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Rice Fields as Mosquito Density Indicators for Malaria Prediction in Nigeria: An Anthropological View

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ABSTRACT

The World Health Organization (WHO) identifies high-risk areas for disease outbreaks in African countries (WHO, 2019a). Sub-Saharan Africa, including Kebbi state in Nigeria, is particularly susceptible to vector-borne diseases (WHO, 2019a). Malaria is a significant health concern in Kebbi state, where rice fields serve as breeding sites for mosquitoes (CDC, 2020). This paper proposes an early warning system that utilizes satellite imagery and household data to predict mosquito populations in Kebbi State. Integrating machine learning and satellite imagery can inform disease control strategies and public health interventions. Additionally, this approach presents opportunities for anthropological research into the political aspects of malaria and rice farming in Kebbi state, Nigeria. Anthropologists can analyse the socio-political and economic factors influencing malaria persistence while considering the perspectives of local communities. Understanding the intricate relationships between farmers, mosquitoes, and public health officials can contribute to the development of more effective and equitable malaria control strategies. The poverty rate of approximately 72.0% in Kebbi state further complicates healthcare accessibility (Nigeria Health Watch, 2021). By focusing on this region and employing a multidisciplinary approach, this paper aims to address the urgent health challenges and support sustainable solutions for malaria prevention in Kebbi state, Nigeria.

Introduction

The World Health Organization (WHO) has determined that tropical and subtropical areas in poorer African countries are at the highest risk for disease outbreaks (WHO, 2019a). Such outbreaks have resulted in numerous fatalities and have overwhelmed healthcare systems. Sub-Saharan Africa is a key focus area for the solution proposed in this paper, as the transmission of vector-borne diseases is most prevalent in this region (WHO, 2019a). According to the WHO, there have been approximately 200 million cases of malaria in the African region, accounting for a staggering 92% of all global cases (WHO, 2019b).

Kebbi state, located in northwest Nigeria, is the largest rice-producing state in the country, with rice being a staple food and a major crop (Federal Ministry of Agriculture and Rural Development, 2017). The state has experienced significant growth in the rice production industry in recent years due to government initiatives (National Bureau of Statistics, 2019). However, the state is also one of the poorest in Nigeria, with a high poverty rate of approximately 72.0%, which affects the population's access to basic needs, including healthcare (Nigeria Health Watch, 2021). Malaria is a major health challenge in Kebbi state, with transmission being highest during the rainy season when there is an increase in mosquito breeding sites, one of the most notable of these sites being rice fields (Centers for Disease Control and Prevention, 2020). The proximity of rice farms to human settlements poses a challenge to malaria control efforts (Oyinbo et al, 2020). Developing an early warning system for vector-borne diseases will create an adaptive system to protect individuals from health threats. This proposed model leverages satellite imagery and household data to predict the growth of mosquito populations in Kebbi State.

The integration of machine learning techniques and satellite imagery to predict mosquito populations and disease spread has implications for disease control strategies and public health interventions. However, it also offers opportunities for the anthropological study of the politics of malaria and rice farming in Kebbi state, Nigeria. Anthropologists can use this technology to identify areas with high mosquito density and explore the social, political, and economic factors that contribute to the persistence of malaria in these areas. By gaining a better understanding of the complex relationships between farmers, mosquitoes, and public health officials, anthropologists can contribute to the development of more effective and equitable malaria control strategies that consider the lived experiences and perspectives of local communities.

Ethical Considerations

This paper adheres to the ethical guidelines for research as stipulated by the American Anthropological Association's Principles of Professional Responsibility (https://www.americananthro.org/ethics-and-methods).
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It should be noted that the use of the term "poverty" in this study is a contentious and subjective decision that may not align with the self-identification of the research participants. The author acknowledges this limitation and strives to use language that is respectful and sensitive to the experiences of the individuals and communities under investigation.

Data Selection

Located in northwest Nigeria, Kebbi state is referred to as the "Rice Bowl" of Nigeria due to its high level of rice production. Rice is a staple food in Nigeria and the second-most-consumed cereal after maize. The rice production industry in Kebbi state has experienced significant growth in recent years due to the government's promotion of the sector through various initiatives (Kebbi State Agricultural Development Programme, 2021). Kebbi state is considered one of Nigeria's poorest states, with a poverty rate of approximately 72.0% based on a 2019 report by the National Bureau of Statistics (2017). This means that most of the population in Kebbi state lives below the poverty line and struggles to access basic needs such as food, shelter, and healthcare.

According to the Kebbi State Agricultural Development Programme (ADP), the state has a total land area of about 3.6 million hectares, out of which about 75% is arable. The state is blessed with fertile soil and has two major rivers, the Niger and the Rima, which provide irrigation for rice farming. As a result, rice is the major crop produced in the state, with about 2.5 million metric tons produced annually (Kebbi State Agricultural Development Programme, 2021).

One notable initiative that has contributed to the growth of the rice production industry in Kebbi state is the Anchor Borrowers Programme (ABP) of the Central Bank of Nigeria (CBN). The ABP provides farmers with access to credit to purchase agricultural inputs such as seeds, fertilisers, and pesticides. The program has helped to boost rice production in the state by providing farmers with the resources needed to increase their yields and income (Federal Ministry of Agriculture and Rural Development, 2021).

There is a link between rice production and malaria in Kebbi state, as the rice farms and surrounding communities provide a suitable habitat for malaria-transmitting mosquitoes. According to the Kebbi State Malaria Elimination Programme, malaria is a major health challenge in the state, with the disease accounting for a significant proportion of morbidity and mortality (Kebbi State Malaria Elimination Programme, 2022). The transmission of malaria in Kebbi state is highest during the rainy season when there is an increase in mosquito breeding sites, including rice fields.

The Kebbi State government, in collaboration with the National Malaria Elimination Programme and other partners, has implemented several malaria control measures, including the distribution of insecticide-treated bed nets, the use of indoor residual spraying, and the provision of malaria treatment services (World Health Organization, 2021). However, the proximity of rice farms to human settlements poses a challenge to malaria control efforts. The stagnant water in the rice fields provides a breeding ground for mosquitoes, and farmers who work in the fields are at risk of being bitten by malaria-infected mosquitoes. Additionally, the use of insecticides in rice farming may lead to the development of insecticide-resistant mosquitoes, further complicating malaria control efforts.

Therefore, it is important for malaria control efforts in Kebbi state to consider the link between rice production and malaria transmission. Control measures should be targeted at both the farms and surrounding communities to reduce the breeding sites for mosquitoes and protect the health of farmers and residents. Implementing integrated pest management practices, such as using biological control methods to manage pest populations, could help reduce the use of insecticides in rice farming and minimise the development of insecticide-resistant mosquitoes. Also, education programs that raise awareness of the link between rice farming and malaria transmission could encourage farmers and communities to adopt practices that reduce the risk of malaria transmission while maintaining high yields of rice.

Program Design

To establish a link accurately and efficiently between rice production and mosquito density in areas of sub-Saharan Africa, three crucial datasets are required. The first is a dataset of historical mosquito outbreaks provided by Kyalo in the geo-encoded inventory. This inventory provides information on the mosquito density of a particular area. Locations maintained in the inventory have high mosquito densities, while there is no information available on the mosquito density in the areas not included. These geo-encoded mosquito density locations are obtained through manual data collection and a thorough examination of past literature.

The second crucial dataset is the satellite imagery across sub-Saharan Africa. The Google Earth Engine portal is utilised to obtain satellite data at scale. Relevant image scaling and processing techniques are applied in the conversion of LandSat data to RGB image data files. Satellite images are obtained for each of the geo-encoded locations with high mosquito density in Kebbi State, Nigeria. This yields a total of 25 samples. An equivalent number of locations with low mosquito density are selected at random from Kebbi State, Nigeria, to yield a total of 50 satellite images in the training dataset.

The third crucial dataset is the land cover information of the 50 collected satellite images. Since land cover information was not readily available for many areas in Kebbi state, a state-of-the-art machine learning model for land cover classification was employed. The ResNet50 architecture was used and trained on the largest available satellite data land cover classification dataset, EuroSat. After training the model, it was evaluated on the satellite data from Kebbi State, Nigeria to yield land cover classes for final training data. Ultimately, the dataset was constructed with information on latitude, longitude, land cover, and mosquito density. A model was then trained to predict mosquito population density from these compiled features.

Data Processing

Satellite Image Pre-processing

Since this research is concerned with LandSat data, several pre-processing techniques are required when obtaining the data through the Google Earth engine. These techniques include atmospheric correction to remove haze, clouds, and other atmospheric artifacts, and radiometric calibration to ensure the data is comparable across different dates and sensors. Additionally, the appropriate image scale and resolution must be selected to provide sufficient detail while minimising computational complexity. The right bands (e.g., red, green, and blue) are chosen for analysis, as these bands typically provide useful information about land cover and land use. After pre-processing, the LandSat TIFF files are converted into RGB images using the selected bands.

Land Cover Data Processing

The land cover data is processed by generating relevant one-hot encoded vectors to represent the class that each satellite geolocation takes on. This encoding method allows for efficient representation and processing of the categorical land cover data in the machine learning model. The three dominant land covers of this dataset include *AnnualCrop*, *HerbaceousVegetation*, and *PermanentCrop*.

- AnnualCrop: This label refers to areas where crops are grown on an annual basis. These crops are typically planted, grown, and harvested within the same year. Examples of annual crops include rice, wheat, maize, and various other grains, as well as some vegetables and legumes.
- HerbaceousVegetation: This label represents areas covered by non-woody vegetation, consisting of grasses, sedges, forbs, and other herbaceous plants. These regions often include natural grasslands, meadows, and pastures, as well as some cultivated lands where herbaceous plants are the primary form of vegetation.
- PermanentCrop: This label refers to areas where crops are grown on a perennial basis, meaning that the plants continue to grow and produce for more than one year without needing to be replanted. Examples of permanent crops include fruit trees, such as citrus, apple, and mango, as well as vineyards, coffee, and cocoa plantations.

Data Labelling

In preparation for the machine learning model, the data is labelled as follows: locations with a high density of mosquitoes and locations with a low density of mosquitoes. The prediction task involves determining the likelihood of mosquito outbreaks effectively and accurately in a particular location, given data on geolocation, land cover, land use, and indirectly, rice field locations. Land cover is used as a proxy for rice field locations, as the presence of specific land cover types, such as AnnualCrop or PermanentCrop, can indicate the presence of rice fields. This labelling process is critical to ensure that the model is effectively trained to predict the growth of mosquito populations and disease spread in Kebbi State, Northern Nigeria.

By carefully processing the data, the machine learning model can more accurately predict mosquito density and potential disease outbreaks. This data processing step plays a crucial role in the overall success of the early warning system, ensuring that the model is effective in predicting disease outbreaks and ready to be deployed in sub-Saharan Africa.

Results

Preliminary results show that land cover and land use serve as meaningful predictors of mosquito density, with land cover acting as a direct proxy for rice field location. Rice fields are known to create ideal breeding grounds for mosquitoes due to the presence of stagnant water, which is necessary for mosquito larvae development. Therefore, identifying rice fields in a region is crucial for determining mosquito density and potential disease spread.

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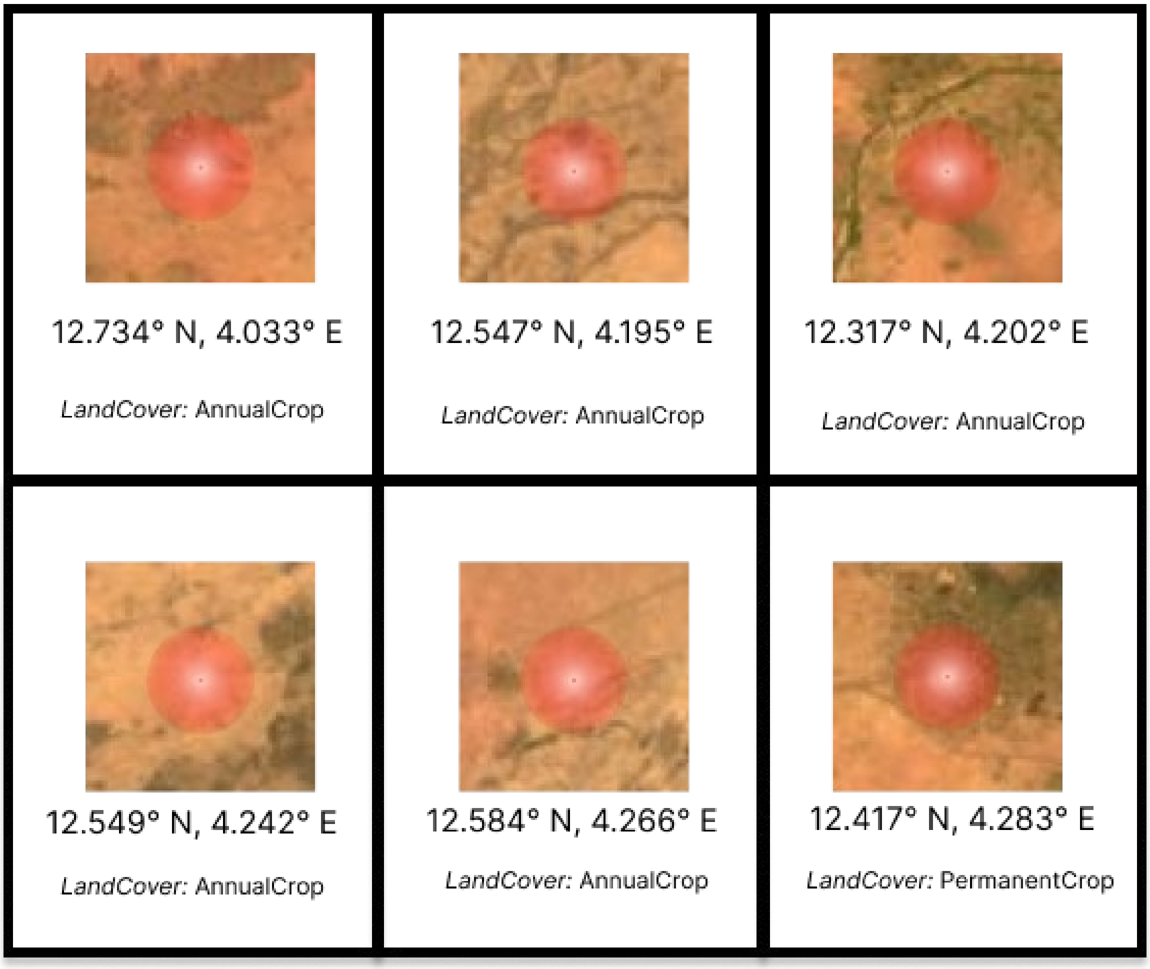
High Mosquito Density Locations



A K Nearest Neighbors Classifier (KNN) model was employed for this analysis. This model was chosen due to its simplicity and effectiveness in handling multidimensional data, such as the geolocation, land cover, and land use information used in this study.

The KNN model was able to ascertain with 70% accuracy the existence of high mosquito densities in a region of Kebbi State, as indicated by the satellite image. This suggests that the model was able to effectively capture the relationship between the geographic features, specifically rice fields, and mosquito density, providing a reliable tool for predicting mosquito populations and disease spread.

By using land cover data as a proxy for rice field locations, the machine learning model was able to identify areas with a high likelihood of mosquito breeding. This is particularly important because rice fields are the greatest indicator of mosquito density in many regions. Therefore, the ability to accurately identify rice fields and their association with mosquito populations can provide valuable insights for targeted disease control strategies and vector management efforts.

Since the land cover model was devised and evaluated specifically on Nigeria satellite imagery, it performed well in labeling the land cover classes, especially in identifying rice fields, and served effectively in predicting mosquito density. The successful integration of the land cover model with the KNN classifier demonstrates the potential for using machine learning models to effectively identify and predict the growth of mosquito populations and disease spread in different regions, providing valuable insights into disease control strategies.

Discussion

The preliminary results of this study demonstrate the potential for using machine learning models to identify and predict the growth of mosquito populations and disease spread in sub-Saharan Africa and beyond. By integrating multiple data sources, such as geo-encoded mosquito density information, satellite imagery, and land cover classifications, the model has shown promising performance in predicting mosquito density.

The 70% accuracy achieved by the machine learning model in predicting high mosquito densities for Kebbi State, Nigeria, suggests that land cover and land use are meaningful predictors of mosquito density. Furthermore, the success of the land cover model in labelling land cover classes indicates that machine learning can effectively classify complex geographic features, providing valuable insights into disease control strategies.

This study also highlights the importance of utilising high-quality and relevant data sources in the development of machine-learning models for predicting mosquito populations and disease spread. The use of a state-of-the-art machine learning model, ResNet50, in combination with the EuroSat dataset, allowed for accurate land cover classification, which served as a critical component of the final prediction model.

It is important to consider potential limitations and areas for improvement in this research. The model's accuracy could be further enhanced by incorporating additional datasets or features, vegetation indices, or socio-economic factors that may influence mosquito density. Additionally, the model could be tested on a broader geographic area or across multiple regions to evaluate its generalisability and performance in various contexts.

Policy Review

This study has utilised a machine learning model to identify areas with high mosquito density in Kebbi State, Nigeria. It is shown that both land cover and land use are meaningful predictors of mosquito density, and the successful integration of the land cover model with the KNN classifier demonstrates the potential for using machine learning models to effectively identify and predict the growth of mosquito populations and disease spread in different regions, providing valuable insights into disease control strategies.

The link between rice production and malaria in Kebbi state highlights the need for integrated approaches to address health and environmental issues. It is important to consider the power dynamics and social structures that shape the interactions between the actors involved in rice farming and malaria control measures. The government's promotion of the rice production industry in Kebbi state has created employment opportunities and contributed to the region's economic growth, but the high poverty rate in Kebbi state also highlights the challenges facing the local population, many of whom struggle to access basic needs such as food and healthcare. A policy review is therefore needed to examine how policies can be amended or improved to address the link between rice farming and malaria transmission when implementing malaria control measures in Kebbi state. Integrated approaches should be considered to address health and environmental issues, as well as socio-economic factors that may influence mosquito density.

Rice farming in Kebbi state is driven by the state government's promotion of the sector through various initiatives, including the Kebbi State Agricultural Development Programme (ADP) (Olanrewaju & Babatunde, 2015). These initiatives provide farmers with support in the form of improved seed varieties, fertiliser, and irrigation facilities. However, the success of these initiatives depends on the ability of farmers to manage their crops and protect their health while working in the rice fields. This means that farmers must navigate a complex web of social and political relationships in order to thrive in the industry.

The link between rice production and malaria transmission in Kebbi state highlights the interconnectedness of human and environmental health (Oyawoye, 2017). Malaria is a major health challenge in the state, with the disease accounting for a significant proportion of morbidity and mortality. The stagnant water in the rice fields provides a breeding ground for mosquitoes, and farmers who work in the fields are at risk of being bitten by malaria-infected mosquitoes. This puts the health of farmers at risk and can have broader implications for the productivity of the rice industry and the economic well-being of the state.

The politics of control measures aimed at reducing the transmission of malaria in Kebbi state reveal the complexities of public health interventions. The Kebbi State government, in collaboration with the National Malaria Elimination Programme and other partners, has implemented several malaria control measures, including the distribution of insecticide-treated bed nets, the use of indoor residual spraying, and the provision of malaria treatment services (Iwuafor et al., 2021). However, these measures face challenges, including the proximity of rice farms to human settlements, which poses a challenge to malaria control efforts. The use of insecticides in rice farming may lead to the development of insecticide-resistant mosquitoes, further complicating malaria control efforts.

One way to mitigate the negative impact of rice farming on malaria rates is through the implementation of integrated pest management (IPM) strategies. IPM is an approach that seeks to control pests, including mosquitoes, using a combination of tactics that are both effective and environmentally sensitive. This approach involves the use of targeted insecticides, biological control agents, and cultural practices, such as the timing of planting and harvesting, to minimise mosquito breeding in rice fields.

Another approach is to encourage the adoption of modern rice farming techniques that reduce the amount of standing water in rice fields. This could include the use of improved irrigation systems that allow for precise water control and the use of rice varieties that require less water. This approach not only reduces mosquito breeding sites but also increases the efficiency of water use and reduces the risk of waterlogging and soil erosion.

Furthermore, the government can collaborate with healthcare providers to implement malaria prevention and control strategies in rice farming communities. This could include the distribution of insecticide-treated bed nets, the provision of free or subsidised malaria treatment, and the establishment of health education programs to raise awareness about the link between rice farming and malaria transmission.

Political theory as a path towards malaria-based policies in Kebbi state

Political theory can provide insights into the power dynamics at play in implementing these policies. For instance, the government may face resistance from rice farmers who are in opposition to changing their traditional farming practices or from agribusinesses that may be resistant to IPM practices that could increase their production costs. The government can overcome these challenges by engaging stakeholders and building coalitions with interest groups, including farmers, agribusinesses, and public health advocates, to create a shared understanding of the benefits of implementing these policies.

Power relations between farmers, government officials, and other actors play a significant role in shaping the distribution of resources, including access to credit and agricultural inputs in Kebbi state, Nigeria (Akudugu & Guo, 2017). The state government, through the Kebbi State Agricultural Development Programme (ADP), provides support to farmers in the form of improved seed varieties, fertiliser, and irrigation facilities. However, access to these resources is not always equitable.

It is important to recognise that power relations are fundamental to the political system of any society. In this context power can be understood as the ability of individuals or groups to influence others or to get what they want (following French and Raven, 1959), and it is often expressed through various forms of persuasion.

One of the key power dynamics in play in the context of Kebbi state can be found in the relationship between the government and the farmers. The government's promotion of the rice production industry through various initiatives such as the Kebbi State Agricultural Development Programme and the Anchor Borrowers Programme has significantly boosted rice production and helped farmers to increase their income. However, this support is not without its challenges, and there is a need for greater accountability and transparency in the distribution of resources and benefits.

Political theorists such as Antonio Gramsci and Michel Foucault have provided useful insights into the workings of power relations in society, which might be usefully applied to these dynamics. Gramsci's concept of hegemony refers to the dominant ideas and values that are accepted as natural or common sense by society, and which serve to maintain the existing power relations. In the case of Kebbi state, the government's promotion of the rice production industry can be seen as an attempt to establish hegemony by presenting rice production as the primary source of economic growth and development in the state. However, this dominant narrative can also mask the underlying power relations and inequalities that exist in the agricultural sector.

Foucault's theory of power, on the other hand, emphasises the ways in which power operates through the control and regulation of knowledge, discourse, and behaviour. In the context of Kebbi state, the identification of rice fields as a key predictor of mosquito density and disease spread highlights the importance of knowledge and information in shaping policies and practices related to public health and environmental management. However, this also raises questions about who has access to this knowledge and how it is used to shape policy decisions.

Furthermore, power relations in Kebbi state are also influenced by factors such as class, ethnicity, and gender. As noted earlier, Kebbi state is considered one of Nigeria's poorest states, with a poverty rate of approximately 72.0%. This suggests that power is concentrated in the hands of a small elite who control access to resources and opportunities, while the majority of the population struggles to meet their basic needs. Moreover, gender disparities in access to resources and decision-making also contribute to power imbalances in the agricultural sector, where women farmers are often marginalised and excluded from key decision-making processes.

Overall, to reduce malaria rates in Kebbi state, it is essential to adopt a multi-sectoral approach that incorporates the agricultural, health, and environmental sectors. This approach can be informed by political theory, which can help to identify the interests and power dynamics of key actors and develop strategies to overcome resistance and build support for effective policy implementation.

Nationalist influences on the Kebbi state rice industry

Nationalist politics have played a significant role in the agricultural development of Kebbi state, particularly in the rice production sector. Nigeria, as a country, has sought to reduce its dependence on rice imports and become self-sufficient in rice production. This has been a major focus of the government's agricultural policies, and Kebbi state, with its fertile soil and abundant water resources, has been identified as a key area for achieving this goal.

In recent history, Kebbi state in particular has been a focus area of rice-based agricultural development projects. For example, in the early 1990s, the International Fund for Agricultural Development (IFAD) provided funding for the Kebbi Rural Development Programme, which aimed to improve agricultural productivity and increase income for rural farmers. This programme focused on rice cultivation, among other crops, and provided training, credit, and infrastructure to farmers.

More recently, the Nigerian government has promoted the development of rice value chains, including processing and marketing, to ensure that rice production is not only increased but also profitable for farmers. The government has also encouraged the private sector to invest in rice production in Kebbi state and other areas.

One example of nationalist politics playing a significant role in the agricultural development of Kebbi state, particularly in the rice production sector, is the promotion of domestic rice production as a means of reducing Nigeria's reliance on imported rice. The Nigerian government, led by President Muhammadu Buhari, has emphasised the need for self-sufficiency in rice production as a way to reduce food imports and promote economic growth (The Guardian, 2016).

This can be viewed through the government's emphasis on promoting "Nigerian rice" as a way to reduce dependence on foreign imports. This has been achieved through the use of slogans such as "eat Nigerian rice" and the branding of locally produced rice with the tagline "Naija Rice". The government has also imposed restrictions on rice imports to protect local producers, including the ban on the importation of rice through Nigeria's land borders in 2019 (Bloomberg, 2019).

Overall, the emphasis on promoting domestic rice production and reducing reliance on imported rice is a clear example of nationalist politics at play in the agricultural development of Kebbi state and Nigeria more broadly. The government's policies and initiatives in the rice production sector are driven by a desire to promote economic growth, reduce imports, and achieve self-sufficiency in food production.

One pertinent anthropological concept to these themes is the idea of "developmentalism," which refers to a set of policies and practices aimed at promoting economic development and modernisation in less-developed countries (Escobar, 1995). In the context of Kebbi State, the promotion of rice production as a means of economic development can be seen as a form of developmentalism.

Developmentalism is often critiqued by anthropologists for its narrow focus on economic growth and its failure to address broader social and cultural issues (Escobar, 1995).

Another relevant anthropological concept is the idea of "political ecology," which examines the intersection of political and economic factors with ecological processes (Bryant & Bailey, 1997). In the context of Kebbi State, political ecology could be used to analyse the ways in which political and economic factors intersect with the ecology of the region to shape agricultural practices and their impact on local communities and ecosystems.

It is difficult to say whether the Kebbi state nationalist agenda would have predicted the outcome of malaria cases rising as it would depend on how they viewed the relationship between their agricultural policies and public health. If they believed that their policies were contributing positively to the overall development of the state and improving the livelihoods of its citizens, they may not have predicted the negative consequences that could arise from increased mosquito breeding and malaria transmission.

However, it is important to note that the link between rice production and malaria transmission is well-established in the literature, and it is possible that policymakers in Kebbi state were aware of this relationship. In this case, it is possible that the nationalist agenda may have prioritised the economic benefits of rice production over the potential negative health consequences,

Conclusion

In conclusion, this study provides promising evidence for the development of early warning systems for vector-borne diseases in sub-Saharan Africa and beyond. The integration of geo-encoded mosquito density information, satellite imagery, and land cover classifications using machine learning techniques has resulted in a model capable of predicting mosquito populations and disease spread with considerable accuracy.

The success of this research offers valuable insights for disease control strategies and has implications for public health interventions. By identifying areas with high mosquito density, policymakers and public health officials can better allocate resources to target mosquito breeding sites and implement vector control measures, ultimately reducing the spread of vector-borne diseases.

Future research should focus on enhancing the model's accuracy and generalisability by incorporating additional data sources and features, as well as testing the model across broader geographic areas. With continued development, this research has the potential to significantly impact the prediction and control of mosquito populations and vector-borne diseases in sub-Saharan Africa and other regions worldwide.

In addition to its implications for disease control strategies and public health interventions, the integration of machine learning techniques and satellite imagery to predict mosquito populations and disease spread can also be useful for the anthropological study of the politics of malaria and rice farming in Kebbi state, Nigeria. Anthropologists can use this technology to identify areas with high mosquito density and explore the social, political, and economic factors that contribute to the persistence of malaria in these areas. By gaining a better understanding of the complex relationships between farmers, mosquitoes, and public health officials, anthropologists can contribute to the development of more effective and equitable malaria control strategies that consider the lived experiences and perspectives of local communities.

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