



Using geospatial analysis to better serve disadvantaged program beneficiaries in low- and middle-income countries

Lessons from an exploratory analysis in Nigeria

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Introduction

Identifying disadvantaged populations and implementing programs specifically for them is key to enhancing health equity (World Health Organization 2018). However, without sufficiently detailed data on target beneficiaries' socioeconomic position (SEP), it is difficult to design programs to reach them—particularly those with lower SEP.¹ Furthermore, data on the distribution of health inequities in low- and middle-income countries often is available only at the national level, and disaggregation of the data at the subnational level is not possible. Although there is national-level evidence suggesting that reproductive and maternal health inequities have decreased over time (Alkenbrack et al. 2015), significant challenges remain in ensuring that inequities *within* countries also decline (Victora et al. 2012; Countdown 2008 Equity Analysis Group 2008). Studies have shown that pro-equity strategies that focus on the most disadvantaged population groups are cost-effective compared to other mainstream approaches to programming (Carrera et al. 2012). Hence, there is a need for innovative approaches that ensure that health programs target disadvantaged populations appropriately to reduce inequities in coverage of high-impact interventions at the subnational level. Geospatial analysis offers opportunities to mitigate challenges with the availability of data on the SEP of program beneficiaries at the subnational level.

Geospatial analysis can reveal patterns of inequities, especially when the analysis layers multiple reliable data sources. One such data source is the Demographic and Health Survey (DHS) modeled surfaces, which interpolate values of DHS household survey indicators (e.g., households with women of reproductive age using an improved water source or without access to a toilet) in unsampled areas, thereby allowing estimation of coverage in smaller areas, such as at a subdistrict level (Burgert-Brucker et al. 2016). Analysts can use these modeled surfaces to understand the underlying characteristics of a geographic area or the relative need for an intervention, which could influence programming (Burgert-Brucker et al. 2016). Other types of geotagged survey data can provide insight on a range of health issues, such as physical access to health facilities or service availability and readiness. Bringing these two types of trusted datasets together offers an opportunity to identify potential patterns of inequities against underlying population characteristics.

¹ Galobardes et al. (2006) refers to socioeconomic position as “the social and economic factors that influence what positions individuals or groups hold within the structure of society.”

With this context in mind, the Maternal and Child Survival Program (MCSP) conducted an exploratory geospatial analysis using multiple geospatial data sources to understand inequities in access to maternal health services in two Nigerian states. The program looked at the relative SEP of the population surrounding MCSP-supported facilities (as measured by a proxy indicator from DHS modeled surfaces for Nigeria). The datasets were DHS spatially modeled surfaces and geotagged facility survey data on multiple indicators, such as availability of emergency obstetric and newborn care (EmONC) services in facilities in Ebonyi and Kogi states. Although the analysis used data from only one country, it sought to answer two broad questions of interest to many low- and middle-income countries:

- How can geospatial analysis help national and international programs identify likely inequities at subnational levels?
- How can geospatial analysis help programs understand whether they are targeting locations in which disadvantaged populations are likely to access services?

Methods

This section describes the data sources and analytical approach that MCSP used to conduct this exploratory analysis. This is an approach that other programs could take in contexts where sufficient data and analytical capabilities are available.

Data Sources

To conduct the analysis, MCSP compiled the following secondary datasets:

1. Geotagged cross-sectional health facility data from a 2016 assessment of 120 health facilities in Kogi and Ebonyi states (Ebener 2016)²;
2. Nationwide DHS spatial (raster) data on SEP proxy variables (e.g., households with improved water source)³; and
3. Census data for pregnant women aggregated at the local government area (LGA) level, which is the administrative level below the state level in Nigeria.⁴

The health facility assessment provided baseline information on the degree of functionality of basic and comprehensive EmONC services at public facilities, classifying each facility as fully functional, partially functional, or not functional for both basic and comprehensive EmONC. The assessment assigned classifications based on facility readiness to provide the standard signal functions of EmONC services.⁵ It categorized basic EmONC health facilities as partially functional if they were able to provide at least one of the seven basic EmONC signal functions. It categorized comprehensive EmONC health facilities as partially functional if they were able to perform at least one of seven basic EmONC signal functions and at least one of two comprehensive EmONC signal functions in the 6 months before the date of the survey (Ebener 2016). The analysis calculated the relative density of facilities providing fully functional EmONC (per 1,000 pregnant women within an LGA) by using the number of facilities ready to provide full comprehensive or basic EmONC services and the estimated number of pregnant women in an LGA. **Table 1** summarizes the data types and sources.

² The MCSP analysis used data from all of the health facilities in this assessment. They included (1) full coverage of tertiary and secondary public facilities, and a random sample of primary public facilities; (2) a random sample of secondary and primary private facilities (no tertiary facilities existed); and (3) full coverage of secondary and primary faith-based facilities (no tertiary facilities existed) (Ebener 2016).

³ This indicator was selected because access to improved water sources has been shown to increase a community's access to sanitation, and "safe water reduces exposure to pollution, disease, and harmful contaminants, thereby promoting health and wellbeing" (Yale University 2018).

⁴ The administrative structure of Nigeria has states and LGAs at respective subnational levels.

⁵ Functionality of EmONC services was determined based on the total number of signal functions assessed at each facility. The seven basic EmONC signal functions were: administer parenteral antibiotics; administer uterotonic drugs (i.e., parenteral oxytocin); administer parenteral anticonvulsants for pre-eclampsia and eclampsia; manually remove the placenta; remove retained products (e.g., manual vacuum extraction, dilation and curettage); perform assisted vaginal delivery (e.g., vacuum extraction, forceps delivery); perform basic neonatal resuscitation (e.g., with bag and mask). Full comprehensive EmONC functionality included all seven basic signal functions plus surgery (e.g., cesarean section) and blood transfusion. A categorical variable was created based on the number of signal functions: no EmONC signal functions; partially functional basic EmONC (at least one of seven of the basic functions); partially functional comprehensive EmONC (at least one of seven basic functions and one of two additional comprehensive functions); fully functional basic EmONC (all seven functions); and fully functional comprehensive EmONC (all nine functions) (Ebener 2016).

Table 1: Data types and sources used in analysis

Data Type	Description	Source
Health facility survey data	A composite score for each facility based on its ability to provide EmONC, converted into a categorical variable	MCSP health facility assessment
Raster data: spatial modeled surfaces for selected SEP proxy indicators	A standard set of spatially modeled map surfaces for selected SEP indicators from recent population-based DHS (2013 for Nigeria)	DHS Spatial Data
Shapefiles for administrative boundaries of Nigeria	Kogi and Ebonyi state and district shapefiles extracted from United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) database last updated in 2016	UN OCHA
Spatial analysis	Description	Sources
Spatial cluster analysis (Getis-Ord General G)	Cluster analysis tool that measures the degree of clustering for either high values or low values using the Getis-Ord general G statistic	Extension within ArcMap 10.5

Analytical Approach

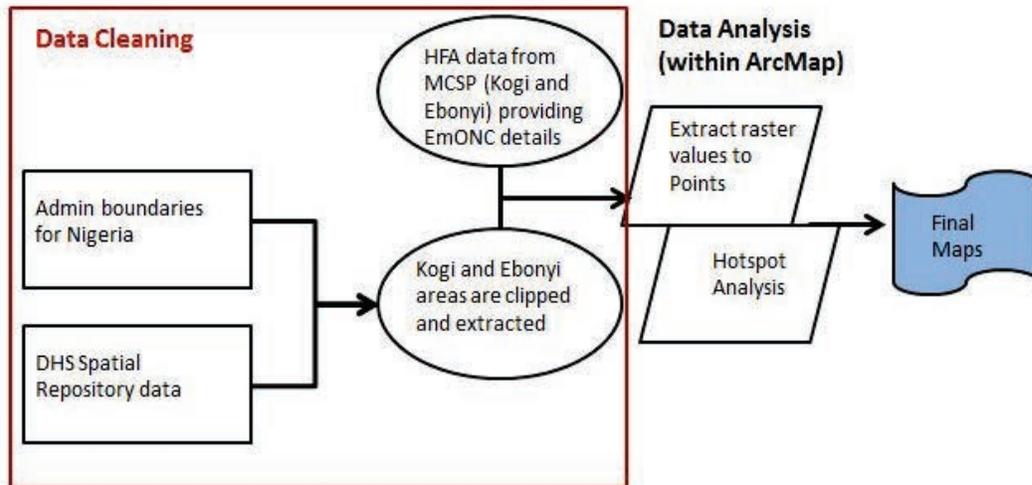
First, the analysis explored the SEP proxy indicators from the DHS spatially modeled surfaces to identify the distribution of underlying population SEP characteristics in Kogi and Ebonyi states. Among the indicators in the DHS wealth index for Nigeria in 2013, the only available modeled surface indicators were households using an improved water source and households without access to a toilet facility. For this analysis, households using an improved water source served as the proxy SEP indicator because there was not sufficient spatial variation in the households without access to a toilet indicator. Furthermore, households with improved water source is a broader measure of the likely SEP characteristics of a household (Cha et al. 2017; Pullan et al. 2014; Aiga and Umenai 2002). Maps of the modeled surface spatial raster data for the proxy indicators for the two states are included in **Appendix A**.

Next, the analysis linked the SEP indicator and the facility location datasets by extracting the DHS spatial (raster) data at the locations of the health facilities, which were geotagged during the facility assessment. Administrative boundary data for the states and LGAs, drawn from the health facility survey, were also mapped (Ebener 2016). Using the DHS SEP proxy indicator data combined with the geotagged facility assessment data, the analysis estimated the relative SEP level of the population surrounding a health facility as measured by the SEP proxy variable (i.e., households using an improved water source). Analysts conducted a hotspot analysis—a spatial technique that assesses extremely high and low values—using the SEP proxy indicator in the two states.

The analysis then mapped the geographic differences in the distribution and functionality of facilities providing EmONC services; the purpose of this was to determine if there was geographic clustering of facility readiness to provide functional EmONC. Analysts combined the map displaying EmONC functionality per facility with the LGA-level EmONC density data.

Finally, the analysis combined the geospatial maps of LGA-level EmONC facility density and the SEP proxy indicators hotspot distribution to identify patterns in EmONC availability and the estimated SEP of the population surrounding a given facility. Analysts used ArcGIS 10 to conduct the analysis. **Figure 1** summarizes the analytical approach.

Figure 1: Analytical approach flow chart



Analytical Outputs

This section presents the outputs of the different phases of the analysis, highlighting their implications for the analysis questions. (See **Appendix B** for enlarged versions of the maps below.)

Availability and Functionality of EmONC Services

Within Kogi and Ebonyi states, availability of EmONC varied widely when measured by the density of EmONC facilities (**Figure 2**). Most LGAs had few facilities capable of providing functional EmONC services (**Figure 3**). Overlaying the facility-specific EmONC categorization data on the EmONC density map shows that overall EmONC functionality was low at the time of the facility assessment, with both states showing evidence of clustering of facilities with no EmONC signal functions.

Figure 2: Density of EmONC availability in Kogi (L) and Ebonyi (R) states

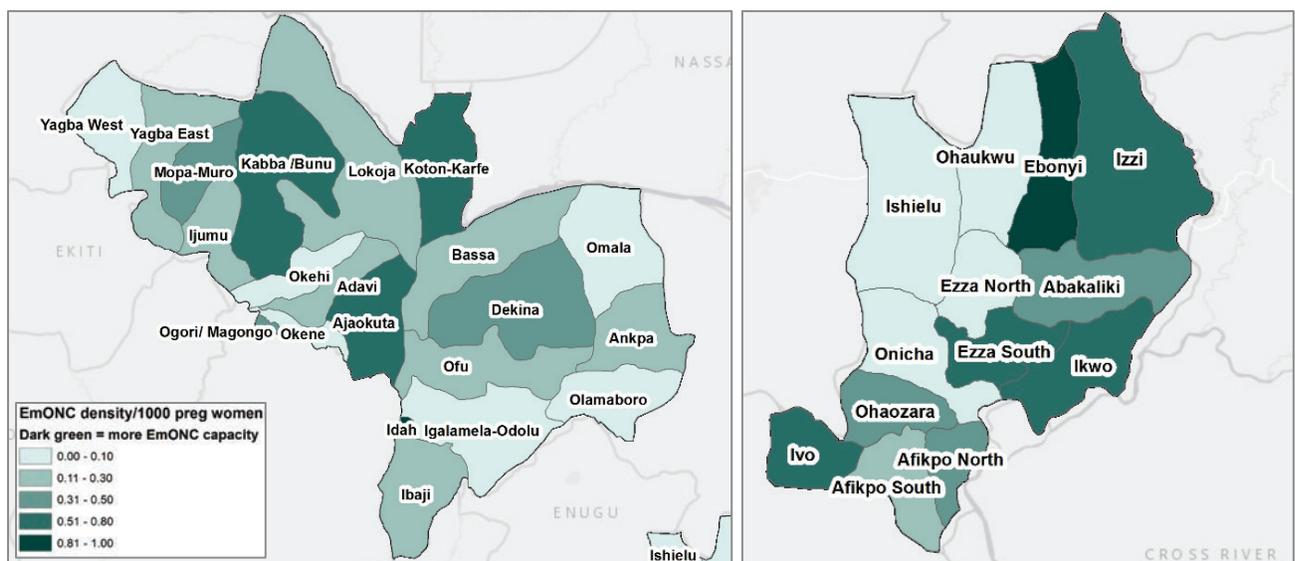
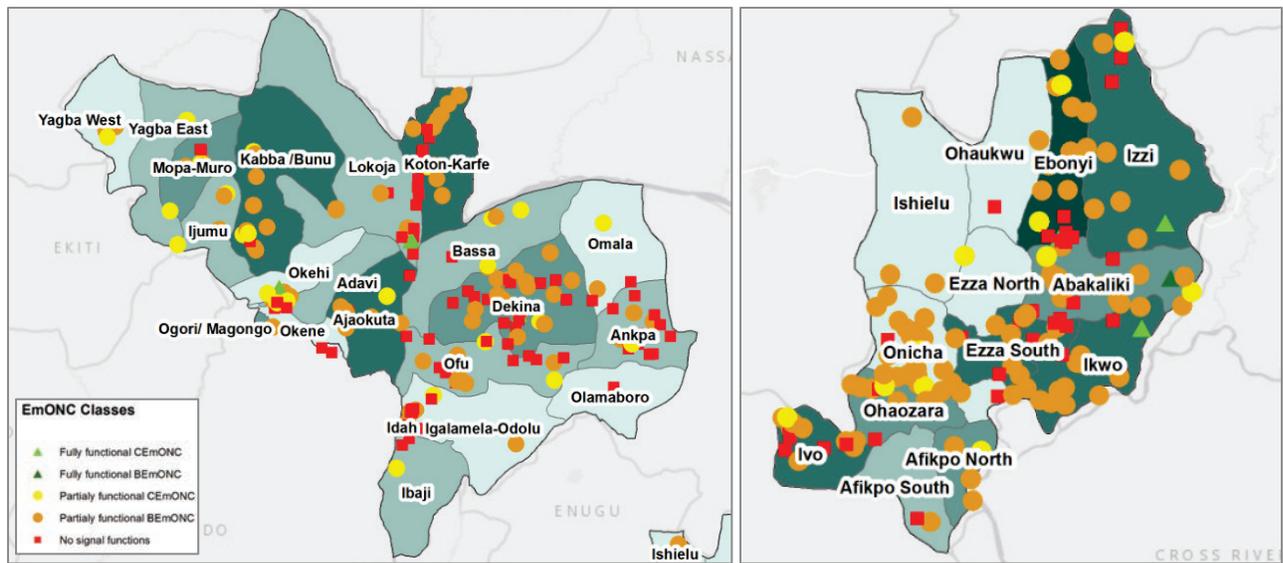


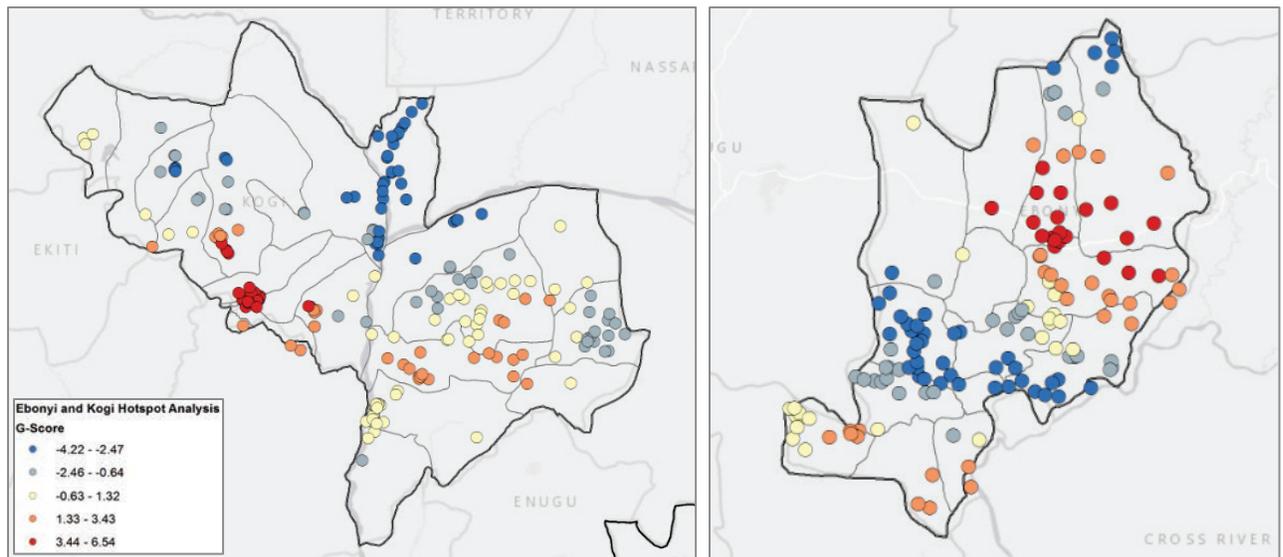
Figure 3: Facility EmONC classification overlaid with LGA-level EmONC density in Kogi (L) and Ebonyi (R) states



Geographic Variation in SEP

The next stage of analysis determined the likely average SEP of households with women of reproductive age that were included in the DHS in the area surrounding a given health facility. **Figure 4** shows the distribution of below-average (blue) and above-average (red) hotspots (at the location of the facility) in coverage of households with an improved water source. The mapping shows distinct clustering of areas of high and low coverage in both states, revealing potential socioeconomic differences among LGAs within each state.

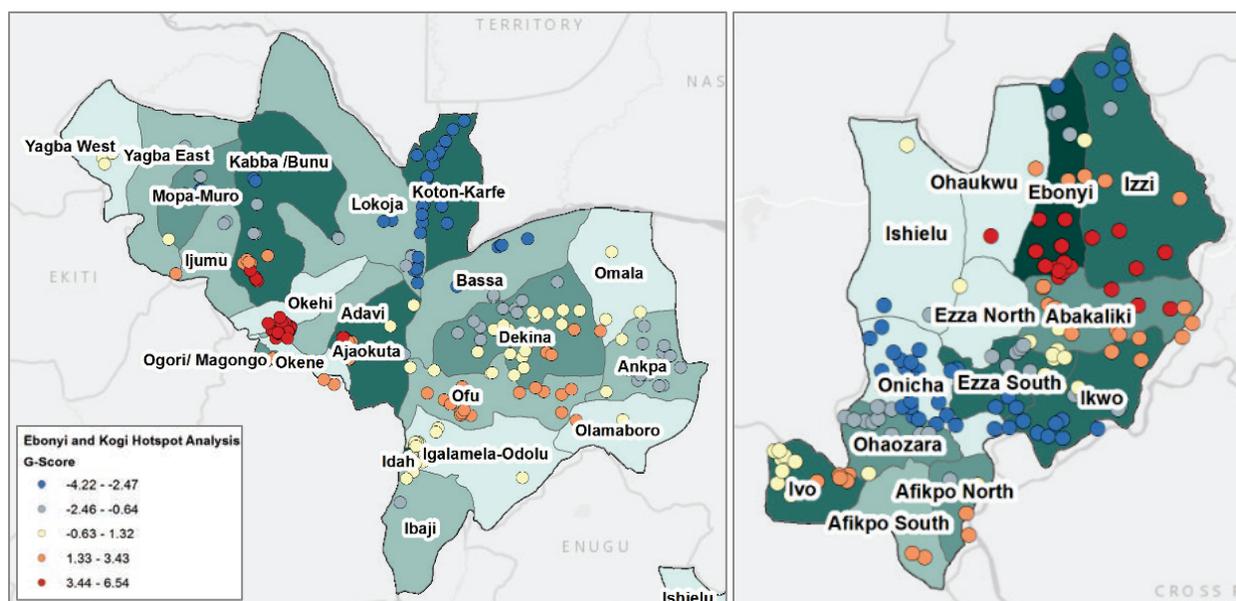
Figure 4: Hotspot analysis of households with improved water in Kogi (L) and Ebonyi (R) states



Combining Service Availability and SEP Data

Combining the data on LGA-level EmONC density and the SEP proxy hotspot analysis showed that EmONC services appear to be available in areas of both higher and lower household SEP (red and blue hotspots, respectively) (Figure 5). For example, in Ebonyi state, one LGA (Ebonyi) with the highest availability of EmONC services (darkest green) appears to have households with relatively high SEP near assessed facilities. Conversely, in Kogi state, one LGA (Koton-Karfe) with the highest availability of EmONC services (darkest green) appears to have households with relatively low SEP near assessed facilities. Furthermore, both states had LGAs with low availability of EmONC services that had populations of both relatively high and relatively low SEP (e.g., Dekina LGA in Kogi and Afikpo North LGA in Ebonyi). Hence, with MCSP working to improve the availability of high-quality EmONC services in the facilities in these LGAs, there are opportunities for increasing facility-level access to care across areas with lower SEP.⁶

Figure 5: Combined hotspot analysis of improved water source overlaid with LGA-level EmONC density in Kogi (L) and Ebonyi (R) states



Limitations

This analysis describes a method for determining the relative SEP of households surrounding a given health facility in the absence of detailed individual- or household-level data on SEP. Although this method can help elucidate some patterns in the SEP of potential program beneficiaries, it is not a substitute for calculating comprehensive measures of SEP (e.g., wealth index) using detailed data on targeted beneficiaries. In addition, the analysis assumes that pregnant women would access services at a facility reasonably close to them, which may not hold true given the factors that influence a patient's care-seeking decisions (Banke-Thomas et al. 2017; Babalola and Fatusi 2009). Another limitation is that DHS modeled surfaces have greater uncertainty in urban areas due to greater heterogeneity in coverage; while both states in this study are predominantly rural, this limitation should be considered in interpreting findings in more densely populated areas. Finally, the use of a single proxy for SEP could have masked other inequities that might exist in both states. For example, the analysis clearly shows areas in which there are fewer facilities. Therefore, inequities in physical access to facilities may exacerbate inequities among individuals desiring to seek services.

⁶ Demand generation and demand-side constraints such as transport and out-of-pocket costs also must be addressed with supply-side strengthening to increase physical access to EmONC services.

Implications for Programming and Further Analyses

The findings and implications from the different stages of this analysis show that the MCSP-supported EmONC facilities cover a population diverse in SEP (as measured via proxy) in Ebonyi and Kogi states in Nigeria. However, extensions of this analysis could reveal additional insights:

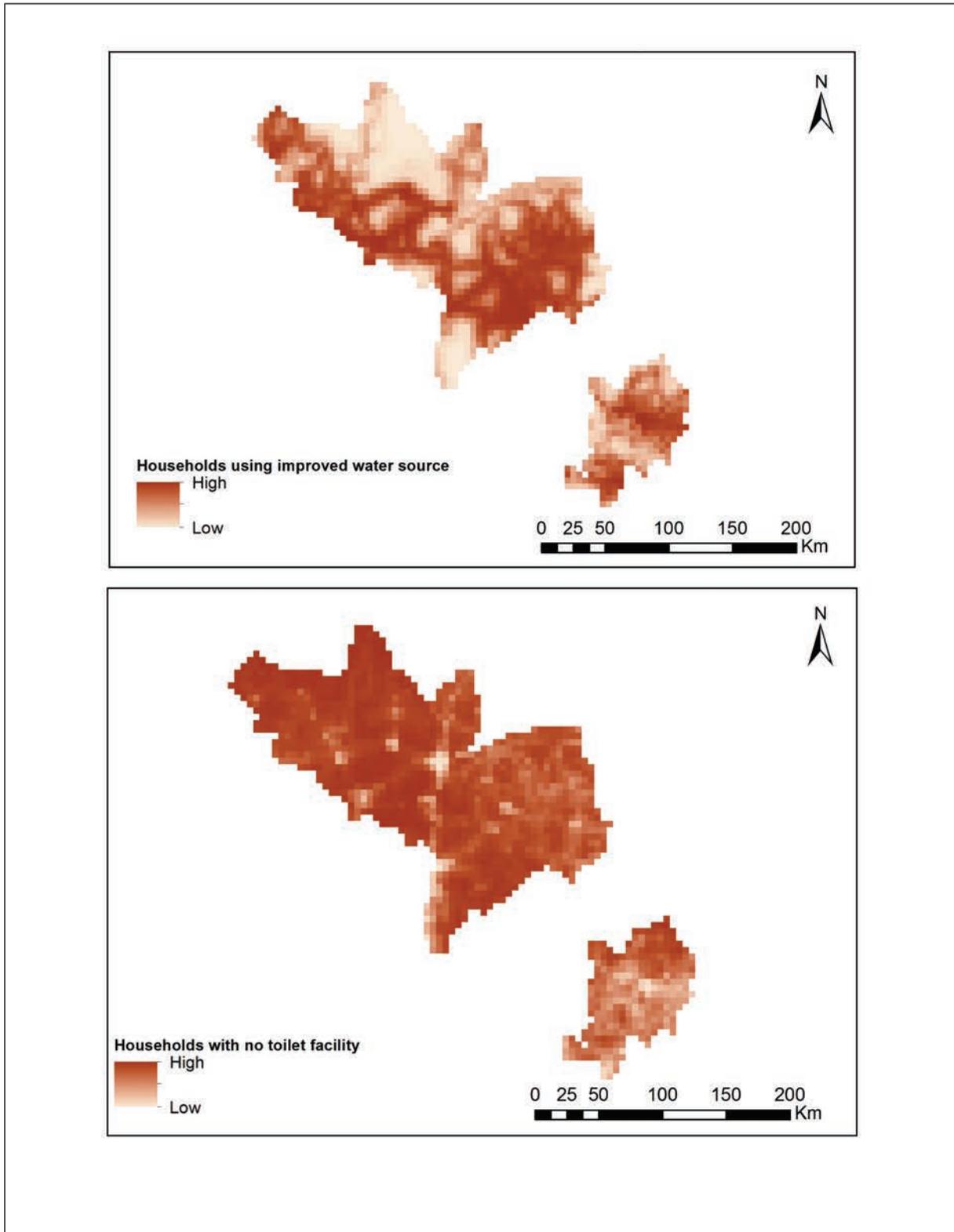
- An assessment of MCSP's contributions to improve EmONC functionality over time against variation in the SEP of surrounding populations would show whether the program was able to provide high-quality services to more disadvantaged populations.
- Knowing the SEP of the populations near facilities could help to highlight potential differences in service utilization by variation in underlying SEP characteristics.
- An exploration of the relationship between other SEP proxy variables and service availability or utilization could reveal different patterns of inequities. Other SEP proxy indicator modeled surfaces from DHS include populations living in households without access to toilet facility and women who are literate.

Given the challenges of collecting detailed SEP data on potential program beneficiaries, program planners might benefit from using geospatial data on proxy SEP indicators to find inequity patterns. This analysis showed that using a geospatial SEP proxy indicator with an imputed value for a given facility could reveal potential characteristics of the population surrounding the facility. **With pro-equity approaches at the forefront of many interventions, an initial exercise like this could help identify disadvantaged areas at the beginning of a program. This information could help programs identify facilities that are more likely to reach the disadvantaged—especially in rural areas (given the limitations of interpreting DHS modeled surfaces in urban areas).**

If additional data on service availability or quality are available, overlaying SEP geospatial data and service availability/readiness data could help reveal where there might be the concurrent challenges of strengthening service delivery and trying to reach disadvantaged populations. The combination of different kinds of geospatial data, therefore, can help to reveal distinct patterns related to SEP and service availability. This type of analysis adds another dimension to program planning and enables the investigation of deeper questions about relationships and assumptions in programming. For example, do the patterns in one community resemble patterns elsewhere in the country, and do these patterns change over time? These techniques are not purely predictive of the location of populations with lower SEP; they can help fill a data gap in a relatively rapid and efficient manner. With the lessons from this exploratory analysis, analysts could apply this technique to other reproductive, maternal, child, and adolescent health services.

Appendix A: DHS Modeled Surface Data of SEP Proxies

Figure I (enlarged): Spatial raster data of SEP proxy indicators from DHS modeled surfaces for Kogi and Ebonyi states (Kogi top left; Ebonyi bottom right)



Appendix B: Enlarged Figures

Figure 2 (enlarged): EmONC density per 1,000 pregnant women in Kogi and Ebonyi states

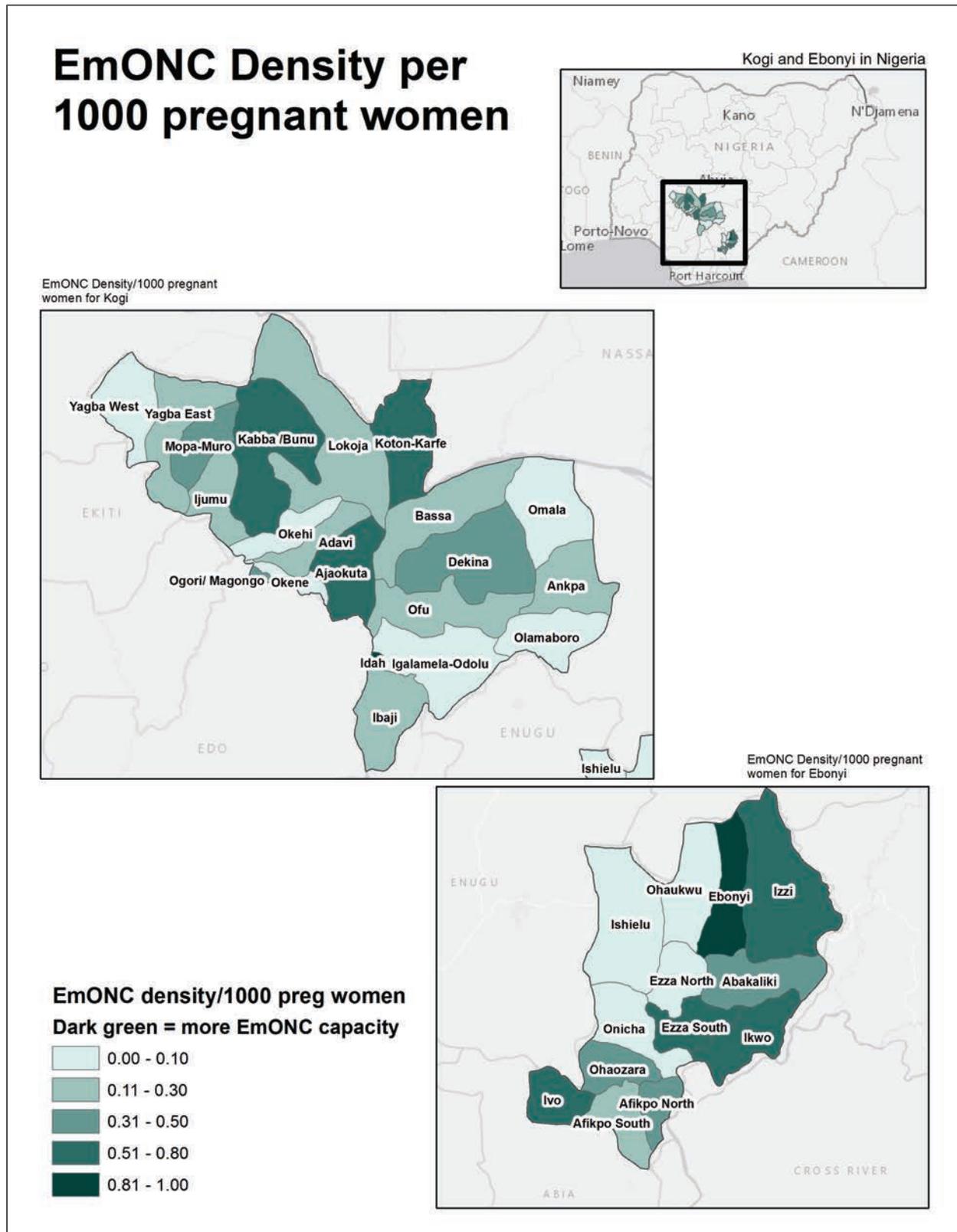


Figure 3 (enlarged): Facility EmONC classifications overlaid on LGA-level EmONC density in Kogi and Ebonyi states

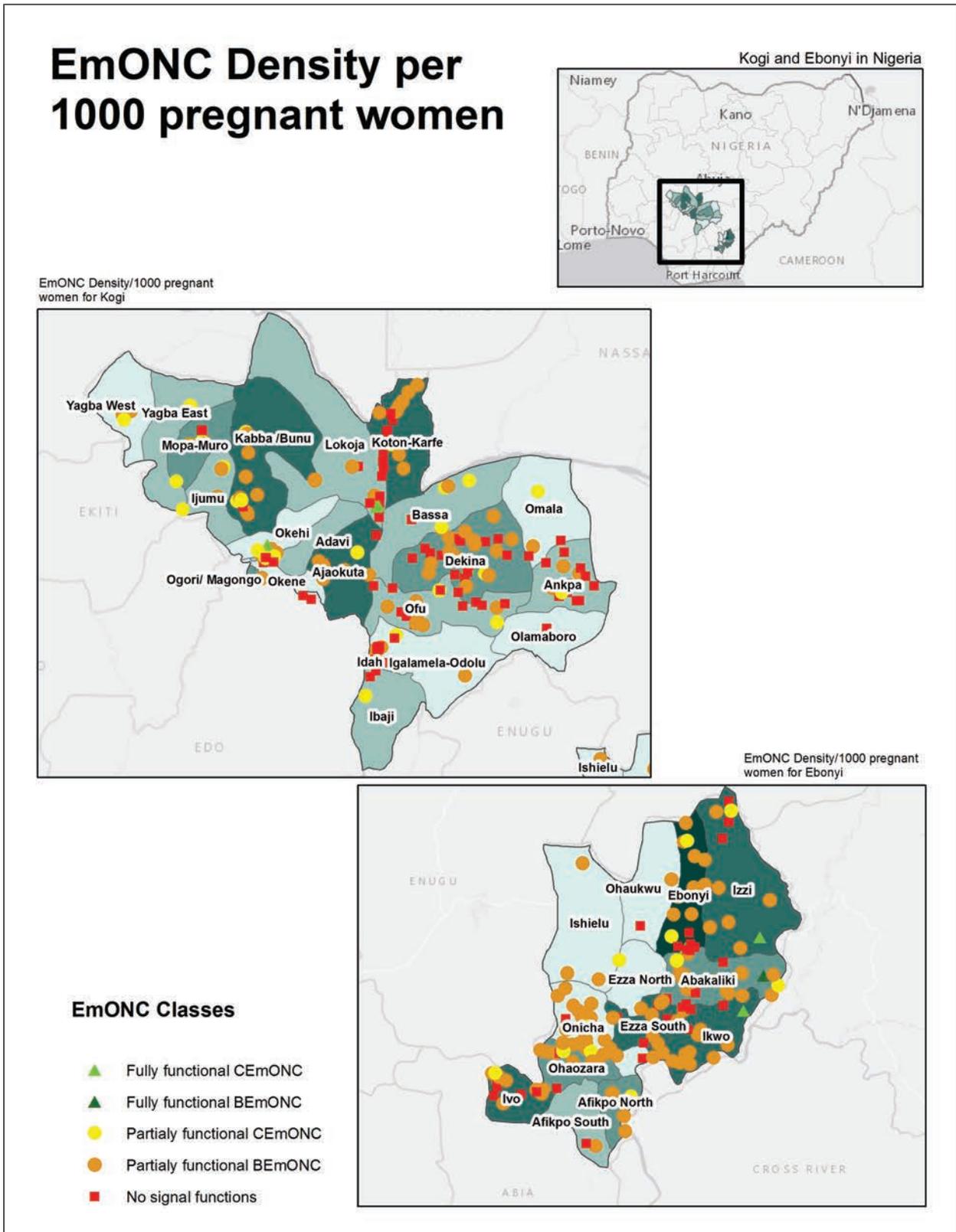


Figure 4 (enlarged): Hotspot analysis of households with improved water source in Kogi and Ebonyi states

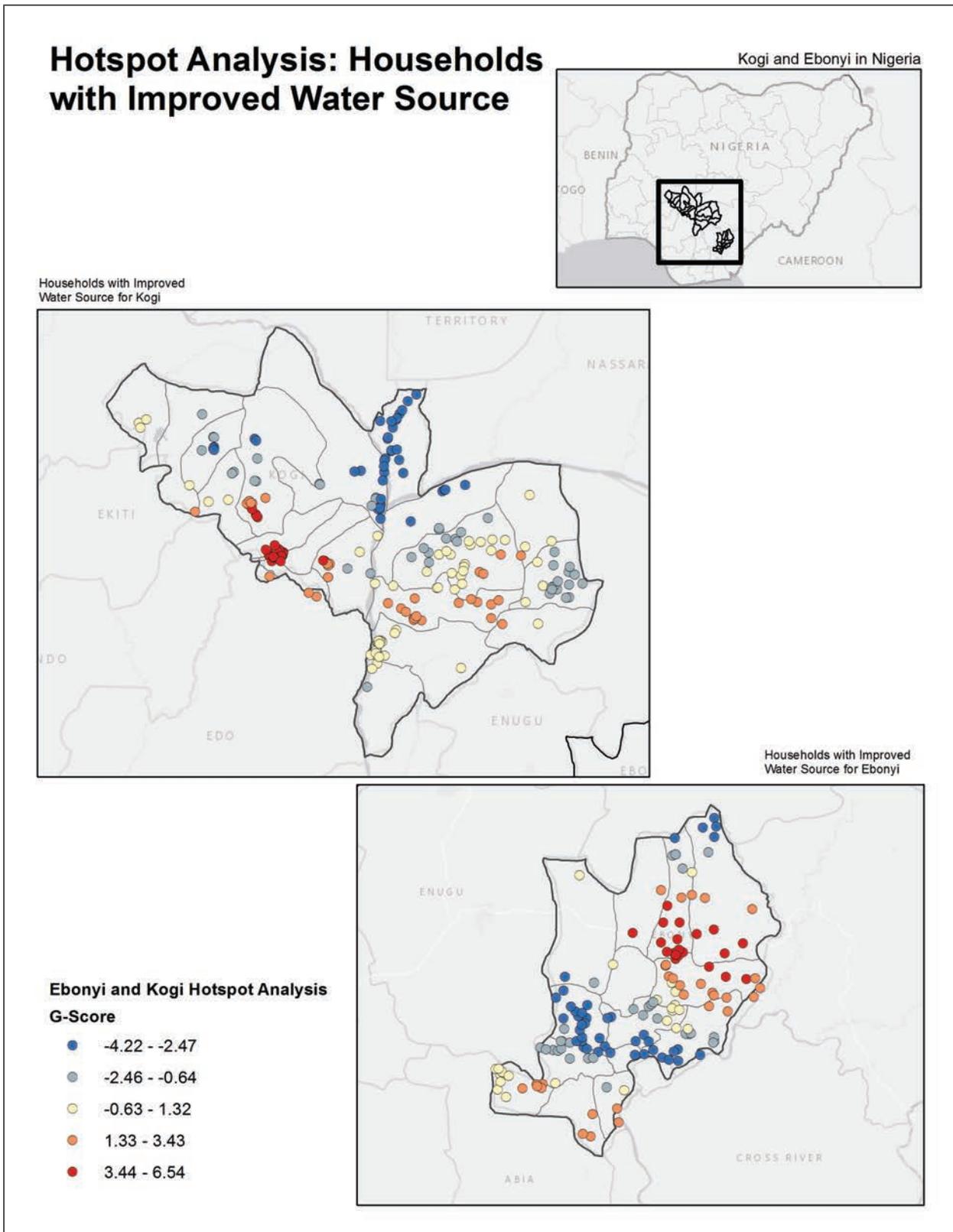
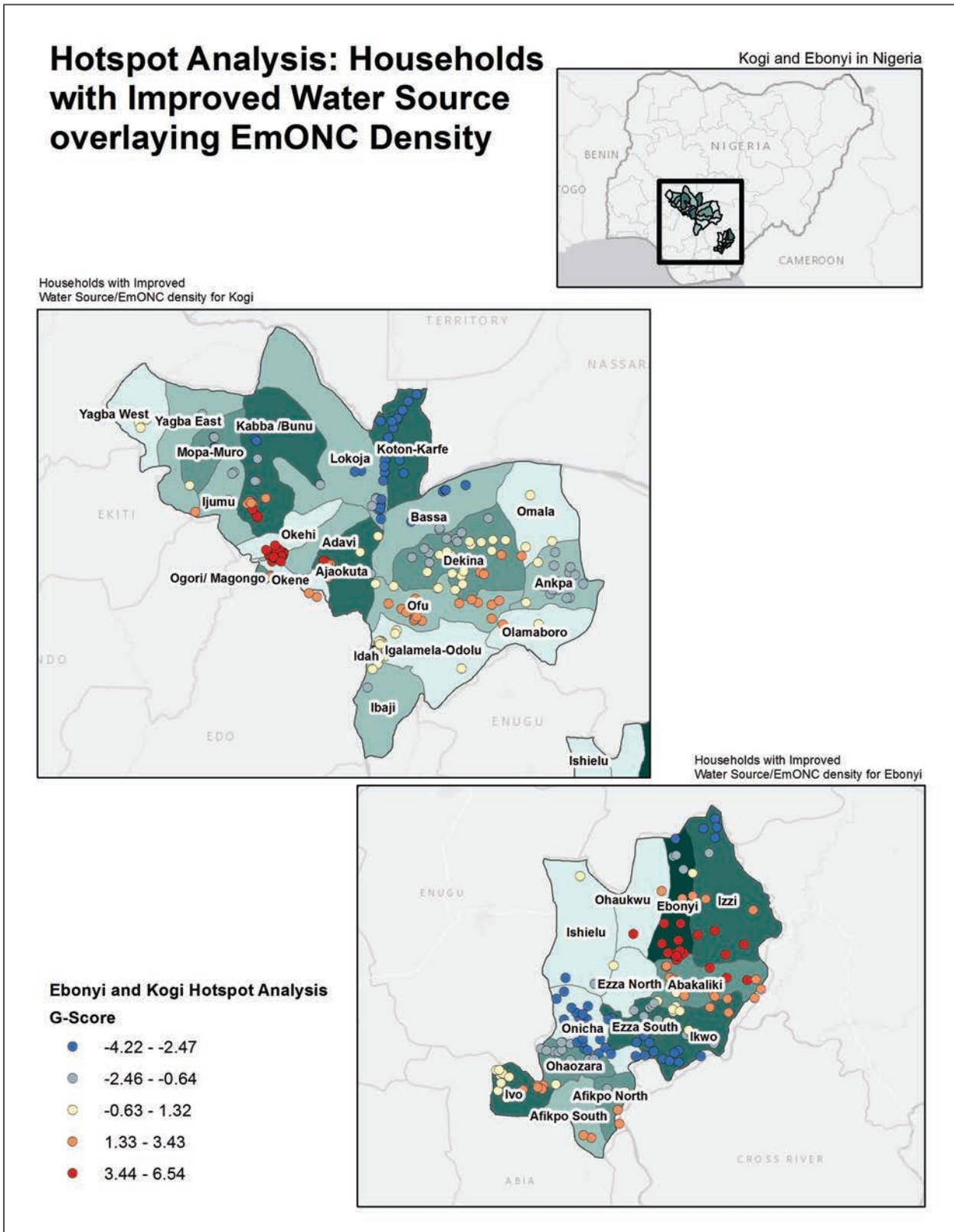


Figure 5 (enlarged): Hotspot analysis of households with improved water source overlaid on LGA-level EmONC density in Kogi and Ebonyi states



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