been observed that embarking on large–scale control of snails seems to be impracticable, however, identification of areas at high risk and application of long-term effective measure have emerged as a possible way of interrupting schistosome transmission (12, 13).

Field epidemiology is often based on the fact that definitive host, snail intermediate hosts and their associated pathogen are associated with certain environmental factors. These environment factors either increase the survival of snail species or inhibit them. (14). However, the development of geographic information system and remote sensing technology have provided more robust way of determining environmental variables which are related to the distribution of snail intermediate hosts of schistosomes (15, 16).

There are about forty known genera of planorbids that are found on all continents where schistosomiasis is prevalent, in almost any freshwater lake, pool, or stream in habitats (17). In all,

there are approximately 37 recognized species of *Bulinus* species (6); however, the specificity of the snail–parasite interaction is such that only certain species are involved in transmission of the parasite. The genus can be further divided into four major groups, namely, *Bulinus africanus* group, *Bulinus forskalii* group, *Bulinus reticulatus* group and *Bulinus truncatus/tropicus* complex. In each group, there are species that act as intermediate hosts of trematodes in different parts of the world (6). The growing interest in biodiversity and its evaluation has highlighted the importance of species identification (18), but the distribution of these snails is related to available freshwater bodies and suitable environmental factors. To understand the transmission dynamics of schistosome infection in relation to snail intermediate host, it is necessary to have a precise knowledge of prevailing environmental variables in time and space. Geographic Information System (GIS) and Remote Sensing (RS) have proved to be useful for epidemiological research purposes, decision making, planning, management and dissemination of information in time and space. GIS applications related to health have been introduced and used in, for example, the surveillance and monitoring of vector-borne diseases (19-21, 22-24, 25). Remote sensing and GIS have also increased their importance and utility in health-related studies (26, 27, 28, 29). Environmental variables such as climate, satellite sensor data, elevation, slope, land use and land cover, soil type, and other map data are overlaid on a base map of standard geographic projection and scale. This study was designed to develop environmental parameters for mapping and predicting suitable habitats for bulinid species in disease endemic areas.

Materials and methods

Coordinates of the sampling sites were determined using a GPS (Magellan Explorist 310, MiTAC Digital Corporation, CA 95050 USA). The study was carried out in Yewa North Local Government Area (YNLGA), a local schistosomiasis transmission site in southwestern Nigeria (latitudes 6°52’08’’N to 7°25’28’’N and longitudes 2°43’09’’E to 3°07’13’’E). It has a land size of about 200,214 km^2. It shares boundaries with Imeko-Afon local government area in the North, Yewa South Local Government Area in the South, Republic of Benin in the West and Abeokuta North and Ewekoro local government areas in the East.

Data collection

Yewa North LGA has the largest landmass in Ogun State with forty-nine identified villages, each village having water contact sites. Each of the villages were visited for snail sampling before the study started. Water contact sites without snail species were excluded from the study. After initial pre-sample collection, a total of twenty-three water contact sites were randomly selected for snail collection and analysis. Once in a month, bulinid species (*Bulinus globosus*, *Bulinus jousseaumei*, *Bulinus camarunensis*, *Bulinus senegalensis* and *Bulinus forskalii*) were collected from water contact sites using scoop net for two years. Snail identification and infection status were done using morphology and molecular methods respectively. Results of the snail identification and infection have been published elsewhere (10).

The monthly spatial rainfall data was obtained from the European Meteorology Research Program (http://apps.ecmwf.int). The dataset has a spatial resolution of 0.7 meters. The data was downscaled using the multi-dimensional tool in ArcGIS software. NDVI was generated using the near infra-red band and the red Band. The value of the NDVI ranges from -1 to 1, values lesser than 1 shows that the areas are not vegetated while vegetation condition improves has it tends to 1. The Digital Elevation Model (DEM) of the Advanced Space-borne Thermal Emission Radiometer (ASTER) was obtained from the National Aeronautical and Space Agency (NASA) host. The Slope image was obtained from the Digital Elevation Model and was converted using the spatial analyst tool in the ArcGIS. The slope was grouped into various classes ranging from the very steepy to flat. The unit of the slope was measured in percentage. The thermal band (10.4-12.5 μm) of Landsat ETM+ sensor was used to derive Land Surface Temperature over the study area. For the Landsat ETM^{+} sensor, images in the thermal band were captured twice: once in the low-gain mode (band 6L) and once in the high-gain mode (band 6H). (30).

Data Analysis

Logistic regression model was used as a method to investigate all potential explanatory variables that may be important contributing environmental factors for estimating the location of snail species. Independent variables such as spatial rainfall, slope, Normalized difference vegetation Index (NDVI), and Land surface temperature (LST) were used while the different snail species serve as the dependent variables. After careful considerations of the theory and examination of

the data using the exploratory regression method, one model presented itself as most suitable for predicting the locations of the snails. The model generates the equation as shown below:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \ \beta n Xn + \varepsilon$$

Where, Y=Dependent variable, X=Explanatory variable e.g environmental factors, Intercept= (β_0), Coefficients= ($\beta_1 \ldots \beta n$), Residuals= (ε)

The probability map was generated for each of the snail species with values ranging from 0 to 1.

$$P = \frac{1}{1 - e^{z}}$$

Where, P= probability of occurrence, e= exponential, z=regression model obtained from the OLS ($Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \ \beta n Xn + \varepsilon$)

Results

Environmental factors used for building the model were extracted from the satellite imagery and digital elevation model (Table 1). Slope of the area was categorized into flat (0.01-4.75), gentle (4.76-9.23), moderate (9.24-15.83) and steepy (>15.84). Eastern areas had steepy slope while southern areas were flat. Moderate NDVI was recorded in the south while the middle belt had slightly lower NDVI values. Northern areas were higher compared to the south which were lower in terms of elevation. LST were within the tolerance limit in the south while the north had higher values. Spatial rainfall pattern were more in the north-west compared to south-east.

Table 1: Minimum and Maximum values of environmental variables

Environmental variables	Minimum and Maximum values
Slope	0.01-67.26
NDVI	0.02-0.52
Elevation (m)	1.0-278
LST(°C)	21.1-27.7
Spatial Rainfall (mm)	1,569.34-1,590.02

Predictive model showed that most areas in YNLGA were suitable for the survival of *B. globosus* except some middle belt. The logistic binary regression analysis showed that temperature, NDVI and slope were the three major significant variables in predicting the geo-spatial distribution of *B.*

globosus (P<0.05). The passing model using the R square and Akaike's Information Criterion (AICC) identified Imasayi, Ijoun, Oja-Odan, Oja-Ota and Ijale- Ketu as major areas where *B. globosus* can survive. A predictive risk map of *B. globosus* habitat was created based on the final logistic binary regression analysis (Figure 1). High risk areas were mainly located in Imasayi, Ijoun, Oja-Odan, Oja Ota and Ijale-Ketu while low risk areas were Ijaka, Sawonjo and Ibese. The binary logistic model of the probability of presence of *B. globosus* is stated below:

Predictive risk model of *B. globosus* habitats =

$$\frac{1}{\{1 + Exp\,[-(-132.202 * Temperature) - (706.48 * NDVI) + (10.14961 * Slope)]\} + 3224.639}$$

The predictive risk map of *B. jousseaumei* followed the same pattern as *B. globosus*, however, the predictive risk map of *B. jousseaumei* had higher R square value of 81%. Temperature, NDVI and slope were the major variables used in the analysis (P<0.05). A predictive risk map of habitat was created based on the final binary logistic regression analysis (Figure 2).

The binary logistic model of the probability of *B. jousseaumei* is stated below:

Predictive risk of *B. jousseaumei* habitats =

$$\frac{1}{\{1 + Exp[-(-71.8093 * Temperature) - (439.156 * NDVI) + (8.613307 * Slope)]\} + 1744.694}$$

Most of the areas in Southeastern part of YNLGA were suitable for the survival of *B. senegalensis* except some areas in the northwest. The logistic binary regression analysis showed that rainfall, NDVI and slope were the major spatial variables used in the model (P<0.05). Areas around Imasayi, Igbogila, Oja-Odan, Mosan, Owode, and Ebute-Igboro were identified as suitable for the survival of *B. senegalensis*. A predictive risk map of habitats was created based on the final binary logistic regression analysis (Figure 3).

Predictive risk of *B. senegalensis* habitats =

$$\frac{1}{\{1 + Exp[-(0.766137 * Rainfall) - (55.1167 * NDVI) + (1.330056 * Slope)]\} - 1199.128}$$

Figure 4 showed the predictive risk map of *B. camerunensis*. The northern parts of the YNLGA were not suitable for the survival of *B. camerunensis* while most areas in the south were suitable for the survival of the species. The following variables: elevation, temperature, rainfall and slope

were maintained in the analysis (P<0.05). The passing model using the R square (99.2%) and Akaike's Information Criterion (AICC) identified Eggua, Ijale-Ketu, Imoto-Odan, Igbogila, Agbon and some other areas with the same digital value as suitable areas where *B. camerunensis* can survive. The binary logistic model of the probability of the presence of *B. camerunensis* is stated below:

Predictive risk of *B. camerunensis* habitats =

$$\frac{1}{\{1 + Exp\,[-(0.43464 * Elev) + (19.3684 * Temp) - (0.49922 * Rain) - (0.97732 * Slope)]\} + 350.1475}$$

The logistic regression analysis showed that NDVI and slope were the two significant variables in predicting the geo-spatial distribution of *B. forskalii* (P<0.05). The passing model using the R square (82.9%) and Akaike's Information Criterion (AICC) identified Ibayun, Mosan, Ebute, Imo-Odan and Tobolo as some of the major areas where *B. forskalii* can survive. A predictive risk map of the habitat was created based on the final binary logistic regression analysis (Figure 5). The binary logistic model of the probability of the presence of *B. forskalii* is stated below:

Predictive risk of *B. forskalii* habitats =

$$\frac{1}{\{1 + Exp[-(-34.2399 * NDVI) + (0.604485 * Slope)]\} + 7.641222}$$

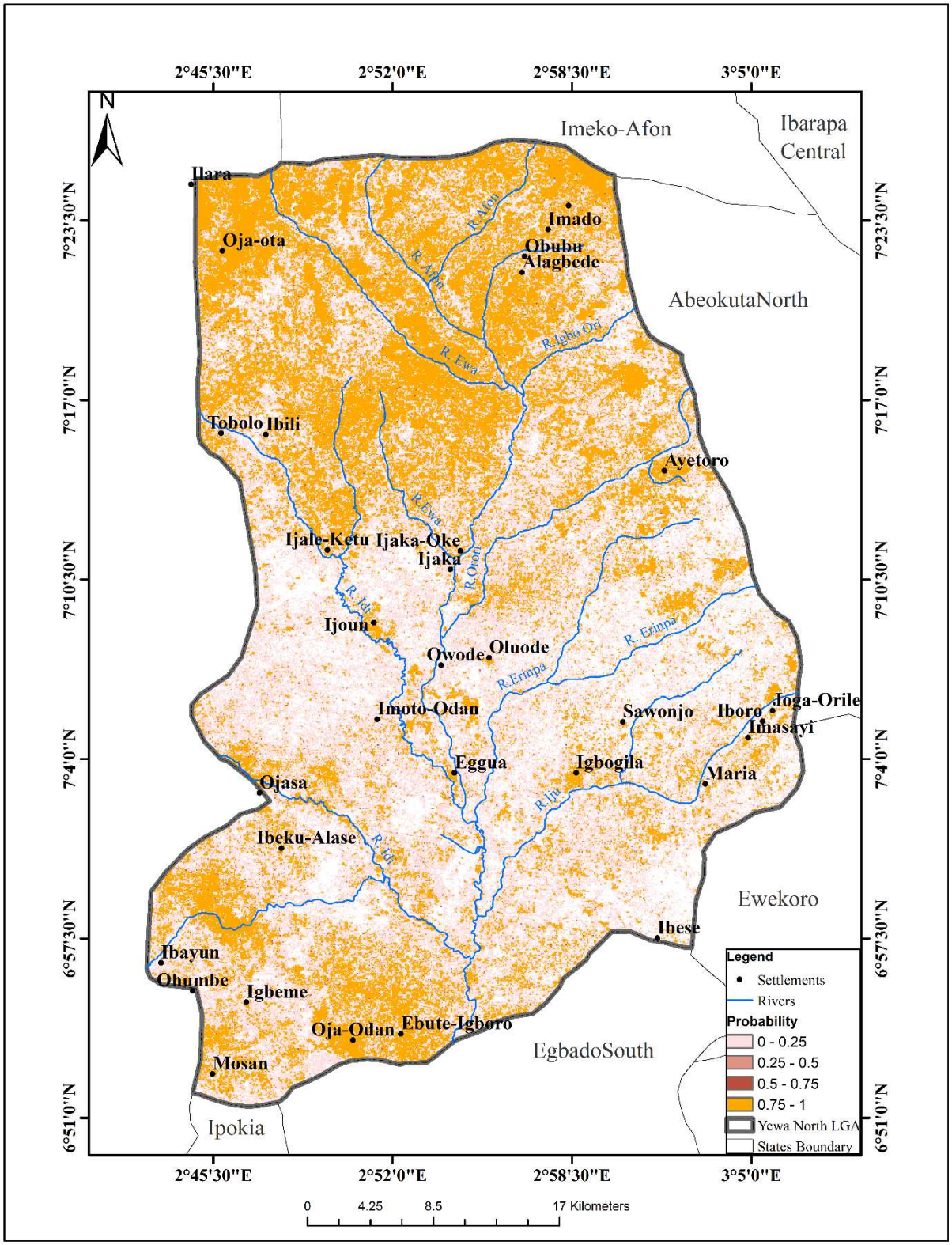

Fig. 1: Predictive Risk Map of *Bulinus globosus* Habitat

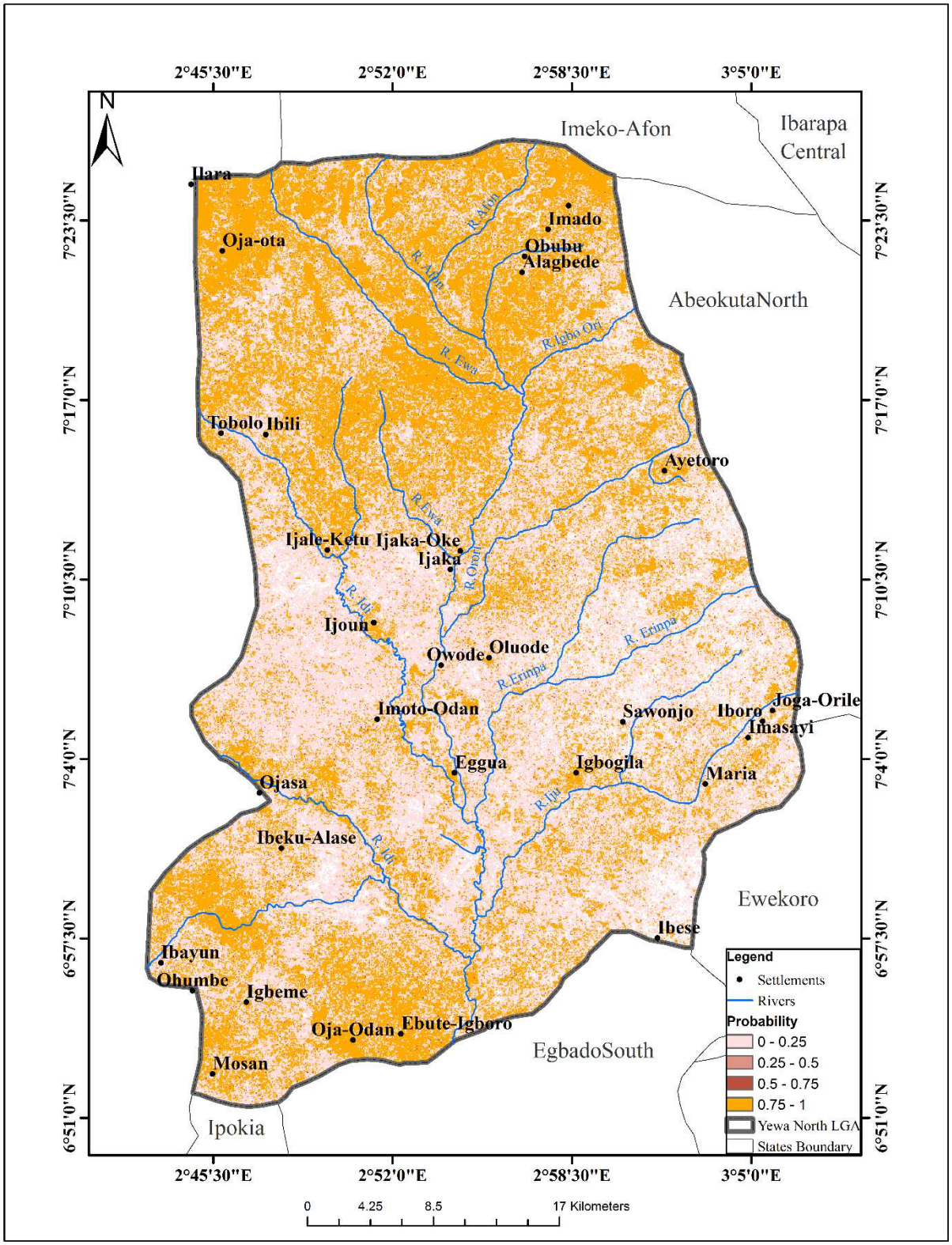

Fig. 2: Predictive Risk Map of *Bulinus jouseaumei* Habitat

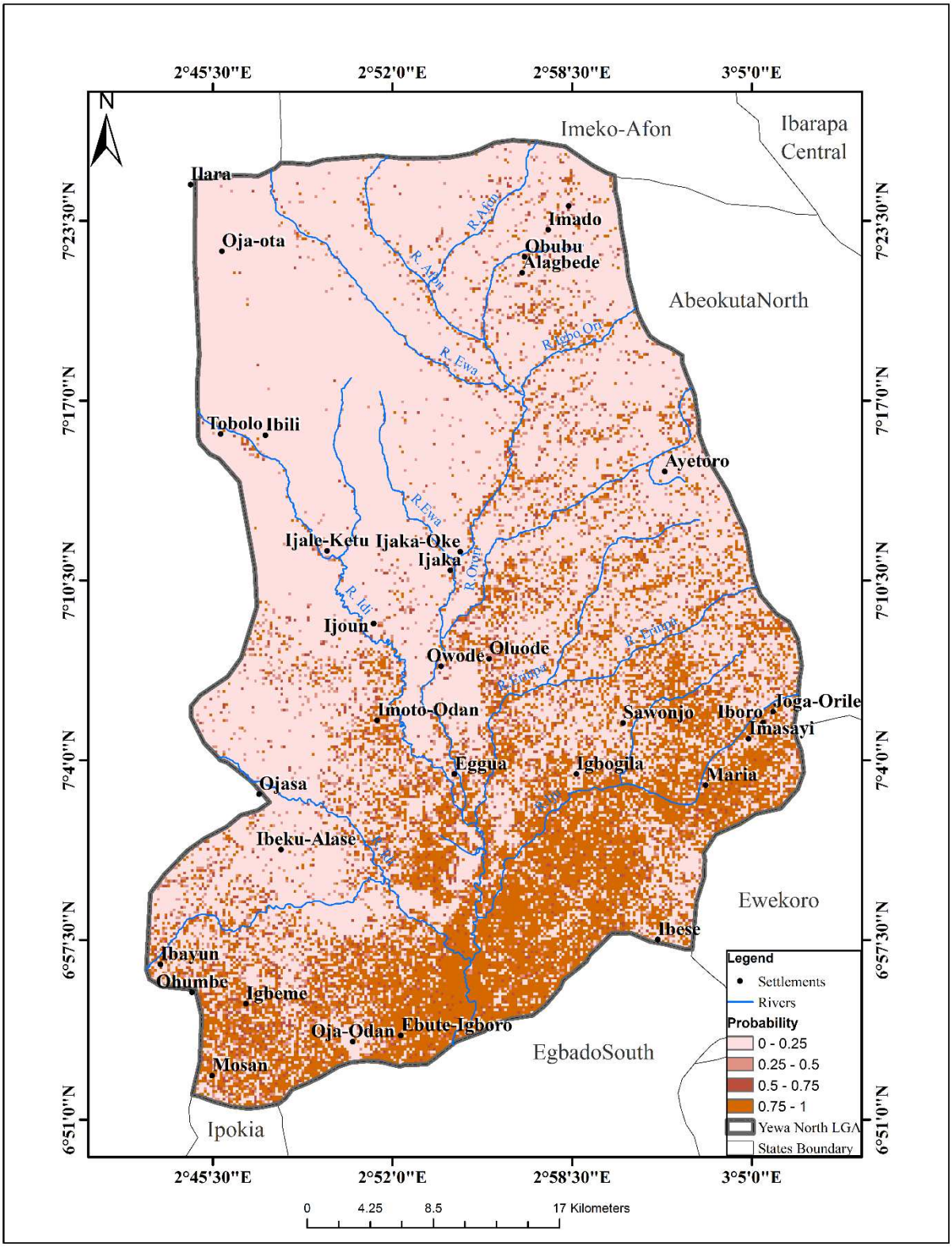

Fig. 3: Predictive Risk Map of *Bulinus senegalensis* Habitat

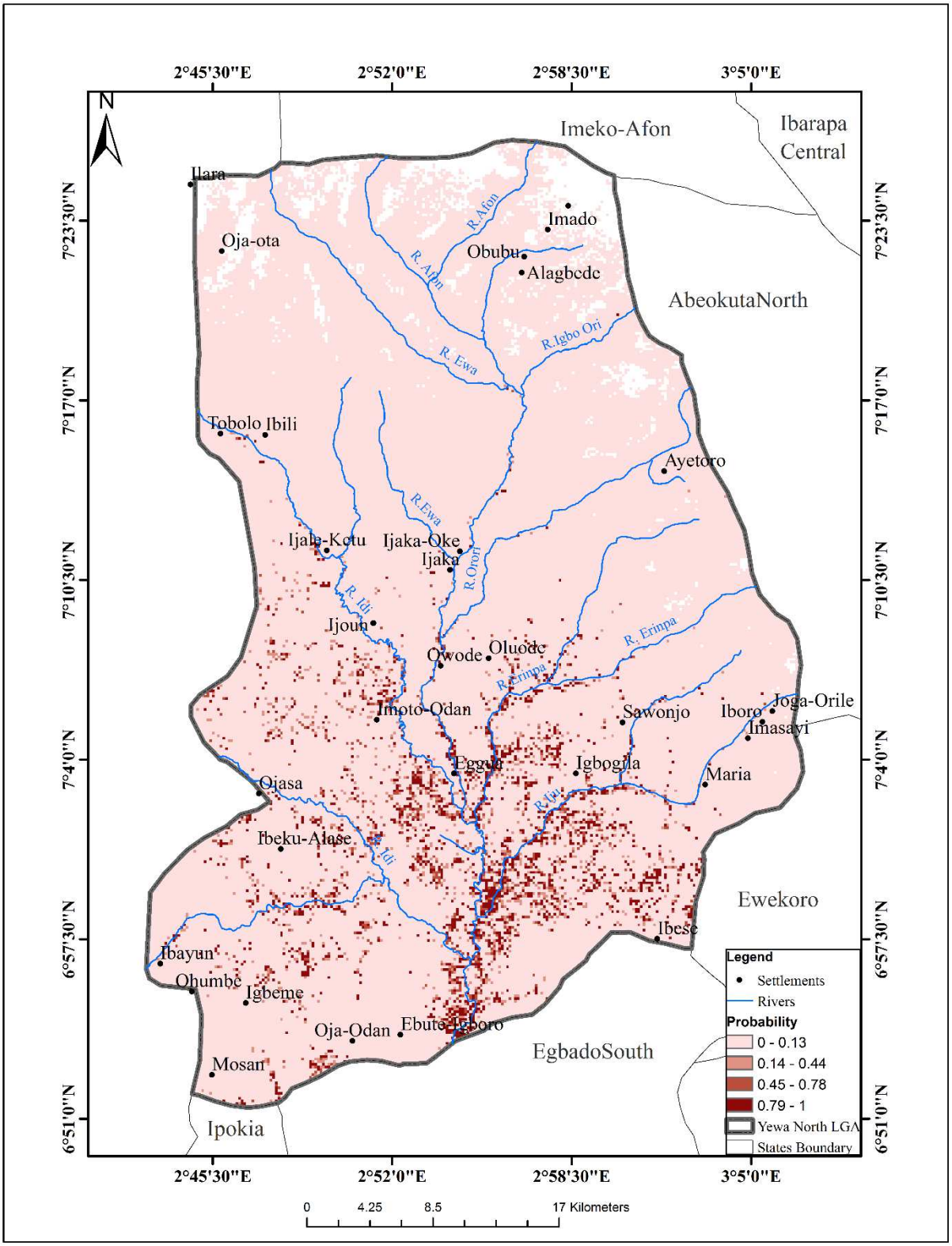

Fig. 4: Predictive Risk Map of *Bulinus camerunensis* Habitat

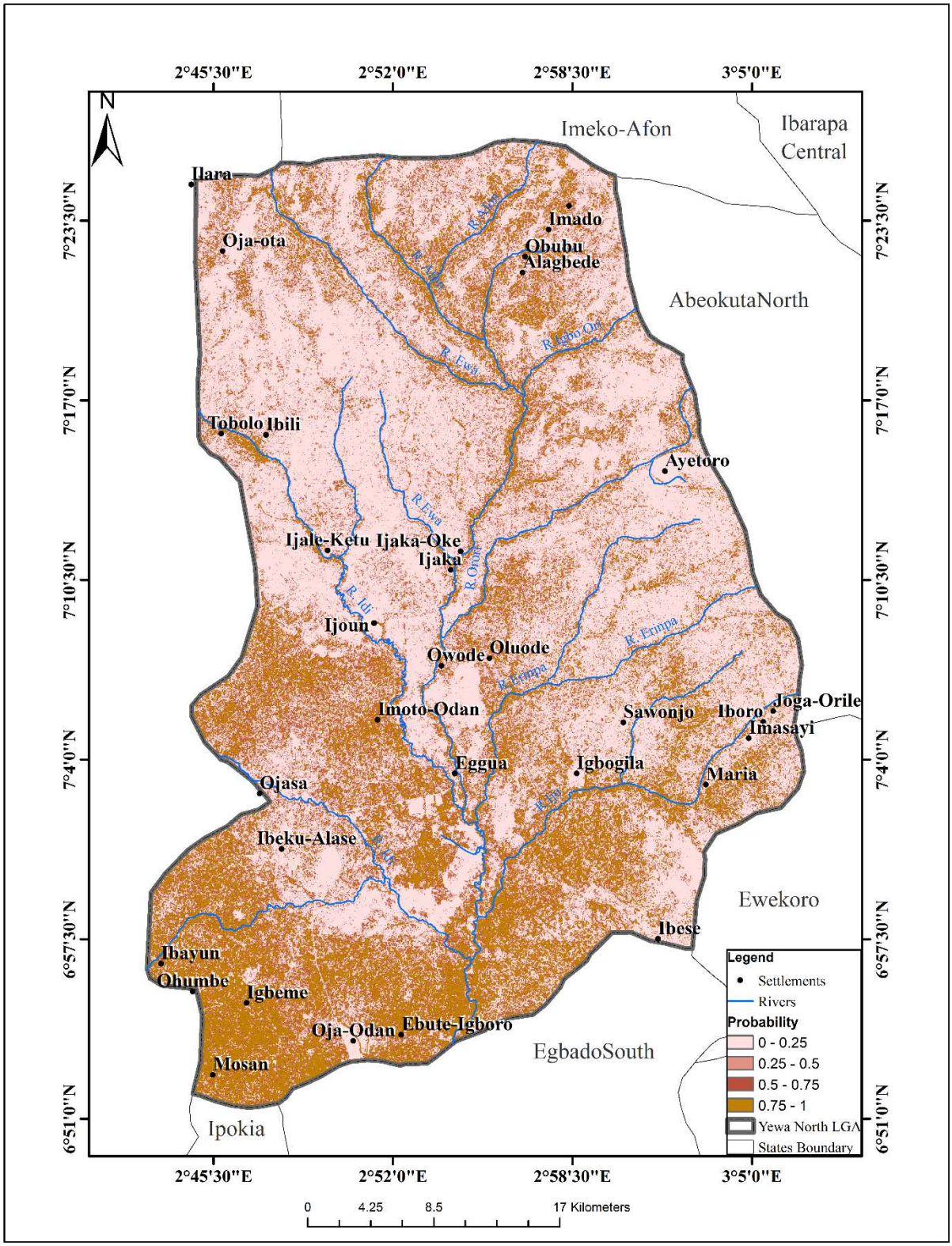

Fig. 5: Predictive Risk Map of *Bulinus forskalii* Habitat

Discussion

Our study used the knowledge of GIS technology and dependent variables to create a model which will be useful in monitoring the survival of snail intermediate host in areas where data collection could be problematic. The application of GIS and remote sensing in science based study is of tremendous importance in disease mapping and prediction, most especially in non-sampled areas (31). The use of GIS/RS have been successfully used for predictions in some parts of African countries (32, 33,34, 35). Our study found that a larger percentage of the study area had NDVI of between 0.19 and 0.52, indicating the presence of vegetation cover and human activities. The negative association observed between the NDVI and most of the bulinids was in deviance with other studies conducted in Brazil and China (36-38), however, it was in consonance with other observations elsewhere (39). The negative relationship suggests that there is a gradual increase in anthropogenic activities in these areas. Vegetation and humidity are important environmental parameters for snail intermediate hosts prediction. NDVI is an important vegetation index and has been used in predicting the habitat of freshwater snail intermediate host of schistosomes in different ecological zones (34, 40, 41). At meso-scale, such as village survey, a moderate NDVI and high wetness could increase the survival of snail intermediate host in an area while a low NDVI values indicate the absence of water, and thus a lower probability of suitable snail habitats suitable snail habitats (37, 42, 43). For macro-scale such as country survey, a higher NDVI values indicate a relatively higher vegetation cover, possibly increasing the probability of potential snail intermediate host habitats (37).

The spatial rainfall data for the study area was within limits; hence, it appeared favourable for the survival of freshwater snail intermediate host. The positive correlation between spatial rainfall data and most of the snail intermediate host was in agreement with other study in Cross River State (44). Rainfall is one of the major climatic conditions that influence the distribution and abundance of snails and the rate of schistosomal development in the snail hosts (45, 46). In our study, the optimum LST suitable for snail intermediate host to thrive very well is between 21.1ºC and 23.4ºC, other LST above 23.5ºC seems to be lethal to intermediate snail hosts. The significant positive relationship between LST and some of the bulinids was in deviance to other studies (38). However, in Tanzania, no significant relationship occurred between LST and snail population (39). Freshwater snail intermediate host of schistosomes have well defined land surface temperature for optimal development. Land Surface Temperature was one of the determinant factors that affect the

transmission dynamics of schistosome infection; it is known to influence the rate of miracidia penetration, shedding of cercaria and the length of the pre-patent infection period (47). A study in Ethiopia showed that satellite derived LSTs of 20-33^{0}C values were able to define the distribution of *schistosoma* prevalence (35). However, in Uganda, by contrast, no association was observed between the prevalence of schistosomes and LST (32).

Apart from the northern part of the study area, elevation values were within the tolerance range for snail species to survive. Landscape pattern analysis can provide indications whether an area offers suitable habitats for snail intermediate host to survive. Repeated analyses and inference from comparable settings might also enable prediction of changes in the snail population resulting from ecologic transformation caused by human activities (48, 49) or deliberate targeted interventions for snail control. From our study, slope ≤4.75 enhances the survival of snail intermediate host while slope ≥15.83 may not provide a suitable habitat for snail intermediate host. The positive association that occurred between slope and most of the bulinid was in consonance with some findings in eastern Africa (37, 50). Low/flat areas had a positive effect with respect to risk of *schistosoma* infection in China (37). In another study, inhabitants of a village situated on steep slopes were at a lower risk of *schistosoma* infection compared to people living in plain areas, this was due to the fact that the plain areas were more economically advanced, and most people were attracted to those areas (51). Water bodies found in high sloppy areas are often characterized with high water flow velocity, which does not hold the water, and the fast flow could be too fast for intermediate host to maintain their existence in such areas. Therefore, the possibility for freshwater snail to colonize and survive in such area decreases as the slope increases (52).

The following bulinids (*B. senegalensis, B. camerunensis and B. forskalii*) had higher probability of surviving in meddle belt and southern part of the study area. These three bulinids belong to the forskalii group and observation from the environmental variables which contributed to their habitat prediction, in different combination, could be as a result of the tolerance level of the environmental variables (LST, spatial rainfall, NDVI, slope and elevation). LST did not contribute to the building model for *B. forskalii* and *B. senegalensis*, indicating their low tolerance for high LST. The predictive risk model for *B. jousseaumei* was similar to the pattern described for *B. globosus*. This could be because the two species are sympatric. The following environmental factors (LST, NDVI and slope) were part of the building model for *B. globosus* and *B. jousseaumei*. Like *B.*

camerunensis, the ability of LST to form part of the building model for *B. globosus* and *B. jousseaumei*, could be as result of the ability of the two species to adapt to high LST. In Nigeria, bulinid species in forskalii group and *B. jousseaumei* are not widely reported, however, *B. globosus* is cosmopolitan in every areas where *Schistosoma haematobium* is prevalent. The ability of *B. globosus* to survive in some areas in our present study could be traced to long term adaptation of the species to different ecological zones, however, the species were not found in higher elevated areas (>250). In conclusion, this study provides a more appropriate approach to identifying a combination of environmental variables in modeling the habitat suitable for the survival of bulinid species. Hence, our predictive risk map could serve as a guide for effective utilization of scares resources in the control of schistosomiasis. Lack of advance satellite imagery for this study is one of our major limitation. Availability of imagery such as GeoEye and WorldView will give more detailed data for better analysis

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Author's contributions

OAB conceived the idea; OGO carried out the sampling procedure, literature review and drafted the first version of the paper. Both authors read, contributed and approved the paper.

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Ethics approval and consent to participate

We obtained an approval to carry out this study from Ogun State ministry of health. We also got an approval from the village heads via thorough focus group discussion.

Consent for publication

Not applicable.

Competing interest

The authors declare that they have no competing interests.

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Figures

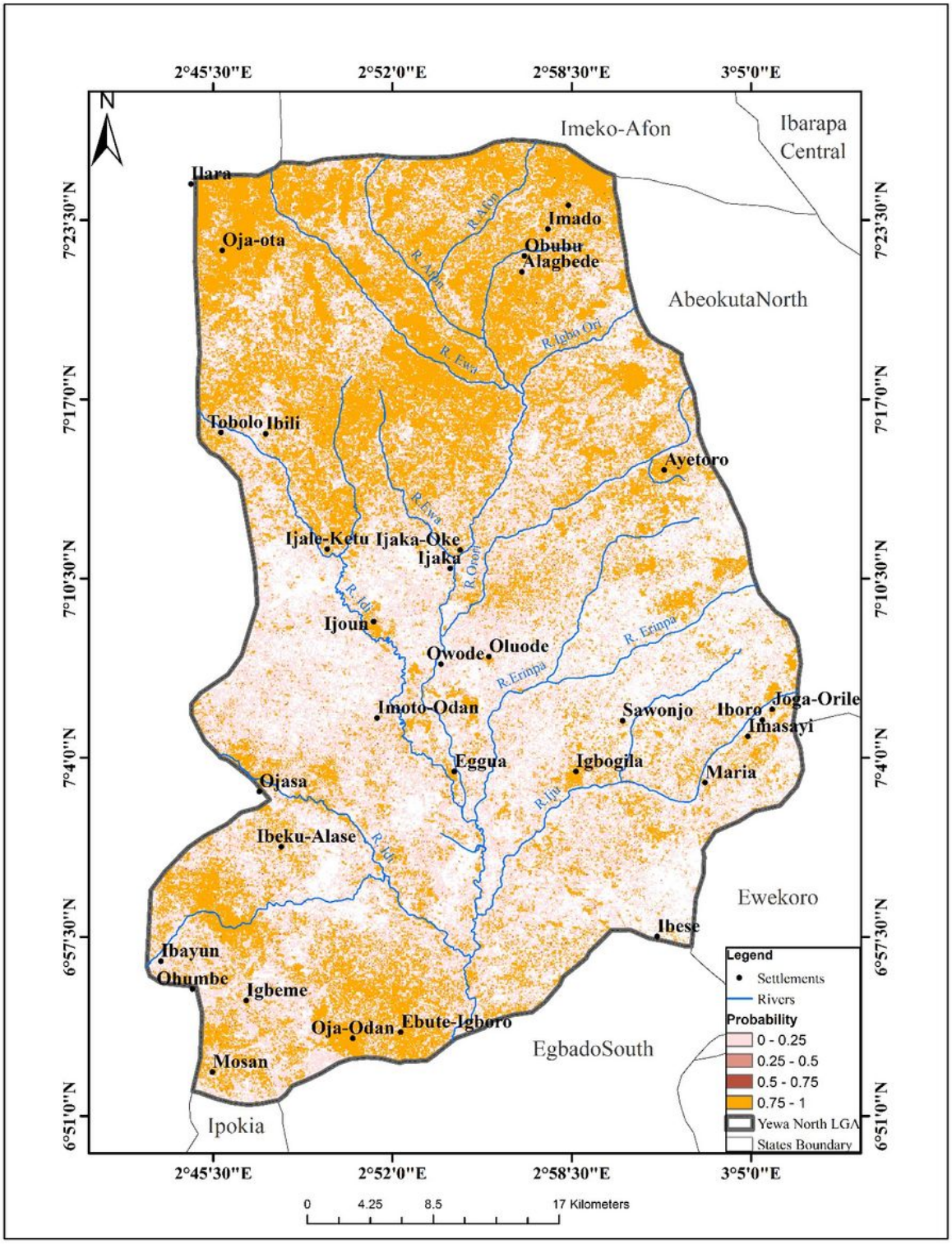

Figure 1

Predictive Risk Map of Bulinus globosus Habitat

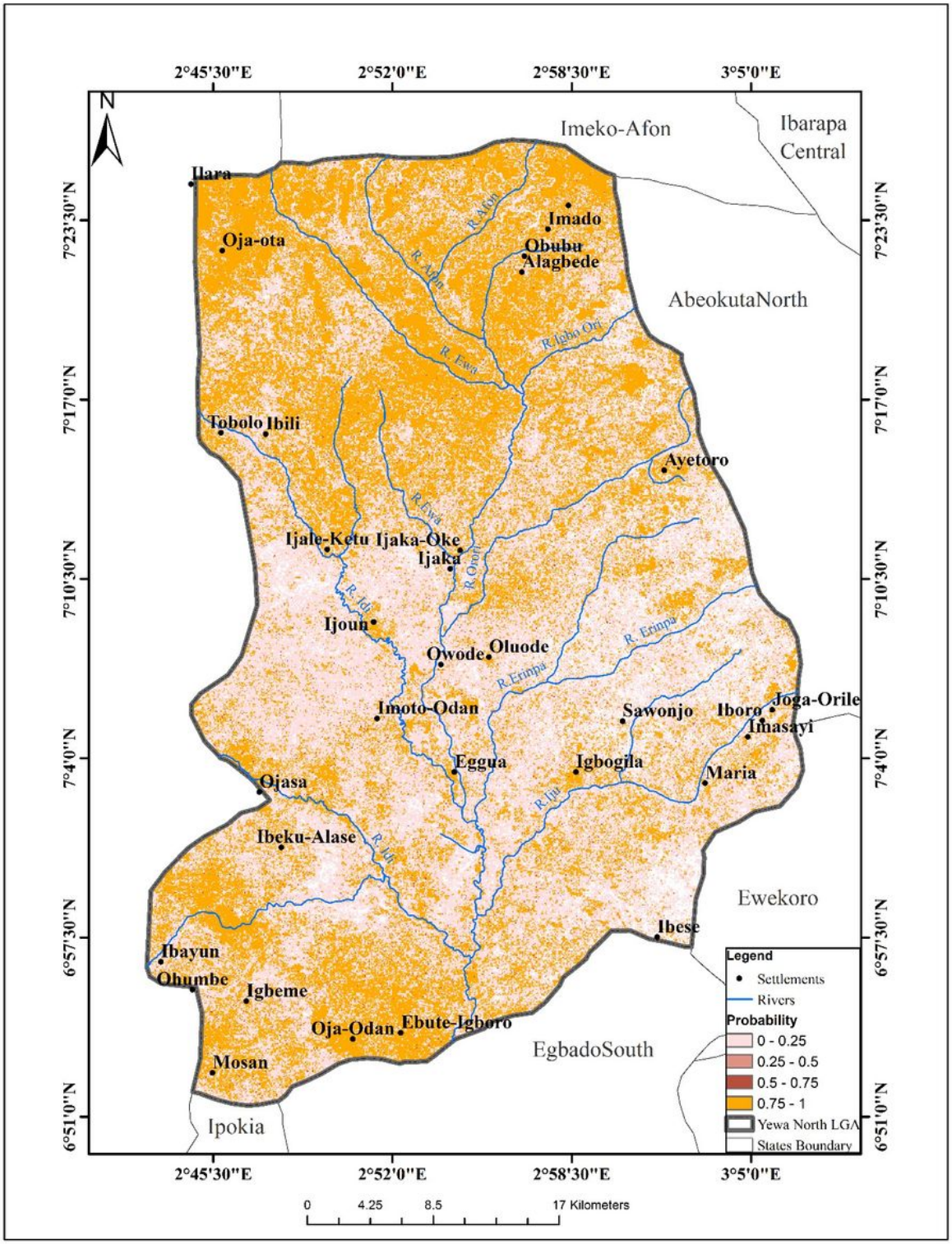

Figure 2

Predictive Risk Map of Bulinus jouseaumei Habitat

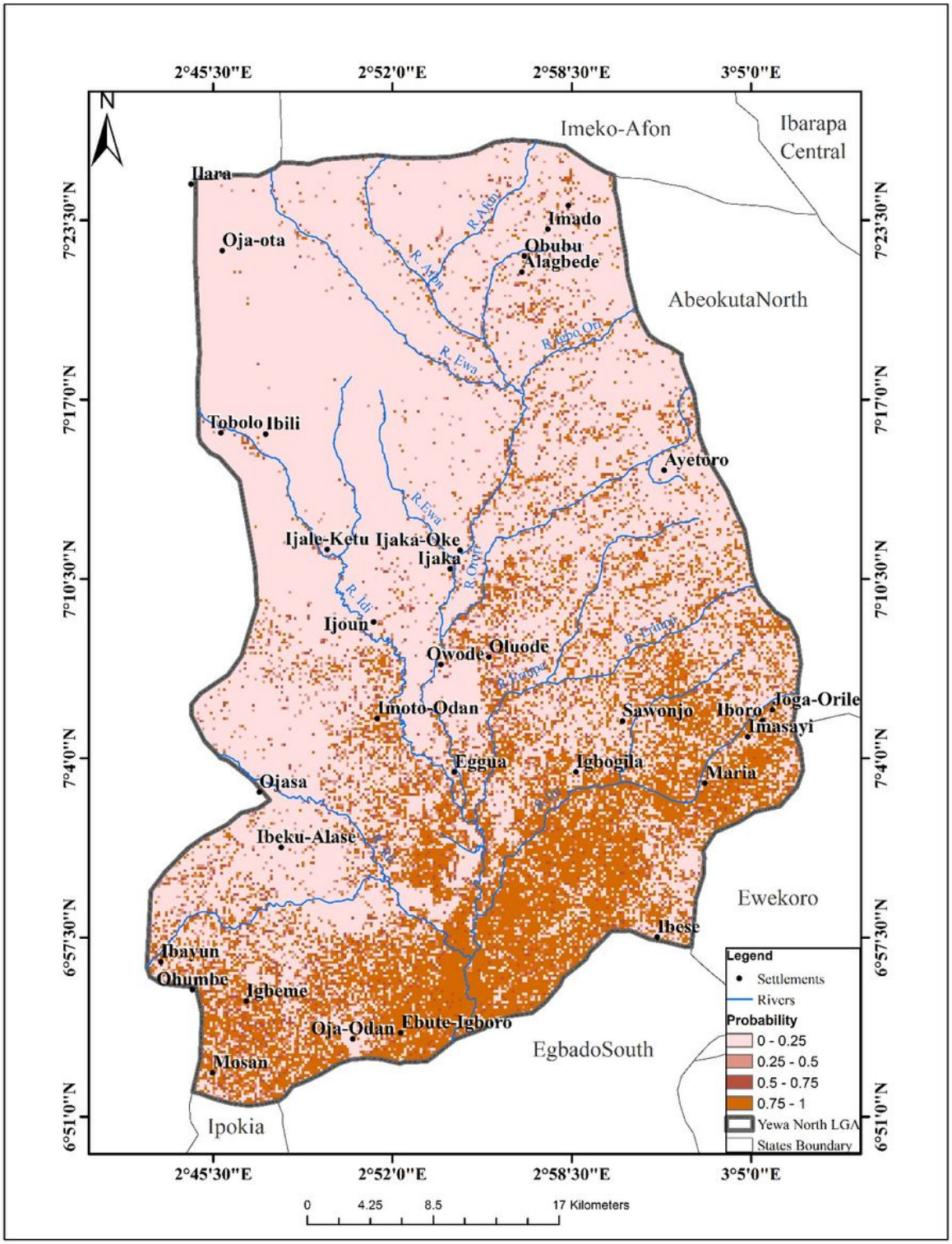

Figure 3

Predictive Risk Map of Bulinus senegalensis Habitat

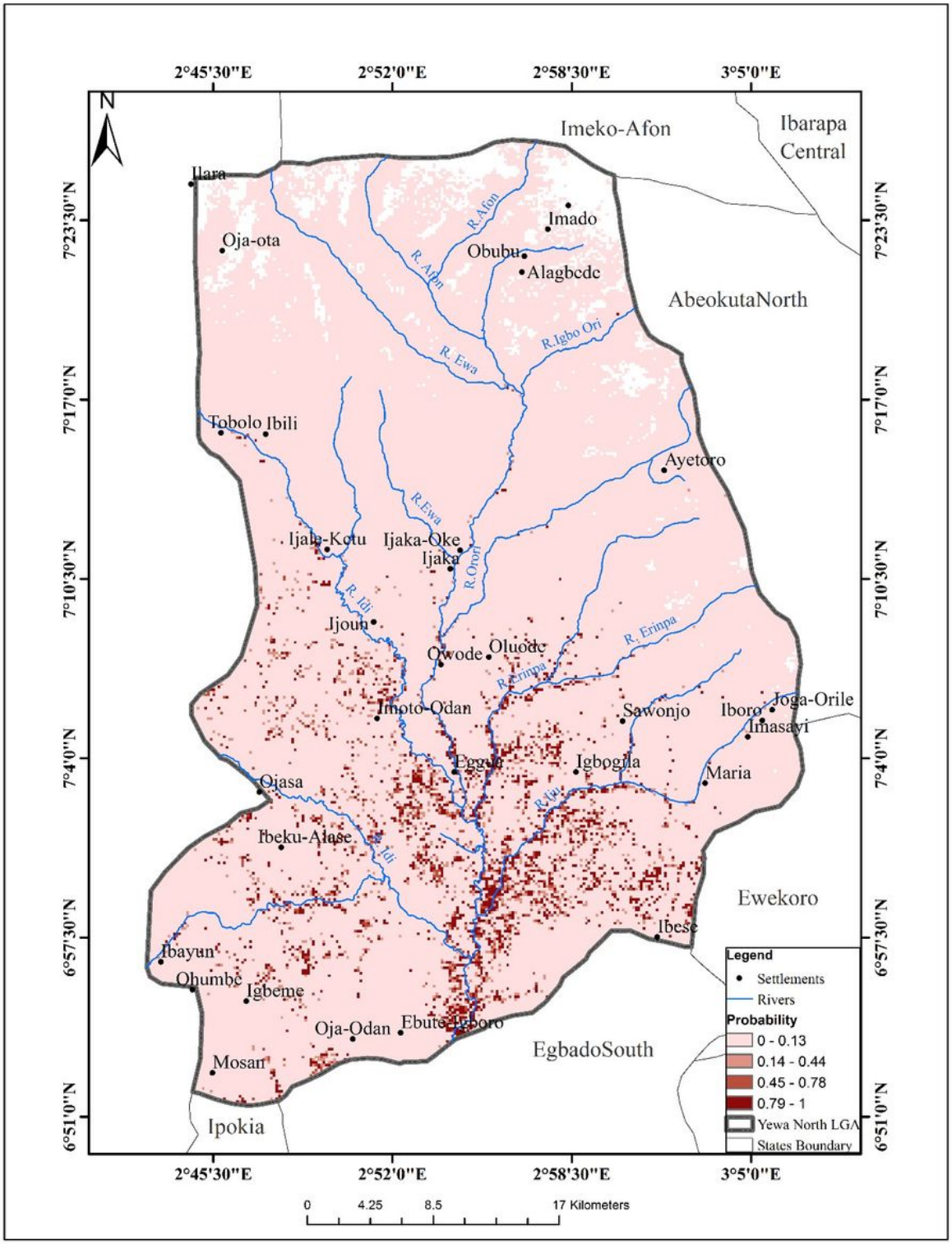

Figure 4

Predictive Risk Map of Bulinus camerunensis Habitat

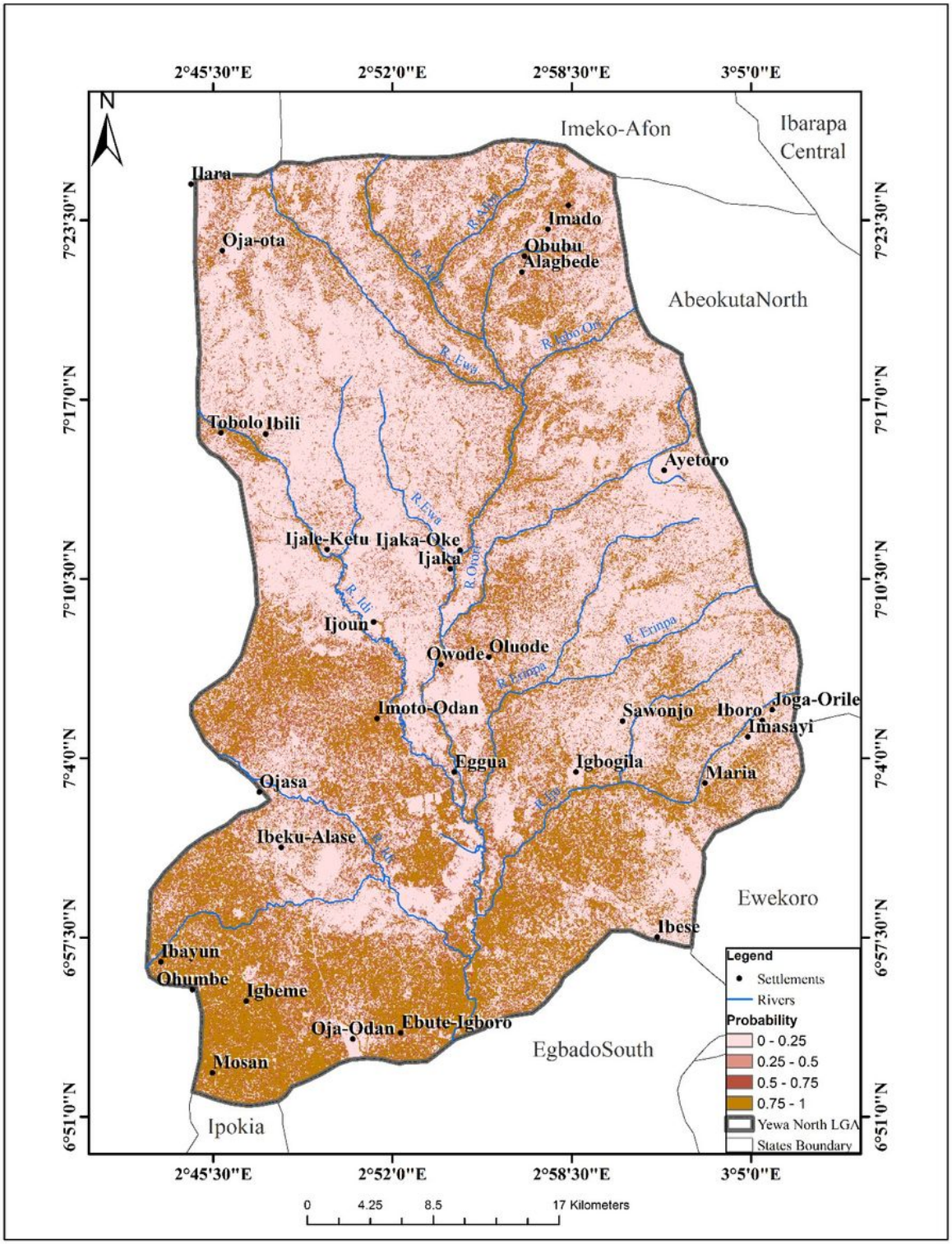

Figure 5

Predictive Risk Map of Bulinus forskalii Habitat