DATA NOTE

Curating maternal, neonatal and child health (MNCH) datasets for spatiotemporal data analytics [version 1; peer review: 1 approved with reservations]

Moses Effiong Ekpenyong ^{1,2}, Patience Usoro Usip¹, Kommomo Jacob Usang¹, Nnamso Michael Umoh¹, Samuel Bisong Oyong¹, Chukwudi Obinna Nwokoro¹, Aminu Alhaji Suleiman ³, Kingsley Attai ⁴, Anietie Emmanuel John¹, Inyang Abraham Clement¹, Ekemini Anietie Johnson¹, Temitope Joel Fakiyesi¹

¹Department of Computer Science, University of Uyo, Uyo, Akwa Ibom, 520003, Nigeria

²Centre for Research and Development, University of Uyo, Uyo, Akwa Ibom, 520003, Nigeria

³Department of Computer Science, Abdu Gusau Polytechnic, Gusau, Zamfara, Nigeria

⁴Department of Computer Science, Rittman University, Ikot Ekpence, Akwa Ibom, Nigeria

V1 First published: 10 Feb 2022, 11:166
<https://doi.org/10.12688/f1000research.73822.1>
Latest published: 10 Feb 2022, 11:166
<https://doi.org/10.12688/f1000research.73822.1>

Abstract

We provide in this Data Note the details of maternal, neonatal and child health (MNCH) datasets curated directly from patients' medical records; comprising 538 maternal, 720 neonatal and 425 child records, captured at St Luke's General Hospital, Anua, Uyo, Nigeria, from 2014 to 2019. Variables included in the datasets are gender, age, class of patient (mother/infant/child), LGA (local government area), diagnosis, symptoms, prescription, blood pressure (mm Hg), temperature (degree centigrade), and weight (Kg). The purpose of this publication is to describe the datasets for researchers who may be interested in its reuse (for analysis, research, quality assurance, policy formulation/decision, patient safety, and more). The curated datasets also involved the capturing of location information (GPS: global positioning system data) from the study area, to aid spatiotemporal and informed demographic analysis. We detail the methods used to curate the datasets and describe the protocol of variables selection and processing. For reasons of data privacy, some patients' personal information such as names were replaced with patient numbers (a sequence generated using Microsoft Excel). Furthermore, the addresses/locations of the patients, date of visit, latitude, longitude, elevation, and GPS accuracy are restricted. Restricted data can be made available to readers after a formal request to the corresponding author (see data restriction statement). The curated datasets are available at the [Open Science Framework](#).

Open Peer Review

Approval Status ?

1

version 1

10 Feb 2022

view

1. **Peter M. Macharia** , KEMRI-Wellcome

Trust Research Programme, Nairobi, Kenya

Lancaster University, Lancaster, UK

Any reports and responses or comments on the article can be found at the end of the article.

Keywords

context-aware system, robust decision support, GeoAI, healthcare indicator, location-based information, MNCH data

This article is included in the **Health Services** gateway.

Corresponding author: Moses Effiong Ekpenyong (mosesekpenyong@uniuyo.edu.ng)

Author roles: **Ekpenyong ME:** Conceptualization, Data Curation, Methodology, Project Administration, Supervision, Validation, Writing – Original Draft Preparation, Writing – Review & Editing; **Usip PU:** Conceptualization, Data Curation, Funding Acquisition, Methodology, Project Administration, Supervision, Writing – Original Draft Preparation; **Usang KJ:** Data Curation, Funding Acquisition; **Umoh NM:** Data Curation, Funding Acquisition, Investigation, Methodology, Validation, Writing – Original Draft Preparation, Writing – Review & Editing; **Oyong SB:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Nwokoro CO:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Suleiman AA:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Attai K:** Data Curation, Formal Analysis, Methodology, Validation, Writing – Original Draft Preparation; **John AE:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Clement IA:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Johnson EA:** Data Curation, Investigation, Validation, Writing – Original Draft Preparation; **Fakiyesi TJ:** Data Curation

Competing interests: No competing interests were disclosed.

Grant information: This work was supported by The Tertiary Education Trust Fund (TETFUND), Nigeria.
The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Copyright: © 2022 Ekpenyong ME *et al.* This is an open access article distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

How to cite this article: Ekpenyong ME, Usip PU, Usang KJ *et al.* **Curating maternal, neonatal and child health (MNCH) datasets for spatiotemporal data analytics [version 1; peer review: 1 approved with reservations]** F1000Research 2022, 11:166
<https://doi.org/10.12688/f1000research.73822.1>

First published: 10 Feb 2022, 11:166 <https://doi.org/10.12688/f1000research.73822.1>

Introduction

Access to health services is essential for promoting health equity and quality of life (dos Anjos Luis & Cabral, 2016). Hence, knowledge of health facilities is crucial for providing informed health planning decisions. Furthermore, available health datasets such as the one presented in this publication show that some patients travel long distances to access health facilities, with the urban areas holding very high concentration of patients' population per facility. Oleribe *et al.* (2019) identified financial barrier, poor governance and limited infrastructure, as major factors mitigating access to quality healthcare, typical of sub-Saharan Africa. Situating these factors to the patients' domain in a country such as Nigeria, reveals the following mitigating factors: finance (poor living condition), increased security threat, type and nature of ailment, geography of residence, race and ethnicity, gender, age, language, and disability. These factors significantly determine the degree at which medical/healthcare services – including availability, timeliness, convenience, and affordability, are utilised (Babalola & Fatusi, 2009). Adoption of modern technology has however simplified healthcare services through the implementation of automated systems. For instance, the integration of electronic health records and predictive intelligence (e.g., smart technology) into healthcare services have achieved efficient, accurate storage and retrieval of patients' records, as well as intelligent data-driven analysis, prediction, and visualisation (Tian *et al.*, 2019).

Unlike developed nations, health facilities in low- and medium-income countries such as the sub-Sahara African region are overly stressed, generating a large pool of manually unstructured and inconsistent data that defies real-time, patient-centred care. Furthermore, the reduced health budget has decreased government's efforts in establishing new healthcare centres to equate the present population growth, hence, increasing the establishment of privately owned healthcare centres, premised on business and which services are not conducive to patients in terms of cost. Even though availability of health facilities is often prioritised over accessibility by decision makers (Tuba *et al.*, 2010), Mishra *et al.* (2019) maintained that geographic accessibility and availability of healthcare facilities are essential parameters in determining the quality of care received, as analysis of both parameters could reveal useful patterns and trends for providing a more robust health system that derives patient-centred care. Patient-centred care (Epstein & Street, 2011) empowers patients to actively participate in their care with physicians and other healthcare providers connecting with patients to effectively address patients' needs. In providing such a service, location-based information, and details of every parameter within the health system should be available in real-time. Also, collaboration between the necessary stakeholders (physicians and other healthcare providers, government, patients) is necessary and can be enabled using geospatial artificial intelligence (GeoAI) (VoPham *et al.*, 2018; Boulos *et al.*, 2020). GeoAI combines spatial science methods such as GIS (geographic information system), data mining, and high-performance computing to extract meaningful knowledge from spatial big data (VoPham *et al.*, 2018;

Janowicz *et al.*, 2020). By integrating machine learning into ArcGIS, GeoAI offers intelligent context-aware models for accurate location-allocation (e.g., assignment of healthcare facilities) and robust healthcare decisions modelling.

We demonstrate in this publication the importance of unstructured data processing to achieve semi-structured maternal, neonatal and child health (MNCH) datasets curated directly from patients' medical file/records, to support intelligent health data mining, informed policy planning and robust decision support system design.

The following constitute our expected hypotheses on the applications of our datasets:

- MNCH datasets would encourage the development of resources for the sub-Saharan African region and advance future research progress in the medical/healthcare system of Nigeria.
- MNCH datasets would drive integrated GeoAI applications for robust spatiotemporal data analysis.
- MNCH datasets would support decision systems with suitable ontologies or knowledge representations, to drive intelligent data analytics.

A study using the MNCH datasets is Usip *et al.* (2021), which developed a preposition-enabled parser that extracts prepositions from clinical notes to visualise unstructured patients' data using generated location items such as noun phrase, geolocation, and place name.

Materials and methods

Ethical approval

Ethical clearance was granted by the University of Uyo Health Research Ethics Committee (UNIUYO-HREC) – Ref. number: UU/CHS/IHREC/VOL.I/017 with the acceptance that the study did not require direct contact with patients.

Data source, sample size and capturing procedure

The source of the datasets is patients' medical records/files retrieved from the St Luke's General Hospital, Anua, Uyo, Akwa Ibom State, Nigeria (the healthcare facility), between 2014 and 2019. The study subjects were randomly selected through physical inspection of the patients' records (or file bundles) manually stored in the hospital's file cabinets or archives. To facilitate this exercise, informed consent was processed through the Chief Medical Director of the hospital, to retrieve the required data. This permission was granted, and logistics were put in place to commence the exercise. The investigators did not have access to the records room or (patients' population) archive. Only files selected by the responsible officers assigned by the Chief Medical Director of the hospital were presented to the investigators. Before giving the files to the investigators for attributes capture, the officers glossed through the files to ensure that the primary attributes of the study (see Table 1) are satisfied.

Table 1. Description of maternal, neonatal and child health (MNCH) data capture template.

Attribute	Description
Date of visit	Date patient visited the hospital
Gender	Gender of patient
Age	Age of patient
Class of patient	Age classification (Mother, Infant or Child)
Address	Home address or location of the patient
Symptom	The cause of the ailment
Diagnosis	Outcome of the examination of patient
Prescription	Administered therapy/drug
Health history	Health history of patient
Health status	Health status of patient (Apgar score), (Finster <i>et al.</i> , 2005)
Blood pressure	Blood pressure of patient in millimetre per mercury (mm/Hg)
Temperature	Temperature of the patient in degree centigrade (°C)
Height	Height of patient in centimetres (cm)
Weight	Weight of patient in kilogrammes (Kg)

To capture the primary attributes for maternal, neonatal and child health, a data template (a table with attributes of the study), was designed with ethical considerations in mind. No sensitive information such as patient's name was captured. Furthermore, patient's location/address was truncated by removing street number, to avoid privacy and security implication. Maternal health data template had the following attributes (Date of visit, Gender, Class of patient [mother/infant/child], Address, Symptom, Diagnosis, Prescription, Blood pressure, Temperature, Weight). Neonatal health data template had the following attributes (Date of visit, Gender, Age, Class of patient, Address, Symptom, Condition, Height, Weight). Child health data template had the following attributes (Date of visit, Gender, Age, Class of patient, Address, Diagnosis, Health history, temperature, Weight). The description of these attributes is tabulated on [Table 1](#).

The total sample of data retrieved (before processing) included maternal (1063), neonatal (1367) and child patients (826), covering the 3 senatorial districts of Akwa Ibom State namely Uyo, Ikot Ekpene and Eket, and the 31 local government areas (LGAs) as presented on [Table 2](#).

Geolocation capture and data processing

To enable the support of GeoAI services, additional attributes were collected by visiting the respective study locations. The visited locations were those associated with the collected

Table 2. Senatorial districts and local government areas of captured data. LGA=local government area.

Senatorial Districts	LGA	Number of LGA
Uyo	Uyo, Itu, Uruan, Etinan, Ibiono Ibom, Nsit Ibom, Nsit Ubium, Nsit Atai, Ibesikpo Asutan	9
Eket	Eket, Ikot Abasi, Mkpato Enin, ONNA, Eastern Obolo, Esit Eket, Ibeno, Okobo, Mbo, Oron, Udung Uko, Urue Offong Oruko	12
Ikot Ekpene	Ikot Ekpene, Abak, Obot Akara, Ika, Ukanafun, Etim Ekpo, Ini, Ikono, Oruk Anam	10
	Total:	31

data. The UTM Geo Map, a simple android application for coordinates capture, GIS, and Spatial analysis was deployed for this purpose. The UTM Geo Map app can be downloaded from the Google play store, and has several modules, but the Map Coordinates module, which maps coordinates in real-time was used to capture the respective location coordinates. The process for obtaining the location coordinates (latitude and longitude) using the UTM Geo Map app are summarised as follows:

Step 1: Launch the UTM Geo Map app when in the vicinity of patient address

Step 2: Select *Map Coordinates*

Step 3: Select *Goto GPS Location* (this step gives the real-time location of the mobile device with GPS accuracy in meters appearing on the screen. Ensure that the GPS accuracy is within an acceptable range).

Step 4: Select *Mark*. A request to enter the Point Name will pop up. Enter the point name or address of the patient

Step 5: Select *Save*. Each saved point is stored on the mobile device. To transfer the measured data to an external file, there is an *Export tool*, which supports different file formats such as KML, CSV, GPX, DXF, TXT, GeoJSON.

Step 6: Select *Export/Import*, *Export to CSV*, type in a filename with ".csv" extension.

Step 7: Select *Save*.

The exported file format used in this publication is the CSV format, and the columns (attributes) extracted are described in [Table 3](#). A GPS accuracy range of 1 – 9.65 metres (i.e., how close the device's calculated position is from the truth, expressed as a radius), was used as an acceptable accuracy range for this publication. A lower GPS accuracy defines the precision of the patient location. The coordinates capturing was carried

out by doctoral students, using different mobile devices. Where the GPS accuracy was too high, such location was recaptured and tuned to the acceptable accuracy range. Due to ethical reasons, we are only interested in the vicinity of the patient, hence the defined accuracy range.

To clearly mark the location boundaries of patients and geographically localise them within a local government unit, the address column was further split to form an additional attribute, called the LGA. Location attributes documented as part of the datasets include Latitude, Longitude, Elevation, Date recorded, and GPS accuracy. For this publication, we were only

able to provide location data for patients within the Uyo metropolis, hence, resulting in a total of 1683 MNCH records and distributed as follows: maternal=538, neonatal=720, child=425. We hope to cover other senatorial districts as soon as future funding is available.

At the end of the data capturing exercise, the data template was converted into electronic format using Microsoft Excel, and manually merged with the geolocation records (exported CSV file) from the field (or study locations visited). The first 10 samples of the maternal, neonatal and child health datasets are given in [Figure 1](#), [Figure 2](#), and [Figure 3](#), respectively.

Table 3. Extracted attributes of location coordinates.

Attribute	Description	Sample data	Data type
ID	Identity or point	PT_4 Etuk Allan street itam	Alphanumeric
Latitude	Latitude is the angle ranges from 0° at the Equator to 90° (North or South) at the poles	5.0437963	Numeric
Longitude	Longitude is the measurement east or west of the prime meridian (0–180°) East or west	7.8936366	Numeric
Notes	Descriptive	Null	Alpha
DMS	Degrees, minutes, and seconds	5° 2' 37.67" N 7° 53' 37.09" E	Alphanumeric
UTM	Universal Transverse Mercator	377355.436E557609.59N32N	Alphanumeric
MGRS	Military Grid Reference System	32NLL 77355 57610	Alphanumeric
CRS	Coordinate Reference System	7.8936366 5.0437963	Numeric
CRS Code	Coordinate Reference System code	EPSG:4326	Alphanumeric
Elevation (MSL)	Elevation of Mean Sea Level	69.46	Numeric
Address	Location	Null	Alphanumeric
Date Record	Capture date	Record Date: 2021-05-20 11:11:02	Numeric
GPS Accuracy (m)	Global Positioning System (GPS) Accuracy	3.900000095	Numeric
Photo	Picture of the location	Null	Image

Patient Number	Gender	Age	Class	LGA	Diagnose	Symptom	Prescription	Blood Pressure (mm Hg)	Temperature (Degree C)	Weight (Kg)
M001	Female	29	Mother	Ibesikpo	Malaria	Cough and catarrh	T.T and Drugs	110/70	37.00	69
M002	Female	24	Mother	Ibesikpo	Liquor drainage	Lower abdominal and waist pain	T.T and Drugs	100/60	36.00	71
M003	Female	33	Mother	Ibesikpo	Normal scan result	Lower abdominal and waist pain	T.T and Drugs	100/60	36.00	70
M004	Female	34	Mother	Uyo	Pre Eclampsia	Insomnia and high BP	T.T and Drugs	140/90	37.00	78
M005	Female	32	Mother	Uyo	Normal scan result	Lower abdominal and waist pain	T.T and Drugs	100/70	36.70	65
M006	Female	29	Mother	Uyo	Normal scan result	Lower abdominal and waist pain	T.T and Drugs	100/60	36.00	82
M007	Female	24	Mother	Uyo	Oedema	Swollen legs	T.T and Drugs	110/70	36.20	73
M008	Female	30	Mother	Uyo	Malaria	Cough and catarrh	T.T and Drugs	110/70	36.00	98
M009	Female	34	Mother	Uyo	Eclampsia	High blood pressure	T.T and Drugs	150/90	36.40	70
M010	Female	31	Mother	Uyo	Urinary Tract Infection	Itching body, cough and fever	T.T and Drugs	120/70	36.80	72

Figure 1. Sample maternal health dataset. LGA=local government area.

Patient Number	Gender	Age	Class	LGA	Symptom	Health Status	Height (cm)	Weight (Kg)
N001	Male	1 day	Infant	Uyo	Live male child	Apgar 7/10	51	2.50
N002	Male	3 Hours	Infant	Uyo	Neonatal septicaemia/Neonatal Jaundice	Nil	Nil	3.60
N003	Female	1 Hour	Infant	Uyo	Observation	Nil	Nil	3.80
N004	Female	1 day	Infant	Uyo	Live female twin child	Apgar 8/10	45	2.20
N005	Male	3 Hours	Infant	Uyo	Neonatal septicaemia/Neonatal Jaundice	Nil	Nil	2.50
N006	Male	1/2 Hours	Infant	Ibesikpo	Neonatal Jaundice	Nil	Nil	2.70
N007	Female	1 day	Infant	Ibesikpo	Live female child	Apgar 8/10	50	2.60
N008	Female	1 day	Infant	Uyo	Live female child	Apgar 9/10	50	3.00
N009	Female	1 day	Infant	Ibesikpo	Live female child	Apgar 7/10	47	2.00
N010	Female	1 Hour	Infant	Ibesikpo	Moderate birth asphyxia	Nil	Nil	2.90

Figure 2. Sample neonatal health dataset. LGA=local government area.

Patient Number	Gender	Age	Class	LGA	Diagnose	Health History	Temperature (Degree C)	Weight (Kg)
C001	Female	2 years	Child	Uyo	otitis media	Discharge from left ear	37	15
C002	Female	1 year	Child	Uyo	Heat rash	Nil	37.1	6.7
C003	Female	2 years	Child	Uyo	otitis media	Discharge from left ear	37	15
C004	Female	1 year	Child	Uyo	Heat rash	Nil	37.1	6.7
C005	Male	4 years	Child	Ibesikpo	Urinary Tract Infection	Stomach pain, lower abdominal pain, fever x 3 days	36.6	20
C006	Male	2 years	Child	Uyo	Severe malaria R/Osepsis	severe fever, catarrhcough	38.7	13
C007	Male	3 years	Child	Ibesikpo	Respiratory Tract Infection Funincutosis	Rashes, Cough	37.1	13
C008	Female	10 months	Child	Ibesikpo	malaria + Respiratory Tract Infection	Difficulty in breathing, cough,vomiting, watery stool, fever	36.1	9.5
C009	Male	2 years	Child	Uyo	Severe malaria R/Osepsis	severe fever, catarrh, cough	38.7	13
C010	Male	7 months	Child	Ibesikpo	Acute Respiratory Infection/Conjunctivitis	Cough and eye discharge	36.5	8.8

Figure 3. Sample child health dataset. LGA=local government area.

The dataset can be found as *Underlying data* (Ekpenyong *et al.*, 2021).

Data availability

Underlying data

Open Science Framework: Maternal, Neonatal and Child Health Datasets for Spatiotemporal Data Analytics. <https://doi.org/10.17605/OSF.IO/J9ZH8> (Ekpenyong *et al.*, 2021).

Data are available under the terms of the [Creative Commons Attribution 4.0 International license](#) (CC-BY 4.0).

GPS data

Access to restricted data (GPS data) will be made available to readers after a formal request to the corresponding author (mosesekpenyong@uniuyo.edu.ng) and on the condition that data will be used strictly for research purposes.

Acknowledgements

We extend our gratitude for staff of the St Luke's General Hospital, Anua, and participating doctoral students, for enabling a smooth data capture of the MNCH datasets.

References

- Babalola S, Fatusi A: **Determinants of use of maternal health services in Nigeria—looking beyond individual and household factors.** *BMC Pregnancy Childbirth.* 2009; **9**(1): 43.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
- Boulos MN, Peng G, VoPham T: **An overview of GeoAI applications in health and healthcare.** *Int J Health Geogr.* 2019; **18**(1): 7.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
- dos Anjos Luis A, Cabral P: **Geographic accessibility to primary healthcare centers in Mozambique.** *Int J Equity Health.* 2016; **15**(1): 173.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
- Epstein RM, Street RL Jr: **The values and value of patient-centered care.** *Ann Fam Med.* 2011; **9**(2): 100–103.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
- Ekpenyong ME, Usip PU, Umoh NM, *et al.*: **Maternal, Neonatal and Child Health (MNCH) Datasets for Spatiotemporal Data Analytics.** *Open Science Framework.* 2021.
<http://www.doi.org/10.17605/OSF.IO/J9ZH8>
- Finster M, Wood M, Raja SN, *et al.*: **The Apgar score has survived the test of time.** *Anesthesiology.* 2005; **102**(4): 855–857.
[PubMed Abstract](#) | [Publisher Full Text](#)

Janowicz K, Gao S, McKenzie G, *et al.*: **GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond.** *Int J Geogr Inf Sci.* 2020; **34**(4): 625–636.

[Publisher Full Text](#)

Mishra S, Sahu PK, Sarkar AK, *et al.*: **Geo-spatial site suitability analysis for development of health care units in rural India: Effects on habitation accessibility, facility utilization and zonal equity in facility distribution.** *J Transp Geogr.* 2019; **78**: 135–149.

[Publisher Full Text](#)

Oleribe OO, Momoh J, Uzochukwu BS, *et al.*: **Identifying key challenges facing healthcare systems in Africa and potential solutions.** *Int J Gen Med.* 2019; **12**: 395–403.

[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)

Tian S, Yang W, Le Grange JM, *et al.*: **Smart healthcare: making medical care**

more intelligent. *Global Health Journal.* 2019; **3**(3): 62–65.

[Publisher Full Text](#)

Tuba M, Sandoy IF, Bloch P, *et al.*: **Fairness and legitimacy of decisions during delivery of malaria services and ITN interventions in Zambia.** *Malar J.* 2010; **9**(1): 309.

[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)

Usip PU, Ekpenyong ME, Ijebu FF, *et al.*: **PeNLP Parser: An Extraction and Visualization Tool for Precise Maternal, Neonatal and Child Healthcare Geo-locations from Unstructured Data.** *Deep Learning in Biomedical and Health Informatics.* CRC Press, 2021; 157–181.

[Reference Source](#)

VoPham T, Hart JE, Laden F, *et al.*: **Emerging trends in geospatial artificial intelligence (geoAI): potential applications for environmental epidemiology.** *Environ Health.* 2018; **17**(1): 40.

[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)

Open Peer Review

Current Peer Review Status: ?

Version 1

Reviewer Report 19 December 2022

<https://doi.org/10.5256/f1000research.77502.r157440>

© 2022 Macharia P. This is an open access peer review report distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peter M. Macharia

¹ Population Health Unit, KEMRI-Wellcome Trust Research Programme, Nairobi, Kenya

² Centre for Health Informatics, Computing, and Statistics, Lancaster Medical School, Lancaster University, Lancaster, UK

Sharing such datasets is key for research. It facilitates reproducibility, generation of new research questions to improve the health of community or develop new research approaches. More important, when these datasets have linked location details, additional insights linked to space can be harnessed. I have a few thoughts which I welcome the authors to consider:

- A location map showing the approximate hospital catchment for which the datasets are available. You could also show other facilities in the vicinity, useful for context.
- In addition to the map, provide general details/characteristics of the study area for researchers/potential users of the data but not familiar with Nigeria and the region.
- The introduction has mainly concentrated on health care access aspects of health facilities. However, not much has been said in relation to other key attributes of the data provided. That is, the data provides attributes that spans beyond a discourse of health care access only.
- ArcGIS should be given as an example of a geospatial software among others but not as the only option. Please paraphrase the sentence.
- In the abstract, you state, "The curated datasets also involved the capturing of location information from the study area, to aid spatiotemporal and informed demographic analysis". Should it not be aid in spatial and spatio-temporal analysis?
- As these datasets were refer to between 2014 and 2019, and one envisioned application will be spatio-temporal analysis, a date attribute should be availed on the main database. You can truncate it monthly or quarterly in each year to align with confidentiality guidelines.

- I wonder whether the title could be edited to Maternal, neonatal and child health (MNCH) datasets from a hospital's catchment area in Nigeria between 2014 and 2019?

Is the rationale for creating the dataset(s) clearly described?

Yes

Are the protocols appropriate and is the work technically sound?

Yes

Are sufficient details of methods and materials provided to allow replication by others?

Yes

Are the datasets clearly presented in a useable and accessible format?

Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Geospatial health/spatial epidemiology

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

The benefits of publishing with F1000Research:

- Your article is published within days, with no editorial bias
- You can publish traditional articles, null/negative results, case reports, data notes and more
- The peer review process is transparent and collaborative
- Your article is indexed in PubMed after passing peer review
- Dedicated customer support at every stage

For pre-submission enquiries, contact research@f1000.com

F1000Research